Determining Cardiopulmonary Resuscitation Parameters with Differential Evolution Optimization of Sinusoidal Curves

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Keywords: CPR Training, Curve Fitting, Evolutionary Algorithm, Cardiac Massage.

Abstract: In this paper, we present a robust sinusoidal curve fitting method based on the Differential Evolution (DE) algorithm for determining cardiopulmonary resuscitation (CPR) parameters – naming chest compression frequency and depth – from skeletal motion data. Our implementation uses skeletal data from the RGB-D (RGB + Depth) Kinect v2 sensor and works without putting non-sensor related constraints such as specific view angles or distance to the system. Our approach is intended to be part of a robust and easy-to-use feedback system for CPR training, allowing its unsupervised training. We compare the sensitivity of our DE implementation with data recorded by a Laerdal Resusci Anne mannequin. Results show that the frequency of the DE-based CPR is recognized with a variance of ± 4.4 bpm (4.1%) in comparison to the reference of the Resusci Anne mannequin.

1 INTRODUCTION

Cardiac arrests represent one of the most prominent diseases and can significantly affect the independent living if medical treatment is not available within 3-5 minutes. Thus, the proper training of medical personnel is as essential as the training of non-specialists, which can offer resuscitation support much faster. Since Advanced Life Support (ALS) resuscitation training, due to the high material and training costs, is only used for medical professionals, technological training systems might represent a well-suited alternative to train both professionals and non-specialists.

The functioning of the human body depends on a continuous support of oxygen and glucose due to the following fundamental biological processes, clarifying the urgency of support. The organs of the human body are composed of various specialized cells, e.g., the nerve cells in the brain. These cells need energy, i.e., in the form of glucose and oxygen to keep structure and function. With the respiration, the air gets into the lungs. In the lungs, the oxygen of the air gets into the blood. The blood carries oxygen and glucose - fragmented carbohydrates from the food - to the cells. The heart pumps the blood through the circulation.

Thus, in case of a cardiac arrest, the transport of oxygen and glucose to the cells stops immediately. First of all the reserves of glucose and oxygen in the cells are consumed and the functionality remains. If the cardiac arrest persists, the function of the cells will be reduced, at first without permanent damage. If there is no blood circulation for a long time the structure of the cells will be irreparably damaged. 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. (Schmidt et al., 2011)

With medical treatment including ventilation, medication, and defibrillation (Advanced Life Support, ALS) (Soar et al., 2015) there is a high probability of maintaining sufficient circulation. In the case of a cardiac arrest, the most critical measure is to do a cardiac massage ideally in combination with rescue breathing (Basic Life Support, BLS) (Perkins et al., 2015). By doing this, a minimal circulation to carry oxygen to the nerve cells is sustained. During a cardiac massage, the heart is compressed by orthogonal pressure onto the breastbone. The depth of this compression is ideally 5 cm. The blood in the heart is ejected. A complete decompression is crucial to fill the heart with blood again. The frequency of the cardiac massage is 100 to 120 beats per minute (bpm). If it is possible to do a sufficient rescue breathing the heart pressure

Lins C., Klausen A., Fudickar S., Hellmers S., Lipprandt M., RÃűhrig R. and Hein A.
Determining Cardiopulmonary Resuscitation Parameters with Differential Evolution Optimization of Sinusoidal Curves.
DOI: 10.5220/0006732806650670
In *Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies (HEALTHINF 2018)*, pages 665-670
ISBN: 978-989-758-281-3

massage will be stopped for a short time and will be continued after two accelerated breathings.

In summary, the following points are important for the BLS:

- the position of the hands in the middle of the breastbone between the nipples,
- orthogonal pressure onto the breastbone,
- depth of pressure of 5 cm,
- frequency of compressions at 100 to 120 beats, per minute,
- complete decompressions of the thorax,
- and when doing a rescue breathing:
  - short interruptions of the heart pressure message after every 30 compressions,
  - 2 rapid ventilations,
  - fast continuation of the heart pressure message

Learning the right technique is necessary, to perform high-quality resuscitation. The method of resuscitation can be trained with simulation mannequins. Most of these mannequins provide a real-time feedback of the quality of cardiac massage and breathing. Although the simulation mannequins provide immediate and precise feedback, they are costly systems. An approach with a low-cost RGB-D camera such as the Microsoft Kinect (or even an RGB camera with software skeleton tracking) would provide such training to a larger audience thus improving the quality of the CPR. Additionally, a technique only relying on external (ambient) sensors would retrieve feedback data even from real resuscitations.

Two crucial parameters of the CPR are the *frequency* at which the compressions are performed and the compression *depth* of the chest. Typically, the frequency is stated as beats (compressions) per minute (bpm) and the compression depth in cm or mm. In this paper, we focus on these two parameters and propose a method to derive these parameters from motion data coming from an RGB-D-based skeleton tracking (Microsoft Kinect v2). We show how the Differential Evolution optimization algorithm can be used to fit a sinusoidal curve which robustly provides the two wanted parameters. The outline of the paper is as follows: in section 2, we discuss related work. In section 3, we introduce the details and specifics of the Differential Evolution algorithm. In section 4, we introduce our concept and a first implementation of our system. Afterwards, we evaluate the sensitivity as a pilot-study in section 5. We conclude with some learned lessons.

2 RELATED WORK

There are a few approaches to support CPR training with RGB-D sensors and resulting feedback.

Tian et al. use Kinect data to model a virtual environment with patient and performer and drive a haptic device in the real world (Tian et al., 2014). In the virtual environment, the performer can see the CPR on a virtual avatar while responding to the sensation of the haptic device. The authors focus more on the basics of cardiac massage than specific optimization of the training.

Semeraror et al. and Loconsole et al. present results from their system called RELIVE which is similar to our approach (Semeraro et al., 2017; Loconsole et al., 2016). RELIVE uses data from the Kinect v1 and extract depth and frequency parameters from the motion data with the intention to improve the quality of CPR (training). In contrast to our approach they use the raw RGB pixel and depth image data of the Kinect to identify hands, arms and the training body. We compare our results of the frequency detection in the last section of this paper. The predecessor to RELIVE is probably the Mini-VREM tool, which is a Kinect with a software-based audio- and video-feedback-system (Semeraro et al., 2013) but requires a colored marker at the subject's hands.

Wang et al. have utilized the Kinect v1 sensor to create a real-time feedback system for CPR training (Wang et al., 2017). The system shows the current compression depth and frequency on a computer screen so that the trainee can adapt her or his actions accordingly. The authors have evaluated their system with 100 health care professionals and conclude that the system can significantly improve the CPR quality at least for trainees with a body weight $< 71kg$.

Higashi et al. developed and evaluated an augmented reality system that enables the user to correct her or his posture while performing cardiac massage compression (Higashi et al., 2017). The focus of this work lays on the correct posture of the performer primarily to differentiate between extended position compression and bent position compression. Unfortunately, they do not provide a quantitative evaluation of their system.

3 CONCEPT

3.1 CPR Parameters Determination with Kinect

With our approach it is possible to derive CPR quality parameters such as the compression (CC) frequency

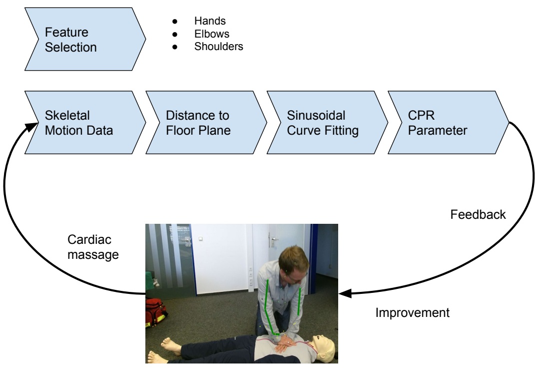

Figure 1: CPR training with Kinect.

and the compression depth with one (or more) external RGB-D sensors. It does not require a simulation mannequin and is therefor suitable for CPR trainings or in-situ observations, e.g. in a shock room. Figure 1 shows the process of our approach within CPR training.

3.2 Differential Evolution Optimization of Sinusoidal Curves

The Differential Evolution (DE) algorithm (Storn and Price, 1997) is a generic evolutionary optimisation algorithm, which is used here to solve four parameters of a sinusoidal curve. Our approach utilizes the periodic nature of the CPR to fit the time series of distances (upper limbs to ground) to a sine curve.

The generic parameters sine function can be written as follows:

$$y(t) = A \cdot sin(2ft + \rho) + D$$

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. To find a solid CPR frequency and compression depth, we fit the time series data of upper limb distances to a sinusoidal curve. On a fitted function, parameter f is the CPR frequency and A is the compression depth.

To fit the function $y(t)$, we minimize the least-squares distances using an evolutionary approach. A common evolutionary algorithm is Differential Evolution 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.

As all evolutionary algorithms, DE is population-based and optimizes the population throughout several generations:

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

$x_{i,G}$ is a 4-dimensional vector of individual i for generation G. So in every generation NP individuals are optimized up to G_max generations.

The optimization is done between a transition from one generation G to another generation $G+1$. Most evolutionary algorithms - as does DE - comprise the steps mutation, crossover and selection.

3.2.1 Mutation

For every generation a mutation step is performed for every individual $x_{i,G}$. We used the step from (Storn and Price, 1997) with a fixed amplification factor:

$$v_{i,G+1} = x_{r_1,G} + 0.8 \cdot (x_{r_{2,G}} - x_{r_{3,G}})$$

with v the mutated individual and $r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}, r_1 \neq r_2 \neq r_3 \neq i$ randomly chosen.

3.2.2 Crossover

The crossover step decides which of the four parameters of one individual are preserved in the next generation. For every parameter a uniform random number $r \in [0,1]$ is chosen. If $r \leq CR = 0.9$ then the parameter from the mutant is chosen, otherwise the one from the original individual.

3.2.3 Selection

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

$$\sum_{t=0}^{T} (s(t) - y_{x_{i,G}}(t))^2$$

with s being a T-length vector of samples (joint-floor-distances) and y the parameterized sinusoid function of individual $x_{i,G}$.

4 IMPLEMENTATION

We implemented the Differential Evolution algorithm and the visualization software using C# on a Windows system. Figure 2 shows a typical screenshot of the application while processing motion data from the Kinect sensor. The RGB image is shown on the

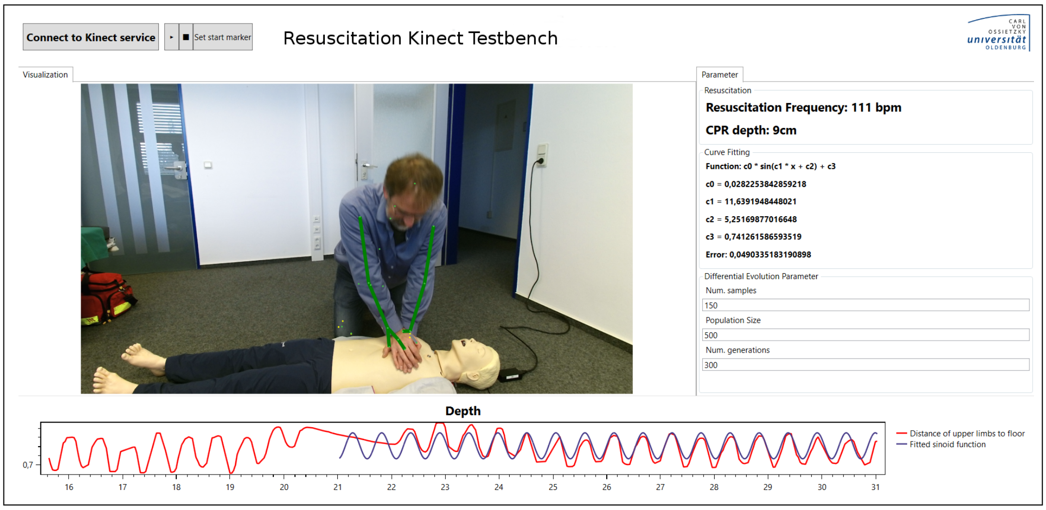

Figure 2: Our software processing Kinect motion data from a CPR training session. The graph at the bottom shows the distances between the floor and the limbs (red) and the fitted sinusoid curve (blue).

screen together with a green line overlay representing the arms. Additionally detected skeleton joints are marked as small yellow dots.

The Kinect sensor API notifies our application when a new data frame is available from the sensor and provides the application with a Skeleton frame containing the joint positions and the floor plane estimation. The application the calculates the distance between the floor plane and the upper limb joints (i.e., wrists, elbows, or shoulders) and pass the result to the sample set. On every ten new samples the last 150 samples are being evaluated against the current fitted sine curve, and the squared errors are calculated. As soon as the error reaches a threshold, the Differential Evolution algorithm is started with a new updated sample set using $NP = 500$ individuals and $G\_max = 300$ generations. The application continuously draws the current fitting in the graph on the bottom (see Figure 2).

5 EVALUATION

5.1 Methods

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

A Resusci Anne mannequin was placed on the floor. The Kinect v2 sensor was placed at a distance of 1,5m at the height of 1m. The person performing the CPR was placed on the other side of the mannequin facing the Kinect camera. The subject was asked to perform CPR compressions on the mannequin with standard CPR frequency and depth for about 90 seconds. The Kinect, as well as the Resusci Anne, were collecting data which was synchronized manually after the recording using the RGB color image of the Kinect. The DE optimization algorithm requires a few compressions to adapt, so the first compressions were omitted until the algorithm's error drops below a reasonable threshold (about 1% of the initial error).

5.2 Evaluation Results

5.2.1 Frequency Prediction

We compare the compressions per minute variable of the Resusci Anne mannequin with the prediction of our system. The Resusci Anne provides a *compMeanFrequency* variable for every recorded compression (*compEvent*). The results for all four trials can be found in Table 1 and graphically in Figure 3 for Trial 1.

5.2.2 Depth Prediction

For every recorded compression the Resusci Anne records a maximum compression depth. We compare these maximum compression depth value with the doubled amplitude ($2 \cdot A$) of the corresponding fitted sinusoidal curve. The results for all four trials can be found in Table 2 and graphically in Figure 4 for Trial 4.

Table 1: Absolute and relative mean frequency variation (in bpm) of our method compared to Resusci Anne mannequin.

	Feature Hands	Feature Elbows	Feature Shoulders
Trial 1 / Subject 1	9.1 (*) bpm / 7.7%	3.3 bpm / 2.8%	5.1 bpm / 4.3%
Trial 2 / Subject 2	14.1 (*) bpm / 12.3%	3.4 bpm / 3.0%	6.0 bpm / 5.1%
Trial 3 / Subject 3	5.1 bpm / 4.6%	4.9 bpm / 4.5%	4.9 bpm / 4.5%
Trial 4 / Subject 3	6.4 bpm / 6.2%	6.1 bpm / 5.9%	5.7 bpm / 5.5%
Ø	8.7 bpm / 7.7%	4.4 bpm / 4.1%	5.4 bpm / 4.9%

Table 2: Absolute and relative mean compression depth variance (in mm) of our method compared to Resusci Anne Mannequin.

	Feature Hands	Feature Elbows	Feature Shoulders
Trial 1 / Subject 1	25mm / 44%	10mm / 18%	18mm / 31%
Trial 2 / Subject 2	19mm / 33%	17mm / 31%	19mm / 34%
Trial 3 / Subject 3	5mm / 15%	39mm / 110%	28mm / 80%
Trial 4 / Subject 3	15mm / 36%	16mm / 41%	6mm / 15%
Ø	16mm / 32%	21mm / 50%	18mm / 40%

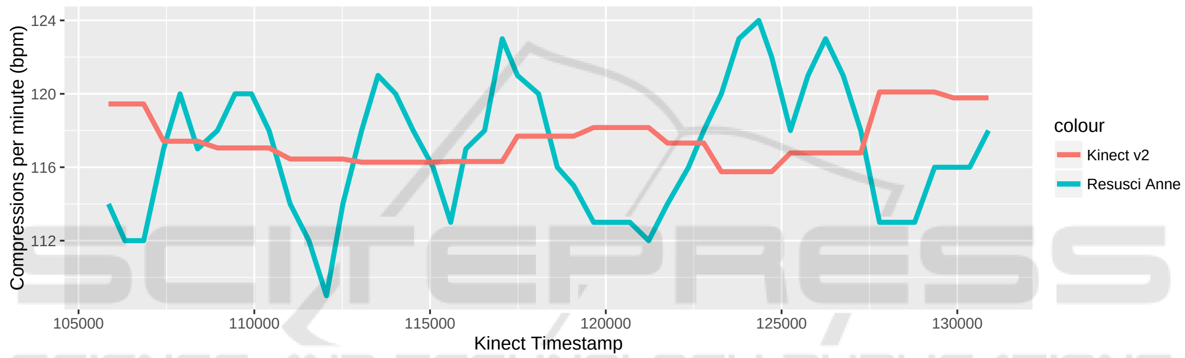

Figure 3: Comparison of detected compression rates of our system and Resusci Anne mannequin (Subject 1, Trial 1).

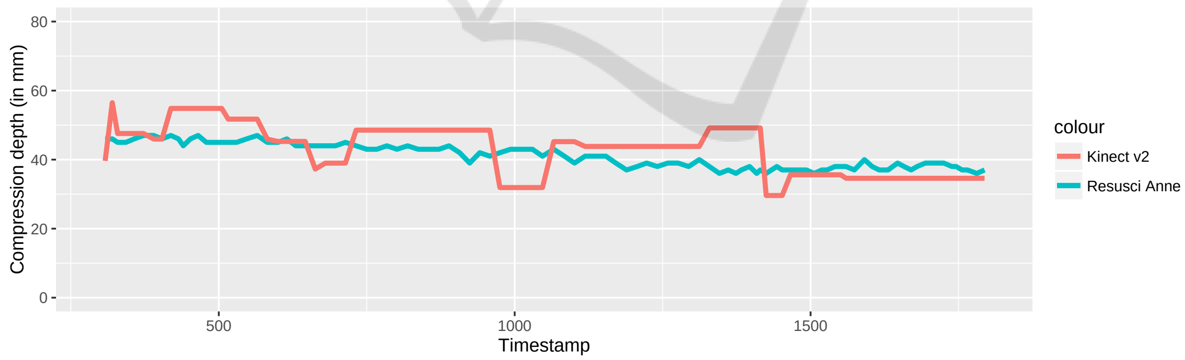

Figure 4: Comparison of compression depths (in mm) between our system and Resusci Anne (Subject 3, Trial 4).

6 LESSON LEARNED

We presented an interactive software system that uses motion data from an RGB-D (Kinect) sensor and the Differential Evolution optimization algorithm to dynamically fit sinusoidal curves to derive frequency and depth parameters for cardiopulmonary resuscitation training. We evaluated the system with three different subjects and tested the data of three different limb regions (hands, elbows, and shoulders) for their suitability to derive the parameters. Using the elbow features of the Kinect skeleton, the results for the frequency determination show a mean variance of 4.1% (4.4 bpm) compared to the results of a Laerdal Resusci Mannequin (acting as the gold standard). This is superior to the shoulder features with 4.9%, which probably suffer from small dampening effects of the elbow joint. The hand features are often occluded even under near-optimal view situations and show a higher variance of 7.7% variance. We will investigate if the combined consideration of all three limb regions will enhance the sensitivity furthermore.

While the results determining the CPR frequency are already promising, the results for the compression depth are not yet conclusive. The discrepancy to the Resusci Anne results ranged between 5-39mm (15-115%) with the hands features working best (mean 16mm). The high variance between the results made it impossible to find a stable constant offset or factor that may improve the accuracy. Here, more investigations are needed, to determine why only singular results are so far promising (see Figure 4).

Thus, our work represents an initial step towards a more complete and precise modeling of the ERC CPR using ambient sensors.

ACKNOWLEDGEMENTS

This work was supported by the funding initiative Niedersächsisches Vorab of the Volkswagen Foundation and the Ministry of Science and Culture of Lower Saxony as a part of the Interdisciplinary Research Centre on Critical Systems Engineering for Socio-Technical Systems II.

The authors would like to thank the anonymous reviewers for their helpful comments.

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