Classification of Asphyxia & Ventricular Fibrillation Induced Cardiac Arrest For Cardiopulmonary Resuscitation

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***Abstract*— In this study we address an important pediatric cardiopulmonary resuscitation problem to identify the cause of a cardiac arrest during the beginning of cardiopulmonary resuscitation. A support vector algorithm was trained and tested using a feature set constructed through wavelet transform analysis of experimental electrocardiography and heart rate data provided by Children's Hospital of Philadelphia. The approach developed in this study yielded an average classification accuracy above 93%.**

I. Introduction

Although accurate numbers are difficult to obtain, it is said that Cardiac Arrest (CA), also known as Sudden Cardiac Arrest (SCA), accounts for more than 300,000 deaths per year in the United States, and millions globally [1]–[3]. As a result, in the United States alone, approximately 200,000 patients receive Cardiopulmonary Resuscitation (CPR) during their hospitalization [4]–[6]. Moreover, recent reports document that 59% of adults and 93% of children have their in-hospital cardiac arrest in ICUs [5], [7]. Despite constant improvements of the CPR guidelines and standards issued by the American Heart Association (AHA), less than 25% of adults and 50% of children survive to hospital discharge [5], [7], [8].

One of the reasons for the low positive outcome of pediatric CPR lies in the pathogenesis of cardiac arrests in children. In contrast to adults, children suffer sudden ventricular fibrillation (VF) cardiac arrests as much as pediatric arrest resulting from asphyxia due to respiratory failure or circulatory shock [9], [10]. Recent studies suggest that the outcome of pediatric CPR highly depends on timely recognition of the underlying cause for the cardiac arrest such that the CPR process can be adjusted according to its pathological cause [3], [6]. In this study, we (a team of critical care physicians and engineering researchers) aim to address this critical challenge from an engineering point of view.

Computational intelligence methods have been broadly and extensively employed in the biomedical research. Many biomedical problems can be formulated as a pattern recognition or classification tasks that can be addressed through machine learning (ML) algorithms. Contrary to the widespread belief that it is the quantity of the data and the available computational power that makes good predictions in classification problems in dynamic systems, the detection of important (but often hidden) characteristics in the data (using mathematics, physics and signal processing) is the critical component. The work presented in this paper in fact demonstrates this fact.

II. Methodology

A. Machine Learning

1) Machine Learning Application: In most general terms machine learning algorithms can be defined as systems that improve their knowledge or performance with experience. The structure of a machine learning algorithm is usually described by three main ingredients: task, model and features. Through a learning process, features are used to build the right model to perform a defined task [11].

The relevant objects or instances in our domain are signals. In essence, the features can be described here as characteristics of a signal that are mathematically mapped from the instance space to some set of feature values called the feature space. It is worth noting that a model is built through a learning algorithm, which is driven by defined features [11], [12]. Thus, the features determine the performance of a machine learning model, essentially rendering the mathematical mapping functions absolutely crucial for the success of a machine learning application.

The task (in a machine learning application) is the abstract representation of a problem, which in this study is to classify two cardiac arrest causes, asphyxia and ventricular fibrillation. A linear support vector machine (SVM) classifier was chosen as a machine learning algorithm to build (train) the desired classification model.

2) Features: As previously indicated, to build the right model through an SVM learning algorithm in order to achieve the desired task such as binary classification, it is crucial to use the right features. However, in this study and in fact, in most ML applications, the data does not come with ready-made features. Because of this, ML is often an iterative process, where one only knows that the right features were extracted after the model was constructed. While this performance evaluation seams somewhat straightforward, it makes it very difficult to analyze the significance of individual features and consequently to understand the physical meaning, and moreover the physical differences of the two classes in the instances domain. It should be noted here, that through our work with biomedical data it was found that this

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evaluation is of high importance and is often overlooked in the development of a ML model. Only by attaching physical meaning to the features can the mathematical mapping functions be revised, which inherently improves the feature set and essentially optimizes the performance of the ML task.

In this study, to identify less reliable (or, in other words, misleading) features, a mutual information (MI) process was adopted from information theory. Features were ranked in accordance with their randomness given the knowledge of the known class output. Using the obtained rank and by evaluating the constructed classifiers with respect to this rank, the most important features were identified and traced back to their physical meaning in the instances domain. As a result, the raw signals in the instances domain were examined further to adjust the mathematical mapping functions and improve the feature set.

B. Data

The desired features were extracted from experimental data obtained through a partnership with Children's Hospital of Philadelphia [5], [7]. The experimental protocol was approved by The Children's Hospital of Philadelphia Institutional Animal Care and Use Committee. The objective of the experiments was to determine if titrating CPR to blood pressure would improve 24-hour survival compared with traditional American Heart Association CPR in a porcine model of ventricular fibrillation and asphyxia-associated ventricular fibrillation.

After induction of anesthesia and 7 minutes of untreated VF, 17 female 3-month-old swine received manual cardiopulmonary resuscitation. Similarly, 22 3-month- old female swine received manual cardiopulmonary resuscitation after 7 minute of untreated asphyxia. Furthermore, it was observed that only the data obtained during the first 2 minutes of the resuscitation period in the interval between $t \approx 7$ min and $t \approx 9$ min is relevant for the purpose of this study, in order to eliminate potential influences on the data introduced through different CPR sequences after $t = 9$ min. Among other measurements, electrocardiography (ECG) and heart rate (HR)were recorded during the experiment and are the measurements used and referred to as data in this study.

After preprocessing the data, while eliminating recordings with missing or corrupt signals, 33 recordings (13 asphyxia and 20 VF) were used to conduct this study.

C. Signal Analysis and Feature Extraction

As mentioned earlier, features play a significant role in the success of any ML application and can be thought of as those characteristics of a signal that should most effectively help the classification algorithm to create the most accurate model, in order to be able to separate them into different classes [11]. In order to obtain the desired domain of the features, a wavelet analysis of the recorded signals (ECG and HR) turned out to be a powerful signal processing technique. The following section briefly illustrates the core ideas of wavelet transform and highlights its strong points through our applications.

1) Wavelet Transform: In signal processing theory, most of the signals can be classified into four categories: deterministic (periodic and transient) and nondeterministic (stationary and non-stationary). However, when dealing with real-world signals and in particular human data recordings, a signal may contain some or several characteristics of the four signal types. As a result, a signal analysis, capable of revealing aspects like transients, trends, breakdown points or discontinuities locally (at specific time) becomes essential.

Short-time Fourier transform (STFT) and wavelet transform allow for such analysis. However, the disadvantage of STFT is that there exists a trade-off between the time resolution and frequency resolution. In other words, the time resolution and the bandwidth of STFT can not be chosen to be small simultaneously [13]. In comparison, the wavelet transform addresses these limitations.

The wavelet transform decomposes a signal into a set of basis functions. Such basis functions are obtained from so called base or mother wavelets that are scaled through dilation and contraction, and time shifted by specific translational value along the time axis [14]. Unlike in STFT the wavelets are not necessarily sinusoidal and can be of different shapes [15].

Mathematically, the wavelet transform of a continuous signal $f(x)$ with respect to the wavelet function Ψ is defined by Eqn. 1 and can be thought of as the cross-correlation of a signal with a set of wavelets of various widths at various temporal locations. The widths, or dilation and contraction of the wavelet is governed by the scaling parameter s and is responsible for the resolution of the transform. The temporal location, or the movement of the wavelet along the time axis is governed by the translational parameter μ.

$$W\{f(s,\mu)\} = \langle f, \Psi_{s,\mu} \rangle = \int_{t=-\infty}^{\infty} f(t)\Psi^{*}\left(\frac{t-\mu}{s}\right) dt \quad (1)$$

Essentially, the wavelet transform process measures the similarity between the signal being analyzed and modified base wavelets. As a result, the wavelet transform is a collection of wavelet coefficients W, with respect to the wavelet function $\Psi_{s,\mu}$ (with the scaling factor s and translational parameter μ), that represent how close the wavelet is correlated with the windowed section of the original signal $f(t)$ [13], [14]. The wavelet transform has been called [15] a 'mathematical microscope', where the scale s is the magnification parameter at explored temporal location, μ.

2) ECG Examination: Referring back to the complexity of human data briefly stated in the Data Section II-B and the advantages of WT outlined in Section II-C.1, WT is increasingly considered a 'fundamental' signal processing tool in the investigation of ECG signals. It provides great details about the underlying frequencies and characteristics of the original signal with respect to their temporal locations. However, when the ECGs being considered consist of samples with pathological conditions in both groups (as is the case for our data), the well familiar and normal ECG sinus rhythm (Fig. 1) is no longer present. Consequently, the established and well documented WT investigations of ECG signals become unsuitable.

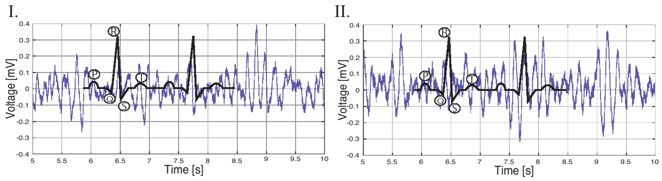

Fig. 1. ECG signal of a VF (I) and asphyxia (II) sample with imposed normal ECG sinus rhythm

A Wavelet Transform was performed on ECG signal with a frequently used *Morlet wavelet* as the mother wavelet with scales s=[1−128]. Fig. 2 illustrates this step and shows the original ECG signal and the generated WT coefficients spectrum. Next, to quantify hidden frequencies in the ECG signal, expressed through the obtained magnitude of the WT coefficients, a metric was established by calculating the energy E with respect to s of each extracted signal $W\{f(1-128,\mu)\}$ according to (Eq. 2). This process was repeated for all 33 ECG signals from all samples, transforming the original signals into a defined feature space with 128 features per sample.

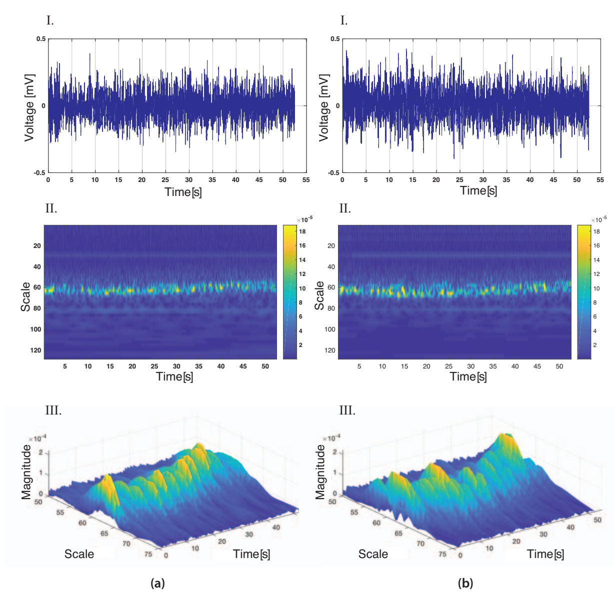

Fig. 2. (a) VF sample and (b) asphyxia sample - I. ECG signal, II. ECG WT coefficients spectrum $W\{f(1-128,\mu)\}$, III. Relevant ECG WT coefficients spectrum $W\{f(50-75,\mu)\}$

$$E = \|W\{f(s,\mu)\}\|^2 \qquad (2)$$

To identify the misleading features, a mutual information (MI) process was adopted from information theory. Using MI, features were ranked in accordance with their randomness given the knowledge of the known class output. Using the obtained rank, it was found that the most relevant features stem from the energy levels calculated from the decomposed signals $W\{f(50-75,\mu)\}$. Although this finding is very apparent in the plots shown in Fig. 2 and can be observed in asphyxia as well as in the VF sample, this was not true for most samples. Feeding the identified 26 features into a trained linear SVM classifier an accuracy of 70%-75% was achieved through multiple classification attempts.

To improve the feature set, the identified ECG WT coefficients $W\{f(50-75,\mu)\}$ were analyzed statistically. The distribution of magnitudes in the WT coefficients spectrum, as shown in Fig. 2 III, was quantified through: interquartile range (IQR), median absolute deviation (MAD), first and second order central moment, range of values, standard deviation (SD) and variance. These 7 statistical values were calculated for each sample resulting in a new feature set of 7 features per sample. Using the new feature set a linear SVM classifier was trained as in the previous case, this time yielding an average classification accuracy of 75%-85%. To amend the features domain for each sample and improve the classification results further the available HR signal was analyzed as described next.

3) HR Examination: The HR signal of each sample was analyzed in fashion similar to that of the ECG signal. Using the same WT and ranking algorithm as outlined in the above section, it was identified that the most relevant features stem from the energy levels calculated from the decomposed HR signals $W\{f(40-120,\mu)\}$. Fig. 3 illustrates this process once more using the HR signal.

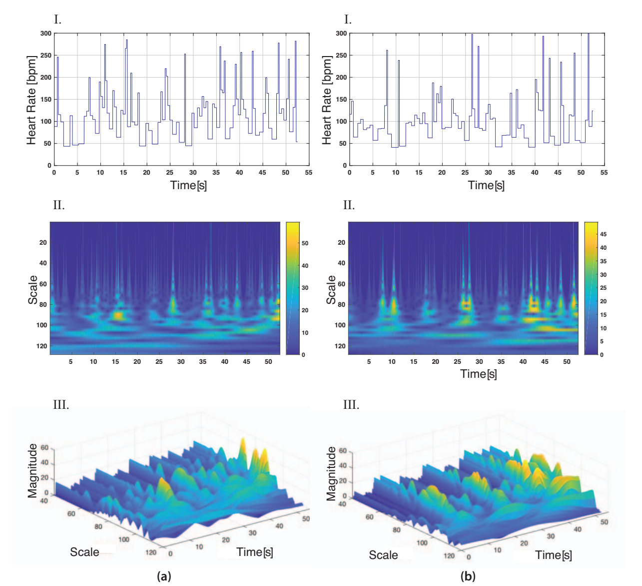

Fig. 3. (a) VF sample and (b) asphyxia sample - I. HR signal, II. HR WT coefficients spectrum $W\{f(s,\mu)\}$, III. Relevant HR WT coefficients spectrum $W\{f(40-120,\mu)\}$

However, when evaluating the energy and statistical features that were calculated as in preceding section, the results of linear SVM classifier were considerably poor. For this reason the WT coefficient spectrum of the HR signal was analyzed further. In particular, two samples of each group with very similar WT spectrums were investigated in more detail.

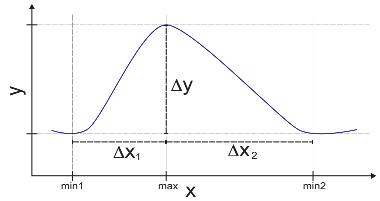

Fig. 4. Geometric sharpness schematic

Closer investigation of the WT coefficients in the plot shown in Fig. 3 III. led to the assumption that the energy calculation as well as statistical values do not capture detailed differences between the two cases that are slightly noticeable in the mentioned plot. Through visual inspection, it was noticed that the characteristics of the individual magnitude peaks of the WT coefficients were different for each sample. In the VF case the dominant peaks seamed to be much higher with a higher slope. Contrary to this, although the number of the eminent peaks of the asphyxia sample was higher, the individual peaks were smaller in height with a lower slope. Based on these observations the sharpness characteristics (3) of the three major peaks of the WT coefficient spectrum were chosen as features of the HR signal.

A basic geometric representation of each peak as detailed in Fig. 4 led to an expression for sharpness as defined in (3). The sharpness was calculated with respect to time- and scale-direction, with both directions passing through the maximum of the peak. The attained sharpness metric of three major peaks of each sample resulted in a feature set of 6 features for each of the 33 samples.

$$S = \left| \frac{\Delta y}{\Delta x_1} - \frac{\Delta y}{\Delta x_2} \right| \tag{3}$$

The obtained feature set was ranked using MI and fed through a trained linear SVM classifier. The average classification accuracy was in the range of 75%-80% when all HR features were used. However, the MI rank indicated that the sharpness with respect to time is more relevant; thus, as expected the linear SVM classifier using only the sharpness defined in the time-direction yielded a consistent average accuracy above 80%.

Finally, all resultant features were combined together, ranked and fed through a trained linear SVM classifier. The average accuracy of the final SVM classifier was above 93%, with a constant 100% classification accuracy of the VF samples and only occasionally misclassifying some asphyxia samples. This is the best result ever achieved for this critical pediatric problem, and we are looking forward to further research to help redefine CPR practices for children.

III. Results & Conclusion

In this work, we sought to establish a methodology for classification of two causes for a cardiac arrest. Through the defined feature space using Wavelet Transforms a reliable feature set was built from the ECG and HR signals that was used to train a linear Support Vector Machiner algorithm, which performed with an average accuracy above 93%. During the feature extraction process, it was discovered that the major ECG frequencies yielding the best class separation were between 2Hz-16Hz (derived from the identified scales 50-75). Similarly, from the analysis of the HR signal it was derived that the frequency change with respect to time is relevant to distinguish between the two groups. The significance of these findings from the medical point of view, has yet to be addressed in future research.

Although the results of this study are very encouraging, the study has one limitation. Due to the limited number of samples a k-fold method (k=8) was implemented during the training phase of the SVM. Although this allowed us to use all the data for training as well as for evaluation without sacrificing the generality principle of the ML algorithm, an evaluation of the trained SVM on a blind set would have yielded a more substantial proof of the developed method.

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