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Cardiopulmonary Resuscitation Quality Parameters from Inertial Sensor Data using Differential Evolution Fitting of Sinusoids

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Abstract

In this paper, we present a robust sinusoidal model fitting method based on the Differential Evolution (DE) algorithm for determining cardiopulmonary resuscitation (CPR) quality-parameters – naming chest compression frequency and depth – as measured by an inertial sensor placed at the wrist. Once included into a smartphone or smartwatch app, our proposed algorithm will enable laypersons to improve cardiopulmonary resuscitation (as part of a continuous closed-loop support-system). By evaluating the sensitivity of the model with data recorded by a Laerdal Resusci Anne mannequin as reference standard, a low variance for compression frequency of ±2.7 cpm (2.5 %) has been found for the sensor placed at the wrist, making this previously not evaluated position a suitable alternative to the typical smartphone placement in the hand.

1 Introduction

Sudden cardiac arrests (SCA) is one of the most prominent diseases (350,000- 700,000 individuals a year in Europe are affected, depending on the definition [1–3]). SCA can significantly affect the independent living of the victims if medical treatment is not available within a few minutes [4,5]. In case of a cardiac arrest, the transport of oxygen and glucose to the cells of the human body stops immediately due to the disrupted heart function. This results in irreparably cell damage if the blood circulation is not re-established, e.g. via cardiopulmonary resuscitation (CPR). For the cells of the nervous system including the brain, that means that the functionality reduces after 10 seconds (i.e., loss of consciousness). The death of the cells begins after about 3 minutes. [6]
Medical personnel such as paramedics are trained in Advanced Life Support (ALS) [7] methodology that includes CPR. Unfortunately, paramedics are usually not immediately available if a cardiac arrest occurs in the field. With the typical median response-time of paramedics being about 5-8 min [4] and a decreasing likelihood of survival with every minute without CPR, victims depend on initial CPR-support of non-specialist bystanders (further referred to as laypersons) within the first “golden” minutes after a cardiac arrest to prevent negative long-term effects. Since these laypersons can offer essential initial resuscitation support, corresponding technical solutions, to support them with online feedback regarding the quality of CPR is required.

For the following discussion, the optimal Basic Life Support (BLS) [4] procedure is worthwhile to be briefly recapitulated: In case of a cardiac arrest, it is essential to ensure sufficient oxygenation of the nerve cells via a correctly conducted cardiac massage (chest compressions) as the most critical countermeasure. During this cardiac massage, the heart is compressed by orthogonal pressure onto the breastbone. In order to sustain a minimal blood circulation to carry oxygen to the nerve cells, a chest compression frequency (CCF) of the cardiac massage should range from $110 \pm 10$ compressions per minute (cpm), and a chest compression depth (CCD) of approximately $5.5 \pm 0.5$ cm is required. Ideally (but not necessarily) the procedure is combined with rescue breathing$^1$, to improve the chance of survival and reduce neurological deficits [4].

While typical laypersons can develop a sufficient feeling of semi-ideal compression depth, the constant application of the correct compression-frequency and -depth is challenging, especially for extended periods of cardiac massage with the associated muscle-fatigue and mental pressure. Thus, instant feedback regarding the correct execution (regarding CCD and CCF) during cardiac arrest will be beneficial for untrained laypersons. Such feedback could be derived from monitoring the quality of the cardiac massage online from the vertical acceleration as measured by inertial measurement units (IMUs) and giving continuous feedback (and adjustment hints) regarding CCD and CCF. Smartphone applications have been shown to be well suited for this purpose due to their high availability [8,9], and their general benefit regarding CCF/CCD has been confirmed by Renshaw et al. for the BHF PocketCPR who recognised an improved performance (from 66 to 91 cpm) and increased confidence of laypersons [10]. However, for such CPR training apps, a highly accurate CPR information (regarding CCF and CCD) is an essential requirement [9] which is achieved partially by the existing implementations (as summarized in Table 1).

Table 1: Accuracies of existing chest-compression algorithms.

| Measurement Position | Algorithm | CCF Error [Hz] | CCD Error [mm] | Reference System | Year / Reference |
|----------------------|-----------|----------------|----------------|------------------|-----------------|
| On chest             | Spectral techniques on short acceleration intervals | $< 1.5$ RMSE | $< 2$ RMSE | photoelectric distance sensor | [11], 2014 |
| On chest             | Butterworth HP filter, 2x integration, manual reset | - | 1.6 (within mannequin) | | [12], 2002 |

$^1$ For rescue breathing, the heart pressure massage will be briefly stopped and will be continued after two accelerated breathings.
Most of these approaches use Fast Fourier Transformation (FFT) to determine the regular frequencies from the inertial data and identifying the main frequencies from the frequency spectrum via peak detection: While being straightforward, this approach is susceptible for erroneous peak selection and a resulting frequency shift of the CCFs by orders of magnitude.

Also, the double-integration of the acceleration signal – a common processing step for the determination of the displacement-vector as a preprocessing step for the CCD is challenging due to the signal drift if the accelerometer is not perfectly aligned with gravity axis.

Consequently, the typical integration process is inherently unstable and leads to relevant errors unless boundary conditions are applied for each compression cycle (e.g. in very short windows). In contrast, the use of a robust sinusoid model i.e. sine curve might cover such phenomena and the subsequent effects on the derived CPR parameters more robustly, due to its implicit periodic accordance with the CPR. A concept which has been successfully shown for depth-image-based Motion Capture recordings of CPR movements [15,16] but yet has to be confirmed for the use with acceleration data, as directly recorded via IMUs on the rescuers.

Furthermore, the discussed algorithms have been mainly evaluated for the use of IMUs in a grasp-in-hand use, a position that has been reported to be a rather uncomfortable and disturbing positioning for lay-persons [17], which as well might mislead them into learning incorrect postures [18]. To overcome this drawback, Park et al. [17] proposed the fixation of smartphones via an armband on the dorsum manus or at the arm and had shown an increased convenience in comparison to the common grasp-in-hand approach. However, they reported a reduced sensitivity, which they explained with the amplified inertial forces resulting from the additional device’s swing. Similarly Ruiz de Gauna et al. compared sensor placement at the dorsum manus with one fixed to the forearm 7 cm above the wrist and confirmed a significantly increased error for the forearm placement with median errors of 3.1 mm (1.4–5.1) and 9.5 mm (6.8–12.9) for the dorsum manus and for the forearm, respectively [19].

Consequently, while IMUs have been confirmed to be in general a sensitive and practical approach to measure CC depth and frequency during CPR, the usability via smartphones is reportedly challenging since affecting the quality of CPR for laypersons. In contrast, smartwatches hold benefits over the use of smartphones regarding usability and could be
expected to achieve higher reliability towards arm-movements, since being potentially less affected by arm movements. Furthermore, they overcome challenging aspects of reduced tactile pressure sensation at the hands. However, the use of IMUs on alternative placements was repetitively found challenging for sufficient accuracy, and the suitability of smartwatches for CPR training and online-support regarding the sensitivity of CCD and CCF detection yet has to be investigated.

Consequently, with the article at hand, we aim to investigate the following two research questions:

1) How suitable is the DE algorithm for fitting a sinusoid model of the chest compression during CPR regarding the accuracy of resulting CCF and CCD parameters for the considered sensor placements in comparison to the Resusci Anne as reference system?
2) How suitable are smartwatch inertial sensors for the online detection of the chest compression during CPR regarding the accuracy of resulting CCF and CCD parameters in comparison to the Resusci Anne and the typical hand-holding as reference systems?

Thereby, in Section 2 our DE fitting approach for inertial data, the study design and applied evaluation methodology are introduced. In section 3 the results of the study are discussed by comparing the results to a Resusci Anne mannequin as a reference. The article is concluded in Section 4.

2 Materials and Methods

2.1 DE fitting of accelerometer data to model

Our approach utilizes the periodic nature of the CPR to fit the signal of the accelerometer to a sine curve (see Figure 1).
The generic parameterized sine function can be written as follows:

\[ \hat{y}(t) = A \cdot \sin(2ft + \rho) + D \]  

(1)

Parameter \( A \) and \( f \) are of primary interest here; \( A \) is the amplitude, \( f \) the ordinary frequency. When we assume that the arms of a person performing CPR are orthogonal (and rigid) on the patient's chest, then the relative distances of his/her arms are equal to the chest compression depth. Moreover, additionally, the frequency of low to high to low compression depth represents one compression cycle.

Unfortunately, it is not applicable to fit the accelerometer data directly to the sine curve (see Equation 1) and derive the displacement of the arm from it. To overcome this issue, we use the second derivative of Equation 2 as model function (Equation 3):

\[ y(t) = \Delta \Delta t^2 A \cdot \sin(2ft + \rho) + D \]  

(2)

\[ y(t) = -A \cdot (2f)^2 \cdot \sin(2ft + \rho) \]  

(3)

On a fitted function, parameter \( f \) is the CPR frequency, \( 2\cdot A \) is the compression depth and \( \rho \) is the phase shift. To fit the function \( y(t) \), we minimize the least-squares distances using an evolutionary approach. Thus, we formulate the minimization problem as follows:

\[ \min \sqrt{\frac{1}{|a|} \sum_{t=0}^{\left|a\right|} (a(t) - y(t))^2} \]  

(4)

In the equation, \( a \) is the vector of accelerometer measurements.

A common evolutionary algorithm is the Differential Evolution (DE) [20] algorithm that works particularly well with nonlinear, i.e. sinusoidal cost functions. DE searches and evaluates a parameter space in parallel and finds multiple near-optimal but distinct solutions to a problem. The DE algorithm is used here to solve the three parameters of a sinusoidal curve (Equation 3). As all evolutionary algorithms, DE is population-based and optimizes the population throughout several generations:

\[ x_{i,G} \text{ with } i = 1..NP, G = 1..G_{max} \]  

(5)

\( x_{i,G} \) is a 3-dimensional vector of individual \( i \) for generation \( G \). So in every generation \( NP \) individuals are optimized up to \( G_{max} \) generations. One individual represents one possible solution to the minimization problem (see Equation 4). The optimization is done between a transition from one generation \( G \) to another generation \( G + 1 \). Within each transition from one generation to the following most evolutionary algorithms - as does DE - comprise the steps mutation, crossover and selection.

**Mutation**

For every generation, a mutation step is performed for every individual \( x_{i,G} \). We used the step from [20] with a fixed amplification factor \( F = 0.8 \) as recommended in [21,22]:

\[ v_{i,G+1} = x_{r_1,G} + F \cdot (x_{r_2,G} - x_{r_3,G}) \]  \hspace{1cm} (6)

In Equation 5 \( v \) is the mutated individual and \( r_1, r_2, r_3 \in \{1, 2, ..., NP\}, r_1 \neq r_2 \neq r_3 \neq i \) randomly chosen.

**Crossover**

The crossover step determines which of the four parameters per individual are preserved in the next generation. For every parameter, a uniform random number \( r \in [0, 1] \) is chosen. If \( r \leq CR = 0.5 \) then the parameter from the mutant is chosen, otherwise the one from the original individual is continued with.

**Selection**

The selection step decides which individual is passed to the next generation by evaluating it against the cost function. In our approach, the squared errors are summed up for every solution candidate \( x_{i,G} \):

\[ \sum_{t=0}^{T} (a(t) - y_{x_{i,G}}(t))^2 \]  \hspace{1cm} (7)

with \( a \) being a \( T \)-length vector of samples (accelerometer data) and \( y \) the parameterized sinusoid function of individual \( x_{i,G} \).

When DE has finished, i.e. when \( G_{\text{max}} \) was reached, the individual with the lowest RMSE represent the parameter of the sinusoid model. From this parameters, the CCF and CCD can be obtained with \( CCF = \left| \frac{f}{\pi} \right| \) and \( CCD = |2A| \).

**2.2 Experimental Setup**

We use the Laerdal Resusci Anne Simulator mannequin as the reference for our system. Electro-mechanical sensors measure the depth of thorax compression and decompression, the frequency of the compressions and the volume of ventilation. On a tablet, one can see all values in real-time and a summary of the training.

*Figure 2: Resusci Anne training mannequin.*
A Resusci Anne mannequin was placed on the floor (see Figure 2). We used two IMU sensors (see Figure 3), one was placed at the left wrist of the participant, and the other one was placed between the two hands of the participant. The participants were asked to perform CPR compressions on the mannequin with standard CPR frequency and depth for about 120 seconds. The sensor, as well as the Resusci Anne, were collecting data which was synchronized manually after the recording.

The IMU sensor contains a Bosch BMA180 triaxial accelerometer with sensitivity ranges from 1G up to 16G and sampling rates up to 1200 Hz. We used a 100 Hz sampling rate.

The study received an ethics approval no. “Drs. 24/2017” of the ethics committee of University of Oldenburg.

2.3 Evaluation Processing Steps

The R scripting language (version 3.2.3) was used together with the DEoptim/2.3.2 package [21,22] for the data processing and the evaluation. For each participant, the sensor data were manually synchronized with the results from the reference system. The acceleration is measured in three dimensions and always includes gravity. Thus, the gravity must be subtracted from the accelerometer signal:

\[
a = \sqrt{(a_x^2 + a_y^2 + a_z^2)} - 9.81 \frac{m}{s^2}
\]  

(8)

For every compression cycle recognized by the reference system, a 2-second window of the sensor data is used to fit the sinus model. Then the absolute and relative error between the model prediction \( P \) and the reference value \( R \) is calculated per compression cycle \( c_1 \ldots c_n \) and averaged per participant \( p_1 \ldots p_m \):

\[
e = \frac{1}{m} \sum_{j=1}^{m} \frac{1}{n} \sum_{i=1}^{n} |P_i - R_i|
\]

(9)

3 Results and Discussion

We performed the study with 15 participants, aged 21-48 (median 33), 11 male, 4 female. For each participant, a two minute long CPR session was recorded.
3.1 Model Prediction Results

We obtained sensor data from three different locations (mannequin, between hands, and on the wrist), used this data to fit a sinusoidal model and compared the prediction of this model to the internal sensor of the Resusci Anne reference system. Table 1 lists the main results comparing the frequency and depth prediction errors for the three different sensor locations.

| Sensor Location | CCF       | CCD       |
|-----------------|-----------|-----------|
|                 | Mean Error (SD) | Frequency Relative Error | Mean Error (SD) | Relative Error |
| Hand            | 3.0 (1.1) cpm  | 2.8 %     | 0.4 cm (0.3) | 8.8 %         |
| Wrist           | 2.7 (1.0) cpm  | 2.5 %     | 1.0 cm (0.6) | 20.1 %        |

Figure 4: Wrist-worn sensor best-case (left, participant 6) and worst-case (right, participant 10) frequency prediction.

Figure 5: Wrist-worn sensor best-case (left, participant 15) and worst-case (right, participant 3) compression depth prediction.
3.2 Discussion

In this study, the following two research questions have been investigated:

1) How applicable is the DE algorithm for curve-fitting of the chest compression during CPR regarding the accuracy of resulting CCF and CCD parameters for the considered three sensor placements in comparison to the Resusci Anne as reference system?

2) How suitable are smartwatch-like inertial sensors for the online detection of the chest compression during CPR regarding the accuracy of resulting CCF and CCD parameters in comparison to the Resusci Anne and the typical hand-holding as reference systems?

Regarding the first research question, the results show, that the use of the DE algorithm represents a suitable alternative, with the error 3.0 cpm in the prediction of the CCF is approximately in the range of the reported in the literature. Even though Ruiz de Gauna et al. [14] reported a lower median error of 0.9 cpm, the differences can be explained by the different reference system and the other sensor. In any case, the error at 3.0 cpm (2.7 %) is in such a low range that it does not affect the practical application. The target range of 110 ±10 cpm can be easily detected.

Regarding the suitability of a smartwatch-like wrist-worn IMU sensor to derive CPR parameters (the 2. research question), the following promising findings have been made.

The wrist sensor was with an error of 2.7 cpm (2.5%) the most accurate regarding CCF among all three considered sensor positions (compared to an error of 3.0 cpm for the common grasp-in-hand use). All three errors remain in the same order of magnitude – confirming the general robustness of the DE algorithm. Consequently, we could confirm the high suitability of the smartwatch-related wrist positioning for CCF calculation.

The error for the CCD prediction for the wrist sensor is with 1.0 cm (20.1 %) considerably higher than the one of the common grasp-in-hand use (with 0.4 cm). This increased error might be a consequence of the wrist-rotations and the non-orthogonal pressure-distribution during the cardiac massage. Nevertheless, even with the relatively high error of the wrist sensor, a basic statement about the depth of compression can be made, since relevant deviations from the optimal compression depth of 5.5 cm (e.g. too weak compression depths of 3 cm) can be still clearly identified.

In comparison to the related approaches, the achieved CCF accuracies are in within the magnitude of the other approaches and well within the requirements of ±10 cpm of the ERC guidelines [4]. In contrast, the CCD results are inconclusive: while the results of some participants are promising, there is much variance in the results (see Figure 5 for a comparison of best-case and worst-case). However, it should be possible to reduce the error further by taking the tilt of the accelerometer into account and apply noise and outlier filters.

Consequently, we could confirm that with wrist-worn devices sufficiently accurate predicting the CCF and CCD, smartwatches are a well suited unobtrusive and high available alternative platform for giving CPR feedback for bystanders in emergency situations.
4 Conclusions

We presented an approach to use sensor data from a wrist-worn IMU and the Differential Evolution (DE) optimization algorithm to dynamically fit a sinusoidal model that can predict frequency and depth parameters for cardiopulmonary resuscitation training or in realistic environments.

We evaluated the approach with 15 different subjects and tested the IMU placement at the wrist and hand for its suitability to derive the parameters.

The feasibility of the sinusoidal model created from accelerometer data using DE algorithm was confirmed. The chest compression frequency (CCF) could be predicted with a mean error of 2.7-3.0 cpm and the compression depth (CCD) with a mean error of 0.4-1.0 cm. Although the CCD leaves room for further improvement, both CCF and CCD can be predicted with sufficient sensitivity for online feedback applications.

Thus, our work represents an initial step towards completer and more precise modeling of the CPR using mobile sensors. While focusing on the algorithmic aspects of the detection of the CPR parameters, the general feasibility of smartwatches for CPR feedback (e.g. via a full-featured smartwatch application) has further to be investigated. The development of a corresponding app and its usability studies must be investigated in a subsequent study.

Data Availability

At the time of submission, the data recorded was not yet publicly available. However, it is intended to make the records and the associated evaluation software available to the public as soon as possible.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Supplementary Materials

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