ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 5, November 2013

Adding Ontologies Based On PCG Analysis in E-Care Project

Amine AHMED BENYAHIA, Ali MOUKADEM, Alain DIETERLEN, Amir HAJJAM, Samy TALHA and Emmanuel ANDRES
Irtes, Université de Technologie Belfort Montbéliard, 90010 Belfort, France.
Newel, 36 rue Paul Cezanne, 68200 Mulhouse, France.
MIPS Laboratory, University of Haute Alsace, 61 rue Albert Camus, 68093 Mulhouse, France
Hôpital Civil, 1 place de l'hôpital, 67000 Strasbourg, France

Abstract*— Thinks to its level of care and its economic aspect in recent years, telemonitoring is increasingly used. Telemonitoring aims to monitor the patient's health in the comfort of its own home. For this, all patient data that can be useful are collected, and represented in the most appropriate mode; after that, a decision support system is used to detect unsafe situations. E-care is a project of telemonitoring for people suffering of heart failure. It is based on a generic and extensible platform to expand the data and integrate other sources of information. E-care platform is based on the use of ontologies for knowledge representation and decision support system to detect dangerous situations. Adding other sources of information such as auscultation, allows having more knowledge on the patient and more efficient decision support system; this can be performed by extracting relevant features from the heart sounds which reveal the mechanical activity of the heart.

Index Terms—**Telemonitoring, e-Health, ontology, decision support system, PCG signal, time-frequency analysis, E-care project.**

I. INTRODUCTION

With the advancement of life expectancy, chronic diseases are becoming increasingly ubiquitous, with an increasing cost of hospitalization. This is why many countries are interested in medical telemonitoring, to keep patients in the comfort of their own home, with a higher level of care, and all this with reduction costs. Several studies have been done on telemonitoring, to treat chronic diseases such as heart failure, diabetes, renal failure, etc. Other studies have demonstrated the need for telemonitoring, and its benefits in all areas, economic, level of care and well-being of patients. On the other hand, medical monitoring reduces unnecessary travel, which becomes a crucial point, because patients do not necessarily live near to a specialized care center, and travel is expensive and tiring for vulnerable people. Telemonitoring is based on the transmission and interpretation of medical indicators (clinical, radiological or biological) [1]. These data are taken with specialized sensors then transmitted from the patient's home to a central server. Data will be interpreted by the physicians, or an intelligent system. In the first system, the data were interpreted by physicians; it became very tedious, especially when the number of patients started to increase. Thereafter platforms and intelligent systems have been developed to interpret these data, and up alerts to physicians when detecting dangerous situations. E-care (www.projet-e-care.fr) is a project of medical monitoring for patients with heart failure. The goal is to achieve early detection of dangerous situations by taking into account all the patient data, and use a methodology to represent and best use of these data. Alerts are lifts to doctors who can at any time access to the data and the patient's profile. To better interpret the data reported from physiological sensors, we must also take into account other information concerning the patient as its environment and its diseases and medications history, etc. But this is not sufficient to have a reliable system, because representation of these data also takes a crucial role in alert detecting. Data must be represented in an intuitive manner that facilitates treatment. For this, ontologies are widely accepted as an appropriate form for the conceptualization of knowledge. E-care platform is based on the use of ontologies to represent knowledge and decision support system to detect alerts. This platform is open and extensible to integrate other data sources, to complete the patient knowledge which will help in diagnostic and anomalies detection. One of the additional data sources is the Phono Cardio Gram (PCG) signal acquired by an electronic stethoscope. PCG and auscultation are noninvasive, low-cost and accurate for diagnosing some heart diseases. The analysis of the cardiac sounds, solely based on the human ear, remains insufficient for a reliable diagnosis of cardiac pathologies, and for a clinician to obtain all the qualitative and quantitative information about cardiac activity. Advanced signal processing tools are applied on the PCG signal to extract relevant features that can be integrated in the E-care ontology. In Part II of this work, related works are presented, then, we talk about knowledge representation in part III. In part IV, generalities on ontologies and their advantages are presented. Part V presents E-care project and its architecture. Part VI presents briefly the PCG signal processing module, and in part VII these signals are integrated in the E-care platform. Finally we conclude.

II. RELATED WORK

There are a lot of works and studies on telemonitoring in the literature; a comparative study has been done in [2]. In what follows, the most important systems are presented. [3] worked on home telemonitoring system for elderly people.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 5, November 2013

This system uses location sensors to see where the patient has spent his time during the day. After that, data are compared by Hamming measure, to know how long the patient spends in each room. Other studies in the same context as [4], [5] and [6] use sensors location of the patient. These systems are based on classification methods to analyze the patient's daily activities. [7] Propose a telemonitoring system with architecture of three levels: the sensor network, the patient server that collects and transmits the information, and the hospital server that processes information and makes them available to physicians. This system uses data mining to detect anomalies. All these systems are based only on data mining, and need constant interaction and feed back with physicians. Also, due to the probabilistic characteristic of data mining, alerts detection module is imprecise. [8] Propose a decision support system for telemonitoring of patients with heart failure. The system includes patient data: posture, pulse sensor, physical activities and alerts. This system does not take into account physiological measures related to the heart failure like blood pressure and weight, nor the patient's environment such as temperature and humidity. [9] propose a system based on multiple ontologies: the personal data of the patient, the house context, social context and alarms. The system uses the rule-based inference of first order, these rules are very dependent on the parameters (eg if temperature> 40 then alert) making them non generic and non-scalable. The rules do not take into account changes in health state of the patient. [10] detail the design and implementation of a platform for reasoning to anticipate and react intelligently in telemonitoring situations. The system manages intelligent agents, whose behavior is defined and validated by ontologies and rules. [11] propose an ontological architecture for modeling a system Smart Home e-health. The goal is to provide an adaptive system for extending the home support of an aging person with diminished cognitive autonomy. Each one of these studies deals with a part of telemonitoring, with very limited information about the patient. Also, the technologies used to describe the patient profile are very old with a limited semantic, which reduces their performance and making them difficult to share and evolve.

III. KNOWLEDGE

To have a reliable alert detecting system, we must use the most robust inference system. Inference system needs a knowledge base and inference rules to work on this knowledge. More our knowledge base is completed and includes all patient information, more our system is efficient.

We can collect lot of data and information about the patient:

- Medical information: antecedents, diseases, medical history, etc.
- Contextual information: pregnancy, smoke cigarette, alcohol and drug dependencies, etc.
- Physiological information: heart rate, blood pressure, oximetry, temperature, weight, etc.
- Environmental data: like ambient temperature, humidity, etc.
- Behavioral data: like if the patient is sleeping or standing or climbing stairs, etc.

Every field of this information is very important to understand and compute the medical state of the patient. All systems and studies in the literature don't take into account all these fields. In this case, alert detection isn't accurate, for example, if the heart rate of 70 isn't dangerous for a normal patient, this will be dangerous if we know that the patient is alcohol dependent. In other words, if we don't use all patient information, the system is unreliable. Even if we take into account all patient information, this is insufficient to have a reliable system, because this depends also on the knowledge representation and the technologies used to handle them. The increasing use of terminologies and thesaurus, in health information systems encourages the use of methodologies and technologies from the Semantic Web community. In other words, machines have to understand the knowledge representation. Ontologies are accepted as the best semantic knowledge representation. For that, we use ontologies to represent every field of patient information, to have a shared definition of all our domain's concepts.

IV. ONTOLOGIES

The first accepted definition for ontology is that of [12], "explicit specification of a conceptualization". This definition has also been clarified by [13] to be: "Ontology is an explicit formal specification and a shared conceptualization". In this definition, it is necessary to correctly interpret each used term. Formal: the machine can understand. Explicit: the concepts, relationships, individuals and axioms are explicitly defined. Shared: knowledge representations are shared by a community. Conceptualization: abstract model of a part of the world that we want to represent. Ontologies provide a common semantics. This means that all individuals and concepts involved can be explicitly defined in terms of their relationships and attributes. Ontologies are interpreted by a machine, so make an automatic system is much easier. This facilitates and improves the quality of diagnosis and the process of decision support. Also, ontologies share knowledge between several people, so they can work together without any ambiguity or loss of information. Analyze knowledge about a domain is possible when specifying the terms of the domain is made. Formal analysis of terms is extremely valuable when we want to reuse existing ontologies, or when we want to extend ontology. The construction of ontology is through consensus, it represents the shared understanding of a group or community, instead, as is the case in most systems, based on a meaning given by a few individuals, to which all must adjust. The definition of ontology is oriented by the use, as understood by a group or community to serve their needs directly. That differs from a system that, at best, can be thought of depending on users. Also, ontologies provide a model of high level abstraction of daily workflow; this model can be adapted to each organization. In other words, any organization can have an ontology adapted to its particular situation. Allowing the reuse of knowledge in a domain was one of the major reasons of research on ontologies in recent years. For example, models of several areas needed to represent the notion of time. This representation includes the notions of time intervals, specific moments in time, on time measurements …etc. When a group of researchers develops such ontology in detail, other groups can simply reuse it for their own ontology. Moreover, if it is necessary to build a larger ontology, it is possible to integrate several existing ontologies describing portions of a domain. We can also reuse a general ontology and expand it to allow describing a specific domain of interest. All this, due ontologies are very easy to maintain and with very minimal cost. Especially in the medical field, there are a lot of classification like WHO Classifications of diseases and drugs (www.who.int), going from theses classification, we can construct domain ontologies and used them in our system in the field of cardiology. There are also a lot of medical ontologies constructed by other systems that we can integrate directly in our system. Ontologies can be classified along several dimensions. Among these, we focus on the typology based on the object of conceptualization; ontologies can be classified as follows:

- Top level ontology [14], this type of ontology is the most generic and describes very general concepts or common sense knowledge such as space, time, event, action, etc. These concepts are independent of a problem or a particular domain;
- Domain ontology [15], this ontology governs a set of vocabularies and concepts describing an application domain or the target world. Most existing ontologies are domain ontologies;
- Task ontology [15], this type of ontology is used to conceptualize specific tasks in systems. It governs a set of vocabularies and concepts describing a structure of performing the tasks domain-independent;
- Application ontology [16], this ontology is the most specific. The concepts in the application ontology are very domain specific and particular application.

V. E-CARE PLATFORM

E-care project is a telemonitoring system for patient with heart failure. Actually they account for France about 1 million patients with heart failure with more than 120,000 new cases per year. E-care scheme (*Fig 1*), use medical and environmental sensors to take measures then transmit them via the Internet to a central server. The central server processes these measures within the patient profile and sends alerts to physicians if dangerous situations are detected.

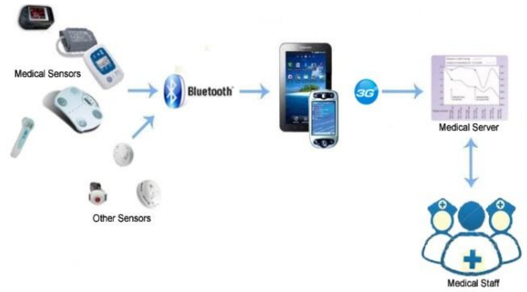

Fig 1: E-Care Project Architecture

Solutions and systems found in the literature use only a part of the knowledge on the patient, which makes their decision support system not very accurate. The representation of knowledge plays an important role in a system of telemonitoring, in these systems, some do not use ontologies, and use old technology that makes the task of detecting alerts very complex and knowledge sharing almost impossible. E-care architecture is based on ontologies for knowledge representation and a decision support system for detecting dangerous situations. We use two types of ontologies, one task ontology and several domain ontologies. The task ontology is central to the system. It describes the patient profile and how measures, alerts and data can be associated to a patient. It describes also all users of the system (physician, nurse, administrator, etc.), their tasks and how they operate together. It contains also definition of all used equipment (sensors, tablets, etc.). The task ontology is generic and extensible, so we can integrate other domain ontologies that can add semantic to our system. These ontologies provide a controlled vocabulary, as for diseases, symptoms and medications. These ontologies can provide a language for sharing and communicating between different actors in the system. An example of integration is shown in *(Fig 2)*. With the semantics of these ontologies, our system can interact easily or integrate other systems like auscultations system. Thus, data and information processed are generic and can be introduced into other systems.

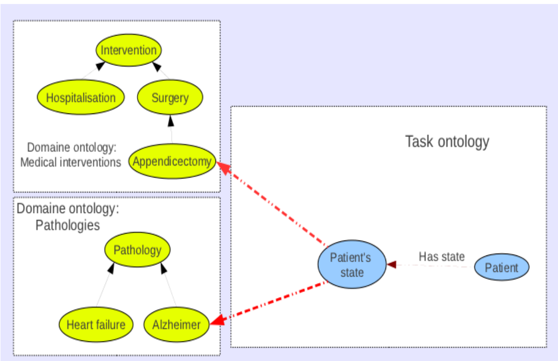

Fig 2: Example of integration of domain ontology

There are different manners to build domain ontology, depending on the available resources. In the medical domain, there are a lot of classifications and ontologies in the literature, for example we can use WHO classifications: International Classification of Diseases (ICD) and

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 5, November 2013

Anatomical Therapeutic Chemical Classification System (ATC/DDD). This makes the task of building ontologies much easier, rather than from a plain text. Task ontology and domain ontologies are described and formalized by knowledge engineers and medical experts to meet their need. The W3C recommends OWL (Web Ontology Language) to build ontologies, and using tools like “Protégé” (protege.stanford.edu), this becomes very simple. The E-Care platform is based on a decision support system that detects anomalies and changes in patient's health status. It is based on an inference engine that uses facts base and inference rules. Facts base is composed of the task ontology that contain all patient data, and domain ontologies. Inference rules should be as generic as possible, and must evolve with the patient's state. Medical experts define these rules and can change them over time. Then knowledge engineers construct theme in a formal language compliant with the description of ontologies like SWRL. Inference must lead to provide recommendations to the patient if necessary. If anomalies are detected, the system sends alerts to the physician. Inferred data can help physicians to diagnose the patient by providing information concerning the evolution of his health.

VII. PCG ANALYSIS MODULE

Advanced methods and techniques of signal processing and artificial intelligence will be applied to extract relevant features from the heart sound after the acquisition of the PCG signal. The heart sounds are non-stationary by nature. The classic Fourier transform analyzes the frequency content of signal without any time information. Therefore, the importance of time-frequency transforms (*Fig 3*) to detect the frequency changes of signal over time and to extract pertinent features form the heart sound.

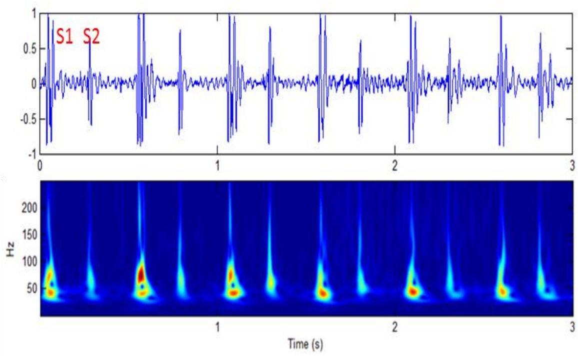

Fig 3: The S-transform (bottom) of a normal heart sounds (top).

These features will then be transmitted to a central server in order to be integrated in the global ontology (*Fig 4*).

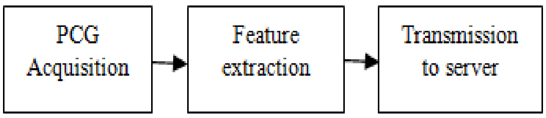

Fig 4: The PCG module to be integrated in E-care project.

One of the first and most important phases in the analysis of heart sounds, is the segmentation of heart sounds which is part of the feature extraction block. Heart sound segmentation partitions the PCG signals into cardiac cycles and further into S1 (first heart sound), systole, S2 (second heart sound) and diastole. Identification of the two phases of the cardiac cycle and of the heart sounds with robust differentiation between S1 and S2 even in the presence of additional heart sounds (S3 or S4) and/or murmurs is a first step in this challenge. Then there is a need to measure accurately S1 and S2 allowing the progression to automatic diagnosis of heart murmurs with the distinction of ejection and regurgitation murmurs. Features, such as the temporal localization of the heart sounds, the duration of the first and the second heart sounds could be extracted directly after the segmentation process. Then, the number of internal components of the first and second heart sounds, their frequency content, and the significance of diastolic and systolic murmurs, could also be studied and extracted directly from the PCG signal. Performing a robust segmentation method enable to perform a targeted feature extraction phase at each segmented part. After the acquisition part, we will present briefly the proposed segmentation algorithm integrated in the E-care project.

A. Acquisition

Several factors affect the quality of the acquired signal, above all, the type of the electronic stethoscope, its mode of use, the patient’s position during auscultation, and the surrounding noise. In the E-care project we use the Littman electronic stethoscope produced by 3M Corporation, with a Bluetooth connection to transmit sounds in real time. The sounds are recorded with 16 bits accuracy and 8000Hz sampling frequency in a wave format. At first, the original signal is decimated by factor 4 from 8000 Hz to 2000 Hz sampling frequency and then the signal is filtered by a high-pass filter with cut-off frequency of 30 Hz. The filtered signal is refiltered in the reverse direction so that there is no time delay in the resulting signal. Then, the Normalization is applied by setting the variance of the signal to a value of 1. The resulting signal is expressed by:

$$x(t) = x(t) / \max\left(x(t)\right) \quad (1)$$

B. Segmentation of heart sounds

The SSE method [17] is used to segment the heart sounds. The SSE method is a time-frequency based method where the Stock well transform (S-transform) is used [18]; it uses the S-matrix and it calculates the Shannon Energy (SE) of the local spectrum calculated by the S-transform for each sample of the signal x(t). Then, the extracted envelope is smoothed by applying an average filter (*Fig 5*).

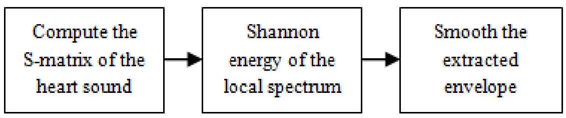

Fig 5: Block Diagram of SSE Method

The S-transform of a time series *x(t)* is defined as (Stockwell, 1996):

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 5, November 2013

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t)w(\tau - t)e^{-2\pi i f t}dt \qquad (2)$$

Where the window function $w(\tau - t)$ is chosen as:

$$w(t, f) = \frac{1}{\sigma(f)\sqrt{2\pi}} e^{\frac{-t}{2\sigma f^2}} \qquad (3)$$

And s(f) is a function of frequency as:

$$\sigma(f) = \frac{1}{|f|} \qquad (4)$$

The proposed method calculates the Shannon energy of each the local spectrum in order to extract the envelope of the signal (*Fig 6*). The SSE envelope can be given as:

$$SSE(x_i) = -\int_{-\infty}^{+\infty} |S(\tau, f)|^2 \log(|S(\tau, f)|^2)df \qquad (5)$$

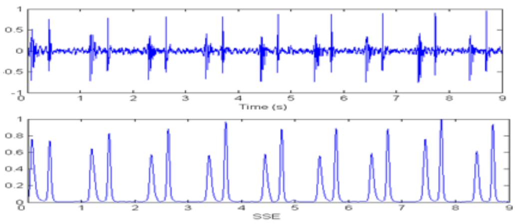

Fig 6: The SSE envelope for a normal heart sound.

Each column of the S-matrix represents the local frequency at a specific sample. The advantage of the Shannon energy transformation is its capacity to emphasize the medium intensities and to attenuate low intensities of the signal which represents the local spectrum in the case the SSE method. A threshold which equals to 10 % of the maximum value of the SSE envelope is applied to define the boundaries of each located sound. *Fig 7* shows the results of segmentation method applied on normal and pathological heart sounds.

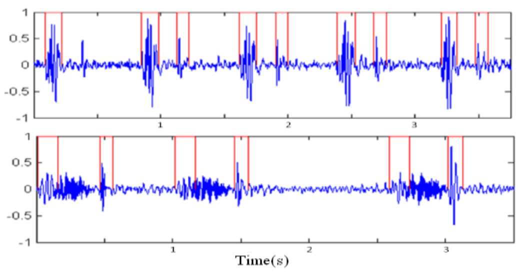

Fig 7: Segmentation module applied on normal heart sound (top) and pathological heart sound (bottom).

VIII. INTEGRATION INTO E-CARE ONTOLOGY

The most important part is the integration of the PCG Analysis Module into E-care platform. E-care platform is generic and easy to evolve since it is based on sharable ontologies. The integration of this module must go through three steps, representation in the task ontology, adding inference rules, and finely, adding domain ontologies if possible. Collected data have to be represented in the E-care Ontology. In other words, a PCG signal is represented in an ontological language going from its markers and attributes extracted by the PCG Analysis Module and validated by the expert (cardiologist). After the representation, relationships with other concepts of the E-care ontology are added; like a patient may have multiples PCG signals, and a PCG signal is specific to one patient. Another important part of integration is the definition of inference rules. There are two types of rules, rules concerning only PCG signals (find abnormal sounds), and rules combining PCG signals and other type of measurements (blood pressure, weight, temperature, blood oxygen saturation, etc.) or patient profile and context (pregnancy, alcohol, etc.). Domain ontologies on PCG signals and auscultation sounds can be integrated to add semantic, so we can work in a collaborative manner with the cardiologists, and share information without ambiguities. We can integrate existing ontologies, or construct ontologies going from classifications or at worst from medical reports. To construct domain ontology, we have to gather terms and concepts on PCG signals, and then we give definition to each concept; finally, work on the semantics of these terms by seeking relationships that may exist between them. [19] have attempted to collect definitions of terms relating to respiratory sounds and have arrived at a collection of 162 terms commonly used in the «Computer Respiratory Sound Analysis» (CORSA). Nevertheless, it still doesn't allow physician to have a common definition of terms that are used.

IX. CONCLUSION

In this paper we present the E-care project, a telemonitoring system for patients with heart failure. We start with presenting some systems and studies found in the literature, with their advantages and inconveniences. The common inconvenience of these systems is the partial representation of the patient's profile. After that, the knowledge considered in the patient's profile in the E-care platform where presented. E-care platform relies on the use of different ontologies; one task ontology to manage the system, and several domain ontologies to add semantic and sharable vocabulary in the medical field. This platform is based also on a decision support system to detect dangerous situations. The decision support system is based on an inference engine that needs both ontologies as knowledge base, and inference rules on these ontologies validated by the cardiologist. By adding other fields of knowledge, our system will be more reliable. Because that gives decision support system more information about patient's health state, so the taken decision is more precise and specific. In this paper we present a PCG Analysis Module. This module, based on time-frequency domain, analyzes PCG signals and generates pertinent features. The PCG features are then integrated in the E-care task ontology. After that, inference rules and domain ontologies on PCG signals are added, if necessary. Our perspective is to add other systems that provide other knowledge and complete the patient's profile. This will make the decision support system

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 5, November 2013

more efficient.

REFERENCES

[1] P. Lasbordes. La telesante : un nouvel atout au service de notre bien-être : Un plan quinquennal éco-responsable pour le déploiement de la télésanté en France.(2009), Rapport remis à Madame Roselyne Bachelot-Narquin, Ministre de la Santé et des Sports par Monsieur Pierre Lasbordes, Député de l'Essonne, 2009.

[2] A. Ahemd Benyahia, A. Hajjam, V. Hilaire, M. Hajjam. Ontological architecture for management of telemonitoring system and alerts detection. Book chapter of: eHealth and Remote Monitoring, ISBN : 978-953-51-0734-7. 2012.

[3] C. Franco, J. Demongeot, C. Villemazet , N. Vuillerme. Behavioral telemonitoring of the elderly at home : Detection of nycthemeral rhythms drifts from location data. 24th International Conference on Advanced Information Networking and Applications Workshops, 759-766. 2010.

[4] Tareq Hadidi, Norbert Noury. A Predictive Analysis of the Night-Day Activities Level of Older Patient in a Health Smart Home. Ambient Assistive Health and Wellness Management in the Heart of the City. 290-293, 2009.

[5] C. Franco, J. Demongeot, Y. Fouquet, C. Villemazet, N. Vuillerme. Perspectives in home TeleHealthCare system: Daily routine nycthemeral rhythm monitoring from location data. International Conference on Complex, Intelligent and Software Intensive Systems. 611-617, 2010.

[6] Anthony Fleury, Michel Vacher, Norbert Noury. SVM-Based Multi-Modal Classification of Activities of Daily Living in Health Smart Homes: Sensors, Algorithms and First Experimental Results. IEEE TRANSACTION ON INFORMATION TECHNOLOGY IN BIOMEDICINE. 274-283. 2010.

[7] Rifat Shahriyar, Md. Faizul Bari, Gourab Kundu, Sheikh Iqbal Ahamed, and Md. Mostofa Akbar. Intelligent Mobile Health Monitoring System (IMHMS). International Journal of Control and Automation, Vol.2, No.3, 13-28. 2009.

[8] Aniello Minutolo, Giovanna Sannino, Massimo Esposito, Giuseppe De Pietro. A rule-based mHealth system for cardiac monitoring. 2010 IEEE EMBS Conference on Biomedical Engineering & Sciences. 2010.

[9] Federica Paganelli, Dino Giuli. An Ontology-Based System for Context-Aware and Configurable Services to Support Home-Based Continuous Care. IEEE Transactions on Information Technology in Biomedecine, VOL. 15, NO. 2, MARCH 2011.

[10] Miguel A. Valero, Laura Vadillo, Iván Pau, and Ana Peñalver. An Intelligent Agents Reasoning Platform to Support Smart Home Telecare. IWANN 2009, Part II, LNCS 5518. 679–686. 2009.

[11] F. Latfi, B. Lefebvre, C. Descheneaux. Ontology-based management of the telehealth smart home, dedicated to elderly in loss of cognitive autonomy , OWLED 2007. June 6-7 Innsbruck, Austria. 2007.

[12] T. Gruber. Towards principals for the design of ontologies used for knowledge sharing. Formal ontology in conceptual analysis and knowledge representation. Kluwer Academic pubishers, 2003.

[13] R. Studer, R. Benjamins, D. Fensel. Knowledge Engineering : Principles and Methods. Data and Knowledge Engineering 25, 161-197, 1998.

[14] J. Sowa. Top-level ontological categories. International Journal of Human and Computer Studies, 43, 669-685, 1995.

[15] R. Mizoguchi, K. Kozaki, T. Sano and Y. Kitamura. Construction and Deployment of a Plant Ontology. The 12th International Conference, EKAW2000113128, 2000.

[16] A. Maedche. Ontology Learning for the Semantic Web. Boston: Kluwer Academic Publishers, 2002.

[17] A. Moukadem, A. Dieterlen, C. Brandt. A Robust Heart Sound Segmentation based on S-Transform, Biomedical Signal Processing and Control 8 (2013) 273– 281, 2013.

[18] R. G. Stockwell, L. Mansinha, R. P. Lowe. Localization of the complex spectrum: the S-transform, IEEE Trans. Sig. Proc. 44 (4) (1996) 998–1001, 1996.

[19] A. R. Sovijarvi, F. Dalmasso, J. Vanderschoot, L. P. Malmberg, G. Righini, S. A. Stoneman. Definition of terms for applications of respiratory sounds, Eur Respir Rev 2000; 10: 597–610, 2000.

AUTHOR'S PROFILE

Amine Ahmed-Benyahia is a PhD student at the University of Technology of Belfort Montbeliard (UTBM), he works on the application of semantic web technologies for the medical field, especially for telemonitoring systems. He received the Master's Degree in Software Engineering from the University of Montpellier II (UM2), specialized in semantic web and search engine. His main research interest includes knowledge engineering using semantic web, decision support system and data mining. He works on different projects on telemonitoring.
Amine.ahmed-benyahia@utbm.fr

Ali Moukadem received the Master's Degree in Software Engineering from the University of Technologie of Belfort-Montbéliard, France and the research Master's Degree and the PhD in signal processing form the University of Haute Alsace, France. His main research interests are time-frequency analysis and methods, segmentation and classification of non-stationary signals and biomedical engineering. Dr. Moukadem is currently a Post-Doctoral researcher at the Laboratory MIPS in the University of Haute Alsace.
ali.moukadem@uha.fr

Alain Dieterlen received his PhD in science in 1991 and his HdR in signal and image processing in 2005 from University of Haute-Alsace (UHA). He is currently a professor at the University Institute of Technology (IUT) and head of a research group at the laboratory MIPS (Modelisation Intelligence Process and Signal). His main research topics are in 3D image processing and time-frequency analysis. The applications are mainly in medical field, principally in 3D fluorescence microscopy and in

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 3, Issue 5, November 2013

biomedical signal analysis. The developed methodology includes the acquisition process modelization and identification to adapt the restauration procedure and to extract the pertinent information for the medical expert.
alain.dieterlen@uha.fr

Amir Hajjam received his Ph.D. in Computer Science from University of Haute-Alsace (UHA) in 1990. He is currently an associate professor in Computer Sciences and Engineering at the University of Technology of Belfort Montbeliard (UTBM) and performs research activity at the IRTES-Systems and Transportation Laboratory. His current research interest includes knowledge engineering and data mining as well as heuristic mechanisms and artificial intelligence applied in a distributed dynamic framework. He is responsible for the research program "knowledge Modelling and optimization in medical field ".
Amir.hajjam@utbm.fr

Emmanuel Andrès received in 1996 his MD degree in Internal Medicine, at the University of Strasbourg, France. He worked as an associated professor in the University Hospital of Strasbourg, France. In 1998 he worked as PhD in Molecular Biology in the Laboratory of Professor Hoffmann (2011, Nobel Prize of Medicine) in the field of cationic antimicrobial peptides and pathogens - host relations. In 2002, he was nominated Professor at the University of Strasbourg, France. He also was in the head of an Internal Medicine Department (of 62 beads) in the University hospital of Strasbourg, France. His recent works also include research and development on human sounds analysis, electronic stethoscope, e-auscultation, and e-medicine. In that function he was recruited as advisor to several pharmaceutical and telemedicine companies or start-up.
emmanuel.andres@chru-strasbourg.fr

Samy Talha received in 2003 his MD degree in Cardiology and Vascular Pathology, at the University of Strasbourg, France. In 2005 he worked as a PhD in Physiology in the Laboratory of Professor Bernard Geny in the field of preconditioning, oxidative stress and apoptosis. In 2008, he was nominated Lecturer at the University of Strasbourg, France and Consultant at the Strasbourg Hospital University (HUS). Main clinical fields include clinical cardiology, echocardiography and development of stress echocardiography in the HUS. Research interest includes heart failure, heart endocrine function and heart transplantation, as well as e-medicine and muscular preconditioning. Member of French Society of Cardiology (echocardiography branch) and European Society of Cardiology.
samy.talha@chru-strasbourg.fr