PhD Dissertation

Intelligent Mining and Pattern Recognition of Medical Data for Context Aware Telemedicine Applications

By

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Dedicated to you, reader and explorer of knowledge and science.

Publications

During the course of this project, a number of publications have been created which are based on the work presented in this thesis. The most representative are listed here for reference:

- Charalampos Doukas, Ilias Maglogiannis, "Emergency Fall Incidents Detection in Assisted Living Environments Utilizing Motion, Sound and Visual Perceptual Components", IEEE Transactions on Information Technology in Biomedicine, doi: 10.1109/TITB.2010.2091140., vol. 15, no. 2, pp. 277 – 289, March 2011.
- Charalampos Doukas, Ilias Maglogiannis, "An Assistive Environment for Improving Human Safety Utilizing Advanced Sound and Motion Data Classification", Journal of Universal Access in the Information Society, Springer, Volume 10, Issue 2 (2011), Page 217-228.
- Charalampos Doukas, Ilias Maglogiannis, "Advanced Classification and Rules-Based Evaluation of Motion, Visual and Biosignal Data for Patient Fall Incident Detection", Artificial Intelligence Techniques for Pervasive Computing, International Journal on AI Tools (IJAIT), World Scientific Press, vol. 19, issue 2, pp. 175-191, 2010.
- Ilias Maglogiannis, Charalampos Doukas, George Kormentzas, Thomas Pliakas, "Optimized Mobile Access to DICOM Images using Wavelet compression with ROI coding support", IEEE Transactions on Information Technology in Biomedicine, volume 13, no. 4, pp 458-466, July 2009.
- Charalampos Doukas, Ilias Maglogiannis, "Point of care monitoring using advanced location based and context-aware services", in Hospital Information Technology Magazine (HITE), Vol.1, No. 2, Summer 2008, pp. 40-42.
- Charalampos Doukas, Ilias Maglogiannis, "Adaptive Transmission of Medical Image and Video using Scalable Coding and Context-aware Wireless Medical Networks", in EURASIP Journal on Wireless Communications and Networking, vol. 2008, Article ID 428397, 12 pages, 2008. doi:10.1155/2008/428397.
- Charalampos Doukas, Ilias Maglogiannis, Ioannis Anagnostopoulos, Kostas Perakis, "A Context-aware Telemedicine Platform for Monitoring Patients in Remote Areas", Journal on Information Technology in Healthcare 2007; 5(4): 255–262.

Abstract

Recent advances in ICT are reshaping health systems and introducing new medical and care schemes with the development of novel tools that enable remote monitoring of patients and management of chronic conditions, timely response in emergency situations, and the delivery of healthcare to the patient's site, while saving time, travel and other expenses. With the enormous costs associated with chronic disease management and the globally increasing ageing population, Ambient Assisted Living (AAL) technologies for unobtrusive monitoring and emergency incident detection (e.g. detection of falls), utilizing bio-sensors and devices such as video cameras, have started to gain significant attention.

The main goal of context aware computing is to acquire and utilize information about the context of a device to provide services that are appropriate to particular people, place, time, events, etc. In the domain of patient remote care, context awareness refers to detection of patient status and appropriate adaptation of the medical services according to the latter status and environmental conditions. Despite the numerous implementations and proposals of telemedicine and e-health platforms found in the literature, only a few works include context awareness

Motivated by this fact, this work proposes and examines the application of innovative technologies and methods for the introduction of context awareness and adaptation in AAL systems. More specifically, the presented work includes applications for patient fall detection utilizing motion, audio, and video data acquisition, scalable compression, retrieval and decompression of medical images, as well as presentation of patient data, on mobile devices, and management of pervasive healthcare data on the Cloud. Moreover, a context-aware framework that is independent of the applications used and the underlying network infrastructure is proposed. Issues and challenges stemming from the deployment of these technologies are also discussed and some possible solutions are proposed.

Περίληψη

Τα τελευταία χρόνια, η εξέλιξη του τομέα των ΤΠΕ έχει αρχίσει να αναδιαμορφώνει τα συστήματα υγείας και να δημιουργεί νέα μοντέλα παροχής φροντίδας και περίθαλψης, βασισμένα σε εργαλεία που επιτρέπουν την παρακολούθηση και διαχείριση χρόνιων ασθενών από απόσταση, την έγκαιρη παρέμβαση σε καταστάσεις έκτακτης ανάγκης, καθώς και την παροχή φροντίδας στο χώρο του ασθενούς, μειώνοντας τις αποστάσεις, τον χρόνο και κατ' επέκταση το κόστος. Λόγω της μεγάλης επιβάρυνσης που προκαλεί η διαχείριση χρόνιων νοσημάτων στο σύστημα υγείας, αλλά αυξανόμενης γήρανσης του πληθυσμού παγκοσμίως, οι τεχνολογίες για την ανεξάρτητη υποβοηθούμενη διαβίωση, οι οποίες επιτρέπουν τη διακριτική παρακολούθηση του ασθενή και την αυτόματη ανίχνευση δυνητικά επικίνδυνων καταστάσεων (π.χ. ανίχνευση πτώσεων) μέσω βιοαισθητήρων και συσκευών όπως βιντεοκάμερες, έχουν εξελιχθεί σε σημαντικό πεδίο έρευνας.

Η επίγνωση πλαισίου (context awareness) στις τεχνολογίες πληροφορικής αφορά τη λήψη και αξιοποίηση δεδομένων μέσω συσκευών, με στόχο την παροχή υπηρεσιών προσαρμοσμένων κατάλληλα για συγκεκριμένο χρήστη, χρόνο, τόπο, κλπ. Ειδικότερα, στο πλαίσιο της τηλεφροντίδας ασθενών, επίγνωση πλαισίου σημαίνει ανίχνευση της κατάστασης του ασθενή και κατάλληλη προσαρμογή των υπηρεσιών φροντίδας με βάση αυτή την κατάσταση, αλλά και τις συνθήκες του περιβάλλοντός του. Παρά τον μεγάλο αριθμό συστημάτων τηλεϊατρικής και ηλεκτρονικής υγείας που έχουν προταθεί και υλοποιηθεί, ελάχιστα ενσωματώνουν την έννοια της επίγνωσης πλαισίου.

Η παρούσα διατριβή εξετάζει την εφαρμογή καινοτόμων τεχνολογιών και πρακτικών για την ενσωμάτωση της επίγνωσης πλαισίου σε συστήματα ανεξάρτητης υποβοηθούμενης διαβίωσης. Πιο συγκεκριμένα, παρουσιάζονται εφαρμογές για την ανίχνευση πτώσεων αξιοποιώντας δεδομένα κίνησης, εικόνας και ήχου, για την συμπίεση ιατρικών εικόνων και την προβολή αυτών και άλλων ιατρικών δεδομένων σε κινητές συσκευές, καθώς και για τη διαχείριση ιατρικών δεδομένων στο Cloud. Επιπλέον, προτείνεται μια context-aware αρχιτεκτονική, ανεξάρτητη από τις τεχνολογίες που χρησιμοποιούνται. Τέλος, παρατίθενται κάποια ανοιχτά ζητήματα που προκύπτουν από την εφαρμογή των παραπάνω τεχνολογιών, μαζί με κάποιες πιθανές λύσεις.

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I would also like to thank all my colleagues and research associates at the University of the Aegean, NCSR Demokritos, Athens Information Technology, National Hellenic Research Foundation and the University of Central Greece for their excellent collaboration during all this time.

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List of Abbreviations

AAL	Ambient Assisted Living
ACL	Access Control List
ADK	Accessory Development Kit
ADMI	Agent-Based Data Mining Info
ADSL	Asymmetric Digital Subscriber Line
AHCS	Ambient Home Care Systems
AmI	Ambient Intelligence
AOA	Angle of Arrival
API	Application Programming Interface
AWS	Amazon Web Services
BASN	Body Area Sensor Network
BSS	Blind Source Separation
CAST	Center for Ageing Services Technologies
CDMA	Code Division Multiple Access
CDO	Care Delivery Organization
CORBA	Common Object Request Broker Architecture
CPU	Central Processing Unit
CR	Computed Radiography
CT	Computed Tomography
DECT	Digital Enhanced Cordless Telecommunications
DICOM	Digital Imaging and Communications in Medicine
DL	Distortion Limiting
DLWIC	Distortion Limited Wavelet Image Codec
DMS	Data Management System
DOA	Direction of Arrival
DVB-H	Digital Video Broadcasting - Handheld
DWT	Discrete Wavelet Transform
EBCOT	Embedded Block Coding with Optimized Truncation
EC2	Elastic Compute Cloud
ECG	Electrocardiography
EDGE	Enhanced Data rates for GSM Evolution
EEG	Electroencephalography
EHR	Electronic Health Record
EMG	Electromyogram
EMR	Electronic Medical Record
EV-DO	Evolution-Data Optimized
EZW	Embedded Zerotree Wavelets
GCC	Generalized Cross-Correlation
GMM	Gaussian Mixture Model
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HaaS	Hardware as a Service
HDSL	High data rate Digital Subscriber Line
HHS	Health and Human Services
HIPPA	Health Insurance Portability and Accountability Action
HIS	Hospital Information Systems
HL7	Health Level-7
HS-SPIHT	Highly Scalable SPIHT
HTTP	HyperText Transfer Protocol

IaaS	Infrastructure as a Service
IDE	Integrated Development Environment
IEEE	Institute of Electrical and Electronics Engineers
IMIA	International Medical Informatics Association
IrDA	Infrared Data Association
ISDN	Integrated Services Digital Network
ISM	Industrial, Scientific and Medical
ISO	International Organization for Standardization
IT	Information Technology
JDBC	Java Database Connectivity
JPEG	Joint Photographic Experts Group
LAN	Local Area Network
LED	Light-Emitting Diode
LoS	Line of Sight
M2M	Machine-to-Machine
MCU	Microcontroller Unit
MDSD	Model Driven Software Development
MFCC	Mel Frequency Cepstral Coefficients
MITM	Man-in-the-middle
MOS	Mean Opinion Score
MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
NEMA	National Electrical Manufacturers Association
NFC	Near-Field Communication
NSN	Nokia Siemens Networks
OB-SPECK	Object-Based extension of the Set Partitioned Embedded BloCK
OB-SPIHT	Object-Based extension of theSet Partitioning in Hierarchical Trees
OS	Operating System
OSGi	Open Service Gateway Initiative
OT	Optical Tomography
OWL	Web Ontology Language
PaaS	Platform as a Service
PACS	Picture Archiving and Communication Systems
PAN	Personal Area Network
PART	Projective Adaptive Resonance Theory
PDA	Personal Digital Assistant
PET	Positron Emission Tomography
PHI	Protected Health Information
PHR	Personal Health Record
PIT	Progressive Image Transmission
PPM	Pixel Persistent Map
PSNR	Peak Signal to Noise Ratio
PSTN	Public Switched Telephone Network
PWT	Personal Wireless Telecommunications
QoS	Quality of Service
RBDWT	Region-Based Discrete Wavelet Transform
RDBMS	Remote Database Management System
REST	Representational State Transfer
RFID	Radio-Frequency Identification
RMI	Remote Method Invocation
RMS	Root Mean Square
ROC	Receiver Operating Characteristic

ROI	Region of Interest
RONI	Region of None Interest
S3	Simple Storage Service
SaaS	Software as a Service
SARD	Sensor Applications Reference Design
SDSL	Symmetric Digital Subscriber Line
SHA-1	Secure Hash Algorithm 1
SLA	Service Level Agreement
SMS	Short Message Service
SOAP	Simple Object Access Protocol
SPIHT	Set Partitioning in Hierarchical Trees
SSIM	Structural Similarity
SSL	Secure Sockets Layer
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
SWAP	Shared Wireless Access Protocol
SWRL	Semantic Web Rule Language
TDE	Time Delay Estimation
TIDE	Technology Initiative for Disabled and Elderly People
TLS	Transport Layer Security
UMTS	Universal Mobile Telecommunications System
US	Ultrasound
USB	Universal Serial Bus
VDSL	Very high data rate Digital Subscriber Line
VM	Virtual Machine
VoIP	Voice Over IP
WAN	Wide Area Network
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network
WPSN	Wireless Passive Sensor Network
WSN	Wireless Sensor Network
WT	Wavelet Transform
xDSL	ADSL/SDSL/HDSL/VDSL
XML	Extensible Markup Language

1. Introduction

In this era of ubiquitous and mobile computing the vision in biomedical informatics is towards achieving two specific goals: the availability of software applications and medical information anywhere and anytime and the invisibility of computing [1]. Both aforementioned goals lead to the introduction of pervasive computing concepts and features in e-health applications. Applications and interfaces that will be able to automatically process data provided by medical devices and sensors, exchange knowledge and make intelligent decisions in a given context are strongly desirable. Natural user interactions with such applications are based on autonomy, avoiding the need for the user to control every action, and adaptivity, so that they are contextualized and personalized, delivering the right information and decision at the right moment [2]. All the above pervasive computing features add value in modern pervasive e-healthcare systems.

It is well known that the proportion of elderly people has kept increasing since the end of last century. The European overview report of Ambient Assisted Living (AAL) investigated this trend. Studies of EUROSTAT [1] have indicated that: *"The share of the total European population (EU 15) older than 65 is set to increase from 16.3% in 2000 to 22% by 2025 and 27.5% by 2050. The share of the population aged over 80 years (3.6% in 2000) is expected to reach 6% by 2025 and 10% by 2050"*. Studies of Counsel and Care in the UK have found out that these elderly people would prefer to live in their own house rather than in hospitals, thus they need support to remain independent at their home [4] .

In order to maintain their independency, elderly people need support and help. The call for medical treatment should be provided from professionals in hospitals and their relatives, while friends and neighbors normally provide the call for social activities. The situation in real-life is that families and friends are not necessarily located nearby, but sometimes live far away. In order to provide help, timely and cost-effectively, especially in emergency situations, the best solution seems to resort to help from their neighbors. Neighbors are adequate for the task of social activities; they are close to the caller and thus their help could be more timely provided. Furthermore, these interactions could increase harmony within the community. To avoid or eliminate the human factor effect, it is necessary to create a fully integrated automated and commercial system, which could acquire the data from sensors, check them in, sort them out, and inform the appropriate person (doctor, relatives or neighbor). Simultaneously, it should actuate available alarm systems, such as horn or lights. In general, Ambient Assisting Living (AAL) would be a system that meets the above specifications.

Providing at home health assistance through pervasive sensor network and other technologies remains a big challenge because of the heterogeneity of devices, network systems and health policies. Extending this work to providing human support to the outdoors, in an urban or other setting, presents even bigger challenges, as the outside of the home environment is not predetermined, cannot be controlled or easily monitored. The technologies that can help are restricted to monitoring the individual through mobile sensors and through public transportation designs that anticipate different types of users interacting. These users might need assistance and others might not. Any technologies involved must be minimally intrusive to the first group and not affect the second group.

2. Scope

2.1. Motivation

A number of telemedicine applications exist nowadays, providing remote medical action systems (e.g., remote surgery systems), patient telemonitoring facilities (e.g., homecare of chronic disease patients), and transmission of medical content for remote assessment [143][146], [152]. Such platforms have been proved significant tools for the optimization of patient treatment offering better possibilities for managing chronic care, controlling health delivery costs and increasing quality of life and quality of health services in underserved populations. Collaborative applications that allow the exchange of medical content (e.g., a patient health record) between medical experts for educational purposes or for assessment assistance are also considered of great significance.

Due to the remote locations of the involved actuators, a network infrastructure (wired and/or wireless) is needed to enable the transmission of the medical data. The majority of the latter data is usually medical images and/or medical video related to the patient. Thus, telemedicine systems cannot always perform in a successful and efficient manner; Issues, like large data volumes (e.g., video sequences or high quality medical images), unnecessary data transmission occurrence and limited network resources can cause inefficient usage of such systems [148] [155]. In addition, wired and/or wireless network infrastructures often fail to deliver the required quality of service (e.g., bandwidth requirements, minimum delay and jitter requirements) due to network congestion and/or limited network resources.

Appropriate content coding techniques (e.g., video and image compression) have been introduced in order to assess such issues [194], however the latter are highly associated to specific content type and cannot be applied in general. Additionally, they do not consider the underlying network status for appropriate coding and still cannot resolve the case of unnecessary data transmission. Scalable coding and context-aware medical networks can overcome the aforementioned issues, through performing appropriate content adaptation.

2.2. Objectives

Following a thorough study of related state-of-the-art works, the main objectives of this PhD thesis are:

- To describe the design of a non-invasive patient status awareness system that may be used for patient activity interpretation and emergency recognition in cases like elder falls.
- To propose innovative methods for transmission and presentation of medical images and pervasive health data over mobile devices and address the challenges of data management, interoperability, security, privacy and ubiquitous access by exploiting the offerings of Cloud Computing.
- To introduce a Context-Awareness Framework that is adaptive to the patient's status and the underlying network conditions.

2.3. Roadmap

The remainder of the dissertation is structured in five chapters, as follows: Chapter 3 provides a literature review and related works. Chapter 4 examines state-of-the-art in patient status recognition and telemedicine services. Chapter 5 presents the work that has been carried out. Chapters 6 and 7 contain a discussion of open issues and conclusions on the thesis' concepts.

3. Related Work – State of the Art

3.1. Ambient Assisted Systems Overview

Recent work on the design of digital city frameworks discusses issues such as how to create technologically supported environments that provide assistance to the elderly or persons in need of public access support. Discussions also center around technologies that lead to "intelligent" cities, with a pool of strategies, the ability to collect and transform collected information and knowledge into decision making, privacy-preserving virtual health clusters, social networks of e-communities, and the seamless integration of physical and virtual spaces (cyberphysical systems [1], [6]). One type of support is through the use of personal digital assistants (PDAs) to monitor patients and test results [8], [9]. Social support projects include projects such as in [7]. This European Union-funded project, called PlayMancer, utilizes 3D networked games to improve people's health.

In another project in the UK [219], a sensing system is used to help persons with dementia, with monitoring technologies that survey a person's movements, provide voice prompts and actively take part in managing appliances. The goal of this system is to help people with dementia to live on their own. Extending such a system to an urban environment would be extremely challenging.

At the Heracleia Human Centered Computing Lab, researchers are developing monitoring tools that take as input a plethora of heterogeneous data in both discrete and continuous format and produce "events" that summarize or evaluate the situation about a person living at home. This event-driven environment predicts cases of risk that may come up as it learns from the person's usual behavior. It uses advanced computation methods to fuse information and combine it with domain expertise as to what is important to look out for. It is an environment that also allows communication among different types of sensors in a wireless networking infrastructure [10]. Among the tools being developed are SW to have robots assist through voice recognition, interfaces that provide customized notices and training, and the ability to detect pain or depression from facial expressions. The Heracleia apartment resides within the laboratory and includes team projects such as the Smart Drawer RFID project [220], designed to track whether the correct medication is taken at the right time, and its impact on behavior afterwards.

Ambient Assisted Living (AAL) technologies aim at enabling independence in the old age with the support of advanced technologies. In AAL, accessibility, usability and learning play a major role in the emerging digital cities area, to enable citizens with specific demands, e.g. handicapped, chronic patients or elderly to live in congenial environments for longer [11]. Ambient home care systems (AHCS) are specially designed for this purpose; they aim at minimizing the potential risks that living alone may suppose for an elder, relying on their capability of gathering user related data, inferring information about their activity and state and taking decisions on the user's potential demands.

In [13], David Hanak et al. describe a mobile Ambient Assisted Living (AAL) solution designed to meet the requirements of modern health services in caring for, monitoring and motivating the elderly in their own environment. The solution goes beyond the function of classical telemonitoring, by delivering integrated functionality that includes health management, mental monitoring, mood assessment as well as physical and relaxation exercises. In addition, they provide communication and delivery services in a location-based manner, using built in GPS, WiFi and 3G mobile connectivity. Bluetooth compatible blood pressure and body weight measurement devices are complemented with a body-mounted wireless physiological sensor to monitor activity, body temperature and stress. Telemetric data is continuously recorded on a local host computer while simultaneously being also sent to a central database, where a rule-based system or monitoring health personnel may make emergency assessment.

Suzanne Kieffer et al. in [221] present the Keep-In-Touch project, which aims at developing an integrated Ambient Assisted Living (AAL) solution, assisting and monitoring elderly people in their daily-life activities, supporting personal autonomy and well-being and maintaining social cohesion. The focus of this effort is the integration of interactive user modeling, the benefit of the combination of user-centered development method and fast prototyping implementation, in order to develop a solution which fits the end-user. The key elements to achieve this goal are multimodality, accessibility, adaptability to user profile and changes and usability.

The final product integrates a set of media and sensors: a touch screen, a microphone, and hear phones (media); accelerometers, force sensors, thermometers and radars (sensors). Therefore, the end-user interacts with the system thanks to different (input) modalities: speech, hand gestures on the touch screen, movements and posture (i.e., gait or posture patterns captured by the sensor network). At the same time, the information from the system to the end-user is conveyed via different (output) modalities: vocal messages, standard graphical display on the screen and alarms. Such a system could be multimodal. The OpenInterface Kernel is a component-based software platform dedicated to multimodal application rapid prototyping, using heterogeneous components [222]. The Kernel is implemented in C++ to optimize performance, as well as to benefit from existing C++ bindings available for other languages.

The benefit of the aforementioned approaches is the early attention paid to end-users and system usability. Furthermore, the two combinations seem to provide a good mean to address challenges such as accessibility, adaptability, and usability. The OpenInterface Platform is an adequate solution to support the rapid prototyping of multimodal systems. However, as they require a substantial amount of collected data during training, communication robustness, further sensors and the availability of representative users, effectors and stakeholders may consist an obstacle to its implementation.

A novel approach of an ontology-centered design in order to create an Ambient Middleware as a reliable, deterministic and economically scalable component is described in [223] by Michael Klein et al. This is developed within the framework of the EU-funded project SOPRANO, aiming to assist older Europeans in living a more independent life at their homes. The core of the system in each house is the SOPRANO Ambient Middleware (SAM), which receives the user commands and sensor inputs, enriches them semantically and triggers appropriate reactions via actuators in the house. The starting point is the development of a context ontology, focusing on the concept of a state. This OWL-Lite ontology is then used as a central reference document during the design process, as well as during runtime, to abstract from concrete sensor inputs and actuator outputs. Planned are sensors for e.g. smoke, temperature, door status, location of the user by Radar or RFID, their health status and so on. Planned actuators are speech synthesizers, digital TVs with avatars, device regulators (for switching devices on/off or modifying their behavior), emergency calls to a central and more. Additionally, the more static context of the house and the user shall be taken into consideration when performing concrete actions. One major goal of SOPRANO will be to infer high-level context from low-level sensor input, detect important context changes (events), determine which rules fire, and break the initiated high-level plans down to concrete actions to be executed via service calls.

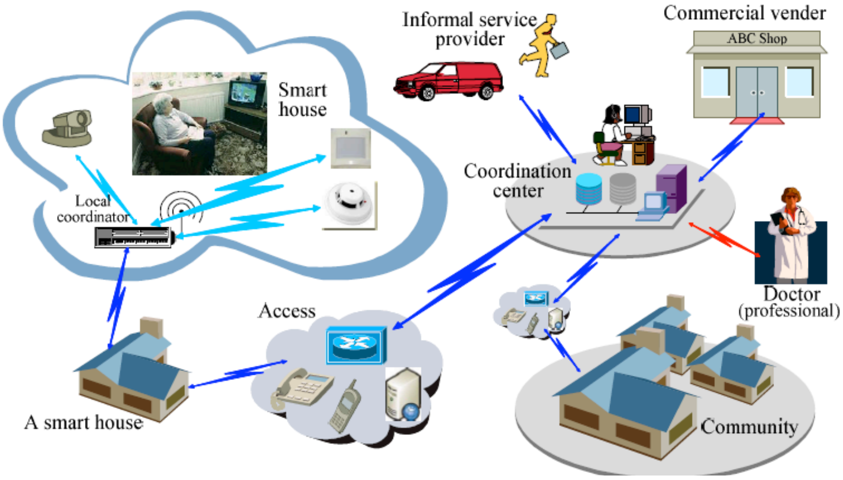


Figure 3.1.1 Organization of Mutual Assistance Community [12]

SOPRANO, as an integrating project, builds upon a body of research on the subject of smart homes and ambient assisted technologies. Some recent examples in the domain are the DAIDALOS project [224] or the AMIGO project [225]. The main difference of the SOPRANO approach is that it brings together a service-oriented approach like [226] with ontologies on an architectural level. The evaluation of the developed concepts of the SOPRANO project is expected.

In [227], Eric Ras et al. list the current research challenges for telehealth systems from an engineering perspective and show how they approach the challenges by means of an assisted living laboratory for engineering and evaluation purposes. Necessary qualities like availability, robustness, extensibility, safety, security, timeliness, adaptivity, natural anticipatory human-computer interaction, resource efficiency and heterogeneity are taken into account. The BelAmI Assisted Living Laboratory (AL-Lab) is located at the Fraunhofer IESE in Kaiserslautern, Germany and consists of a 60m² apartment with living-, sleeping-, bath room, and kitchen. The AL-Lab plays a central role in performing research and development in the domain of assisted living and telehealth: real-life prototypes, integration of heterogeneous technologies, gathering of different data sets at the same time and location, analysis and testing of technical solutions, and providing measuring facilities. The demonstrator developed in the AL-Lab is called amiCA (ambient intelligent Care and Assistance system). The aim of amiCA is to support elderly so that they can live longer in a self-determined way in their usual environment.

Plenty of researchers have dealt with theoretical analysis of Ambient Assisted Living. Other researchers have explicated parts of AAL, such as data acquisition or signal processing. A number of context-aware services (heart rate monitoring, medication prompting, generation of agenda reminders, weather alerts, emergency notifications, etc.) for the elder and his caregivers are presented in [228]. They run on the top of an Ambient Home Care System (AHCS), which collects data from a network of environmental, health and physical sensors. The AHCS follows a layered fusion architecture, formed by an in-home developed context acquisition framework and a context manager (customized on the Context Toolkit) that holds the inference and reasoning functionalities. On the deployed prototype, Ana Hristova et al. [228] analyze the suitability of the selected technical approach for ambient assisted living applications. Lower levels of context acquisition are performed by an in-home developed framework (CASanDRA), which provides us with some reusable acquisition services (such as positioning or ambient sensors handling). Upper levels of the acquisition procedure are implemented using the Context Toolkit. Widgets and aggregators implement the logic needed to build context features. For example, an aggregator called BUserPosition implements the fusion algorithms that decide the most accurate position estimate from the different CASanDRA location services (which are capable of obtaining WiFi, ZigBee and RFID-NFC positioning estimates). Apart from that, the Context Toolkit manages the requests for information the applications have. It also holds the reasoning procedure that triggers the applications and activates the notifications through SMS that are sent to the elder when needed. On it, it has been built the application interface for the caregiver. In order the system to work properly, the elder must carry a wireless device (in particular a PDA with WiFi and Bluetooth connectivity and an NFC SD-slot reader), both to enable the acquisition of context data and to communicate with the assisted person. In order to gather biometrical data, it is also necessary for the user to have a heart monitor. To enable some types of positioning algorithms, carrying a ZigBee sensor (mote) is needed. The logic infrastructure is supported by an applications' container (Apache Tomcat), which encapsulates the processing of the data that the widgets deliver to the application, and several databases (MySQL) to store the information needed. A wireless communication network connected to the wide area network (WAN) is also needed. The system is wholly implemented in Java and XML interfaces are used for communication.

A design drawback in the system is the patient's need of carrying multiple devices with him: a heart rate monitor, a PDA or other mobile device with an NFC (RFID) reader, a sensor for measuring the signal strength from the other static motes. This is not a realistic approach if this system is to be deployed for a testbed with real users. Therefore, integrating some of these technologies and minimizing the burden to the user of consciously carrying several devices, is something to be further explored.

In [229], B. O'Flynn et al. discuss the development, design characterization and test of a miniaturised wireless, wearable blood pressure and ECG (electrocardiography) monitor developed at the Tyndall National Institute for medical applications. This wireless platform is incorporated with the Data Management System (DMS) architecture, which aims to optimize accurate data delivery within a Wireless Sensor Network (WSN) medical environment. Good data management infrastructures within a medical environment help improve productivity levels for medical practitioners, and can improve patient diagnosis. The Tyndall25 hardware platform is a 25mm x 25mm stackable developmental platform designed to be modular in nature and to be suitable for a variety of WSN applications. Layers can be combined in an innovative and robust plug and play fashion and include communications (a selection of ISM band 2.4 GHz transceivers), processing (a low power consumption 8-bit micro-controller with 128kB of program memory) and a variety of sensing interconnect, sensor layers and power supply layers. This provides application specific solutions for WSN systems. An embedded antenna is integrated into the system to enable the 25mm form factor. The power layer may include a number of energy supply / harvesting methods i.e. vibration, electromagnetic fields, solar cells or piezo-electric power generating mechanisms Ambient-intelligence (AmI) systems raise a series of new challenges in software and system development: Mobility, adaptability and heterogeneity are new concerns that have to be addressed. Many of these concerns are common and therefore should be addressed by a common AmI infrastructure instead of each individual application. The primary role of the DMS is to provide mobile medical practitioners with accurate data delivery within a wireless passive sensor network (WPSN). Pervasive medical environments require intelligent management of patient data. The software agents work in three logical layers: data collection, data correlation and data presentation. Their primary task is to handle and present data in the required format while ensuring that all context and situation derived data are taken into account. DMS consumes data from a number of input streams (e.g. PDA, patient module), and it correlates this data checking certain explicit relationships. Data communication is facilitated through agents over a Wi-Fi network.

Future developments of the DMS architecture will incorporate data consistency models to ensure all medical practitioners are viewing up-to-date data sources. Techniques for validation of communication and sensor readings techniques need to be developed to ensure that relevant and accurate data is transmitted within an ambient medical environment.

A reference architecture for AAL systems and propose of a development toolbox to simplify the implementation of such systems using a Model Driven Software Development (MDSD) approach is presented in [230] from Werner Kurschl et al. The context-processing tier provides persistent storage for context data. Moreover, it derives high-level context (situations) from low-level context (raw context data from the sensors) using feature extraction, machine learning, and pattern recognition algorithms. These high-level context data, if described in terms of an ontology, are the foundation for situation awareness. Reasoning on situations permits to assess situations and predict future developments (situation evolution).

In [231], Michalis Anastasopoulos et al. have proposed a reference middleware architecture for Ambient Intelligence Applications. A series of services have been discussed and a bottom-up approach for the development of such a middleware infrastructure, which allows for easy customization to different hardware topologies, has been elucidated. Moreover, the tailoring support with respect to the hardware nodes available in a given situation has been outlined. The work presented here is currently in an initial phase. The next activities planned subsume the proof of concept through the prototypical implementation (e.g. with CORBA or OSGi) of the middleware platform along with the refrigerator application. The latter is to be extended soon with additional use-cases regarding context-sensitivity (e.g. the item information service can adapt expiry dates according to the temperature). Apart from that the request for adaptability will be investigated by the introduction of a variability service, which will supplement the dynamic integration service by managing the variability of computing nodes at run-time. Finally, the long-term plans include the enrichment of the platform with additional services like security as well as the investigation of safety concerns.

An overview on assisted technology in elderly care is also given in [232]. It addresses video-monitoring, remote health monitoring, electronic sensors, and equipment such as fall detectors and door monitors. Toshiba has two teams working on "home life support robots" designed to aid Japan's aging population [1]. Japan's population growth is near zero and its citizens' average age is climbing rapidly. The assumption is that by 2050, there will be not enough kids care for their aging relatives.

The objective of the PHMon (Personal Health Monitoring System with Microsystem Sensor Technology) project [233] has been the development of the world's first Personal Health Monitoring System, which allows measuring all of a patient's relevant vital parameters either continuously or at determined time intervals without restricting the patient’s mobility. The system enables the patient to spend much more time at home during examination, treatment, and rehabilitation periods compared to the ordinary procedures, which leads to an immense cost reduction for in-hospital treatments. Starting in 1993, the Technology Initiative for Disabled and Elderly People (TIDE) has promoted research and technological development to meet social and industrial goals, stimulating a single market in Assisted Technology in Europe, to facilitate the socio-economic integration of disabled and elderly people [234]. Within the 6th Framework Programme, the EU has funded research and development of Ambient Assisted Living (AAL) solutions for the Aging Society [235]. Established in 2003, the Center for Aging Services Technologies (CAST) [236] has become a national coalition of more than 400 technology companies, aging services organizations, research universities, and government representatives working together under the auspices of the American Association of Homes and Services for the Aging (www.aahsa.org).

Finally, the BelAmI (Bilateral German-Hungarian Collaboration Project on Ambient Intelligent Systems) project [230] aims at developing innovative technologies and system development methods in the area of Ambient Intelligence. One of the addressed application domains is assisted living. In this context, the researchers devise integrated methods that can be used to develop assisted living solutions with the characteristic requirements, i.e., adaptivity, dependability, interoperability, resource efficiency, safety & security, and usability in a goal-oriented way [237]. An overview of the aforementioned Ambient Assisted Systems is provided in the following Table.

Table 3.1.1 Overview of Ambient Assisted Systems

Reference	**Technologies utilized**	**Provided Features**
[1], [6], [32]	Intelligent knowledge processing, Knowledge Bases, Decision making	Social networks of e-communities, virtual spaces and social support enabling communication and interaction between the elderly
[8], [9]	Sensors and PDAs	Monitoring the physical status of patients
[238]	Sensing system (person's movements)	Help persons with dementia
[10], [12]	Sensor technologies (biosignals, voice recognition, facial expressions, RFID tools)	Evaluate patient status and state at home, provide interfaces for interaction, assist medication
[11]	Sensor technologies, Decision making	Ambient Home Care System
[13]	Mobile sensors, mobile devices, advanced user	Health management, mental monitoring, mood assessment as well

	interfaces	as physical and relaxation exercises
[221]	Media and sensors: a touch screen, a microphone, and hear phones (media); accelerometers, force sensors, thermometers and radars	Monitoring elderly people in their daily-life activities, supporting personal autonomy and well-being, and maintaining social cohesion
[223]	Ontologies and intelligent reasoning, sensors detecting context changes (light sensors, RFID sensors)	Assist older Europeans in living a more independent life at their homes
[227]	Environmental, health and physical sensors	Support elderly that they can live longer in a self-determined way in their usual environment
[228]	Fusion algorithms, location services, wireless devices	Suite of ambient assisted living applications
[229]	Wireless Sensor Networks	Development, design characterization and test of a miniaturized wireless, wearable blood pressure and ECG monitor
[231]	CORBA and other middleware technologies	Reference middleware architecture for Ambient Intelligence Applications
[5]	Robotic systems	Home life support robots
[233]	Mobile sensor Technologies	Personal Health Monitoring System, which allows measuring all of a patient's relevant vital parameters either continuously or at determined time intervals without restricting the patient’s mobility

[230]	Ambient Intelligence Technologies	Develop assisted living solutions with the characteristic requirements, i.e., adaptivity, dependability, interoperability, resource efficiency, safety & security, and usability

4. A Context – aware Architecture for Patient status recognition and Telemedicine Services

Monitoring of patient status involves the acquisition of data related both to user's environment and the physical status: Various monitoring devices collecting visual data, motion and sound (e.g., cameras and microphones) or evaluating patient entries in specific areas (e.g., infrared and RFID) can be utilized in indoor environments. On body sensors like EEG (electroencephalograph), temperature, EEG and motion analysis sensors provide an estimation concerning the health state of the individual. All acquired data are transmitted to the monitoring unit utilizing wireless technologies like WiFi, Bluetooth, ZigBee and 3G.

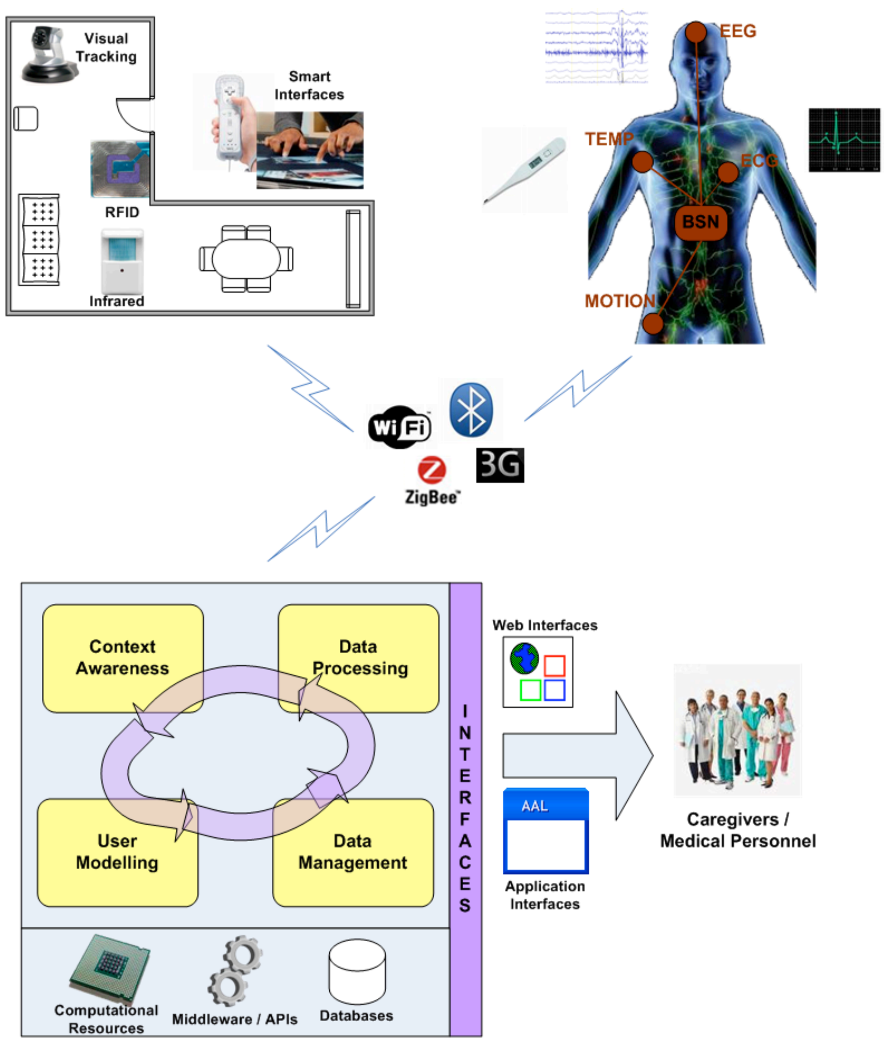


Figure 3.1.1 Basic Architecture for Ambient Assisted Systems

The monitoring unit in a typical AAL system consists of several processing modules (e.g., context awareness, data processing, user modeling and data management modules) that generate estimations regarding the patient's status and content related to the latter (e.g., suggestions to the users). Proper interfaces, either web based or standalone, enable the remote access to the acquired data and forward patient status estimations to caregivers and/or medical personnel.

4.1. Patient Data Acquisition

4.1.1. Biosignals

A broad definition of a signal is a 'measurable indication or representation of an actual phenomenon', which in the field of biosignals, refers to observable facts or stimuli of biological systems or life forms. In order to extract and document the meaning or the cause of a signal, a physician may utilize simple examination procedures, such as measuring the temperature of a human body or have to resort to highly specialized and sometimes intrusive equipment, such as an endoscope. Following signal acquisition, physicians go on to a second step, that of interpreting its meaning, usually after some kind of signal enhancement or 'pre-processing', that separates the captured information from noise and prepares it for specialized processing, classification and decision support algorithms.

Biosignals require a digitization step in order to be converted into a digital form. This process begins with acquiring the raw signal in its analog form, which is then fed into an analog-to-digital (A/D) converter. Since computers cannot handle or store continuous data, the first step of the conversion procedure is to produce a discrete-time series from the analog form of the raw signal. This step is known as 'sampling' and is meant to create a sequence of values sampled from the original analog signals at predefined intervals, which can faithfully reconstruct the initial signal waveform. The second step of the digitization process is quantization, which works on the temporally sampled values of the initial signal and produces a signal, which is both temporally and quantitatively discrete; this means that the initial values are converted and encoded according to properties such as bit allocation and value range. Essentially, quantization maps the sampled signal into a range of values that is both compact and efficient for algorithms to work with. The most popular biosignals utilized in pervasive health applications [1], [15], [16], [19], [20], [26], [27], [30], [31], [37] are summarized in the table below.

Table 4.1.1 Broadly used biosignals with corresponding metric ranges, number of sensors required and information rate

Biomedical Measurements (Broadly Used Biosignals)	**Voltage range (V)**	**Number of sensors**	**Information rate (b/s)**
ECG	0.5-4 m	5-9	15000
Heart sound	Extremely small	2-4	120000
Heart rate	0.5-4 m	2	600
EEG	2-200 µ	20	4200
EMG	0.1-5 m	2+	600000
Respiratory rate	Small	1	800
Temperature of body	0-100 m	1+	80

In addition to the aforementioned biosignals, patient physiological data (e.g., body movement information based on accelerometer values), and context-aware data (e.g., location, environment and age group information) have also been used by pervasive health applications (1, 17, 15, 16, 18, 21, 22, 23, 29, 31, 33, 38). The utilization of the latter information is discussed in the following sections.

In the context of pervasive healthcare applications, the acquisition of biomedical signals is performed through special devices (i.e. sensors) attached on the patient's body (see Figure 4.1.1) or special wearable devices (see Figure. 4.1.2). The transmission of the collected signals to the monitoring unit is performed through appropriate wireless technologies discussed in Section 2.2. Regarding the contextual information, most applications are based on data collected from video cameras, microphones, movement and vibration sensors

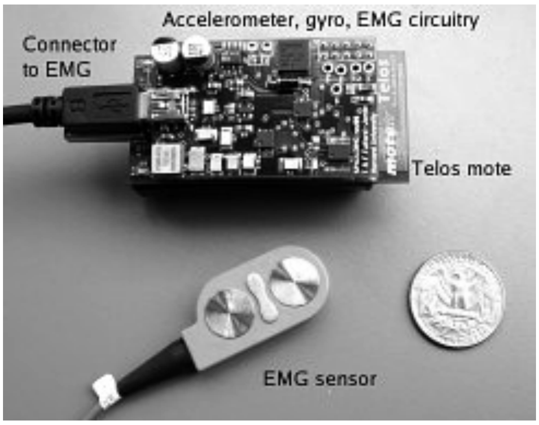


Figure 4.1.1 Accelerometer, gyroscope, and electromyogram (EMG) sensor for stroke patient monitoring [39]

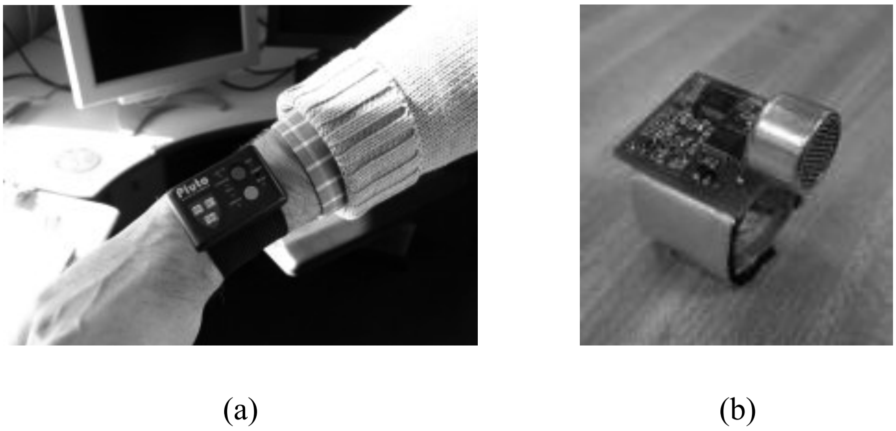


Figure. 4.1.2 Wearable medical sensor devices: (a) A 3-axis accelerometer on a wrist device enabling the acquisition of patient movement data [39], (b) A ring sensor for monitoring of blood oxygen saturation [28]

4.1.2. Location Based Technologies

Positioning of individuals provides healthcare applications with the ability to offer services like supervision of elderly patients or those with mental illnesses who are ambulatory but restricted to a certain area. In addition, assisted care facilities can use network sensors and radiofrequency ID badges to alert staff members when patients leave a designated safety zone. Network or satellite positioning technology also can be used to quickly and accurately locate wireless subscribers in an emergency and communicate information about their location. Proximity information services can direct mobile users to a nearby healthcare facility. Location-based health information services can help find people with matching blood types, organ donors, and so on. A more extensive list of location-based health services can be found in [174].

Positioning techniques can be implemented in two ways: Self-positioning and remote positioning. In the first approach, equipment that the user uses (e.g., a mobile terminal, or a tagging device) uses signals, transmitted by the gateways/antennas (which can be either terrestrial or satellite) to calculate its own position. More specifically, the positioning receiver makes the appropriate signal measurements from geographically distributed transmitters and uses these measurements. Technologies that can be used are satellite based (e.g., the Global Positioning System (GPS) and assisted-GPS), or terrestrial infrastructure-based (e.g., using the cell id of a subscribed mobile terminal).

The second technique is called remote positioning. In this case the individual can be located by measuring the signals traveling to and from a set of receivers. More specifically, the receivers, which can be installed at one or more locations, measure a signal originating from, or reflecting off, the object to be positioned. These signal measurements are used to determine the length and/or direction of the individual radio paths, and then the mobile terminal position is computed from geometric relationships; basically, a single measurement produces a straight-line locus from the remote receiver to the mobile phone. Another Angle of Arrival (AOA) measurement will yield a second straight line, the intersection of the two lines giving the position fix for this system. Time delay can also be utilized: Since electromagnetic waves travel at a constant speed (speed of light) in free space, the distance between two points can be easily estimated by measuring the time delay of a radio wave transmitted between them. This method is well suited for satellite systems and is used universally by them. Popular applications that are based on the latter technique for tracking provision are the Ekahau Positioning Engine [171], MS RADAR [172] and Nibble [173]. More information regarding positioning techniques and systems can be found in [176].

4.2. Communication Technologies

Regarding communication, there are two main enabling technologies according to their topology: on-body (wearable) and off-body networks. Recent technological advances have made possible a new generation of small, powerful, mobile computing devices. A wearable computer must be small and light enough to fit inside clothing. Occasionally, it is attached to a belt or other accessory, or is worn directly like a watch or glasses. An important factor in wearable computing systems is how the various independent devices interconnect and share data. An off-body network connects to other systems that the user does not wear or carry and it is based on a Wireless Local Area Network (WLAN) infrastructure, while an on-body or Wireless Personal Area Network (WPAN) connects the devices themselves; the computers, peripherals, sensors, and other subsystems and runs at ad hoc mode. Table 4.2.1 presents the characteristics of wireless connectivity and mobile networking technologies correspondingly, which are related to off-body and on-body networks. WPANs are defined within the IEEE 802.15 standard. The most relevant protocols for pervasive e-health systems are Bluetooth and ZigBee (IEEE 802.15.4 standard). Bluetooth technology was originally proposed by Ericsson in 1994, as an alternative to cables that linked mobile phone accessories. It is a wireless technology that enables any electrical device to communicate in the 2.5-GHz ISM (license free) frequency band. It allows devices such as mobile phones, headsets, PDAs and portable computers to communicate and send data to each other without the need for wires or cables to link the devices together. It has been specifically designed as a low-cost, low-size, and low-power radio technology, which is particularly suited to the short range of a Personal Area Network (PAN). The main features of Bluetooth are: a) Real-time data transfer usually possible between 10–15m, b) Support of point-to-point wireless connections without cables, as well as point-to-multipoint connections to enable ad hoc local wireless networks, c) data speed of 400 kb/s symmetrically or 700–150 kb/s of data asymmetrically. On the other hand, ZigBee (IEEE 802.15.4 standard) has been developed as a low data rate solution with multi-month to multiyear battery life and very low complexity. It is intended to operate in an unlicensed international frequency band. The maximum data rates for each band are 250, 40, and 20 kbps, respectively. The 2.4 GHz band operates worldwide while the sub-1-GHz band operates in North America, Europe, and Australia.

Table 4.2.1 Wireless connection technologies for pervasive health systems

Technology	**Data rate**	**Range**	**Frequency**
IEEE 802.11a	54 Mbps	150 m	5 GHz
IEEE 802.11b	11 Mbps	150 m	2.4 GHz ISM
Bluetooth (IEEE 802.15.1)	721 Kbps	10 m - 150 m	2.4 GHz ISM
HiperLAN2	54 Mbps	150 m	5 GHz
HomeRF (Shared Wireless Access Protocol, SWAP)	1.6 Mbps (10 Mbps for Ver.2)	50 m	2.4GHz ISM
DECT	32 kbps	100 m	1880-1900 MHz
PWT	32 kbps	100 m	1920-1930 MHz
IEEE 802.15.3 (high data rate wireless personal area network)	11-55 Mbps	1 m - 50 m	2.4GHz ISM
IEEE 802.16 (Local and Metropolitan Area Networks)	120 Mbps	City limits	2-66 GHz
IEEE 802.15.4 (low data rate wireless personal area network), ZigBee	250 kbps, 20 kbps, 40 kbps	100 m - 300 m	2.4 GHz ISM, 868 MHz, 915MHz ISM
IrDA	4Mbps (IrDA-1.1)	2 m	IR (0.90 micro-meter)

Pervasive healthcare systems set high demanding requirements regarding energy, size, cost, mobility, connectivity and coverage. Varying size and cost constraints directly result in corresponding varying limits on the energy available, as well as on computing, storage and communication resources. Low power requirements are necessary also from safety considerations since such systems run near or inside the body.

Mobility is another major issue for pervasive e-health applications because of the nature of users and applications and the easiness of the connectivity to other available wireless networks. Both off-body and personal area networks must not have line-of-sight (LoS) requirements. The various communication modalities can be used in different ways to construct an actual communication network. Two common forms are infrastructure-based networks and ad hoc networks. Mobile ad hoc networks represent complex systems that consist of wireless mobile nodes, which can freely and dynamically self-organize into arbitrary and temporary, "ad hoc" network topologies, allowing devices to seamlessly inter-network in areas with no pre-existing communication infrastructure or centralized administration. The effective range of the sensors attached to a sensor node defines the coverage area of a sensor node. With sparse coverage, only parts of the area of interest are covered by the sensor nodes. With dense coverage, the area of interest is completely (or almost completely) covered by sensors. The degree of coverage also influences information processing algorithms. High coverage is a key to robust systems and may be exploited to extend the network lifetime by switching redundant nodes to power-saving sleep mode.

4.3. Body Sensor & Body Area Networks

A Body Area Network is formally defined by IEEE 802.15 as, "a communication standard optimized for low power devices and operation on, in or around the human body (but not limited to humans) to serve a variety of applications including medical, consumer electronics / personal entertainment and other". In more common terms, a Body Area Network is a system of devices in close proximity to a person's body that cooperate for the benefit of the user.

Sensors for wellness assessment can be provided in clothing/body preferably with the application of power-harvesting technology. Integration of the data collection and analysis for manageable reporting will be crucial. Even more life critical than the current practice in industrial automation event reporting, efficient false-alarm management needs to be provided in order to minimize nuisance reporting. The wireless communication protocols discussed in the previous section are very popular for Body Sensor Networks. They are low-power optimized protocols for battery-powered sensor nodes. The appropriate choice depends on the specific application, which differs by function, compatibility, and cost.

Despite the fact that the Wireless Sensor Networks (WSN) technologies have evolved for a wide range of medical applications, they do not specifically tackle the challenges associated with human body monitoring. The human body consists of a complicated internal structure that responds to and interacts with its embodiment. Attaching sensors on the skin and/or implanting them into tissues may achieve human body monitoring using a network of wireless sensors.

Body area sensor network (BASN) nodes create an interface to humans, typically encapsulating an energy source, one or more sensors, a mixed-signal processor, and a communication transceiver. Some nodes also support data storage or feedback control to body-based actuators, such as an insulin pump or robotic prosthetic. Although BASN and WSN nodes have similar functional architecture, differences in their operational characteristics—sensing, signal processing, communication, caching, feedback control, and energy harvesting—present unique challenges and opportunities for BASN nodes.

Sensors in typical WSNs are numerous, homogeneous, and generally insensitive to placement error. BASN sensors, in contrast, are few, heterogeneous, and require specific placement. Indeed, ineffective placement or unintended displacement from movement can significantly degrade the captured data's quality. Such requirements call for strategies that will minimize and detect placement error, such as better packaging combined with on-node signal classification.

Signal processing is needed to extract valuable information from captured data that stems from transient events, such as falls, as well as from trends, such as the onset of fever. BASNs may need to concurrently capture, process, and forward information to different stakeholders. Time critical information from both events and trends would go immediately to emergency services, for example, but information that is not sensitive to delays would go to the physician for review later on. BASN nodes must however break complex signal-processing tasks into manageable segments to minimize algorithmic complexity while meeting real-time deadlines.

Communication is essential to node coordination. BASNs are unique in that they attempt to restrict the communication radius to the body's periphery. Limiting transmission range reduces a node's power consumption, decreases interference among adjacent BASNs, and helps maintain privacy. WSNs typically communicate over radiative radiofrequency (RF) channels between 850 MHz and 2.4 GHz. Unlike WSNs, wireless BASNs are challenged by the dramatic attenuation of transmitted signals resulting from body shadowing—the body's line-of-sight absorption of RF energy, which, coupled with movement, causes significant and highly variable path loss

4.4. Cloud Computing services and Healthcare

The realization of pervasive health information management through mobile devices introduces several challenges:

- Data storage and management: Storing such sensitive data raises issues about physical storage (e.g., the location of data) and availability; data must always be available and accessible from different platforms (devices and operating systems) and locations (supporting mobility). Proper management of healthcare data also requires maintenance procedures (e.g., backups, etc.). Thus, data storage and management requires proper design and utilization of several storage and computational resources.

- Interoperability and availability of heterogeneous resources: Healthcare data consists of heterogeneous data (e.g., clinical data, medical images, health records, etc.) acquired from and stored into different resources (e.g., electronic health record systems, radiology information systems, laboratory information systems, etc.). An aggregate access to aforementioned data from mobile devices involves the establishment of mechanisms that provide global access to the latter resources seamlessly.

- Security and privacy: Securing healthcare data involves security and encryption mechanisms both at the data storage elements and the transmission links. Protocols and mechanisms used must be compliant with the majority of operating systems and device types. Permission control must be carefully designed and deployed for prohibiting unauthorized access to sensitive data assuring privacy.

- Unified and ubiquitous access: Provide users with proper interfaces for accessing data from different platforms (e.g., mobile devices, web, etc.) and infrastructures (e.g., public or private networks, etc.) using a single entry point.

One potential solution for addressing all aforementioned issues is the introduction of Cloud Computing concept in electronic healthcare systems. Cloud computing has been receiving much attention as an alternative to both specialized grids and to owning and managing data centers. It represents a new way, in some cases a more cost effective way, of delivering enterprise IT. The increasing adoption rate of cloud computing is currently driving a significant increase in both the supply and the demand side of this new market for IT. Many healthcare providers and insurance companies today have adopted some form of electronic medical record systems, though most of them store medical records in centralized databases in the form of electronic records. Typically, a patient may have many healthcare providers, including primary care physicians, specialists, therapists, and other medical practitioners. In addition, a patient may use multiple healthcare insurance companies for different types of insurances, such as medical, dental, vision, and so forth. Currently, each healthcare provider typically uses its private datacenter for Electronic Health Records (EHRs). Sharing and process information between healthcare practitioners across administrative boundaries is translated to sharing information between EHR systems. The interoperation and sharing among different EHRs has been extremely slow due to cost and poor usability, which have been cited as the biggest obstacles to adoption of electronic health care.

4.4.1. Health Cloud Overview

Cloud computing provides an attractive IT platform to reduce the cost of EHR systems in terms of both ownership and IT maintenance burdens for many medical practices and to enable techniques for advance process of their data without the need of hosting the processing power. It is widely recognized that cloud computing and open standards are important to streamline healthcare whether it is for maintaining health records, monitoring of patients, managing diseases and cares more efficiently and effectively, or collaboration with peers and analysis of data. The concept of cloud computing complies with the emerging trend to move from the economy of ownership to the economy of use. The field of pervasive and ubiquitous healthcare services requires that resources and information can be available anywhere and anytime, since the rapid and safe exchange and disposal of large amounts of information at the point of care is needed.

Enabling the access to healthcare ubiquitously not only will help to improve healthcare as the data will always be accessible from anywhere at any time, but also it helps reducing the costs drastically. Several studies have demonstrated that the limited access to patient-related information during decision-making and the ineffective communication among patient care team members are proximal causes of medical errors in healthcare [177], [178]. Thus, the pervasive and ubiquitous access to healthcare data is considered essential for the proper diagnosis and treatment procedure. Cloud Computing is also a model for enabling convenient, on-demand network access to a shared group of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.

Based on cloud service models, we can divide healthcare cloud systems into three layers:

- **Applications in the cloud (Software as a Service – SaaS):** This layer provides capability for consumers to use the provider's applications running on a cloud infrastructure. For instance, the applications are accessible from various client devices through a thin client interface such as Web browser. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities. In this type of cloud service model, the security and privacy protection is provided as an integral part of the SaaS to the healthcare consumers.

- **Platforms in the cloud (Platform as a service – PaaS):** This layer offers capability for consumers to deploy consumer-created or acquired applications written using programming languages and tools supported by the cloud provider. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, or storage, but has control over the deployed applications and possibly application hosting environment configurations. In this type of cloud service model, two levels of protection for security and privacy are required. At the lower system level, the cloud provider may provide basic security mechanisms such as end-to-end encryption, authentication, and authorization. At the higher application level, the consumers need to define application dependent access control policies, authenticity requirements, and so forth.

- **Infrastructure in the cloud (Infrastructure as a Service – IaaS):** This type of cloud service model provides the capability for consumers to provision processing, storage, networks, and other fundamental computing resources, in which consumer is able to deploy and run arbitrary software, including operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, deployed applications, and possibly limited control of select networking components (e.g., host firewalls). In the Infrastructure cloud model, the healthcare application developers hold full responsibility for protecting patients' security and privacy.

We can also use the cloud deployment models below to give the taxonomy of healthcare clouds.

- **Private cloud:** The cloud infrastructure is operated solely for a healthcare delivery organization. It may be managed by the organization or a third party and may exist on or off premise. In this type of cloud deployment model, the cloud provider provides the same capability in terms of security and privacy protection as those in the Electronic Medical Record (EMR) system running by such an organization.

- **Hybrid cloud:** The cloud infrastructure is shared by several organizations and supports a specific community that has shared concerns (e.g., mission, security requirements, policy, and compliance considerations). It is most likely managed by the third party or the content organizations and may exist on or off premise.

- **Public cloud:** The cloud infrastructure is made available to the general public or a large industry group and is owned by a cloud service provider. In this deployment model, the healthcare application developers and consumers hold full responsibility for protecting patients' security and privacy.

Much of health care is transactional—admitting a patient, encountering a patient at the bedside or clinic, ordering a drug, interpreting a report, or handing off a patient. Yet transactions are only the operational expression of an understanding of the patient, and a set of goals and plans for that patient.

4.4.2. Cloud and Data Management Issues

The expansion of this IaaS market is leading to a rapid increase in the complexity, and users have to face when they strive to acquire resources in a cost-effective manner in such a market, while still respecting their application-level quality of service (QoS) constraints. Continuing standardization efforts in virtualization technology and IaaS offerings will further increase the options available to a consumer when acquiring resources "in the cloud". This issue is exacerbated by the fact that consumers often also own private IT infrastructure, especially for healthcare organizations where security of data is important. Through the creation of hybrid clouds [180], one can use this internal infrastructure in tandem with public cloud resources, thereby capitalizing on investments made, and catering for specific application requirements in terms of data confidentiality, security, performance and latency.

Due to the current lack of support tools to deal with the inherent complexity of cost-optimal resource allocation within such a hybrid setting, this process is error-prone and time-consuming. In addition, a structured approach is required that caters for optimizing such resource allocations in a multi-consumer context. Indeed, the addition of volume or reservation-based price reductions in the pricing options of public cloud providers allows for the further reduction of costs if an organization collectively engages in delivery, contracts for its entire user base. This differs from the practice of allowing users to individually acquire resources from cloud providers.

4.4.3. Data and Resources Management and Scaling

Presuming the existence of large integrated medical of data, another major challenge is in managing those data, in an efficient, secure and cost effective way. Some of the important dimensions of medical information management include the data semantics and annotation.

Raw data almost never speak for themselves, and their interpretation inevitably relies on metadata -annotations to the primary data that provide the necessary context. For example, the primary data for the human genome consist of a sequence of some 3 billion nucleotides. Metadata associated with the primary data help scientists to identify significant patterns within those data -a given sequence might be annotated as a gene or a regulatory element. Metadata could also be used to trace the provenance or lineage of data. For example, the value of certain data in an electronic health record could be enhanced if the data included information about the conditions under which certain data were obtained (e.g., physician observations of a patient's description of symptoms might be accompanied by video and audio recordings of the session with the patient). With metadata, a primary problem is the design and development of tools to facilitate machine-readable annotations in large databases.

4.4.4. Information extraction from large amount of heterogeneous medical data.

New techniques are needed for extracting information such as patient names, doctor names, medicine names, and disease names from visual or textual notes, and for generating automatic linkages between different relevant entities. Such extraction would make it possible to piece together a larger picture automatically while pulling information from multiple heterogeneous data and information sources. Extraction of data from tables and figures in reports is another example of a useful information extraction capability.

4.4.5. Security and Privacy Issues

Research on the various security issues concerning healthcare information systems has been heated over the last few years. ISO/TS 18308 standard gives the definitions of security and privacy issue for EHR [181]. The Working Group 4 of International Medical Informatics Association (IMIA) was set up to investigate the issues of data protection and security within the healthcare environment. Its work to date has mainly concentrated on security in EHR networked systems and common security solutions for communicating patient data [182]. The European AIM/SEISMED (Advanced Informatics in Medicine/Secure Environment for Information Systems in MEDicine) project is initiated to address a wide spectrum of security issues within healthcare and provides practical guidelines for secure healthcare establishment [183]-[185]. US Health and Human Services (HHS) recently published a report about personal health records (PHRs), aiming at developing PHRs and PHR systems to put forward a vision that "would create a personal health record that patients, doctors and other health care providers could securely access through the Internet no matter where a patient is seeking medical care."

In healthcare clouds the term "patient-centric" is commonly used, which is a term used mostly in community/hybrid healthcare systems. Hybrid healthcare system offers an open platform for patient to collect, store, use, and share health information in a controlled manner with ubiquitous accessibility. It also offers secure storage and management of patients' EHRs for multiple applications (e. g. disease treatment, lab research, insurance, and other social-networking applications). Most of the community healthcare cloud service models, such as Microsoft HealthVault and Google Health, adopt a centralized architecture with patient-centric views. By patient-centric, it means that the information stored in the community EHR system is imported by patients and only can be made available to a variety of applications under the control of patients.

The common security issues shared by healthcare cloud applications are ownership of information, authenticity, authentication, non-repudiation, patient consent and authorization, integrity and confidentiality of data.

- Ownership of information: In general, the owner is defined as the creator of the information. Establishing the ownership of the information is necessary for protection against unauthorized access or misuse of patient's medical information. The "owner" can refer to the person responsible for the information or the organization creating and storing the information. The term of “owner” may refer to “creator”, “author” and “manager” of the information.

- The “Creator” indicates the person generating the data. In healthcare system, practitioner or laboratory staff is the creator of medical data about a patient. “Author” means the person or entity responsible for the content of the information. In healthcare system, author is the creator of the information, be it the clinician or the organizations, which the creator belongs to. “Manager” is for the person or entity responsible for management, provision and protection of information. In patient- controlled healthcare system, manager is the patient self. While in decentralized healthcare system, manager may refer to a trusted third party, who is authorized by the patient or healthcare providers. The ownership of information can be protected through a combination of encryption and watermarking techniques.

- Authenticity and Authentication: Authenticity in general refers to the truthfulness of origins, attributions, commitments, and intentions. Authentication is the act of establishing or confirming claims made by or about the subject are true and authentic. The authentication of information can pose special problems, especially man-in-the-middle (MITM) attacks, and is often implemented with authenticating identity. Most cryptographic protocols include some form of endpoint authentication specifically to prevent MITM attacks. For instance, Transport Layer Security (TLS) and its predecessor, Secure Sockets Layer (SSL), are cryptographic protocols that provide security for communications over networks such as the Internet. TLS and SSL encrypt the segments of network connections at the Transport Layer end-to-end. Several versions of the protocols are in widespread use in applications like web browsing, electronic mail, Internet faxing, instant messaging and voice-over-IP (VoIP). One can use SSL or TLS to authenticate the server using a mutually trusted certification authority. In a healthcare system, both for healthcare information offered by providers and identities of consumers should be verified at the entry of every access.

- Non-repudiation: Non-repudiation implies one's intention to fulfill its obligations to a contract. It also implies that one party of a transaction cannot deny having received a transaction nor can the other party deny having sent a transaction. Electronic commerce uses technology such as digital signatures and encryption to establish authenticity and non-repudiation.

- Patient consent and authorization: Patient can allow or deny sharing their information with other healthcare practitioners or Care Delivery Organizations (CDOs). To implement patient consent in a healthcare system, patient may grant rights to users on the basis of a role or attributes held by the respective user.

- Integrity and confidentiality of data: Integrity means preserving the accuracy and consistency of data. In the health care system, it refers to the fact that data has not been tampered by unauthorized use. The International Organization defines confidentiality for Standardization (ISO) in ISO-17799 as "ensuring that information is accessible only to those authorized to have access". Confidentiality is one of the design goals for many crypto systems and made possible in practice by the techniques of modern cryptography. Confidentiality can be achieved by access control and encryption techniques in EHR systems.

- Availability and utility: For any EHR system to serve its purpose, the information must be available when it is needed. This means that the computing systems used to store and process the EHR data, the security controls used to protect it, and the communication channels used to access it must be functioning correctly. High availability systems aim to remain available at all times, preventing service disruptions due to power outages, hardware failures, and system upgrades. Ensuring availability also involves preventing denial-of-service attacks, and preserving utility of EHR data. Utility here refers to the ability to preserve the usability of EHR data after exercising and enforcing security and privacy protection and HIPPA (Health Insurance Portability and Accountability Action) compliance.

- Audit and archiving are two optional security metrics to measure and ensure the safety of a healthcare system. Audit means recording user activities of the healthcare system in chronological order, such as maintaining a log of every access to and modification of data. Auditing capability enables prior states of the information to be faithfully reconstructed. Archiving means moving healthcare information to off-line storage in a way that ensures the possibility of restoring them to on-line storage whenever it is needed without the loss of information [186].

Regarding patient data safety, the Health Insurance Portability and Accountability Action (HIPAA) [179] provides national minimum standards to protect an individual's health information. HIPAA covers protected health information (PHI) which is any information regarding an individual's physical or mental health, the provision of healthcare to them, or payment of related services. PHI also includes any personally identifiable information, including for example Employer Identification Number, social security number, name, address, phone number, medical condition when linked to a patient, and some types of billing information.

HIPAA's privacy rule regulations include standards regarding the encryption of all data in transmission and in storage. The same data encryption mechanisms used in a traditional computing environment, such as a local server or a managed hosting server, can also be used in virtual computing environments. HIPAA's security safeguards also require in-depth auditing capabilities, data back-up procedures and disaster recovery mechanisms.

4.4.6. Distributed Processing of Pervasive Healthcare Data

The development of pervasive health-care systems is a very promising area for commercial organizations active in the health-monitoring domain. The considered pervasive infrastructure creates numerous business opportunities for players like emergency medical assistance companies, the telecommunication operators, insurance companies, etc. Numerous portable devices are available that can detect certain medical conditions—pulse rate, blood pressure, breath alcohol level, and so on—from a user's touch. Many such capabilities could be integrated into a handheld wireless device that also contains the user's medical history. All the latter produce a vast amount of data that need to be distributary managed and processed within a cloud infrastructure.

The distribution of tasks in a cluster for parallel processing is not a new concept, and there are several techniques that use this idea to optimize the processing of information. The Map-Reduce paradigm [188], for example, is a framework for processing huge datasets of certain kinds of distributable problems using a large number of computers (nodes), collectively referred to as a cluster. It consists of an initial Map stage, where a master node takes the input, chops it into smaller or sub-problems, and distributes the parts to worker nodes, which process the information; following there is the Reduce stage, where the master node collects the answers to all the sub-problems and combines them to produce the job output. The process is illustrated in Figure 4.4.1.

A popular Map-Reduce implementation is Apache's Hadoop [189], which consists of one Job Tracker, to which client applications submit Map-Reduce jobs. The Job Tracker pushes work out to available Task Tracker nodes in the cluster, which execute the map and reduce tasks.

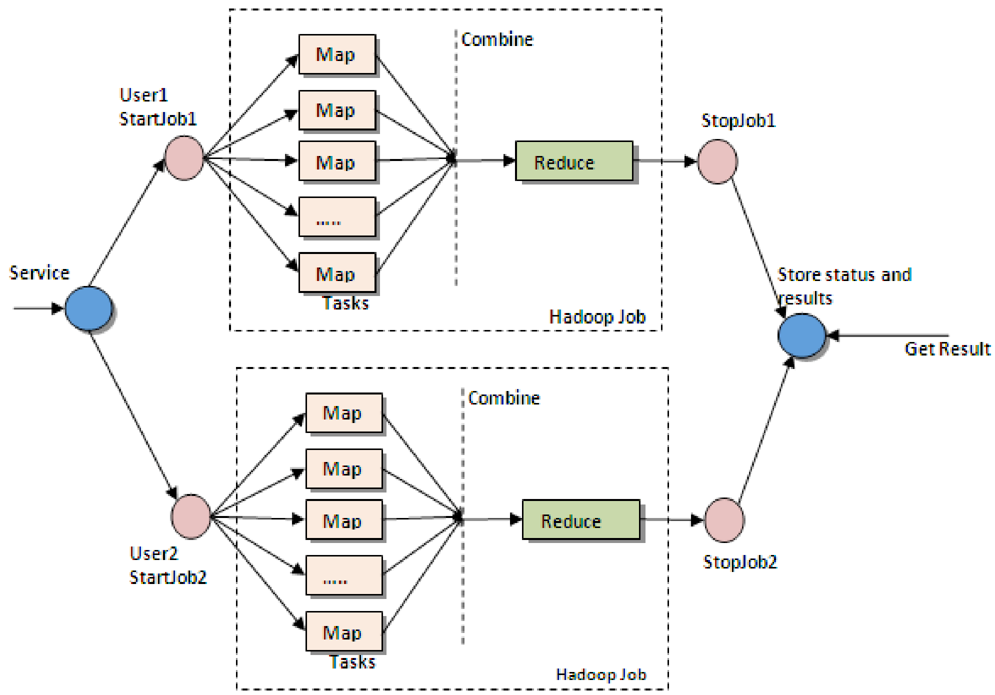


Figure 4.4.1 Map Reduce Architecture

However, despite being a very appealing and efficient technique for processing large volumes of data, there are a number of challenges associated with the deployment of Map-Reduce architectures. One of them is the required infrastructure. To make the process truly effective, one needs several machines acting as nodes, which often requires a large upfront investment in infrastructure.

This point is extremely critical in situations where the processing demand is seasonal. In addition, fault tolerance issues and the need of a shared file system to support mappers and reducers make the deployment of a Map-Reduce architecture complex and costly.

In cases where there is a seasonal computation demand, the use of public Clouds, for information processing and storage, is emerging as an interesting alternative. The Hardware as a Service (HaaS) [191] paradigm relieves the burden of making huge investments in infrastructure, and at the same time supports on-the-fly resizing of resources, and adaptation to current needs.

With a public Cloud, one can quickly make provision for the resources required to perform a particular task, and pay only for the computational resources effectively used. This is good solution, not only because it deploys faster, as opposed to having to order and install physical hardware, but it also optimizes overall costs, as resources can be released immediately after the task is completed.

One of the largest providers in the public Cloud is Amazon Web Services (AWS), with its Elastic Compute Cloud (EC2) [190] and Simple Storage Service (S3) [192] services. Amazon EC2 is a web service interface that provides resizable computing capacity in the cloud, allowing a complete control of computing resources and reducing the time required to obtain and boot new server instances. This feature is of particular interest because it allows applications to quickly scale up and down their processing and storage resources as computing requirements change. Amazon S3 provides a simple web services interface that can be used to store and retrieve data on the web, and provides a scalable data storage infrastructure.

In the specific case of applications requiring parallel processing using Map-Reduce architecture, one may also use the Elastic Map Reduce, which implements a hosted Hadoop framework running on the infrastructure of Amazon EC2 and Amazon S3.

The Map-Reduce architecture is an interesting approach, once it is versatile enough to be deployed in both environments. However, the Map Reduce architecture isn't generic enough to be used in all classes of problems that deal with large amounts of data to be processed, once there are some issues that are not addressed efficiently, such as the use of different Reduce algorithms for some specific pieces of information, or the chunk ordering before the Reduce step.

A good example where Map-Reduce could be generalized is the compression of high definition video files and especially for medical video, which requires intensive information processing. In this compression process, streams of audio and video are processed with different algorithms, and there is a great correlation between subsequent video frames, especially when there is temporal compression. The order in which pieces of audio and video are recombined after having been processed must also be taken into account so as to avoid that significant distortions are incorporated in the output. Moreover, issues such as fault tolerance, security and scalability need to be thoroughly considered, so that the proposed architecture becomes robust enough to meet the requirements of different video compression applications.

4.4.7. Distributed Video Processing

Video compression refers to reducing the quantity of data used to represent digital video images, and is a combination of spatial image compression and temporal motion compensation. Video applications require some form of data compression to facilitate storage and transmission. Digital video compression is one of the main issues in digital video encoding, enabling efficient distribution and interchange of visual information.

The process of high quality video encoding and analysis is usually very costly to the encoder, which, and require a lot of production time. When we consider situations where there are large content volumes, this is even more critical, since a single video may require the server's processing power for long time periods. Moreover, there are cases where the speed of publication is a critical point. Journalism and breaking news are typical applications in which the time-to- market the video is very short, so that every second spent in video encoding may represent a loss of audience.

We note that the higher the quality, i.e., the bitrate of the video output, the lower the speed of encoding. In order to speed up encoding times, there are basically two solutions. The first one is to augment the investment in encoding hardware infrastructure, to be used in full capacity only at peak times. The downside is that the infrastructure will be idled the remaining of the time.

The second solution is to try and optimize the use of available resources. The ideal scenario is to optimize resources by distributing the tasks among them evenly. In the specific case of video encoding, the intuitive solution is to break a video into several pieces and distribute the encoding of each piece among several servers in a cluster. The challenge of this approach is to split, as well as merge video fragments without loss in synchronization.

4.4.8. Dynamic Resource Allocation in Distributed Environments for Medical Data

In a data center, the primary goal of a dynamic autonomous resource management process is to avoid wasting resources as a result of under-utilization. Such a process should also aim to avoid high response times as a result of over-utilization, which may result in violation of the service level agreements (SLA) between the clients and the provider. Furthermore, it needs to be carried out continuously due to the time variant nature of the workloads of application environments.

At a high level, this process can be decomposed into two separate, and inter-dependent phases:

1. The first phase consists of defining a mapping between the application's service level and resource level requirements. Resource level requirements are generally derived from SLAs based on certain parameters such as response time, throughput, etc.; whereas, resource level requirements are often outlined as CPU usage, memory, bandwidth, etc. As the workload of an application changes in time, this mapping is used to determine the amount of resources that should be assigned to each component— encapsulated in virtual machines (VMs)—in order to satisfy the terms outlined in the SLA. This phase also requires performance modeling and demand forecasting for applications. The accuracy of the output from this first phase has direct effects on the accuracy of the configuration produced in the second phase.

2. The second phase involves the computation and application of a new configuration by distributing the resources in a data center among the VMs that represent application environments. The configuration is computed based on the output of the mappings produced in the first phase. Maintaining this configuration is a resource allocation problem and is generally defined as a Knapsack Problem or as a specific variant of it, namely Vector Bin Packing Problem, both of which are known to be NP- Hard. This phase consists of selecting a suitable configuration from a solution space with respect to a set of criteria. The criteria are used to define the quality of the solution in terms of certain requirements such as satisfying SLAs, overall data center utilization, and the overhead of applying an alternative configuration. The methods to be adopted in this phase need to be flexible so that the providers can easily redefine the configuration goals by adding new criteria or tuning the importance assigned to them.

3. In the second phase, certain constraints and limitations need to be taken into consideration.

Two of these are the time-spent during the selection of a new configuration, and the feasibility of it. Due to the time variance in workloads, a new configuration must be computed in a reasonable amount of time so that it is not stale under the current conditions. The selected configuration must also be feasible in terms of the number migrations necessary. The number of migrations that can be performed in a data center still has limits with the current technologies.

5. Context Aware Telemedicine Applications and Intelligent Management, Mining and Pattern Recognition of Medical Data

5.1. Patient fall detection

Telemonitoring the physical status and health of humans or patients at home, is an interesting solution compared to hospitalization in healthcare facility institutions since it offers a medical surveillance in a familiar atmosphere for the patient and can reduce the costs of medical treatment [47]-[51]. Within the same context, the monitoring of human physiological data, in both normal and abnormal situations of activity, is vital for the purpose of emergency event detection, especially in the case of patients suffering from chronic diseases or elderly people living on their own. Special interest is paid in the detection of the severity of the case that can indicate injury level and assistance request type. Several techniques have been proposed for identifying such distress situations using either motion, audio or video data from the monitored subject and the surrounding environment. The great challenge in such personal health systems is to provide less invasive monitoring technologies, increase mobility and at the same time achieve high accuracy rates in patient status interpretation [52].

The presented work introduces a solution to the problem of less invasive patient monitoring, describing the design and an initial implementation of a patient status awareness system that may be used for human or patient activity interpretation and emergency recognition in cases like elder falls and patient collapses. The proposed system utilizes motion information, audio and video data, which are captured from both the patient area and the surrounding environment. Visual information and audio from the monitored site are acquired using overhead cameras and microphone arrays respectively, while motion data and patient-generated audio sounds are collected through appropriate body-sensors on the patient. Appropriate tracking techniques are applied to the visual perceptual component enabling the trajectory tracking of the subjects and proper audio data processing and sound directionality analysis in conjunction to motion information and subject's visual location can verify fall and indicate an emergency event. Post fall visual and motion behavior of the subject indicates the severity of the fall (e.g., if patient remains unconscious or patient recovers and stands up). The severity analysis is performed through an ontological representation of the patient's context awareness, rules-based evaluation and activity classification. A number of advanced classification techniques have been evaluated for this purpose and the performance of the classifiers has been assessed in terms of accuracy and efficiency. The innovation of the presented system against existing works resides in four key elements: The utilization of three separate information channels (motion, audio and visual data) for patient status interpretation, the information fusion and streaming capabilities of the latter data, the ontology and rules-based evaluation for proper characterization of incidents and finally the context awareness concept which is newly introduced in such systems.

Although the concept of patient activity recognition with focus on fall detection is relatively new, there already exists significant related research work, which may be retrieved from the literature [51]-[60]. Information regarding the human movement and activity in assisted environments is frequently acquired through visual tracking of the subject's or patient's position. In [56] overhead tracking through cameras provides the movement trajectory of the patient and gives information about user activity on predetermined monitored areas. Unusual inactivity (e.g., continuous tracking of the patient on the floor) is interpreted as a fall. Similarly, in [59] omni-camera images are used in order to determine the horizontal placement of the patient's silhouettes on the floor (case of fall). Success rate for fall detection is declared at 81% for the latter work. A different approach for collecting patient activity information is the use of sensors that integrate devices like accelerometers, gyroscopes and contact sensors. The latter approach depends less on issues like patient physiology (e.g., body type and height) and environmental information (e.g., topology of monitored site) and can be used for a variety of techniques enabling user activity recognition [51], [54], [58]. Regarding fall detection, authors in [53], [57] and [60] use accelerometers, gyroscopes and tilt sensors for movement tracking. Collected data from the accelerometers (i.e., usually rotation angle or acceleration in the X, Y and Z axis) is used in order to verify the placement of the patient and time occupation in rooms and detect abrupt movement that could be associated with fall. Detection is performed using predefined thresholds [51], [54], [55], [57] and association between current position, movement and acceleration [53], [60]. In previous works [64], [65], we have presented a patient fall detection system based on such body sensors that utilized advanced classification techniques and Kalman filtering for producing more accurate results.

Sound processing has been also utilized for fall detection. Most of the related work focuses on collecting and analyzing sound data captured from the patient's close environment. In [70]-[72] authors present a sound analysis system enabling the detection of special sounds and their association with events related to specific activities or situations where first aid is needed (e.g., falls, glass breaking, call for help, etc.). The sound event detection is based on feature extraction through Discrete Wavelet Transformation (DWT) whereas classification to predefined events or vocal expressions is performed through a Gaussian Mixture Model (GMM) technique. In [73], Mel Frequency Cepstral Coefficients (MFCC) are used in order to detect a variety of sound signatures of both distressful and normal events. The examined sounds are categorized into classes according to their corresponding average magnitude levels that emerge from the application of Fourier Transform on the sound signal. Cepstral coefficients are used as features fed into a GMM model for proper classification. Accuracy of proper classification achieves 91.58% according to the authors. The aforementioned methods are based on acquisition and processing of sound data that originates from user's monitored environment. In [65] and [81] we have proposed a different method for detecting patient distress situations utilizing sounds captured by microphones attached on body sensors and spectrogram analysis sound processing. This technique has provided satisfying accuracy in detecting body fall sounds and distress speech expressions, while it was proved more tolerant to background noise and sounds not originating from the patient.

The presented work integrates user movement information and sound using wireless sensors, visual tracking of the patient and sound source localization using microphone arrays aiming at more accurate activity recognition systems. The proposed system is based on previous works by the authors in the context of movement characterization utilizing motion and sound and visual data individually [64], [65], [81], [82], and it is enhanced through semantic representation of the user's status and context awareness, while rules-based evaluation can provide an estimation of the severity of the incident (e.g., patient has recovered from fall, or patient is inactive, etc.). To our best knowledge there is no relative work in the literature that combines both visual, sound and motion sensor information and uses semantics for improving human safety through incidents detection in assisted living environments.

5.1.1. System Architecture

The presented system follows the architecture illustrated in Figure 5.1.1. Camera devices and microphone arrays are installed at the patient's site. Special sensor nodes with networking capabilities are required for collecting and transmitting related activity data (i.e. accelerometer and sound data). These sensors can be attached on several locations on the subject's body. A monitoring node is required for collecting the aforementioned data and performing required processing in order to enable an estimation of the human status. Recorded video frames provide feed to the video tracker that tracks the movement of the patient's body and generates body shape features (i.e. coordinates of a bounding box containing the subject's body). Recorded sounds are utilized in order to detect emergency events like distress speech expressions or body fall sounds. Sound source localization provided by the microphone arrays can also be applied and facilitate the status awareness; background noise can be easily filtered through sound source redundancy, Additionally, in the cases where the patient is the sound source, the localization of the latter in conjunction with visual trajectory information can provide more robust estimation of the actual incident and avoid false alarms generated by other sound sources.

The data are properly transformed in a suitable format for the classifier and the classification phase begins. Based on a predefined classification model (i.e. train model), the patient status is detected (i.e. emergency status when an emergency event is detected, normal status otherwise).

Apart from the indication of an emergency incident (e.g., a patient fall), an estimation of the severity of the incident can be provided based on the patient's behavior after the fall as recorded visually; visual inactivity or soft activity combined with distress sounds originating from patient's location suggest that patient has not lost consciousness and is trying to recover from the fall. In case no visual or sound activity is recorded after fall estimation, higher severity of the incident might be estimated. In order to provide a more accurate estimation a semantic model of the patient's status and context is built and proper rules evaluation follows.

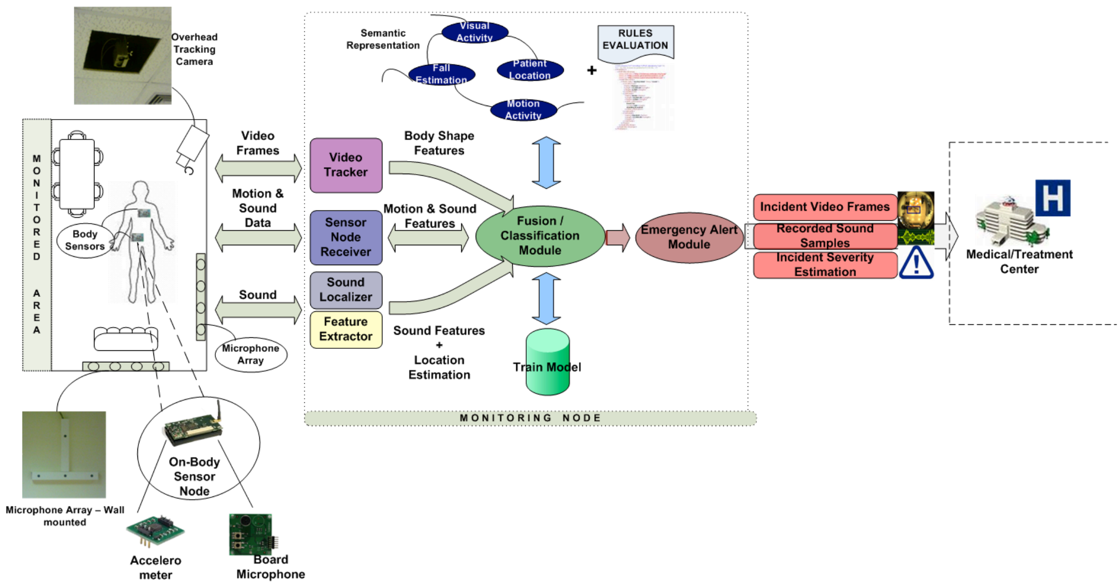
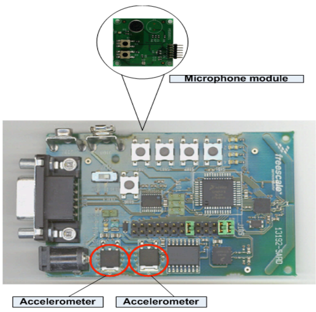


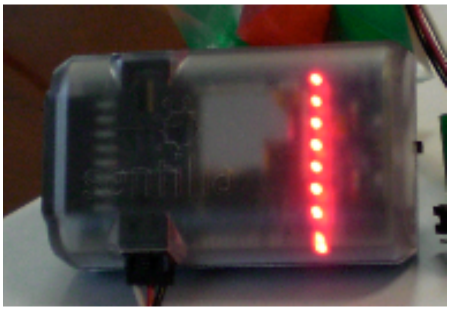
Figure 5.1.1 Proposed system architecture illustrating basic modules: motion, sound, visual perceptual components and respective equipment and the monitoring node

Based on emergency event detection, the treatment personnel at a remote or local site can be alerted. In conjunction to the incident type and severity estimation, corresponding video frames and audio samples from the patient and the monitored environment can be transmitted, facilitating the diagnosis process. Methods for analyzing visual, motion and audio data that allow human body trajectory analysis, sound source localization and incident detection are described in following Sections.

5.1.2. Motion and Sound Data Acquisition

Sensor data acquisition may be accomplished through wireless on-body (wearable) networks. On body networks or WPANs are defined within the IEEE 802.15 standard. The most prominent protocols for pervasive systems such as the proposed system are Bluetooth and ZigBee (IEEE 802.15.4 standard). The ZigBee has been developed as a low data rate solution with multi-month to multiyear battery life and very low complexity. It is intended to operate in an unlicensed international frequency band. The maximum data rates for each band are 250, 40, and 20 kbps, respectively. Two types of sensor nodes have been used in the implementation of the proposed system; A SARD ZigBee node [85] and a Sentilla Perk [84] sensor (see Figure 5.1.2). Both of them contain a 2.4 GHz wireless data transceiver RF reference design with printed circuit antenna, which provides the necessary hardware required for a complete wireless node using IEEE 802.15.4 (ZigBee) [17] packet structure. The first one includes an RS232 port for interface with a personal computer, whereas the second one uses a USB port interface instead. Both of them feature debug modules for in-circuit hardware debug, switches and LEDs for control and monitoring, a low-power, low-voltage MCU (MicroController Unit) with 60KB of on-chip Flash which allows the user flexibility in establishing wireless data networks. 3D Accelerometers for measuring acceleration at X, Y and Z axis have been attached on the nodes (SARD node contains two accelerometers and Perk node one respectively). A separate SensiNode [86] board has been also attached containing a microphone and additional sensors like illumination and temperature sensors. The Perk nodes are provided in a plastic robust small-sized enclosure (6x3x1.5cm) making them more suitable for placing on patient's body and tolerating falls.





A B

Figure 5.1.2 A) The SARD ZigBee node. The node acts as both receiver and transmitter. The RS232 interface provides connectivity with the monitoring device (e.g., a PDA) when the node is used as receiver. Two 3D accelerometers and one microphone module are attached on the node B) The Sentilla Perk node containing one 3D accelerometer that can be attached on user and send motion data through the ZigBee wireless protocol. The plastic enclosure can protect the node from falls and makes it more suitable for carrying it on patient's body

More than one sensor nodes can be placed on patient's body. Preferable positions are close to user's chest and user's belt or lower at user's foot. The latter positions have proven based on conducted experiments to be more appropriate for distinguishing rapid acceleration on one of the three axes that is generated during a fall. Appropriate J2ME [83] and C code is developed and deployed on the nodes for reading the accelerometer values and transmitting them wirelessly to the monitoring unit. At the latter a Java application built using the Sentilla Integrated Development Environment

(IDE) [84] receives the movement data and performs further processing as described in the following sections. The X, Y and Z acceleration values from both sensors are interlaced. In order to improve the accuracy of the latter decision, Kalman filtering [22, 23] has been applied on the sequence of the movement type association of each acceleration data set, according to the following algorithm. The measurement noise and acceleration noise factors have been set to 10 and 0.5 respectively based on conducted experiments. The noise has been considered white and therefore a known covariance matrix has been used.

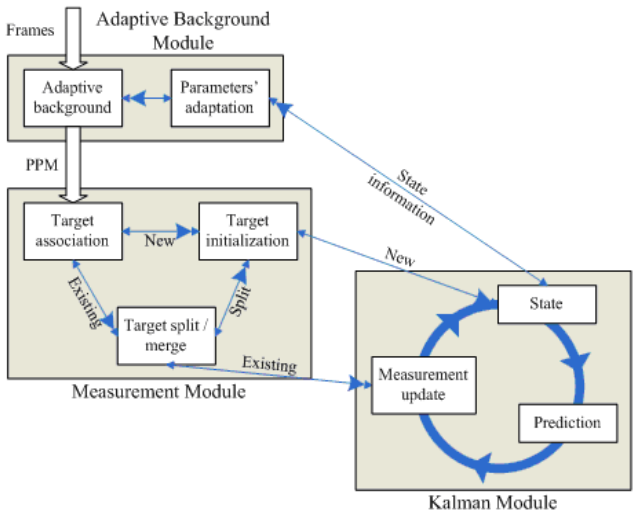
```
Start Kalman filter algorithm

Step 1:
Read acceleration value Xn from sensor
Step 2:
Calculate the noise covariance Nq and the Measurement error
covariance R based on the MeasurementNoise factor and
AccelerationNoise factor.

Nq = AccelerationNoise ^2 * [0.1^4/4 0.1^3/2; 0.1^3/2 0.1^2]
R = measnoise^2

For the previous 10 acceleration values Xi, i€[n-10, n-1]:
        Calculate the noise:
        Noise = AccelerationNoise * Xi* [(0.1^2/2); 0.1]
        Calculate the measurement with the estimated noise:
        Meas = measnoise * Xi
        z = Xi + MeasurementNoise;
        Calculate the Innovation:
        I = z - c * xhat;
        Calculate the covariance of Innovation:
        s = Xi * P * Xi' + R;
        Calculate  the Gain matrix:
        K = a * P * Xi' * inv(s);
        Calculate  the estimate for the next acceleration value:
        Xest = a * Xest + K * I;
end

GoTo Step 1

End algorithm
```

Each filtered acceleration value (Xest, Yest and Zest respectively) are used as inputs to the classification process.

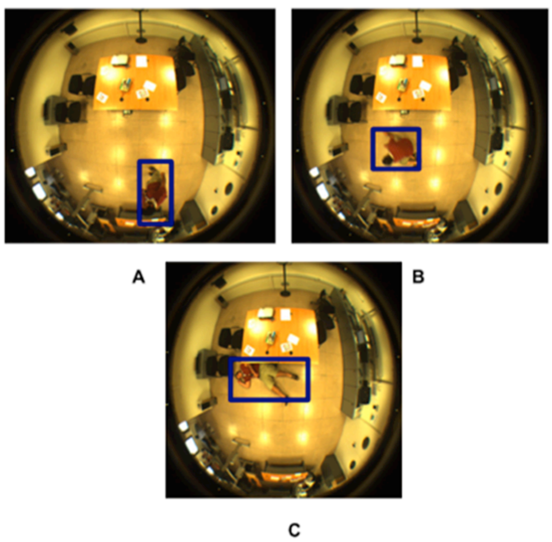
5.1.3. Human Body Visual Tracking

The goal of the body video tracker is in brief the provision across time the frame regions occupied by human bodies. The tracker is built around a dynamic foreground segmentation algorithm [62] that utilizes adaptive background modeling. This is based on Stauffer's algorithm [63] to provide the foreground pixels. Stauffer's algorithm models the different colors every pixel can receive in a video sequence by Gaussian Mixture Models (GMM). One GMM corresponds to every pixel at given coordinates across time. As a result, a map can be built in which every pixel is represented by the weight of the Gaussian from its GMM that best describes its current color. This is the Pixel Persistence Map (PPM): Regions of the map with large values correspond to pixels that have colors that appear there for a long time, hence they belong to background. On the contrary, regions with small values correspond to pixels that have colors that appear there for a short time, hence they are foreground. The deficiency of Stauffer's algorithm is related to foreground objects that stop moving. In its original implementation, targets/objects that stop moving are learnt into the background. To avoid this in our system, the learning rates of the adaptation that increase the weights of Gaussians are not constant, neither across space, nor across time. Instead, they are spatiotemporally controlled by the states of Kalman filters [61] (see Figure 5.1.3-1). Every foreground area corresponds to a target being tracked by a Kalman filter. The foreground pixels are combined into body evidence blobs, used for the measurement update stage of the Kalman filters. The states are used to obtain the position, size and mobility of each target, the latter being a combination of translation and size change. This information is fed back to the adaptive background modelling module to adapt the learning rate in the vicinity of each target: frame regions that at a specific time have a slow-moving target have smaller learning rates. The block diagram of the introduced body tracker is shown in Figure 5.1.3-A. Using the feedback configuration of the tracker, the learning of the slow moving foreground objects into the background is slowed down long enough for the intended application, i.e. tracking people moving indoors and possibly falling down. The tracker results, as produced by the visual feed of an overhead camera are illustrated in Figure 5.1.3-B.

Tracking through overhead cameras has been selected due to the fact that it provides a better visual representation of the monitored area and allows the tracker to gain a better estimation of the body shape when subject moves, falls and lies still after fall. The presented tracker detects and tracks a rectangular blob around the detection of the moving body within the frames and reports the upper left corner coordinates and respective width and height of the blob. As indicated in Figure 5.1.3-B, the size of the blob changes during the fall and after it.



A



B

Figure 5.1.3 A) Block diagram of the body video tracker. Kalman filters spatiotemporally adapt the learning rates of the adaptive background algorithm, effectively avoiding learning of immobile foreground objects into the

background B) Visualization of video tracking performance. The tracker detects the movement of the body and correlates it with the movement of a rectangular blob within the visual domain. Upper left X, Y coordinates and respective width and height of the blob are reported for each visual frame. Frame A corresponds to normal walking, Frame B to captured movement during fall and Frame C illustrates detection of body in horizontal position after fall

5.1.4. Sound Processing and Event Detection

The detection of emergency events is also facilitated through appropriate sound processing of surrounding audio captured by the microphone arrays and patient sounds acquired by the body sensors. Microphone arrays are mostly utilized for sound source localization whereas sounds captured from on-body microphones provide important features that can be properly classified and lead to event detection.

An important aspect of the proposed system is the sound source localization that can lead to an estimation of the position of the individual in the event of an emergency. Localization can be performed using the estimation of the Direction of Arrival (DOA) of an acoustic source using Time Delay Estimation (TDE). Typically, the problem is addressed using microphone arrays that collect data in frames so that the current estimate can be provided. The most popular approaches rely on defining the relative delay between a pair of microphones by means of comparing function that returns a peak at the correct DOA of the source. Common methods for TDE are the Generalized Cross-Correlation (GCC) [67] and Blind Source Separation (BSS) [68]. The proposed system utilizes sound source localization using an implementation similar to BSS provided by [69].

Assuming the existence of two microphones, a single source would lead to the following discrete signal recorded at the ith microphone $i \in [1,2]$

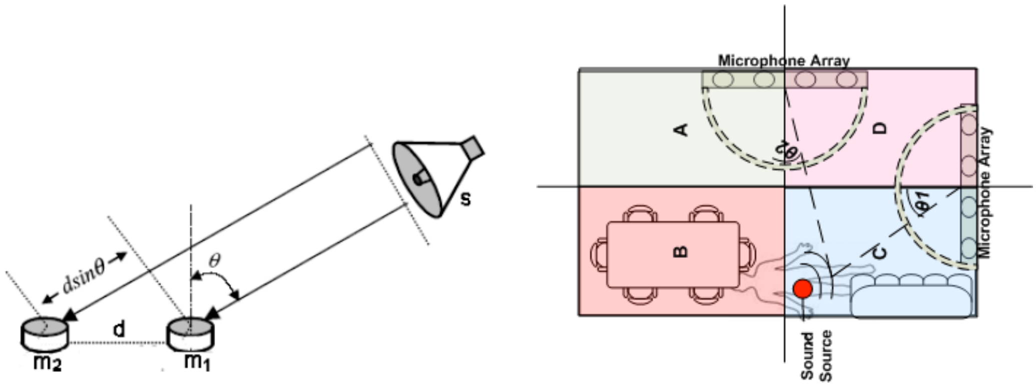
$$x_i(k) = s(k - \mathrm{T}_i) \qquad (1)$$

where Ti denotes the time in samples that it takes for the source signal to reach the ith microphone.

For the case of two microphones (see Figure 5.1.4 A) Direction of Arrival θ (DOA) estimation using microphone arrays and Time Delay Estimation (TDE) B) Estimation of patient location using sound source localization) and considering that T1=0, the delay at i2 is the relative T=t2 between the two recorded signals. The corresponding DOA θ in degrees is defined with respect to the broadside of the array that is connected with T in the following way:

$$\theta = \arcsin\left[\frac{TC}{f_s d}\right] \qquad (2)$$

where fs is the sampling frequency of the recording system and c the speed of sound. More details of the sound localization implementation can be found in [69].



A B

Figure 5.1.4 A) Direction of Arrival θ (DOA) estimation using microphone arrays and Time Delay Estimation (TDE) B) Estimation of patient location using sound source localization

The correlation of the sound source location and patient's body location is performed as follows: Consider two microphone arrays being attached on the walls of a monitored area as show in Figure 5.1.4-B. The arrays can cover a direction of arrival Θ = 1800. The area has been divided into four quadrants. When a sound is captured each microphone array gives an estimation of the angle of arrival θ1 and θ2. Based on their values, the quadrant that contains the sound source can be easily determined. The presence of the patient within the latter can be then verified by the visual tracker as well. The deployment of a larger number of microphones per array and the introduction of arrays within the monitored array can increase the sound source localization accuracy by also allowing the utilization of more advanced techniques like angle tranquilization. The latter can be translated into the following algorithm:

```
Start Angle of Arrival Algorithm

T1,2 = timestamp of signal recorded at the microphones
for all microphones in the array:
Calculate the average time delay T as:
T = abs(T2-T1+T3-T2+T3-T1)
Calculate the angle of arrival as:
Θa = arcsin [(T * C)/ 22100] (C equals to the speed of light)
end
if(Θ1 > 900 && Θ2 > 90)
        Quadrant = A;
else if (Θ1 > 900 && Θ2 < 90)
        Quadrant = B;
else if (Θ1 < 900 && Θ2 < 90)
        Quadrant = C;
else if (Θ1 < 900 && Θ2 > 90)
        Quadrant = D;
end

End Algorithm
```

If the quadrant indicated area contains the subject's body as indicated by the visual tracker, a binary feature with the value of 1 is used. Otherwise the feature has the value of zero.

5.1.4.1. Sound Feature Extraction

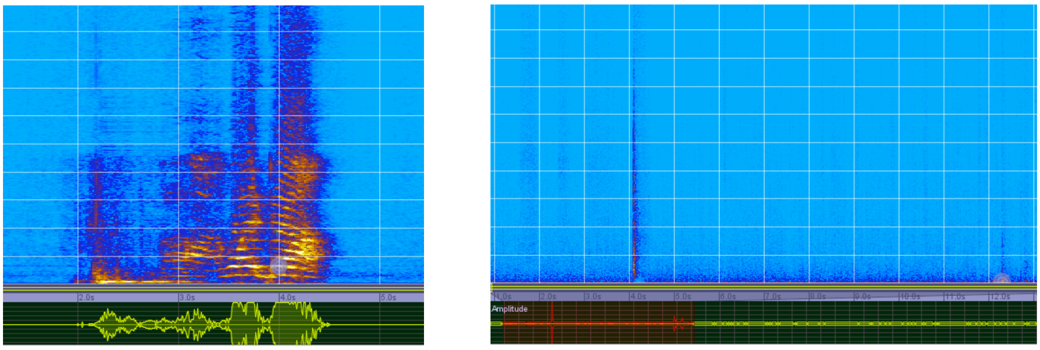
In this research work we have used spectrogram analysis, based on short-time-Fourier Transform (STFT) for the detection of sounds features characterizing the fall of the human body or the vocal stress in speech expressions indicating distress events. Given a signal x(t) and its Fourier Transform X(τ, ω) the STFT is defined as:

$$\mathrm{STFT}\{x()\} \equiv X(\tau,\omega) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-j\omega}dt \qquad (3)$$

The spectrogram is respectively given by the magnitude of the STFT of one function:

$$\mathrm{spectrogram}(t,\omega) = \left|\mathrm{STFT}(t,\omega)\right|^2 \qquad (4)$$

In the most usual format of a spectrogram, the horizontal axis represents time, the vertical axis is frequency, and the intensity of each point in the image represents amplitude of a particular frequency at a particular time. Based on conducted experiments the relative amplitude of a signal and the peak frequency at a given time can give a successful indication of a patient fall sound as captured by the microphone arrays; Body falls generate low frequency sounds with high amplitude. Using a threshold of >90% for relative signal amplitude and <200 Hz for peak frequency, the differentiation of a fall sound against other sounds is possible. More precisely, over a series of 20 sound samples containing both body fall sounds and background noise (e.g., radio, object falls, etc.) the detection of the fall was possible for 80% of them [81]. Different types of floor (i.e. wood, cement and flooring tile) were also used. Neither the different floor types used, nor the various background noises seem to have influenced the performance of the system. The presented method has low computational complexity and can be easily integrated on sensor devices for real time sound processing. The same analysis has been applied on vocal sounds in an effort to detect distress expressions.



A B

Figure 5.1.5 Illustration of spectrogram analysis on A) distress speech expression, B) Sound generated by patient body fall

The latter can be translated into the following algorithm for calculating the Average Sound Peak Frequency and Average Signal Relative Amplitude features:

```
Start Sound Feature Extraction Algorithm

Xs[] Five second segment of recorded data

for i=0 to all the number of recorded segments:
        Calculate STFT for the given Xs[i];
        Calculate spectrogram for STFT[i];
        for: all the signal segments:
                Find maximum signal amplitude, Amax
                Find coherent signal amplitude, Ac, where Ac>0.9*Amx
                for: all the Ac:
                        if Fpeak of Ac < 200 Hz
                        Use Fpeak and Ac for classification
                end
        end

end

End Algorithm
```

The following section provides more information on how motion, visual and audio data can be collected in order to achieve the optimum motion analysis and fall detection.

5.1.5. Experimental Protocol Details

In order to combine the aforementioned information channels and detect emergency fall incidents, an experimental protocol has been defined. The protocol describes issues like the movement types that can be analyzed, the suggested placement of the sensors for optimum results, and technical details like sampling rates and testbed setup. Three different combinations of movement types have been considered for assessment; a) simple walk, b) simple walk and fall, c) simple walk and run. The sensors have been placed on subject's chest and belt (using special straps glued on sensors) in order to provide better estimation of the body movement and placement with respect to the ground. Each experiment containing one of the aforementioned movement types has an average duration of 120 seconds. Each individual performs at least two experiments including all three movement types. The sampling frequency (i.e. the rate sensors are collecting and transmitting data) is 20 Hz for movement data and 22.1 KHz for audio data (default sampling rate of the microphone sensor). The frequency of falls in the second type of experiments is 2 or 3 falls per recording. The volunteers - subjects are directed to perform all movement types as realistically as possible, behaving like in real life (i.e., adding random stopping intervals in movement and changing acceleration at will). More specifically for the fall trials, the individuals are advised to initially walk within the experiment area (a flat room of 40 square meters with obstacles like furniture) and then perform falls simulating events like stumbling on furniture or falling down because of loss of consciousness (e.g., in case of a heart attack). Each combined movement type experiment (i.e. simple walk and run or simple walk and fall) can be considered to contain about 80% of its recording time of walking and the rest for running or falling). Post fall behaviors are also simulated by standing still (unconscious state), moving (trying to recover from fall) and getting up (recovering from fall). An overhead camera is capturing visual frames and two microphone arrays are capturing sounds (see Figure 5.1.1 for testbed setup). Recorded data are segmented into time segments of 5 seconds. Each segment is processed and the generated sound data and body motion features are utilized for creating classification models. Classification of all incoming data is performed every 5 seconds to maintain time granularity. All incoming data are time-stamped and buffered until the classification process. Sound features consist of average peak frequency and average relative amplitude for the specific time segment as calculated using spectrogram analysis. Respectively, body motion features are the standard deviation of the blob size generated by the visual tracker (see Figure 5.1.3-2) and the average movement speed of the tracked body over captured frames. Finally, a binary feature (true/false) is used in order to indicate whether a detected sound has occurred within close proximity of the patient or not. Table 5.1.1 summarizes all the aforementioned features utilized for performing the experiments. The correlation of the motion and sound data with the patient body trajectory data can provide much more accurate results as presented in the following section.

Table 5.1.1 Description of Utilized Motion, Sound and Visual Features

Features		**Short Description**
Motion Features		
	X, Y, Z acceleration values	X, Y and Z acceleration values in [-1, 1] as obtained from on-body sensors.
Sound Features		
	Sound Proximity	Binary feature indicating whether a captured sound has been recorded in close proximity to the patient body. This information is generated by sound source localization and visual information (see Section 3.4.1)
	Average Peak Frequency	Numerical featured calculated using STFT transform on acquired sound signal (see Section 3.4.2)
	Average Signal Relative Amplitude	Numerical featured calculated using STFT transform on acquired sound signal (see Section 3.4.2)
Visual Features		
	Visual Blob size	The standard deviation of the blob (i.e. rectangular area containing subject's body) size as indicated by the visual tracker (see Section 3.3)
	Average Movement speed	The average movement speed of the tracked body over captured frames

5.1.6. Severity Estimation through Semantic representation and Rule-based evaluation

In order to semantically represent an emergency incident as indicated by the motion, sound and visual perceptual components, the ontology illustrated in Figure 5.1.6 has been developed. An emergency incident can be characterized by its severity (e.g., high or low) based on fall estimation and more precisely if high or low visual and motion activity is identified after the fall, respectively. The patient movement ability level can also provide important information regarding the patient's ability to recover from falls and finally the correlation of the sound source and the patient's location is also very important.

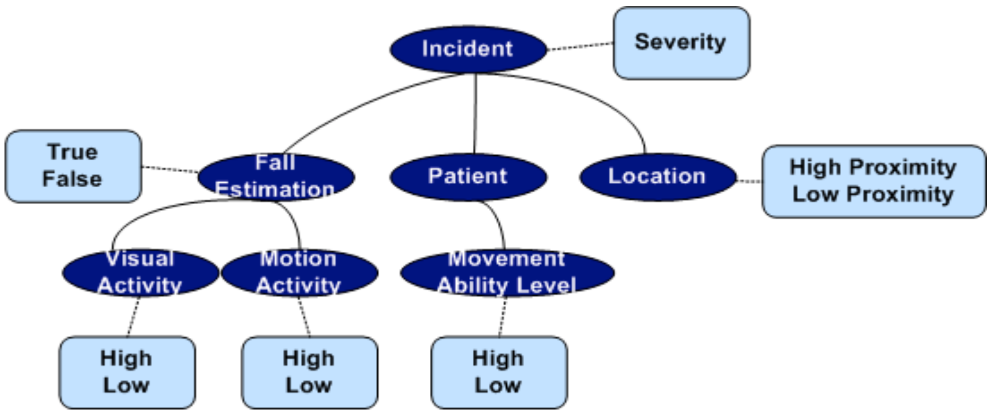


Figure 5.1.6 Semantic representation of the ontology modeling an emergency incident based on fall estimation, patient and location parameters

The ontological model has been developed within the Protégé [88] semantic framework using the Ontology Web Language (OWL). The main advantages of the semantic representation of the incident in the context of the patient status can be summarized into the following:

- Flexibility to modify and extend the contextual scheme by adding more classes. In case the parameters that define the context of the patient (e.g.., status, environment, location, etc.) need to be modified, the ontological model can be altered without invoking modifications to the implementation modules or the architecture of the platform.

- Using advanced semantic rule evaluation techniques content adaptation decisions can be made according to a plethora of contextual parameters. The rules can be updated and extended without any need for system platform software modifications.

- Additionally, ontologies are explicit because define the concepts, properties, relationships, functions, axioms and constraints that compose the contextual model. They are formal because they are machine readable and interpreted.

The creation of semantic rules required the description of the latter through abstract semantic languages like the Semantic Web Rule Language (SWRL) [89]. Within this context, the SWRL Factory [88] mechanism and an integrated Jess rule engine [90] using the Protégé tool have been utilized. Jess provides both an interactive command line interface and a Java-based application programming interface (API) to its rule engine. This engine can be embedded in Java applications and provides a flexible two-way run-time communication between Jess rules and Java. The Jess system consists of a rule base, a fact base, and an execution engine.

Two indicative samples of SWRL rules follow that can be used within the presented framework in order to facilitate the decision on the emergency incident estimation:

```
Patient(?x)^Location(?y)^hasFallEstimation(?x,?y, ?FallEstimation)^
hasVisualActivity(?x,?VisualActivity)^hasMotionActivity(?x,?MotionAc
tivity)^ Location(?Proximity)^
swrlb:equals(?FallEstimation,?true)^swrlb:equals(?Proximity,?High)
^swrlb:equals(?VisualActivity,?High)^swrlb:equals(?MotionActivity,?H
igh)
->DefineIncidentSeverity(?Severity,"LOW")

Patient(?x)^Location(?y)^hasFallEstimation(?x,?y, ?FallEstimation)^
hasVisualActivity(?x,?VisualActivity)^hasMotionActivity(?x,?MotionAc
tivity)^ Location(?Proximity)^
swrlb:equals(?FallEstimation,?true)^swrlb:equals(?Proximity,?High)
^swrlb:equals(?VisualActivity,?Low)^swrlb:equals(?MotionActivity,?Hi
gh)
->DefineIncidentSeverity(?Severity,"HIGH")
```

Both rules examine the correlation of patient's location to the sound source, the fall estimation and post-fall visual and motion activity. In the both cases, a fall has been detected and the body fall sound and/or other distress sounds have been captured in close proximity of the patient. In first case there is high visual and motion activity indicating thus that the patient has probably recovered from fall, whereas in the second case low visual but high motion activity indicates that the patient is still on the floor trying to recover from fall. Thus the first incident is characterized of low severity and the second of high severity respectively. The first rule can also be modified to the following one, in order to avoid any false positives generated by the characterization of motion or sound data; in case an estimation of fall is generated but is followed by high visual and motion activity and the movement speed of the body's visual trajectory is above a predefined threshold then the subject has not fallen but moves rather fast:

```
Patient(?x)^Location(?y)^hasFallEstimation(?x,?y, ?FallEstimation)^
hasVisualActivity(?x,?VisualActivity)^hasMotionActivity(?x,?MotionAc
tivity)^ Location(?Proximity)^ TrajectorySpeed(?Speed)^
swrlb:equals(?FallEstimation,?true)^swrlb:equals(?Proximity,?High)
^swrlb:equals(?VisualActivity,?High)^swrlb:equals(?MotionActivity,?H
igh) ^swrlb:equals(?speed,?High)
->DefineIncidentSeverity(?Severity,"VERY LOW")
```

5.1.7. Results and Experimental Evaluation

This section presents the results and experimental evaluation of the proposed system. The incorporated algorithms and tools for classifying the motion, audio and visual perceptual components acquired by the methodology described above are discussed in the following subsections. The evaluation of the system involves the assessment of the system's accuracy in properly characterizing falls as well as the user-based evaluation in terms of acceptance and effectiveness and technical acceptability.

Several advanced classification techniques have been utilized in order to build proper models for proper activity and status recognition. The selection of the specific algorithms was based on their utilization in related work for fall detection. The features used for classification are summarised in Table 5.1.1. The examined algorithms were: Bayes Networks, Naïve Bayes, Naïve Bayes Multinomial, Support Vector Machines (SVM), Logistic regression, Multilayer perceptron, Nearest

Neighbour and K-Nearest Neighbour, Neural Networks, PART, NBTree, and SimpleCart. In addition, the following meta-classifiers have also been used:

AdaBoost [74] : Class for boosting a nominal class classifier using the Adaboost M1 method. Often dramatically improves performance, but sometimes overfits.

Classification via regression [75]: Class for doing classification using regression methods. Class is binarized and one regression model is built for each class value.

CVparameterSelection [76]: Class for performing parameter selection by cross-validation for any classifier.

RandomSubSpace [77]: This method constructs a decision tree based classifier that maintains highest accuracy on training data and improves on generalization accuracy as it grows in complexity. The classifier consists of multiple trees constructed systematically by pseudo randomly selecting subsets of components of the feature vector, that is, trees constructed in randomly chosen subspaces.

NestedDichotomies [78]: A meta classifier for handling multi-class datasets with 2-class classifiers by building a random class-balanced tree structure.

Dagging [79]: This metaclassifier creates a number of disjoint, stratified folds out of the data and feeds each chunk of data to a copy of the supplied base classifier. Predictions are made via majority vote, since all generated base classifiers are put into the Vote meta classifier. This metaclassifier is useful for base classifiers that are quadratic or worse in time behavior, regarding number of instances in the training data. Usually in this case, Support Vector Machines are used as base classifiers.

ThresholdSelector [66]: A metaclassifier that selecting a mid-point threshold on the probability output by a Classifier. The midpoint threshold is set so that a given performance measure is optimized. Currently this is the F-measure. Performance is measured either on the training data, a hold-out set or using cross-validation. In addition, the probabilities returned by the base learner can have their range expanded so that the output probabilities will reside between 0 and 1 (this is useful if the scheme normally produces probabilities in a very narrow range).

The evaluation of the proposed system has been performed based on the experimental protocol and testbed setup as described in previous sections. Two male volunteers of average height and weight at the ages of 28 and 35 wearing the sensors devices performed combinations of movement types. Twelve recordings in total have been utilized (each individual performing two experiments of three different motion combination types), that have provided 1440 seconds of recorded data (motion, sound and visual data). The latter have been segmented into 5 second time frames (for sound processing) and annotated. The procedure involves the evaluation of classifiers, effectiveness of features and information fusion, where the efficiency of the proposed classification model is calculated using a predefined procedure. The dominant method presented in literature, mainly used in situations where the total amount of data is limited, in order to provide a sufficient amount of data for training and separately testing the developed model, is N-fold cross validation [99]. The most widely applied value for parameter N is 10, which is the value we selected for our experiments in order to verify each model's accuracy and performance: The 1440 seconds of recorded data were segmented into 5 second time frames resulted into 288 experimental time frames. 260 randomly selected time frames were used as a training data set whereas the remaining 28 frames were used for testing. The latter process has been repeated 10 times and the total error rate has been calculated from the average of each individual test error rate. The evaluation has been divided into two parts; initially the characterization of motion using acceleration and sound data from the on-body sensors has been validated. Finally, the visual channel information has been added and the rules-based evaluation provides the essential fusion for complete fall incidents detection.

Based on the number of sequential occurrence of a specific movement type, decision regarding a patient fall is taken. In order to improve the accuracy of the latter decision, Kalman filtering [22, 23] has been applied on the sequence of the movement type association of each acceleration data set. Figure 5.1.7 represents the classification results and the significance of Kalman filtering from the conducted experiments (utilizing only motion and sound data) using the trained SVM model. Light colored lines represent original results whereas dark colored lines results after applying Kalman filtering. The improvement in classification accuracy by utilizing both motion and sound features is also visible in Figure 5.1.8 by the corresponding receiver operating characteristic (ROC) curves. Before applying Kalman filtering the false positives for the case of falls were 60% of the total classified instances and after applying Kalman filtering were minimized to 33% respectively. For annotation purposes, the three movement types were associated with three integers; 1 for walk, 2 for run and 3 for fall respectively. Actual run and fall events are also annotated on the diagrams. For each experiment two different diagrams were generated; one illustrating classification results based exclusively on acceleration data and one illustrating classification based on both acceleration and sound data. As it is indicated, Kalman filtering improves the overall detection by smoothing the sequential occurrences of run or fall events respectively. In addition, the use of sound as additional classification feature has increased the accuracy of fall detections by minimizing the false ones in cases of simple walk and of walk and run. A threshold t =10 has been selected for determining the occurrence of a fall or run event from the total sequence of classified movement types (i.e. if sequential occurrence of fall movement types > 10 then a fall is detected). Using the aforementioned classification and the latter threshold value, fall events were successfully detected in all cases, whereas run events were successfully detected at 96.72%.

In addition, the classification results utilizing the algorithms described in Section 5.1 and the combination of motion, visual and audio perceptual components and information fusion using semantic rules evaluation are presented in Table 5.1.2. A number of statistical analysis performance metrics have been used: the accuracy, the kappa statistic [80] (which measures the agreement between two raters, who each classify N items into C mutually exclusive categories), and the root mean square error of the latter.

Table 5.1.2 Evaluation results for the different classification algorithms used on motion, sound and visual perceptual components

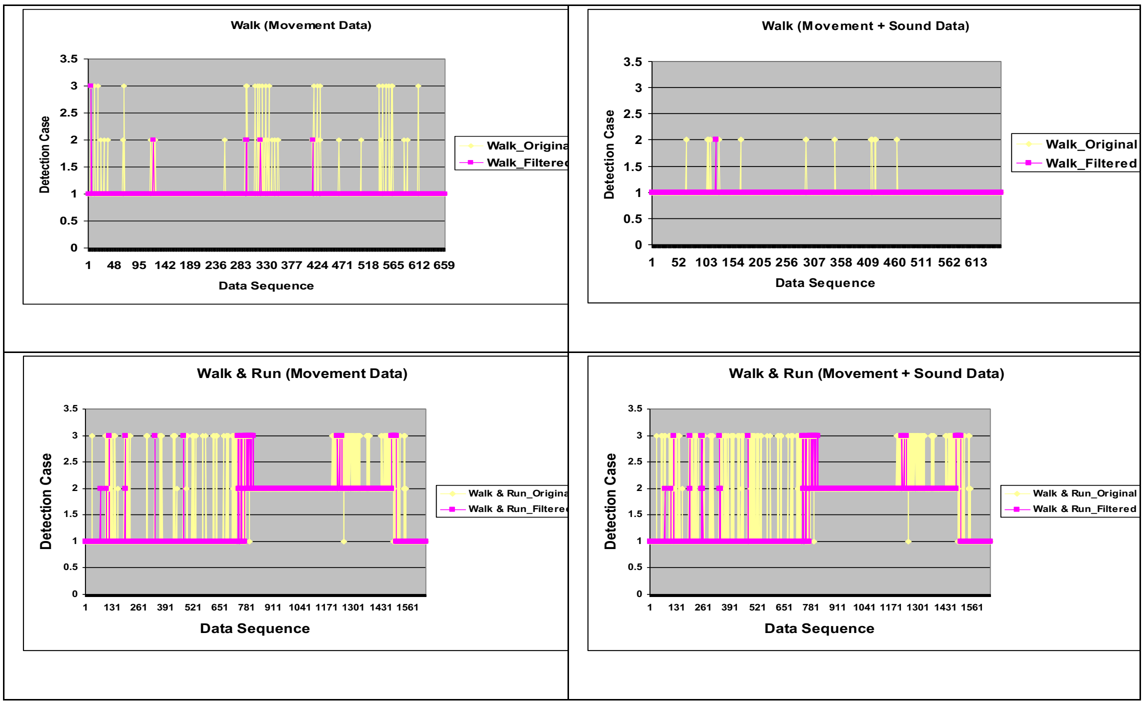
Classification Algorithm	**Algorithm Parameters**	**Correctly Classified Instances (%)**	**Kappa statistic**	**Root mean squared error**	**Sensitivity/ Specificity (%)**
BayesNet	Simple Estimator, A: 0.5, search	97.54	0.9392	0.1169	97/93

	algorithm: hill climbing				
NaiveBayes	No input	96.49	0.8923	0.1337	96/88
Logistic	Ridge value in log-likelihood: 1.0E-8	95.32	0.7389	0.2251	95/91
MultiLayerPerceptron	Learning rate: 0.3, learning time: 500 validation threshold: 20, num of epochs: 500	98.58	0.9478	0.0984	98/93
SVM	Kernel: RBF, C:1024, g : 0.125	100	1	0.0181	100/100
IB1 (Nearest Neighbor)	No input	93.33	0.5547	0.2734	93/88
IBK (K Nearest)	KNN:1, Search Algorithm: LinearNNSearch [66], Euclidean distance	94.53	0.6547	0.2724	94/90

NNge	No Input	94.66	0.7094	0.231	94/92
PART	Confidence Factor: 0.25,	99.29	0.9674	0.0851	99/96
NBTree	No input	100	1	0.0219	100/100
SimpleCart	heuristic: true, numFold Pruning: 5	98.85	0.9361	0.1193	98/95
AdaBoost	Number of Iterations: 10, Weight Threshold: 100	100	1	0.0211	100/100
Classification ViaRegression	Classifier M5P, minNumIns tances: 4	97.58	0.9347	0.1562	97/93
CVParameterS election	Classifier: O-R [66]	88.17	0.2365	0.3343	88/80
RandomSubSp ace	Classifier: REP-Tree [66]	99.87	0.9044	0.1238	99/90
NestedDichoto mies	Classifier: J48 [66], confidence factor: 0.25	98.56	0.9391	0.1222	98/96
Dagging	Classifier: Support	86.8	0.1895	0.3054	86/72

	Vector, Kernel type: PolyKernel				
ThresholdSelector	No Input	93.01	0.6958	0.228	93/87

Additional evaluation metrics apart from accuracy are essential, since the latter is not sufficient itself for comparing the performance of different classifiers. For instance, lower kappa statistic (0.8923) and higher RMS error (0.1337) in NaiveBayes than in BayesNET (0.9392 and 0.1169 respectively) suggests that BayesNET performs quite better than NaiveBayes, though the accuracy metric does not indicate such difference directly (96.49 versus 97.54 respectively). BayesNET is also expected to perform better when including motion data, since NaiveBayes is based on the inherent assumption that features are conditionally independent and modelled by a normal distribution, which has been proved to be invalid when dealing with accelerometer data according to L. Bao et. al [97], [98].



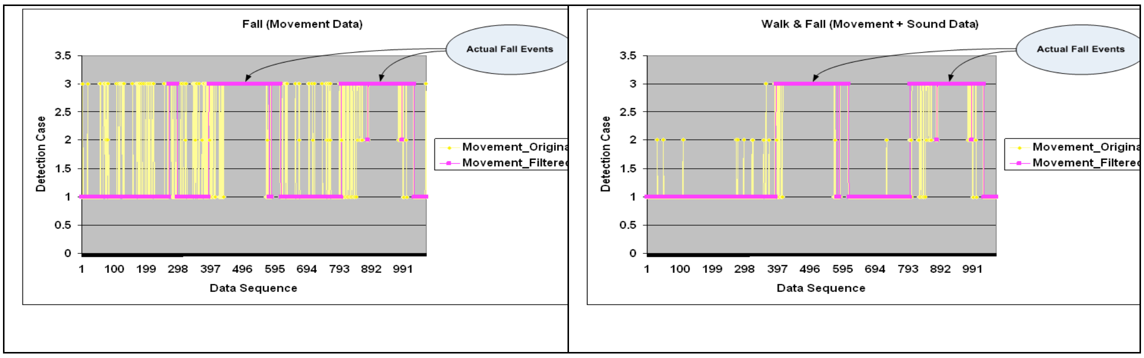
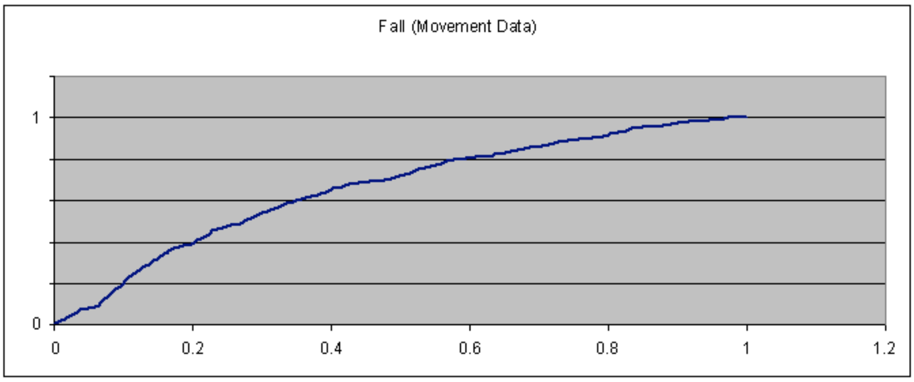
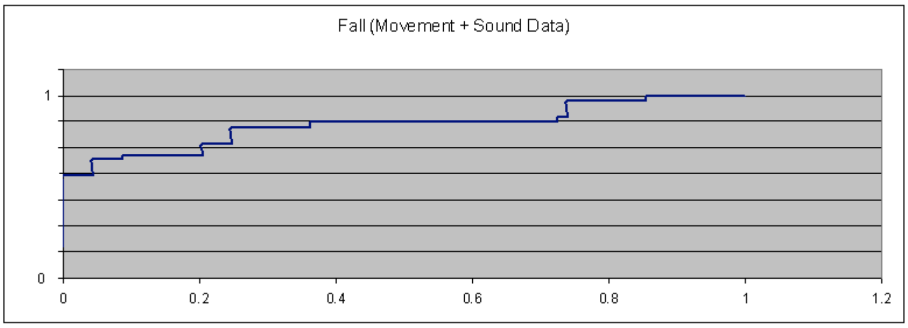


Figure 5.1.7 Classification results from the conducted experiments using the trained SVM model. Light colored lines represent original results whereas dark colored lines results after applying Kalman filtering. Diagrams on the left present accuracy results based on movement data whereas diagrams on the right present accuracy results utilizing both motion and sound data.

As indicated by the evaluation results, the majority of the algorithms achieve high accuracy results. All fall incidents were successfully indicated in the case of SVM and AdaBoost meta-classifier, whereas related works in fall detection achieve up to 81% for visual information classification [59], and 91,58% for audio features classification [73]. The base classifier used with AdaBoost is the DecisionStump tree classifier, which performs regression based on mean-squared error. For SVM, the radial basis function kernel type has been used. The utilization of all the acquired perceptual components also improves the overall performance of the system since fall determination accuracy is over 90 % for the majority of classifiers with an average false positive range of 16.67% (in conjunction to 33% of false positive rate when using motion and sound data only). The utilization of rules-based evaluation (see Section 4) can potentially minimize false positives to zero.



(a)



(b)

Figure 5.1.8 ROC curves of SVM Classifier performance in fall detection using: a) Motion data individually. Area under curve: 0.655, b) Motion and Sound data. Area under curve: 0.885

5.1.8. System User-based Evaluation

The system in addition to his correctness on the detection of specific human activities was evaluated in terms of usability, user friendliness and reliability. According to literature review several factors can be utilized in order to evaluate patient-related applications. The most common way of measuring the aforementioned factors is the Mean Opinion Score (MOS). In a subjective test, a number of people rate their quality of experience on a scale of 1 (bad) to 5 (excellent). The average of the scores is called a MOS. The resulting MOS depends on the range of experiences that were exposed to the group and to the type of experience being rated. Based on the evaluation performed by [87], four criteria of human factors evaluation are utilized: (A) technical acceptability, (B) operational effectiveness, (C) clinical appropriateness and (D) equipment selection. Technical acceptability refers to issues like sensor communication, battery life, etc., operational effectiveness refers to system effectiveness (i.e. detection correctness), clinical appropriateness refers to usability as accepted by the treatment personnel, and equipment selection to issues like sensor wear-ability and convenience as judged by the patients.

In this context a survey has been performed asking users and treatment personnel to evaluate the developed platform using the aforementioned method. A total number of 10 individuals acting as patients (i.e. wearing the sensors) and 10 experts in medical treatment have used the system and completed the survey. The corresponding results are presented inTable 5.1.3. Both patients and personnel were asked to evaluate all four criteria, since all four of them can affect either the acceptability or the usability of the system. The performance of the system in fall detection has not been evaluated in the particular survey.

Table 5.1.3 Mean Opinion Score (MOS) for (A) technical acceptability, (B) operational effectiveness, (C) clinical appropriateness and (D) equipment selection as indicated by the conducted survey between patients and medical personnel that evaluated the presented platform

	A	B	C	D
Patient	4.8	5.0	5.0	4.2
Personnel	4.2	4.6	5.0	4.8

As indicated by the survey, the system has met great acceptability in the context of effectiveness (criteria B) and usability (criteria C). Technical acceptability has achieved some lower score due to the fact that users expected higher communication range between the sensors and the monitoring unit and better battery life. Patients also noted that sensors could be more light and comfortable (criteria D). Future evolution of sensor technologies will address such issues improving communication, energy consumption and wearability.

5.2. Region of Interest image coding and transmission over mobile devices and heterogeneous networks

Various types of mobile devices (e.g., Pocket PCs, PDAs, etc.) support applications used by medical personnel for retrieving and examining patient data [45]-[46]. Most of these applications deal with medical images, such as CT (Computed Tomography) scans, CR (Computed Radiography) scans, and MR (Magnetic Resonance) images, stored in Picture Archiving and Communication Systems (PACS) and/or Hospital Information Systems (HIS). The visual quality of the medical images/scans is required to be high, in order to ensure correct and efficient assessment resulting in correct diagnosis. In this context, a mobile device has to handle medical images of significant sizes, while also taking into account its own limitations concerning memory and processing resources. For reducing the size of medical images, the Discrete Wavelet Transform has been widely used in various applications for medical image manipulation. Indicative examples include wavelets - based applications for medical images compression [100]-[101], for MR and ultrasound images denoising [102]-[103], and for medical images features' extraction [104]-[105].

A plethora of medical image file viewers can be found in international literature (for a collection of them see [106]). Most of them include functionalities that allow image and header information extraction (in case of DICOM compliant images), as well as partial image manipulation. The Digital Imaging and Communications in Medicine (DICOM) standard launched by the National Electrical Manufacturers Association (NEMA) facilitates the distribution and viewing of medical images. DICOM defines a special file format that contains a header (that stores information about the patient's name, the type of image, image dimensions, etc.), and the rest image data. Figure 5.2.1 shows a DICOM compliant image file representation including the header section.

Header

Transfer Syntax UID	Definition	Value
0002,0000	File Meta Elements Group Length	150
0002,0001	File Meta Info Version	256
0008,0008	Image Type	SINGLE PLANE A
0008,0020	Study Date	19941013
0008,0030	Study Time	141917
0010,0030	Patient Date of Birth	19751025
0010,0040	Patient Sex	M
0028,0004	Photometric Interpretation	MONOCHROME2
0010,0020	Patient ID	556342B
0008,0090	Referring Physician's Name	Dr. A
0008,0080	Institution Name	Medical Centre
0010,0010	Patient's Name	Patient A

Image

Figure 5.2.1 DICOM compliant image file format representation

Commercial versions of medical image file viewers appropriate for mobile devices are 'RemotEye' [107] 'DicomViewer' [108], and 'ReviewMD PDA' [109]. Most of the above applications do not provide any means of scalability in image compression and/or Region of Interest (ROI) encoding/decoding. Furthermore, the current medical image viewers do not take into consideration the special requirements and needs of a heterogeneous radio access environments composing of different radio access technologies (e.g., GPRS/UMTS, WLAN and DVB-H).

In the above context, this work presents a medical application, which enables scalable compression, retrieval and decompression of medical images on mobile devices, enhanced with ROI coding for advanced image examination of specific areas within the image. The proposed application can be used for accessing medical images at a health care center, where the electronic medical record system resides, at a medical treatment/care center established at a sports facilities center, at a treatment center on an island, on an urban area, or even remotely on patient's site, and in an ambulance. An inherent feature of the proposed application is its support for mobility making this suitable for heterogeneous radio access network infrastructures. Such a setting where the proposed application can be adopted is depicted in Figure 5.2.2, where several treatment site locations are interconnected.

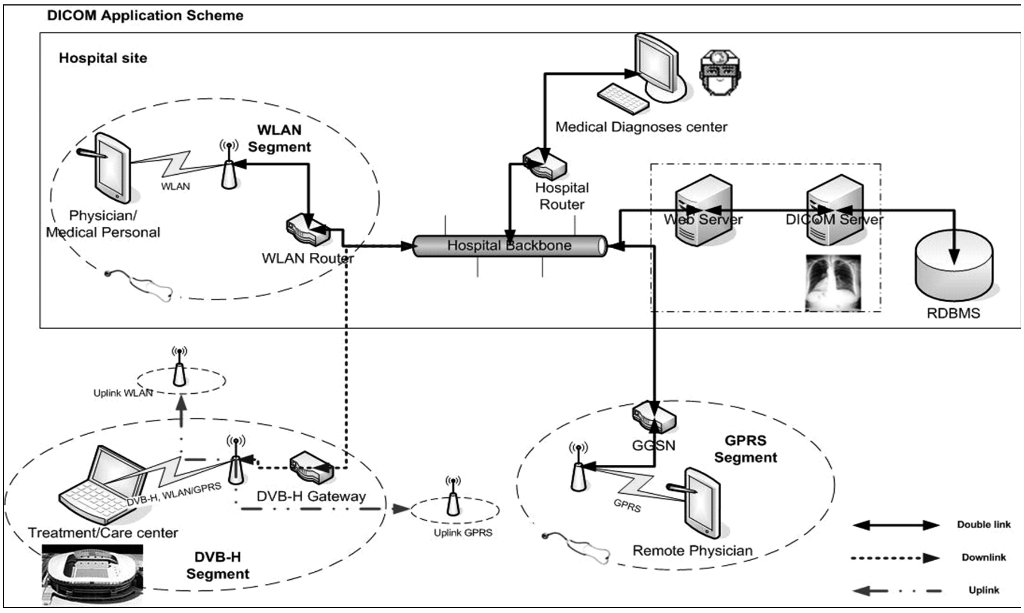


Figure 5.2.2 A heterogeneous radio setting suitable for the proposed application

5.2.1. Overview of ROI coding scalable techniques applied on medical images

The JPEG2000 Imaging Standard [110] has been tested in previous published works on medical images [111]. The standard uses the general-scaling method, which scales (shifts) coefficients so that the bits associated with the ROI are placed in higher bit-planes than the bits associated with the background. Then, during the embedded coding process, the most significant ROI bit-planes are placed in the bit-stream before any background bit-planes of the image. The scaling value is computed using the

MAXSHIFT method, also defined within the JPEG2000 standard. In this method the scaling value is computed in such a way that it makes possible to have arbitrary shaped ROIs without the need for transmitting shape information to the decoder. The mapping of the ROI from the spatial domain to the wavelet domain is dependent on the used wavelet filters and it is simplified for rectangular and circular regions. The encoder scans the quantized coefficients and chooses a scaling value S such that the minimum coefficient belonging to the ROI is larger than the maximum coefficient of the background (non-ROI area).

A major drawback however of the JPEG 2000 standard is the fact that it does not support lossy-to-lossless ROI compression. In [112], a lossy-to-lossless ROI compression scheme based on Set Partitioning In Hierarchical Trees (SPIHT) [113] and Embedded Block Coding with Optimized Truncation (EBCOT) [114] is proposed. The input images are segmented into the object of interest and background and a chain code-based shape coding scheme [115] is used to code the ROI's shape information. Then, the critically sampled shape-adaptive integer wavelet transforms [116] are performed on the object and background image separately to facilitate lossy-to-lossless coding. Two alternative ROI wavelet-based coding methods with application to digital mammography are proposed by Penedo et al. in [118]. In both methods, after breast region segmentation, the Region-Based Discrete Wavelet Transform (RBDWT) [117] is applied. Then in the first method an Object-Based extension of the Set Partitioning In Hierarchical Trees (OB-SPIHT) [113] coding algorithm is used, while the second method uses an Object- Based extension of the Set Partitioned Embedded bloCK (OB-SPECK) [119] coding algorithm. Using RBDWT it is possible to efficiently perform wavelet sub-band decomposition of an arbitrary shape region, while maintaining the same number of wavelet coefficients. Both OB-SPIHT and OB-SPECK algorithms are embedded techniques, i.e. the coding method produces an embedded bit-stream which can be truncated at any point (in the context of bit-plane level), equivalent to stopping the compression process at a desired quality. The wavelet coefficients that have larger magnitude are those with larger information content. In a comparison, with full-image compression methods as SPIHT and JPEG2000, OB-SPIHT and OB-SPECK exhibited much higher quality in the breast region at the same compression factor [118]. A different approach is presented in [120], where the Embedded Zerotree Wavelets (EZW) coding technique is adopted for ROI coding in Progressive Image Transmission (PIT). The method uses sub-band decomposition and image wavelet transform to reduce the correlation in the sub-images at different resolutions, thus the whole frequency band of the original image is divided into different sub-bands at different resolution. The EZW algorithm is applied to the resulting wavelet coefficients to refine and encode the most significant ones. Compression scalability is also supported in HS-SPIHT (Highly Scalable SPIHT) [121], where SPIHT is enhanced to support spatial scalability providing a bitstream that can be easily adapted (reordered) to given bandwidth and resolution requirements by a simple transcoder. Another approach using wavelet localization for ROI specific scalable compression is presented in [122]. The wavelet coefficients at each level are correlated to weighting factors allowing scalability based on the received Peak Signal to Noise Ratio (PSNR). Apart from compression scalability for the whole image or a specific ROI, additional rate scalability can be introduced during network transmission of the image. The latter technique however applies mostly on cases of video transmission [123], [124].

5.2.2. The proposed method for ROI coding of medical image data

The proposed application adopts the Distortion Limited Wavelet Image Codec (DLWIC) algorithm [125]. In DLWIC, the image to be compressed is firstly converted to the wavelet domain using the orthonormal Daubechies wavelet transform [126]. The transformed data is then coded by bit-levels and the output is coded using QM-coder [127], an advanced binary arithmetic coder. The algorithm processes the bits of the wavelet transformed image data in decreasing order concerning their significance in terms of Mean Square Error (MSE). This produces a progressive output stream enabling the algorithm to be stopped at any phase of the coding. The already coded output can be used to construct an approximation of the original image.

The above feature is useful when a user browses medical images using slow bandwidth connections, where the image can be viewed immediately after only few bits have been received; the subsequent bits then make it more accurate. DLWIC uses the progressivism by stopping the coding when the quality of the reconstruction exceeds a threshold given as an input parameter to the algorithm. The presented approach solves the problem of Distortion Limiting (DL) allowing the user to specify the MSE of the decompressed image. Furthermore, this technique is designed to be as simple as possible consuming less amount of memory in the compression-decompression procedure, being thus suitable for usage on mobile devices.

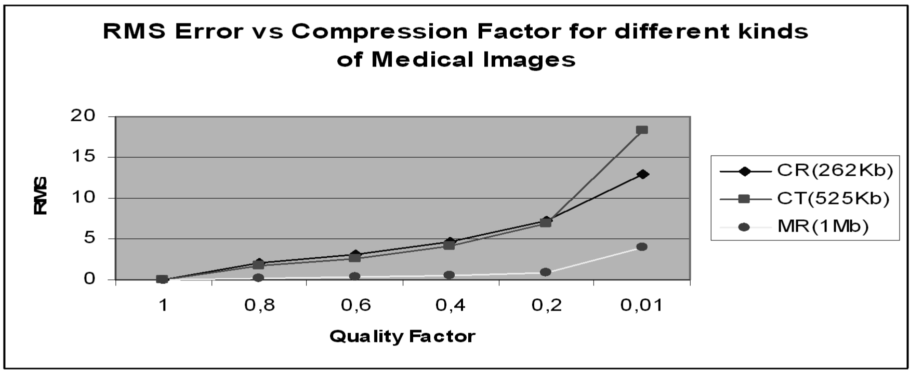


Figure 5.2.3 RMS error for different medical images according to quality factor

Figure 5.2.3 depicts the Root Mean Square (RMS) error results concerning the application of DLWIC algorithm for both lossless (quality factor equal to one) and lossy compression (quality factor smaller than one) for CR (Computed Radiography), CT (Computed Tomography) and MR (Magnetic Resonance) medical images of sizes 262Kb, 525 Kb and 1Mb respectively. The medical image data sets used in this study were collected at Sotiria General Hospital of Athens, Greece. The data set included 117 CT scans, 90 CR and 112 MR images in the upper chest (thorax) and the abdominal area. The numerical data presented in the paper are average values from experiments executed on images from the specific data set. A second study has been also conducted using the Structural SIMilarity (SSIM) index found in [128] as an image quality indicator of the compressed images. The specific metric provides a mean of quantifying the perceptual similarity between two images. Perceptual image quality methods are traditionally based on the error difference between a distorted image and a reference image, and attempt to quantify the error by incorporating a variety of known properties of the human visual system. In the case of SSIM index, the structural information in an image is considered as an attribute for reflecting the structure of objects, independent of the average luminance and contrast, and the thus image quality is assessed based on the degradation of the structural information. A brief literature review [140]-[142] has shown clear advantages of the SSIM index against traditional RMS and peak signal to noise ratio (PSNR) metrics and a high adoption by researchers in the field of image and video processing. Average SSIM index values for different compression factors are presented in Table 5.2.1.

Table 5.2.1 Structural SIMilarity (SSIM) quality index for three different image types using different compression factors. The SSIM index provides an indication of perceptual image similarity between original and compressed images.

	Average SSIM index (%)				
	Compression Factor	0.1	0.3	0.5	0.7
Image Type	MR	88.3975	96.0845	97.3111	99.0466
	CT	81.2853	91.1986	94.2828	97.6702
	CR	90.2179	94.5156	96.0221	96.8969

As derived by the similarity comparison experiments using SSIM, the quality degradation even in high compression ratios is not major (i.e. 88.4% and 99.04% for compression factors 0.1 and 0.7 respectively, in case of the MR image data set). This fact proves the efficiency of the proposed algorithm.

At this point it should be noted that concerning lossy compression, DLWIC performs better in case of medical images of large sizes; Lossy compression is performed by multiplexing a small number of wavelet coefficients (consisting the base layer and a few of additional layers for enhancement). Thus, a large number of layers are discarded, resulting in statistically higher compression results concerning the file size. However, lossy medical image compression is considered to be unacceptable for performing diagnosis in most of imaging applications, due to quality degradation. Therefore, in order to improve the diagnostic value of lossy compressed images, the ROI coding concept is introduced in the proposed application to improve the quality in specific regions of interest only by applying lossless or low compression in these regions, maintaining the high compression in none interest regions of the image. The wavelet based ROI coding algorithm implemented in the proposed application is depicted in Fig. 4 (block diagram). A dyadic decomposition is used that repeatedly divides the lower sub-band into 4 sub-bands. Let D denote the number of decomposition level, then the number of sub-bands *M* equals to *4+3(D-1)*. Assuming that the ROI shape is given by the client as a binary mask form on the source image, the wavelet coefficients on the ROI and on the Region of None Interest (RONI) are quantized with different step sizes. For this purpose, a corresponding binary mask is obtained, called *WT* mask, on the transform domain. The whole coding procedure can be summarized in the following steps:

- The ROI mask is set on the source image.
- The mask and the requested image are transferred to the application server.
- The corresponding WT mask *B* is obtained.
- The DWT coefficients are calculated.
- Bit allocations for the ROI and RONI areas are obtained.
- The DWT coefficients are quantized with the bit allocation from the previous step for each sub-band of each region.
- The resulting quantized coefficients are encoded.
- The WT mask B is encoded.

The entropy coded coefficient and WT mask are multiplexed in order to create the bit stream.

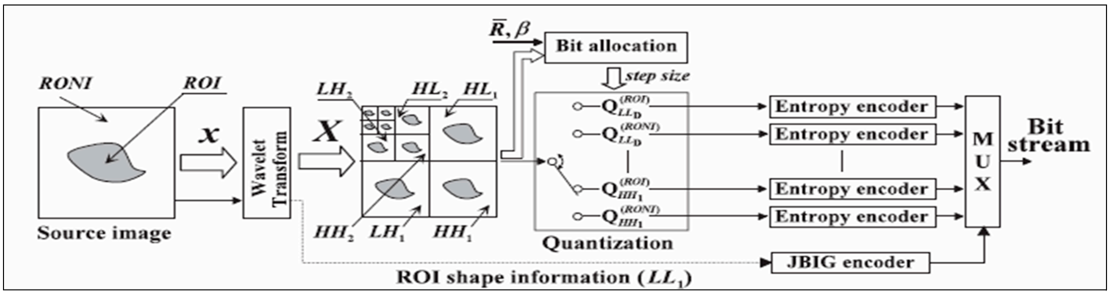


Figure 5.2.4 ROI coding system

The decoding process follows the reverse order at the client side. The major advantage of the proposed ROI coding method is that it produces a progressive output stream; thus the ROI is decoded progressively at the receiver. The user has the capability to stop the transmission at any phase of the coding, while the already transmitted output can be used to construct an approximation of the original image. The specific feature is especially desired for browsing medical images in low bandwidth mobile networks. In comparison to the JPEG2000 standard the proposed scheme is preferable since it supports lossy-to-lossless ROI compression. When compared to the rest of the methods discussed in previous section the proposed method has superior characteristics in terms of complexity and simple implementation, enabling this way its application in portable and mobile devices with limited computing power. The mobile computing paradigm is quickly entering the electronic healthcare sector since it supports the moving and commuting physician; therefore, technical solutions aligned with this concept are extremely desirable.

5.2.3. Implementation Details

As depicted in Figure 5.2.5, the proposed medical application follows a three-tier architecture, consisting of the client part, the DICOM Server and the Electronic Medical Record System - Remote Database Management System (EMR-RDBMS). Client requires a Java enabled web - browser and communicates using HyperText Transfer Protocol (HTTP) and Remote Method Invocation (RMI) protocols with the server. The transactions between the server and the database are performed through Java Database Connectivity (JDBC) [132]. Generally, client's operations may be divided into two categories according to whether they are performed locally or through the server. Image manipulation (e.g., brightness, contrast, negative adjustment, drawing annotations, etc.) are handled by appropriate Java applets at the client's side. User authentication, image and header retrieval, as well as compression and encryption are performed through the server.

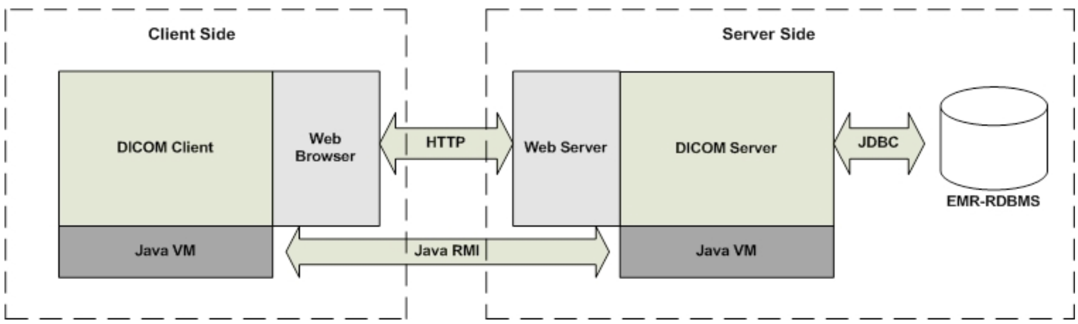


Figure 5.2.5 Three-tier architecture of the proposed medical application

The proposed medical application supports lossless and lossy image compression through scalable wavelet-based transforms with ROI support that provides the user the ability to select desired regions on the compressed DICOM image. The medical personnel using the application can draw annotations on the images and store them through the DICOM header as comments. The DICOM header can be extracted and presented separately. Furthermore, it can be parsed into XML (Extensible Markup Language) format providing in this way interoperability with other medical file standards (e.g., HL7 [131]). Concerning security features, the proposed application supports user authentication through credentials (i.e. username and password) and data encryption using a symmetric key of 128 bits length. Additionally, various helping image manipulation functions (such as brightness and contrast adjustment) accompany the basic image retrieval feature of the discussed application.

Figure 5.2.6 presents the sequence of messages exchanged between the client and server entities. The messages can be grouped according to their functions into four categories: User authentication, DICOM image retrieval, ROI coding and XML parsing. Most of the messages concern, either Remote Method Invocation (RMI) lookup calls for initializing communication, or procedure calls for data exchange. The procedure calls differ according to the action triggered by user. Between server and EMR-RDBMS appropriate message queries are exchanged.

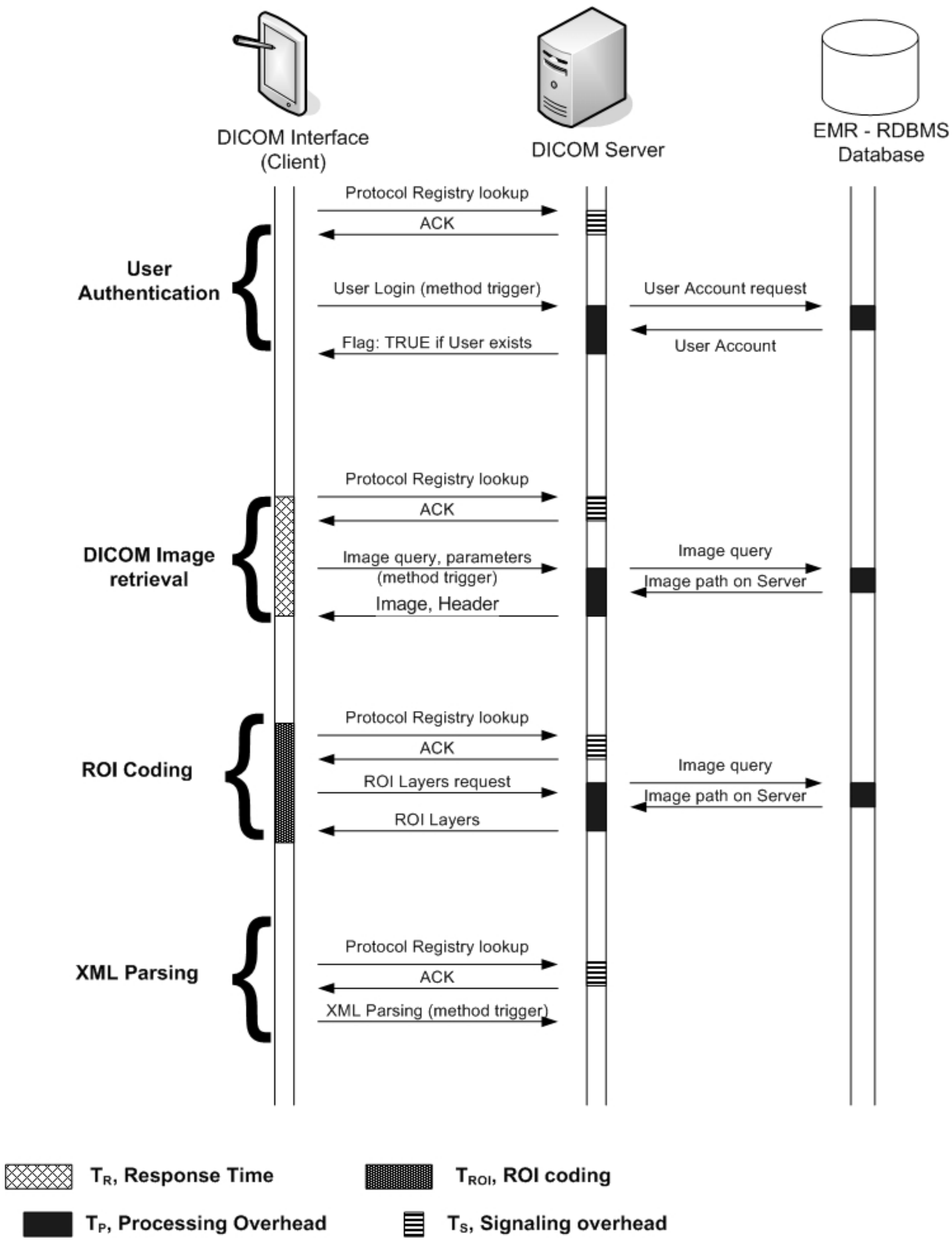


Figure 5.2.6 Sequence of exchanged messages

Closing this section, Figure 5.2.7 depicts three screenshots from the proposed medical application in use. The first screenshot refers to a Tablet PC, the second one to a PDA, and the last one illustrates basic functions of compressed medical image retrieval and ROI coding.

(a) (b) (c)

Figure 5.2.7 Application screenshots: (a) for a Tablet PC, (b) for a PDA, (c) for ROI support on lossy compressed image

5.3. Data collection in ambulatory cases utilizing Context Awareness

Remote patient care and telemedicine platforms have been proved during the last years significant tools for the optimization of patient treatment in isolated areas [143]-[154]. Transport, accommodation and medical personnel-related costs are reduced, and a full time 24 hours per day, 7 days per week patient status monitoring is provided [149], [150]. Health monitoring may be delivered not only in a hospital environment but at home as well, through the establishment of modern patient telemonitoring systems. The reasons are better possibilities for managing chronic care, controlling health delivery costs, increasing quality of life and quality of health services and distinct possibility of predicting and thus avoiding serious complications. In addition, remote telemedicine systems can address healthcare issues (both treatment of urgent incidents and managing chronic care) on remote isolated areas (e.g., small islands of north Aegean region) saving precious time during patient transmission to medical facilities on adjacent regions and improving the quality of life in such areas.

Methods of treating and monitoring patients remotely include the use of bio-sensors, additional monitoring devices (e.g., video cameras) and patient-physician interaction applications (e.g., video conference, prescription management, etc.). Due to the remote locations of the involved actuators, a network infrastructure (wired and/or wireless) is needed in order to enable the transmission of the medical information. Telemedicine systems cannot however always perform in a successful and efficient manner; Issues, like large data volumes (e.g., video sequences), unnecessary data transmission occurrence and limited network resources can cause inefficient usage of such systems [155], [148]. In addition, wired and/or wireless network infrastructures often fail to deliver the required quality of service (e.g., bandwidth requirements, minimum delay and jitter requirements) due to network congestion and/or limited network resources. Context-aware medical networks can overcome the aforementioned issues, through performing appropriate content adaptation. This work presents an improved patient state and network aware telecare and telemonitoring platform. The used framework allows medical data transmission only when determined necessary encodes the transmitted data properly according to the network availability and quality, and to the patient status. The specific framework's architecture is open and does not depend on the monitoring applications used, the underlying networks or any other issues regarding the telemedicine system used. A prototype evaluation platform has been developed based on the aforementioned framework. The proposed system comprises a combination of portable and/or fixed equipment which allow for the acquisition and transmission of diagnostically critical biosignals of the patient, such as various-lead ECG, Blood Pressure, Oxygen Saturation, Body Temperature, along with acquisition and transmission of still images of the patient (upon which annotations can be made) and/or real-time audio-visual communication between the involved parties. The high mobility of the monitoring side of the platform favors its establishment on isolated areas (e.g., small islands) lacking patient care facilities, whereas its distributed architecture allows the remote collaboration of medical experts and physicians enhancing thus the resolution of medical incidents.

Despite the numerous implementations and proposals of telemedicine and e-health platforms found in the literature (an indicative reference collection can be found in [143]-[154]), only a few works include context awareness. The main goal of context aware computing is to acquire and utilize information about the context of a device to provide services that are appropriate to particular people, place, time, events, etc. [161]. According to the latter, the work presented in [159] describes a context-aware mobile system for inter-hospital communication taking into account patient's and physician's physical location for instant and efficient messaging regarding medical events. J. Bardram presents in [160] additional use cases of context-awareness within treatment centers and provides design principles of such systems. The project

‘AWARENESS’ (presented in [163]) provides a more general framework for enhanced telemedicine and telediagnosis services depending on the patient status and location.

The presented telemedicine context aware framework is based on the active services concept presented in [162]. Active services can dynamically adapt themselves to various underlying networking environment conditions, according to the instruction of appropriate networking entities (i.e. a Network Broker) and the requirements posed by the end user. The Network Broker is a special software agent, which monitors network resources and activities. Its intelligence enables it to take decisions regarding services and network usage leading this way to optimum network utilization. Given a specific conventional service, the corresponding active service constitutes the outcome of the application to the conventional service. Taking into account that the particular format of the services functions depends on the underlying networking environment, an active service can have various instances according to the particularities of the defined functions.

In our case, the active services consist of the patient monitoring tools that can dynamically adapt the coding of the generated data (in terms of rate, compression and/or encryption used) to both underlying network conditions and the patient status itself. A more detailed description of the discussed context-aware medical platform is provided in the following section.

5.3.1. The Context-Awareness Framework

The architecture of the proposed context-aware medical networking framework is illustrated in Figure 5.3.1.

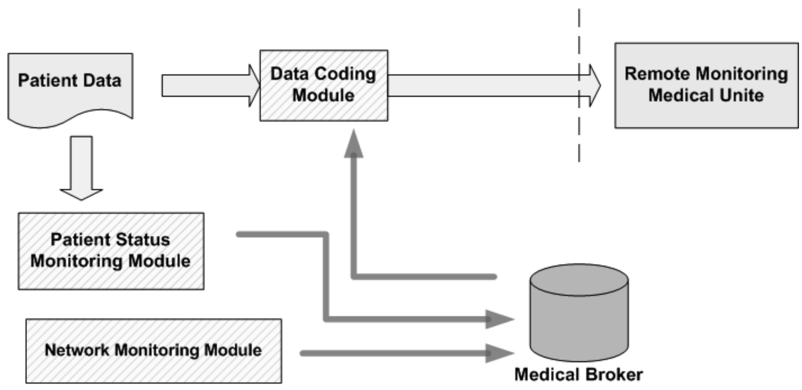
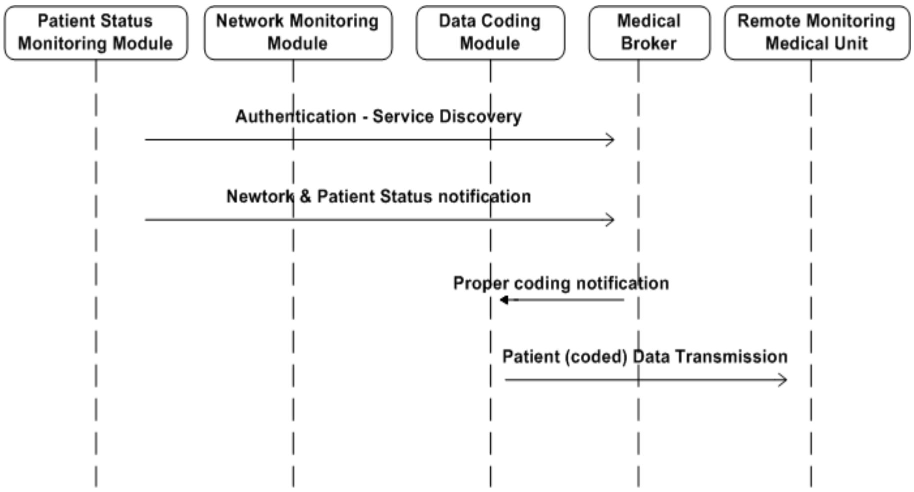


Figure 5.3.1 The context-aware medical networking framework architecture

The major modules consisting the proposed framework are; a) the network monitoring module that determines the current network interface used and the corresponding status, b) the patient status monitoring module that collects patient data and determines the patient status, c) the data coding module which is responsible for properly coding (compressing, encrypting, etc.) the transmitted patient data, according to instructions given by d) the medical broker (i.e. usually a repository containing predefined or dynamically defined threshold values for determining patient and network status). The patient state can be determined through a number of health sensors (i.e. heart rate and body temperature sensors) and corresponding vital signals. Defined threshold values in the latter signals determine the case of an immediate data transmission (alarm event) to the monitoring unit. Depending on network availability and quality, periodical transmission of the patient data is performed for evaluation by physicians. According to the network interface used, appropriate coding (e.g. video compression, data encryption, etc.) is applied on the transmitted medical data, avoiding thus possible transmission delays and optimizing the whole telediagnosis procedure.

The framework's architecture is open and does not depend on the monitoring applications used, the underlying networks or any other issues regarding the telemedicine system used. For this purpose, Web Services [164], [165] have been used as a communication mechanism between the major framework components and the external patient monitoring applications used. The message exchange has been implemented through SOAP (Simple Object Access Protocol) [158], a simple yet very effective and flexible XML-based communication mechanism. The latter involves the session initialization (which more precisely includes user authentication and service discovery) and the exchange of status and control messages. The status messages include information regarding the patient data as generated from the monitoring sensors and the underlying network status and quality, whereas the control messages contain instructions regarding the proper coding of the transmitted data. It should be noted that the involved modules for the aforementioned communication (see Figure 5.3.1) can all reside at the patient's site, or alternatively the Medical Broker can reside at the remote treatment site for the direct collection of medical data and the reactive instruction's provision.



(a)


```xml
<?xml version="1.0" encoding="UTF-8"?>
   <soapenv:Envelope xmlns:soapenv="http://schemas.xmlsoap.org/soap/envelope/"
xmlns:xsd="http://www.w3.org/2001/XMLSchema" xmlns:xsi="http://www.w3.org/2001/
XMLSchema-instance">
      <soapenv:Header>
      </soapenv:Header>
      <soapenv:Body>
         <create xmlns="urn:enterprise.soap.sforce.com">
            <sObjects xsi:type="ns3:EventData"
xmlns:ns3="urn:sobject.enterprise.soap.sforce.com">
               <ns3:EventType>Urgent</ns3:EventType>
               <ns3:Device>PDA</ns3:Device>
               <ns3:NetworkType>GPRS</ns3:NetworkType>
               <ns3:NetworkQuality>Medium</ns3:NetworkQuality>
               <ns3:PatientID>13001</ns3:PatientID>
               <ns3:BloodPressure>75mmHg</ns3:BloodPressure>
               <ns3:PulseRate>55min</ns3:PulseRate>
               <ns3:HeartRate>45/min</ns3:HeartRate>
            </sObjects>
         </create>
      </soapenv:Body>
   </soapenv:Envelope>
```


(b)

Figure 5.3.2 (a) Message Exchange between the framework's modules (b) Sample SOAP message indicating an urgent event and corresponding information regarding the network and patient status

Figure 5.3.2 illustrates the aforementioned message exchange between the framework's components and presents a sample SOAP message indicating an urgent event and describing corresponding information regarding the network and the patient status.

5.3.2. Platform Architecture and Communication Issues

The platform's telemedicine architecture abandons the client-server architecture which the majority of telemonitoring systems nowadays adopt, and introduces the notion of nodes. Thus, there are 3 main participating nodes in each session, which can increment during the session (see Figure 5.3.3). The "Transmission" node is responsible for the acquisition of data from the medical devices, their local display, and triggers the request for the initialization of a medical monitoring session, in order to transmit the data to specialized medical personnel. In our prototype evaluation platform, the latter node consists of customized medical suitcase carrying a mobile biosignal monitoring device (capable of monitoring ECG, Blood Pressure, Oxygen Saturation, and Body Temperature) and a PDA device for collecting and transmitting the medical data. The PDA is also capable of transmitting audio and video streams and thus contains the context-awareness modules for monitoring the patient and network status and proper coding of data (see Figure 5.3.1). A photograph of the aforementioned medical suitcase is provided in Figure 5.3.3). Its high mobility makes it ideal for usage on isolated areas like small islands and on mobile treatment means like ambulances, ships, etc. The "Monitoring" node is responsible for the reception of the "Transmission" node request for monitoring, for the collection of the transmitted data and for the provision of tele-consultation and tele-diagnosis. Last but certainly not least, the "Administrator" node, is responsible for the monitoring of all nodes, and for the dispatching of monitoring requests from "Transmission" nodes to "Monitoring" nodes. One of the main innovations of the platform is that a "Monitoring" node can make an invitation to another "Monitoring" node, to acquire what is called a "second expert opinion", and thus the dynamic network that had been created amongst the three nodes is enhanced with peer to peer communication.

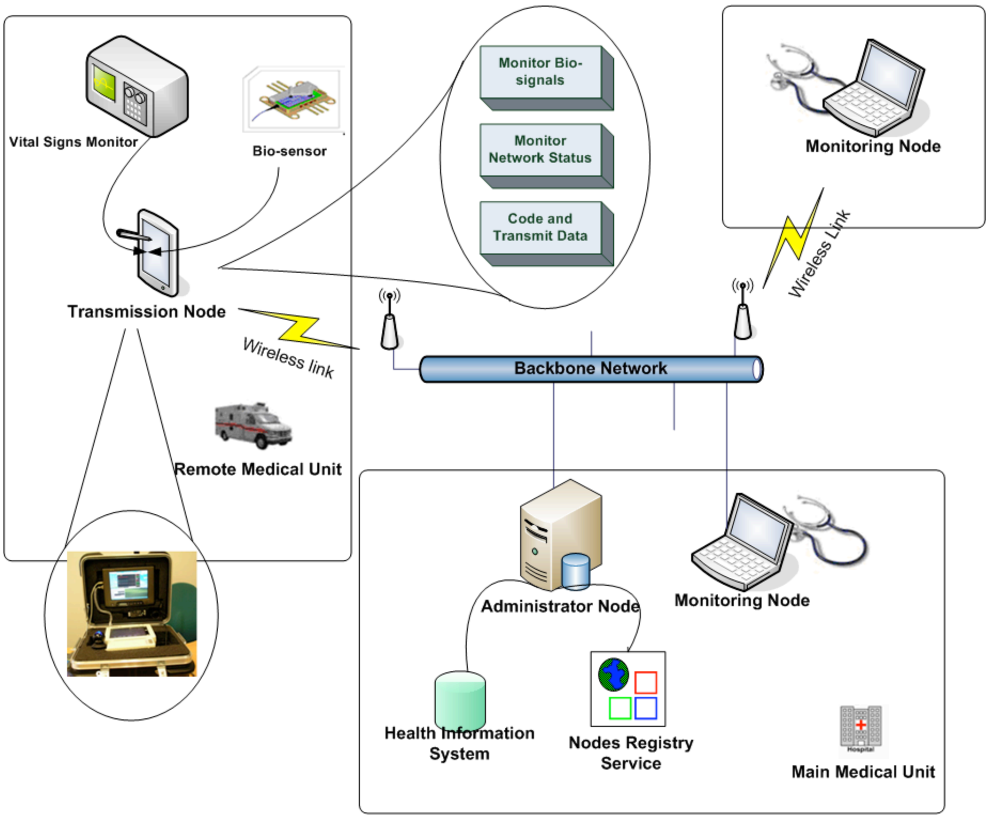


Figure 5.3.3 Telemedicine Platform Architecture and Communication Illustration

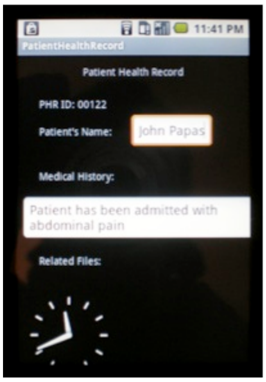
The proposed platform allows data transmission through various fixed (PSTN, ISDN, xDSL, LAN) and wireless (GSM, GPRS, 3G, Wi-Fi) telecommunication technologies and utilizes IP technology for the secure and transparent communication between the involved equipment. Depending on the underlying network infrastructure and its quality, proper data coding in terms of compression, encryption and transmission mode is selected in conjunction to the monitored patient status.

Furthermore, the proposed platform allows for the interconnection and communication with HISs. In order to achieve this, the HL7 (Health Level-7) standard protocol has been utilized. Thus, original messages are transformed into HL7 messages, which are sent to the HIS, while the reverse procedure is followed in the case a request is made from the HIS.

5.4. *Presentation of patient data on mobile devices*

5.4.1. The @HealthCloud Application

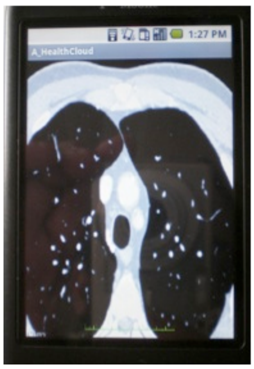
This section discusses the main features of the @HealthCloud application and presents implementation details. The prevalent functionality of the application is to provide medical experts and patients with a mobile user interface for managing healthcare information. The latter interprets into storing, querying and retrieving medical images (e.g., CT scans, MRIs, US etc.), patient health records and patient-related medical data (e.g., biosignals). The data may reside at a distributed Cloud Storage facility, initially uploaded/stored by medical personnel through a HIS. In order to be interoperable with a variety of Cloud Computing infrastructures, the communication and data exchange has to be performed through non-proprietary, open and interoperable communication standards.



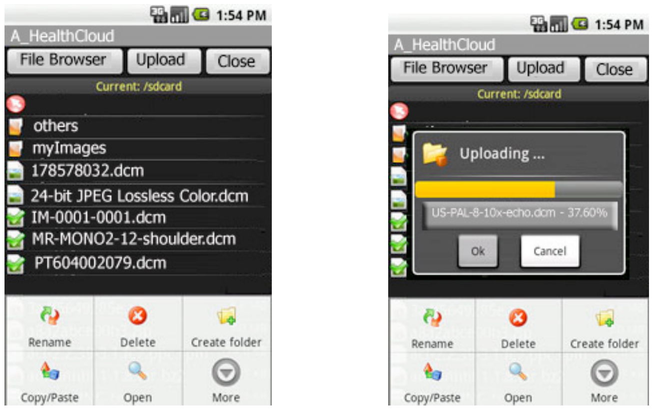
(a)

(b)

(c)



(d)



(e) (f)

Figure 5.4.1 Screenshots of the @HealthCloud mobile application: a) Displaying a patient health record, b) illustration of DICOM header extraction, c) JPEG2000 progressive decoding of a CT scan at first resolution level (out of five), d) final output of JPEG2000 progressive decoding of a CT scan, e) The main application interface displaying available files on the Cloud and available operations, f) illustration of the uploading procedure of a file into the Cloud

@HealthCloud utilizing Web Services connectivity and Android OS supports the following functionality:

- Seamless connection to Cloud Computing storage utilizing Web Services and the REST API [239]: The main application allows users to retrieve, modify and upload medical content (medical images, patient health records and biosignals). The content resides remotely into the distributed storage elements but access is presented to the user as the resources are located locally in the device (see Figure 5.4.1-e).

- Patient Health Record Management: Information regarding patient’s status, related biosignals and image content can be displayed and managed through the application’s interface (see Figure 5.4.1-a).

- DICOM image viewing support: The DICOM [240] medical image protocol is supported. Medical images are decoded and displayed on the device among with the information stored into the file’s header (see Figure 5.4.1-b).

- JPEG2000 viewing support: JPEG2000 [110] standard has already been widely used for the coding of medical images. It supports lossy and lossless compression, progressing coding and Region of Interest (ROI) coding [241].

The progressive coding allows the user to decode large image files at different resolution levels according to available network bandwidth optimizing this way network resources and allowing image acquisition even in cases network availability is limited (see examples in Figure 5.4.1-c and Figure 5.4.1-d). The code for performing wavelet decoding on mobile devices in [194] has been modified to support the JPEG2000 standard on the Android platform.

- Image annotation support: User can annotate medical images using the multitouch functions of the Android OS. The annotation information is stored separately and retrieved automatically every time the image is retrieved.

- Proper user authentication and data encryption: User is authenticated at the Cloud Computing Service with SHA-1 [242] hashing for message authentication and SSL [243] for encrypted data communication.

The main components of a Cloud Computing Service usually are [40] the platform front-end interface that communicates directly with users and allows the management of the storage content. The interface can be a web client or a standalone application. The Cloud Storage Facilities manages the physical infrastructure (e.g., storage elements) utilized for managing data and is also responsible for performing maintaining operations (e.g., backing up data, etc.) The Cloud Platform interface is also connected to the Cloud Service module, which is responsible for accepting and queuing user requests. Finally, the Cloud Infrastructure module manages user account, accessibility and billing issues.

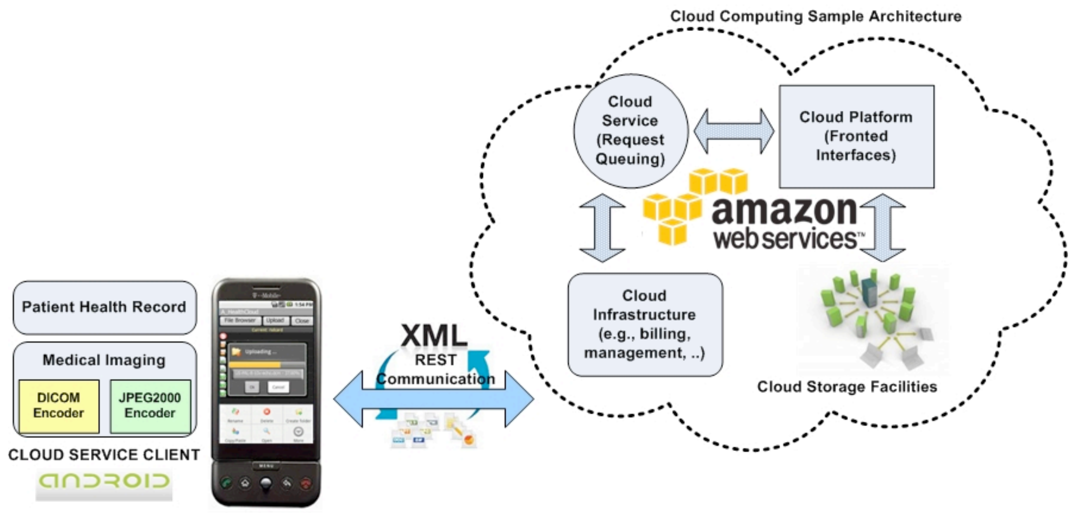


Figure 5.4.2 Illustration of the proposed system architecture

Previous work by authors [194] has demonstrated the applicability of mobile devices into retrieving medical image data from remote repositories wirelessly utilizing proper content coding (i.e., wavelet compression with region of interest support). The mobile application used has been initially developed using Java for mobile devices (J2ME [244]) and communication for data exchange was performed using Remote Method Invocation (RMI [245]). This work has been now extended to include the functionality of communicating with Cloud Computing platforms and support communication through Web Services. In this context, @HealthCloud has been developed based on Google's Android mobile Operating System (OS) [246] using the appropriate software development kit (SDK). Android is a mobile operating system running on the Linux kernel. Several mobile device vendors already support it. The platform is adaptable to larger and traditional smartphone layouts and supports a variety of connectivity technologies (GSM/EDGE, CDMA, EV-DO, UMTS, Bluetooth, and Wi-Fi). It supports a great variety of audio, video and still image format, making it suitable for displaying medical content. Finally, it supports native multi-touch technology, which allows better manipulation of medical images and generally increases the application's usability.

The Cloud Service client running on Android OS consists of several modules. The Patient Health Record application acquires and displays patient records stored into the cloud. The Medical Imaging module is responsible for displaying medical images on the device. It decodes images in DICOM format displaying both image and heard information data. When JEPG2000 compression is used, the appropriate sub-module decodes the image.

The communication with the Cloud is performed through an implementation of Web Services REST API that is supported natively by Android. Web Services are emerging as a promising technology to build distributed applications and is suitable for creating Cloud Computing client applications. It is an implementation of Service Oriented Architecture that supports the concept of loosely-coupled, open-standard, language - and platform-independent systems. Web services provide several technological and business benefits, a few of which include application and data integration, versatility, code re-use and cost savings. The inherent interoperability that comes with using vendor, platform, and language independent XML technologies and the ubiquitous HTTP as a transport mean that any application can communicate with any other application using Web services. Web services are also versatile by design. They can be accessed through Web-based client interfaces, other applications including mobile ones and other Web services.

Data in Cloud are seamlessly stored and presented to the user as if they reside locally. This means that the Cloud repository is presented as a virtual folder and does not provide the features of a database scheme. In order to provide the user with data querying functionality, medical records and related data (images and biosignals) are stored into a SQLite [247] file. SQLite is the database platform supported by Android. The file resides into a specific location at the Cloud and is retrieved on the device every time user needs to query data. The query is performed locally and the actual location of the data in the cloud is revealed to the applications. The database file is updated and uploaded into the Cloud every time user modifies data, respectively.

5.4.2. Utilizing Amazon S3 Cloud Computing Service

For the realization of the mobile pervasive healthcare information management system the Amazon Simple Storage Service (S3) has been utilized. The main reason for selecting the specific Cloud Computing platform is that it is a commercial service well established and used successfully in several applications [248]. It provides users with several interoperable web interfaces for managing data (SaaS model) and developers with the ability to create their own applications for accessing the latter (PaaS model) and is suitable for managing healthcare information.

5.4.3. Security Issues and HIPAA compliance

The Amazon S3 Service as a part of AWS provides a reliable, scalable, and inexpensive computing platform "in the cloud" that can be used to facilitate healthcare customers' HIPAA compliant applications [249]. HIPAA's privacy rule regulations include standards regarding the encryption of all protected health information (PHI) in transmission and in storage. The same data encryption mechanisms used in a traditional computing environment, such as a local server or a managed hosting server, can also be used in a virtual computing environment, such as Amazon S3. Using Amazon Web Services (AWS), customer's system administrators can utilize token or key-based authentication to access their virtual servers. Amazon

EC2 creates a 2048 bit RSA key pair, with private and public keys and a unique identifier for each key pair to help facilitate secure access.

Using Amazon S3, access can be easily controlled down to the object level. The system administrator maintains full control over who has access to the data at all times and the default setting only permits authenticated access to the creator. Read, write and delete permissions are controlled by an Access Control List (ACL) associated with each object.

HIPAA's security safeguards also require in-depth auditing capabilities, data back-up procedures and disaster recovery mechanisms. AWS services contain many features that help customers address these requirements. Amazon S3 provides a highly available solution for data storage and automated back-ups. By simply loading a file or image into Amazon S3, multiple redundant copies are automatically created and stored in separate data centers. These files can be accessed at any time, from anywhere (based on permissions) and are stored until intentionally deleted by the customer's system administrator. Using Amazon S3, customer's data is replicated and automatically stored in separate data centers to ensure reliable data storage with a service level of 99.9% availability and no single points of failure [249].

5.4.4. @HealthCloud in Practice: Initial Evaluation

In order to prove the system's usability, some initial experiments evaluating the system's performance have been conducted. Experiments concern the time needed to transmit data to the Amazon S3 Cloud storage service. Due to the fact that textual data like a patient's health record or a biosignal sequence do not consist of large data files and do not require high bandwidth, the presented results involve the transmission of medical images. The @HealthCloud application as presented in previous sections has been used on a HTC G1 [250] mobile phone running Android OS version 1.6. A number of medical images of different modalities (MR, CT, PET, OT and Ultrasound) and different file sizes have been used. The transmission times are displayed in Table I. As indicated, two different wireless network infrastructure types have been utilized; a WLAN and a commercial 3G Network.

Table 5.4.1 Transmission time of medical images using Amazon S3 Cloud Service and different network types

Image Type (encoding)	File Size (MB)	Time (sec)	
		3G Network	WLAN Network
OT (24-bit JPEG2000 Lossless Color)	6.8	42.532	7.894
CT (Uncompressed)	0.528	4.023	2.382
CT (JPEG2000)	0.102	1.223	0.892
MR (JPEG Lossless)	0.721	9.738	3.894
PET (JPEG2000 Lossy)	0.037	0.923	0.793
Ultrasound (sequence of 10 images, JPEG2000 Lossless)	0.487	3.892	3.251

The performance of both WLAN and 3G networks can be easily biased by traffic and other network conditions, since commercial networks have been utilized in both cases. Also, the response time of the Amazon S3 Cloud service can play an important role on the total transmission time. However, the acquired results can be considered as indicative since the experiments reflect a real case scenario where the specific service and commercial wireless networks are utilized in order to transmit medical data. In addition, the time needed to decode and present the specific images used in the experiments has been measured. For the HTC G1 mobile phone used, the time needed by @HealthCloud to display uncompressed CT images at a resolution of 512x512 pixels was 0.52 sec, compressed CT images with JPEG2000 coding at a resolution of 512x512 pixels was 4.53 sec. The time needed to decode OT images compressed with JPEG2000 at resolution of 3072x2048 was 21 sec. and 7.5 sec. for a sequence of 10 ultrasound images of 600x430 pixels.

5.5. Managing wearable sensor data on the Cloud

The proper delivery of healthcare services among with patient monitoring are considered key issues for improving the quality of life and ensuring efficient health and social care. Mobile pervasive healthcare technologies can support a wide range of applications and services, including mobile telemedicine, patient monitoring, location-based medical services, emergency response and management, personalized monitoring and pervasive access to healthcare information, providing great benefits to both patients and medical personnel [194]. The realization, however, of health information management through mobile devices introduces several challenges, like data storage and management (e.g., physical storage issues, availability and maintenance), interoperability and availability of heterogeneous resources, security and privacy (e.g., permission control, data anonymity, etc.), unified and ubiquitous access. One potential solution for addressing all aforementioned issues is the introduction of Cloud Computing concept in electronic healthcare systems. Cloud Computing provides the facility to access shared resources and common infrastructure in a ubiquitous and pervasive manner, offering services on-demand, over the network, to perform operations that meet changing needs in electronic healthcare application.

In this context, a distributed platform based on Cloud Computing for management of pervasive healthcare data has been developed. The platform contains the appropriate mechanisms for collecting sensor data. It is based on Cumulocity, a horizontal Machine-to-Machine (M2M) Cloud Solution platform provided by Nokia Siemens Networks (NSN). It contains a comprehensive set of tools for managing meters and sensors, collecting and validating data and providing it to enterprises back-office applications. A use case regarding the collection and management of pervasive motion data for fall detection is demonstrated.

5.5.1. The Cumulocity Cloud Computing Platform

Cumulocity is a horizontal Machine-to-Machine (M2M) Cloud Solution platform provided by Nokia Siemens Networks (NSN). It contains a comprehensive set of tools for managing meters and sensors, collecting and validating data and providing it to enterprise back-office applications. In addition to this, Cumulocity contains the best-of-breed tools for building sensor-based and M2M applications. The platform is used both for integrating sensors and meters into enterprises back-office business processes, as well as a stand-alone environment for designing and running a number of innovative M2M. The primary benefit of this integration is increased visibility into the real assets of enterprises and thus improved performance of business processes as well cost saving.

A Cumulocity based solution consists of three layers: Connected meters and sensors, the Cumulocity M2M management platform, and the integrated vertical applications and enterprise processes. Any meter or sensor can be integrated to Cumulocity platform through its open smart device integration API. The platform itself consists of device and sensor management functionalities like data collection and validation, fulfillment, monitoring, performance management, configuration management, inventory, identity service, tenant management and open northbound interfaces for application integration. Users can manage and monitor all of these components and features through the embedded management dashboard.

Cumulocity has mainly three different exposure Application Programming Interfaces (APIs): Functional REST, batch data and near-real time publish/subscribe. The first one is RESTful exposure API for northbound applications to use its functionalities. The batch interface is used for exporting large datasets. It is used for example in billing integration, where meter readings are transferred to a billing system. The Event API is a Publish/Subscribe interface that allows for receiving event information from a device or set of devices in near real time. This allows for the creation of independent event driven applications. Through the latter APIs, the interconnection and interoperability with pervasive healthcare applications is direct and straight-forward. The sensors can be connected directly through their wireless interfaces to the platform and use simple REST calls for sending and retrieving data. Alternatively, appropriate s/w gateways with similar functionalities can be developed for the sensors that cannot connect directly to Cumulocity. Regarding the caregivers, treatment experts and monitoring personnel, appropriate web applications will be developed giving them access to collected data and events.

The following section presents the proposed architecture for utilizing the Cumulocity Cloud platform as a means for distributed management of pervasive healthcare data.

5.5.2. The Proposed Architecture utilizing the Cumulocity Cloud Computing Platform

Figure 5.5.1 presents an illustration of the proposed architecture for managing pervasive healthcare data over the Cumulocity Cloud platform. A variety of pervasive sensors can be utilized for monitoring the patient status and context. The latter can be wearable and textile sensors that monitor vital biosignals and patient motion and generate alerts in cases of stroke or fall detection. Contextual sensors like overhead cameras and microphone arrays can provide more information about the patient condition, context and location and assist with the better assessment of an emergency situation. All sensors are equipped with appropriate networking interfaces (e.g., WiFi, Bluetooth or ZigBee) for communicating directly with the Cloud platform or through intermediate nodes, e.g., like a smartphone. Software interfaces are developed that can act as the intermediate nodes for forwarding the data to the Cloud using REST web service calls. Web applications have been developed that are also hosted by Cumulocity and visualize the data to the caregivers providing them the ability to retrieve information anywhere and anytime. Mobile applications can also be developed especially for alert management, in cases of fall event detections (utilizing the Event API).

An example of a REST web service call for storing a sensor value to the Cloud is the of the following form:

https://cumulocity.ip.adress: port/webapplication/storevalue?=sensorvalue&key=xxx

'Sensorvalue' represents the reading from the sensor and 'key' is a secret key for authenticating the sensor to the system. Sensors that communicate directly with the Cloud can make the Web Service call which can also very easily be embedded to the intermediate nodes and/or mobile applications.

The communication between the sensors or the intermediate nodes and the Cloud is performed over the SSL protocol providing the essential encryption of the data over transmission. The Cumulocity platform, built on top of the Amazon AWS, and is HIPAA compliant. The latter means that all appropriate security techniques and technologies have been adopted in order to store data safely and at the same time maintain the appropriate data anonymity.

Figure 5.5.1 The proposed architecture for managing pervasive healthcare data in the Cloud

5.5.3. Managing Fall Detection Data through Cumulocity Cloud Platform

A use case of management of pervasive healthcare data through Cumulocity platform is presented here. Fall-related injuries are among the most common, morbid, and expensive health conditions involving older adults [193]–[205]. Falls account for 10% of emergency department visits and 6% of hospitalizations among persons over the age of 65 years and are major determinants of functional decline, nursing-home placement, and restricted activity [206]-[209]. The most common and way to monitor patients for fall detection and emergency management is through wearable motion sensors – accelerometers.

In previous works [213]–[217], several sensors have been used for collecting motion data. The Arduino microcontroller [210] equipped with 3-axis accelerometer and tilt sensor has also been utilized. Arduino is an open-source electronics prototyping platform based on flexible, easy-to-use hardware and software. It supports a variety of extensions (shields) that provide additional functionality (e.g., collecting motion data) and networking capabilities (ZigBee, Bluetooth, WiFi, 3G/UMTS, etc.). It exists in various forms with different sizes. It also exists as wearable solution (LilyPad Arduino [211]) that can be sewn to fabric and similarly mounted power supplies, sensors and actuators with conductive thread.

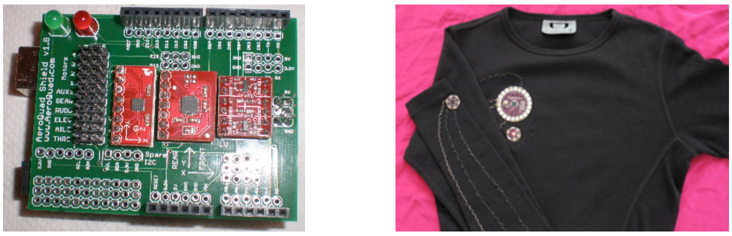


Figure 5.5.2 Arduino sensor board equipped with WiFi module, accelerometer and tilt sensor the LilyPad Arduino sewed on cloth along with accelerometer textile sensors

Figure 5.5.3 Screenshot of the web-based application hosted on Cumulocity for monitoring the output of sensors

By using the appropriate network interface (e.g., WiFi and/or 3G/UMTS), Arduino can collect and transmit motion data wirelessly in both indoor and outdoor environments maximizing this way the availability of the platform. Additionally, the recently introduced Google's Android Open Accessory Development Kit (ADK) [212] provides an implementation of Android USB accessories that are based on the Arduino open source electronics prototyping platform. This means that the Arduino can be easily interfaced with android-enabled mobile phones, providing better means of data communication between the sensors and the cloud platform especially in cases where user is located outdoors.

Arduino with the appropriate libraries can make directly calls to the REST API of Cumulocity. An appropriate web-based application has been developed on the platform (see Figure 5.5.3) that receives and displays the sensor data. Through the same REST API, external applications like in [214] can retrieve data for further analysis and fall detection.

During the initial experimentation with the system, a drop packet rate of 20-30% has been detected. This fact is either due to the Arduino low resources for high rate sampling of sensors and transmitting the data at the same time, or due to network congestion because of the repetitive REST calls at such a high sampling rate (i.e. 10 acceleration samples per second). In order to address this issue, a memory buffer has been introduced on the Arduino side that collects motion data during a 10 second time frame and then transmits the latter to the Cloud. This way the drop rate has been minimized between 2-5%, which is quite acceptable for the application.

6. Discussion

6.1. *Remaining Issues and Challenges for Intelligent Telemedicine Applications*

The deployment of all the aforementioned technologies and methods in AAL systems introduces several issues and challenges. Most important of them concern interoperability and communication issues between the different systems, security and privacy issues, usability and acceptance from both the patients and the caregivers. In this section we attempt to discuss the most important of these issues and we provide our thoughts and estimations for the near future.

6.1.1. Interoperability and collaboration

The integration of AAL systems depends significantly on the ability to build, maintain and augment interoperable systems: different software and hardware components and systems that are required to interact to achieve the user's overall goals. Most important interoperability issues concern:

Service and device integration: Pervasive systems often contain devices, which must operate in very different environments and connect together in different ways, e.g., over ad-hoc wireless connections to a variety of systems. Thus, communication of sensor devices from different vendors require common protocols for data exchange or appropriate gateways for interconnection. Assisted technologies require access to additional information regarding the patient and his/her environment. Such information (e.g., user profiles, medical records, etc.) is stored in various repositories requiring thus common ways of information annotation, interpretation and access. In addition to the latter information access requirements, proper interpretation of user's contextual information is required, meaning that common ways of annotating collected data are required (e.g., through semantic languages, ontologies, etc.) [167]. Potential solutions that address the aforementioned issues, such as pervasive web services for either developing proper middleware software solutions or providing interoperable interfaces have been proposed [166].

6.1.2. Usability and User Acceptance

In order to prepare the elderly population to live longer and more independent lives with the help of information technology, the notion of pervasive health systems must be introduced into their lives. Awareness and acceptance can be fostered and increased by education and example. Industry must be cognizant of the fact that awareness training must go hand-in-hand with good design and that knowledge of the end users is as important as functionality, since without the end user's cooperation, functionality will be ineffective. Usability of AAL systems and platforms can require that:

- The design needs to be adapted to the end user's physical impairments.
- The interfaces must offer a relative degree of familiarity to overcome any reservations felt by the end user.
- The benefit of using monitoring and/or assisted devices must be appreciable, and the balance between intuitive use and practicable teaching methods, addressing the learning needs of this age group, must be established [168].

User acceptance is the outcome of proper design and implementation considering always the usability requirements. However, the opinion of both patients, especially in the case of the elderly, and caregivers should always be evaluated through appropriate experiments during the initial deployment of prototype systems [169], [170].

6.1.3. Security and Privacy

There are potential ways of information leaking [166] under many circumstances even when data have been de-identified and encrypted [168] during transmission. For example, because of the continuity of motion data, locations of a single user (or object) can be tracked using various algorithms. If sensors periodically report his/her location data to the server, then when the frequency of reporting is high enough and the density of users is low enough, a tracking algorithm can accurately estimate the trajectory of a single user. Furthermore, if a user's trajectory goes through sensitive or identifiable places, a user might see this as private information and these places may also provide connections to the user's identity. For another example, equipped with some devices, an attacker can determine the source location(s) originating messages by analyzing the traffic patterns even if the communications are all encrypted. Since it is then possible for them to interfere with the phenomena being sensed or even mount physical attacks on the monitored objects, the exposure of the source location information can be quite dangerous.

6.1.4. Mining of Streaming Data and Intelligent Agents

The enormous amount of streaming data produced by AAL systems will drive efforts to inductively manipulate, interpret and discover 'useful' knowledge from the collected data. As already mentioned in the enabling technologies section, the classification and activity recognition tasks of AAL is considered quite important and research work in this field is anticipated. Due to the existence of multiple heterogeneous data sources, advanced Data Mining and Fusion Techniques are necessary. Multi Agent-Based Data Mining Info-Structure (ADMI), responsible for the generation of data-mediated decision-support and strategic services have been proposed in this context. The latter takes advantage of a multi-agent architecture, which features the amalgamation of various types of intelligent agents.

Intelligent agents can be viewed as autonomous software (or hardware) constructs that are proactively involved in achieving a predetermined task and at the same time reacting to its environment. According to [175], agents are capable of:

- performing tasks (on behalf of users or other agents).
- interacting with users to receive instructions and give responses.
- operating autonomously without direct intervention by users, including monitoring the environment and acting upon the environment to bring about changes.
- showing intelligence – to interpret monitored events and make appropriate decisions.

Agents can be proactive, in terms of being able to exhibit goal-directed behavior, reactive; being able to respond to changes of the environment, including detecting and communicating to other agents, autonomous; making decisions and controlling their actions independent of others. Intelligent agents can be also considered as social entities where they can communicate with other agents using an agent-communication language in the process of carrying out their tasks. Software agents can also be used in order to perform distributed analysis of vital data and alarm indication to previously-selected physicians and family members. Agents may also assist patients or treatment experts to perform basic tasks like meal preparation and medication.

7. Conclusions

The costs of health care impose an enormous burden on the economy. The latest projections from the Centers for Medicare & Medicaid Services show that annual health-care expenditures are expected to reach $3.1 trillion by 2012, growing at an average annual rate of 7.3% during the forecast period or 17.7% of gross domestic product, up from 14.1% today [92]. Recent advances in communication and information technologies have impulsed the development of novel tools that enable remote management and monitoring of chronic disease, emergency conditions, and the delivery of health care on patient's site, saving time, travel and other expenses. Health monitoring in home environments can be accomplished by establishing ambulatory monitors that utilize wearable sensors and devices that record physiological signals, sensors embedded in the home environment to collect behavioural and physiological data or a combination of the latter. Studies for such non-invasive monitoring technologies have shown good acceptance rates by patients, presenting overall a positive impact on their perceived quality of life, as well as reducing hospitalization costs [93].

In this work, an emergency fall incident detection platform has been presented that combines motion, visual and audio information. It is a combined effort and elaboration of previous works of the authors [64], [65], [81], [82] assessing the latter perceptual components for motion characterization. Patient falls, especially in the case of elderly, are a great cause of injuries and happen both in home and hospital environments with great frequencies: a few thousands of incidents have been reported in the USA annually [94], [95]. In the presented system overhead cameras can track patient body movement whereas microphone arrays record emergency sounds. Motion data and patient-generated audio sounds are collected through body-sensors on the patient. Audio data processing and sound directionality analysis in conjunction to motion information and subject's visual location can verify fall and indicate an emergency event. Post fall visual and motion behavior of the subject indicates the severity of the fall based on semantic incident representation and rule-based evaluation. Proper rules among with information from all three channels can be used to minimize any false positives that can be generated by motion or audio characterization. Classification results among with user-based evaluation have shown promising results for the systems accuracy and acceptability in the context of incidents detection in assisted living environments. The system can also operate and provide estimations by utilizing the acquired data and contextual information individually. Even in cases where visual information is not available, the previously recorded information (e.g., the motion trajectory of the patient going to the bathroom) in conjunction to context modelling through the ontology and rules evaluation (e.g., being in bath for several hours) could be used for estimating a distress situation (e.g., patient being unconscious in the bath).

All fall events have been simulated by volunteers, trying to be as much realistic as possible, under normal indoor lighting conditions, normal background noise and relative distance to sensor receivers. Simulated falls can affect the overall system evaluation and performance, however actual evaluation of the platform in a real environment by patients (e.g., the elderly) introduces the problem of collecting real falls and related incidents in a reasonable time frame. The evaluation results presented in the manuscript have been acquired using a relatively small number of subjects, however initial results especially those concerning the characterization of falls against other movement types (i.e., walking and running) are very promising, especially when compared against results in related work (e.g., 81% fall detection in [59] using cameras, and 91.58% in [73] using sound information). The low false positive rates achieved (average false positive rate 16.67% when all perceptual components are utilized) are also very competitive against the values reported by related works in literature. The improvement in performance has been achieved when adding sound features to accelerometer data and when adding visual features to the latter as well. Resolving any potential redundant features issues has not been therefore considered. Furthermore, the total number of features used for classification for all perceptual components is eight (8) and thus no complexity or time training issues have been raised.

A limitation of the platform may be considered the equipment that needs to be installed within the monitored area (microphones and overhead cameras) and the sensors worn by patients. Despite the acceptability the system has met as discussed in section 5.3, the body sensor networks are still considered as invasive technology and require special treatment by users (e.g., proper body placement, battery replacement, etc.). Future evolution of sensor technologies will address such issues improving communication, energy consumption and wearability, by consisting of more lightweight and less invasive sensors. Significant research effort is expected to be consumed in this field in the near future [96].

Extended clinical evaluations of fall detection systems, like the one presented in this work with more potential users and care experts, collecting real falls and related incidents in a reasonable time frame, and conforming to strict protocols for clinical evaluation, remain now to persuade industrial healthcare partners to invest in such technologies and produce corresponding commercial products. These studies of patient and elder outcomes require large numbers of participants and significant budgets, which are not always easy to find and escape the capabilities scope of scientific research.

The presented platform may also be extended to facilitate the monitoring of patient's behavior. Motion and sound data analysis can be utilized to recognize unexpected patterns in the behavior of patients diagnosed with cognitive impairments (e.g., dementia). Proper modification of the train model and semantic representation of the patient's context can help the assessment of the phenomenon progress and detect related incidents like amnesia attacks. The on-body wireless nodes can be enhanced with biosignal sensors (e.g., ECG, glucose and temperature sensors) and provide a more complete assessment of the patient's status. Finally, methods like in [91] can be incorporated to prevent injury and improve human safety in cases of patient fall.

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