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RAPID COMMUNICATION

Wavelet transform-based prediction of the likelihood of successful defibrillation for patients exhibiting ventricular fibrillation

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Abstract

We report on an improved method for the prediction of the outcome from electric shock therapy for patients in ventricular fibrillation: the primary arrhythmia associated with sudden cardiac death. Our wavelet transform-based marker, COP (cardioversion outcome prediction), is compared to three other well-documented shock outcome predictors: median frequency (MF) of fibrillation, spectral energy (SE) and AMSA (amplitude spectrum analysis). Optimum specificities for sensitivities around 95% for the four reported methods are $63 \pm 4\%$ at $97 \pm 2\%$ (COP), $42 \pm 15\%$ at $90 \pm 7\%$ (MF), $12 \pm 3\%$ at $94 \pm 5\%$ (SE) and $56 \pm 5\%$ at $94 \pm 5\%$ (AMSA), with successful defibrillation defined as the rapid ($<$60 s) return of sustained ($>$30 s) spontaneous circulation. This marked increase in performance by COP at specificity values around 95%, required for implementation of the technique in practice, is achieved by its enhanced ability to partition pertinent information in the time–frequency plane. COP therefore provides an optimal index for the identification of patients for whom shocking would be futile and for whom an alternative therapy should be considered.

Keywords: shock outcome prediction, defibrillator, ventricular fibrillation, ECG, wavelet transform, sudden cardiac arrest, resuscitation

1. Introduction

Two factors improve survival from cardiac arrest: attempted cardioversion of ventricular fibrillation (VF) via a defibrillation shock and cardiopulmonary resuscitation (CPR) to maintain the viability of the heart and brain until spontaneous circulation can be re-established. Despite improvements in defibrillator technology, most shocks do not cause return of spontaneous circulation (ROSC). Variations in the VF waveform correlate with the rate of ROSC, and recent experimental [1–3] and clinical [4] studies indicate that the VF waveform can be improved by CPR. This is consistent with recent clinical studies [6, 7] where pre-shock CPR improved the rates of ROSC and survival to hospital discharge for ambulance response times exceeding 4–5 min. With this in mind, the need for an effective predictor of shock outcome becomes apparent. This would enable the emergency responder to provide a therapy tailored to the patient's needs.

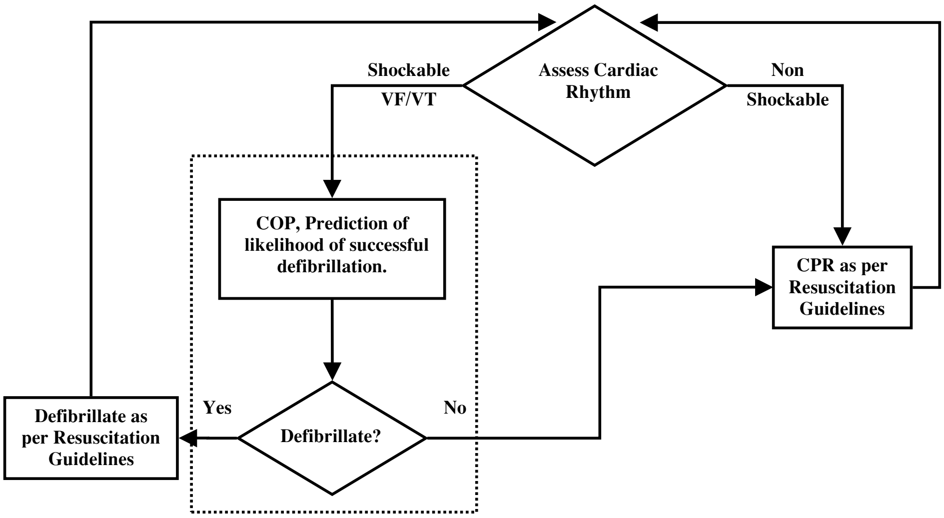

Figure 1. Flow diagram outlining therapeutic decision process with respect to the additional information supplied by a shock outcome prediction technology.

The 'shock first or CPR first' question becomes answerable for an individual rather than being a statistically based heuristic within a standard protocol.

Figure 1 envisages such use of shock outcome prediction technology. The predictor advises on immediate defibrillation *or* CPR when a shockable rhythm is detected—as shown within the dotted box. This is a significant departure from current protocols where a shock is administered to all shockable rhythms. Thus, with poor likelihood of cardioversion, a preferred therapy of CPR is applied rather than a futile defibrillation attempt.

The electrocardiogram (ECG) during VF was, until recently, considered to represent unstructured cardiac electrical activity variously described as random, noisy and chaotic. Techniques used to analyse the VF waveform include amplitude which has not proved to be a reproducible marker of defibrillation success [8, 9], Fourier-based spectral analysis [10, 11] and techniques from non-linear dynamics such as fractal [12] and phase delay [13] which in practice can often be shown to be related to previously investigated methods [14].

Wavelet transform analysis is especially valuable because of its ability to elucidate simultaneously local spectral and temporal information from a signal [15]. The identification of coherent structure in VF signals using wavelet transform-based techniques has been reported previously by the authors [16–19]. In [19], we introduce the concept of wavelet methods for shock outcome prediction using wavelet techniques with non-parametric Bayesian analysis. Here, however, we obtain novel markers derived from the modulus maxima of the wavelet transform scalogram. These markers provide superior results to [19] using a simple threshold value without the need of such non-parametric probability density estimates. Results are presented in the context of other well-documented shock outcome predictors: median frequency (MF) of fibrillation [10], spectral energy (SE) [20] and AMSA (amplitude spectrum analysis) [11].

2. Methods and results

The wavelet transform of a signal $x(t)$ is defined as

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

where $\psi^{*}(t)$ is the complex conjugate of the wavelet function $\psi(t)$, a is the dilation parameter of the wavelet and b is the location parameter of the wavelet. We define the wavelet scalogram as the time-scale half-space of any suitably scaled power of $|T(a,b)|$, the modulus of wavelet transform coefficient value, for varying scales and locations. A key advantage of wavelet techniques is the variety of wavelet functions available, thus allowing the most appropriate to be chosen for the signal under investigation. This is in contrast to Fourier analysis which is restricted to one feature morphology: the sinusoid. In the work described here, a tunable *Morlet wavelet* is used [21] where a characteristic frequency of the mother wavelet is chosen to best accentuate the features under investigation.

Using wavelet transforms, temporal behaviour of local signal features can be quantified from the scalogram. A measure of this temporal behaviour can be derived from an intermittency measure computed over one or more of the scalogram scales. The efficacies of these measures are enhanced through the reduction of the scalogram to its turning points in b for each scale a: the modulus maxima of the scalogram [22]. In this work, a novel wavelet-entropy marker was used as a metric of the temporal behaviour of the signal. This wavelet-entropy marker is defined as

$$\mathrm{WE}_{a'} = \frac{\int \ln|T(a',b)|\,\mathrm{d}b}{\int |T(a',b)|\,\mathrm{d}b}, \qquad (2)$$

where $|T(a',b)|$ are the wavelet transform modulus values at scale a'.

From this wavelet marker value, the probability of successful defibrillation can be derived using Bayesian statistics [19, 20] or a linear decision threshold can be derived

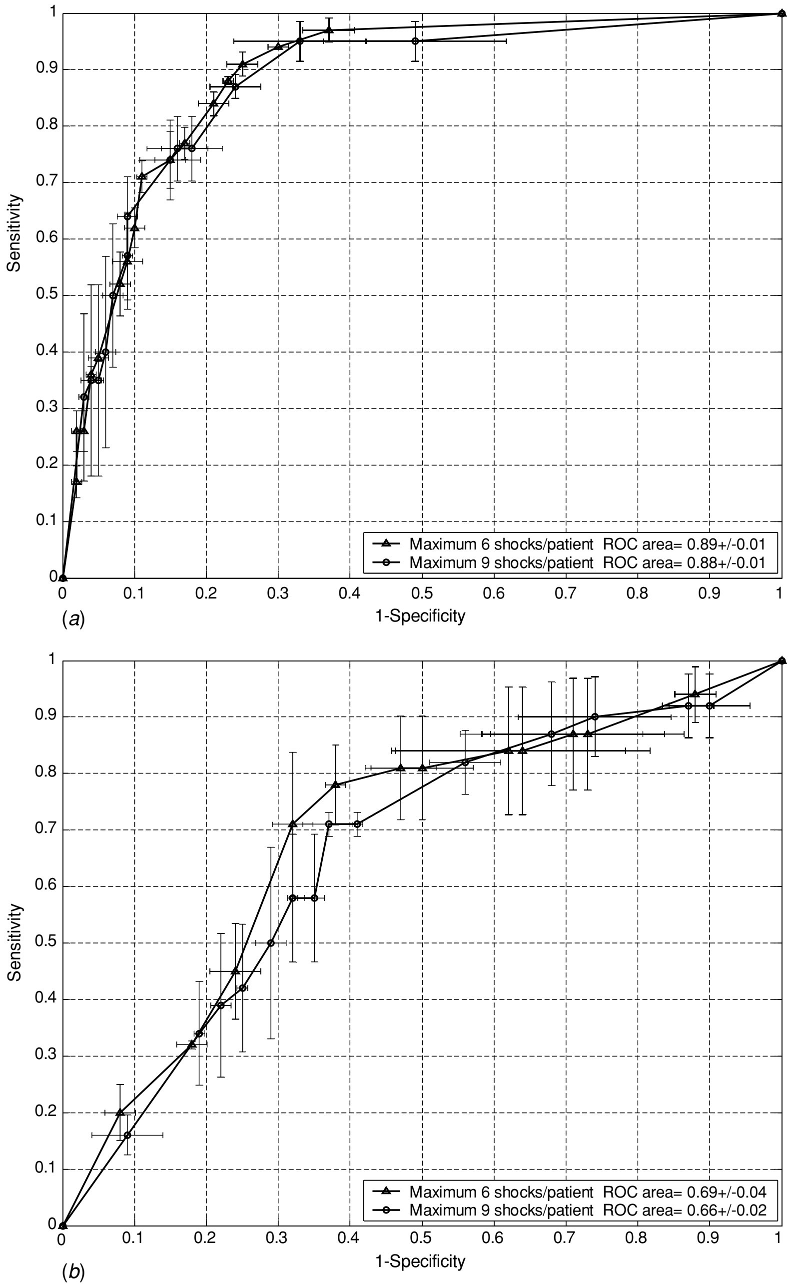

Figure 2. (*a*) ROC curve for the COP (wavelet-entropy) based system. (*b*) ROC curve for the median frequency based system. (*c*) ROC curve for the spectral energy based system. (*d*) ROC curve for the AMSA (amplitude spectrum analysis) based system.

identifying whether defibrillation should be attempted. Here we derive a linear threshold value from a proportion of a historical data set, the training set, such that a minimum performance sensitivity is achieved. This decision threshold is then applied to the remainder of the data set, the test set, to obtain that system's test sensitivity and specificity. Here, the system sensitivity is defined as the proportion of patients that are successfully defibrillated which are correctly identified. The system specificity is the proportion of patients that do not respond to defibrillation (failures) that are correctly identified. Unless these success and failure classes as completely differentiable, there is always a trade-off in the sensitivity and specificity achievable by a system. This trade-off is described by plotting sensitivity/specificity pairs in a receiver operator characteristic (ROC) curve, as described below.

The results presented are from a human out-of-hospital data set containing 878 pre-shock ECG traces, all of at least 10 s duration from 110 patients with cardiac arrest of cardiac aetiology. A full review of the data acquisition procedure and statistics can be found in [5]. We define 'successful defibrillation' as those attempts which result in ROSC sustained for a period greater than 30 s and originating within a minute of the applied shock. We have used all data *as provided* whilst limiting our system to hands-free periods of trace (i.e. the period immediately preceding the shock during which no CPR is applied). We report results where the number of shocks from each patient is limited to the first six and first

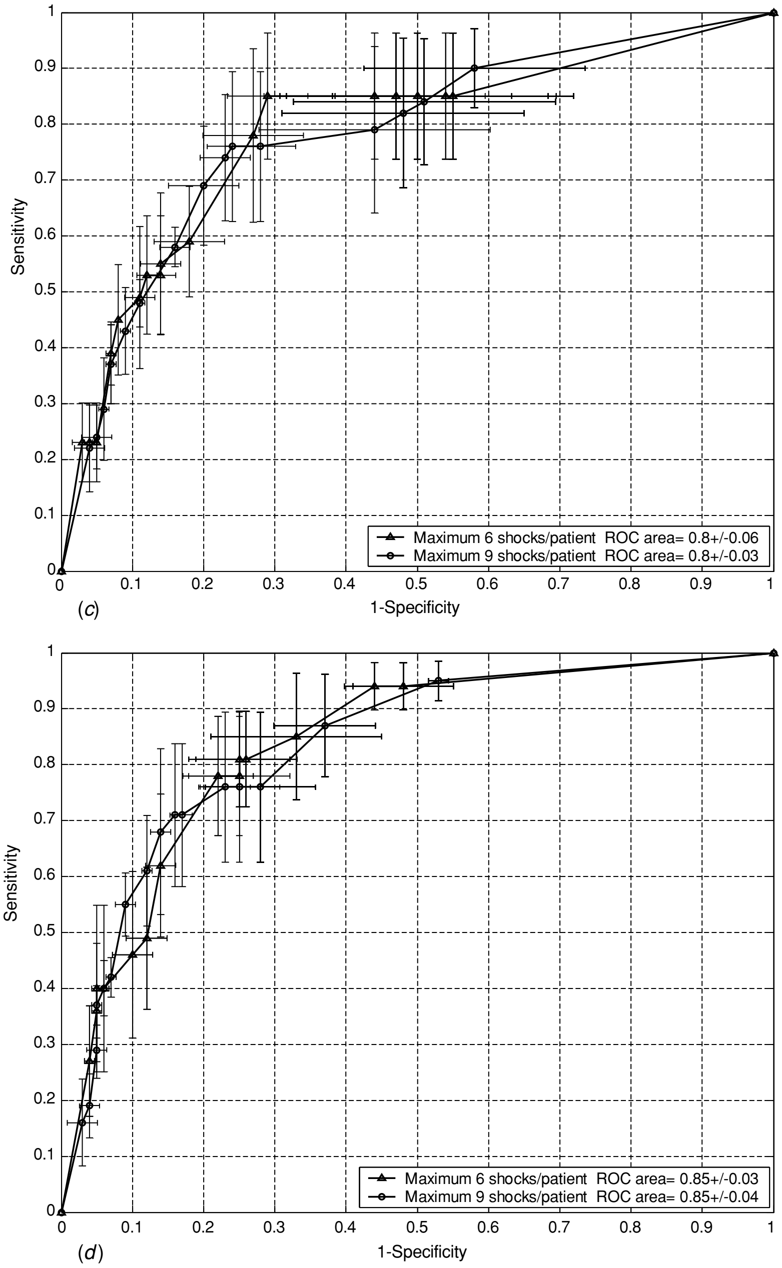

Figure 2. (Continued.)

nine, so reducing the chance of the system efficacy statistics becoming loaded due to intra-patient correlation.

The classifier performances are presented using ROC curves as used widely in the medical literature to assess diagnostic test performance. These ROC curves plot the (1 − specificity) values against their associated sensitivities. The area under the ROC curve summarizes diagnostic performance. An area of 1 represents a perfect diagnostic test whereas 0.5 represents a worthless test. Each ROC curve in figures 2(*a*)–(*d*) contain *standard error* bars. Each study was cross validated twice using different data subsets to parameterize and subsequently test the system each time. That is, the classifying (linear threshold) boundary for a given required sensitivity is derived using training data (to parameterize) and evaluated using the withheld test data iteratively. Cross-validation data sets were identical for the four investigated techniques. No patient had data in both training and test set for that cross-validation iteration because of the likelihood of intra-patient correlation. It has also been ensured that the distribution of patients per cross-validation set, shocks per set and shocks per patient in the sets remain broadly the same. Parametric investigations showed optimal length of pre-shock trace for this defibrillator of around 5 s located immediately prior to shock.

The COP marker is derived from the wavelet scalogram of the 5 s of pre-shock ECG trace (equation (1)) using a Morlet [21] wavelet with characteristic frequency of 3.5 rad s^{-1}. It is the wavelet entropy (equation (2)) of the non-zero modulus maxima of the scalogram scale associated with a central frequency of 45 Hz. The modulus maxima, $T_m(a, b)$, is

Table 1. Comparative mean system efficacies with standard errors.

	Maximum six shocks per patient		Maximum nine shocks per patient	
	Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)
Optimum specificities for sensitivities around 95%				
COP (wavelet entropy)	97 ± 2	63 ± 4	95 ± 5	67 ± 9
Median frequency	94 ± 5	12 ± 3	92 ± 6	13 ± 3
Spectral energy[a]	–	–	–	–
AMSA (amplitude spectrum)	94 ± 5	56 ± 5	95 ± 4	47 ± 1
Optimum specificities for sensitivities around 90%				
COP (wavelet entropy)	88 ± 1	76 ± 1	87 ± 2	76 ± 4
Median frequency	87 ± 10	29 ± 12	90 ± 7	24 ± 10
Spectral energy	85 ± 11	71 ± 6	90 ± 7	42 ± 15
AMSA (amplitude spectrum)	85 ± 11	67 ± 11	87 ± 9	63 ± 7

[a] NB: the spectral energy system did not attain a mean sensitivity above 95% for test set data.

described by equation (3) below.

$$T_{\mathrm{m}}(a,b) = |T(a,b)|, \qquad \text{where} \quad \frac{\mathrm{d}|T(a,b)|}{\mathrm{d}b} = 0 \quad \text{and} \quad \frac{\mathrm{d}^2|T(a,b)|}{\mathrm{d}b^2} \neq 0, \tag{3}$$

else $T_{\mathrm{m}}(a,b) = 0$.

The ROC curve produced from the wavelet marker, COP, is shown in figure 2(*a*).

The ROC curves of the median frequency (figure 2(*b*)) and spectral energy markers (figure 2(*c*)) were both obtained using frequencies of 1–25 Hz as these have been identified previously [20] as optimal for this data set. A stretched Hann (Tukey) window was used prior to Fourier transformation as this was found to improve results. Figure 2(*d*) shows the ROC curve indicating system performance when using the spectral area, AMSA, marker. (AMSA is a weighted sum of the spectral amplitudes with higher frequencies given a heavier weighting.) We evaluated the AMSA performance with high- and low-pass frequency filters, bandpass filters, and with and without windows (e.g. Hamming, Hann) on the temporal trace. The optimal results are reported in this figure where frequencies of 1–50 Hz are included and a Hann window applied to the raw ECG data. The system efficacies for sensitivities around 95% and 90% taken from the ROC curves of figure 2 are further summarized in table 1.

3. Discussion

Recent experimental and clinical studies have indicated that cardiopulmonary resuscitation (CPR) before defibrillation can increase the likelihood of success for some cases of ventricular fibrillation (VF). An effective predictor of defibrillation shock outcome would enable the emergency responder to provide the most appropriate therapy for the patient. Currently, the International Liaison Committee on Resuscitation (ILCOR) is formulating a number of *Evidence Evaluation Worksheets* including a review of published technologies and techniques for advanced cardiovascular life support (ALS). Included in this letter is evidence to answer the key question: *Is it possible to reliably predict success of defibrillation from the fibrillation waveform?* Preliminary published work from the group, although it does not as yet represent a recommendation, suggests such a technology would be safe and useful for the treatment of VF [23]. The full Consensus on Science and Treatment Recommendations (CoSTR) statements are due to be published in November 2005.

The apparent superior performance observed using wavelet techniques is, we believe, due to a fundamental difference between wavelet transform and other, alternative, methods. While these alternatives characterize an aspect of the behaviour of the signal over a period of time, the wavelet method can identify pertinent information in time. Thus, temporal partitioning of salient aspects of the transformed ECG becomes achievable prior to the classification step. This in turn increases the effectiveness of the derived marker. The more effectively the marker separates ROSC and non-ROSC, the less sophisticated the applied classification method need be. With limited data this is particularly important, as obtaining the required sensitivity via a more sophisticated classification method is more likely to result in data-specific performance and loss of generality.

The computing power necessary to calculate and analyse the high resolution—and highly redundant—continuous wavelet transform is necessarily large. However, through sensible selection of wavelet function and scales analysed along with implementing techniques such as modulus maxima, the computational complexity of COP is of the order of conventional Fourier methods. The number of COP software calculations can be further reduced when implemented on currently employed digital signal processors where the majority of its component tasks are supported as hardware instructions.

Within the constraints of our limited data set, we have taken a rigorous approach to this analysis with cross-validated results shown in the form of ROC curves. However, we qualify this with the caveat that care is needed when comparing ROC areas. Similar ROC areas can provide very different specificity values for similar sensitivities. In this case, where the number of positive samples (successful defibrillations) is limited, the values at the top end of the curve (i.e. at high sensitivities) are particularly susceptible to data outliers caused by poorly defined markers or sample set noise. However, this will only have a limited effect on the measured curve area. Further, it is expected that any implementation of such a predictive technology will require high sensitivity values for the prediction of likely successful defibrillations (of the order of 95%); so ensuring effective therapy (defibrillation) is not withheld from any patient who would benefit from it. Hence, our presented results focus on the high sensitivity (90–100%) region and do not dwell on comparisons of ROC areas.

Whilst recent experimental and clinical studies have indicated that CPR can increase the likelihood of successful defibrillation for established VF [6], it should also be noted that the same studies suggest that providing CPR first for patients with short duration VF may decrease the likelihood of successful shock outcome. Accordingly, predictive technologies such as COP would be most applicable for an initial assessment prior to the first shock. Unfortunately, because only 8 of the available 110 'first shock' traces resulted in successful defibrillation, such an analysis was infeasible for this study. Studies of this nature will require a larger data set, preferably of an open access type, allowing the benchmarking of various system performances. Ideally, this would include a facility for the blind testing of developed systems.

It is apparent that COP provides a 10–20% or so improvement in specificity over Fourier-based methods. The work of Wik *et al* [6] indicates that around 50% of patients will not achieve ROSC for any set protocol. If these alternative methods are predominantly identifying patients who will not respond positively to any therapy (as is reasonable to suspect), then little improvement in survivability will result through their use. Thus, in practice, it is exactly the increase in the specificity provided by COP, which we believe will be necessary to provide a significant measurable improvement in patient outcomes.

Acknowledgment

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