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EXPERIMENTAL PAPER

Improving countershock success prediction during cardiopulmonary resuscitation using ventricular fibrillation features from higher ECG frequency bands☆,☆☆

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Ventricular fibrillation;
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Summary
Background: Countershock outcome prediction using ventricular fibrillation (VF) feature analysis needs undisturbed electrocardiogram (ECG) signals and therefore requires interruption of cardiopulmonary resuscitation (CPR). Features that originate from higher frequency bands of the VF power spectrum may be less affected by CPR artefacts and as such reduce cumulative hands-off intervals.
Materials and methods: From 192 patients with in-hospital and out-of-hospital cardiac arrest, four countershock outcome prediction features (peak—peak amplitude, mean slope, median slope, power spectrum analysis) were analysed in 550 short time ECG records, each including a CPR corrupted and a subsequent undisturbed sequence. ECG features calculated from the main frequency band (0—26 Hz) and from bandpass-filtered subbands (>10—26 Hz) were compared using the similarity level method and differences in shock advice numbers.

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Results: The feature similarity between ECG periods with and without CPR artefacts was higher in bandpass-filtered (Sim = 0.79, 0.8, 0.78, 0.66) than in unfiltered ECG traces (Sim = 0.58, 0.69, 0.68, 0.47). For the features evaluated, the difference in number of shock advices between subsequent traces with and without CPR artefact was significantly reduced using VF analysis from higher frequency bands.

Conclusion: The accuracy of shock outcome prediction during CPR could be increased by using filtered ECG features from higher ECG subbands instead of features derived from the main ECG spectrum.

Introduction

High quality cardiopulmonary resuscitation (CPR) and early defibrillation are key measures to improve survival of cardiac arrest.[1–3] Automated external defibrillators (AEDs) contribute to this improvement as the time to first shock delivery by laypeople or by emergency medical service professionals is considerably reduced. AEDs are capable of detecting ventricular fibrillation (VF) by analysing the patient's electrocardiogram (ECG). In the future, defibrillators with improved ECG analysis might further increase countershock success by giving advice for the best moment to defibrillate. However, ongoing closed chest compressions have been shown to disturb VF feature analysis and countershock outcome prediction.[4,5] In addition, increasing cumulative hands-off intervals, which are needed for artefact-free VF feature analysis, were inversely related to CPR outcome.[2] Therefore, VF analysis during ongoing chest compressions would be highly desirable.

In previous studies,[5,6] bandpass filtering with a lower edge frequency of 4.3 Hz effectively removed artefacts of ongoing chest compression, but deteriorated the predictive power of median or dominant frequency analysis in humans.[5,6] Various strategies including complex filter methods, such as adaptive filters, have been suggested to remove chest compression artefacts from the human VF ECG.[4,7] In a recent study, several VF features have been shown to predict countershock success with a specificity of more than 50% at a sensitivity level of 95%.[8] Some of these features originate from frequency bands clearly above the CPR frequency range, and might therefore be less affected by CPR artefacts.

The purpose of this study was to estimate the robustness of specific countershock outcome prediction features using higher ECG frequency bands against CPR artefacts. Our hypothesis was that VF features employing only high frequency bands are less affected by CPR artefacts than those employing the whole frequency spectrum.

Materials and methods

The present data are taken from an observational prospective study of patients with out-of-hospital[9] and in-hospital[10] cardiac arrests between March 2002 and July 2004. Approval for this study was obtained from the Regional Committee for Research Ethics and the Norwegian Data Inspectorate and by the Institutional Review Board of the University of Chicago Hospitals. Heartstart 4000SP defibrillators (Laerdal Medical, Stavanger, Norway), including a compression pad equipped with acceleration and pressure sensors, were used for guiding depth and timing of chest compression,[11] applying countershocks and recording ECG data with a sampling rate of 500 Hz. Demographic data were documented according to the Utstein guidelines[12]; details have been described elsewhere.[9] Programs written in MATLAB R14 (The Math-Works Inc., Natick, MA) were used for signal processing, data visualisation and statistical analysis.

Dataset

Patient data were collected prospectively by emergency medical services in London, UK; Stockholm, Sweden; Akershus, Norway[9]; the University of Chicago Hospital in Chicago, IL[10]; and the University Hospital of Vienna, Austria, between March 2002 and July 2004. Resuscitation attempts were performed according to the CPR 2000 guidelines.[13] A total of 192 cardiac arrest patient episodes where analysed in this study. Corresponding to our previous study, a countershock was defined as successful when VF was converted to a supraventricular pulse generating rhythm within a 10 s postshock interval. The patient collective is similar to those of our previous study.[8] Small differences in patient number originate from different focus on ECG traces in both studies.

Signal processing and statistical analysis

In contrast to other studies, we did not try to clean the VF ECG from artefacts in itself but tested countershock outcome prediction features derived from higher ECG frequency bands (e.g. 12–24 Hz) for their robustness against CPR artefacts (Figure 1). Such features have a comparable outcome prediction accuracy to those calculated from the entire 0 to 25 Hz frequency band.[8] In this manuscript we use the term ''unfiltered features'' for features that are calculated from the 0–25 Hz ECG band, while ''bandpass filtered features'' describes features calculated from ECG frequency bands with a lower edge frequency above 10 Hz. As filters, fifth order IIR bandpass filters with 30 dB stopband attenuation were used (Figure 2).

VF ECG segments of 12 s each, including a period of ongoing CPR (6 s) and a subsequent interruption of closed chest compressions (6 s), were extracted for feature analysis (Figure 3). We found 622 CPR to no CPR transitions in 146 out of 192 patients. Seventy-two episodes had to be excluded from analysis because of CPR interruptions or artefacts in the post-CPR segment. Also, ECG rhythms other

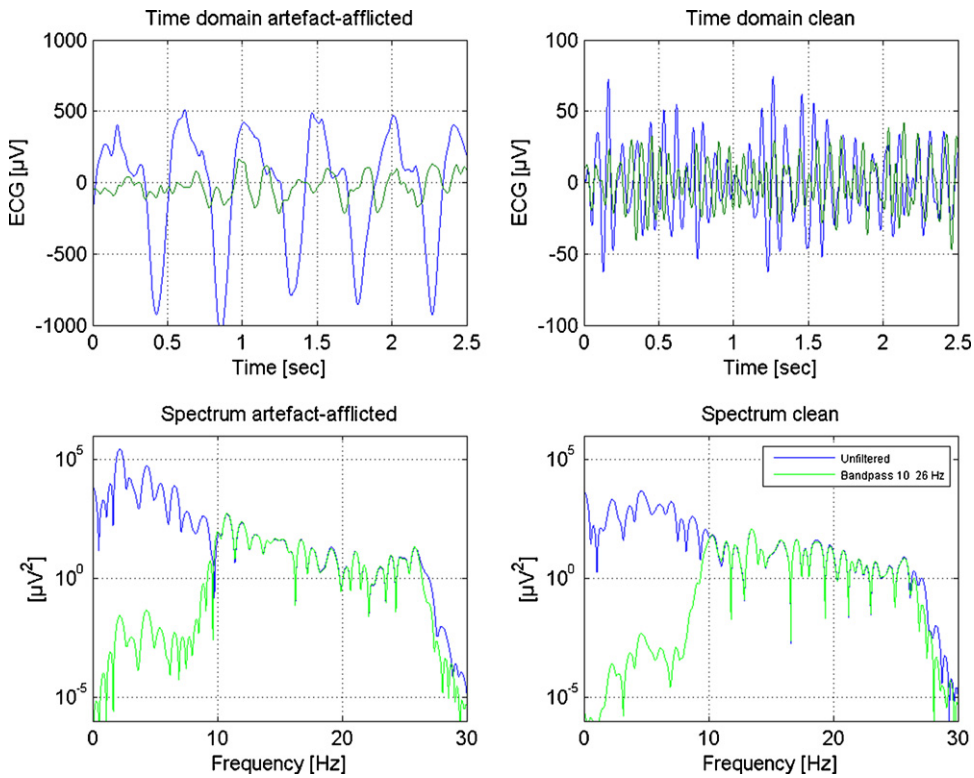

Figure 1 Time and frequency domain ECG signals; unfiltered signals appear in blue, filtered ones in green. The two plots on the left side refer to a CPR artefact corrupted segment; the plots on the right to a clean segment. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

than VF were an exclusion criterion, leaving 550 episodes for final analysis. For each 12 s ECG observation of a CPR transition, four 2.5 s segments of the ECG signal were analysed, two segments during CPR (periods I and II) and two segments immediately after interruption of CPR (periods III and IV) (Figure 3). The features peak—peak amplitude, median slope, mean slope and power spectrum analysis (PSA), which have been shown to be highly predictive of

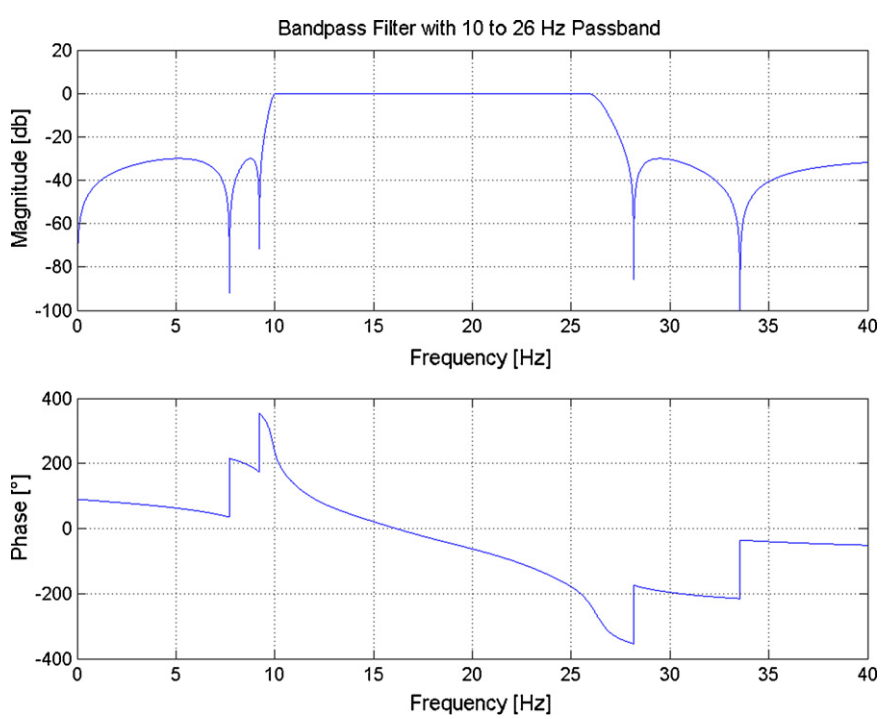

Figure 2 Example for a 10—26 Hz bandpass filter with 30 dB of attenuation in the stopband and 0.3 dB of ripple in the passband. The first plot shows the magnitude and the second one the phase of the filters frequency response.

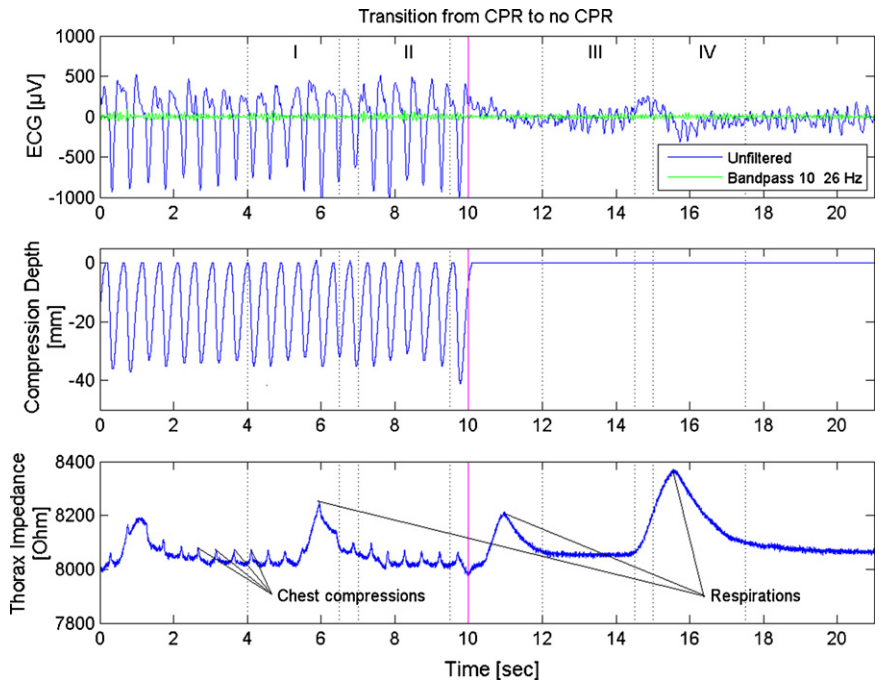

Figure 3 ECG trace, chest compression depth and trans thoracic impedance measured and recorded by the Heartstart 4000SP defibrillator. For every CPR to no CPR transition, four segments were extracted, two CPR artefact corrupted (I and II) and two clean ones (III and IV). In this example, artefacts caused by chest compressions are obvious in the raw ECG and impedance signal but not in the filtered ECG. However, filtered ECG also clearly differs from the raw ECG when no CPR is performed.

return of spontaneous circulation (ROSC) following shock (Table 1), were calculated for each CPR transition observation from the unfiltered as well as from the filtered ECG signal.[8]

Two different methods were used to analyse the robustness of VF prediction features against CPR artefacts.

First, feature values themselves were tested for differences between periods with and without chest compressions by comparing segment II to segment III. In addition, time-dependent variations were tested by comparing the two clean time segments III and IV to each other. For this analysis, a similarity level similar to a least square estimate was used. To compare features of two segments to each other, feature values of all N observations were fed as dots into x—y-scatter plots. The x-value x_i of each dot gives the feature value of the prior segment while the y-value y_i belongs to the corresponding subsequent one. From x_i and y_i the similarity level Sim is calculated as follows using help quotients q_i:

$$\mathrm{Sim} = \frac{\sum_{i=1}^{N} q_i}{N} \quad \text{with} \quad q_i = \begin{cases} \frac{x_i}{y_i} : \frac{x_i}{y_i} \leq 1 \\ \frac{y_i}{x_i} : \frac{x_i}{y_i} > 1 \end{cases}$$

Sim can range between 0 and 1. A value of 1 indicates absolute equality between all N, x_i and y_i, while values near 0 indicate large differences.

In the second part of this robustness analysis, we evaluated whether countershock outcome prediction based on VF features was affected by CPR artefacts. We used the previously defined decision borders of each feature that indicated for which feature value a successful shock outcome (in terms of leading to ROSC) could be expected. These decision borders were set to a sensitivity next to 95%.[8] For well-predictive features, the corresponding specificity should be at least 50%. The decision borders of each feature are displayed in Figure 4 and given in Table 1 which also provides the sensitivity specificity pairs of the features. First, we compared feature distribution of the VF ECG immediately after CPR interruption to those before countershocks from which the features were originally evaluated using Kolmogorov—Smirnov test with a significance level of 5%. It was done to prove that the distribution of features analysed here was similar to the distribution of those features the decision borders were calculated from.

Shock advice values were defined with respect to the decision borders of the feature values for all of the four segments. Typically, values greater than the decision border correspond to shock advices indicating a good moment to deliver a shock. They were defined as 1, and values below the decision border were defined as 0. Subsequently, we compared shock advice for CPR artefact corrupted segments (I and II) to clean segments (III and IV). Additionally, we compared segments I—II as well as III—IV to estimate general fluctuations. For comparison of two segments, the number of equalities and differences in shock advice were counted. This was done for each filtered and unfiltered feature. The numbers counted were filled into cross-tables sorted by equality between both segments (equal and unequal) and the use of a filter (filtered and unfiltered) (Table 1). Dependence between filtering and equality was calculated using the Chi-squared test. A $p < 0.05$ was regarded as statistically significant.

Table 1 Cross-tables about equality in shock advice of prediction features in artefact corrupted and clean segments with respect to filtering.

Feature:		PP Amplitude	12-26 Hz	Mean Slope	10-26 Hz	Median Slope	10-22 Hz	PSA	12-26 Hz
Sensitivity:	Specifity:	92.9	53.5	95.2	49.2	95.2	49.7	95.2	45.1
Dec Bord:	ROC AUC:	33.67	0.85	1.283	0.852	0.9667	0.863	5782	0.843
		unfiltered	filtered	unfiltered	filtered	unfiltered	filtered	unfiltered	filtered
II vs. III									
	unequal	156	97	126	90	141	111	134	91
	equal	394	453	424	460	409	439	416	459
			p: 0.000		p: 0.006		p: 0.031		p: 0.001
I vs. IV									
	unequal	172	111	138	101	147	104	141	105
	equal	378	439	412	449	403	446	409	445
			p: 0.000		p: 0.007		p: 0.002		p: 0.009
III vs. IV									
	unequal	55	54	38	36	44	43	48	47
	equal	495	496	512	514	506	507	502	503
			p: 0.920		p: 0.810		p: 0.911		p: 0.915
I vs. II									
	unequal	29	70	34	47	48	52	21	43
	equal	521	480	516	503	502	498	529	507
			p: 0.000		p: 0.133		p: 0.675		p: 0.005

Each cross-table compares two subsequent ECG traces with CPR artefacts (I, II) or without CPR artefacts (III, IV). The fields contain the counts for equal and unequal shock advice for filtered and unfiltered outcome prediction features. PP Amplitude, peak—peak amplitude; PSA, power spectrum analysis; Dec Bord, decision border.

Results

The similarity of the prediction features peak—peak amplitude, mean slope, median slope and PSA between subsequent ECG traces without CPR artefacts (periods III and IV) was comparable for the bandpass-filtered (Sim = 0.85, 0.88, 0.85 and 0.75, respectively) and unfiltered ECG traces (Sim = 0.8, 0.88, 0.87 and 0.74, respectively). In contrast, the feature similarity between ECG periods with (II) and without CPR artefacts (III) was higher in bandpass-filtered (Sim = 0.79, 0.8, 0.78 and 0.66, respectively) than unfiltered ECG traces (Sim = 0.58, 0.69, 0.68 and 0.47, respectively).

The feature distributions calculated from post-CPR segments and preshock segments were similar at the 5% significance level. Their decision borders should therefore be comparable as well, and the relation between the feature values and their decision borders be used as a measure for equality.

VF feature analysis with respect to the decision borders resulted in a comparable number of shock advices of two subsequent ECG traces without CPR artefacts (segments III vs. IV) for all observed features. For two subsequent ECG traces with CPR artefacts (segments I vs. II) we found a very similar number of shock advices only for median slope and for mean slope. The difference in number of shock advices between two subsequent traces, one with and one without CPR artefacts (I vs. IV and II vs. III) was significantly reduced using VF features from higher frequency bands (Table 1).

Discussion

Countershock outcome prediction features computed from higher frequency bands seem to be more robust against CPR artefacts than those taken from the entire ECG spectrum. Features from higher frequency bands reach nearly the same similarity levels between artefact corrupted and clean ECG segments as conventional features do for two subsequent clean segments.

Various methods for removing or suppressing CPR artefacts from human ECG have been investigated in the past. Adaptive filters have been shown to successfully remove CPR artefacts for ECG analysis, but multichannel methods require additional reference channels.[4,14,15] In addition, adaptive filters including Kalman filtering for artefact suppression[16] suffer from inadequate low specificity necessitating further improvement before this technique can be used in clinical practice. Mechanical artefacts resulting from CPR could be effectively removed from porcine ECG signal using a 4.3 Hz high-pass[5] but a similar approach to eliminate CPR oscillations from the human ECG was not effective due to spectral overlap of artefacts and human VF signal.[6]

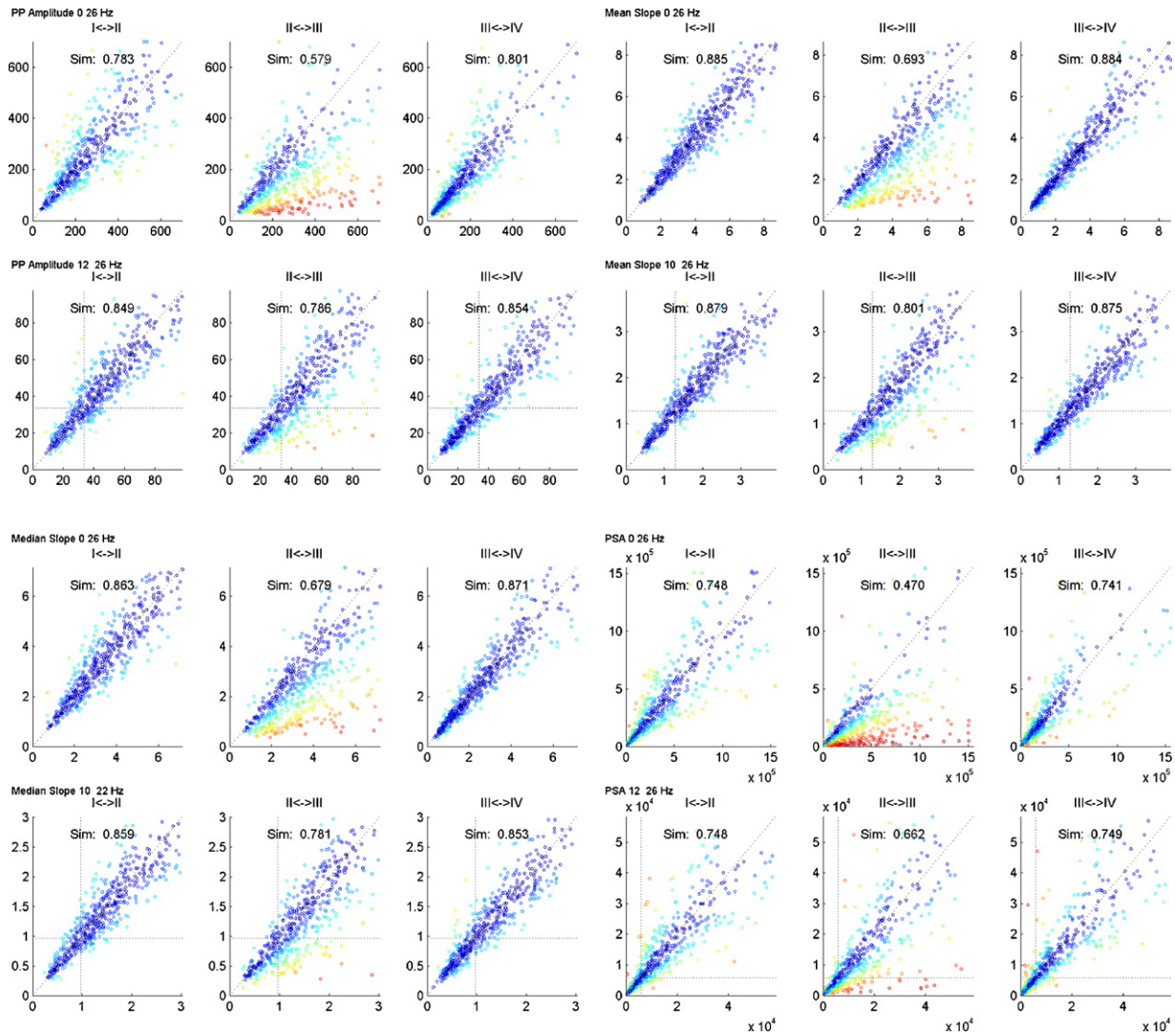

Figure 4 Scatter plots that compare feature values of two subsequent ECG segments, with the first plotted on the *x*-axes and the second on the *y*-axes. Similar feature values between two segments are located near the bisector lines and appear in blue, different values are given in red. For each feature, the upper plots show values for the unfiltered ECG, the lower ones for the filtered ECG. In addition, the calculated similarity value is given. For features employing filtered ECG, decision borders are marked with a horizontal and vertical dotted line. These lines divide the plot into four sections. Notice, all points lying outside the lower left and upper right sections reflect different countershock advices between the two compared segments.

More recently, VF features originating from higher frequency bands (>10 Hz) have been shown to predict countershock success better than features taken from the entire power spectrum.[8] Therefore, it seemed valuable during analysis of human VF to apply a filter that eliminates signal components <10 Hz including CPR artefacts and focus on the promising VF band >10 Hz with respect of countershock outcome prediction.[8]

From a theoretical point of view, there are several ways chest compressions affect the VF ECG signal. First, artefacts that originate from movement of the patient, electrodes and cables result in impedance and potential changes within the measurement system. These artefacts are additional non-biological noise to the VF biosignal and could occur in any electrical measurement system disturbed by mechanical activities. In such a case, it may be possible to restore the original signal by accurate filtering of the CPR introduced artefact components into the ECG, e.g. by using an additional reference channel.[4] Outcome prediction features derived from higher frequency bands are supposed to be less affected by these mechanical artefacts. Second, ''physiological'' artefacts that result from the impact of chest compressions on organs including the heart, blood vessels and tissue in general. Chest compressions directly affect activation potentials of myocardial cells which indicates that the original VF signal and the trans-thoracic impedance are changed by deforming tissue.[17] In that case, removing artefacts using the adaptive filtering method will be less effective as changes on the cellular level will also be recorded by the surface ECG. We suggest that both kinds of artefacts contribute to the artefacts seen in human ECG during CPR. Results of our study are in agreement with this hypothesis as countershock outcome prediction features and decision border values computed from higher frequency

bands were robust against CPR artefacts. Differences in decision border between two subsequent traces, one with and one without CPR artefacts, were significantly reduced by VF feature analysis from the high frequency band. In the same way, the similarity levels of two clean segments or two segments with CPR artefacts were nearly but not completely reached with this particular method of artefact suppression.

There are several limitations in this study. As shown in Figure 4, there are not only differences of feature values between artefact corrupted and clean segments, but also between two corrupted or two clean segments. Variations in the ECG or other external influences may also result in short-term fluctuations of the ECG features. There are several cases when shock advice differs between the filtered and the unfiltered clean ECG segment but receiver operation characteristic (ROC) areas under the curve (AUC) of the filtered and unfiltered features are approximately in the same range. When comparing different features to each other their predictive powers also have to be taken into account. A feature which is absolutely robust against CPR artefacts is worthless if it has only a weak shock outcome prediction power. Another limitation refers to the kind of error we analysed. We only looked for differences in shock advice, and did not classify the strength of the error in the sense of: 'What is worse, wrongly recommending a shock or missing an ideal time point to defibrillate?' As we only analysed test robustness of bandpass filtered features against CPR artefacts in this study, an important prospective for a subsequent study would be to estimate countershock outcome prediction of those features for artefact corrupted preshock segments. In the present study we analysed a mean of 3.93 (median: 3, range: 1—17) CPR-to-no CPR transitions per patient. Therefore, it has to be mentioned that the analysed episodes are not completely independent which might add some systematic bias to the results. However, repeating the Sim analysis for just the first relevant CPR-to-no CPR transition for each patient delivered qualitatively comparable results.

We conclude that compared to features derived from the main ECG spectrum, the accuracy of shock outcome prediction during CPR could be increased by using ECG features from higher ECG subbands. However, the similarity levels of two subsequent clean or artefact-corrupted segments were not completely reached with this particular method of artefact suppression.

Conflict of interest

The study was supported, in part, by Laerdal Medical AS, Stavanger, Norway, which offers products and system solutions for health care providers with particular emphasis on emergency medicine and training. At the time of the study, Helge Myklebust and Joar Eilevstjønn were employees of Laerdal Medical. Petter A. Steen was a Board member of directors of Laerdal Medical. Andreas Neurauter received financial support from Laerdal Medical for this research.

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