A Health Prognosis Wearable System with Learning Capabilities using NNs

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Abstract

The deployment of Wearable Health Monitoring Systems (WHMS) is expected to address several important healthcare-related issues such as increasing healthcare costs, the rising number of the elderly population and treatment of chronic conditions. However, most of the currently developed WHMS simply serve as ambulatory physiological data loggers and transmitters in order to make the recorded bio-signals remotely available for inspection from a supervising physician.

In this paper we describe our efforts towards setting-up a WHMS prototype that is capable of providing individualized embedded decision/diagnosis support for round-the-clock remote health monitoring of people at risk. To realize this goal an ANN-based approach is adopted, whereby a supervised learning period is required in order to embed patient-specific medical knowledge into the system, which will then enable it to make more accurate and "safer" estimations about the user's health condition.

1. Introduction

The fact that the global population is both growing and ageing [1] poses a series of challenges to healthcare providers worldwide. Furthermore, the total number of people suffering from some type of disability (either life-long, or injury related or more commonly related to chronic conditions) will continue to rise [2]. These issues along with the issues of managing and treating several chronic diseases, such as diabetes, congestive heart failure and obstructive pulmonary disease, have created a requirement for new and innovative ways to deliver healthcare to patients. Information and communication technologies are expected to provide the means to realize personalized and citizen-centered healthcare solutions to address the previously stated challenges as well as rising health care costs [3].

Numerous research groups and companies worldwide have focused during the past few years on realizing low-cost wearable health-monitoring systems (WHMS) that can monitor a patient's health status in a ubiquitous and unobtrusive manner [4], [5]. Constant advances in miniaturized sensors, portable devices and microelectronics, advanced algorithms, wireless communication techniques and battery technologies have propelled the development of various promising prototypes. Regardless of the underlying hardware technology, be it textile sensors and smart garments [6], [7] or mote-based [8] and Bluetooth sensor-based [9] body area networks, most of the developed systems provide the basic functions of sensing, recording and transmitting physiological data and that of basic alarm generation in case the monitored parameters exceed predefined value ranges. In these cases the doctor is charged with the burden of going through massive amounts of physiological recordings for each patient, which is obviously impractical and expensive both time-wise and financially.

More advanced systems include: i) the Personal Health Monitor [10], where the authors have employed a mobile phone to gather and analyze real-time ECG data and to acquire user feedback about his/her symptoms in the form of a questionnaire as a self-test for heart attacks and ii) HeartToGo [11], another cell-phone based wearable platform, which is capable of continuously monitoring the ECG, detecting abnormal patterns pertaining to cardiovascular disease and adapting to the individual user's physiological conditions through the use of Artificial Neural Network (ANN) learning schemes.

In the current paper we elaborate on our attempt to develop a WHMS that is based on off-the-shelf components and that is capable of providing multi-parametric monitoring and individualized detection of health risks. The motivation behind our approach is that the monitored physiological parameters, such as blood pressure, heart rate, ECG, respiration rate, oxygen saturation etc, may have significantly varying normal or healthy levels (or morphologies when talking about the

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ECG) amongst individuals. In that direction, we propose a system that first requires a supervised learning period in order to learn the user's "healthy physiological behavior" by using an ANN-based approach and then in normal and autonomous operating mode it is capable of providing individualized user-adopted detection of health abnormalities and risky conditions. However it should be noted that our efforts are not aiming towards a system that will replace the doctor in any way, but towards a healthcare solution that will ensure patient safety round-the-clock via early detection of health hazards and that will thus potentially improve the quality of life of people at risk.

2. The Current "Prognosis" WHMS Prototype

The underlying feature extraction, data fusion and decision making strategy of our system that we call "Prognosis" has been described in [12]. Furthermore the system's operational and design framework has been modeled and simulated in [13]. Based on these previously described principles we seek to set-up a "Prognosis" prototype based on commercially available off-the-shelf components. The components of our current prototype are depicted in Figure 1.

Figure 1. The components of the current "Prognosis" WHMS prototype.

The system is built around the BlackBerry Bold 9000 PDA/smart-phone, which has been chosen due to its powerful processing capabilities (624 MHz processor) and J2ME and multi-threading support. The set of sensors that are currently employed in our system consist of the Bioharness BT chest belt by Zephyr [14], which is capable of measuring 1 lead ECG, heart rate, respiration rate, skin temperature, posture and activity, and a wireless wrist-mounted pulse oximeter with a finger clip sensor from Nonin Medical [15]. Figure 2 shows two screenshots of real-time displayed data on the smart-phone. It is our goal to expand our system by using additional wireless physiological sensors, such as a blood pressure and glucose monitors.

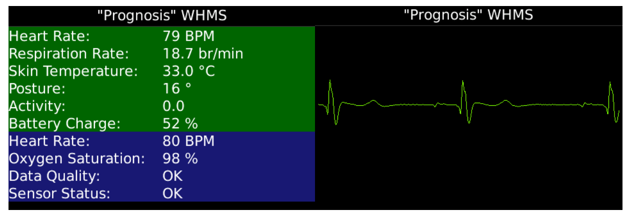

Figure 2. a) Real-time data display, b) Real-time ECG plot

The communication between the cell-phone and the wireless sensors is performed by forming a Bluetooth Personal Area Network (PAN). In this formation the PAN's master (e.g. the BlackBerry smart-phone) assigns dedicated time slots to the peripherals and data are received in a protocol-inherent round-robin manner via Serial Port Profile (SPP), e.g. virtual serial port connections. For every sensor there is a dedicated thread on the phone, which is responsible for i) collecting new data, ii) performing sensor status checks and data validation, iii) performing basic signal processing and feature extraction according to the methods described in [12], iv) displaying and plotting the data and v) handing over the new data to the main thread which will then process the measurements based on the "Prognosis" formal language and will finally derive an estimation of the user's health.

In case that a health risk has been detected or that there is a significant abnormality in the measured bio-signals, the system may choose to ask the user for additional feedback (via a simple questionnaire) or to notify a medical center, a supervising physician or even a close contact by means of the 3G cellular network or a Wi-Fi connection. In our work-in-progress we are trying to integrate verbal interaction between the user and the phone in order for the system to record non-measurable symptoms and a Web-accessible database application for the doctor to be able to have a complete overview of the patient's recent and past medical history.

3. Learning the User's Healthy Physiological Behavior

3.1. The Healthy-History Database concept

As we have already explained, the Prognosis WHMS is capable of continuously measuring, recording and transmitting a wide variety of physiological signals.

However in our system we seek to integrate additional functions instead of just data logging. Namely, the system has to be able to extract higher level of information from the collected data by itself and transmit this information as well to the medical center's database and/or to the supervising physician if required.

To clarify the previous point, consider the following: As described in [12], the physiological data that are measured by the WHMS' sensors may indicate a corresponding healthy or pathological status. For example, regarding the heart rate, a measurement between 60 and 100 beats per second (bpm) is generally considered as normal, while a heart rate less than 60 bpm is considered as a bradycardia and a value greater than 100 as tachycardia (provided that the heart rhythm is regular). However, for a given patient/user a certain tachycardic heart rate value might be quite acceptable and not endangering at all, while for another one the same heart rate measurement may indicate a hazardous or unstable health state. Similar reasoning pertains to the rest of the continuously measured physiological signals. To summarize this point, as it can be seen in Fig.3, we need the system to be able to move from the raw measured data, to basic extracted health information and then by using an individualized "healthy-history" database to create actual medical knowledge about the patient/user. This extracted higher-level knowledge can save time (and in the long run also reduce medical costs) when it comes to making quick decisions and possibly taking emergency actions about a patient and especially when there are several patients to consider or supervise in the same time frame.

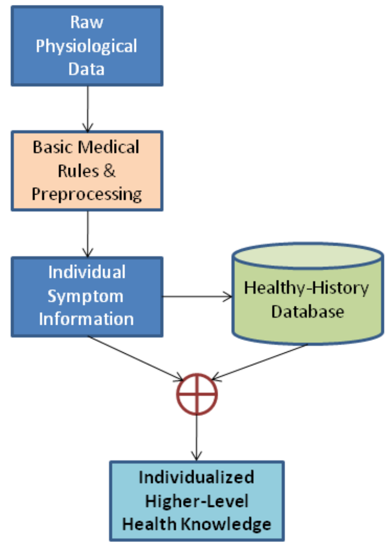

Figure 3. Creating higher-level health knowledge about the user.

3.2. User Health-Knowledge generation using a Neural Network approach

As described in the previous section, we seek to integrate in the Prognosis WHMS the necessary intelligence for it to be able to make patient-specific decisions/estimations regarding the health status of the corresponding patient. In addition to that, when making such decisions, the system must also take into account the context in which the corresponding bio-data were captured.

To further explain this we can consider again the case of a heart rate value being measured over 100 bpm, e.g. tachycardia, for a certain period. Such a heart rate value range may be perfectly normal when the corresponding individual is exercising, which the system can "verify" by checking one or more of the following: if there is or has been immediately before high degree of movement (e.g. by checking the magnitude of the acceleration vector) and/or if the user is showing a decrease in skin temperature (due to perspiration) and increased respiration rate. On the contrary, the same heart rate measurement along with increased blood pressure while the patient is laying on a bed (e.g. the posture value is close to -90 degrees), might have a completely different meaning and might indicate a hazardous health state. A tachycardic heart rate might also still be benign in the previous scenarios, except for example in the case that there is an accompanying ECG abnormality, like an absence of P waves or irregular heart rhythm, or for example in the case that the user is experiencing chest discomfort.

The previous example attempts to point out the level of complexity involved in the task of classifying a user's physiological data as either normal (healthy) or pathological. Ideally, the patient's medical history, his personal attributes (age, height, weight etc), his current context and the rest of the concurrently measured physiological parameters will need to be taken into account. Such a task could be performed by comparing vectors of measured data with the contents of a corresponding database. Although the issue of maintaining a database on a mobile device can be addressed with today's mobile platforms (such as the BlackBerry 9000), there would still be 2 drawbacks in such an effort: Firstly, frequent searching even in a relatively small database can be quite tedious and computationally expensive for a hardware-constrained portable platform and secondly it would be practically impossible to construct a database including all possible

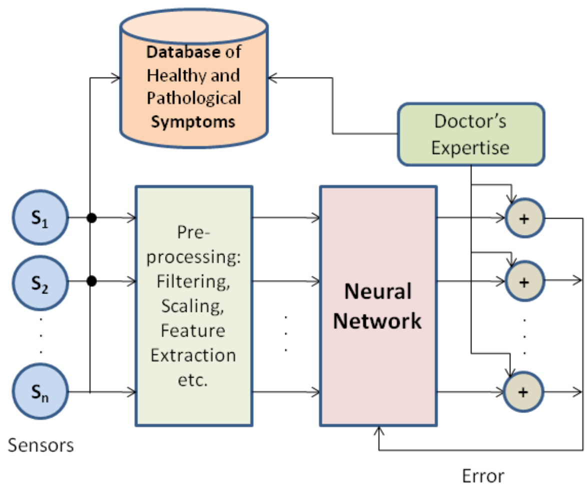

Figure 4. The NN-based healthy history learning scheme.

combinations of data vectors and corresponding patient symptoms.

To address this issue we propose an approach based on an Artificial Neural Network (ANN). Our approach is motivated by the fact that Neural Networks have been proven capable of generalizing successfully to unknown datasets. In order though to embed that type of knowledge into the Neural Network, the NN must first be trained using a supervised learning scheme. As a result, to provide the required labeled examples for the NN training process, cooperation with a supervising doctor is required. The doctor himself will be responsible for labeling physiological data, features and patterns extracted from recorded bio-signals and also corresponding health symptoms as pathological or normal. During that process, standardized and well studied databases (such as the MIT-BIH Arrhythmia ECG database [16]) may be also used in the training process, as proposed in [11] as well.

The proposed approach is summarized in the schematics shown in Figure 4 and 5. Fig.4 illustrates the learning scheme, whereby before feeding the sensors' outputs into the NN, the data are preprocessed appropriately, e.g. filtered, normalized and in the case of the ECG the corresponding features (QRS complex width, R peak's height, wave morphologies etc) are extracted. The doctor's expertise is then utilized to characterize the sensor's outputs as normal or abnormal and corresponding synaptic weight adjustments are then made accordingly. In addition to training the NN, a history of specific health condition profiles are saved in database, which will be used from the Prognosis Formal Language [12] to make appropriate decisions/diagnosis.

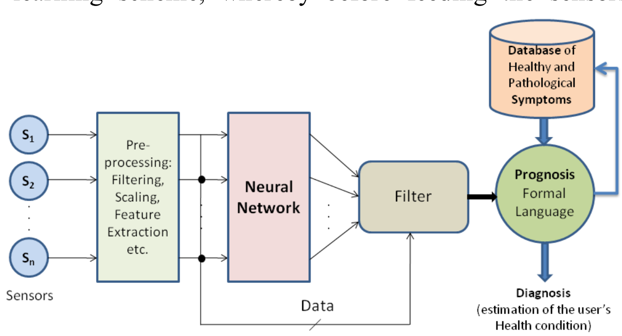

Figure 5. Unsupervised system operation.

Finally Figure 5 shows the unsupervised operation of the whole system. The Neural Network functions as a data filter and will only pass on the detected pathological symptoms to the Prognosis Formal Language, which will then create the corresponding Prognosis word and parse it using the database created in the learning scheme, in order to derive a specific estimation of the user's health condition.

4. Conclusion

In this paper we described our approach towards establishing a novel multi-parametric WHMS prototype, which can adapt to the individual user. This is achieved via an ANN based scheme, whereby the system is first trained to learn the "healthy behavior" of the individual. By embedding that knowledge into the WHMS, the system can make more accurate estimations about the corresponding patient based on the current physiological measurements, on the user's context, on any possible non-measurable symptoms and finally based on his past medical history. Future work includes refining the implemented feature extraction and signal processing capabilities of the system, integrating the verbal interaction with the user and conducting a large set of real-life trial tests with our prototype.

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