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SPN-Model based Simulation of a Wearable Health Monitoring System

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Abstract — **The deployment of Wearable Health Monitoring Systems (WHMS) can potentially enable ubiquitous and continuous monitoring of a patient's physiological parameters. Moreover by incorporating multiple biosensors in such a system a comprehensive estimation of the user's health condition can possibly be derived. In this paper we present a Stochastic Petri Net (SPN) model of a multi-sensor WHMS along with a corresponding simulation framework implemented in Java. The proposed model is built on top of a previously published multi-sensor data fusion strategy, which has been expanded in this work to take into account synchronization issues and temporal dependencies between the measured bio-signals.**

Index Terms — **Stochastic Petri Net, Wearable Systems, Health Monitoring, Biosensors, Simulation, Java**

I. INTRODUCTION

HEALTH monitoring via wearable or portable systems has been widely researched during the past ten years[1],[2]. The main purpose of such systems is to realize out-of-hospital monitoring of the user's most critical physiological parameters in a non-invasive and ubiquitous manner and thus facilitate personalized and/or user-operated health management. It is expected that the deployment of such systems will lead to better understanding and treatment of several chronic conditions and also potentially enable early diagnosis and prevention of various medical incidents or diseases [3].

There have been several approaches towards the realization of wearable health monitoring systems (WHMS). Typically WHMS have been set up around the concept of Body Area Networks (BAN) [4],[5] or they have been based on the implementation of either specialized devices [6] or smart textile garments [7],[8]. The majority of these research efforts have focused on addressing various issues regarding WHMS such as reliable data sensing, power management, wireless transmission and security of collected measurements and unobtrusive system design. As a result most of the WHMS prototypes [9],[10] or products [11] provide the functionality of continuously logging physiological data and possibly also that of alarm generation in case the sensed data are detected to be above or below some fixed threshold value. Moreover in some cases on-system parameter extraction or pattern classification may also be performed [12]. However by incorporating multiple biosensors in a WHMS, advanced embedded decision support can potentially be enabled via multi-parametric analysis. Furthermore equipping a wearable health monitoring system with the capability of performing proper statistical and intelligent processing of multiple collected bio-signals in terms of pre-defined "medical rules" [13], could lead to on-site health incident detection or prevention. In addition to that, the amount of physiological data a supervising physician may thus need to go through (and accordingly the time he would need to spend on a particular patient) can be minimized in that manner, thus reducing also the corresponding medical costs for the patient.

In this paper a Stochastic Petri Net (SPN) model of a multi-sensor WHMS is presented. The described model is designed around a bio-signal data-fusion strategy we have presented in [14], that was based on the Prognosis formal language model according to which extracted symptoms from physiological measurements were represented as context-free language symbols. Finally a corresponding simulation framework implemented in Java is also presented, which resembles the simulator described in [15] although that work was centered around managing the energy consumption in BANs which is not considered here.

II. SPN MODEL

A. SPN in general

Using SPNs as a graphical modeling tool, we are able to provide a detailed and at the same time easy-to-comprehend functional description of the wearable health-monitoring system. Furthermore SPNs enable a hierarchical top-down modeling of the system while capturing the effects of concurrency and synchronization of events that take place in the system.

B. Level 1

Fig.1 presents the first level of the hierarchical SPN model of the WHMS. There is always a token at the place representing the user/patient denoting the fact that the user is constantly "ON", meaning that the human body provides the WHMS with body signals in a continuous fashion. Furthermore the user is able to provide voice feedback to the system to record non-measurable health symptoms.

The WHMS device is capable of directly communicating with the user in terms of an automated HMI dialog system, whenever the system detects a health status of high risk or the user notifies the system about a symptom like for example chest pain that may "require further investigation".

Furthermore, the WHMS provides either regular updates of the user's health condition or upon request from the medical center. Finally the system may "decide" that the user requires immediate medical attention based on the aggregated physiological symptoms and thus may send an alert to the medical center or even request for an ambulance to be dispatched in case the medical center approves that action as well.

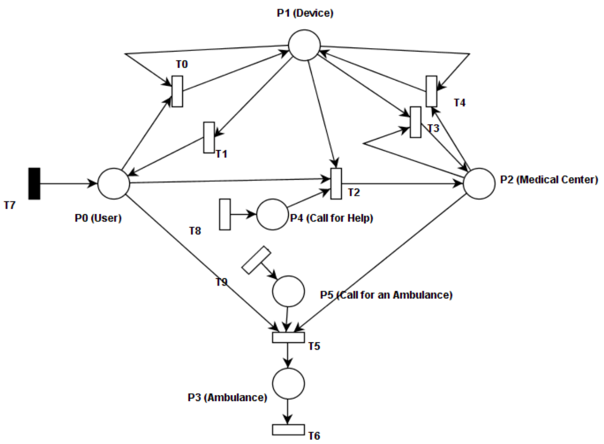


Fig. 1 Level 1 of the SPN model:
User-Device-Medical Center-Ambulance interaction.

C. Level 2

In the following we describe the second level of the hierarchical SPN model of the WMHS, which is depicted in Fig.2. In this level, the functionality of the wearable device is simulated in a scenario in which the following sensors are available: ECG, SpO2, thermometer, respiration sensor, blood pressure monitor, GPS and a voice recognition/synthesizer system to capture direct patient feedback.

The central node of the WHMS (microcontroller board, PDA, smart-phone etc) continuously gathers physiological parameters from the wearable sensors in a round-robin fashion to create input vectors for the Prognosis language. For example the pulse oximeter sends an estimation of the oxygen saturation and the heart rate of the user every 1 second. Similarly, the central node polls the thermometer and the respiration rate sensor every second to acquire a measurement.

However since available blood pressure monitors are cuff-based, the central node needs to request from the BP device to initiate a measurement and it should also be able to collect it when it is made available. Regarding the ECG collection, because the electrocardiogram is sampled at a high rate, e.g. 250 Hz or even more, it is more reasonable to transmit packetized samples of the ECG every sec. That approach allows also for easier synchronization with the collection of the rest of the bio-signals.

Finally the voice recognizer module has the ability to deliver information about non-measurable symptoms to the central node, in case the user has recorded such a phenomenon. As in the case of the ECG sensor, to favor the round-robin-based synchronized collection of signals, the central node polls the voice recognizer for any possible detected symptoms. This polling scheme can be thought of either as sequential polling of digital and analog ports on a microcontroller board or as the beaconing mechanism available in Zigbee which allocates specific time intervals to distributed sensor nodes or finally as a Bluetooth piconet, where master and slaves take turns communicating in an inherent round-robin scheme.

D. Level 3

In the final level of the top-down hierarchical SPN model depicted in Fig.3 we describe the way the central node operates. We provide an insight as to how the collected physiological (and voice) data are used to create input vectors, e.g. words of symptoms for the Prognosis language, which in turn looks up the created word to make a decision/estimation about the user's health condition.

There are three basic types/categories of data that the WHMS can collect: a) "scalar" data, like the temperature value, the systolic or diastolic blood pressure etc, which according to their value give rise to specific symptoms or not, b) "morphology" specific data, which in the current scenario are comprised of the ECG signal, which need to be analyzed to possibly detect patterns of high risk and c) voice data which may correspond to non-measurable symptoms that the user has chosen to communicate to the device.

When either a new type a) or type b) measurement is collected, it is buffered in the system in a dedicated ring buffer for each bio-signal. Then that data are checked for validity, e.g. a decision on whether the data are erroneous or valid needs to be made based in terms of statistically examining the

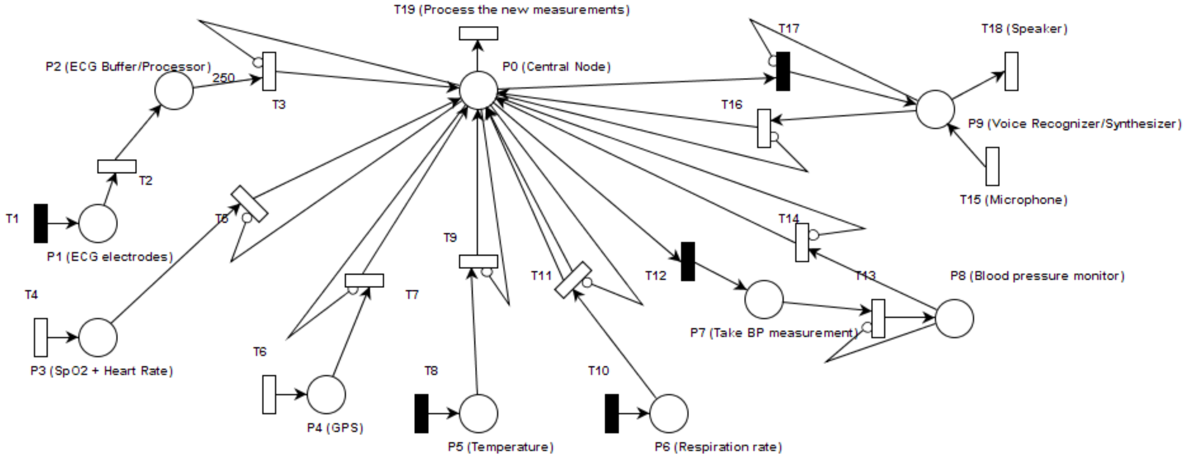


Fig. 2 Level 2 of the SPN model: Description of the wearable system's functionality and its interaction with the peripherals/wearable sensors.

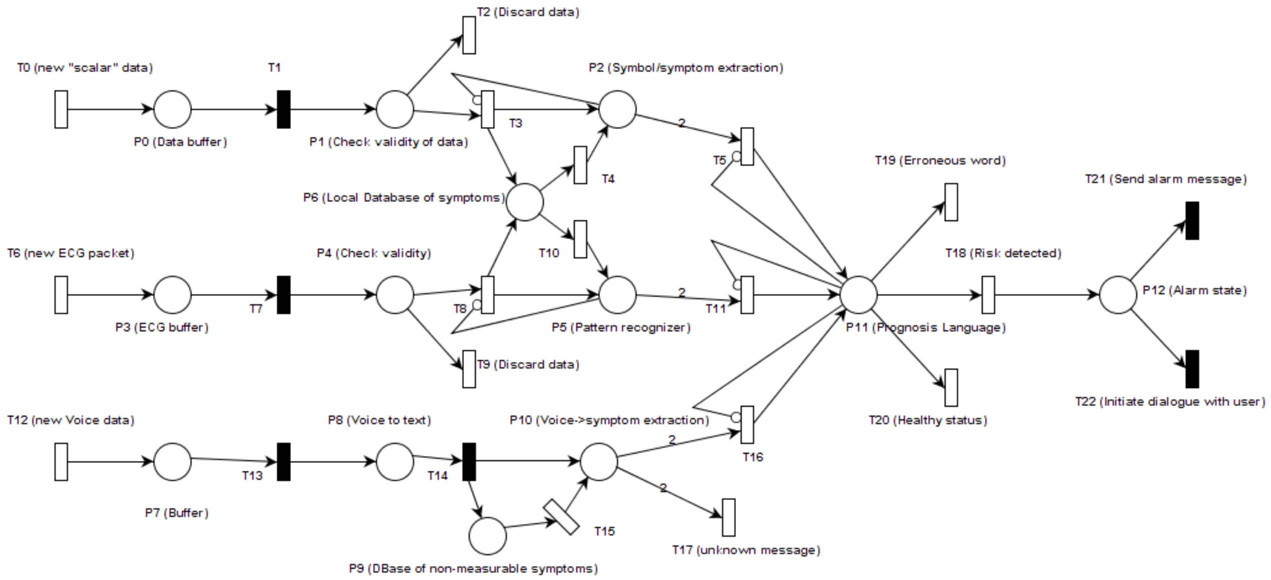


Fig. 3 Level 3 of the SPN model: Functional description of the central node.

signal's trend to possibly eliminate outliers or by using any provided sensor status info. If the data are found to be valid, they are used to extract the corresponding symptom of health through either a database range look-up process or a pattern extraction and recognition phase. In the end the extracted symptoms or language symbols are passed on to the Prognosis language which updates or creates the word which gives a thorough estimation of the user's health.

Regarding voice recordings, which can also be void in terms of null feedback, they are processed and converted to text in order for them to be "understood" by the system's language. After cross-checking the detected word(s) with a database of non-measurable symptoms, an indication of some incident like for example "back pain" may be created and given to Prognosis as further contribution to the input vector of the word extraction mechanism.

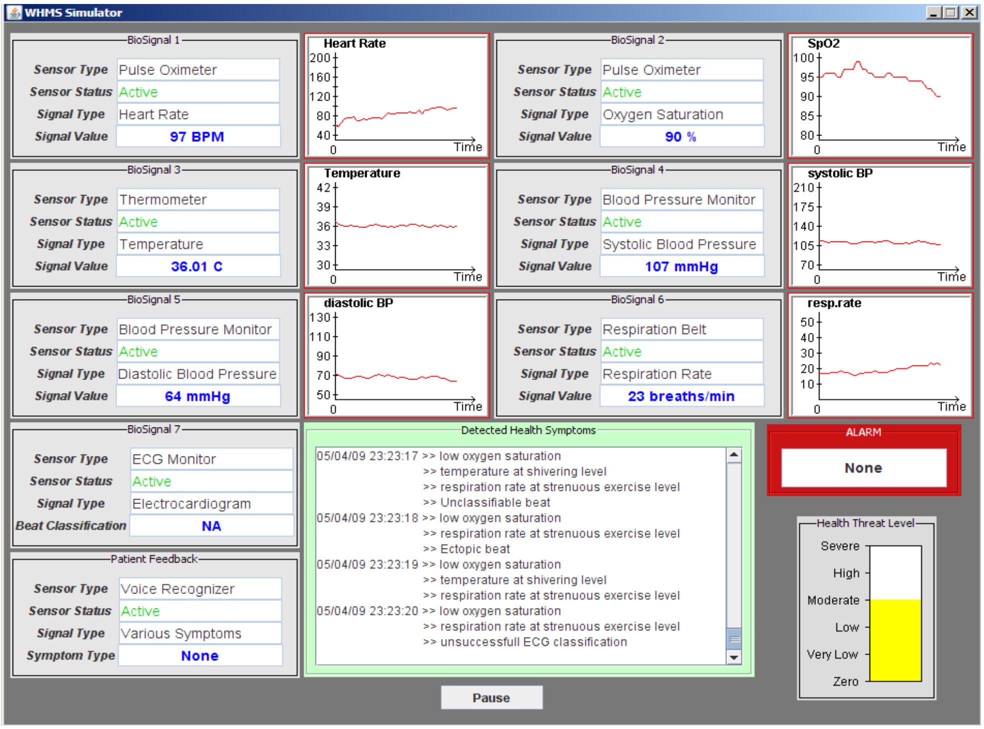
Finally, the Prognosis scheme produces an output in terms of a word, which may give rise to either a normal/healthy indication of the user's status or to an unknown/erroneous status or more importantly to an alarming state. These states correspond to detectable diseases or general health conditions which require some type of medical assistance. In such a case an alarm message will be generated and sent to the medical station and moreover the system may "decide" to take further action in terms of initiating a dialogue with the user or suggesting him to take several actions which may help prevent an escalation of the occurred or even future event.

III. SIMULATION

In accordance to the SPN functional model of multi-sensor WHMS presented in the previous section, we have developed a corresponding simulation framework implemented in Java. The reason for choosing Java is because it can facilitate the modular and hierarchical design, which is inherent in SPNs, as well as because it can provide the required synchronization and concurrency primitives for simulating the multiple components and tasks that are present in the WHMS model.

The main part of the simulation framework is the wearable system's central node, which as explained previously continuously "polls" the distributed biosensors and the rest of the peripheral components in a round-robin manner. The acquired data from every sensor are then stored in a dedicated ring buffer and checked for validity. Each time a "full-circle" of collecting physiological data has been performed and thus a new input vector of features has been formed, the health condition of the user is reevaluated. In case the corresponding created word of symptoms is interpreted by the Prognosis language as a health threatening condition an alarm is generated. Moreover in order to take into account possible temporal relations between the collected physiological measurements, the most recent past data stored in the ring buffers are used to create all possible combinations of input vectors to check for malicious health conditions. That way a more reliable estimation of the user's health condition may be derived.

The types of sensors (along with their range of values and variance) to be included in the simulation of a given scenario are selectable upon startup and constitute the continuous source of input for the tool. Fig.4 shows the GUI of the WHMS simulator. For every sensor the most recent value is depicted along with a real time graph of the most recent measurements. In addition to that a text box is provided where the extracted symptoms (with corresponding time tags) from every signal are printed out along with a separate display for any detected alarm states. In addition to that, a separate text-box pops up every time a user-system dialogue is initiated. Finally it needs to be noted that the depicted bio-signal values in Fig.4 are not corresponding to real measurements and that in the current work we are assuming that the WHMS is equipped with an automated ECG classifier.



BioSignal 1

Sensor Type	Pulse Oximeter
Sensor Status	Active
Signal Type	Heart Rate
Signal Value	97 BPM

BioSignal 2

Sensor Type	Pulse Oximeter
Sensor Status	Active
Signal Type	Oxygen Saturation
Signal Value	90 %

BioSignal 3

Sensor Type	Thermometer
Sensor Status	Active
Signal Type	Temperature
Signal Value	36.01 C

BioSignal 4

Sensor Type	Blood Pressure Monitor
Sensor Status	Active
Signal Type	Systolic Blood Pressure
Signal Value	107 mmHg

BioSignal 5

Sensor Type	Blood Pressure Monitor
Sensor Status	Active
Signal Type	Diastolic Blood Pressure
Signal Value	64 mmHg

BioSignal 6

Sensor Type	Respiration Belt
Sensor Status	Active
Signal Type	Respiration Rate
Signal Value	23 breaths/min

BioSignal 7

Sensor Type	ECG Monitor
Sensor Status	Active
Signal Type	Electrocardiogram
Beat Classification	NA

Patient Feedback

Sensor Type	Voice Recognizer
Sensor Status	Active
Signal Type	Various Symptoms
Symptom Type	None

Detected Health Symptoms

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05/04/09 23:23:17 >> low oxygen saturation
                  >> temperature at shivering level
                  >> respiration rate at strenuous exercise level
                  >> Unclassifiable beat
05/04/09 23:23:18 >> low oxygen saturation
                  >> respiration rate at strenuous exercise level
                  >> Ectopic beat
05/04/09 23:23:19 >> low oxygen saturation
                  >> temperature at shivering level
                  >> respiration rate at strenuous exercise level
05/04/09 23:23:20 >> low oxygen saturation
                  >> respiration rate at strenuous exercise level
                  >> unsuccessfull ECG classification
```

ALARM: None

Fig. 4 The GUI of the WHMS simulator

IV. CONCLUSION

In the current paper we have presented a novel SPN-based functional model for wearable multi-sensor health-monitoring systems that focuses on facilitating multi-parametric analysis and thus enabling embedded decision support. The proposed system model is independent of the actual hardware implementation, although ergonomic or power consumption restrictions may impose certain practical limitations on the system's performance considering the current state of sensor technology.

However the proposed model along with the accompanying simulation framework point out the following fact: WHMS equipped with "sufficient" machine intelligence able to not only perform advanced physiological data analysis and fusion, but also to interact with the patient/user in a meaningful and helpful manner will potentially increase the quality of personalized and user-operated healthcare to a very high standard. Our next step is to complete the setting-up of our corresponding system prototype and comparatively evaluate our system design with the proposed simulation model by using real-time real-life data.

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