An innovative system that runs on a PDA for a continuous monitoring of people *

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Abstract

Continuous pervasive monitoring has the potential to improve the quality of life of many persons (for example those who suffer from heart arrhythmias or elderly people who suffer from chronic diseases). We show the three main steps related to the monitoring process and supported by our system. First, how data are ***captured*** *by sensors which send those data using wireless communications to a PDA (Personal Digital Assistant). Second, how data are* ***analyzed****, locally on the PDA, using techniques proposed in the areas of the Semantic Web and Machine Learning. Finally, how data stored at the PDA can be* ***queried*** *remotely using web services. Those three steps are illustrated in two different scenarios that the system can deal with: tele-assistance and monitoring of arrhythmias. Moreover, through the paper we highlight the main advantages provided by the system:* ***active*** *monitoring which consists in reacting to anomalous situations without direct intervention of the user;* ***universal assistance****, i.e.* irrespective of time or place *through the use of wireless communications and PDAs;* ***vital signs monitoring*** *which consists in using sensors that capture the value of those vital signs, and subsequently feed them to a decision support system that analyses them and generates an alarm if necessary; and* ***remote monitoring*** *which allows authorized personal to consult data on monitored patients, using the Internet. Finally we present some performance results which demonstrate the feasibility of the system.*

1 Introduction.

The combination of new advances in sensor technology, PDAs and wireless communications favors the development of a new type of monitoring systems that can provide patients with assistance anywhere and at any time. Of particular interest are the monitoring systems designed for people who suffer from heart arrhythmias and/or from chronic diseases. In this paper we present a monitoring system that has two main components: a user PDA and the Control Center (see Figure 1). Each monitored person carries a PDA along with multiple, single or no wireless sensors. The sensors sample physiological data from a person and send them to the PDA.

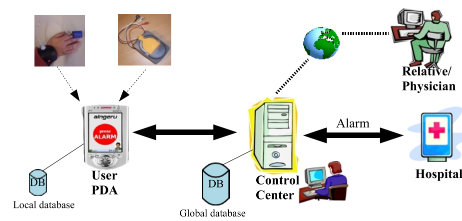

Figure 1. Main components

The main goal of the PDA is twofold; firstly, to monitor the user, and secondly, when required, to enable communication between the person and the Control Center responsible for monitoring her/him. Contact with the Control Center can be made manually or automatically. For example, in the manual scenario, if the user feels unwell, the user presses a panic button on the PDA interface and an alarm is activated at the Control Center. In the other scenario, the alarm is directly activated at the Control Center in response to anomalous situations detected in the user's PDA, after analysis of data sent wirelessly by the sensors. Since the sensors are body-worn and a PDA is a wearable device, *portability* is a key issue for our system. Moreover, another key issue in our approach (and, as far as we know, not yet supported by related works) is *locality* which consists in detecting anomalous situations using the PDA. Locality permits on the one hand, low latency which is important because some medical emergencies need to be detected quickly and, on the other hand, optimizations of wireless communications. The other component, the Control Center is in charge of monitoring people. Its main task is to react in response to user's alarms ensuring that appropriate action is taken and to manage the

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web services which are offered to relatives and physicians.

In the remainder of this paper, we show in sections 2 and 3 two different scenarios in which the system can be used: tele-assistance and monitoring of heart arrhythmias. Next in section 4 we present some performance results of the system in the previously mentioned scenarios and we finish with our conclusions.

2 Scenario 1: Tele-assistance

The goal of the system in this scenario is to provide a tele-assistance service that overcomes the main constraints associated with currently available tele-assistance services using the most recent advances in the fields of Semantic Web, mobile computing and networking [1].

Currently, tele-assistance services use an electronic device plugged into the traditional Public Switched Telephone Network (PSTN) and a small button that the user carries. When the user feels ill, he/she pushes the button and the terminal calls the Control Center where an operator answers. That operator asks the user for detailed information and usually, he/she forwards the call to a physician, to a Social Service, etc.

Considering those existing tele-assistance services, there are two main aspects that our system improves on. The first one is related to the reduced field of action. As the electronic device has to be plugged to the PSTN in order to maintain a voice conversation with operators using that device, the coverage area is, at most, the user's home. The other aspect is that the user has to initiate the notification; if he/she cannot push the button because he/she is not in condition to do so, the system loses its utility and the user finds himself at risk. The first issue, that is, the reduced coverage, is overcomed by our system using cellular communications. Technologies such as GSM, GPRS and UMTS give us the possibility to keep the monitored user under surveillance outside his/her home (ubiquity). Referring the second issue, active monitoring, our system incorporates biomedical sensors that send information about vital signs to the PDA. As we will show later, the PDA uses those data to feed a decision support system, which in turn evaluates the current state of the user. If the user is at risk, the PDA itself notifies the Control Center about the situation and sends data about the user in order to help him to take the proper actions (pro-activity).

Concerning the related works, we classify tele-assistance systems in two groups. In the first group, we include those existing systems which provide limited coverage, already mentioned. In the second group we include more advanced systems. Some of those focus their efforts on offering an active assistance (e.g. TeleCare [2]) while others use PDAs and take advantage of wireless communications to provide better assistance (e.g. doc@HOME [3] and TeleMediCare [4]). In the majority of the later systems, PDAs are used only as intermediary elements and their goal is merely reduced to transmit data from sensors to a central computer where data analysis is made. In our system local analysis is made at the PDA (locality). Other related works use application-specific devices to provide assistance (e.g. Sensatex [5] and SILC [6]).

Let us present briefly here the three main steps related to the data management in this scenario.

Data capture. There are several sensors that capture different kind of data: for example, physiological data (heart rate, oxygen percentage in blood, etc.) or location data, and send them to the PDA. In addition, located on the users' PDA are different kinds of sensor agents (each one specialized on a kind of sensor) that are responsible for interpreting raw data sent by the sensors and making them available to other components of the system. For example, the agent associated to a sensor that captures oxygen percentage in blood data, receives, processes that information and send it to the decision support component.

Another example of sensor agent is the GPS Agent, which knows how to decode NMEA[1] streams and provide information about user's position, speed, heading, altitude, etc. This information is very useful to locate users.

Furthermore, the data sent by sensors are stored in a local database in the PDA in order to answer queries formulated through web services; however, within a time granularity those data are dumped in the global database stored at the Control Center.

Data Analysis. The key element of the decision support component that is in charge of managing the received data is an ontology, called *MedOnt*. In the *MedOnt* ontology where different user's symptoms are described with respect to his/her vital signs (monitored by several sensors), the usual illnesses that people suffers from, are also described. Moreover, this ontology can be customized for every user. The selected mechanism to reason with the ontology is the RACER [2] system that, with the collaboration of its authors, we have managed to run on the PDA [7]. The reasoning process takes less than one second in average. In this step any potential anomalous situations are detected.

Data query. Authorized external persons, for example relatives and physicians, related to the monitored person can consult the data which are stored on the PDA or on a server situated at the Control Center via the Internet. An example of developed web services that use SOAP in their implementation is: the *Vital Signs*. This web service provides information about users' vital signs in real-time. This feature is very important as it gives physicians the most up to date and accurate information about users.

[1] NMEA is the standard protocol that GPS devices use to inform about location, altitude, speed, heading, information about satellites, etc.

[2] RACER. www.fh-wedel.de/ mo/racer/

3 Scenario 2: On-line monitoring of heart arrhythmias

The goal of the system in this scenario is to provide an ECG monitoring service that performs local real-time ECG signal classification by detecting possible rhythm irregularities "in situ". Although existing holters [8] present the advantage of allowing patients to live a normal life, they also present a serious drawback: if a person suffers from a serious rhythm irregularity, the holters only record it, i.e. they do not react to it. New commercial monitoring systems and research proposals that react to rhythm irregularities are appearing but they present different restrictions. We classify those systems into two groups: 1) systems that *perform remote real-time ECG classification*. These systems capture an ECG signal and send it to a monitoring center where an analysis is performed (e.g. Vitaphone [9] and MobiHealt [10]). In this kind of systems there is a loss of efficiency because: i) normal and abnormal ECG signals are sent; ii) the network instability can lead to a loss of ECG signals with the corresponding risk of not detecting some anomalies. 2) Systems that *perform local real-time ECG classification on PCs*. These systems make use of home PCs in order to perform local real time classification. Wireless communications between sensors and those PCs confine users to their homes by reducing their mobility range (e.g. @Home [11] and PhMon [12]). Considering the current situation, we advocate for a system that *performs a local real-time ECG classification* but on a mobile device like a PDA carried by the user because in that way a real anywhere and at any time assistance can be provided. Moreover, we advocate for the use of a PDA mainly because the developed software can then run on different platforms and can also be customized for each person; these advantages are not provided by proprietary systems. Let us present briefly the three main steps related to the data management in this scenario.

Data capture. Specialized sensors capture the ECG signals and send them to PDAs. In the PDA one specialized agent interprets the row data sent by the ECG sensor and makes those ECG data available to other components of the system as fixed-size sequence samples packages (each length package corresponding to 4 seconds [3].)

Data Analysis. The ECG signal analysis consist in a beat and rhythm identification and classification processes originating from sample packages. This process is performed in several steps (see Figure 2):

1) First, the sequence of samples is taken as an input, then a set of important signal events is detected (where an event is constituted by: the P wave, the QRS complex, the T wave and the morphology of the T wave). 2) Second, every independent beat is detected by our automaton (generally a beat is formed by the P, QRS and T waves, but sometimes some of them do not appear, specially if there are anomalies). 3) Every beat is classified and its type is then obtained (our system deals with 14 different types of beats). 4) Every sequence of four beats is classified and the rhythm type is obtained (our system considers 13 different types of rhythms). In the next paragraph we explain how the beat and rhythm classifiers were built.

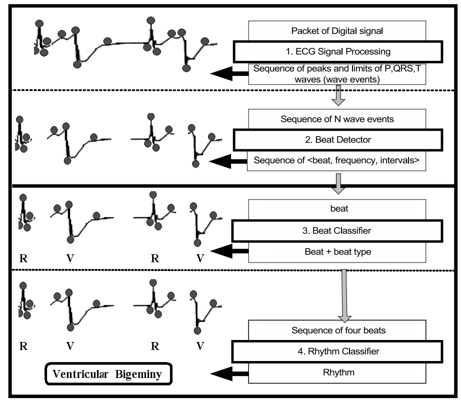

Figure 2. System Modules

Beat Classifier. In order to develop a heart beat classifier that provided competitive results, we built and evaluated a set of experiments, using some available tools (Weka [13] and AnswerTree [13]) in the Machine Learning area, which apply some methods (typically used to classify beats and rhythms [16]) over a known ECG data source (the MIT-BIH Arrhythmia Database[14]). The data were pre-processed by using the ECGPUWAVE tool [15] and our Beat Detector (automaton). Once we got the data in the right format, where one row represented one beat, the data set was divided into two random groups: 66% of the data for training and 33% for validation. The training data and the validation data were the input data for the tool which produced the beat classification model and the validation model respectively.

The reason for running the experiments was to obtain the most accurate beat classifier. We tried sixteen experiments (see [17] for more details) and we selected the j48.part method that implements the C4.5 algorithm, which obtained the best result: the 96.128% accuracy (i.e. the beats identified as x by the physicians and classified as x by the decision tree). The set of rules used to classify the beats was inferred and it constituted the set of *if-then* rules that were codified in a programming language. Once the most accurate beat classifier was obtained [4], it was necessary to determine an

[3]After doing several experiments with an ECG sensor (in this version we use the sensor called ActiveECG) and a PDA where a local analysis of ECG signals was made we concluded that 4 seconds was the optimal processing cycle duration

[4]The beat classifier considers: F (Fusion of ventricular and normal beat); N (Normal beat); L (Left bundle branch block beat); E (Ventricular escape beat); R (Right bundle branch block beat); j (Nodal junctional

accurate rhythm classifier.

Rhythm Classifier. Descriptions of arrhythmias can be found in the specialized cardiologic literature. Although they are not very explicit, it is possible to represent them using a computer language. However, in order to select the most appropriate set of rules, we used the following approach: 1) we rewrote the rules corresponding to the arrhythmia descriptions found in the literature; 2) in addition, we obtained the arrhythmia rules by using decision trees based techniques; 3) at last, we used the rules combination that provided competitive results [5].

Once we got an accurate rhythm classifier we classified different types of rhythms, according to their level of risk: 1) rhythms of type 1 (arrhythmias VFL and IVR) require medical assistance in less than 3 minutes; 2) rhythms of type 2 (arrhythmia VT) require medical assistance in less than one hour; 3) rhythms of type 3 (arrhythmias T and NOD) are considered predictive arrhythmias, that is, arrhythmias that occur before a heart attack; 4) rhythms of type 4 are the remaining kinds of arrhythmias; 5) and finally, rhythms of type 5 are the normal ones. Rhythms of type 1, 2 and 3 are considered high-risk arrhythmias. Our ECG classifier provides a very good accuracy when classifying rhythms: all 1-high-risk types were correctly classified; 97.95% of 2-high-risk types were correctly classified, and 95% of 3-high-risk types were correctly classified. On the other hand, the accuracy percentage for normal sinus rhythms was 67.35%. The rhythm detection average delay is 8.62 +/- 1.74 seconds.

Data query. In the above mentioned scenario, web services offered to physicians were implemented taking into account the querying functionalities provided nowadays by monitoring systems. One of those web services is (see more details in [19]): the *Arrhythmia Identification service.* It shows the different rhythm types that the user suffers during a monitoring period and the number of episodes involved for each rhythm with its corresponding average duration, minimum and maximum frequency.

4 Performance issues

In this section we present some performance results that highlight the feasibility of the system. The framework used for the test was the following: for the Control Center, an AMD Athlon XP 2600+ (2 GHz) computer with 1 GB of RAM and two 200 GB hard disks; for the PDA, an iPaq 6550 with a PXA 255 400 MHz processor, 128 MB SDRAM and 48 MB Flash memory. Tests have been performed without battery saving techniques (display lit up and the processor running at full speed). Battery at full capacity holds 1350 mAh. We used Java as a programming language and JADE as agent platform which is also written in Java. For the communication between the sensor and the PDA we used the Bluetooth 1.1 wireless connection and for the communication between the PDA and Control Center, we used a GPRS connection [6].

Regarding system size, we have divided it in three main components: (i) execution environment, (ii) external required software and (iii) our application. The execution environment includes the Java Runtime Environment (18,7 MB) and the JADE agent platform (3,3 MB), both required to run our code. The main external required software is RACER (9,6 MB), the reasoning engine needed to discover anomalous situations. Since RACER is written in LISP, a LISP interpreter is needed (CLISP: 2,6 MB). In addition, to implement the text-to-speech functionality we used Flite (5,9 MB). And finally, our agents, represented by Java classes and other Java libraries (keeping apart those related to JADE), add 307 KB to the total amount of required space. As the required memory is greater than the available in the PDA, an external SD card is used to store the system.

Another storage related issue is the data produced as the program execution. Currently, the battery runs out before the storage is full. As a result, we focus on battery autonomy in the rest of this paper.

We present three different situations: 1) The person only carries a PDA; 2) The monitored person carries a PDA and a pulse-oxymeter wireless sensor or an ECG sensor; 3) The monitored person carries a PDA, the pulse-oxymeter wireless sensor and the ECG sensor.

Case 1: PDA with no sensors. The goal of this experiment is to measure the autonomy of the PDA battery in relation with the number of *manual* alarms sent [7] and the external accesses through Web services [8]. The autonomy of the battery without notifications and external accesses is 6h 45m. In Figure 3 we can see that a Web service invocation and an alarm notification by GPRS access reduces battery autonomy by 4 seconds; 10 alarms and 30 Web service invocations per day reduces battery autonomy by 1 minute (battery life is 6h 44m).

Case 2: Pulse oxymeter sensor. The goal of this experiment is to measure the autonomy of the PDA battery in relation with the number of *automatic* alarms and the external consults through Web services. In this case we present

escape beat); f (Fusion of paced and normal beat); ! (Ventricular flutter wave); A (Atrial premature beat); J (Nodal premature beat); a (Aberrated atrial premature beat); V (premature ventricular contraction); / (Paced beat); and S (Supraventricular premature beat)

[5] Our rhythm classifier considers: N (Normal sinus rhythm); VFL (Ventricular flutter); VT (Ventricular tachycardia); NOD (Nodal A-V junctional rhythm); B (Ventricular bigeminy); P (Paced rhythm); T (Ventricular trigeminy); IVR (Idioventricular rhythm); AFL (Atrial flutter); AFIB (Atrial fibrillation) and SVTA (Supraventricular tachyarrhythmia)

[6] Bluetooth can transmit data up to a rate of 1 Mbps and GPRS up to a rate of 56 kbps

[7] Each alarm fired means sending about 200 bytes

[8] Each Web Service has different communication weights, from 100 bytes to more than 1 kilobyte. The estimated mean size among all messages is 500 bytes

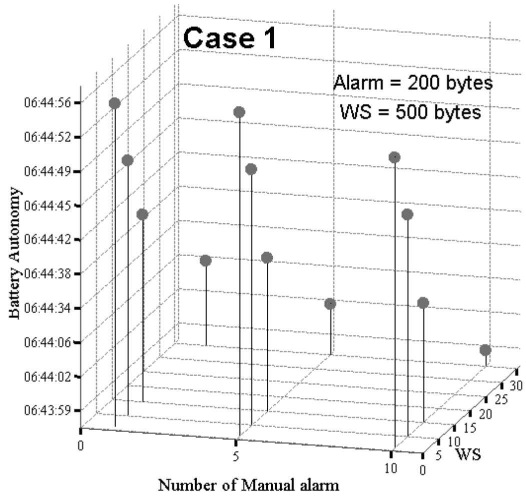

Figure 3. Case 1: PDA with no sensors.

two different situations. In the first situation the user wears a pulse oxymeter sensor that uses Bluetooth communication to send captured data to a PDA (the PDA consults sensor data every ten seconds. Between consults, Bluetooth is idle). This case is shown in Figure 4. It is worth noticing that considering a similar situation, the same number of alarms (but in this case automatic) and Web services invocations by GPRS access, reduces the battery autonomy by 1h 10m (battery life is 5h 35m).

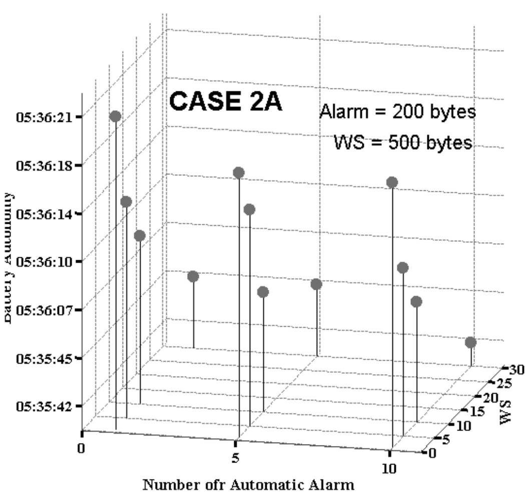

Figure 4. Case 2a: pulse oxymeter sensor.

In the second situation (see Figure 5) the user wears an ECG sensor that requires continuous data capture, so Bluetooth is working all the time. Moreover the volume of transmitted data is greater in the case of alarms (2400 bytes vs 200 bytes) as well as in the Web services case (720 bytes vs 500 bytes). As a result of this (more use of Bluetooth and GPRS) 10 alarms and 30 web service invocations reduce battery autonomy by 2h 07m (battery life is 4h 38m).

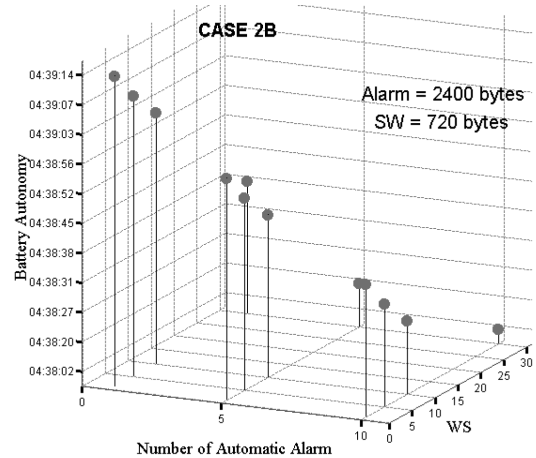

Figure 5. Case 2b: ECG sensor.

Case 3: Pulse oxymeter plus ECG. In this case, the user suffers from a severe heart pathology and wears a pulse-oxymeter and ECG sensors. Figure 6 shows that an increase in the number of notified alarms (100) and external consults (30) implies a high battery consumption and, consequently, reduces battery autonomy by 2h 13m (battery life is 4h 32m).

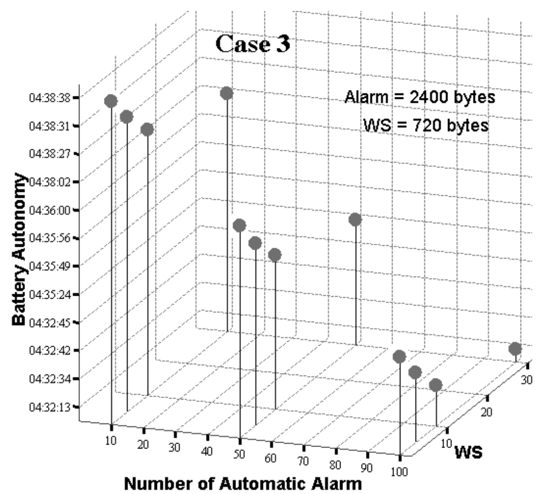

Figure 6. Case 3: pulse oxymeter plus ECG.

Comparing the three cases we can observe that the factor that has a bigger influence on the battery autonomy is the use of Bluetooth. It is worth noticing that from case 1 to case 2a the battery autonomy is reduced by 1h 08m because Bluetooth is used every 10 seconds in case 2a. Moreover from case 2a to case 2b the increase in the amount of data transmitted by GPRS and the permanent use of Bluetooth all the time reduces the autonomy by 57 minutes. Finally, in Figure 6 we can observe that increasing the data transmitted using GPRS (with respect to case 2b) only reduces battery autonomy by 6 minutes. Therefore, the use of Bluetooth is the relevant factor when considering battery autonomy.

Finally, managing cardiologic data in a mobile device like a PDA brings several difficulties due to its limited storage and processing capacity, specially when we know that the ECG sensors data-generating capacity is very high (from 180 to 360 samples per second that means from 648000 to more than one million samples per hour). In this case, the use of compressed files seems more appropriate if we want to reduce the data amount to storage and to send. Nevertheless, this kind of approach is not the most suitable to answer high level queries formulated over stored data, that is, queries about ECG analysis. Therefore, the solution we chose was, on the one hand, to store the ECG signals as compressed files using for that purpose a combination of two algorithms, DPCM (Differential Pulse Code Modulation) and bz2, obtaining an 88% rate of compression. On the other hand, we chose to store the information extracted from the analysis in a local database [18].

5 Conclusion

In this paper, we have presented one system that supports an intelligent, continuous and pervasive monitoring of people. We advocate for the use of a PDA as the core of the system. Thus, we have incorporated an intelligent and efficient monitoring process in a PDA. Therefore, portability and locality are two important features supported by the system. Moreover, performance issues have also been considered when developing the system in order to optimize wireless communications between the PDA and the Control Center, taking into account for that: 1) the amount of data transmitted; 2) the number of situations which must be monitored at the Control Center. Finally, we have shown the behavior of the system when considering one limited resource in a PDA: battery autonomy. The experiments show that pervasivity can be accomplished by the system.

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