Prognosis—A Wearable Health-Monitoring System for People at Risk: Methodology and Modeling

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***Abstract*—Wearable health-monitoring systems (WHMSs) represent the new generation of healthcare by providing real-time unobtrusive monitoring of patients' physiological parameters through the deployment of several on-body and even intra-body biosensors. Although several technological issues regarding WHMS still need to be resolved in order to become more applicable in real-life scenarios, it is expected that continuous ambulatory monitoring of vital signs will enable proactive personal health management and better treatment of patients suffering from chronic diseases, of the elderly population, and of emergency situations. In this paper, we present a physiological data fusion model for multisensor WHMS called *Prognosis*. The proposed methodology is based on a fuzzy regular language for the generation of the prognoses of the health conditions of the patient, whereby the current state of the corresponding fuzzy finite-state machine signifies the current estimated health state and context of the patient. The operation of the proposed scheme is explained via detailed examples in hypothetical scenarios. Finally, a stochastic Petri net model of the human–device interaction is presented, which illustrates how additional health status feedback can be obtained from the WHMS' user.**

***Index Terms*—Decision support system (DSS), formal language, fuzzy finite-state machine (FSM), fuzzy sets, human–machine interaction, stochastic Petri net (SPN), vital signs, wearable health-monitoring system (WHMS).**

I. INTRODUCTION

IT IS a fact that the global population is both growing and ageing [1], [2]. As a consequence of this demographic change, there has also been a corresponding increase in chronic age-related diseases, such as congestive heart failure, dementia, sleep apnea, cancer, diabetes, and chronic obstructive pulmonary disease [1], [3], [4]. 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 [5]. In addition to that, approximately 33% of persons over the age of 65 and 50% of persons over the age of 85 experience a fall each year [6], [7]. For this population, healthcare costs are increasing [8], quality of life and productivity are reclining, and in many cases, family members serve as primary-care assistants.

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These issues along with the challenges of effectively managing and treating postoperative rehabilitation patients, disabled people, and persons with special abilities, highlight the requirement for new and innovative ways to deliver healthcare to patients. In response to that, information and communication technologies are expected to provide the means to realize personalized, low-cost, and citizen-centered healthcare solutions to address the previously stated challenges [9]. Recent advances in sensor communication, sensor miniaturization, and microelectronics have enabled healthcare providers to monitor and manage chronic diseases and detect potentially urgent or emergent conditions [10]. Health monitoring in the home environment can be accomplished by either or both of the following [11]: 1) ambulatory monitors that utilize wearable sensors and devices to record physiological signals and 2) sensors embedded in the home environment and furnishings to collect behavioral and physiological data unobtrusively. Acceptance and positive psychological impact of monitoring technology have been confirmed in studies that have included people with dementia as well as other chronic conditions [12].

Moving a step further, early detection and diagnosis of critical health changes could enable prevention of most of these problems, saving billions of dollars annually [13], [14]. Early detection, however, requires continual vigilance. Due to the nature of their conditions or the lack of training and experience, many among this population are either disinclined or unable to detect and report the critical observations that could make a difference. Early approaches toward addressing this issue were for healthcare professionals to monitor patients directly or via relatively crude and bulky physiological data collection devices. Obviously, devices of such size and cost, which also include several wires and require the patient to be immobilized in order to acquire reliable measurements, are unsuitable when ubiquitous, unobtrusive, long-term, and low-cost health monitoring is desired. However, the new generation of inexpensive, unobtrusive wearable/implanted devices [15] could potentially lead to early and automatic detection of critical changes onto a patient's health condition. In this context, such devices should not just be simple data collection appliances, nor should they only report variations from sampled population norms. Rather, they should be able to learn individual user baselines and also employ advanced information processing algorithms and diagnostics in order to discover problems autonomously and detect alarming health trends, and consequently, inform medical professionals for further assistance. These wearable systems should also be engineered to integrate seamlessly both with portable equipment carried by first-responders and with fixed-location systems installed in hospitals. As a result, these devices will continuously capture data, organize it into customized patient and condition models, and communicate each patient's unique information to first-responders and hospital personnel.

In this paper, we present our approach toward establishing an operational framework for a novel interactive, individualized, and intelligent wearable health-monitoring prototype, which we call *Prognosis*. The rest of the paper is organized as follows. Section II will give a brief review on wearable health-monitoring systems (WHMSs) and decision-support mechanisms. Section III will introduce the overall concept of the proposed system, based on a described generic architecture and current availability of wearable biosensors. In Section IV, the proposed physiological data fusion strategy will be elaborated, by providing a formal definition of the model and illustrative examples of its operation. In Section V, we will provide an SPN-based model of the interaction scheme between user and the system. Finally, the paper will be concluded with a discussion on current and future work.

II. Related Work

Ambulatory monitoring of physiological parameters through the use of wearable or even implantable biosensors has been a research area of high interest during the past years [15], [16]. Mainly driven by increasing healthcare costs and the need to provide medical care to the increasing population of elderly [8], WHMS have the potential to realize consumer-operated personal health management and early risk detection and prevention [16].

We have provided a comprehensive review of the current state of the art in WHMS in [17]. In our survey, we emphasized on the several features that WHMS must meet, such as wearability, unobtrusiveness, low-cost, robustness, scalability, security, and privacy of medical data, low-power consumption, ease of use, and embedded decision support. We identified several approaches toward designing wearable system for health-monitoring purposes, e.g., systems based on 1) smart-textiles [18], [19]; 2) custom-designed platforms [20], [21]; 3) wireless sensor motes [22], [23]; and 4) Bluetooth-enabled biosensors and smart-phones [24], [25]. This paper has identified several shortcomings in current WHMS technology, the most important being battery and power issues for long-term monitoring, security of private information, clinical validation of prototypes, and system bulkiness. Future research in nanotechnology, sensor miniaturization, low-energy IC design, energy scavenging techniques, wireless sensor networks, and signal processing promise to provide the means to efficiently address these issues.

In addition to the previously described requirements, an important and possibly required feature of WHMS is the ability to provide embedded decision support, e.g., a means to extract higher level of information or knowledge from raw biosignal measurements. In a scenario that numerous wearable systems are deployed to continuously monitor several critical patients, a large amount of multidimensional data will be constantly created for each user. These data will need to be tediously examined by professionals in order to detect abnormalities and alarming health trends. Furthermore, as it was mentioned in the previous section, the ultimate future goal of employing wearable health-monitoring technology is to perform early identification or even prevention of diseases and health episodes. As a result, advanced inference logic and embedded intelligent information processing are required in order for the WHMS to be able to identify alarming trends in the health status of the user and also to provide patient adaptive alarms or even diagnoses.

Some preliminary efforts toward addressing the previously mentioned issues are reported in [24] and [26], where researchers have employed mobile phones to implement machine-learning algorithms to detect heart arrhythmias using the recorded ECG signals. However, wearable sensor technology enables the recording of several additional physiological parameters concurrently with the user's context [17]. By fusing together all this information while employing standard medical knowledge bases, advanced diagnostics, intelligent inference, and learning mechanisms, an overall estimation of the user's health state can possibly be derived at any given time.

Systems that provide such type of functionality, e.g., interpreting medical information, are usually termed as medical or clinical decision-support systems (DSSs). Numerous approaches toward DSS can be found in the corresponding literature [27]–[30]. Traditionally, these systems will require the input of observed symptoms and acquired laboratory results, and then, through the use of an inference engine and an accompanying knowledge base, they will derive some diagnostic conclusions. These systems, however, do not usually address the scenarios of fusing physiological parameters that are extracted in an unsupervised setting by wearable biosensor technology. In addition to that, reported systems [31], [32] often rely on continuous streaming of physiological data to a remote centralized location for automated analysis and do not provide embedded decisional capabilities.

Our work presented in this paper aims at establishing a novel paradigm for an intelligent and interactive WHMS, which is capable of estimating the user's health status and which can provide alerts and information regarding the current status and context of the user, as well as regarding alarming health trends. The proposed framework, as in any other DSS, is not meant to replace the doctor in any way and derive diagnosis for the patient, but rather to provide estimations regarding the user's condition and as such to "to enhance and support the human, who is ultimately responsible for the clinical diagnosis" [30].

III. Physiological Parameters and System Architecture

A wearable biosensor is a miniature sensing device, such as a surface electrode or a skin patch, which is capable of measuring a certain physiological parameter. A WHMS employing a variety of biosensors is thus capable of collecting real-time measurements of vital signs and other physiological signals. By applying proper signal processing on the measured data, important diagnostic features can be extracted from every individual signal.

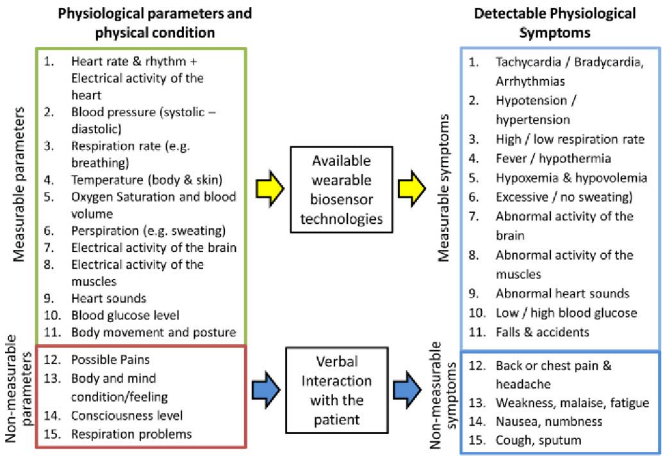

Fig. 1. Tables describing the extraction of symptoms from body signals by available biosensor technologies and human–system interaction.

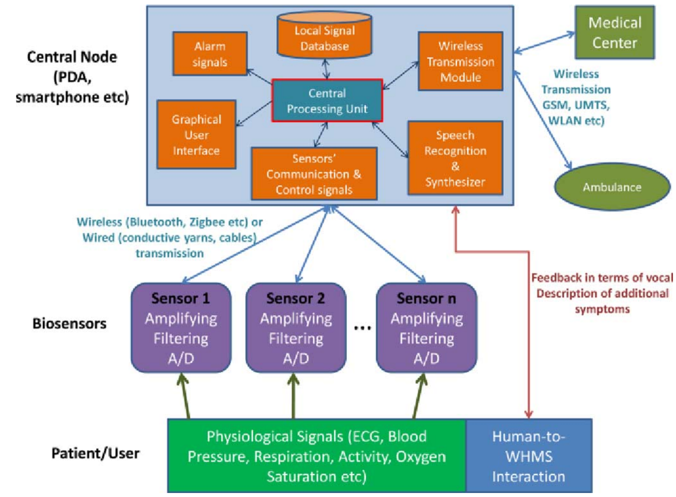

Fig. 2. Generic WHMS architecture.

However, the fact is that for an accurate estimation of one's health condition and the diagnosis of many, if not the most, diseases several symptoms than just the ones detected from biosensor measurements, need to be taken into consideration [33]. These symptoms, like cough, malaise, or chest discomfort for example, are not quantifiable or measurable via sensors. On the contrary, in order to get feedback from the patient about the possible existence of these symptoms, the patient himself needs to indicate their occurrence. As a result, by incorporating a speech-recognition module in the system design along with an automated speech dialogue between device and user, additional nonmeasurable symptoms related to the physical condition of the patient could be captured by the WHMS.

The aforementioned concept is illustrated in Fig. 1, where the table on the left provides a list of physiological parameters and other information that can be recorded about a given patient. Then, by using available biosensor technology and also by realizing verbal interaction with the user, the symptoms depicted on the right can be detected, which can provide a comprehensive description of what is referred to as the clinical presentation.

A generic system architecture that pertains to the described scenario is depicted in Fig. 2. Physiological biosensors constitute the front-end components of the system and they can be employed to measure a variety of biosignals, such as the ones listed in Fig. 1. These wearable physiological sensors can be either embedded in clothing as smart textiles, or they can be integrated on other types of wearable devices, such as wrist devices, ear-lobe sensors, finger sensors, arm bands, chest belts, waist belts, etc. In the latter case, the distributed biosensors are capable of wirelessly communicating their measurements and thus constitute a body area network (BAN), which can be either formed through Bluetooth-enabled devices or through Zigbee motes. Basic signal conditioning operations such as filtering, amplifying, and AD conversion or even basic feature extraction is usually performed by dedicated hardware, which is either embedded on the sensor as a single IC or on the central node.

The central node of the WHMS consists of some type of portable platform, such as a personal digital assistant (PDA), smart-phone, pocket PC, or even a custom-designed microcontroller board. In either case, the WHMS central node is responsible for several tasks, which are as follows.

1) Handling the communication with the on-body-distributed biosensors, which involves collecting physiological measurements and voice recordings, communication synchronization, sending control signals for adjusting sensors' parameters, e.g., sample rate, accuracy, etc., and finally, also receiving sensor status data.
2) Performing additional digital signal processing on the acquired signals for feature extraction.
3) Verifying the received data, e.g., checking the validity of the received data via an advanced algorithm and discarding those that are found to be erroneous.
4) Comparing the extracted features or values from each signal with the thresholds, limits, or patterns located in the local signal database, which may contain patient-specific information about abnormal states, in order to possibly detect any health risks (embedded decision support).
5) Generating alarm signals for the user.
6) Displaying the collected measurements on the GUI in real time.
7) Transmitting the extracted medical information about the user to a remote medical station, e.g., to a medical center or to a physician's cell phone, either in real time or in terms of report forms upon request or upon detection of events.

IV. Modeling of the Prognosis Methodology

The *Prognosis* language is a theoretical model, around which the wearable monitoring and early prognosis system is being designed. The basic hypothesis of this model is that the various body or physiological signals produced by the human body are composed of "symptoms of health," whose occurrence under certain conditions may indicate the presence of a specific health risk. The aim of the *Prognosis* formal language is to provide an efficient and compact representation of the multiple combinations of extracted physiological measurements in order to aid in the association of "pathological" symptoms and patterns with the detection or estimation of a corresponding health condition.

The proposed formal language model is coupled with the generic WHMS architecture described in the previous section. Specifically, the sensors that are included in the WHMS provide real-time measurements of physiological data, from which corresponding symptoms of health are extracted. These symptoms may be considered as normal (benign) or alarming (e.g., dangerous or hazardous). However, the degree of dangerousness (or severity) and the degree of actual occurrence of a specific symptom is fuzzy in nature [34]. As the philosopher of medicine, Sadegh-Zadeh has stated in [35], "health is a matter of degree, illness is a matter of degree and disease is a matter of degree."

As a result, the fuzzy symptoms extracted from the physiological sensors generate the set of terminal symbols of the *Prognosis* formal language. The three basic types of symptoms that can be extracted from the acquired physiological signs correspond to the three basic types of signals or information, which the system is able to collect about the patient, namely: 1) signals that are "value-specific" or "single-point", e.g., their instantaneous value carries the actual diagnostic content; 2) signals that are "morphology-specific", e.g., their structural morphology and timing are the elements that carry important diagnostic information; and 3) voice recordings that may reveal the presence of a specific health symptom, as described by the user.

A. Symptom Extraction

For the first type of physiological data, such as systolic and diastolic blood pressure, body temperature, respiration rate, oxygen saturation, etc., signal values are commonly divided in several levels of importance. For example, blood pressure measurements are commonly classified as indicating hypotension [low blood pressure (lbp)], a normal blood pressure level, prehypertension (slightly high blood pressure), stage-1 hypertension (high blood pressure), and stage-2 hypertension (very high blood pressure). This categorization of signal values to levels of importance serves the purpose of indicating the severity level of a physiological measurement and also the purpose of formally describing the progression of a possible abnormal health incident.

Instead of characterizing signal levels in a crisp manner, we can employ linguistic variables, e.g., fuzzy sets [36], to describe the degree of occurrence of a certain symptom. By fuzzifying the limits between signal levels, we get the corresponding *fuzzy symptoms*. As a result, in the case of systolic blood pressure for example, we can have the fuzzy signal levels depicted in Fig. 3. A similar approach can be adopted for defining fuzzy sets for other types of biosignals, such as very high heart rate (HR) (vhhr, *tachycardia*), very low temperature (vlt, *hypothermia*), very high respiration rate (*tachypnea*), etc.

Regarding morphology-specific biosignals, we will only consider ECG signals in this paper. ECG is a recording of the electrical activity of the heart and can be recorded and monitored in a noninvasive and relatively unobtrusive manner by chest electrodes [17]. Automatic interpretation of ECG is a complicated process [37] that requires the following steps:

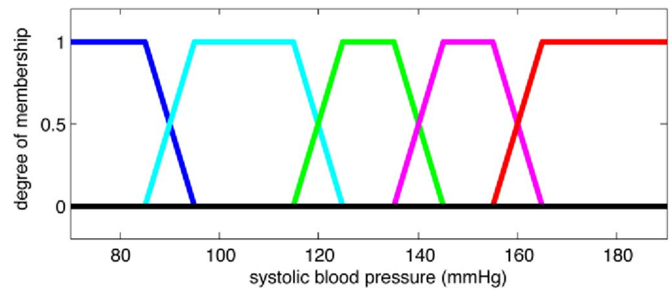

Fig. 3. Fuzzy symptoms extracted from systolic blood pressure.

1) filtering for noise removal (movement artifacts, power-line interference, and electromyographic noise);
2) detection of heart beats (QRS complexes);
3) extraction of ECG wave parameters and features;
4) classification of beats and rhythms as normal or arrhythmic (premature ventricular or atrial contractions, left or right bundle branch blocks, ventricular or atrial arrhythmias, etc).

ECG is a well-studied medical tool, which has also been widely employed in WHMS [17]. Furthermore, the automatic detection of heart beats, the extraction of ECG-related parameters, and the classification of beats and rhythms as normal or arrhythmic has been widely researched by the engineering and medical community [38]–[40].

However, the automated analysis (including noise-level estimation) of ambulatory ECG recordings by embedded devices in unsupervised scenarios is an area of active research with open problems [24], [41], in which our group is also currently involved. For now, we can assume (without loss of generality) that the WHMS is equipped with a robust ECG beat and rhythm classifier that can also provide confidence levels for its outputs.

Finally, as it is illustrated in Fig. 2 and as it will be explained in Section V, we assume that the WHMS is capable of capturing additional symptom feedback from the user via an automated human–device dialogue system.

B. Definition of the Prognosis Language

The way that we will define the *Prognosis* formal language is conceived as a means of following the progression of health symptoms so as to be able to derive, at any given time, an estimation of the user's health condition in order to possibly detect health risks by identifying dangerous health trends.

To be able to do that, we need to embed knowledge into our model regarding how the occurrence of several symptoms is related to a variety of disorders and to what degree the presence of a specific symptom under a certain context points toward a specific medical disorder or health state. This is what is commonly regarded as medical knowledge and it is the element that will help us to determine the confidence factors relating the occurrence of a symptom to the detection of a certain disorder.

Description of common disorders and accompanying symptoms in the medical literature [33] is usually given in the

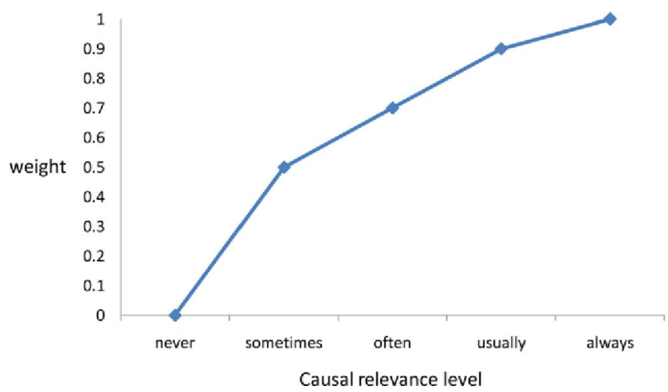

Fig. 4. Correspondence between causal relevance level and weight.

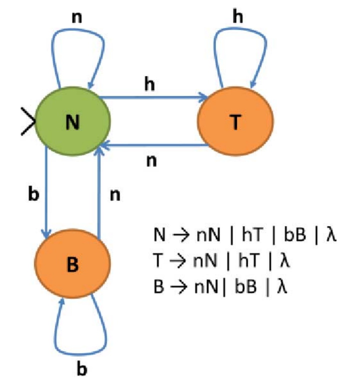

Fig. 5. Fuzzy FSM for Example 1.

following form: the typical setting of a disorder will be approximately defined, e.g., the age, gender, physiology, and medical history of typical patients, and then, the clinical presentation, e.g., a list of the symptoms associated with the disorder, will be given. The association of symptoms to disorders is usually quantified in terms of frequency of occurrence given the disease is present, e.g., always, usually, often, sometimes, and never. As suggested by Seising [34], these linguistic variables can be quantified by defining corresponding causal association levels, for example, as it is depicted in Fig. 4.

We can now proceed to the definition of the *Prognosis* language.

Definition: The *Prognosis* language is defined as a fuzzy regular formal language or equivalently as a fuzzy finite-state machine (FSM). As such, it can be represented as a 7-tuple (Q, Σ, δ, q_0, F, φ, $\oplus$), where:

1) The *set of states* Q or equivalently *the set of nonterminals* V denote the set of all possible health states of the patient/user. These states signify the various possible combinations of health symptoms, which are extracted from the measured physiological data, from the user's context, and from the user's nonmeasurable symptoms. There are no explicitly defined accepting/*final states* F, as any state included in the FSM signifies a possible health status of the user and, as a result, there is a continuous transition (trajectory) between states from the moment the system is turned on until it is turned off.
2) The *alphabet* Σ consists of the set of all observable symptoms (and contexts) in the system. Examples of these symptoms include: tachycardia, hypertension, fever, tachypnea, low oxygen saturation (*lspo2*), ectopic heart beat, abnormal heart rhythm, cough, chest pain, lying on back, running, etc. These symptoms are defined as fuzzy (linguistic) variables and each one has a degree of membership (DOM) $0 \leq \mu(i, j, x) \leq 1$ associated with it, where $i \in \{$set of all biosignals measured by the WHMS$\}$, $j \in \{$set of all symptoms that can be extracted from the ith sensor$\}$, and x is the actual measured value. The DOM denotes the certainty or strength of the corresponding symptom.
3) The *initial state* q_0 or the start symbol S signifies the initial (normal) health state of the user.
4) The *weighting function* φ: $(Q \times \Sigma \times Q) \rightarrow [0, 1]$ associates a weight to every transition or production rule in the language and represents the causal associations between symptoms and disorders/health states.
5) The *production rules* P (and equivalently the *transition function* δ) of the *Prognosis* language are of the form $A \rightarrow \alpha B$, where A signifies the current health state of the user, B is the new estimated health state (B can be equal to A), and α is a new observed symptom that is being processed (consumed) by the language.
6) $\oplus$ is a t-norm (in this case the min operator).

In order to clarify how transitions are made and how the corresponding confidence score of the current state of the model is evaluated, we will now consider a somewhat trivial example, which we will then gradually make more complex to illustrate the operation of the *Prognosis* regular language:

Example 1: Let us consider the trivial case, whereby the WHMS measures only one parameter, e.g., HR, which can only give rise to three individual fuzzy symptoms: *bradycardia*, *normal HR* (nhr), and *tachycardia*. We will denote these states as B, N, and T, respectively, and consider B and T as pathologic and N as healthy. In addition to that let us assume that the symptoms that can be extracted from the HR measurements are three as well, e.g. "low HR" (denoted as "b"), "normal HR" (denoted as "n") and "high HR" (denoted as "h"). In this simplistic example, we can consider all the weights corresponding to transitions (or production rules) to be equal to one, e.g., $w_{N \rightarrow N} = w_{N \rightarrow T} = w_{N \rightarrow B} = w_{T \rightarrow T} = w_{T \rightarrow N} = w_{B \rightarrow B} = w_{B \rightarrow N} = 1$.

The FSM that corresponds to Example 1 can be seen in Fig. 5 (N is the starting state). Now assume that the following sequence of symptom-confidence pairs is extracted: $n(1.0)$, $n(0.8)$, $h(0.7)$, $h(0.8)$, $h(0.9)$, $h(1.0)$, $h(1.0)$, $h(0.8)$, $h(0.6)$, $n(0.6)$, $b(0.6)$, where in this case, we have only considered the symptom with the highest confidence in each time instant. The sequence of transitions for this case is given in Table I (membership levels are actually computed for all three physiological states in the FSM, but here only the state corresponding to each new transition is depicted).

We now want to go through the sequence of extracted symptoms and derive the estimated state of the fuzzy FSM along with the corresponding confidence level. We assume that we begin at state N with confidence 1.0. At every derivation step, we will

TABLE I
STATE TRANSITION SEQUENCE FOR EXAMPLE 1

Current State	State Confidence	New Transition	Transition Confidence
N	1	n	1
N	1	n	0.8
N	0.9	h	0.7
T	0.4	h	0.7
T	0.55	h	0.9
T	0.73	h	1
T	0.87	h	1
T	0.94	h	0.8
T	0.87	h	0.6
T	0.74	n	0.6
N	0.43	b	0.6
B	0.3	-	-

apply the following compositional rule of inference:

$$\mu = \max_{s \in S}\{\min(\mu_{S_i}(s), w_R(s))\}. \tag{1}$$

In the aforementioned formula, $\mu_{S_i}(s)$ signifies the DOM or the confidence level of the S_i symptom and $w_R(s)$ denotes the connection weight between the current state and the state we are transitioning to. The aforementioned formula means is that when a new symptom is acquired, we will look for the most plausible transition (or production rule), by trying to find the one that maximizes the confidence level. The confidence level of a transition is defined as the "fuzzy AND," e.g., the minimum value of the symptom fuzziness level and the weight of the transition. Finally after the value μ has been computed, we will evaluate the confidence of the new state as the average of the previous state and the new computed confidence μ. However, when a transition is made to a new state, the complement of the previous stage's confidence level is averaged with the transition's strength in order to estimate the confidence of the new state. This is done in order to account for the *degree of evidence against* that new state, given that the user was previously in different kind of state.

Example 2: We now consider a more complex example, which is based on the previous paradigm. We assume now that the WHMS can measure the HR and the body temperature, and that the corresponding states that interest us are the same states, as mentioned earlier for the HR and the following three states for the temperature: *fever* (F), *normal temperature* (N), and *hypothermia* (C). As a result the total number of states in the current FSM will be $3 \times 3 = 9$ states: *NN, NF, NC, TN, TF, TC, BN, BF, and BC*, whereby the first letter signifies the state of the HR value and the second letter the one of body temperature.

Furthermore, in our current example, we account for the case where the symptoms extracted from the HR measurement include additional and finer fuzzy sets, e.g., "very low HR" (vlhr), "low HR" (lhr), nhr, "high HR" (hhr), and vhhr. Correspondingly for the temperature values, we will have vlt, "low temperature" (lt), "normal" (nt), "high temperature" (ht), and "very high temperature" (vht). Consequently, in the current case, the weights on the transitions will have a bigger impact, as for example, there is a different contribution of a "hhr" value to the state tachycardia than the contribution from the symptom "vhhr". The corresponding FSM of Example 2 is depicted in Fig. 6.

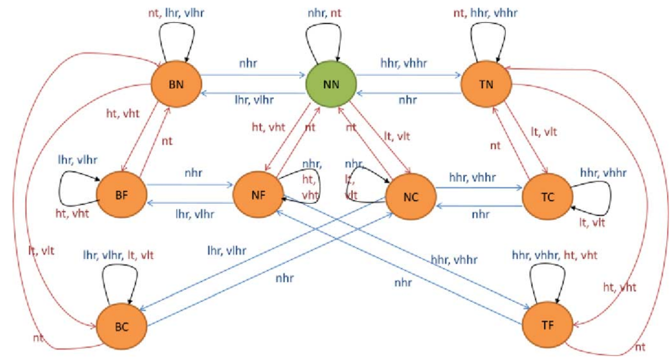

Fig. 6. Fuzzy FSM for Example 2.

In this case, we can consider the *Prognosis* model as simulating two fuzzy FSMs in parallel. For every type of biosignal, corresponding fuzzy symptoms are continuously extracted and contribute to state transitions in the manner that was described in Example 1. By combining the confidence level of parallel states, we can deduct an overall confidence for the current state in Fig. 2. Using this approach, the aforementioned model can be expanded to consider all types of symptoms extracted from the physiological measurements described in the previous subsection. However, in the case of detectable conditions, symptom contributions to the corresponding state should be weighted appropriately, according to the causal association relevance. This is illustrated in the following example.

Example 3: Finally, we will consider a more concrete example, which will illustrate the application of the proposed formal language approach in estimating the user's health, and consequently, accessing the risk level of the user's health status. In this example, we will assume that the system is capable of continuously monitoring the following physiological parameters: ECG, HR, blood pressure, oxygen saturation, respiration rate, and that, it is also able to capture verbal feedback from the user. Furthermore, let the set of extractable symptoms be of the form lspo2, vhhr, "low blood pressure" (lbp), etc. Additionally, consider the following symbolic representations for user health states.

1) S_1: Hypoxemia.
2) S_2: Coughing.
3) S_3: Hypotension.
4) S_4: Tachycardia.
5) S_5: Dizziness, weakness, or nausea.

In Fig. 7, a part of the *Prognosis* fuzzy FSM that corresponds to the aforementioned system is shown. In Fig. 7, several selected user health states are depicted along with a small subset of symptoms that cause transitions between these states (not all possible transitions are being shown to avoid confusion). The combination of S_3, S_4, and S_5 have been known to be an indication (are always present) of *acute cardiogenic shock* [33], [42]

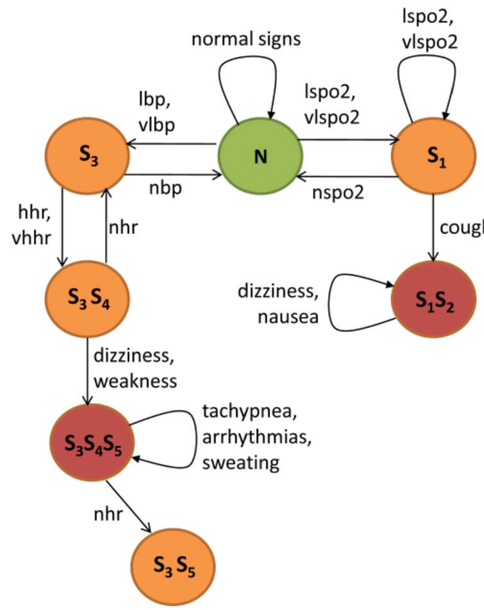

Fig. 7. Fuzzy FSM for Example 3.

and possible additional symptoms, such as tachypnea, arrhythmias, and sweating can further enhance that indication and also increase the severity level of the condition. In addition to that, the state S_1S_2 corresponds to a strong indication of *anoxic syncope*, a hypothesis that is enhanced by the presence of dizziness or nausea.

We can now consider the following scenario. The user is initially in state N, and then, gradually his blood pressure levels start dropping and his pulse rate starts increasing. This transition is depicted in Table II, where a series of hypothetical fuzzy symptoms (along with their confidence level) are extracted and the corresponding estimated health state is shown (of course, this could happen in a more gradual or complex manner, but we assume relatively rapid transitions here for the sake of discussion and without loss of generality). As the state S_3S_4 is close to the "high risk" state $S_3S_4S_5$ the system decides to inquire the user regarding the presence of additional symptoms. Given the case that the user indicates the presence of dizziness, the system may deduct a transition to the neighboring state $S_3S_4S_5$, which requires immediate attention, and thus, the system will generate an alarm and notify the healthcare provider or a supervising physician.

To evaluate the confidence or degree of support of a user health state after every "collection cycle" of physiological measurements (2), as shown at the bottom of this page, is applied, where N is the number of biosignals that did not change state, M is the number of biosignals that did change state, μ_{S_i} is the confidence for the state of the ith biosignal, and $\mu(n)$ is the overall confidence of the health state estimation at discrete time n.

TABLE II
STATE TRANSITION SEQUENCE FOR EXAMPLE 3

Current State	HR	SpO2	BP	Resp Rate	VF	ECG
N 1.0	n 0.9	n 1	n 0.7	n 1	-	n 0.9
N 0.95	n 0.8	n 1	lbp 0.6	n 1	-	n 0.9
S_3 0.64	n 0.7	n 0.9	lbp 1	n 1	-	n 0.8
S_3 0.78	n 0.6	n 0.9	vlbp 0.6	n 0.9	-	n 0.9
S_3 0.79	hhr 0.6	n 0.9	vlbp 0.8	n 0.8	-	n 0.8
S_3S_4 0.61	hhr 0.9	n 0.8	vlbp 1	n 0.7	-	n 0.8
S_3S_4 0.73	vhhr 0.7	n 0.8	vlbp 1	n 0.6	-	n 0.7
S_3S_4 0.76	vhhr 0.9	n 0.8	vlbp 1	hrr 0.6	dizzy-ness	pvc 0.6
$S_3S_4S_5$ 0.57	vhhr 1	n 0.8	vlbp 1	hrr 0.7	-	pvc 0.6

In estimating the confidence of the state $S_3S_4S_5$, a weighted average of the strength of the symptoms that are causally associated with the specific condition will be calculated. In addition to that, a bias b will be used, representing the following confidence level that the user is indeed in the previous stage S_3S_4:

$$\mu_D = \frac{b + \sum_{i=1}^{N} w_R(s_i)\mu(s_i)}{1 + \sum_{i=1}^{N} w_R(s_i)}. \tag{3}$$

V. SPN INTERACTION MODELING

As it was mentioned in Section III, the *Prognosis* WHMS includes a human–device interaction (HDI) component. This component enables the human user to interactively communicate with the WHMS device and provide to it additional information, which is particularly important for a more accurate prognosis of his/her health condition. Thus, in this section, we graphically present the stochastic Petri net model (SPN) for the interaction scheme between the human user and the Prognosis wearable device. But first, let us define what an SPN model is [43], [44].

Definition: A SPN model is defined as an 11-tuple $\{P, T, A, I, O, M, X, C, L, D, S\}$, where:

1) P: a finite set of places $\{P_i, i \in Z\}$ that represent particular states of a physical component;
2) T: a finite set of transitions, $\{T_j, j \in Z\}$ that represent a process performed between two states;
3) A: a finite set of arcs $\{a_{ij}^r, r, i, j \in Z\}$ that represent relationships among places (P_i, P_j);
4) $I_i \subset (P \times T)$, represents the input function;
5) $O_j \subset (T \times P)$, represents the output function;
6) M_i: a vector of marking (tokens) $(m_{ij}, i, j \in Z)$ that represent the status of the places;
7) **X**: a vector of time values $(x_i, i \in Z)$ related with the time required by a process to be performed;

$$\mu(n) = \frac{(1/(N+1))\{(\sum_{i=1}^{N} \mu_{S_i}(n-1)) + \mu(n-1)\} + (1/M)\sum_{i=1}^{M} \mu_{S_i}(n-1)}{2}. \tag{2}$$

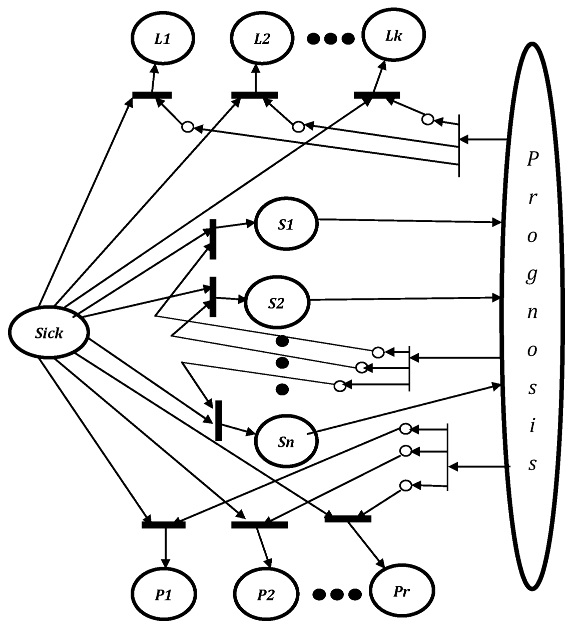

Fig. 8. SPN state diagram of the user's health conditions. The circles represent states, the thick lines represent transitions (associated with probabilities), and the arrows represent the flow of the tokens that reflect the operation of the model and the transitions from one state to other states.

8) C: the alphabet $\{c_i, i \in Z\}$ of communication;
9) L: a finite set of possibly marking-dependent firing rates $\{l_i, i \in Z\}$ associated with the transitions;
10) D: a finite set $\{d_i, i \in Z\}$ of delays associated with the transitions;
11) S: a finite set of structural properties $\{s_i, i \in Z\}$ associated with places.

The SPN models functional properties of a system, such as timing, parallelism, concurrency, synchronization, and probabilities of occurrence of events. Fig. 8 graphically shows the SPN model of the human health conditions [symptoms $(S_1, S_2, \ldots, S_n)$, positions $(P_1, P_2, \ldots, P_r)$ of the symptoms on the human body, and intensity levels $(L_1, L_2, \ldots, L_k)$ of the symptoms]. In particular, when the user is ill, the state "sick" (which can be considered as a subset of states in the *Prognosis* fuzzy FSM) is active in the SPN diagram. At that health condition, the user will be able to verbally inform the Prognosis device about his/her symptoms associated with no sensory data. More specifically, if the user has pain (state P_i), the device will always issue a token to the transition (t_i) in order for the response from the user to be taken (or accepted) by the device and the device to issue an additional token, so that the user might be able to verbally provide information regarding his/her health condition. The aforementioned example displays such a scenario.

VI. Conclusion

In this paper, we have presented a physiological data fusion methodology that is applicable to WHMSs. We defined a novel model based on a fuzzy regular formal language to describe the current state of health of the WHMS user, which considers symptom ambiguity and causal relationships between various disorders and symptoms to derive a thorough estimation with a certain degree of confidence. It should be once again stressed that the goal of this system is not to provide an accurate diagnosis of the user's condition, but rather we are hoping that such a solution can lead to early detection, and hopefully, also to prevention of health episodes by carefully following, capturing, and describing the health trends recorded from physiological and contextual sensors. Finally, we have presented a detailed SPN model of the HDI, which illustrates the way an automated dialogue can take place between the user and the WHMS.

Future work includes setting up a full system prototype and also employing machine-learning methodologies to achieve system adaptability to the individual user [45]. Efficient methodologies for embedded ECG analysis will also be investigated. Finally, a large set of clinical tests will need to be carried out in order to evaluate the proposed system and to fine-tune its parameters.

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