The HTP Tool: Monitoring, Detecting and Predicting Hypotensive Episodes in Critical Care

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Abstract—**The sudden fall of blood pressure (hypotension - HT) is a common complication in medical care. In critical care patients, HT may cause serious neurological, heart, or endocrine disorders, inducing severe or even lethal events. Recent studies report an increase of mortality in HT prone hemodialysis patients in need of critical care. Predicting HT episodes in advance is crucial to enable medical staff to minimize its effects or even avoid its occurrence. Most medical systems have focused on monitoring and detecting current patient status, rather than determining biosignal trends or predicting the patient's future status. Therefore, predicting HT episodes in advance remains a challenge. In this paper, we present a solution for continuous monitoring and efficient prediction of HT episodes. We propose an architecture for a HT Predictor (HTP) Tool, capable of continuously storing and real-time monitoring all patient's heart rate and blood pressure biosignal data, alerting probable occurrences of each patient's HT episodes for the following 60 minutes, based on non-invasive hemodynamic variables. Our system also promotes medical staff mobility, taking advantage of using mobile personal devices such as cell phones and PDA's. An experimental evaluation on real-life data from the well-known Physionet database shows the tool's efficiency, outperforming the winning proposal of the Physionet 2009 Challenge.**

Keywords: Intelligent medical care systems; Biosignals analysis and processing; Hypotension detection and prediction.

I. INTRODUCTION

Blood pressure (BP) is the force exerted by circulating blood on the walls of blood vessels, being one of life's main vital signs. BP is generated by the heart when it pumps blood into the arteries, and is regulated by the response given by the arteries to the blood flow. Hypotension (HT) occurs when there is an abrupt fall of BP leading to below normal values, causing several symptoms. When the blood flow is too low to deliver enough oxygen and nutrients to vital organs such as the brain, heart, and kidney, they do not function properly and may get permanently damaged. HT is a common complication in patients in need of critical care actions such as hemodialysis. This type of treatment is accompanied by a wide variety of complications. Despite all technical improvements, the most frequent complication in hemodialysis is intradialytic HT (IDHT), occurring in 20% of dialysis sessions, on average [9]. IDHT occurs when the biological compensatory mechanisms cannot cope with the removal of intravascular fluid in a short period of time, in a specific patient. Negative effects of IDHT are patient's discomfort and decrease of hemodialysis efficacy due to the interruption of dialysis and need for intravenous infusions. IDHT can induce other severe complications such as serious heart, endocrine or neurological disorders and can even lead to death. Moreover, a recent study reports the increase of mortality in HT prone hemodialysis patients [6]. Therefore, reducing HT episodes in such patients remains a challenge. Most medical systems store biosignal data for a short time, in order to monitor the patient's most recent vital signs, and usually do not forecast or alert about a patient's predictable hazardous situation [1]. Therefore, current medical systems are typically focused on detecting the current health status of a certain number of vital signs, rather than attempting to predict near future trends. Thus, current standard methods are mainly centered on feature detection rather than feature prediction.

The Physionet Challenge 2009 [5] promoted solutions for predicting HT patient status. The paper in [4], using a neural network approach, was the winner, scoring 47 correct predictions out of 50 for the whole event. Our work continues the former research and proposes a full HT monitoring, detecting and predicting medical care system. Our proposal allows medical staff to continue carrying out their daily tasks without needing to stare at a monitor for continuous patient surveillance, because we provide applications able to run on a mobile phone or PDA, issuing a real-time alert when a HT episode is detected or predicted. As shown in Section IV, our proposal was highly efficient, showing an accuracy of 98% in HT prediction, scoring 49 out of 50 for the 2009 challenge.

The remainder of this paper is organized as follows. In Section II, we present the tool's architecture and explain how it works. In Section III we explain our HT detection/prediction methods. In Section IV we present an experimental evaluation using Physionet Challenge 2009 [5] biological datasets. Finally, Section V presents our conclusions and future work.

II. THE HTP TOOL SYSTEM

The architecture of the *HTP Tool* is shown in figure 1. The *Biosignal Acquisition Machinery (BAM)* represents all the equipment connected to patients for acquiring their main blood pressure (BP) and heart rate (HR) values (in Section III we shall explain our HT prediction methods, showing why we require both HR and BP biosignals). *BAM* are standard existing medical equipment, capable of continuously acquiring common patient biosignals such as BP and HR.

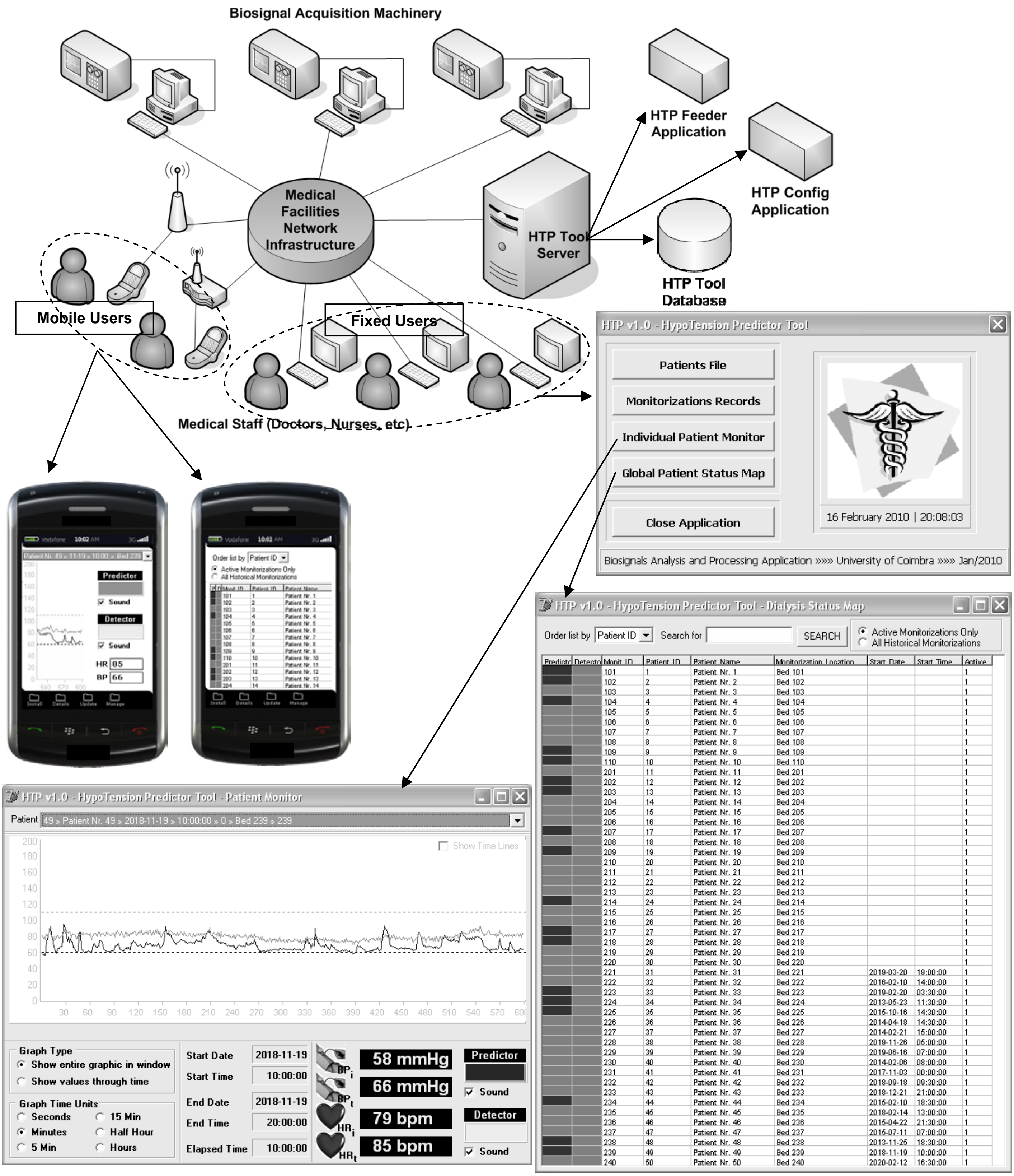

Figure 1. The HTP Tool Architecture. The medical staff group using fixed PC's to perform patient monitorization is shown detached from the medical staff group using mobile devices. This is because the fixed PC's use different HTP Tool interfaces, as shown on the right and lower parts of the page, while mobile users are given access to interfaces as can be seen in the Personal Digital Assistant (PDA) figures. The interfaces show the Patient Monitor (which shows individual status for each patient) and the Global Patient Status Map (which allows real-time monitoring of all patients under surveillance).

This equipment produce standard ASCII text files with the acquired biosignals data, or output similar files to personal computers (PCs) to which they are attached. They are properly and promptly configured and initiated by medical staff at the start of each monitorization. Therefore, the acquisition of patient biosignals is assured by the *BAM*, not posing itself as an issue in this paper. Each *BAM* text file holds the respective patient's (BP, HR) measured values, which are sequentially appended to the file. These text files will be moved as frequently as possible to the *HTP Tool Server* by a server application running on it, named *HTP Feeder*. The *HTP Feeder* acts as a data server, being responsible for periodically (typically, every 60 seconds) looking up the *HTP Tool Database (HTP DB)* for querying active patient monitorizations and then checking if there are any new BP or HR files created by the *BAM* for those monitorizations. If there are new files, the *HTP Feeder* will load their data into the *HTP DB*, which is also hosted on the *HTP Tool Server*. After completing each file load, the *HTP Feeder* erases that file and runs the HT prediction/detection algorithms for updating the *PatientsStatus* table. If there is no new file to load, the *HTP Feeder* just waits until it is time to check for new files again. The *HTP DB* was designed for storing all monitorizations' data of all patients analyzed by the *HTP Tool*. We define a monitorization as an event where one patient is accommodated to get connected to a biosignal acquisition gear in order to be watched over by medical staff. A monitorization concerns one monitoring action of one patient only. All monitorizations are kept in the *HTP DB*. The database has the following tables:

Table *Monitorizations* stores the information for each monitorization. It records the monitoring start and finish date and time, as well as patient's location. It also has an attribute for checking if the monitorization is still currently occurring or has already finished. This table also contains information about the path and filenames where the *BAM* will create and append the BP and HR values acquired from the patient throughout the monitorization procedures, so *HTP Feeder* can withdraw them;

Tables *MonitorBP* and *MonitorHR* are filled up by the *HTP Feeder*, storing all BP and HR values, respectively, for each monitorization. When the *HTP Feeder* loads new data into these tables, each value is calculated to its true value, based on data transformation specifications (base and gain) given by the *BAM*. Data filtering actions execute as follows: if there are missing values or calculations leading to abnormal values (<=40 or >=180), the last accepted written value is assigned;

Table *PatientsStatus* holds the current HT predictor and detector status for each patient being monitored. This table is queried by the monitorization interfaces for issuing real-time alerts whenever a HT episode is forecasted or detected. Whenever a new monitorization starts, a new record is created;

Table *Patients*, which is just a common patient data file containing each patient's name, birth date, height, weight and clinical conditions (diabetes, hepatitus, heart condition diseases, etc) relevant for aiding clinical decision making;

Table *FeederCfg*, used for defining the variables for the *HTP Feeder* data loading procedures, such as the timespan between new data loads, file reading timeouts and a flag variable to indicate if the *HTP Feeder* is currently loading data or not. The *HTP Config* application allows defining the *HTP Feeder*'s variables in table *FeederCfg*.

The *HTP Server* provides interfaces to medical staff through fixed devices (such as PCs) and mobile devices (such as cell phones or PDAs with web browsing means). The main interfaces, shown in figure 1, are for monitoring an individual patient (*Patient Monitor*) or all patients under surveillance (*Global Patient Status Map*). Both types of interfaces issue alerts when forecasting a HT episode in the following 60 minutes, or when detecting a HT episode.

III. THE HYPOTENSION DETECTION/PREDICTION METHODS

HT detection has been dealt with in [7, 8]. As stated earlier, this work continues former research focusing on HT prediction. After thoroughly analyzing research on HT in critical care [2, 3, 4, 7, 8, 9, 10], we have concluded that HR plays a key role. Thus, we assume BP and HR as the most relevant variables for predicting HT. Cardiac adjustment (CA) (which increases HR for rising BP by increasing blood flow) is referred common in the studied HT cases in that research. We concluded that each patient's initial HR value (referred to from this point forward as HR_0) is relevant for determining the patient heart's ability to perform a cardiac adjustment whenever BP pressure falls. After thoroughly analyzing the data referring to groups of HT and non-HT patients presented in the mentioned research work, we have concluded that when a patient's heart is capable of rising its HR at least 20% its initial HR_0 value, it is likely to avoid the sudden fall of BP values into HT situations. We have also verified that near future values of BP depend on most recent past values of BP, matching linearity representations when the timespan of analysis is short (<=60 minutes). Therefore, the most important functions needed for predicting a patient's HT status for the following 60 minutes at a moment in time T_i, are:

1) The HR trend since moment T_0 up to T_i, for predicting what will probably be the patient's HR for the next 60 minutes (T_{i+60}), to see if his global HR is capable of avoiding BP values falling below standard HT values, due to CA (given that if $HR(T_{i+60}) >= HR(T_0) \times 120\%$, HT is avoided); and

2) The trend of BP given the patient's BP values for the previous 60 minutes from T_i (T_{i-60}), in order to determine the probable value of BP for the following 60 minutes (T_{i+60}) (given that if the majority of the predictable BP values between T_i and T_{i+60} are below 70 mmHg, a HT episode will probably take place).

To determine both HR and BP trends, we use linear regression. Consider figure 2, showing 10 hours (600 minutes) of a patient's BP and HR data.

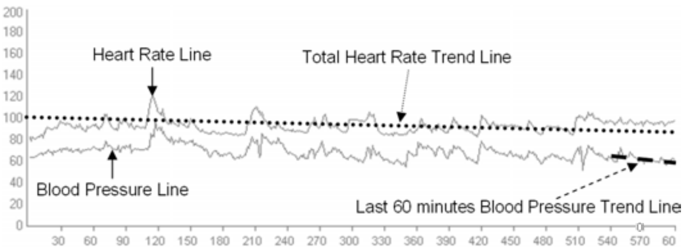

Figure 2. BP and HR analysis graphic for the HT prediction method

The timeline is on the *xx* axis, in minutes. The *yy* axis shows the patient's BP and HR absolute values. Supposing we want to predict the patient's status between minute 600 and

660, our HT predictor determines two trends: the HR biosignal trend (y_{HR}), from the beginning (minute 0 = T_0) up to the current moment (minute 600 = T_{600}), shown in the figure by a thick dark dotted line; and the BP biosignal trend (y_{BP}), from the last 60 minutes (from minute 540 to 600 = T_{540} to T_{600}), shown in the figure as a thick dark slashed line. To determine those trends at the moment where the HT status is to be predicted (minute 600), we use mathematical linear equations:

$$y_{HR(T0-T600)} = a_{HR(T0-T600)} + b_{HR(T0-T600)} * x$$
$$y_{BP(T540-T600)} = a_{BP(T540-T600)} + b_{BP(T540-T600)} * x$$

Determining the values of $a_{HR(T0-T600)}$, $b_{HR(T0-T600)}$, $a_{BP(T540-T600)}$ and $b_{BP(T540-T600)}$ by linear regression, we are able to predict the future values of y_{HR} and y_{BP}. To predict if a HT episode will probably occur, we use the condition:

$$\text{IF } y_{BP(630)} \text{ <= 70 AND } y_{HR(660)} \text{ <= } y_{HR(0)} \text{ * 120\%}$$
$$\text{THEN HypotensionPredicted = TRUE}$$
$$\text{ELSE HypotensionPredicted = FALSE}$$

We use the middle time value (minute 630) for BP, because if this value is equal or lesser than 70, we can state that at least half the values between minute 600 and 660 on that linear regression are also equal or lesser than 70 within that timespan.

IV. Experimental Evaluation

A prototype for the HTP tool was built using Delphi and Java for building a software suite with four applications: *HTP Feeder*, *HTP Config*, *HTP Front* and *HTP Web*. The first two were explained in section II. *HTP Front* and *HTP Web* act as medical staff front end applications, for fixed and mobile users, respectively, and are illustrated in figure 1. A standard commodity PC and a common PDA were used for testing the *HTP Front* and *HTP Web* applications, respectively. We used *HTP Feeder* for loading the Physionet Challenge 2009 ATM datasets [5], implementing the database on MySQL Server 5 in a Pentium IV 3.0GHz CPU with 2GB RAM and a 250GB SATA hard drive. These datasets consist on 10 hours of BP and HR data, sampled at one record of each biosignal per second per patient, resulting in 1,800,000 biosignal *MonitorBP* and *MonitorHR* rows, concerning 50 patients.

We simulated a real-life situation in which all 50 patients were being monitored at the same time. Consequently, each BP and HR value for each patient was generated per second and sequentially appended in a flat text file for the *HTP Feeder* to acquire. The *HTP Feeder* was configured to check for new files every 30 seconds. Therefore, an average of 30 BP values of plus 30 HR values for each patient, in 50 files, were acquired and loaded into the database, every 30 seconds. The system worked well with this setup, lacking performance bottlenecks in data loading, monitorization, and HT prediction and detection procedures. The *Individual Patient Monitor* interface for patient Nr. 49, bed 239 (patient 239 in [5]) is shown in figure 1. As can be seen, the predictor alert (on the bottom right of the interface) turned red (dark colour), alerting a probable HT episode in the following hour, which is proven to be true. Besides HT prediction and detection indicators, the individual patient monitor shows the graphic of both HR and mean BP biosignals, indicating the initial and current value of each signal for the patient to it refers. In figure 1 the *Global Patient Status Map* can also be seen, showing the status for all the Challenge's patients, where darker colors represent the prediction of HT episodes. The purpose of this interface is to allow medical staff to surveille all patients currently monitorized, simultaneously, functioning as a HT alert board.

All interfaces act as means for online real-time patient surveillance, even when medical staff is absent or on the move. Observing figure 1 and consulting the Physionet Challenge's documentation, it can be seen that our solution scores 49 out of the 50 Challenge cases, achieving an efficiency of 98% on correctly predicted HT and non-HT episodes. The only failure, by the Challenge's results, concerns patient Nr. 32 (patient 222 in [5]), which had a HT episode, but has BP and HR values that contradict our HT prediction algorithm. These are even better results than the Challenge's winner [4].

V. Conclusions and Future Work

Regarding efficient real-time biosignal data integration, we present a real-time database for storing all patient's BP and HR data, working with a set of applications capable of continuously monitoring each patient's status and efficiently predicting if a HT episode will occur during the next 60 minutes. It enables medical staff mobility by taking advantage of using personal mobile devices, such as cell phones and PDA's. Experimental results demonstrate a high efficiency rate in HT forecasting, making it a promising overall solution in the field. As future work, performance issues on scalability and data throughput, as well as the prediction algorithm's efficiency, need to be tested in real-life scenarios with the monitorization of a couple hundred patients on middle or large-scale medical facilities. Strategies and mechanisms for data security should also be proposed.

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