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Exploiting the Existence of Temporal Heart-Rate Patterns for the Detection of Trauma-Induced Hemorrhage

Liangyou Chen, Andrei Gribok, Andrew T. Reisner, and Jaques Reifman

Abstract—**Unattended hemorrhage is a major source of mortality in trauma casualties. In this study, we explore a set of prehospital heart rate (HR) time-series data collected from 358 civilian casualties to examine whether temporal HR patterns can be used for automated hemorrhage identification. Continuous and reliable HR time series are fragmented into overlapping segments of 128 s, with a 118-s overlap between each two neighboring segments, which are projected into a wavelet coefficient space using the Haar wavelet function. A supervised nearest-neighbor clustering algorithm is developed to explore the existence of temporal HR patterns represented by the wavelet coefficients to discriminate casualties with and without (control) major hemorrhage. The clustering algorithm identifies 162 HR patterns. The most frequent pattern is observed in 11 (23%) hemorrhage and 16 (5%) control patients, which is a significant association (p<0.05, chi-square test). When the top 10 patterns are combined for hemorrhage detection, their sensitivity and specificity are 0.68 and 0.79, respectively, and when the top 20 patterns are used sensitivity increases to 0.77 and specificity decreases to 0.71.**

I. Introduction

UNATTENDED hemorrhage is a major source of mortality in trauma casualties. Early identification of major hemorrhage could be lifesaving and useful for triage, resource mobilization, and therapeutic decision making. Our goal is to investigate novel methods that enable early detection of major hemorrhage. Ideally, such methods would function at the scene of injury and require only standard noninvasive transport monitors or miniaturized noninvasive monitors, such as the ones being developed by the U.S. Army for the Warfighter Physiological Status Monitoring system [1].

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L. Chen is with the Bioinformatics Cell, Telemedicine and Advanced Technology Research Center (TATRC), USAMRMC, Frederick, MD 21702 (e-mail: lchen@bioanalysis.org).

A. Gribok is with the Bioinformatics Cell, TATRC, USAMRMC, Frederick, MD 21702, and with the Nuclear Engineering Department of the University of Tennessee, Knoxville (e-mail: agribok@bioanalysis.org).

A. T. Reisner is with the Bioinformatics Cell, TATRC, USAMRMC, Frederick, MD 21702, and with the Massachusetts General Hospital Department of Emergency Medicine, Boston, MA 02114 (e-mail: areisner@partners.org).

J. Reifman is a Senior Research Scientist and Director of the Bioinformatics Cell, TATRC, USAMRMC, ATTN: MCMR-TT, Bldg. 363 Miller Drive, Fort Detrick, MD 21702 (corresponding author; phone: 301-619-7915; fax: 301-619-1983; e-mail: jaques.reifman@us.army.mil).

Heart rate (HR) is one of the most basic cardiovascular vital signs, and it can be continuously and reliably monitored with convenient noninvasive devices. We investigated the diagnostic value of the average HR in prior studies [2, 3]. Our goal in this study is to investigate whether continuously measured HR data contain distinctive temporal patterns that are discriminatory of major trauma hemorrhage.

II. Methods

A. Dataset

This study is based on discrete attribute data and physiologic time-series data collected from 898 trauma casualties during and after transport by helicopter service from the scene of injury to the Level-I unit at the Memorial Hermann Hospital in Houston, Texas [4]. The time-series variables are measured by Propaq 206EL vital-signs monitors and downloaded to an attached personal digital assistant. The variables consist of electrocardiogram, photoplethysmogram, and respiratory waveform signals recorded at various frequencies and their corresponding monitor-calculated variables, such as HR, respiratory rate, and oxygen saturation of arterial hemoglobin, recorded at 1-s intervals. In addition, systolic, mean, and diastolic blood pressures are collected at multiminute intervals. The casualties' attribute data include discrete information, such as demographic data, injury description, and treatments. There are over 100 variables of this type for each patient, and these data have undergone prior analysis [2-5].

These prehospital time-series data are noisy. We have previously developed multiple algorithms to quantify the reliability of each sample of the time series [6]. It was reported that reliable data are physiologically more meaningful than unreliable data [3]. In this study, we use reliable HR data determined by these algorithms. However, we also use unreliable intervals shorter than 3 s interspersed with reliable HR, where we linearly interpolate the unreliable HR. Patients with at least 128 s (≈2 min) of continuous and reliable HR are selected for analysis (358 patients).

B. Outcome

Patients with major hemorrhage are defined as those who received a blood transfusion within 24 h upon arrival at the hospital and also had documented injuries that are consistent with hemorrhage, as determined by chart review. These injuries are one or more of the following: a) laceration of solid organs, b) thoracic or abdominal hematomas, c) explicit vascular injury and operative repair, or d) limb amputation. Patients who received blood but do not meet the documented injury criteria and patients who died before arrival at the hospital were excluded from the analysis.

C. HR Pattern Discovery

We develop a HR pattern discovery algorithm based on wavelet-transform and nearest-neighbor clustering methods. The algorithm consists of three stages: fragmentation, clustering, and heuristic search. In the fragmentation stage, HR time series are fragmented into segments of a fixed length and each segment is transformed into wavelet coefficients. In the clustering stage, patterns of wavelet coefficients are clustered using a nearest-neighbor method, where the most discriminatory clusters are selected. Finally, we use heuristic search methods to expedite the search of discriminatory clusters. Next, we provide additional detail of the three stages.

1) Fragmentation: Continuous and reliable HR data of each patient are fragmented into overlapping segments of 128 s long, with a 118-s overlap between each two consecutive segments. Each segment is zero-meaned and transformed into wavelet coefficients using the Haar wavelet function [7]. The first 16 coefficients are kept and represented as a vector, whose first element is always zero because of the mean subtraction. Note that the coefficient vector can be inversed-transformed into a HR pattern, which is smoother than the original HR segment because of the removal of higher-order coefficients, and reflects the overall trend of the original HR segment. The coefficient vectors of all HR segments of each patient form a matrix of wavelet coefficients.

2) Clustering: Given a matrix of wavelet coefficients, we employ a nearest-neighbor method to discover similar HR patterns in the wavelet-coefficient space. We use the Euclidian distance to indicate the relative similarity between two coefficient vectors (or HR patterns). We employ an iterative procedure to find the shortest distance between each pair of vectors. The two vectors with the shortest Euclidian distance are clustered and merged into a single vector by averaging their coefficients, with the resulting vector replacing the two original vectors in the next iteration. The iterative procedure continues until all input vectors are merged into a single cluster. The resulting clustering procedure can be represented by a tree structure, where each internal node of the tree represents a merging action and each leaf represents a HR pattern (Fig. 1). The coefficients of each internal node can be inversed-transformed into a HR pattern, termed a "template pattern," which represents the overall trend of all HR patterns under the node. Figure 1 illustrates an example of the clustering procedure, where seven HR segments, four from control (1, 2, 3, and 7) and three from hemorrhage patients, are clustered and the final template pattern, corresponding to node vi and plotted on top of each of the seven segments, reflects the overall trend of all HR segments.

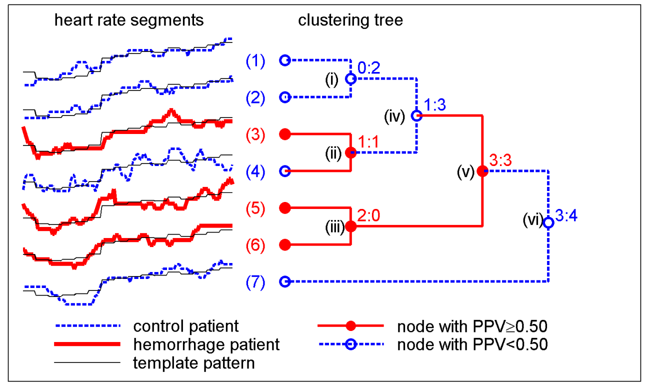

Fig. 1. Illustration of the clustering algorithm. The illustration shows the clustering of heart rate (HR) segments for four control and three hemorrhage patients. Nearest-neighbor clusters are merged in the order of (i) to (vi). The positive predictive value (PPV) is shown for each internal node of the clustering tree. Nodes with opaque red circle represent cases where PPV≥0.50, and with clear blue circles otherwise. The final template pattern representing the overall HR trend of all seven segments is plotted on top of each HR segment.

After the clustering tree is generated, we prune it to select the most discriminatory clusters by considering each node of the clustering tree as a candidate cluster. The pruning is based on the size of the cluster, i.e., the total number of HR patterns in the cluster, and its positive predictive value (PPV, the ratio between the number of HR patterns belonging to hemorrhage patients and the size of the cluster). Note that PPV is considered here with respect to the number of unique HR patterns in the cluster, but not the overall number of unique patients, which is usually smaller. By maintaining a condition of PPV above a given threshold (0.50 in this study, in comparison with a hemorrhage incidence of 13% in the overall study population) and maximizing cluster size, we select all clusters satisfying this condition and prune the rest of the tree. For example, with a PPV threshold of 0.50 in Fig. 1, the largest cluster includes all the branches under node v, which contains three control and three hemorrhage patterns. The resulting clusters are ranked by the number of hemorrhage patterns in the cluster.

3) Heuristic search: The clustering algorithm described above may be computationally demanding when a large number of HR patterns are presented. Hence, we employ a set of heuristic-search methods to expedite the discovery of discriminatory clusters, including a method to divide the input patterns into subgroups and a method to discover patterns with a certain degree of temporal variability. First, we divide the HR patterns into smaller subgroups based on their overall similarity, assuming that similar patterns have a similar variance in the wavelet coefficients. The clustering procedure is applied to each subgroup and patterns of the resulting clusters are collected and used as input to a global clustering procedure to search for the final clusters. By this means, we avoid unnecessary comparisons between dissimilar HR patterns and reduce the total computation time. Second, we search for HR patterns that show a certain degree of temporal variability by demanding that the wavelet coefficients pass a certain variance threshold. This is based on the fact that most patterns have relatively low variability (i.e., the patterns are relatively flat), and these patterns tend to be prevalent in the resulting clusters. By employing a variance threshold we specifically search for patterns with certain variability. In this study, we use 10 variance thresholds that are evenly selected from one standard deviation above and below the average variance of the input patterns. A consequence of maintaining multiple variance thresholds is that a pattern may end up in multiple clusters, each found by a different threshold and including a different set of HR patterns. We keep all such clusters in our analysis.

D. Data analysis

We test the association between the presence of HR patterns found by the clustering algorithm and the hemorrhage and control outcomes using the chi-squared test, or the Fisher-exact test if the number of entries in any of the cells of the confusion matrix for the chi-squared test is less than five. A significance level of 0.05 is used in this exploratory study. We also compute the sensitivity and the specificity of the top 10 and the top 20 HR patterns in discriminating control and hemorrhage patients.

III. Results

The study population consists of 311 control and 47 hemorrhage patients. Table I shows the summary statistics of the population. The study population has a lower mortality rate than the total population ($p<0.05$), which is in accordance to our prior finding that higher-acuity casualties tend to have less reliable (i.e., noisier) HR data [3]. The two populations, however, have no significant difference in the distribution of gender, age, type of injury, and the major hemorrhage outcome.

TABLE I
DEMOGRAPHICS OF THE TOTAL AND STUDY POPULATIONS

Characteristics	Total population	Study population[a]
Population size	898	358
Male	660[b] (73%)	264 (74%)
Female	234 (26%)	94 (26%)
Mean age	38 (SD[c] 15)	37 (SD 14)
Blunt injury	778[d] (87%)	320 (89%)
Penetrating injury	101[d] (11%)	33 (9%)
Mortality	94 (10%)	19 (5%)
Major hemorrhage[e]	90 (10%)	47 (13%)

[a]Patients with at least 128 s (≈2 min) of continuously usable HR data
[b]4 patients had no assigned gender in the total population
[c]Standard deviation
[d]19 patients had no assigned mechanism of injury
[e]Received at least one unit of blood within 24 h upon arrival at the hospital and also had documented injuries that were consistent with major hemorrhage. Patients who died before arrival at the hospital were excluded

The clustering algorithm identifies 162 clusters whose sizes range from 3 to 108 HR patterns, from 3 to 55 distinct patients. We select the top 10 clusters with the largest number of positive (hemorrhage) patterns and show their corresponding template patterns in Fig. 2. The first template pattern (TP 1) shows a small initial increase in HR, followed by a continuous drop of 9 beats/min during a 1-min interval, and then a short recovery. The pattern is observed in 11 (23%) hemorrhage and 16 (5%) control patients. The chi-squared test shows that this pattern is significantly associated with the hemorrhage outcome ($p<0.05$). Similar information is shown for other patterns, all significantly associated with the hemorrhage outcome ($p<0.05$). Note that some of the template patterns differ only slightly (e.g., TP 1 and TP 2) because they are generated by our heuristic search algorithm with different variance thresholds, which occasionally includes overlapping patterns. The top 20 template patterns (not shown) are also significantly associated with the hemorrhage outcome ($p<0.05$), and the 20th template pattern is observed in 5 control and 5 hemorrhage patients.

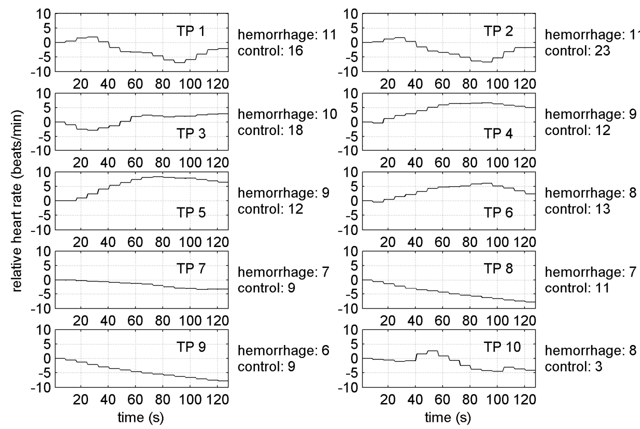

Fig. 2. The top 10 HR template patterns identified by the clustering algorithm along with the number of hemorrhage and control patients possessing the pattern.

Figure 3 shows the distribution of control and hemorrhage patients possessing different numbers of template patterns in the top 10 list. The majority of the control patients (79% vs. 32% in hemorrhage) do not have any of the top 10 template patterns, and the majority of the hemorrhage patients (68% vs. 21% in control) have one or more of the template patterns in their HR time series. The sensitivity for hemorrhage detection using the top 10 template patterns (i.e., identify a patient as hemorrhagic if any of the template patterns is detected) is 0.68 and the specificity is 0.79. As expected, by including the top 20 template patterns the sensitivity increases (to 0.77), while

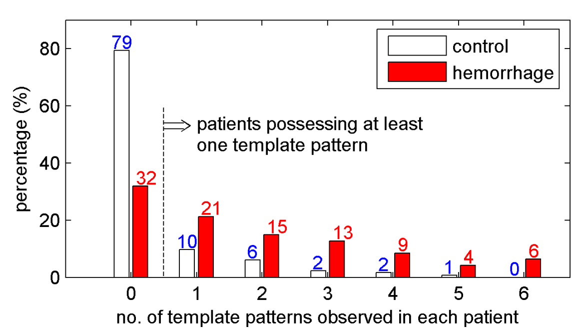

Fig. 3. Distribution of hemorrhage and control patients possessing any of the top 10 HR template patterns.

the specificity drops (to 0.71). The sensitivity of the top 10 patterns drops when we employ longer HR patterns; however, it is mildly affected by changes in the length of overlap between HR segments.

IV. Discussion

In this study, we explore a set of prehospital HR time-series data to find potential temporal patterns that may be useful for automated hemorrhage detection. Multiple HR patterns have been discovered, and they are significantly associated with a hemorrhage outcome. A sensitivity of 0.77 and a specificity of 0.71 can be achieved when the top 20 template patterns are used for hemorrhage detection.

It is natural to assume that hemorrhage patients may show different HR patterns than control patients. Prior research has shown varied HR responses to reduced blood volume, including normotension with moderate tachycardia, moderate hypotension with bradycardia, and severe hypotension with tachycardia [8]. This suggests that both increased HR and decreased HR are possible in hemorrhagic patients [9], and depending on the absolute value of HR alone one will not be able to discriminate all hemorrhage cases. By extension, we speculate that unique HR patterns continuous in a period of time, potentially corresponding to transitions between multiple hemorrhage stages, may be discriminatory of major hemorrhage. We tested this hypothesis here and achieved a moderate success—indeed, there are HR patterns significantly associated with major hemorrhage, however, the most frequent pattern exists in only 11 (23%) hemorrhage patients.

A combination of HR patterns may be valuable in an automated decision system for hemorrhage detection. Our use of the top 10 patterns shows a sensitivity of 0.68 with a specificity of 0.79, and the top 20 patterns show an improved sensitivity of 0.77, with a reduced specificity of 0.71. This performance is not outstanding. However, it suggests a promising direction for future studies, i.e., to automatically combine patterns of multiple vital signs, each with only moderate discriminatory value, to achieve improved hemorrhage detection.

Because of several limitations of this study, caution is required in interpreting our results. First, this is a retrospective study, and no detailed records about medic interventions are available. It is possible that some of the HR trends we have discovered may be related to medic behavior, such as volume transfusion or patient movement. Second, our major hemorrhage definition is obtained from hospital records based on documented injuries and therapies. We have, however, no information about when the hemorrhage actually started or whether the hemorrhage was present when the vital-sign data were collected. Consequently, we are not able to verify if the discovered HR patterns are related to pre- or post-hemorrhage cardiovascular physiology. Third, our dataset is relatively small, with only 47 hemorrhage patients. Patterns we have discovered and shown in this paper may be idiosyncratically specific to this dataset. To obtain more general and accurate hemorrhage-associated HR patterns, a larger dataset in a prospectively designed study may be warranted. Finally, we do not split the dataset into training and testing sets because of the limited population size and the initial exploratory nature of this research with the objective to investigate if temporal HR pattern can detect trauma-induced hemorrhage. In spite of all these limitations, our initial results indicate the possibility of using sophisticated computer algorithms to mine vital-sign patterns that may be useful for automated diagnosis. The HR patterns we discovered may be combined with patterns from other vital signs for improved hemorrhage detection.

Disclaimer

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