31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

# Optimizing Cardiac Resuscitation Outcomes using Wavelet Analysis

K. Umapathy[1,2], *MIEEE*, S. Krishnan[2], *SMIEEE*, S. Masse[1], X. Hu[3], P. Dorian[3], and K. Nanthakumar[1]
THFCFM Laboratory[1], Toronto General Hosp., Ryerson University[2], St. Michael's Hosp.[3], Toronto, Canada

*Abstract*— **Ventricular fibrillation (VF) is the most lethal of cardiac arrhythmias that leads to sudden cardiac death if untreated within minutes of its occurrence. Defibrillation using electric shock resets the heart to return to spontaneous circulation (ROSC) state, however the success of which depends on various factors such as the viability of myocardium and the time lag between the onset of VF to defibrillation. Recent studies have reported that performing cardio pulmonary resuscitation (CPR) procedure prior to applying shock increases the survival rate especially when VF is untreated for more than 5 minutes. Considering the limited time within which the VF has to be treated for better survival rates, the choice of the right therapy (shock parameters, shock first or CPR first, drug administration) is vital. In aiding this choice, it would be of immense help for emergency medical staff (EMS) if an objective feedback could be provided at near real-time rate on the VF characteristics and its relation to the shock outcomes. Existing works in the literature have demonstrated correlation between the characteristics of the VF waveform and the outcome (ROSC) of the defibrillation. The proposed work improves on this by attempting to arrive at a near real-time monitoring tool in aiding the EMS staff. Using data collected from 16 pigs during VF, the proposed wavelet methodology achieved an overall accuracy of 94% in successfully predicting the shock outcomes.**

*Index Terms*— **Ventricular fibrillation, CPR, ROSC, Wavelet Analysis**

## I. INTRODUCTION

Cardiac resuscitation is a process of reviving the heart to the ROSC state after a cardiac arrest. Timing is crucial in cardiac resuscitation as the viability of myocardium decreases with prolonged untreated VF. Literature recommends direct defibrillation in cases where the time of VF onset is less than 5 minutes and for cases greater than 5 minutes chest compression and ventilation prior to the defibrillation shocks are shown to increase the survival rates [1]. To aid the EMS staff and improve the survival rates, prediction methodologies were proposed that would analyze the VF waveform characteristics and recommend appropriate sequence of therapy that might result in ROSC. Many amplitude and spectral features were proposed with varying sensitivity and specificity in predicting the success of the shocks using retrospective defibrillator data [2], [3], [4]. Amplitude Spectrum Analysis (AMSA) measure extracted from the pre-shock VF waveform is one of the well known predictor of resuscitation success [2]. A value of 21 mv Hz was recommended as a threshold, above which a successful outcome is predicted. Scaling exponent is another measure of VF waveform morphology whose values increase with the duration of VF and can be used to recommend different combination of therapies [3].

While most of the existing prediction techniques rely on temporal or spectral features, the best way of analyze non-stationary VF waveform characteristics would be a joint time-frequency/time-scale approach. Time-scale analysis would be more suitable if morphological features are desired. Wavelet transform is a time-scale approach where a signal is modeled using dilated and scaled versions of a mother wavelet and computationally less expensive for near real-time extraction of features. There are existing works using wavelets in predicting the success of defibrillation and in these works, wavelet entropy based measure reflecting the temporal behavior of the VF waveform was identified to perform better in discriminating the shock outcomes [4], [5]. Compared to these works, the proposed work has the advantage of computing a near real-time temporal evolution of VF characteristics in terms of a novel and meaningful wavelet feature which mimics a real world scenario. Moreover, the proposed work also correlates the CPR outcomes with the prediction of the proposed technique. The paper is organized as follows: Section II provides the details on the proposed technique, database, and experimental protocol, Section III discusses the results obtained in discriminating the ROSC and non-ROSC outcomes using the proposed wavelet feature, and conclusions are provided in Section IV.

## II. METHODS

### A. Database and Experimental Protocol

Pig VF has been used extensively in the literature to study human VF as the heart size appears closest to humans. The database used in this study consisted of 16 healthy Yorkshire pigs weighing 25-35 kgs. Each of the pigs were anesthetized for the duration of the experiment. The surface ECG was acquired using lead II and the coronary perfusion pressure (CPP) was computed by subtracting the aortic (Ao) pressure from right atrial (Ra) pressure both measured using Millar catheters. The surface ECG was sampled at 1 kHz and the pressures at 500 Hz, however for the analysis all the signals were down-sampled to 250 Hz to reduce the computational complexity. Baseline sinus rhythm was recorded and VF was induced using burst pacing. After the initiation of VF, ECG, Ao, Ra, and airway pressures were recorded continuously throughout the experimental protocol. The pig was left untreated for 5 minutes in VF simulating the ischemic phase. After the 5-minute duration the pigs were ventilated and CPR was performed for 3 minutes. After the 3-minute CPR period the pig was shocked using defibrillator with 360 Joules. A return to sinus rhythm and persistence of the same for 10

This work is supported by Heart and Stroke Federation Fund, Canadian Institutes of Health Research Grant NA 777687, and Ryerson University

minutes post shock was considered ROSC and non-ROSC otherwise. The block diagram in Fig. 1 briefly describes the protocol and our proposed methodology.

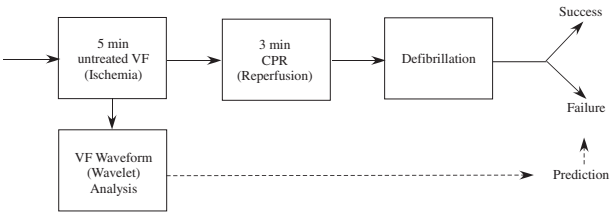


Fig. 1. Block diagram explaining the proposed methodology and experimental protocol

### B. Wavelet Analysis

The proposed method uses continuous wavelet transform (CWT). In CWT a signal $x(t)$ is modeled using all possible translated and dilated version of a mother wavelet $\psi_{a,b}$ where $a$ and $b$ are the dilatational (or scale) and translational parameters. It is given by

$$CWT_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\ \psi^* \left( \frac{t-b}{a} \right) dt \qquad (1)$$

The signal $x(t)$ in our case will be the ischemic (pre-shock & pre-CPR) portion of the VF waveform and the wavelet used for the analysis is Morlet wavelet. Morlet was chosen as it had a better match with the VF waveforms especially when the VF waveforms exhibited organization. We did test with other wavelets (Daubechies, Gaussian, Shanon) and our initial analysis showed Morlet wavelet yielding better results. Prior to decomposing the VF waveforms using wavelet analysis, a band pass filter (3 - 21 Hz) was applied to eliminate low and high frequency artifacts. Filtering did help the processing and improved the results minimally. Filtered VF waveforms during ischemic phase were then segmented into 5s (i.e. 1250 samples at 250 Hz) segments to mimic a real-time acquisition with a buffer of 5s data. Sequentially each of the 5s data was decomposed using a range of wavelet scales whose corresponding frequency spanned the range of VF bandwidth.

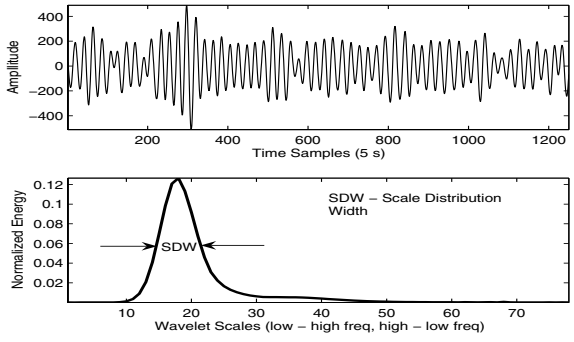


Fig. 2. Illustration of scale distribution width (SDW) feature extracted from an organized portion of VF

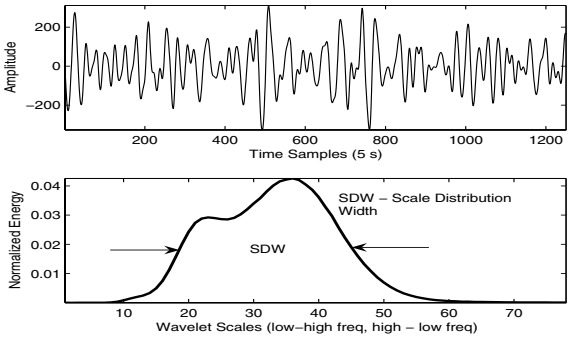


Fig. 3. Illustration of scale distribution width (SDW) feature extracted from an disorganized portion of VF

### C. Scale Distribution Width (SDW)

The wavelet decomposition coefficients obtained by decomposing 5s VF segments were analyzed and found that depending upon the signal composition of the VF waveform, the energy distribution over the range of scales varied. In other words the analyzing wavelet at each scale $a$ captured different amounts of signal energy depending upon the signal characteristics. If $E$ is the total signal energy and $a_1$ to $a_N$ are the scales used in the wavelet analysis that could model the signal completely, then it can be written as

$$E_{sig} = E_{a_1} + E_{a_2} + E_{a_3} + ... + E_{a_N} \qquad (2)$$

The normalized distribution of the energy over all scales were computed and the width of the distribution i.e. scale distribution width (SDW) was extracted as the wavelet feature. Depending upon the signal composition the number of scales that would have a significant contribution to the total signal energy captured varies and this is reflected in the width of the distribution. So for a monocomponent portion of a VF waveform the distribution will be a sharp and tall peak indicating that very few scales were required to model most of the signal energy. The vice-versa for a multicomponent portion of a VF waveform where the distribution width will be larger. This could serve as an indicator of the morphological changes happening during VF and could be indirectly used as a measure of signal composition that could be tracked over time. As a demonstration in Figs. 2 and 3 we have shown in the top panels two 5s VF segment extracted at different times from a 5 minute VF during ischemia in a pig. The 5s segment in the top panel of Fig. 2 is more organized and will need fewer scales to model compared to the 5s segment in the top panel of Fig. 3. The corresponding bottom panels show the wavelet scale-energy distribution and the difference in the SDW is highlighted. This clearly demonstrates that the SDW could be used as an indicator (feature) of signal composition during the temporal evolution of VF. We chose to measure the width of the distribution at half the height of the peak of the distribution. This choice was made to avoid the width measurement not to be influenced by minor or insignificant changes in the signal and at the same time not to make it too insensitive (which will defeat the purpose of the feature).

The proposed feature can be seen as a measure of bandwidth over time which could also be extracted from short-time Fourier methods, however the achievable time-frequency resolution and the flexibility in the choice of the analyzing wavelet and size of the windows make the proposed feature attractive for the application in hand. The proposed feature closely follows the concepts of computing the scale-energy distribution explained in [6], however does not compute the wavelet entropy from the distribution values, instead measures the width of the distribution. Entropy is a information theory measure that quantifies uncertainty (or randomness) without attaching a physical meaning to it. It is insensitive to the arrangement of the distribution i.e. the entropy will be same as long as a set of distribution values are present irrespective of in which order they occur. Since the proposed SDW feature is always measured around the peak of the scale-energy distribution i.e. around the dominant scale or inversely a proportional dominant frequency, it can be seen as an objective and meaningful bandwidth measure around the dominant signal frequency. Statistically SDW has similarities to the derivatives of standard deviation (STD) and interquartile range of the normalized energy distribution. We compared SDW with STD and found SDW performing better as the distribution is not always normal. The proposed feature is also different from the wavelet entropy marker proposed in [4] where the entropy is computed in the temporal (i.e. along $b$ in Equ. 1 ) direction using the maximum modulus of the scalogram at a particular scale. SDW on the other hand is computed from the scale-energy distribution and the width of the distribution is measured along the vertical axis of the scalogram (i.e. along $a$ in Equ. 1).

## III. RESULTS

### A. Temporal Evolution of SDW

In our database of 16 pigs, 11 of them were successfully resuscitated and 5 of them did not return to ROSC. We extracted the wavelet SDW feature for each of the pig during the 5 minutes of ischemia in segments of 5s. Segmentation was done to mimic a real-time update monitor as explained before. Hence for 5 minutes we had 60 5s segments and discarding the initial 25 s and the last 25 s to avoid border effects, we were left with 50 points showing the temporal evolution of SDW feature during ischemia. Faster implementation of CWT can be used to further reduce the computational complexity [7]. We then correlated the temporal evolution of the SDW feature with the successful and unsuccessful results. The discussion of the results in this subsection assume that the CPR and Defibrillation stages did not influence the outcomes. However, in the later Section III-C we will revisit the results to verify if CPR and Defibrillation stages did influence the observed results.

The top panel of Fig. 4 shows the SDW feature over approx. 4.1 minutes (i.e. over 50 points of 5 s each) for all the 11 successful ROSC cases. In the figure (top panel), all the 11 cases are superimposed on each other. A clear upward trend can be observed in the evolution of the SDW

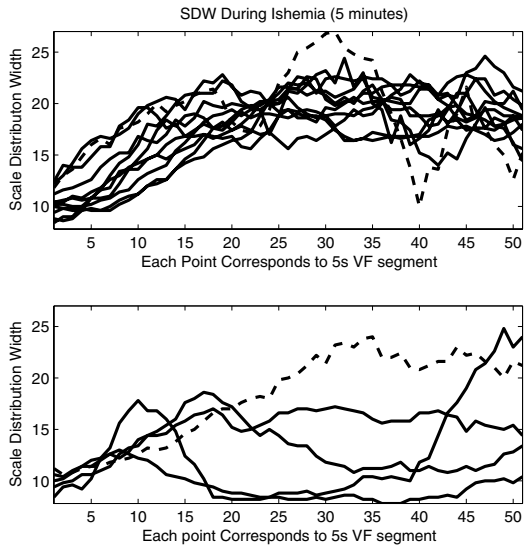


Fig. 4. Temporal evolution of SDW feature for all successful (top panel) and unsuccessful (bottom panel) cases

feature over time. Since smaller widths indicate more organized components (mono) and larger widths unorganized components (multi), from the plot it could be inferred that the VF waveforms of the pigs that were successfully resuscitated in this database tend to get disorganized over time during ischemia. In the plot, we have shown one successful case in dotted line just to indicate that it deviates from other curves and when we verified the corresponding VF data we did see changes in signal morphology that is reflected by SDW. Comparing this result with that of the 5 unsuccessful cases in the bottom panel of Fig. 4, it is evident that in most cases the trend is in opposite direction compared to that of the successful cases. Except in one of the unsuccessful case, the mean value of the plateau of the curves (i.e. after the initial portion of the curve) is significantly different. In the plot, we have also shown one unsuccessful case that is deviating from the rest in dotted line to indicate that it matches better with the successful cases.

We then averaged out the individual cases to obtain the average evolution pattern of the SDW feature for both successful and unsuccessful cases. The average curves are shown Fig. 5. The difference between the average curves are clearly evident. Even excluding the outliers (the cases shown in dotted lines in Fig. 4) from the curves, we would still be able to visualize a clear distinction between the average curves and this could serve as a reference to the EMS staff to monitor the VF waveforms over ischemia and decide on the course of action. Most of the existing works use 2.5 s - 10 s pre-shock VF data for predicting ROSC and hence may not be directly comparable to our above approach of using the temporal evolution of SDW as a clue for predicting ROSC.

### B. Pattern Classification

In the second part of the analysis we extracted the mean value of the SDW feature for each of the pigs over the 5 minute duration (i.e. one mean value of all the SDW feature

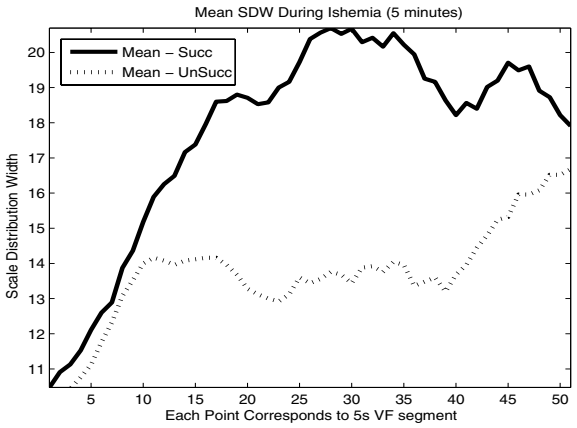


Fig. 5. Average temporal evolution of SDW feature for successful (solid line) and unsuccessful (dotted line) cases

values extracted in 5s segments over 5 minutes) and fed to a linear classifier to perform a statistical separation between the groups using linear discriminant analysis. The analysis was performed using SPSS software [8]. Since the database was small we cross validated the results using Leave-One-Out method (LOOM) [9]. In LOOM in each trial one sample is taken out of the database and the classifier is trained with the remaining samples. After training the classifier, the left out sample is used as a test set to identify its class membership. This is repeated for each of the samples and the average classification accuracy is computed over all the trails. The average classification accuracy is then presented as the cross validated performance of the classifier. The results are shown in Table I. From the table it could be observed that all the 11 successful cases were correctly classified while only 4 of the unsuccessful cases were correctly classified. An overall classification of 93.8% was achieved. When we verified the temporal evolution of SDW feature for the misclassifed unsuccesful case, it did match with the average curve of the successful case than the unsuccessful cases. The misclassfied unsuccessful case is same as the one shown in dotted line in the bottom panel of Fig. 4.

| Method | Groups | Unsuccessful | Successful | Total |
|---|---|---|---|---|
| Cross-validated | Unsuccessful | 4 | 1 | 5 |
| | Successful | 0 | 11 | 11 |
| % | Unsuccessful | **80** | 20 | 100 |
| | Successful | 0 | **100** | 100 |

TABLE I

CROSS-VALIDATED: LINEAR DISCRIMINANT ANALYSIS WITH LEAVE-ONE-OUT METHOD, % - PERCENTAGE OF CLASSIFICATION.

### C. Influence of CPR and Defibrillation Stages

We computed the diastole CPP for all successful and unsuccessful cases during CPR to validate that the efficacy of CPR did not bias the results. A CPP of >15mmHg considered to be an indicator of good CPR. The average CPP measured over the last 5 beats before defibrillation for the successful cases was found to be 33 mmHg with only 2 of the 11 cases having a CPP of <15 mmHg. The average CPP for the unsuccessful cases was found to be 10 mmHg with only 1 of the 5 cases having a CPP of >15 mmHg. An exception in the pressure value in the successful category (i.e. <15mmHg) does not affect the hypothesis as the supposedly bad CPR (indicated by <15 mmHg) did not change the result from what the trend of the SDW feature predicted during ischemia. The vice-versa is informative i.e. when the trend of SDW predicts an unsuccessful outcome but in reality if it ends up as a successful outcome than this could be due to a good CPR which helped the resuscitation process. We did not have this scenario in our database. However, we did have another possibility where among the unsuccessful cases, in one of the unsuccessful case the trend of SDW feature indicated a better fit with the successful cases (this is the unsuccessful case shown in dotted line in Fig. 4) but the actual result was unsuccessful. When we verified the CPP for this particular case, interestingly the CPP was 20.94 mmHg (i.e. >15 mmHg, good CPR) indicating indeed this was a candidate for a successful defibrillation, but it failed in reality. Except for this one unsuccessful case we did not observe a negative influence on the results by either the CPR or defibrillation stages and hence the model developed using SDW feature in discriminating successful from unsuccessful shock outcomes is valid and robust.

## IV. CONCLUSIONS AND FUTURE WORKS

We have presented a novel wavelet based feature to predict the cardiac resuscitation outcomes by analyzing the VF waveforms during ischemia. The proposed SDW feature can be used to obtain a near real-time update of the VF characteristics which could be used by the EMS staff to choose the right therapy. The proposed methodology achieved high classification accuracies and the results were verified using the LOOM cross validation technique. However the proposed method needs to be verified using larger human VF databases and compared with similar existing approaches.

## REFERENCES

[1] L. Wik, *et al.*, "Delaying defibrillation to give basic cardiopulmonary resuscitation to patients with out-of-hospital ventricular fibrillation a randomized trial," *JAMA*, vol. 289, no. 11, pp. 1389–1395, 2003.

[2] H. Povoas, *et al.*, "Predicting the success of defibrillation by electrocardiographic analysis," *Resuscitation*, vol. 53, no. 1, pp. 77–82, 2002.

[3] J. Menegazzi, *et al.*, "Ventricular fibrillation scaling exponent can guide timing of defibrillation and other therapies," *Circulation*, vol. 109, no. 7, pp. 926–931, 2004.

[4] J. Watson, *et al.*, "Wavelet transform-based prediction of the likelihood of successful defibrillation for patients exhibiting ventricular fibrillation," *Measurement Science and Technology*, vol. 16, no. 10, p. 1, 2005.

[5] ——, "Improved prediction of defibrillation success for out-of-hospital VF cardiac arrest using wavelet transform methods," *Resuscitation*, vol. 63, no. 3, pp. 269–275, 2004.

[6] O. Rosso, *et al.*, "Wavelet entropy: a new tool for analysis of short duration brain electrical signals," *Journal of Neuroscience Methods*, vol. 105, no. 1, pp. 65–75, 2001.

[7] A. Muñoz, R. Ertlé, and M. Unser, "Continuous wavelet transform with arbitrary scales and O (N) complexity," *Signal Processing*, vol. 82, no. 5, pp. 749–757, 2002.

[8] SPSS Inc., "SPSS advanced statistics user's guide," in *User manual, SPSS Inc., Chicago, IL*, 1990.

[9] K. Fukunaga, *Introduction to Statistical Pattern Recognition*. San Diego, CA: Academic Press, Inc., 1990.