An Intelligent System for Classification of Patients Suffering from Chronic Diseases

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Abstract. The CHRONIOUS system addresses a smart wearable platform, based on multi-parametric sensor data processing, for monitoring people suffering from chronic diseases in long-stay setting. An intelligent system, placed at a Smart Assistant Device, analyzes incoming data, facilitating data mining techniques and decides upon the severity of a probably pathological episode. Part of the intelligent system is the Mental Support Tool, which calculates a stress index and classifies the mental condition and stress levels of the patient. An additional component aiming at the personalization of the monitoring system is the Profiler which defines several patients' profiles and facilitates clustering techniques in order to associate each resulting cluster with one of the predefined profiles.

Keywords: Personalized treatment, Wearable Monitoring, Management of chronic disease.

1 Introduction

The CHRONIOUS system defines a European framework addressing people with chronic health conditions. In particular, it intervenes on the field of two chronic pathologies, chronic obstructive pulmonary disease (COPD) [1] and chronic kidney disease (CKD) [2], these being widespread and highly expensive pathologies in terms of social costs [3]. The CHRONIOUS goals achieved by developing a multidisciplinary, sophisticated, and adaptive chronic disease platform that integrates state of the art sensors and services in order to cover both patients and healthcare professional's needs [4], [5].

An open architecture design has been used to exploit the benefits of the final platform upon other chronic diseases, besides COPD and CKD. The system,as depicted in Fig. 1, consists of six primary functional blocks, which are the Sensors Framework, Data Handler (DH), Home Patient Monitor (HPM), Smart Assistant Device, CHRONIOUS Central System and Clinician Framework. Each block interacts to each other as well as with thetwo secondary functional blocks, which are the Communication Module to connect the primary blocks to each other and maintain interoperability

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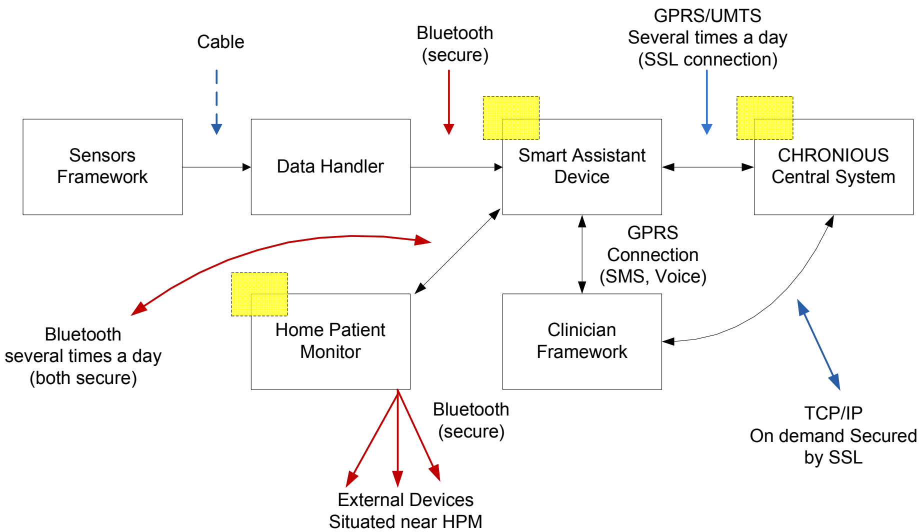

Fig. 1. The functional blocks of the CHRONIOUS system

and efficiency and the External Devices constituting by Body Weight Device, a Blood Pressure, a Blood Glucose Device and a Spyrometer device.

2 System Overview

The Sensors Framework is one of the most critical parts of the system. It consists of a tight-fitting and washable shirt which provides the support for the stabilization of the body sensor network. Several miniature sensor devices utilizing non-invasive methods are responsible for the recording of the characteristic signals and their further transmission for the analysis. The types of sensors which are utilized in this framework are: a 3-lead Electrocardiogram (ECG), a microphone as a context-audio sensor, a pulse oximeter, two respiration bands, an accelerometer and a sensor for measuring humidity as well as body and ambient temperature. Their position at the wearable jacket as well as their connectivity with the Data Handler device are shown in Fig. 2.

The data handler device is placed on the wearable part of the system at the lower part of the shirt. It has been designed and developed aiming at the collection of all the signals coming from the body sensor network. However, its role is the accurate collection and the transmission of the vital signals wirelessly – via a Bluetooth connection– to the Smart Assistant Device for their analysis.

The CHRONIOUS system facilitates several data mining techniques to extract knowledge and classify patient's health status with different levels of severity. These techniques are being nested in three different modules with various functionalities which interact to each other: The Patient Profiler placed in Central System; The Mental Support Tools and the Decision Support System formulating the CHRONIOUS Intelligence with emergency-direct feedback, which are placed in Smart Assistant Device.

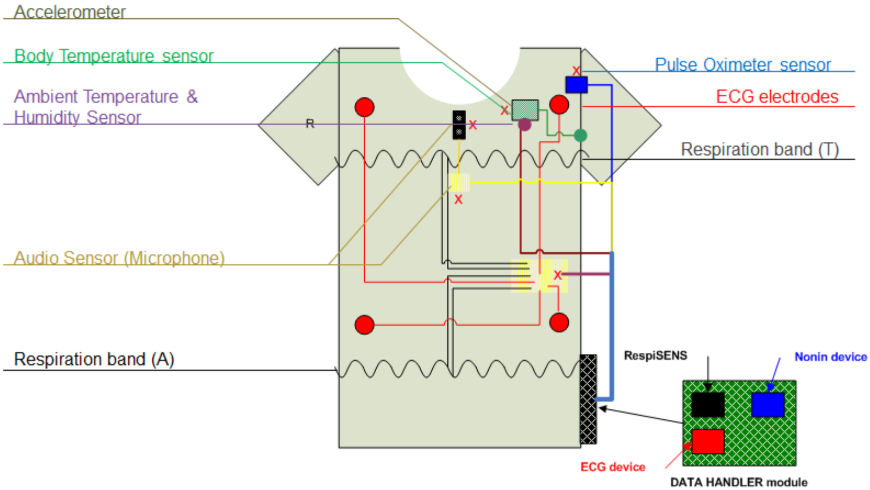

Fig. 2. The Sensors Framework integrated with the Data Handler device

The CHRONIOUS Intelligence constitutes of several sub-modules whose responsibility is to analyze the incoming data from the various sources, extract the useful features and retrieve knowledge using data mining techniques. In order to eliminate the energy consumption of the Sensors Framework and the Smart Assistant Device, a mechanism has been implemented as an add-on value to the integrated system. Several threshold values of the most critical signals are computed and stored in the Data Handler's (DH) memory. Each time these computations result to values outside the normal ranges, the Smart Assistant Device is restored from stand-by to normal mode.

The Decision Support System (DSS) is placed at CHRONIOUS intelligence core and constitutes one of the most important modules of the CHRONIOUS platform. Physically, it is installed and functions in the Smart Assistant Device. This module is an intelligent sub-system [6], combining an expert rule-based system and a supervised classification system, which may be an artificial neural network (aNN). The intelligent sub-system is responsible to categorize any abnormalities in the acquired data, evaluate the severity of the situation and provide an advice/recommendation and/or an alert to a caregiver/clinician regarding the health status of the patient. In case no abnormal situation has been tracked, the DSS takes no action and remains deactivated until the next pack of data are acquired. This triggering process takes part in the DH device when the values of the collected signal exceed the appropriate threshold for the specific patient. The normal ranges for each patient were extracted during the initial setup of the system(training phase), which is held several days before the real recording of patient's data.

Besides DSS, a patient's Mental Support Tool, located at CHRONIOUS Intelligence, is being implemented aiming in the control of patient's mental state and the parameters that affect it, in terms of detecting them on-time and providing the appropriate feedback to elevate patient's moral and strengthen his/her mental health. The purpose of this tool is to effectively detect and alert the patient for a stressful and possibly harmful condition in which he may be, by monitoring environmental parameters such as noise or air quality, physical parameters such as physical activity, heart rate variability (HRV), body temperature, blood pressure and all the parameters which are identified by the clinicians as stress indicators.

Patient Profiler, located at the CHRONIOUS Central System, aims at creating a patient model by using several datasets (including recent data acquired by sensors or inserted manually by patient, laboratory data, guidelines given by clinicians and clinical models including previous patient's models) in order to achieve personalization of the severity estimation for each patient. Mean values and variations of the most recent acquired data as well as data concerning patient's history, are input to the expert system (Patient Personal Model Trainer) in order to build a more dynamic profile. The Patient Profiler uses clustering algorithms to create a new, more personalized and accurate patient profile.

3 Data Analysis and Decision Support

3.1 Pre-processing and Feature Extraction

In CHRONIOUS platform, data acquired by sensors are being encapsulated in XML files by the Data Handler. The XML file that is being formed and transmitted contains the acquired data, error codes that might have occurred and threshold values indicated by the user.Several thresholds of the values of the wearable sensors as well as specific rules, specified and validated by clinicians, have been inserted in the kernel of the Data Handler to perform a preliminary validation of the patient's current health status. In case the system identifies an abnormal value, the Data Handler transmits a triggering signal, accompanied with the sensors' recent values, to the Smart Assistant Device for an advanced an analytical estimation of the current situation. Nevertheless, incoming data are complex enough to deter knowledge extraction and a pre-processing stage has been foreseen. The Feature Extraction Module applies XML de-encapsulation and reconstructs the acquired signal. In addition, de-noising and analysis methods are being applied specifically for the three continuous signals: ECG, audio and accelerometer signal.

The last phase of signal processing is the Feature Extraction which extracts the required features that have been indicated by clinicians or characterized as features with high diagnostic value by the evaluation process. These features constitute the attributes facilitated by the Intelligent System.There are several measures that can be obtained by the above mentioned signals, either in time or in frequency domain. The most important features, with a short description, are:

Heart rate variability (HRV). Is a physiological phenomenon where the time interval between heart beats varies. It is measured by the variation in the beat-to-beat interval. The HRV can be directly derived from the RR interval, using the formula:

$$\mathrm{HRV} = \frac{60}{\mathrm{RR}} \tag{1}$$

SDNN (msec). Standard deviation of all normal RR intervals in the entire ECG recording,

$$\mathrm{SDNN} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{NN}_i - m)^2}, \tag{2}$$

where NN_i is the duration of thei_{th}NNinterval in the analyzed ECG, n is the number of all NNintervals, and m is their mean duration.

SDANN (msec). Standard deviation of the mean of the normal RR intervals for each 5 minutes period of the ECG recording.
SDNNIDX (msec). Mean of the standard deviations of all normal RR intervals for all 5 minutes segments of the ECG recording.
pNN50 (%). Percent of differences between adjacent normal RR intervals that are greater than 50 msec, computed over the entire ECG recording.
r-MSSD (msec). Square root of the mean of the sum of the squares of differences between adjacent normal RR intervals over the entire ECG recording

$$rMSSD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n-1}(NN_{i+1} - NN_i)^2}, \tag{3}$$

where NN_i is the duration of thei_{th}NN interval in the analyzed ECG andn is the number of all NN intervals.

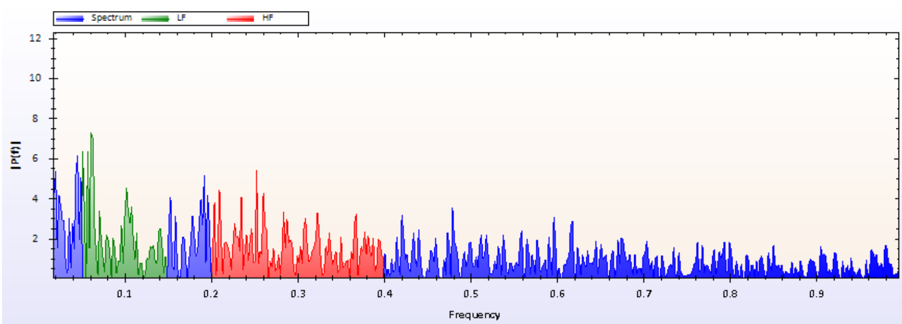

Fig. 3. The spectrum of HRV and the extracted Low–Frequency band (LF) and High–Frequency band (HF)

Regarding the frequency domain features, the main features involve sub-band powers. More specifically, the two bands that were utilized in the analysis are (Fig. 3):

The *Low–Frequency band* (LF), which includes frequencies in the area [0.03 – 0.15] Hz, the *High–Frequency band* (HF), which includes frequencies in the area [0.15 – 0.40] Hz and the ratio *LF/HF* is also utilized.

From the Respiration signal the more diagnostic features that have been extracted are:

Respiration Rate – The number of breaths per minute determined by the identification of the peaks of the respiration signal as displayed in Fig. 4.

Tidal Volume (VT). The normal volume of the air inhaled after an exhalation.

Vital capacity (VC). The volume of a full expiration. This metric depends on the size of the lungs, elasticity, integrity of the airways and other parameters.

Residual volume (VR). The volume that remains in the lungs following maximum exhalation.

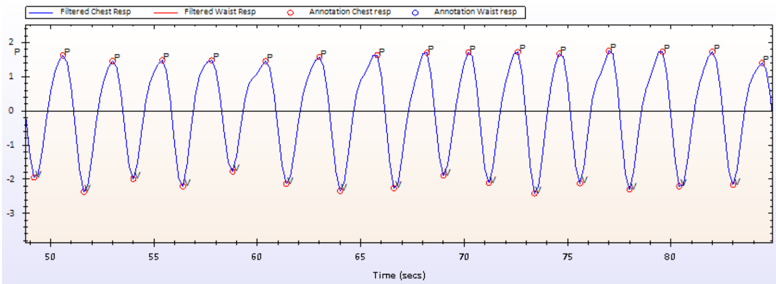

Fig. 4. Identification of the respiration signal peaks

3.2 Intelligent System

The DSS operates on demand, being triggered either by the Stand-by end mode Module, located at DH or by an internal clock a couple of times per day. Afterwards, the data are processed by an expert rule-based system and a supervised classification system running in parallel. The rule-based system is being used to make a first categorization of the nature of the severity of the episode and accompanies the output of the classifier in order to give an explanation of the severity assessment. On the other hand, the supervised classifier is being trained only during the training phase (once) and evaluates the severity of the identified episode. During this (training) session, clinicians identify different values of severity and mark the thresholds that divide the five layers of abnormality. Several patients, belonging to different staging classes and disease levels, are used at this training phase in order to acquire more data, track more abnormal events and improve the accuracy of categorization system by succeeding more precision in severity levels division.

At a second stage, after data have been mined, the Severity Estimation Module is being triggered, using simple if-then rules, in order to classify the decision of Decision Support Component and corresponding that with the respective action. These rules correlate the output of DSS with pre-specified thresholds, which have been indicated by clinicians and stored at CHRONIOUS repository.

An add-on value to CHRONIOUS Intelligence is the Mental Support Tool, where a stress index parameter is being calculated using a rule-based system. These rules have been formed after cooperation with clinicians in order to have clinical justification and physical meaning in real life scenarios. According to identified stress levels, there have been indicated four levels of stress: Normal, Mild, Moderate and Severe. In addition, the system provides to the patient the appropriate feedback (advice/alert) to assist him/her to overcome his/her stressful situation.

3.3 Applied Protocol and Classification Methods

Two healthy volunteers were recruited to the breath-down protocol based on the University of California, Institutional Review Board (UCSF-IRB) regulations [7]. Informed consent was obtained from volunteers prior to study commencement. The initial dataset is split to 11 instances with an applied time window and the 10 folds cross-validation method is used for testing.

Several algorithms have been utilized for the classification procedure. Mainly decision trees [8] have been explored since can classify both categorical and numerical data and are easy to understand which is crucial for the initial validation of the system. PARtial decision Trees [9]creates rules by repeatedly generating partial decision trees and builds a rule, while the J48 [8] algorithm generates a classification–decision tree for the given dataset by recursive partitioning of data. The Random tree [10] is a tree drawn at random from a set of possible trees and Naïve Bayes [11]is a simple probabilistic classifier.A multilayer perceptron (MLP) [12] is a feed-forward aNN model that consists of multiple layers of nodes in a directed graph. Due to the preliminary phase of the analysis and the small amount of collected data, the aNN has one hidden layer that isn't properly trained. Finally, Support Vector Machines (SVM) [13] have been developed and used for the classification system, but their proper training is still pending since the collected data aren't enough.

A preliminary implementation of the several supervised classifiers that are used for the initial analysis has been performed, but their performance isn't the same with the final that will conclude after the collection of more healthy and pathological data as well as after the annotation of the collected data by the clinicians. The mean absolute error will decrease drastically after the proper training of the classifiers and the re-adjustment of the attributes' weights.

4 Conclusions

The CHRONIOUS system exploits innovative IT solutions providing effective description of the health status of the patient as well as advanced messages and alerts about the severity estimation of the condition or possible critical health episodes. The Decision Support System exploits both a supervised classifier and a rule-based system in order to limit the error of the decision, increase the accuracy of the system and justify the identified events by providing the rule or the critical parameter to clinicians. A personalization of the decision is even more feasible with the CHRONIOUS system due to the fact that several profiles have been created, describing with accuracy the health status of the patient, and used as an input to the intelligent part of the System. In addition, the Mental Support Tool is an added-value to the final system, evaluating the stress level and contributing to disease monitoring by helping the patient to avoid or face stressful situations that may have implications to his health.

In order to increase the effectiveness and the accuracy of the CHRONIOUS system, healthy and pathological data will be collected as well as their clinical annotation resulting in the improvement of the accuracy of the system.

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