A 24/7 Monitorization Tool for Avoiding Hypotensive Episodes in Critical Care

Ricardo Jorge Santos
CISUC – DEI – FCTUC
University of Coimbra
3030-290 Coimbra – Portugal
lionsoftware.ricardo@gmail.com

Jorge Bernardino
CISUC – ISEC – IPC
Polytechnic Institute of Coimbra
3030-199 Coimbra – Portugal
jorge@isec.pt

Jorge Henriques
CISUC – DEI – FCTUC
University of Coimbra
3030-290 Coimbra – Portugal
jh@dei.uc.pt

ABSTRACT
The sudden fall of blood pressure (hypotension) is a common complication in medical care. In critical care patients, hypotension (HT) may cause serious heart, endocrine or neurological disorders, inducing severe or even lethal events. Moreover, recent studies report an increase of mortality in HT prone hemodialysis patients in need of critical care. If HT could be predicted in advance, medical staff could take action to minimize its effects, or even avoid its occurrence. Typically, most medical systems have focused on monitoring and detecting current patient status, rather than determining biosignal trends or predicting a patient's future status. Therefore, predicting HT episodes in advance remains a challenge. Furthermore, since critical care actions such as hemodialysis are oftenly inconvenient and uncomfortable procedures, HT prediction or detection methods should be non-invasive, whenever possible. In this paper, we present a solution for continuous monitorization and prediction of HT episodes, using heart rate (HR) and mean blood pressure (BP) non-invasive measured biosignals. We propose an architecture for a HT Predictor (HTP) Tool, presenting a set of tools and a real-time database capable of continuously storing and real-time monitoring all patient's historical HR and BP biosignal data, and efficiently alerting both probable and detected occurrences of HT episodes for each patient for the following 60 minutes. Additionally, the system promotes medical staff mobility, by taking advantage of using mobile personal devices such as mobile phones and PDA's, optimizing human resources. Finally, an experimental evaluation on real-life data from the well known Physionet database shows the efficiency of the tool, outperforming the winning proposal of the Physionet 2009 Challenge.

Keywords
Hypotension detection and prediction, medical care systems and applications, biosignals analysis and processing.

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1. INTRODUCTION
Blood pressure (BP) is the force exerted by circulating blood on the walls of blood vessels, and is 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 arteries to the flow of blood. Hypotension (HT) occurs when there is an abrupt fall of BP leading to below normal values, so low it causes symptoms or signs due to the low flow of blood through the arteries and veins. 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 normally and can get permanently damaged. Hypotension is classified as a common complication in patients with critical care needs, such as hemodialysis [2]. Hemodialysis is the combination of ultrafiltration of fluid excess and the clearance of solute waste products such as urea by diffusion. This treatment is accompanied by a wide variety of complications. Despite all technical improvements, the most frequent complication is intradialytic hypotension (IDHT), occurring in up to 20% of dialysis sessions [16]. IDHT occurs when our normal 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 the patient's discomfort and decrease of hemodialysis efficacy due to interventions such as interruption of dialysis and the need for intravenous infusions. IDHT can induce other severe complications such as serious heart, endocrine or neurological and can even lead to the patient's death. Moreover, a recent study reports an increase of mortality in HT prone hemodialysis patients [13]. Therefore, reducing HT episodes in critical care patients remains a challenge.

Typically, 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 issue an alert concerning a patient's predictable hazardous situation [1]. Therefore, most medical systems are typically focused on detecting the current health status of a certain number of vital signs, rather than attempting to predict immediate future trends on any of those features. Thus, standard methods are mainly centred on feature detection rather than feature prediction.

The main issues concerning useful time prediction and detection of HT episodes evolve around two main aspects: 1) How can we efficiently store the biosignal data that is needed in a continuous manner and enable real-time hypotension monitorization and prediction; and 2) Which are the algorithms to be used for efficient hypotension detection and prediction. The Physionet Challenge 2009 [10] promoted solutions for predicting HT patient status. The paper [7], using a neural network approach, was the challenge's winner, scoring 47 correct predictions out of 50 for the whole event. Our work continues the former research, proposing a full HT monitoring, detecting and predicting medical care system that also promotes medical staff mobility. Regarding efficient real-time biosignal data integration, we present a database for storing all patients BP and heart rate (HR) data. Using this data, we have developed a new HT prediction technique, working with a set of applications capable of monitoring each patient's status and efficiently predicting if a hypotensive episode will occur during the next 60 minutes.

Our proposal allows medical staff to continue carrying out their daily tasks without needing to remain staring a fixed monitor for continuously watching over a patient, because we provide applications able to run on a mobile phone or PDA, issuing a real-time alert every time a hypotensive episode is detected or predicted. This enables continuously monitoring the status of a patient at all times (on a 24/7 schedule) without needing to be physically present, promoting medical staff mobility and allowing them to continue carrying out their work unrestrained by patient critical situations, therefore optimizing technical human resources. As we demonstrate in the experimental evaluation section, the used methods were highly efficient, showing an accuracy of 98% in HT prediction, scoring 49 out of 50 cases of the Physionet Challenge 2009. The database and software prototype built for testing and evaluating our findings was developed in order to validate our hypotension prediction techniques and the system's overall feasibility. The system is therefore in an early stage of its development. At this stage, issues concerning database optimization, data privacy/security and backup strategies have not been addressed, and are beyond the scope of this paper.

The remainder of the paper is organized as follows: in section 2 we present related work in research focusing on both medical systems and detecting and/or predicting HT. In section 3 we explain the HTP Tool's architecture, describing its database and software applications. Section 4 illustrates our HT prediction methods. In section 5 we present an experimental evaluation of our solution and the final section contains conclusions and future work.

2. RELATED WORK

The work presented in [1] presents a solution for a portable telemedicine system for high risk cardiac patients, using bluetooth technology and mobile phones. The system allows transmitting the acquired ECG signal from a patient and transmitting it to a doctor's mobile phone. It also has a microcontroller that will notify the doctor on the patient's panic situations concerning irregular heart beating. This proposal seems an interesting patient heart status detection system. However, it does not achieve anything concerning heart status prediction, and is therefore incapable of issuing early warnings.

Research presented in [16] is an excellent compendium on HT during hemodialysis using non-invasive monitoring of hemodynamic variables. This work illustrates a series of real-life situations and analysis on various sets of hemodialysis patients. The main conclusions are that measuring dry weight and hematrocits during hemodialysis seem irrelevant for assessing HT predictability. Contrarily, significant HR, cardiac output and stroke volume changes seem intimately linked with hypotensive episodes and allow distinguishing between the set of IDHT and non-IDHT patients, along with BP measurements. Using cardiac output, stroke volume and HR, the author presents Systemic Vascular Resistance (SVR), which seems to be the best variable for predicting IDHT. SVR is calculated using the Kubicek formula [19], measuring cardiac output and stroke volume through impedance cardiography methods [11, 17, 18]. In this study, all IDHT patients showed an average decrease in SVR values during hemodialysis, while non-IDHT patients SVR values tend to increase. However, this is a specific hemodialysis feature and there is no evidence that it should be applied to generic HT episodes. Therefore, we shall not use SVR as a variable for our HT prediction methods, although it seems to deserve full attention if the purpose is to build an IDHT prediction system.

Stroke volume appears highly correlated to left ventricular resynchronization in heart failure, explored in [4]. Taking stroke volume as an important variable for HT prediction leads us to conclude that HR plays a key role. This idea has been reforced by [3], in which a telecardiology framework for providing clinical decision support is presented, showing an application of the study of HR variability during hemodialysis. This is also supported by [14, 15], where HT detection algorithms based on HR variability and ectopic beats are developed using the ECG. These frameworks are used for patient monitoring purposes only, not for prediction. The work in [12] states that the most significant predictive factors in their study were the pre-hemodialysis HR, i.e, the initial HR for each patient before starting hemodialysis. Thus, BP and HR monitoring seem to be the most relevant non-invasive variables that could be used for detecting/predicting hypotensive episodes.

The 2009 challenge presented by the well known Physionet web site [8, 9] promoted the appearance of solutions for predicting patient status in what concerns hypotension. The most relevant published solutions were [6, 7]. Both proposals use only patient BP values to predict if a hypotensive episode will occur in the following 60 minutes. The paper [7], using a neural network approach, was the challenge's winner, scoring 47 correct predictions out of 50 for the whole event. Our work continues the former research and proposes a complete HT monitoring, detecting and predicting medical care system, while enabling medical staff mobility.

3. THE HYPOTENSION PREDICTOR (HTP) SYSTEM

The architecture of the HTP Tool System is shown in figure 1. The *Biosignal Acquisition Machinery (BAM)* represents all the equipment connected to patients for acquiring their BP (mean blood pressure) and HR (heart rate) values (in section 4 we shall explain our HT predictions methods, showing why we require both BP and HR biosignals). *BAM* represent common standard existing medical equipment, capable of continuously acquiring common patient biosignals such as BP and HR. This equipment, is also capable of producing standard ASCII text files with the acquired biosignals data by itself, or output similar files to personal computers (PC) to which they are attached. Therefore, the acquisition of patient biosignals is guaranteed by the *BAM*, not posing itself as an issue of discussion in this paper. Each *BAM* text file contain the respective patient's (BP, HR) value measurements, which are sequentially appended to the file.

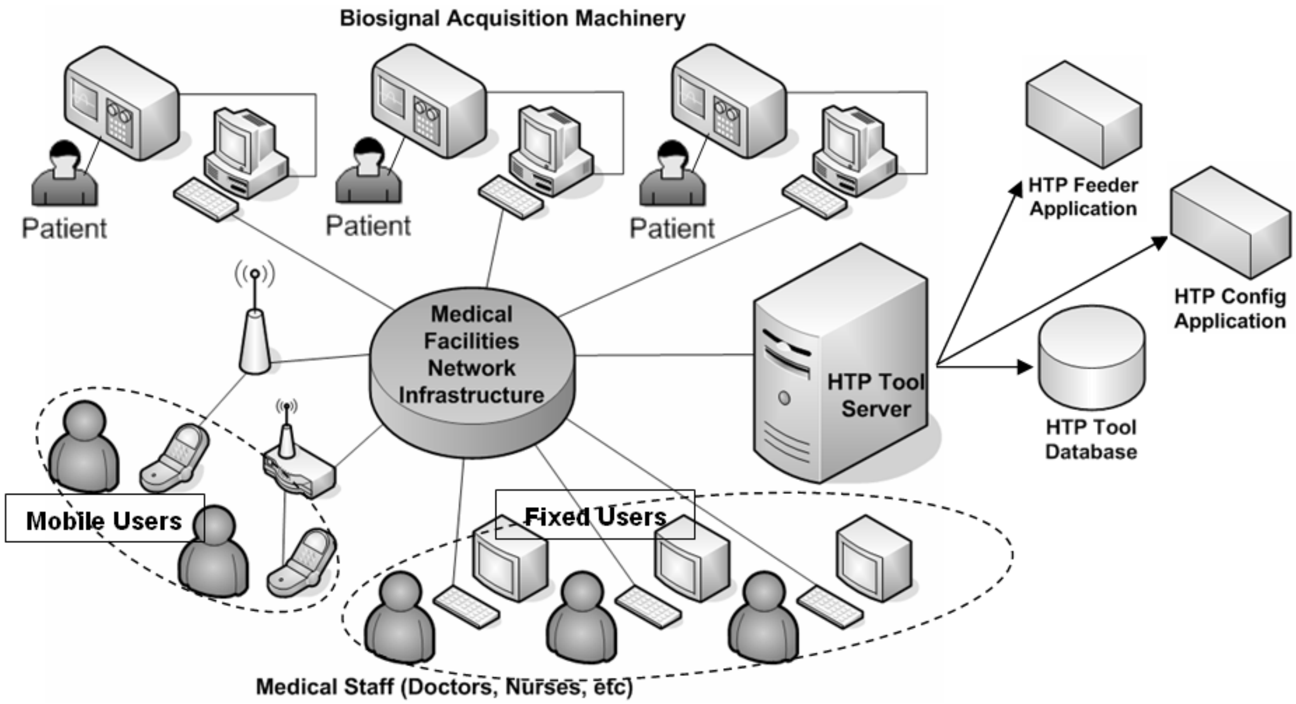

Figure 1. The HypoTension Predictor Tool System Architecture

These *BAM* text files contain the sequential BP will be moved as frequently as possible to the *HTP Tool Server* by a server application on it, named *HTP Feeder*. The *BAM* are operated by medical staff, for each patient's monitorization. This *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 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 `PatientStatus` table (which is responsible for keeping each monitored patient's HT detection and prediction status) in the *HTP DB*. If there is no new file to be loaded, the *HTP Feeder* just waits until it is time to check for new files again.

3.1 The HTP Tool Database

The HTP DB was designed for storing all monitorizations' data of all patients to be analyzed by the HTP Tool. Its schema is composed by a set of tables as shown in figure 2. 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 historically kept in the database.

Table `Monitorizations` contains the header information for each monitorization which is to be performed for each patient to be monitored by the *HTP Tool*. It contains a unique identifier for each patient monitorization (`M_MonitorID`), recording both the monitorization start and finish date and time (`M_StartDate`, `M_StartTime`, `M_EndDate`, and `M_EndTime`), as well as the patient's location (`M_Location`). Attribute `M_Active` acts as a flag variable, indicating if the monitorization is still currently occurring or has already finished, using `TRUE` or `FALSE` values, respectively. This table also contains the information concerning the path and filenames where the *BAM* will create and append the BP and HR values acquired from the patient throughout monitorization procedures (`M_BPFilePath`, `M_BPDataFile`, `M_BPInfoFile`, `M_HRFilePath`, `M_HRDataFile`, and `M_HRInfoFile`), so that the *HTP Feeder* application can withdraw them.

The `MonitorBP_*` and `MonitorHR_*` tables are responsible for storing all acquired BP and HR values, respectively, for each monitorization, where `*` represents the monitorization's unique ID (`M_MonitorID`). This means that each monitorization has its own BP and HR table, optimizing data access for each patient's monitorization. These are the tables loaded by the *HTP Feeder* application. When the *HTP Feeder* application loads new data into these tables, each value attribute which represents a value for the respective biosignals HR and BP is calculated in order to hold the true biosignal value, using data transformation specifications (base and gain) given by the *BAM*. The data filtering actions are performed as follows: if there are missing values or the calculations lead to abnormal values (lower than 40 or higher than 180), the last accepted written value is assigned.

Table `PatientStatus` holds the current HT predictor and detector status (attributes `HTS_Predicted` and `HTS_Detected`, respectively) for each active monitorization. This is the table queried by the monitorization interfaces (shown in the next subsection of the paper) for issuing real-time alerts whenever a HT episode is forecasted or detected. Whenever a new monitorization starts, a new record is created in this table. Attributes `HTS_Predicted` and `HTS_Detected` are `FALSE` by default, changing to TRUE whenever a HT episode is predicted or detected, respectively, in the concerning patient. When the monitorization of the patient finishes, the related record in PatientStatus is deleted.

Table Patients is just a common patient data file with fields containing information regarding each patient's name, birth date, height, weight and several clinical conditions (if they have diabetes, hepatitis, heart condition diseases, etc) relevant for aiding clinical decision making.

Tables FeederCfg is used for determining the variables for the *HTP Feeder* application 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 new data. Table FeederLog functions as a log for the data loading application, recording a row with the resume of each file loading accomplished by *HTP Feeder*. In the next subsection, we present the main interfaces of the *HTP Tool* applications and explain how they work.

3.2 The HTP Tool Applications

The *HTP Tool* software suite consists on four separate applications: *HTP Feeder*, *HTP Config*, *HTP Tool Front* and *HTP Web*. The first, as mentioned previously, acts as a data server and is responsible for periodically looking up the *HTP Tool Database* for querying which monitorizations are active (by selecting the rows in the Monitorizations table where M_Active is TRUE), and then checking to see if there are any new BP or HR files created by the *BAM*. The data loading time interval – for checking out for new BP or HR files to load every *N* seconds – is defined by the FC_LoadInterval attribute in the FeederCfg table. If there are new files available, the *HTP Feeder* will load their data into the respective MonitorBP and MonitorHR tables of the *HTP Tool Database*. The *HTP Config* application allows changing the values in table FeederCfg, which determines the *HTP Feeder* application parameters, as explained previously.

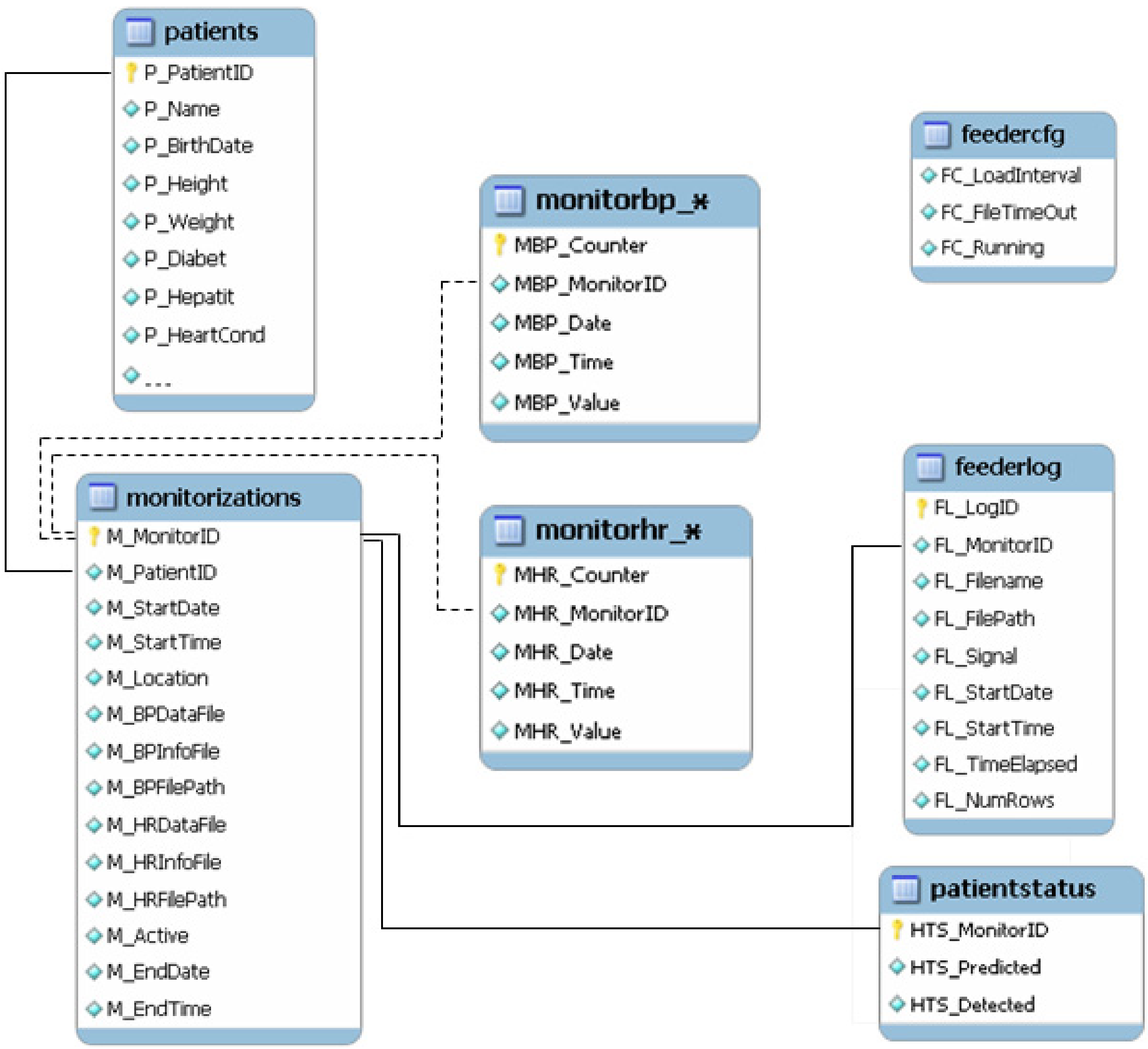

Figure 2. The HypoTension Predictor Tool Database Schema

An example of the *HTP Front* main menu interface is shown in figure 3. The *HTP Front* application will act as the front end of the system for fixed terminal surveillance, enabling all medical and support staff to manage all patients' data and their monitorizations. The first option – `Patients File` – allows managing patient records, according to table Patients in the *HTP Tool Database*. The second option – `Monitorizations Records` – allow managing monitorization records, according to table `Monitorizations` in the *HTP Tool Database*, including the initiation and termination of each monitorization. The third option – `Individual Patient Monitor` – provides an interface for individual patient monitorization, that allows monitoring each patient's current and historical BP and HR evolution and includes HT detection and prediction status indicators. An example of the `Individual Patient Monitor` interface is shown in figure 4. The fourth option – `Global Patient Status Map` – allows monitoring each patient's current HT detection and prediction status indicators, for all active monitored patients at once. The purpose of this interface is to allow medical staff to surveille all patient's currently being monitored, simultaneously, functioning as a HT alert board. An example of the `Global Patient Status Map` is shown in figure 7 (see section 5. Experimental Evaluation).

Finally, figure 5 shows the web based interfaces for the *HTP Web* applications, which are interface adaptations for using mobile personal devices to access the `Individual Patient Monitor` (on the left) and the `Global Patient Status Map` (on the right), for monitoring the same as on the fixed devices, but through web based features for mobile users.

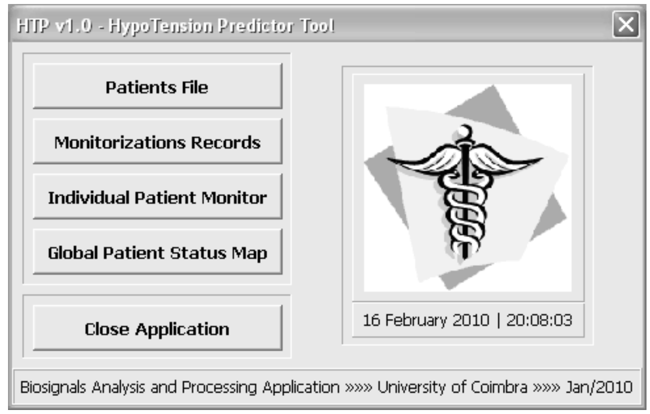

Figure 3. The HTP Front Application Main Menu Interface

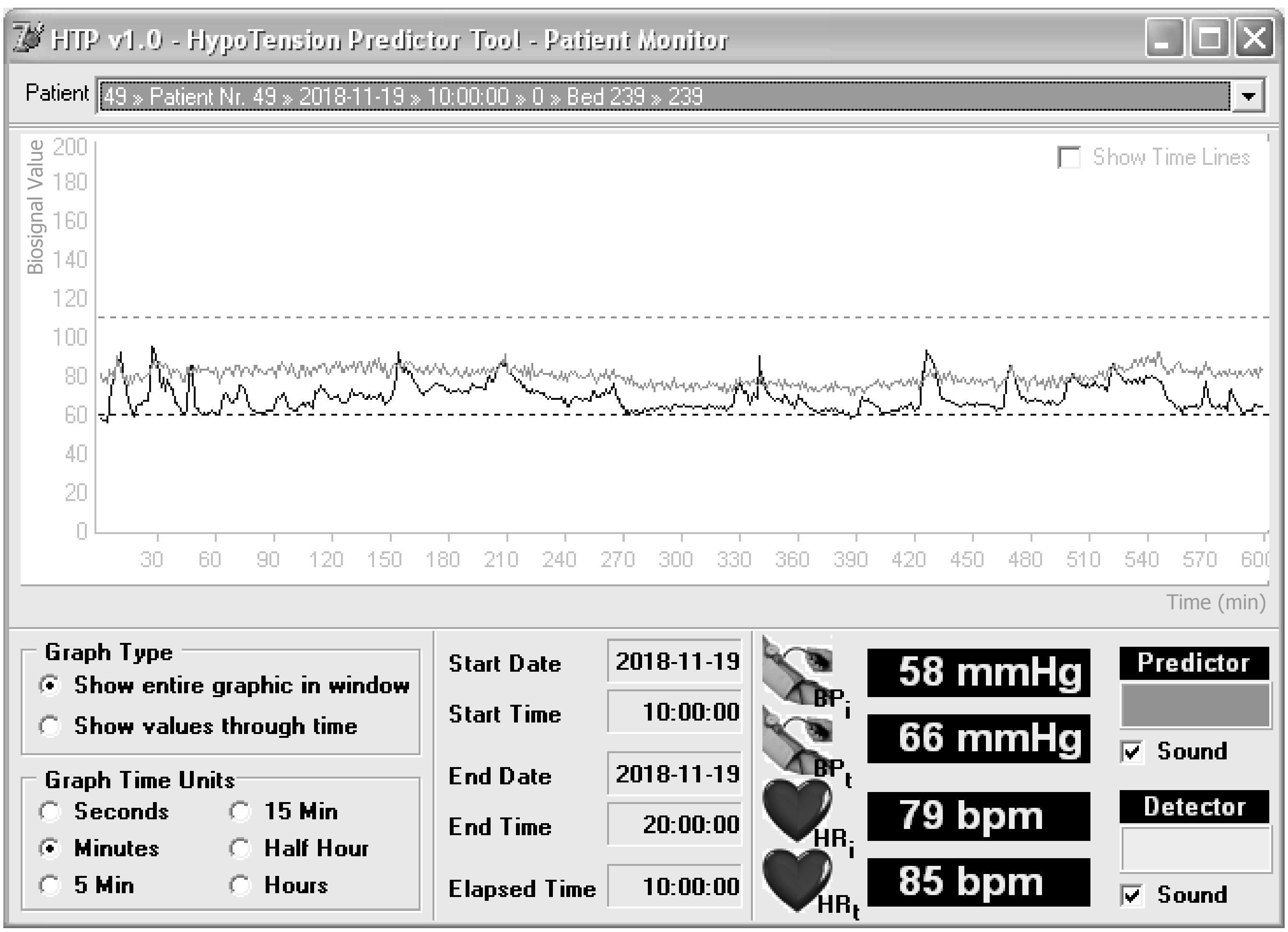

Figure 4. The HTP Front Individual Patient Monitoring Interface

Figure 5. The HTP Web Individual Patient Monitor and Global Patient Status Map Interfaces

4. HYPOTENSION DETECTION AND PREDICTION ALGORITHMS

Intradyalitic HT is defined as a symptomatic decrease of more than 30 mmHg in systolic blood pressure or as an absolute systolic BP under 90 mmHg [16]. Decades of research revealed that the cause of IDH is multifactorial. There is a difference in BP stability between isolated ultrafiltration and hemodialysis [5]. There are several mechanisms counteracting unbalanced events in our body, such as the consequent relative intravascular hypovolemia that can happen during a dialysis session, aiming to preserve adequate BP. Failure of these compensatory mechanisms leads to intradialytic hypotension. It is not in the scope of this paper to analyze the biological mechanisms involved in BP compensation in hemodialysis, such as capillary plasma refilling (which tries to compensate the gap from loss of water and solutes), systemic vascular resistance, etc. However, cardiac adjustment (which increases the heart rate in order to increase BP by increasing blood flow) is common for the hypotensive cases that have been presented, analyzed and referred to in the work mentioned in the previous section of this paper. As we mentioned in the former section, after carefully and extensively analysis on related state-of-the-art research work in this field and performing a series of analysis on real-life data, we found that the near future trend given by biosignals mean BP and HR are able to efficiently predict a hypotensive episode within the following 60 minutes. We shall now present the methods used for HT detection and prediction resulting from our study.

4.1 The Hypotension Detector

The features that characterize the occurrence of a hypotensive episode have been extensively studied and its standard definition is well accepted. Recent work has focused on early HT detection [14, 15], which displayed good results. Therefore, we are not concerned in improving HT detection methods. We have chosen a very simple HT detector, based on the Physionet Challenge 2009 [10], to be included in our system to work together with our HT prediction tool, just for proving that our predictor works. For purposes concerning the Physionet Challenge 2009, it is considered a hypotensive episode if at least 90% of the patient's mean blood pressure (MBP) values for the last 30 minutes are below or equal to 60 mmHg. Considering T_i the moment in time where we mean to detect if HT is occurring, if 90% of the patient's MBP values within the last 30 minutes of T_i are below or equal to 60 mmHg, HT is detected. This algorithm is executed once every minute for each patient (a minute of data latency is considered as sufficient by medical staff in HT monitoring and predicting purposes). In the next section we shall explain our hypotension predictor algorithm.

4.2 The Hypotension Predictor

After carefully analyzing recent research about HT in critical care [3, 6, 14, 15, 16], we concluded that HR plays a key role. Thus, we take BP and HR as the most relevant non-invasive variables for predicting HT. Cardiac adjustment (which increases the HR in order to increase BP by increasing blood flow) is common for the HT cases that have been analyzed and referred to in the mentioned research work. We have concluded that knowing HR tendency can indeed play a significant role in this matter. Based on the work in [12], we concluded that each patient's initial HR value (referred to from this point forward as HR_0) is relevant and important 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 confirmed that future values of BP depend on the most recent past values of BP, concluding that these values match linearity representations when the timespan of analysis is short (equal or less than 60 minutes). Therefore, the functions for predicting a patient's HT status for the following 60 minutes at a moment in time T_i, are:

1) The trend of HR since moment T_0 up to T_i, for predicting the probable values of the patient's HR for the following 60 minutes (T_{i+60}), in order to see if the patient's global HR is capable of avoiding BP values to fall below standard HT values, due to cardiac adjustment (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 values of BP for the following 60 minutes (T_{i+60}) (given that if the majority of the predicted 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. As an example to illustrate our HT prediction method, consider figure 6, showing 10 hours (600 minutes) of a patient's BP and HR data, where BP is the lower continuous line in the graph and HR is shown as the upper continuous line.

The timeline is on the *xx* axis, in minutes. The *yy* axis is used for the absolute values of the patient's BP and HR. Supposing we intend to predict the patient's status for the following 60 minutes, i.e., between minute 600 and 660, our HT predictor determines the two trends: the HR biosignal trend (y_{HR}), from the beginning of the monitorization (minute $0 = T_0$) up to the current moment (minute $600 = T_{600}$), represented 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 the analytical expression of those trends at the moment where the HT status is to be predicted (minute 600), we use the mathematical linear equations (where x represents time):

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

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}. Recurring to the values in the dataset 101bn for patient 101 from the Physionet Challenge 2009 database as an example, we determined the following values for minute 600, using linear regression for calculating the a and b coeficients:

$$a_{HR(0-600)} = 91,24$$
$$b_{HR(0-600)} = 0,000058$$
$$a_{BP(540-600)} = 109,15$$
$$b_{BP(540-600)} = -0,0014$$

Using the linear equations, the expected values for HR at minute 660 (60 minutes after the current moment – minute 600), and BP at minute 630 (half way in the 60 minute timespan) can be obtained by calculus:

$$y_{HR(660)} = 91,24 + 0,000058 * 660 * 60 = 93,54$$

$$y_{BP(630)} = 109,15 - 0,0014 * 630 * 60 = 53,71$$

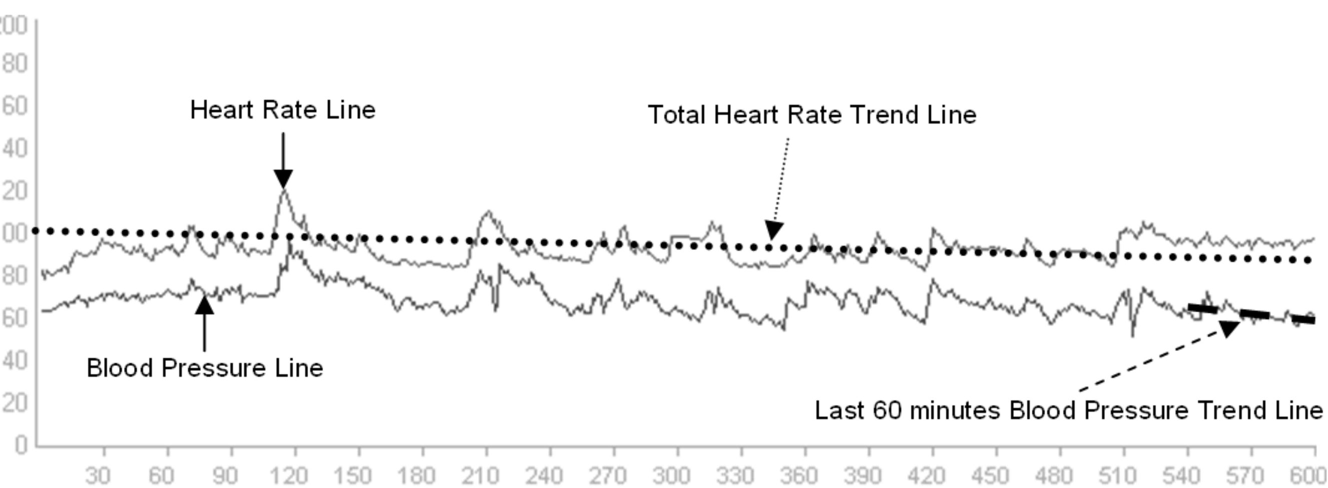

Figure 6. A Blood Pressure and Heart Rate Graphic for illustrating the HT Prediction Method

To predict if this patient will be having a hypotensive episode, we use the condition:

```
IF yBP(630) <= 70 AND yHR(660) <= 110
   THEN HypotensionPredicted = TRUE
   ELSE HypotensionPredicted = FALSE
```

We use the middle time value between minute 600 and 660 (minute 630) calculus 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 period of time. Applying the estimated values of $y_{HR(660)}$ and $y_{BP(630)}$ to the predictor condition, it can be seen that patient 101 has a predicted hypotension status to occur between minute 600 and 660, what is in fact confirmed by the Physionet Challenge database in the testSetA 101cn data.

In the next section we present an experimental evaluation of our solution, demonstrating its efficiency rate.

5. EXPERIMENTAL EVALUATION

A prototype for the HTP Tool was built using Delphi and Java and implementing the database on MySQL Server 5, using a Pentium IV 3.0GHz CPU, with 2GB of RAM and a 250GB 7200rpm SATA hard drive. A standard commodity PC and a common PDA were used for testing the *HTP Front* and *HTP Web* applications, respectively.

To test our solution, we used *HTP Feeder* to load a set of datasets provided by the Physionet Challenge 2009 ATM [9] into the *HTP Tool Database*. These datasets consist on 10 hours of BP and HR data, sampled at one record of each biosignal per second per patient, giving 36,000 biosignal rows for each patient's `MonitorBP` and `MonitorHR` tables, relating to 50 different patients, resulting in a total of 3,600,000 biosignal records in the database.

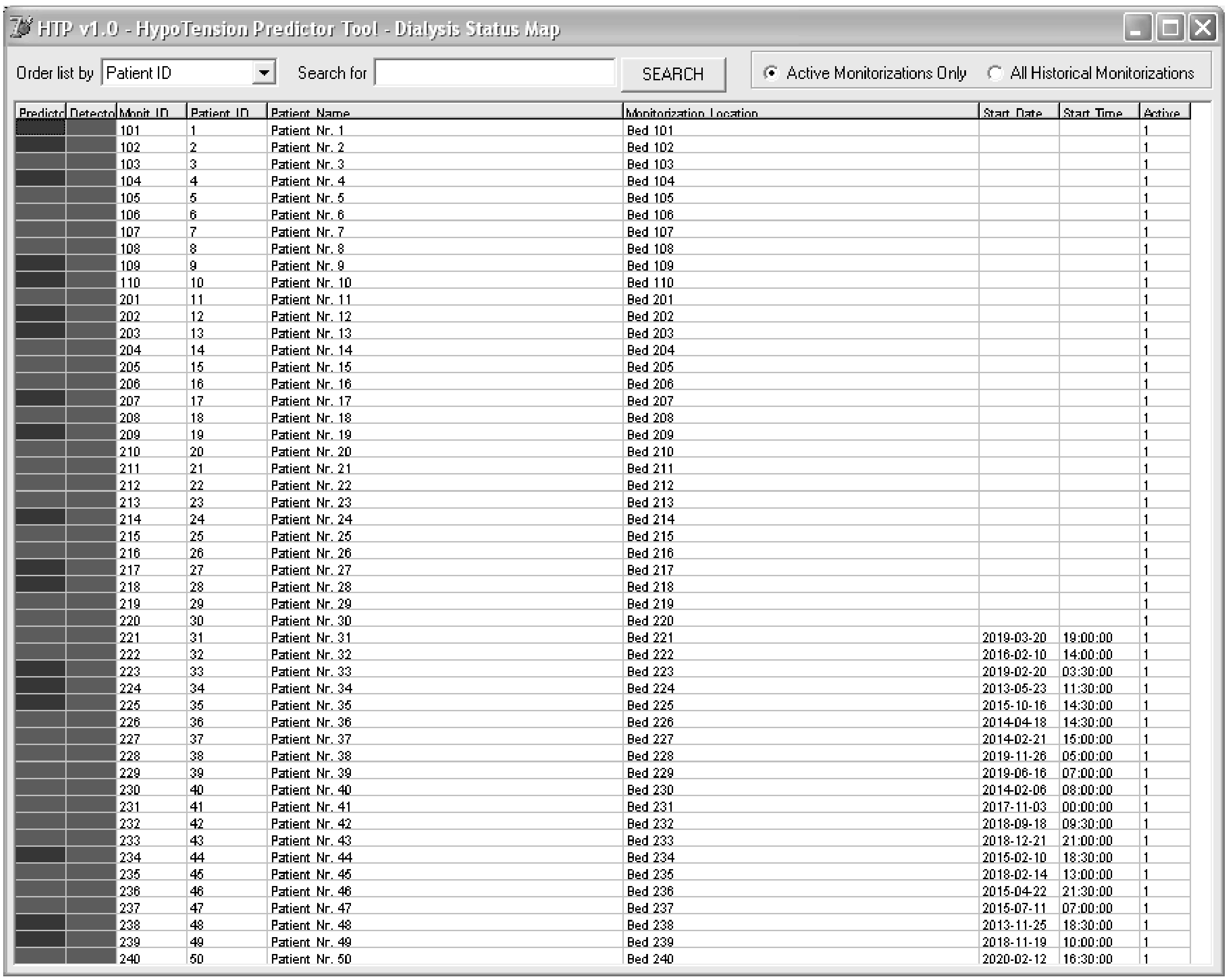

Figure 7. The HTP Front Global Patient Status Map Monitoring Interface

To evaluate the system's performance, we simulated a real-life situation in which all the 50 patients where 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* application to acquire. The *HTP Feeder* was configured in order to check for new files every 30 seconds. Therefore, an average of 30 values of BP + 30 values of HR for each patient, in 50 files, were acquired and loaded into the database, every 30 seconds. The system worked well with this setup, and did not present any performance bottleneck in loading data and executing monitorization and HT prediction/detection procedures, registering delays of a few seconds between the production/load of the biosignal data and the HT status results, for each patient.

In figure 7, presented in section 4.2, is shown the Global Patient Status Map of all the Physionet Challenge's patients. Consulting the Physionet Challenge documentation, Patients Nr. 1, 2, 4, 9, 10, 12, 13, 17, 19, 24, 27, 28, 32, 33, 34, 35, 44, 48 and 49 suffered a hypotensive episode in the following hour. Observing this figure carefully, where darker colors represent the prediction of a hypotensive episode for the following 60 minutes, 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 [Challenge2009]), which did have 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 [7].

6. CONCLUSIONS AND FUTURE WORK

Regarding efficient real-time biosignal data integration, we present a real-time database for storing all patient's historical 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 supports medical staff mobility by taking advantage of using personal mobile devices, such as cell phones and PDA's. Experimental results outperform the Physionet Challenge 2009 winning proposal, demonstrating a high efficiency rate in HT forecasting and making it a promising overall solution in the field.

As future work, performance issues concerning data throughput, processing and scalability, as well as the prediction algorithm's efficiency, joined with data privacy and security requirements, need to be tested in real-life scenarios involving the monitorization of a couple hundred simultaneous patients on middle or large-scale medical facilities.

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