Human Health Monitoring by Sensors: Analysis of Contextual Uncertainties Through Dempster-Shafer Evidence Theory

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Abstract. This paper describes the authorsâ observations about the uncertainties associated with monitoring based on sensors, through the Dempster-Shafer Evidence Theory. It presents the results of an experiment which is part of an ongoing research about dealing with uncertain contextual information in the human health monitoring system based on sensors. The experiment employs evidence theory on reasoning over context. Recommendations to improve the systems to monitor the human health within a framework that addresses uncertainty are also provided.

Keywords: Remote monitoring system, human health, uncertain information, Dempster-Shafer theory.

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1 Introduction

Ubiquitous and context-aware computing provides important innovations and changes in the Health area especially on medical and patient relationships and at hospital and emergency rooms routine [1]. Treatment and remote monitoring represents one of the many advances on applying technology on health.

The human health remote monitoring is a trend in health care once it contributes to the continuous monitoring of physiological human function even at distance; by collecting and sending physiological data to the health professional.

The human health monitoring (HHM) [2] involves some research questions as the contextual uncertainties and this kind of information is inherent in sensor technology. For instance, the uncertainties appear in the system through the sensors used to get data because it can break or it can report wrong data into no planned situations.

This research considers that the acquisition of knowledge about the types of uncertainties present in the monitoring of human health through sensor's technology and understanding how they are originated can give better comprehension about how to cope with them. Additionally, realizing how uncertain information should be presented to the end user allows the developer improve the structure of data presentation.

Thus, this paper presents as contribution some reflections about how to deal with uncertain contextual information in the human health monitoring system based on sensors applying Dempster-Shafer theory to identify and represent uncertain contextual information. There are some works ([3], [4], [5], [6]) that treat this aspect, but they do not explore all the uncertainties treated in this work, in a scenario of monitoring of patients.

In this paper, we present part of the solution in treating uncertain information in HHM by employing some probabilistic reasoning techniques to identify and represent this kind of contextual information. Section 2 relates considerations about human health monitoring;

Section 3 provides information about uncertain information; Section 4 describes some aspects about the representation of uncertainty information. Section 5 presents some results of an experiment employing evidence theory to identify and to represent uncertain information in the monitoring of the patients.

2 Monitoring Human Health Through Sensors

Nowadays the expected level of living has increased worldwide and for some group of age as elderly people are not required staying at the hospital to take care of their health. They can remain in their home space attending their health through using technology as sensor networks.

According to Jung et al. [7] WBSN can provides more efficient utilization of physicians, shortened hospital stays, reducing the skill level and frequency of visits of home-care professionals, reducing hospital readmission rates, and promoting health education can all contribute to reduced healthcare costs. The ubiquitous healthcare system enables medical professionals to remotely perform real-time monitoring, early diagnosis, and treatment for potential risky disease.

Furthermore, the medical diagnosis and patient consultations can be delivered via wire/wireless communication channels. Disorders which require continuous monitoring are one of the most appropriated set to apply the resources provided by human health monitoring based on sensors since it associates health care services with the convenience of technology. For example, some diseases as diabetes and high blood pressure what are common to elderly people and involve continuous monitoring [8].

In this kind of application, the patient usually interacts with the system through sensor devices which collect patients and environment data; the computational system can apply techniques to treat data from sensors and present them by a user interface to the health professional who can give diagnosis to the patients and directions to its treatment on emergency situation or not.

Important aspects such as collecting and interpreting vital data (physiological data), diary life activities as eating and sleeping (behavioral data) and the environmental conditions as temperature, luminosity, humidity (environmental data) are observed in this system.

Sensors are the basic technology applied in HHMS. Body Area Network (BAN), Wireless Body Area Network (WBAN), Body Sensor Network (BSN), Wireless Body Sensor Networks (WBSN) and Wearable Wireless Body Sensor Network (WWBSN) are names usually applied for the sensor network technology used in the health remote monitoring.

Figure 1 shows a model to health remote monitoring where patient, sensors, medical team and computing systems are elements working together in data collecting, data managing and data fusion.

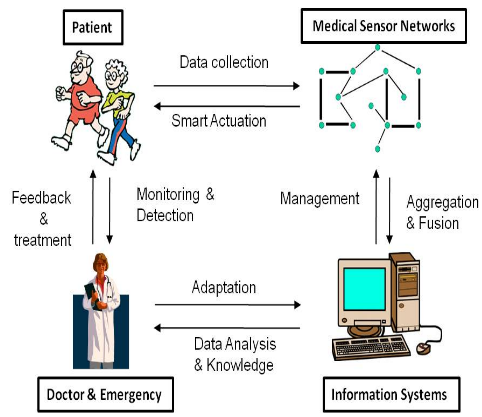

Figure 1: Human Health Monitoring System

A BSN consists of several physiologic sensors which monitor vital signals and data from the environment and send them to the health professional who can use such data to make decisions about the patient's treatment This technology provides the monitoring of patient's physiologic signals, including ECG, EEG, blood pressure, blood flow, glucose level and others.

According to Ren et al. [9] the WBAN is a result of convergence among biosensors technology, wireless communication and network technology. The WBAN consists of a collection of low energetic power biosensors devices which integrate an embedded microprocessor, radio and limited storage capacity. Wireless sensor network has been applied in several areas providing environmental, climatic and biological monitoring.

In general, a WSN is a network formed by several nodes sensors which collect and transmit some characteristics from the ambient where they are. WSN uses resources with restrict energy, dynamic topology and large quantity of nodes.

The Wireless Sensor Network provides basic support to the Body Area Network and consequentially to the health remote monitoring. WSN offers several kinds of sensor such as for illumination, movement, acceleration, localization, positioning and proximity, temperature, humidity, biological signals and others which, even at distance, can collect data that will benefit both health professionals and patients.

3 Incertainties in the Health Monitoring

The uncertainties in the information collected are a challenge in ubiquitous and context-aware computing [2], once it means to collect and reasoning on contextual data which maintain relationship among inaccurate, conflicting and uncertain data. For example, it is difficult to deduce if a user is sleeping based only on the information collected by the sensor in its bed, the sensor of illumination and the sensor of sound. Moreover, the logical foundation and reasoning mechanisms based on rules in context aware systems do not support reasoning on uncertain data [3].

Also, sensors are inherently imprecise [2] since they can break or relay wrong data when they are not correctly designed or when they are in a new situation; inaccurate data in sensors can result in misunderstanding to the user or in an incorrect behavior from system i.e. applications will take decisions based on the data obtained by unreliable sensors.

In Human Health Monitoring by sensors factors such as the mutual influence among physiologic, behavior and environmental data also can be considered as a source to uncertainties information, once from the state of behavioral data or environmental data the physiological condition of the patient can change.

Figure 2 presents a scenario to apply a human health remote system monitoring in which three important elements are highlighted: the environment where the person is, the person's activities and his physiological data. Sensors of movement, proximity and medical sensors are present in this system in addition to RFID and cameras.

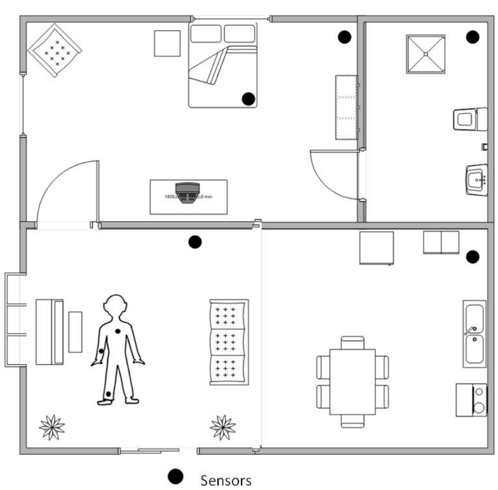

Figure 2: Remote Monitoring System of Human Health

This system involves sensors which collect data from a low-level context, reasoning techniques on context which interpret and/or transform the context and finally the data presentation on a high-level context.

The low-level context is related with data obtained by sensors, and the high-level context is obtained by the composition of information from low level context or from sophisticated processing techniques or from artificial intelligence.

The main motivation on identifying and specifying uncertain information in human health monitoring based on sensors is due to the complex nature of this application. As well as the unsatisfactory combination of the attributes inherent to the monitored context; the ambiguity among data which prevents reasoning on correct context; the inaccuracy and the natural unreliability in some sensors what are samples of sources of uncertainties.

4 The Praninc

Uncertain contextual information is a reality in context aware systems and for this reason it is relevant studying its behavior in the scenario where it is applied. An important mechanism to understand what is not yet known is the modeling of this object or thing. Thus, several approaches are applied on representing uncertain information.

In the case of human health monitoring based on sensors the uncertainties are associated with each level of context and it involves different characteristics.

The human health monitoring involves the employment of different technologies as the wireless body area network. WBAN implicates in utilization of the sensor technology which is inherently imprecise since the sensors can break or to relate wrong data when on not planned situation.

Walker [10] considers two standpoints to represent this kind of information, one based on possibility theory and another based on probability theory.

On generating reliable contextual information, a level of uncertain is observed and these uncertainties can be associated with the reasoning process on the context, with the data collected by several and different sensors or with the technology and sensors used [6].

Apart from uncertainties associated with the technology used in monitoring others uncertainties which are related to the information need to be considered, since data on the patient's behavior may be related to the physiological data of this, and the environmental data may influence the blood pressure and / or patient's heart rate [11].

Different approaches have been used to deal with uncertain contextual information such as fuzzy logic, Bayesian networks, and theory of evidence Dempster Schafer [12].

Fuzzy logic is useful in capturing inaccurate representation of notions such as "high", "faithful" and "reliable" and reason about them. The elements of two or more fuzzy sets can be combined to create a new fuzzy set with its own membership function. Fuzzy logic is also suitable for the description of subjective contexts, performing multi-sensor fusion of subjective contexts and resolving potential conflicts between different contexts.

Bayesian networks are particularly effective in the representation and storage of conditional probabilities, if the dependencies in the joint distribution are sparse.

In general, Bayesian networks are well suited for the combination of uncertain information originating from many sources and deduction of higher-level contexts.

The Dempster-Shafer theory is a mathematical theory of evidence based on reliable functions and plausible reasoning, which is used to combine separate pieces of information (evidence) to calculate the probability of an event. It is often used as a method of sensor fusion, through the provision of levels of confidence when they are based on independent items of evidence [9].

In this research, the Theory of Evidence of Dempster Shafer is applied as the core to analyze uncertainties in information present in human health monitoring systems. However, the aspects related with the sensor's behavior are also treated by simulation of scenarios where real physiological data are involved.

5 Praninc Validation

Remote monitoring can provide can provide a cheaper and smarter way to manage and care for patients suffering from chronic diseases since it requires continuous, long-term monitoring rather than episodic assessments. Thus, chronic diseases as Diabetes mellitus and Hypertension can use remote monitoring as auxiliaries to the medical supervision.

Diabetes mellitus is a medical condition in which body does not adequately produce the quantity or quality of insulin needed to maintain normal circulating blood glucose [14].

Hypertension is high blood pressure. Blood pressure is the force of blood pushing against the walls of arteries as it flows through them [8]. Arteries are the blood vessels that carry oxygenated blood from the heart to the body's tissues.

Because high blood pressure is the leading cause of strokes and a major risk factor for heart attacks, one of the most important aspects of preventive cardiology should be to identify as many people who have the disease as possible and to take steps to lower the blood pressure before it causes damage to the blood vessels, heart, kidneys, eyes, and other organs [15].

Once diabetes and hypertension are chronic diseases it requires continuous monitoring rather than episodic, the WBSN may be an effective for the patient's attendance. However, as the system is composed by sensors it can also be pervaded by uncertainties it is important to investigate this scenario of application.

The proposal to deal with uncertain information in the monitoring of the patients is composed by two stages: 1) mapping and specifying the sources of uncertain information in the monitoring and; 2) showing the level of uncertainties present in the results of monitoring, following related.

5.1 Mapping and specifying uncertain information

The first step in this approach involves the identification of uncertain information and its characteristics in the health scenario.

In the scope of this research three kinds of uncertainties are studied.

1. Uncertainties inherent to own sensor;
2. Uncertainties which coming from the relationships between the data obtained by sensors;
3. Uncertainties from the communication technology.

Table 1 presents some examples of parameters which can be associated to each type of uncertainty.

Table 1: Examples of parameters associated with types of uncertainties

Uncertainties	Parameters
Uncertainties from the communication technology Permanence	Bandwidth Sampling rate Information Rate
Uncertainties which coming from the relationships between the data obtained by sensors.	Interplay
Uncertainties inherent to own sensor	Confidence Accuracy Sensibility Resolution

Confidence, accuracy, sensibility and resolution are parameters which correspond to each sensor device involved into the monitoring [16].

Bandwidth, sampling rate and information rate are elements observed on transmitting data though wireless communication.

The relationship between data sensed by sensor devices is called here as Interplay once the data from physiological situation can be changed by the condition of the environment and by the patient behavior [11].

To identify uncertainties to each parameter a scale is proposed what allow categorizing uncertainties ranging between zero and one, since it implies using probabilities techniques.

The classification of uncertainties is proposed based on classification in decision support systems. This classification was proposed by Walker [10] and claims uncertainties information can involve lack of confidence or ignorance.

Walker presents a four-level scale that encompasses since statistic uncertain to total ignorance as presented in figure 3.

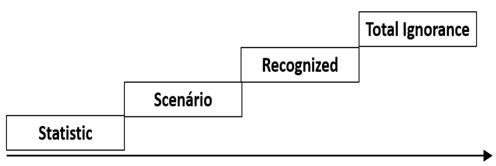

Figure 3: A uncertainty classification scale

This means:

1. Statistic uncertain: it represents a situation where everything is known with exact and absolute certainty, i.e., possible outcomes and their related probabilities are known. For instance, in health system if the evidences are known is possible to know the possible outcomes and their associated probabilities.

2. Scenario of uncertainty: it describes a state where all possible outcomes are known but their probabilities are not reliable. At this level of scale, it is possible to list some hypothesis but due to interaction with the environment is not possible to know their odds.

3. Recognized ignorance: it describes a state where are not known both potential outcomes and related probabilities. In this level mechanisms and functional relations are in identification but there is not sufficient scientific base for reliable assertion; in most case involves the application of further investigation about the scenario for their better knowledge and understanding.

4. Total ignorance: it indicates a deep level of uncertainty about the results and their probabilities which includes even the lack of knowledge of how much needs to know about the scenario.

5.1.1 Analyzing uncertain information through Dempster Shafer Theory

The experiment presented in this section involves the use of evidential theory on a scenario of human health remote monitoring. The objective is to analyze the behavior of uncertain contextual information belonging to this scenario. It considers data obtained from several and different sources of sensors.

The scenario involved is described below.

"A cardiac patient has in his house some sensors such as humidity, temperature, noise, luminosity, position, motion, blood pressure and heart rate which representing three categories of sensors environmental, behavioral and physiological data".

Table 2 presents some examples of data sensed by sensors.

Table 2: Sensors Applied on the Experiment

Environmental Sensors	Physiological Sensors	Behavioral Sensors
Temperature	Blood pressure	Motion
Luminosity	Heart Frequency	Presence
Noise	Heart Frequency	Presence

The main specialist knowledge involved in this experiment is provided by Mion et al. [11], who states that while a person is eating or walking a natural increase in his blood pressure occurs in the same way the environmental temperature influences the physiological patient data.

From the scenario provided the goal of the Dempster Shafer experiment was to verity the type of uncertainty Θ associated given the status of motion sensor as "Active" and the status of blood pressure sensor as "High". For this purpose, it was considered the domain of classification of uncertainties=Θ, as outlined below:

$$\Theta = \{statistical, scenario, recognized\}$$

Given this scenario it was assumed that there was a confidence of 0.6 on the evidence that indicated the type of uncertainty would be the "Statistics" :

So, has the assignment of masses:

$$M_1(\{Statistic\}) = 0.6 \text{ and } M_1(\{\Theta\}) = 0.4$$

From this attribution to Θ =0.4 none value was associated to its subsets even it included {statistic} {scenario} {recognized}.

New evidences: sensor of presence is "inactive" and sensor of noise is "inactive".

Face of new evidences a new mass is provided as M2({statistic})=0.4. Thus the belief mass to statistic uncertainty are:

$M_1(\{\text{statistic}\}) = 0.6$ e $M_1(\{\Theta\})=0.4$

$M_2(\{\text{statistic}\}) = 0.4$ e $M_2(\{\Theta\})=0.6$

Intersections and resulting sets

From the Dempster-Shafer rule of combination the table 4 was obtained.

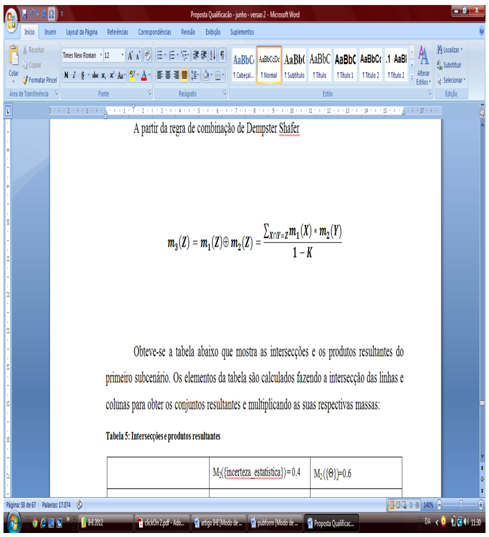

Figure 4: Dempster-Shafer rule of combination.

Table 3 shows the intersections and resulting sets. The table elements were calculated through the lines and columns which results the sets and multiply its respective mass.

Table 3: Intersections and resulting sets

	$M_2(\{st\}) = 0.4$	$M_2(\{\Theta\})=0.6$
$M_1(\{st\}) = 0.6$	$\{st\} = 0.2$	$\{st\} = 0.3$
$M_1(\{\Theta\})=0.4$	$\{st\} = 0.1$	$\Theta = 0.2$

According to Dempster rule, the resulting sets must be added:

m3({statistic}) = m1 $\oplus$ m2 ({statistic })
= 0.24 + 0.16 + 0.36 = 0.76

m3({Θ}) = m1 $\oplus$ m2 ({Θ}) = 0.24

Therefore:

- m_3 ({statistic}) represents belief in combined evidence of statistic.
- m_3 ({Θ}) it implies in additional information, as it includes { statistic}, it is plausible that contributes in believing statistic hypothesis.

Therefore, its mass is 0.24 which can be added to belief of 0.76 on set {statistic} to produce maximum belief in statistic uncertainty.

Thus, a belief interval in the statistic evidence between 0.76 and 1.0, represented by [0.76 e 1.0]. In other words, lower limit – Belief – is 0.76 and upper limit – Plausibility - is 1.0.

Thereby, the belief functions are:

- Bel1 $\oplus$ Bel2 ({statistic}) = m1 $\oplus$ m2 ({statistic}) = 0.76
- Bel1 $\oplus$ Bel2 (Θ) = m1 $\oplus$ m2 (Θ) + m1 $\oplus$ m2 ({statistic}) = 0.24 + 0.76 = 1.

About the confidence intervals (CI) we have that: CI (S) = [Bel (S), Pls (S)]

Where:

- Bel (S) represents the degree to which the evidence supports the hypothesis S, it provides a lower limit of belief.
- Bel (S') represents a degree with the hypothesis S is refuted.
- Pls (S) = 1 – Bel (S') represents total confidence not attributed to S', it provides an upper limit of confidence to S.
- Pls (S) – Bel (S) express the degree of uncertainty related to S.

If S = {statistic}, S'= {scenario, recognized}, so:

- Bel ({scenario} {recognized}) = Bel1$\oplus$Bel2 ({scenario} { recognized}) = 0,

Because it is not focal elements, this is, no mass was not attributed to S'.

Therefore:

Pls ({statistic}) = 1 – 0 = 1, and CI ({statistic}) = [0.76, 1.0].

New Evidences: Heart Frequency sensor is "Normal" and sensor of temperature is "Normal" which indicates a conflicting evidence of 0.96 that uncertainty is not statistic type. In other words: $_3$ ({scenario}) = 0.96 e m_3 ({Θ}) = 0.04 (Table 4).

Table 4: New evidences

	$m_1 \oplus m_2$ ({st}) = 0.7	$m_1 \oplus m_2(\{\Theta\}) = 0.2$
$M_3(\{scen\})=0.9$	{ $\varnothing$ } =0.7	{scen} =0.2
$M_3(\{\Theta\})=0.04$	{st} =0.03	Θ =0.01

The empty set $\varnothing$ occurs because {statistic} and {scenario} do not have any common element.

The K factor is the sum of empty set which results from the intersection, this is, K = 0.73.

So, 1 – K = 1 – 0.73 = 0.27

Applying a function of combination in each resulting sets results in:

- $m_1 \oplus m_2 \oplus m_3$ ({scenario}) = 0.23 / 0.27= 0.852

- $m_1 \oplus m_2 \oplus m_3$ ({statistic}) = 0.03 / 0.27= 0.111

- $m_1 \oplus m_2 \oplus m_3$ (Θ) = 0,001 / 0.27= 0.004

The total confidence in the set {statistic} is now:

Bel ({statistic}) = m1 $\oplus$ m2 $\oplus$ m3 ({statistic}) = 0.111; and Bel ({scenario}) = Bel ({scenario}) = m1 $\oplus$ m2 $\oplus$ m3 ({scenario}) =0.852.

Pls ({statistic}) = 1 - Bel ({scenario}) = 1 – 0.852 = 0.148. So CI ({statistic}) = [0.111; 0.148].

The hypothesis (Bel) and the potential confidence (Pls) to {statistic} were reduced because of the evidence {scenario}.

Thus, with new evidences from the CI ({statistic}) [0.76 and 1.0] to CI ({statistic}) = [0.111 and 0.148], which indicates there is evidence against the hypothesis.

5.1.2 Comments about the Experiment

Based on this experiment was possible to conclude that the default statements in Medicine need to be considered in the evaluation on data obtained from sensors once it can be used as a reference source to be compared with the new results.

It means that any results obtained from the analysis of the uncertainties inherent to the environment monitored, it is important to consider the importance of expert knowledge that must be analyzed together with the results achieved after experiment. Moreover, only doctor can provide diagnosis and directions about the treatment to the patient.

Applying Dempster-Shafer theory was possible to analyze the behavior of a hypothesis given a confidence degree in front of the inclusion of new evidences.

6 Final Considerations

This paper presented the results of an experiment to treat uncertainties information in human health monitoring system. These outcomes are relevant once it provides directions about aspects to consider into the next step in the research ongoing which involves representing uncertain contextual information in the monitoring diabetic and hypertensive patients.

This paper presents important conclusions about the use of a mathematical theory such as Dempster Shafer's Theory of Evidence and the Certainty Factors Model as the basis for the design of a process for the analysis of uncertain contextual information present in the monitoring of human health through of sensors - PRANINC process.

The medical scenario is permeated with uncertainties, and these can be observed by different theories that analyze their behaviors. In the experiments presented in this work, the PRANINC process was applied with the purpose of initially analyzing the influence that the context can have on the results obtained in a monitoring.

In the analysis of the influence of the context on the results achieved, two types of experiments were performed, one that analyzed only the physiological data made available through the platform Physionet.org and another experiment that through data of ambient temperature and human movement, captured using the Iris sensor, model xm2110, Crossbow.

The results obtained by the first and second experiments made it possible to confirm the statements made at the beginning of the research, such as the influence of the context on the results of the monitoring and the contextual information uncertain about the results obtained in these monitoring.

Another goal of PRANINC was to observe the influence of uncertain information on the outcome of the monitored data. In order to do so, we sought to analyze the difference between the data obtained with and without the uncertainty values. This analysis occurred with the inclusion of the calculation of the level of precision adopted by possible sensors used in this type of experiment.

From the calculations of uncertainties associated to the sensors used in the monitoring, performed in the third and fourth experiments, it was possible to reach the main objective of the work, which was to verify the influence of uncertain contextual information on the data captured by sensors. This finding was possible due to the precision levels of each sensor, which were considered in these last experiments.

The process of analysis of contextual uncertainties presented in this paper can be performed on other data, such as values that can be used as sources of contextual uncertainties in sensors, in communication technology and in the interaction between behavioral and environmental variables on the physiological variable.

It is recognized the need for continuity of this work, which includes the in loco realization of these experiments, in closed and open environment (the residence of the monitored), employing specific technologies for the sensors and for the transmission.

In the medical field an important verification could be the influence of the contextual variables - behavior and environment - on the health of the patient. It is understood that the quantification of this type of influence makes it possible to perform more precise measurements, even in scenarios in which the sensor technology is employed in an invasive manner.

Because this research of a multidisciplinary nature on a recent area of application is understood that any advance, in the use of the technology of sensors in the monitoring of the human health, depends on the guarantee that one has on the results achieved and, investigations like this reveal the necessity of integration between the areas involved, so that the necessary care with human health prevails. Finally, comparing the objectives initially outlined, it is possible to affirm that these were achieved and that the research questions were also satisfactorily answered.

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References

1. NG, H. S. S.; M. L.; Tan, C. M.; Wong, C. C. Wireless Technologies for telemedicine. BT Technology Journal. Vol. 24. Nro.2. Apr. 2006.

2. Nasser, N. Chen, Y. Anytime and Anywhere Monitoring for the Elderly. IEEE 6th International Conference on Wireless and Mobile Computing, Networking and Communications. 2010.

3. Clear, A. K.; Dobson, S.; Nixo, P. An approach to dealing with uncertainty in context-aware pervasive systems. In *Proc. of the UK/IE IEEE SMC Cybernetic Systems Conference*, 2007

4. Padovitz, A., Loke, S.W., and Zaslavsky, A. On Uncertainty in Context-Aware Computing: Appealing to High-level and same-level context for low-level context Verification. In S K Mostefaoui et. al. (eds), Proceedings of the 1st International Workshop on Ubiquitous Computing 2004, Porto , Portugal.

5. Troung, B. N; Lee, Y.; Lee, S. Modeling uncertainty in context-aware computing. Computer and Information Science, 2005. Fourth Annual ACIS International Conference on , vol., no., pp. 676 - 681, 2005b. doi: 10.1109/ICIS.2005.89.

6. Henricksen, K.; Indulska, J.; Modelling and using imperfect context information. Proc. of the Second IEEE Annual Conference on, vol., no., pp. 33-37, 14-17 March 2004 .

7. Jung J., Ha K., and Lee J., Kim Y. and Kim D."Wireless body area network in a ubiquitous healthcare system for physiological signal monitoring and health consulting", International Journal of Signal Processing and Pattern Recognition, Vol.1, pp. 47-54, 2008

8. MilenkoviĆ, A., Otto,Emil Jovanov. Wireless sensor networks for personal health monitoring: Issues and an implementation Computer Communications. Special issue: Wireless Sensor Networks: Performance, Reliability, Security, and Beyond, Vol. 29 (2006), pp. 2521-2533.

9. Ren, Hongliang; Meng, Max Q.-H.; Chen, Xijun. Physiological Information Acquisition through Wireless Biomedical Sensor Networks. Proc. of the 2005 IEEE International Conference on Information Acquisition. June 27 - July 3, 2005, Hong Kong and Macau, China.

10. Walker, W. E. Defining Uncertainty. A conceptual basis for uncertainty management in model-based decision support. Integrated Assessment. 2003. Vol. 4. No. 1, PP. 5-17.Mion Jr D. M; Nobre, F.; Oigman W. MAPA – MonitorizaÃ§Ã£o Ambulatorial da PressÃ£o Arterial. 4Âª EdiÃ§Ã£o. Ed. Atheneu 2007.

11. Bettini, Claudio; Brdiczka, Oliver; Henricksen, Karen; Indulska, Jadwiga; Nicklas, Daniela; Ranganathan, Anand; Riboni, Daniele. (2010). A survey of context modeling and reasoning techniques. Pervasive and Mobile Computing. 6. 161-180. 10.1016/j.pmcj.2009.06.002.

12. Dempster AP, Yager RR, Liu L. The Classic Works on the Dempster–Shafer Theory of Belief Functions. Springer; 2008.

13. Naqvi, S. R., N. Z. Azeemi, A. Hameed, R. Baddar, and T. Rasool Improving Accuracy of Non-Invasive Glucose. Monitoring Through Non-local Data Denoising. Proceedings of the 2008 IEEE, CIBEC'08.

14. Moser, M.D. Chapter 12. High Blood Pressure. Available at: http://www.med.yale.edu/library/heartbk/12.pdf. Access in 2012.

15. Thebas, Vantuil Manoel. Caracteristicas dos Sensores. Instituto Federal do Espirito Santo. Serra, 2009.

16. Barua, 2011. Barua, M.; Alam, M.S.; Xiaohui Liang; Xuemin Shen; Secure and quality of service assurance scheduling scheme for WBAN with application to eHealth . In Wireless Communications and Networking Conference (WCNC), 2011 IEEE.