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Clinical paper

An accurate method for real-time chest compression detection from the impedance signal☆

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ABSTRACT

Objective: Real-time feedback improves CPR performance. Chest compression data may be obtained from an accelerometer/force sensor, but the impedance signal would serve as a less costly, universally available alternative. The objective is to assess the performance of a method which detects the presence/absence of chest compressions and derives CPR quality metrics from the impedance signal in real-time at 1 s intervals without any latency period.

Methods: Defibrillator recordings from cardiac arrest cases were divided into derivation ($N = 119$) and validation ($N = 105$) datasets. With the force signal as reference, the presence/absence of chest compressions in the impedance signal was manually annotated (reference standard). The method classified the impedance signal at 1 s intervals as *Chest Compressions Present*, *Chest Compressions Absent* or *Indeterminate*. Accuracy, sensitivity and specificity for chest compression detection were calculated for each case. Differences between method and reference standard chest compression fractions and rates were calculated on a minute-to-minute basis.

Results: In the validation set, median accuracy was 0.99 (IQR 0.98, 0.99) with 2% of 1 s intervals classified as *Indeterminate*. Median sensitivity and specificity were 0.99 (IQR 0.98, 1.0) and 0.98 (IQR 0.95, 1.0), respectively. Median chest compression fraction error was 0.00 (IQR −0.01, 0.00), and median chest compression rate error was 1.8 (IQR 0.6, 3.3) compressions per minute.

Conclusion: A real-time method detected chest compressions from the impedance signal with high sensitivity and specificity and accurately estimated chest compression fraction and rate. Future investigation should evaluate whether an impedance-based guidance system can provide an acceptable alternative to an accelerometer-based system.

Introduction

Sudden cardiac arrest is a major public health challenge with thousands of persons dying worldwide each year.[1] Successful resuscitation is possible with a coordinated set of actions, and the cornerstone of resuscitation is CPR – specifically, effective chest compressions.[2] CPR performance that limits interruptions and achieves a specific compression rate or depth has been associated with better outcomes.[3–8] Real-time feedback can improve CPR performance,[9] but acquisition of reliable chest compression data currently requires an accelerometer or force sensor, and those devices have not been widely adopted, particularly outside of research settings.

The thoracic impedance signal, which is the impedance measured between defibrillator electrodes, is an alternative source of chest compression data.[10] An advantage of the impedance signal is that it is available on most automated external defibrillators and monitor-defibrillators without an additional patient interface. Accurate detection of chest compressions from the impedance

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would enable identification of pauses and measurement of compression rate and fraction, although not depth. Any real-time method would additionally require a minimal latency period, which can be defined as the interval between the classification time and the last recorded signal, because even modest interruptions in compressions have been associated with a lower likelihood of survival.[6,11] Accelerometer-based systems generally do not have any latency.

Currently, there are no published, impedance-based methods which are suitable for real-time CPR feedback, as existing methods are limited to retrospective application or have an unspecified latency period.[12–16] In this investigation, we evaluated a novel method which classifies the presence or absence of chest compressions at 1 s intervals without latency. The objective was to assess its performance in terms of classification (accuracy, sensitivity and specificity for chest compression detection) and measurement of CPR quality metrics (chest compression rate and fraction).

Methods

Study design, setting and data description

This cross-sectional study evaluated a convenience sample of 224 cardiac arrest patients who received resuscitative efforts by one of three EMS systems from 2006 to 2012. All patients were treated with a resuscitation strategy in which compressions were interrupted for ventilations (30:2 compression-to-ventilation ratio), rhythm analysis, pulse checks and shock delivery. The derivation and validation sets consisted of 119 and 105 cases, respectively, and all cases had a Philips MRX defibrillator recording with simultaneous ECG, impedance (recorded at 200 samples per second) and force data. Cases were not selected according to any characteristics of the impedance or force signal. The force signal served as the reference, and in order to ensure its adequacy, only data following the first chest compression and preceding the final chest compression of each case were included. Additionally, a maximum of 10 min of data were included from each case in order to generate a dataset which was representative of the entire cohort by not oversampling from any single case. The study was approved by the University of Washington Investigational Review Board.

Definition of reference standard

Using the force signal as the reference for chest compressions, the impedance signal was manually annotated by marking transitions between phases with and without compressions. The impedance signal was then divided into consecutive, non-overlapping, 1 s frames. A frame was classified as *Chest Compressions Present* if a chest compression phase extended over at least one-fourth of that frame and as *Chest Compressions Absent* otherwise (the elapsed time from the "peak" of a typical compression to its "valley" is roughly a quarter-second). These classifications served as the reference standard for assessment of accuracy, sensitivity, specificity and chest compression fraction. Chest compression rate was assessed on a minute-to-minute basis, and the reference standard was the number of compressions with ≥5 kg of force per minute of chest compressions.

Chest compression detection method

CPR is characterized by periods of chest compressions interspersed with pauses of variable length. As a result, the presence of compressions at one moment in time is related to the presence of compressions at the next. This temporal dependence provides an opportunity to overcome classification inaccuracy, because artifact in the impedance signal tends to be random, while changes from compressions are typically periodic. The method accounts for this temporal dependence with a statistical tool called hidden Markov modeling. Hidden Markov modeling is used to analyze sequential processes in a variety of fields[17–19] and can improve accuracy when applied to continuous electrocardiogram analysis during chest compressions.[20]

In this method, the impedance signal is divided into consecutive, 1 s frames and modeled as a sequence of discrete, "hidden" states, with one state per frame (Fig. 1A). The possible hidden states are *Chest Compressions Present* and *Chest Compressions Absent*. While the hidden/unknown states are not directly observed, they are reflected by their observed emission features (the term "emission" refers to an imaginary process in which the hidden state emits a signal). The emission features are signal processing parameters extracted from the 1 s of impedance data within each frame.

The method incorporates four emission features. The first feature is the relative amplitude, which is the amplitude of the largest peak in the frame divided by the median amplitude of the twenty previous frames (Fig. 1B, left). The other three features are frequency-based and are obtained from the Fourier transform of the impedance signal within the frame after applying a band pass filter from 1 to 10 Hz: (1) the maximum magnitude; (2) the dominant frequency, defined as the frequency at which the maximum magnitude is found; and (3) the integral of the magnitude between 1.5 and 2.5 Hz (Fig. 1B, right).

The *Chest Compressions Present* and *Chest Compressions Absent* states have different joint distributions of the emission features. The joint distributions are termed "emission distributions" and were estimated from the derivation data using the reference standard classifications. For a new frame with an unknown classification, the probability of its hidden state being *Chest Compressions Present* (or, conversely, *Chest Compressions Absent*) depends upon the statistical similarity of its four emission features to each emission distribution.

A hidden Markov model incorporates temporal dependence between frames by assuming that the sequence of hidden states forms a Markov chain. In a Markov chain, future states in a sequence depend upon the present state but not past states. The process of transitioning from one state to the next state, 1 s later, is governed by a collection of transition probabilities that were estimated from the derivation set. A hidden Markov model also requires an initial state distribution, which is the probability distribution for the first frame of a case or the first frame following a defibrillation attempt. *Chest Compressions Present* and *Chest Compressions Absent* have equally probabilities in the initial state distribution.

To perform real-time analysis, the hidden Markov model and Bayes' rule are used to calculate the "forward probability" at each time.[17,20] For this method, the forward probability is defined as the probability that the current state is *Chest Compressions Present* using data from the current and all preceding frames of the impedance signal, and it is updated each second as new data accumulate (Fig. 2). For the purposes of the current investigation, the forward probability determines the frame classification: (1) *Chest Compressions Present* if ≥0.80; (2) *Chest Compressions Absent* if ≤0.20; and (3) *Indeterminate* if between 0.20 and 0.80.

For any frame classified as *Chest Compressions Present*, the dominant frequency in Hz (i.e., compressions per second) is used to calculate the instantaneous chest compression rate, whose units are compressions per minute. The chest compression rate of any 1 min interval was estimated as the median of the instantaneous chest compression rates for the frames within that interval.

Data analysis

The primary metrics were accuracy, sensitivity, and specificity with measurements occurring at 1 s intervals. Metrics were