

# Comparing the automatic evaluation of CPR compression rates using a smartwatch vs a smartphone.

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## Abstract

This paper presents a novel algorithm for automatically evaluating the compression rate for Cardio Pulmonary Resuscitation (CPR) from the sensor data from a smartwatch. The results are compared with manually derived ground truth and with the results of an automatic system based on the analysis of video from a smartphone.

**Keywords:** Image Processing, CPR, Motion Analysis

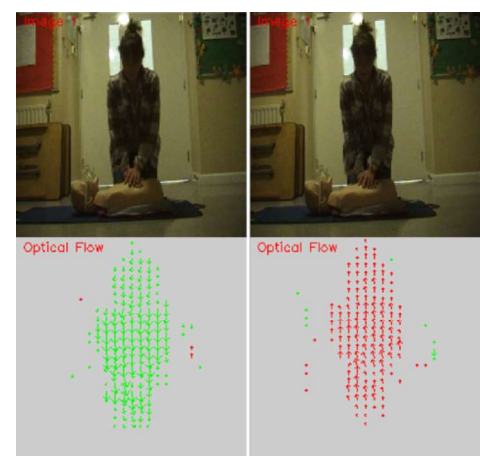
## 1 Introduction

For Out of Hospital Cardiac Arrest (OHCA), the likelihood of survival is quite slim. A 2017 study looking at 28 European countries showed an average survival rate of 8% [Gräsner, et al., 2020] and the percentage of cases where a bystander performed CPR ranged from 13% to 82%. The application of CPR early after the onset of cardiac arrest is crucial. The percentage of patients who survive 1 month after experiencing cardiac arrest is 2.2% in cases where no CPR is performed, but increases when CPR is performed by a layperson (4.9%) or a healthcare professional (9.2%) [Herlitz et al., 2005].

The use of real-time feedback during training substantially increases the quality of CPR being performed [Baldi et al., 2017]. There are several existing solutions for providing feedback on CPR quality during training but these are typically expensive and as a result inaccessible to most organisations. The focus of the research here is the provision of feedback using commonly available technologies (such as smartphones and smartwatches). If a smartwatch or smart phone can provide reliable feedback to a rescuer performing CPR, whether in training or also in OHCA, it could result in increased survival rates.

## 2 State of the Art

Arguably the most important aspects of CPR are the Chest Compression Rate (CCR) which should be 100-120 compressions per minute and the Chest Compression Depth (CCD) which should be 5- 6cm. Many defibrillators are capable of measuring the CCR and CCD but as these will not, at least initially, be available other technologies have been investigated. The CCR can be computed reliably from a smartphone camera facing the person performing CPR [Corkery and Dawson-Howe, 2019] (See Figure 1) or using a view looking upwards at the person applying CPR [Meinich-Bache et al., 2017], where the smart-phone is lying flat on the ground. Other work has demonstrated the use of smartphone accelerometers (which also exist in smart



**Figure 1: Analysis of CPR using optical flow [Corkery & Dawson-Howe, 2019]**

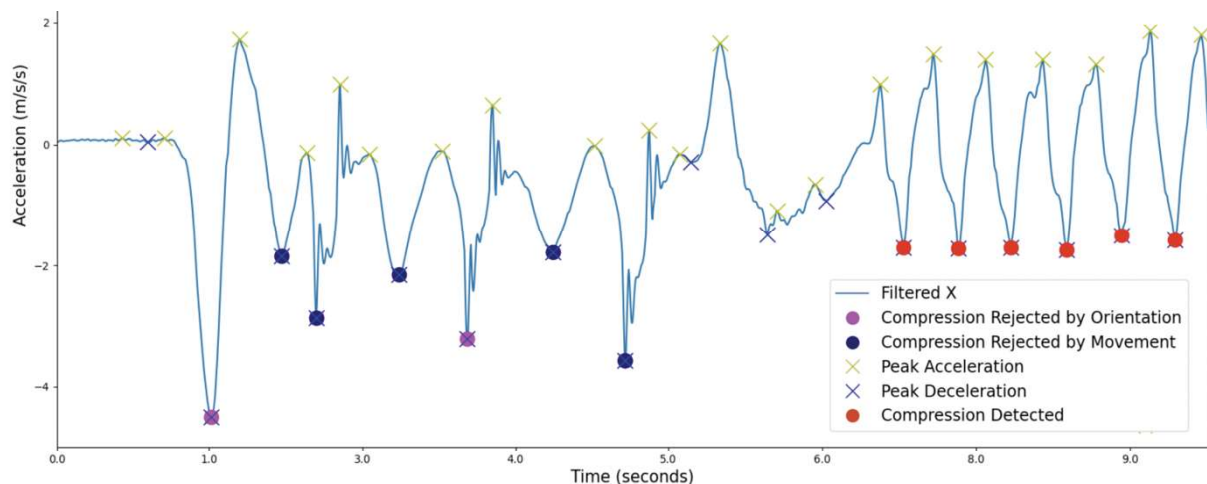
watches) to evaluate the CCD [Song et al., 2015] with a resulting inaccuracy of only  $\sim 3\text{mm}$ . Ahn et al. have also demonstrated the use of smartwatches for providing feedback for externally calculated CCR & CCD [Ahn et al., 2017].

### 3 Detecting compressions using a smartwatch

The watch used in this project was an LG G Watch W100 which provides information on acceleration (including the force of gravity) as well as the force of gravity itself, rotational information and magnetic orientation information. The sensors yielded acceleration information in 3 axes: X, Y and Z. If the watch is worn on the outside of the left arm, the positive X-axis points from the elbow to the fingertips, the positive Y-axis points across from the thumb to the little finger and the positive Z-axis points directly outwards from the watch face. For the detection of compressions the principle axis is along the arm wearing the watch of the person giving the compressions which corresponds to the X axis. Typically that arm will be almost vertical as the compressions are done downwards. The forces recorded in the Y and Z axes are primarily caused by the watch shaking on the rescuer's wrist. As such, the only axis that provides reliable, consistent data was the X axis.

The raw data from the smartwatch is very noisy and therefore a mean smoothing filter was applied. This smoothing filter was experimentally chosen to cover a range of 200ms centred around the observation being considered. This removed the vast majority of spurious peaks (which were relatively high frequency) and troughs, without damaging the compression data (which was around 2Hz).

Compressions result in sharp peaks and troughs in the X axis acceleration data. We designate the trough as the compression although any point on this regular cycle could be chosen. The method used to locate the peaks and troughs involved taking each data point and determining if it was the lowest or highest point within the previous 125ms and the next 125ms. This range allows for smaller local minima and maxima to be ignored. Examples are shown in Figure 2.



**Figure 2:** Filtered acceleration data from the X axis of the watch from the clapping at the start of the recording (left) followed by 6 compressions (right). The peak deceleration points are all possible compression locations but the invalid have been rejected due to movement on other axes, incorrect orientation of the watch or by an insufficient change between the highest and lowest points.

Having found the peaks and troughs we label each valley as a compression if:

1. The trough follows a peak and is followed by another peak where the absolute differences in acceleration between both peaks and the trough are at least  $1 \text{ m/s}^2$ .

2. The force in the X-axis is at least 70% of the total magnitude of the force of gravity which allows for a maximum deviation of approximately 45 degrees from vertical. This ensures that the arm of the person is more-or-less vertical.
3. At least 30% of the movement was in the X direction (i.e. there was limited movement orthogonal to the movement of the arm).

The generous allowance of deviation from vertical tolerates cases where the watch may be pressing on the rescuer's wrist or the rescuer's arms may not be positioned completely vertically, both of which result in the orientation of the watch deviating slightly from vertical.

## 4 Results

Five separate recordings of a person administering CPR to a dummy were made where each recording comprised both video (from the camera phone) and sensor data (from the smartwatch). Overall in these videos 440 compressions were recorded. The ground truth was created by manually stepping through each frame of the video and marking the frames that were the top or bottom of a compression. Note that the video assessment of compressions was performed using the techniques described by Corkery and Dawson-Howe [Corkery and Dawson-Howe, 2019].

In order to be able to assess the compressions detected from smartwatch sensor data it was necessary to first align the sensor data and the ground truth. This was achieved by requiring the rescuer to clap their hands three times at the start and end of each recording. This clapping was clearly visible in both the recorded video and in the data from the smartwatch, which were then manually aligned using unfiltered X axis acceleration data.

The results of evaluating the output of the two approaches and comparing them to the ground truth can be seen in Table 1. This shows a very high level of overall accuracy for both algorithms although the computer vision based algorithm resulted in more misidentified compressions than the smartwatch based algorithm.

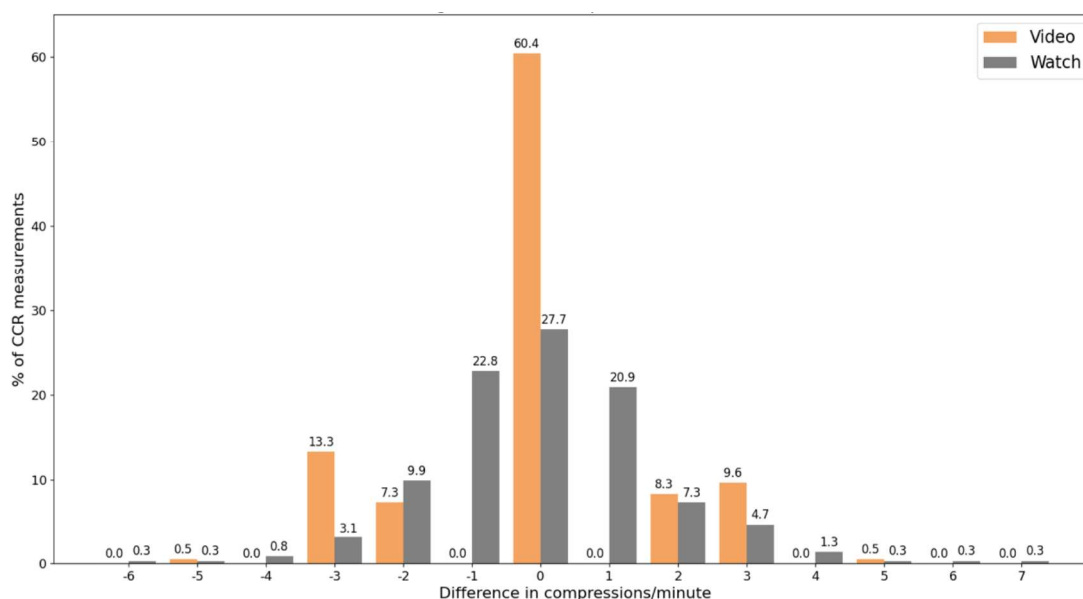
|                                       | TP  | FP | FN | Precision | Recall | Accuracy |
|---------------------------------------|-----|----|----|-----------|--------|----------|
| Smartwatch (this paper)               | 438 | 0  | 2  | 1.00      | 0.99   | 0.99     |
| Video [Corkery and Dawson-Howe, 2019] | 440 | 12 | 0  | 0.97      | 1.00   | 0.97     |

**Table 1: This table shows the compressions correctly detected (TP), missed (FN), and incorrectly detected (FP) by both algorithms summarised across all 5 test videos. Precision =  $TP/(TP+FP)$ , Recall =  $TP/(TP+FN)$ , Accuracy =  $TP/(TP+FP+FN)$**

The detected compressions are used to compute the CCR and the difference in the CCR for the Smartwatch and the Video measurements as compared to the Ground Truth are shown in Figure 3.

## 5 Conclusions

Overall analysis of the smartwatch data provided CCR data which was as good as, if not better than, that obtained from video analysis using smartphone video. It appears that a smartwatch can be used to detect CCR and CCD to high precision, while a smartphone can detect CCR to high precision. It is unclear if a smartphone can be used to reliably measure the CCD as there are issues converting pixel measurements to physical distances.



**Figure 3: The difference in frames between the calculated CCR for both algorithms and the ground truth as a fraction of all calculated CCRs. CCR calculated using 4 compressions.**

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