A Formal Language Approach for Multi-Sensor Wearable Health-Monitoring Systems

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***Abstract*—Wearable Health-Monitoring Systems (WHMS) promise to revolutionize health care 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 for them to become more applicable in real-life scenarios, it is expected that continuous ambulatory monitoring of vital signs will enable pro-active personal health management and better treatment of patients suffering from chronic diseases, of the elderly population and of emergency situations.**

In this paper a novel formal language based model for multi-sensor data fusion and early-detection of various conditions is presented. Patterns or even signal states indicating pathological symptoms that are presented in the signals, which can be collected from on-body distributed biosensors, are modeled as symbols of the Prognosis context-free formal language, whose grammar and production rules define the prognosis-words. The proposed approach is based on a described generic WHMS model and on a simple but at the same time efficient method for characterizing body-signal's patterns and/or states. Finally, we provide several illustrative examples for better comprehension of the proposed model.

***Index Terms*—Biosensors, Wearable Health Monitoring Systems, ECG, vital signs, Formal Language**

I. INTRODUCTION

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 [1], [2], [25]. Mainly driven by increasing healthcare costs and the need to provide medical care to the increasing population of elderly [3], Wearable Health-Monitoring Systems (WHMS) have the potential to realize consumer operated personal prevention and early risk detection [1,21]. Moreover, by enabling long-term unobtrusive monitoring of a patient's physiological parameters through his daily activities and thus providing real-time feedback information about his health condition, WHMS can lead to better treatment of chronic diseases, postoperative rehabilitation patients [4] and high risk patients.

In order for health monitoring via wearable systems to become more applicable to real-life scenarios and also accepted by the potential users, WHMS need to satisfy certain requirements [1]-[3]. These include low-power consumption, small weight and size, security and privacy of medical data, ease of use, unobtrusiveness and possible aesthetic issues of system design, low cost and robust and reliable operation. Current and future research advances 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. This is enabled through implementing intelligent information processing of the physiological data measured from the system's biosensors. A great number of academia research efforts and industry initiated projects have resulted in the development of WHMS that support decision mechanisms for prognosis and detection of various health or even mental states/conditions.

AMON [5], a project financed by the EU FP5 IST program, developed a wrist-worn device, which is capable of measuring blood pressure, skin temperature, oxygen saturation in blood, one lead ECG and activity level via embedded accelerometers. The system aimed at high risk/respiratory patients and could derive a classification of the estimated health condition of the user as being normal, deviant, in risk or in high risk by using specific limit values for every measured vital sign. MyHeart [6], another project supported by the European Commission and which also included industrial partners such as Nokia, Vodafone and Philips, targeted the treatment of patients suffering from cardiovascular diseases by enabling prevention and early diagnosis. It adopted the use of sensing fabrics as wearable biosensors, resulting in a smart-clothing system that is comfortable for the user and capable of measuring and classifying bio-signals such as ECG, activity and respiration rate. WEALTHY (Wearable Health Care System) [7] and MERMOTH (Medical Remote Monitoring of clothes) [8] are additional examples of EU supported projects, which employ smart fabrics and interactive textiles to enable wearable multi-parameter health monitoring of various categories of high-risk patients.

Another example of multi-parameter WHMS is LiveNet [9], developed in the Media Laboratory of MIT. It is a flexible distributed mobile platform, which is capable of real-time data processing and streaming and context classification. The system targets several scenarios, such as automated Parkinson symptom detection, epilepsy seizure detection and long-term behavior modeling. AUDABE [10], designed from researchers in the University of Ioannina in Greece, is a novel wearable system that performs evaluation of an individual's emotional state. A prototype including sensors for facial EMG, ECG and respiration rate has been developed, which is capable of recognizing and estimating basic emotional states such as high stress, euphoria or disappointment. Other examples of portable systems with decision support, include the works described in [11] and [12] where researchers have managed to classify ECG beats in mobile platforms such as PDAs and cell phones.

TABLE I
PHYSIOLOGICAL PARAMETERS AND PHYSICAL CONDITION

Measurable Parameters	1. Electrical activity of the heart + heart rate & rhythm
	2. Blood pressure (systolic and diastolic)
	3. Temperature (body & skin)
	4. Respiration rate
	5. Oxygen saturation and blood volume
	6. Perspiration (e.g. sweating)
	7. Electrical activity of the brain
	8. Electrical activity of the muscles
	9. Heart sounds
	10. Glucose
	11. Body movements
	12. PCO2 (Partial Pressure of Carbon Dioxide)
	13. Electrolytes (sodium, potassium)
zNon-measurable Parameters	14. Possible pains
	15. Body and mind condition/feeling
	16. Consciousness level
	17. Respiration Problems

TABLE II
AVAILABLE WEARABLE BIOSENSOR TECHNOLOGIES

1. ECG electrodes
2. Blood pressure monitor
3. Temperature sensor
4. Respiration rate sensor
5. Pulse oximeter
6. Galvanic skin response
7. EEG electrodes
8. EMG electrodes
9. Cardiac auscultation (stethoscope)
10. Glucose sensor
11. Accelerometer

FEEDBACK FROM PATIENT

TABLE III
DETECTABLE PHYSIOLOGICAL SYMPTOMS

Measurable Symptoms	1. High / low heart rate & cardiac arrhythmias
	2. Hypotension / hypertension
	3. Fever / hypothermia
	4. High / low respiration rate
	5. Hypoxemia, hypovolemia
	6. Excessive / no sweating
	7. Abnormal el. activity of the brain
	8. Abnormal el. activity of the muscles
	9. Abnormal heart sounds
	10. Low / high blood glucose
	11. Falls, accidents
Non-measurable Symptoms	12. Pain (back, chest or headache)
	13. Weakness, malaise or fatigue
	14. Nausea
	15. Numbness
	16. Cough
	17. Sputum

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

Finally, the LifeShirt from Vivometrics [13] and the SmartShirt from Sensatex [14] constitute examples of commercially available products, which are based on sensing fabrics and conductive materials to incorporate bio-sensing capabilities on some type of comfortable garment.

In this paper we present our effort to describe signal patterns and/or states, which may be presented in the various types of physiological parameters and vital signs measured by wearable biosensors, as symbols of a formal language. The grammar and the production rules of the Prognosis context-free formal language define the prognosis-words, which are combinations of the language's symbols and indicate the detection of a certain health condition. Our approach is based on the availability of wearable biosensors discussed in Section II and on a generic WHMS model described in Section III. Furthermore, Section IV describes our approach for extracting pathological symptoms from body-signals and defines the structure, the grammar and the rules of the Prognosis language. Section V provides some illustrative examples for better understanding of the proposed approach and finally the paper is concluded in the last section, which provides also a brief discussion on future work.

II. PHYSIOLOGICAL PARAMETERS, COMMON SYMPTOMS AND AVAILABLE BIOSENSORS

A wearable biosensor is a miniature sensing device, usually 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 and by combining and fusing these data together an estimate of the health condition of the patient/user can be deduced [2], [3].

However, for a more accurate estimation of one's health condition and the diagnosis of many, if not the most, diseases, several other symptoms need to be taken into consideration [15], [16]. These symptoms, like cough or malaise, are either not measurable at all or they cannot be estimated without using invasive methods, e.g. as in the case of determining electrolyte levels in the body. Table I gives a comprehensive overview of most of the physiological parameters and the most common symptoms that need to taken into consideration and properly evaluated to derive a specific diagnosis. This list is not exhaustive and it does not include findings, which can only be obtained from thorough clinical examinations and tests like MRI, CT scan, chest radiology and other medical and laboratory examinations typically performed in a hospital.

Table II provides a list of biosensor technologies, which enable the measurement of several of the parameters listed in Table1. Examples of such biosensors, which are commercially available, include ECG electrodes from Corscience (Erlangen, Germany), 3M (St. Paul, MN) and Foster-Miller (Waltham, MA). Moreover, several companies like Nellcor (Boulder, CO), Nonin (Plymouth, MN) and Smiths Medical OEM (Waukesha, WI) have developed small portable finger-tip pulse oximeters for measuring oxygen saturation in blood and pulse rate. Further examples include the portable blood pressure monitor by A&D Medical (Tokyo, Japan), the pH sensor by Vernier (Beaverton, OR) and the non-invasive glucose monitor by InLight Solutions (Albuquerque, NM).

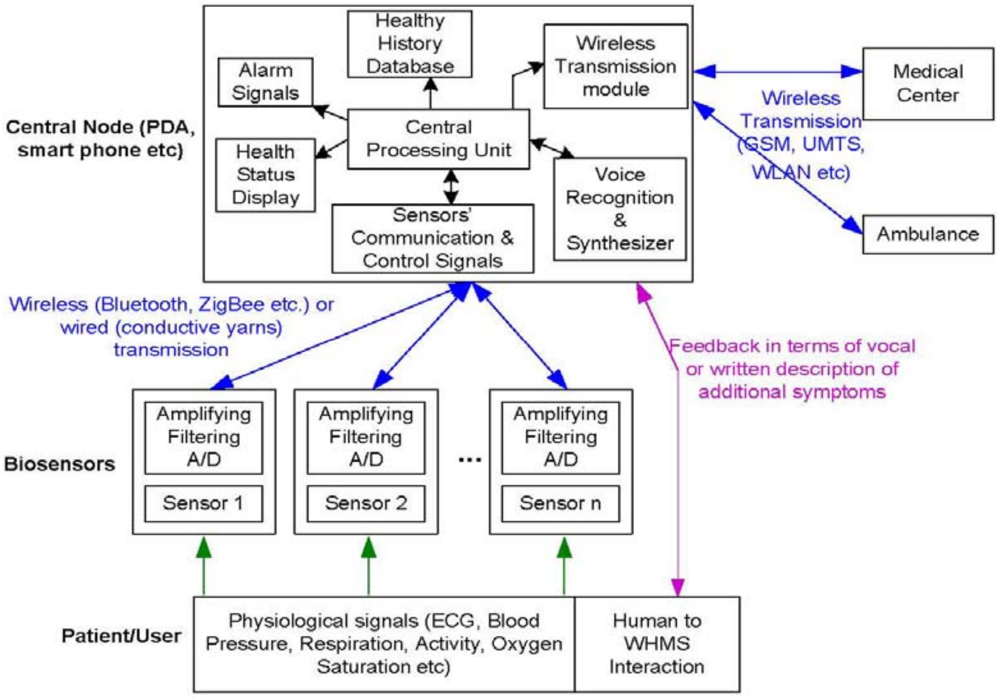


Fig.2. A generic WHMS architecture [25]

Physiological parameters and vital signs from 1 to 11 listed in Table 1 constitute signals and data, which are measurable via the corresponding sensors and devices in Table II. The Table I entries from 12 to 19 are additional symptoms and physical signs, which are associated with a great variety of diseases. These symptoms, once detected or quantified, provide important information, which together with the measured vital signs provide a more comprehensive description of what is referred to as the clinical presentation, which under proper interpretation may lead to a specific diagnosis. However, in order to get feedback from the patient about the possible existence of these symptoms either the patient himself has to describe them or in case of some of these physical signs, they can only be measured in an invasive way using current sensor technologies.

Taking the previous discussion into consideration, Table III lists several symptoms which are associated either with measurable parameters from Table I, e.g. 1-11, or with non-measurable symptoms related to the physical condition of the patient and which can only be obtained through patient feedback.

III. The Generic WHMS Model

Fig.1 depicts the architecture of a generic WHMS model. Physiological biosensors constitute the front-end components of the system and they can either be integrated as textile sensors on smart clothes [6]-[8], [13], [14] or as hardware modules on wireless sensor nodes in a Body Area Network (BAN) [17], [18]. In the latter case the collected measurements can be amplified, filtered and digitized on the sensor nodes and then transmitted to the BAN's central node through embedded ISM Band transceivers. In the former case, physiological signals can be transmitted in analog form and then be digitally processed at the system's central node.

The WHMS central node is responsible for several possible tasks: 1) collecting of various types of physiological data from the biosensors, 2) applying further DSP on the signals (e.g. for feature extraction), 3) comparing the extracted features from the body signals with the "Healthy History Database", which contains patient-specific normal vital-sign values and analyzing the extracted features using intelligent algorithms to provide embedded decision support, 4) generation of alarm signals for the user, 5) displaying the estimated health status of the user and/or the collected data on the node's screen, 6) transmitting medical data to a remote base station (e.g. hospital or cell phone of a supervising physician) or even to a dispatched ambulance and finally 7) generating sensor's control signals (e.g. for initializing measurements or setting up parameters such as sampling interval and A/D frequency).

The presented functional description of the WHMS model encompasses the "concept" under which most of the developed wearable system prototypes or commercially available products for health-monitoring operate. However, we envision a system that is also able to get feedback from the patient in an additional manner, namely through voice (or through writing on the central node's keypad). This functionality, once implemented could enable the user to provide feedback to the system concerning the presence of symptoms that cannot be measured through standard non-invasive biosensors. These symptoms, as discussed in the previous section, could include the presence of coughing, nausea, malaise, back or chest pains etc. Implementing this feature on a WHMS, which employs a wide variety of wearable and/or implantable biosensors, could enable the detection of a wide variety of health symptoms as the ones listed in Table III and possibly of several others we have not considered in the current study.

Finally, alarm signals and measured physiological data along with the feedback from the patient can be transmitted through the cellular network or the Internet to the medical center and possibly also to a dispatched ambulance. As the healthcare center keeps a database with long-term detailed medical history of the patient, the received data and patient symptoms and the accompanying alarms can be further evaluated to derive a more accurate estimation or even verify the detected health risk level.

IV. PROGNOSIS FORMAL LANGUAGE [24]

The Prognosis language is the theoretical model, which the wearable monitoring, prognosis and prevention system model relies on (Prognosis is the Greek word for predicting a future condition from past knowledge/history and current pieces of information). It is based on the efficient detection and association of various signals produced by the human body expressing its current health status. These body signals themselves are composed by "symptoms of health", where their presence under certain conditions may lead into a prognosis of the health status of a patient.

The Prognosis formal language is applicable to multi-sensor wearable health-monitoring systems, whose model was described in the previous section, and which are capable of measuring most of the physiological signals listed in Table I and thus capable of detecting several of the symptoms listed in Table III. In the following the process of extracting healthy and pathological symptoms from measured body signals is described. This approach is based on discriminating two different categories of physiological signals: a) signals whose "diagnostic content" is simply provided in the value of each acquired sample and b) signals, whose structural morphology and timing are the actual features that convey important diagnostic information.

A. Category of value-specific physiological symptoms

The most typical physiological signals, which are included in this category, are systolic and diastolic blood pressure, respiration rate, body temperature, glucose level and heart rate. The following definitions describe how "symptoms" of interest, which contain diagnostic information, are determined and Fig. 3 depicts this categorization graphically.

Definition 1: A body signal S_s is defined as $S_s = x(nT)$, where $x \epsilon R$ and x are values associated with healthy and pathological symptoms, n denotes the nth sample and T is the sampling interval.

Definition 2: A symptom of a body signal S_s at time nT is defined as "healthy" and denoted $S_h(nT)$ if and only if $A<x(nT)<B$, where A is a lower bound and B an upper bound, that define a healthy condition.

Definition 3: A symptom of a body signal S_s at time nT is defined as "pathological or abnormal" and denoted $S_p(nT)$ if and only if $x(nT) \leq A$ or $x(nT) \geq B$.

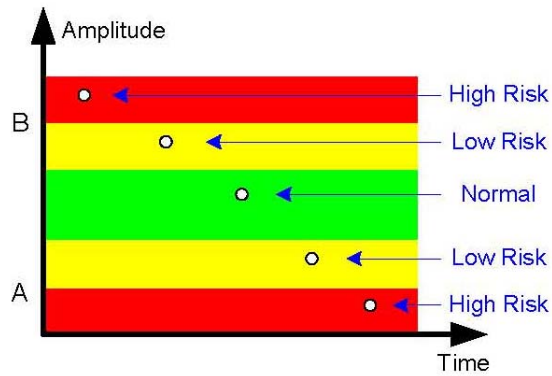


Fig.3. Representation of hypothetical sample values (white circles) of a body signal in various levels of importance. The red layers represent high-risk levels; yellow layers represent moderate/low risk levels; and the green layer represents the "healthy" range of values.

B. Category of morphology-specific physiological symptoms

This category includes body signals, which describe the electrical activity of various body parts, amongst which the most common ones are the electrocardiogram (ECG), the electroencephalogram (EEG) and the electromyogram (EMG). Detecting healthy and pathological symptoms in such kind of signals is a complicated process and it requires careful conditioning of the signal (e.g. filtering, amplifying etc) and intelligent signal processing for feature extraction.

Our approach is based on a simple but efficient scheme called LG-Graph. In brief, the concept of this methodology is a) detecting significant maxima and minima in the signal and b) describing the patterns, waves or potentials presented in the signal as triangle-like shapes with individual geometrical and morphological characteristics (e.g. segment's lengths and slopes, area, peak value etc). This approach provides an accurate and fast method for describing the patterns' features. Based on this approach, signals like the ECG can be easily analyzed and searched for patterns of interest.

Figure 4 illustrates how a part of an ECG waveform is converted using the LG-Graph methodology to a sequence of triangle-like-shapes (LG_{gt}). Using this representation the abnormality or the symptom can be defined and expressed as a subsequence of these "triangles" (which do not need to be adjacent). The waveform depicted in Fig.4 is taken from the MIT-BIH Arrhythmia Database (record mitdb/233) available online at Physionet [19], [20]. Figures 5 and 6 provide further examples of how peaks can be detected and characterized in ECG waveforms. Fig.5 depicts a signal taken from the MIT-BIH ST Change Database (record stdb/327) and the signal in Fig.6 is taken also from the MIT-BIH Arrhythmia Database (record mitdb/209).

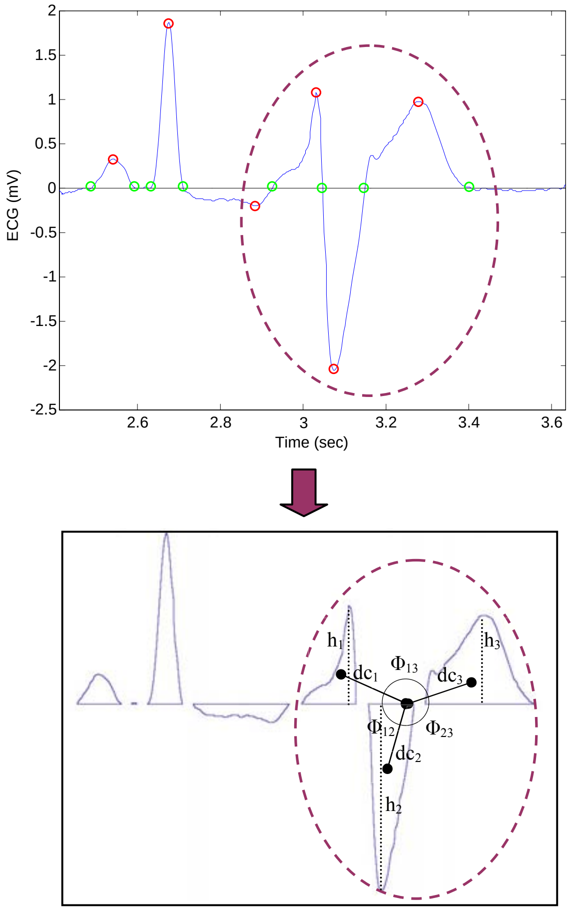


Fig.4. Top: An ECG waveform with one normal beat and an abnormal one indicating Premature Ventricular Contraction (purple dashed ellipse). Characteristics of this irregular beat are the wide and premature QRS complex and the fact that there is no preceding P wave. Bottom: Extraction of LG_{gt} triangles and depiction of some of their geometrical features.

As it can be seen form the provided figures, the LG_{gt} methodology is strongly dependent on the signal baseline (e.g. the isoelectric line) [23]. For that reason, proper heart-rate-dependent digital filtering must be applied to ECG signal to efficiently remove the baseline wander without introducing extra noise to the waveform.

Using the described LG_{gt} approach, the recognition and detection of abnormal patterns (e.g. symptoms) is done by sequentially searching the acquired signal for the corresponding LG_{gt} patterns that define and/or describe the individual symptoms and which are stored in a LG_{gt} database. Furthermore, the fact that ambulatory ECG recordings contain various types of noise is taken into consideration by our approach, by using several metrics (with corresponding acceptable deviation-margins) to do appropriate pattern matching, e.g. the shape's height, width, area, steepness, as well as the distance between subsequent triangles' centroids.

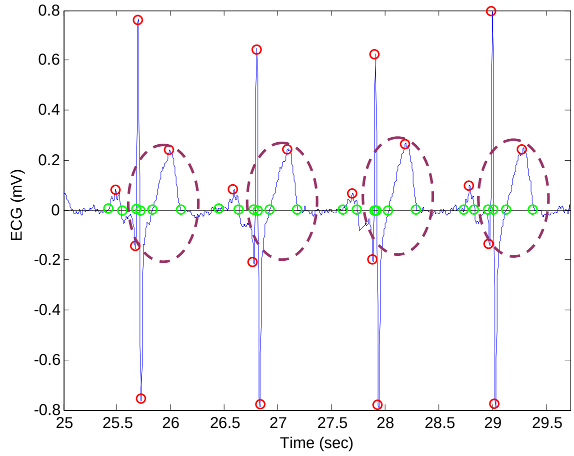


Fig.5. An ECG waveform exhibiting ST-segment elevation and hyper-acute, symmetric and prominent T waves.

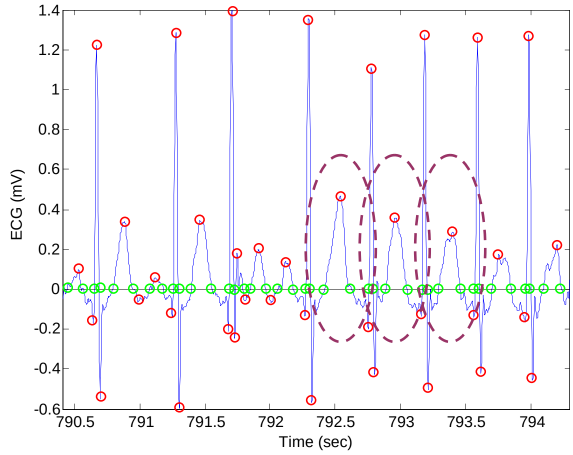


Fig.6. An ECG waveform depicting the occurrence of several premature atrial beats and the initiation of paroxysmal supraventricular tachycardia (from the 4th beat and on). Purple dashed ellipses indicate the absence of P-waves between QRS complexes.

C. *Theoretical Modeling of the Prognosis Language*

Definition 5: A body signal is composed by the synthesis (@) of healthy symptoms and pathological symptoms (if any):

$$S_s = [\{S_h(n_iT)\}@\{\,S_p(n_jT)\}]_{i,j\in\mathcal{Z}}$$

We define Prognosis as a context-free formal language consisting of various types of letters (symbols). These special symbols represent pathological symptoms from body signals. Thus, the generic alphabet ∑ of the Prognosis language is the set of all the pathological or abnormal symptoms extracted from the body signals.

$$\sum = \{S_{pi}, S_{pj}, S_{pk}, \dots, S_{pr}\},$$

where: $S_{pi}\epsilon S_{s1}$, $S_{pj}\epsilon S_{s2}$, $S_{pk}\epsilon S_{s3}, \dots$, $S_{pr}\epsilon S_{sn}$, are the pathological symptoms of every body signal.

The Prognosis Grammar

We define a grammar **G** = ($\boldsymbol{V_N}$, $\boldsymbol{V_T}$, $\boldsymbol{S_T}$, ***PR***), where:

- $\boldsymbol{V_N}$ is the set of non-terminal symbols:

$V_N = \{S_s, S_h, S_p, \{T_i\}_{i\epsilon\mathcal{Z}}, \{T_j\}_{j\epsilon\mathcal{Z}}, \{T_k\}_{k\epsilon\mathcal{Z}}, LG_{gt}, T_{sx}\{h,b,area,d,\varphi,\theta\}, dc_k, w_i, t, i, j, k, r, S_T\}$, where:

- S_s is a body signal.
- S_h is a healthy symptom.
- S_p is a pathological symptom.
- T_i is the set of terminal symbols that correspond to the various categories of S_p in category A.
- T_j is the set of terminal symbols that correspond to the various categories of S_p with LG_{gt} represenation (category B).
- T_k is the set of terminal symbols that correspond to the various categories of S_p which are described by patient feedback.
- LG_{gt} is the representation of a S_p using a sequence of triangle-like-shapes.
- T_{sx} is the triangle-like-shape representation of a single pattern or wave or peak in LG_{gt}.
- h is the height of T_{sx}.
- b is the width (duration) of T_{sx}.
- ***area*** is the area of T_{sx}.
- d is the set of slope/derivative values of the T_{sx} segments.
- φ is the set of φ-slope angles of the T_{sx} segments.
- θ is the set of θ-connection angles between T_{sx} segments.
- dc_k is the distance between the centroid of k^{th} T_{sx} in the LG_{gt} and the temporal center of the corresponding LG_{gt}.
- Φ_{kr} is the angle between the centroids of the k^{th} and r^{th} T_{sx}.
- w_i is a word belonging to language L.
- t is the time stamp of a symptom.
- $i,j,k,r\ \epsilon\ \mathcal{Z}$ are indexes.
- S_T is the start symbol of grammar **G**.

• V_T is the set of terminal symbols:
$V_T = \{\Sigma_{sp}, A_i, B_i, \Omega_{jk}, \Pi, @, \#\}$, where:
- Σ_{sp} is a system- or application-specific alphabet.
- A_i and B_i are the lower and upper bounds (in corresponding signal units, e.g. ^{o}F for temperature etc) for determining pathological symptoms in body signal i.
- Ω_{jk} is the set of values for the k^{th} parameter (e.g. height, angles, width etc) of the LG_{gt} -representation of the j^{th} signal in category B.
- Π is the set of non-measurable symptoms (patient-feedback).
- The symbols # and @ represent operators of the language.

• ***PR*** is the set of production rules:
$PR = \{S_T \rightarrow T_i;\ S_T \rightarrow T_j;\ S_T \rightarrow S_T\#\ T_j\ (or\ T_i)\}$

The Prognosis Formal Model

The Prognosis words that can be produced have the form:

$$w_i = S_{pi(t)}\#S_{pj(t)}\#\ldots\#S_{pk(t)},$$

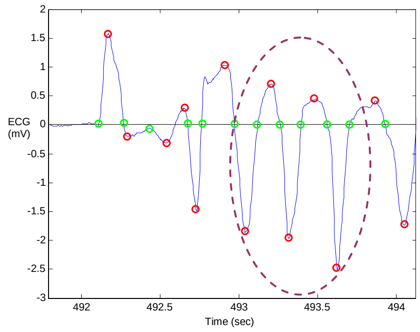
where the common time stamp t in all detected pathological symptoms forming w_i indicates the fact that the production of a Prognosis word is time-dependent (e.g. the symptoms forming w_i have been detected in the same time window $[t_1,t_2]$).

Finally the generative definition of the Prognosis Language can be written as:

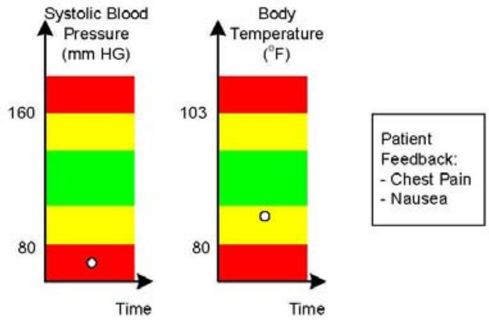
$$L(G) = \{w_i\ \epsilon\ V_T^* \mid S_T \rightarrow_G^* w_i\}$$

V. Illustrative Examples

In this section we provide two illustrative examples for understanding of how the Prognosis language works to combine detected pathological symptoms and thus to derive an estimation of the individual's underlying pathological health condition. It is important to note that the signals (except from the ECG waveforms) presented in this section as well as the corresponding co-occurrence of these pathological symptoms are hypothetical.



(a) Onset of ventricular tachycardia.

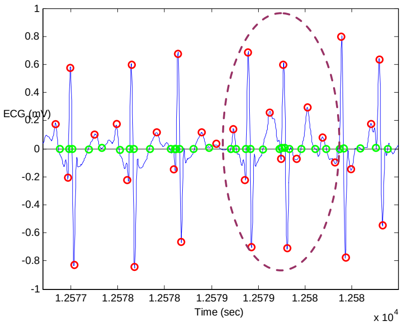


(b) (c) (d)

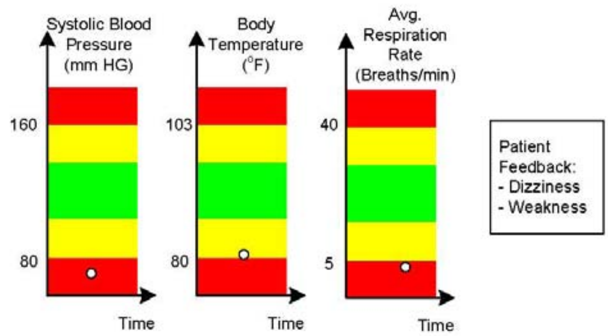
Fig.7. Symptoms (a)-(d) describe a hypothetical patient's profile at time t.

The symptoms depicted in Fig.7 belong to the specific alphabet Σ_{sp} = {a, b, c, d} and the detected pathologies according to the Prognosis language form the corresponding word: w_1=a#b#c#d. According to the language's grammar, w_1 is an indication of *acute cardiogenic shock*. (The waveform in Fig.7(a) is taken from record cu02 of the CU Ventricular Tachyarrhythmia Database at Physionet [20].)

In Fig.8 another hypothetical case is presented. We assume that a patient is having the following symptoms: severe drop in body temperature, hypotension, reduced respiration rate, dizziness and weakness as well as a specific atrial dysrhythmia (e.g. atrial fibrillation). The combination of these symptoms according to the Prognosis grammar indicates the occurrence of severe *hypothermia*. (The waveform in Fig.8(a) is taken from record afdb/08219 of the MIT-BIH Atrial Fibrillation Database at Physionet [20].)



(a) Onset of atrial fibrillation.



(b) (c) (d) (e)

Fig.8. Symptoms (a)-(e) describe a hypothetical patient's profile at time t.

VI. Conclusion

In this paper we have presented a novel approach to characterize and represent pathological symptoms, detected in various types of physiological signals, as symbols of a formal language model called Prognosis. Specific combinations of the Prognosis symbols may produce a word that is defined in the language and thus give rise to the prognosis of a specific medical health condition. In addition to that we have presented our own approach to describe and represent pathological patterns found in body signals, whose morphology conveys important diagnostic information.

Furthermore, Prognosis is targeting applications in Wearable Health-Monitoring systems. For this reason we have also presented a generic WHMS model and also based our definition of the language's grammar upon the current availability of wearable biosensors.

Future work includes modeling of the WHMS – Prognosis system using Stochastic Petri Nets and studying the use of Neural Networks to derive a system that is capable of adjusting to the individual user.

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