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APPLIED RESEARCH

A Proof-of-Concept Study on Smart Gloves for Real-Time Chest Compression Performance Monitoring

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ABSTRACT Correctly performed Cardiopulmonary Resuscitation (CPR) is a critical element in preventing deaths caused by cardiac arrest (CA). To improve the outcomes and quality of CPR, stand-alone devices that monitor the performance and provide feedback have been developed. However, these devices have multiple limitations due to their rigidity and stiffness. Furthermore, most of the devices do not account for complete chest recoil as a metric of quality CPR, reducing the quality of compressions. To overcome these limitations, this study proposes smart gloves equipped with e-textiles-based pressure sensors and inertial measurement units (IMUs) to monitor the quality adult CPR in real-time. The prototype development combined data-driven design and Research Through Design (RtD) methods, taking into account not only the accuracy but also the usability of the smart gloves. A preliminary study with nine participants performing CPR on a doll was conducted to evaluate the accuracy and wearability of the smart gloves. Study results show that the smart gloves accurately detect chest compression parameters, including compression depth, compression rate, chest recoil and interruption between compressions based on the intelligent fusion of pressure sensors and IMUs. In addition, the newly developed smart gloves are lightweight, hand adaptable, and easily replicable as an alternative for hard case devices. The design methods used in this study can be applied to design other accessible and comfortable wearable devices in healthcare settings.

INDEX TERMS Wearable sensor, smart textiles, motion measurement, healthcare technology.

I. INTRODUCTION

Cardiac arrest (CA) occurs when the heart stops pumping, resulting in loss of blood flow to vital organs [1]. Cardiac arrest leads to certain death if resuscitation is not started immediately and performed effectively [2]. Chest compressions are key elements of Cardiopulmonary Resuscitation (CPR) [3]. By performing chest compressions, rescuers mimic the function of a heart and help the patient's blood to circulate into vital organs at a low efficiency (around 20-30% of what the heart is capable of). According to the 2021 European Resuscitation Council (ERC) Guidelines,

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the effectiveness of chest compressions depends on several components, such as hand position, minimal interruption, compression depth, compression rate, and degree of chest wall recoil [4]. Therefore, quality chest compressions applied without significant interruption are an important component for the return of spontaneous circulation (ROSC) [5]. Once a cardiac arrest is confirmed, rescuers should begin chest compressions immediately for better outcomes [3]. However, previous studies have indicated that professionals, and especially laypersons, often perform chest compressions incorrectly [6].

Various devices have been marketed to monitor the quality of chest compression parameters [6], [7], [8]. These devices provide real-time feedback on compression quality, helping rescuers adjust their techniques [9]. Many of the devices on the market are integrated with other larger multi-functional devices such as defibrillators and simulation manikins [8], [10]. They are particularly suitable for use in well-equipped hospitals and teaching institutions [11].

In addition, new standalone and portable products with integrated sensors and feedback systems have been developed [12]. Those standalone devices are either placed on the manikin/patient's chest or held on the rescuer's hands during chest compressions [3], [8], [10], [13]. Ideally, standalone devices are suitable for use in communities where well-trained medical professionals and complex devices are not readily available [10].

Although standalone devices monitor CPR performance, they have several limitations. First, they are small and portable, mostly made using traditional electronics and hard cases. Hence, rigidness and stiffness can cause extra friction and pressure on the skin and muscles of the CPR performer, leading to wrist discomfort and pain [8], [14], [15]. These hard surfaces and rigid devices can also cause chest pain and discomfort in recovered patients. Second, having a detached object between the performer and the training surface can cause incorrect data collection due to unintentional sensor displacement [8]. Third, as a solution to the disadvantages of rigid devices, smartwatch-based wearable devices have been developed to improve the quality of chest compressions [11], [16]. However, these devices are placed on the rescuer's wrist, which is far from the actual point of compression, making accuracy questionable and feedback observation difficult. Fourth, although portable devices provide feedback on chest recoil, there is no evidence to suggest that they significantly improve the quality of chest recoil.

The use of smart textiles can be beneficial for the development of flexible, soft and wearable devices compatible with the human body to address the challenges outlined above [17]. Smart textiles, or e-textiles, are generally considered to be fabrics with electrical properties or electronic components embedded into them. As soft materials, smart textiles provide better fit and wear comfort compared to rigid electronics [18], essential for user acceptance of smart wearables [19]. On the other hand, textile materials' malleability influences e-textiles' reliability [20] and causes mechanical incompatibility with hard electrical components, unavoidable in e-textile-based systems [21].

Novel textile materials with electrical properties have proved to be suitable for creating stretchy smart gloves capable of monitoring body signals such as touch or pressure [22], [23]. Smart gloves specifically designed to measure chest compression depth and force during neonatal CPR showed promising results [24]. However, a similar approach has not been applied in adults, which will pose new challenges in terms of technique adoption due to the scale change. Our interdisciplinary collaborative project takes up these remarks and aims to investigate the feasibility of using smart textiles to manufacture smart gloves to monitor the quality of chest compressions in adults. The newly designed smart gloves can measure key parameters of chest compression quality, including compression rate, depth, interruption and full chest recoil, utilizing pressure sensors and IMU. The sensor's misplacement issue is also targeted by integrating them directly into the glove. Wearability and manufacturability of the smart gloves are also taken into account in the design.

A user test with 9 participants at the University of Turku proved that our prototypes achieved high detection accuracy while considering the wearability and manufacturability of the gloves. To the best of our knowledge, this work represents the first e-textile-based smart gloves for real-time assessment of chest compression quality during adult CPR.

The main contributions of our study are as follows:

- We present a Research through Design process combining methods from smart textile design and data analytics in developing a smart garment.
- Our study yields proof-of-concept smart glove prototypes that are lightweight, hand adaptable, and easily replicable.
- We integrate chest recoil monitoring into existing compression depth and frequency algorithms with pressure sensors.

II. BACKGROUND AND RELATED WORK

A. PORTABLE CHEST COMPRESSION MONITORING DEVICES DURING CPR

During cardiac arrest, CPR should be started immediately to maintain perfusion to the cerebral and coronary vasculature systems [3], [4]. According to CPR guidelines [25], high-quality chest compressions should be done on the lower half of the sternum. These compressions should be 5 to 6 cm deep and at a rate of 100 to 120 per minute. The chest must be completely released (chest recoil) to allow the heart to refill between compressions [3], [4]. An alternation of

30 compressions and two rescue breaths should be maintained if there is a possibility to provide ventilation [3], [25].

Subjective assessment of the chest compression parameters mentioned above is challenging [26]. Therefore, the innovation of devices that monitor chest compression performance is critical to the delivery of high-quality CPR. Various portable devices have been developed in recent years to monitor the quality of chest compressions [8], [9]. Portable devices, such as Beaty [27] and Laerdal CPRmeter 2 [28], are placed between the patient's chest and the rescuer's hands to monitor chest compression performance and provide real-time feedback on compression depth, compression rate and chest recoil. Such devices are stiff and rigid and can cause chest injuries to the patients and hand pain to the rescuers [29].

More involved devices exist in an attempt to accurately track the pose and position of hands in general, such as Müezzinoğlu and Karaköse [30]. These devices are complex sensor systems aiming to solve a more generalized form of the CPR monitoring problem, i.e. pose tracking, and as such is not a subject of our study.

As a subset of portable devices, wearables provide options for chest compression monitoring during CPR. Such devices can be worn in a hand as a wristband [31], smartwatch [32], or ring [33]. The devices are developed not only to precisely determine compression depth, rate, interruption, and chest recoil detection but also to increase user-friendliness, comfort, and safety for the user [8]. The wearable devices are typically based on measuring acceleration to detect compression depth and rate.

Nevertheless, the aforementioned existing portable devices have limitations. The accuracy of compression depth detection is not high due to significant drift accumulated in the double integration process from acceleration to displacement [14], [15]. Studies then focus on correcting this drift in several different ways. A common method is high-pass or bandpass filtering, which removes the low-frequency contributors of the noise that cause the drift. de Gauna et al. [15] recognised the connection between integration and low-pass filtering, combining the two into a single bandpass filter method. Other approaches attempted to circumvent the integration issue instead of improving it. These might rely on statistical measures, such as M-statistic [32], which is somewhat reminiscent of a moving average. Another example is reliance on an underlying sinusoidal model that has parameters describing the CPR depth and frequency [34]. Finally, there are some non-algorithmic approaches. Hermann et al. [31] tested different positions for the accelerometer to minimise the inaccuracies in the acceleration readings. In the same article, the authors comprehensively compared different algorithms for depth estimation.

Another limitation in many previous devices is that one significant issue is left unaddressed and even worsened, by some of the approaches mentioned above [15], [31]. Complete chest recoil is potentially masked by methods that rely on drift removal. There may be actual, deepening drift present in the compressions, which is eliminated in the readings by the bandpass, M-statistic, and other periodic methods. A naive solution is increasing the quality and quantity of accelerometers to reach sufficient precision in readings. Another often suggested approach is to use pressure sensing to determine if the chest has been allowed to recoil [15]. Some portable devices [28], [35] use pressure sensors exclusively to measure depth. This approach circumvents the issue of chest recoil. This paper will address the challenges presented, particularly focusing on chest recoil and wearability.

B. SMART GLOVES FOR HEALTHCARE

In addition to the technical limitations, the existing devices present usability issues due to their rigidity and stiffness, which can lead to fatigue and wrist discomfort during chest compressions [8], [14], [15]. To tackle this, smart textiles-based solutions have been beneficial in the quest for comfortable wearable body monitoring options in healthcare. These applications can be fabricated, for example, by embedding conductive fibres, flexible printed circuit boards, and electrical components with information processing capabilities onto a textile substrate [36] or into textile structures [37]. Besides electrically functional features, smart textiles enable harnessing the properties of textile materials, such as softness, lightweight, and adaptability to the human body.

In healthcare applications requiring activity monitoring, clothing apparel such as the Hexoskin shirt [38] has been proven promising interfaces for diagnostic, monitoring, and therapeutic purposes [39]. Due to the relevance of the hands and their contact with the body during CPR, this paper will focus particularly on smart gloves for healthcare. The variety of examples range from gloves for determining loss of movement in rheumatoid arthritis patients [40] to gloves for physiotherapy [22] and mirror therapy [23]. These examples illustrate the potential of smart gloves to collect multimodal data such as pressure, position, or movement, making them a suitable interface for versatile use cases.

The potential of smart gloves for CPR quality assessment has also been investigated. Dellimore et al. [24] showcased the development of a diagnostic tool designed to measure the chest compression depth and force during neonatal CPR. The smart glove includes three accelerometers complemented with force sensors fabricated from a soft and flexible piezo-resistive textile composite embedded into rubber fingertips. The experimental results show that the glove can reasonably measure chest compression depths and force in the target range required for neonatal CPR [23].

In addition, their approach emphasises the textile-based solution's softness and wearability, essential for the

TABLE 1. Interdisciplinary team roles.

Field	Roles
Data Science	Collecting sensor data in user studies Analyzing the collected data Building algorithms for quality assessment
Smart Textiles	Planning and conducting user studies Planning and conducting brainstorming sessions Fabrication of sensors Glove prototypes design and manufacturing Analysing the collected data
Clinical Researchers	Planning and conducting user studies Participation in brainstorming sessions
Electronic Engineers	Electronics prototyping

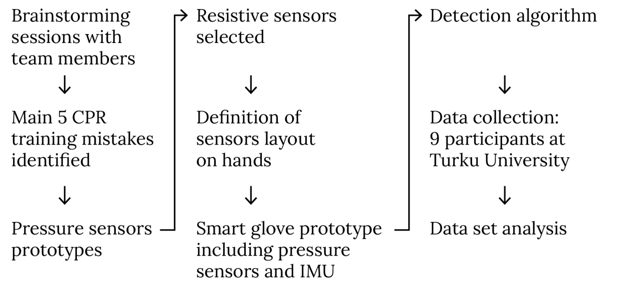


FIGURE 1. Design process combining low-cost fast prototyping, user tests and data-driven methods for CPR quality monitoring.

unobtrusive use of monitoring devices. Thus, smart gloves provide a promising alternative to portable and wearable devices typically used in CPR quality monitoring.

However, the use of smart gloves to monitor high-quality chest compressions in adults has yet to be studied. The concept of CPR is similar for neonates and adults, but there are significant differences in application due to differences in physiology, bone density, and body size [41]. Neonatal body is not as developed as adults' [41], [42], and it requires different techniques and equipment when performing CPR [43]. Unlike adults, neonatal chest compressions are usually performed with the thumbs of both hands or two middle fingers of one hand [43]. In addition, adult chest is stiffer than neonates chest [41]. Wearable devices designed and calibrated for neonatal resuscitation may not be used reliably and effectively for adult resuscitation. Therefore, this study investigates the feasibility of building smart gloves for real-time quality assessment of adult CPR.

III. DESIGN PROCESS

In the following chapter, we present the interdisciplinary process of creating our smart gloves for CPR quality assessment and explain the design and data-driven methods.

A. METHODS

As a multidisciplinary field, wearable technology and smart textiles unify knowledge across disciplines ranging from textile and industrial design to electronic engineering and data science [44]. Thus, our research approach is interdisciplinary, applying and intertwining methods from the collaborating disciplines. The roles of team members from different disciplines can be seen in Table 2. This publication will focus mainly on the design process following a Research through Design (RtD) approach [45] using constructive design methods to create a first proof-of-concept functional prototype for CPR Quality monitoring. As an approach, RtD is a generative process which constantly aims to identify and evaluate design challenges and iterate the process accordingly.

As shown in Figure 1, the design process started with gaining an understanding of the use context and its requirements through brainstorming sessions [46]. These insights were translated into product characteristics (e.g. materials) to be tested by producing prototypes of various levels of resolution [47]. The relevant features were evaluated either through laboratory testing, mainly to obtain initial data from the textile-based sensors using an Arduino set-up, or user studies [48] at University of Turku with the consent of the participants. During the user studies, qualitative data was obtained by asking the participants about their experiences using the prototypes, to better understand the factor of usability and wearability. Here, usability refers to the ease of use of the gloves by the user tests participants to achieve the defined goal effectively, while wearability assesses the comfort and capacity of the gloves to withstand wear. The process of each user study was documented via video recordings, pictures, observations, and field notes. In addition, the readings collected from gloves prototypes were recorded for training and testing algorithms for CPR quality assessment.

The following subsections will describe the steps taken to create gloves prototypes starting from brainstorming sessions.

B. BRAINSTORMING SESSIONS

The RtD process started with investigating the needs and requirements for performing high-quality chest compressions in the CPR context to lay the foundation for the prototyping process. For this, four workshops were organised among the project team members, which consisted of both medical professionals and lay persons. The workshops aimed to identify the key characteristics of high-quality chest compression and the shortcomings of the current chest compression quality assessment solutions related to usability and wearability. Three workshops were organised online to pinpoint the challenges identified via literature, surveys and some team members' experiences as clinical researchers specialising in CPR. In addition, one workshop was organised in person to demonstrate the components of high-quality chest compression with Little Anne QCPR Manikin [49].

After the four sessions, five typical mistakes that occasionally occur when performing CPR were identified. The typical mistakes were (1) the compression depth was out of the required range; (2) frequency was lower or higher than recommended; (3) leaning during chest compression was common, which leads to inadequate chest recoil; (4) hands are not correctly positioned on the chest, and (5) interrupting the compressions for more than 10 seconds during CPR. Other challenges were related to the high costs of the existing CPR feedback devices, leading to limited accessibility. Those mistakes and limitations were conceptualized into requirements and further translated into prototype characteristics. The prototype should detect the depth and rate of compressions, full chest recoil, and length of interruptions during CPR. In addition, considering the importance of exploring more accessible chest compression devices, the prototype should be fabricated using low-cost materials, easy-access tools such as sewing machines, and ready-made components such as Arduinos and IMUs.

During brainstorming sessions, several ideas for portable quality monitoring systems were discussed, including a smart vest and a smart chest blanket that can be placed on the chest of a CPR Manikin. To avoid compatibility issues with training facilities and real patient resuscitation,smart gloves were deemed the most accessible approach to move forward with. Thus, the correct hand positioning on the chest was excluded from the prototype requirements since it includes interfering with the contact surface and will be approached in future work.

C. SENSORS SELECTION

The first prototyping phase investigated which textile-based sensors are the most suitable for creating a first proof-of-concept glove for CPR training. The essential aspect of CPR is the pressure between the provider's hands and the patient's chest. Therefore, pressure sensing is necessary to detect the proper amount of force to guarantee the depth of compression required. Furthermore, pressure and pressure relief can determine the full chest recoil and detect interruption during CPR.

Considering the requirements for a lightweight smart glove, the two most common types of textile-based pressure sensors, including capacitive and resistive pressure sensors, were chosen for test. A **capacitive pressure sensor** can be constructed as two layers of conductive fibres with a dielectric material, such as a polyester fabric, in between. It measures the change in the coupling capacitance, which happens when pressure is exerted over the corresponding sensor area [50]. On the other hand, **resistive pressure sensors** measure the change in resistance values obtained when applying pressure to the sensing area. They can be constructed by layering conductive fibres separated by a piezoresistive layer which changes its resistance when deformed [51]. Because of their good flexibility, sensitivity, lightweight, and adaptability, these types of sensors are useful for the field of wearables to measure subtle or large human motions [52].

To compare the sensor's noise between capacitive and resistive pressure sensing, we created two sets of square-shaped samples (4 × 4cm, 6 × 6cm), respectively,

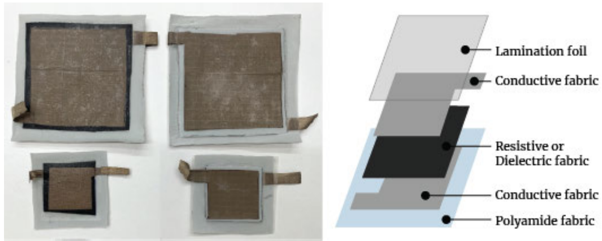


FIGURE 2. Resistive and capacitive pressure sensors samples in 2 different sizes (4 × 4 cm and 6 × 6 cm).

to obtain data and determine which type would be more suitable for the first glove prototype. As illustrated in Figure 2, on top of a base polyamide knitted fabric, two layers of conductive title (Shieldex Bremen RS) are placed with a layer of piezoresistive textile (Velosat EeonTex^{TM} LTT-SLPA 20K ohms) or dielectric textile in between, depending on the type of pressure sensors. All these layers are bonded together by a thermoplastic lamination foil. The sensors were connected to an Arduino board which collects the sensor readings and forward them to a computer. The sensors were evaluated by placing different weights on each sensor sample to obtain the corresponding readings. The weights had a diameter of 5,5 cm and mass of 0.2g, 10g, 30 g, 185 g and 935 g. When the sample size is 4 × 4 cm, the whole sensor area is covered; however, for the sample size 6 × 6 cm, some areas are not covered by the weight.

Figures 3 and 4 are the results of the sensor measurements. The sensor readings are min-max normalized, that is the readings are scaled to the [0, 1] range, so that it is possible to compare them to each other. Figure 3 shows the changes in sensor readings for different weights. An ideal sensor would yield a monotonous increase in readings for an amount of added weight, e.g. a 0.2 increase in output for every 200g of weight added. Figure 4 illustrates the standard deviation of each sensor with different weights. For each measured weight, the standard deviation is indicative of sensor noise. Resistive sensors yield the lowest level of noise based on the results in Figure 4 and also, by a small margin, are the most sensitive to changes in Figure 3. The sensor size appears to have a marginal effect.

D. PRESSURE SENSOR LAYOUT

The next step in the development process was to determine the layout and number of pressure sensors integrated into a glove. For that, we applied an embodied design ideation method [53] and drew insights through engaging in CPR training. Following the CPR expert's instructions on how to position the hands and perform the compressions correctly, two members of the team practised CPR on a training manikin. The manikin's chest was covered with a sheet painted over with a red pigment as illustrated in Figure 5. Once finished, the paint stains on the researchers clearly showed the main touch points on the palm and finger joints as seen in Figure 5. The method provided a clear

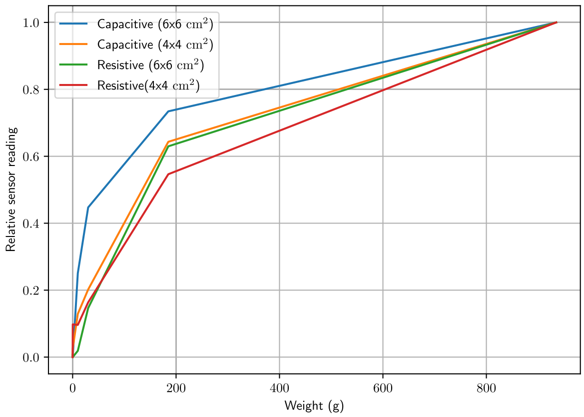


FIGURE 3. Normalized sensor readings against weight. The figure illustrates the change in sensor readings when the weight is changed, with larger reading changes at low weights.

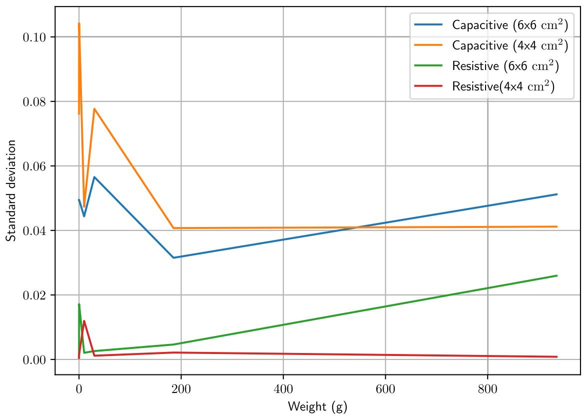


FIGURE 4. Comparison of the normalized standard deviation in sensor readings at different weights. The standard deviation is indicative of the sensor noise as weight is constant.

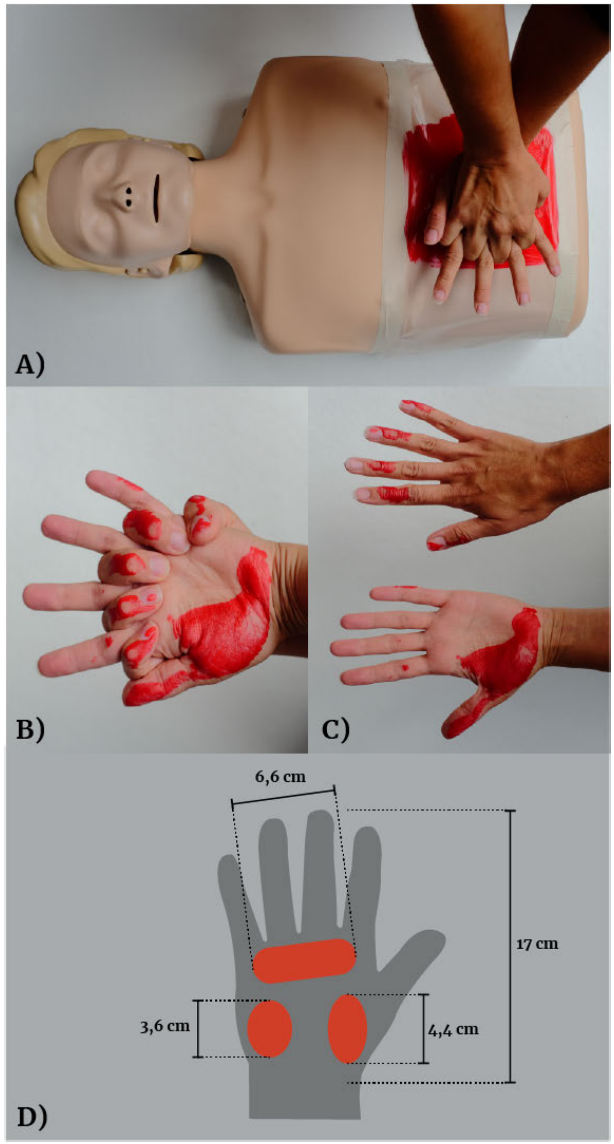


FIGURE 5. (A,B,C) Hand painting for pressure points visual cues (D) Final sensors layout for size M right glove.

visual representation of the hand's touch points during CPR execution, informing the team to design the number and placements of pressure sensors. Although CPR instructions typically ask people to interlace fingers while performing CPR [54], there is in practice no single right way for hand placement, according to the observations of experts' CPR performance. Thus, we decided not to place sensors on the fingers, but integrate three pressure sensors as indicated in Figure 5(d) on the palm'.

E. GLOVE PROTOTYPE

The insights from the previous phases informed the design of smart glove prototype for CPR performance monitoring. The chest compression tracking requirements and correlating design choices are shown in Table 2, while the prototype is shown in Figure 6.

The final design (Figure 6) was based on a pair of left and right-hand gloves specially made of elastic knitted polyamide and cotton fabric. A basic M-size pattern was chosen for its simplicity and fast manufacturing in a laboratory setting. The fingertips were cut for better adjustment to different hand sizes, and a wrist strap was added to avoid displacement. Three resistive pressure sensors were embedded in the palm of the right-hand glove, which faces the chest when performing CPR. These textile-based sensors comprised two layers of conductive fabric (Shieldex®Bremen RS), with a layer of resistive fabric (EeonTex™ LTT-SLPA 20K ohms) in the middle. The layers were placed onto the glove fabric and kept in place by adding a last layer of thermoplastic lamination foil, which melts under a hot flat iron. Metallic snap buttons and insulated cables were used to connect the soft components to the hardware. An elastic band was added to the wrist to keep the cables in place and avoid disconnections to the board caused by the arm's movement.

The pressure sensors were complemented with an IMU (Adafruit LSM6DS33 6-DoF), which detects motion and orientation via an accelerometer and a gyroscope to increase

TABLE 2. CPR monitoring requirements and correlating design choices.

Requirements	Design Choices
Compression depth 5-6 cm	IMU
Compression rate 100-120 per minute	IMU
Interruption should not exceed 10 seconds	Pressure sensors and IMU
Full chest recoil	Pressure sensors
Sensors stay in place and close to the body	Integration of pressure sensors into textiles. Wearability design

FIGURE 6. Final prototype of pressure sensing glove for right hand.

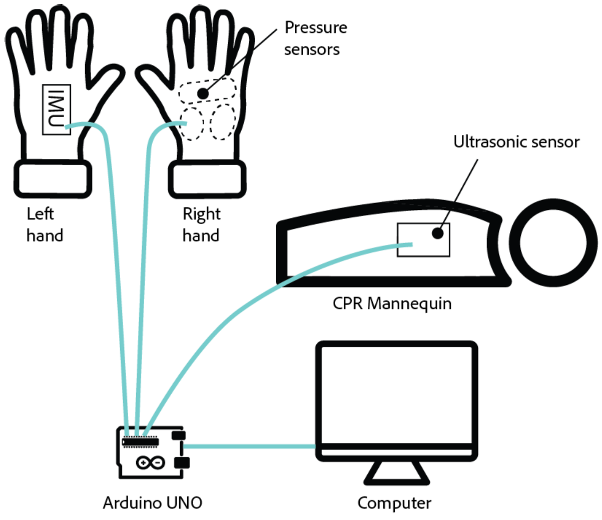


FIGURE 7. Setup of the chest compression performance monitoring system. The prototype is designed for the right hand to go under. For a left-handed person, the pressure sensors and IMU should be swift.

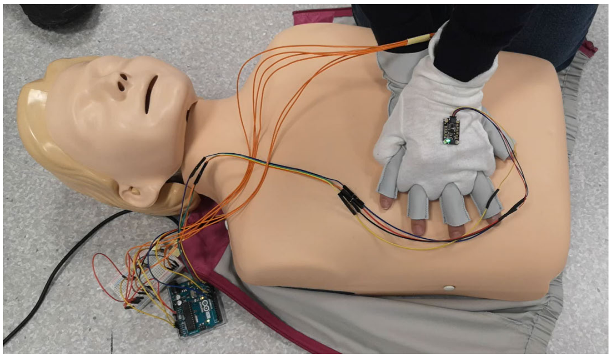


FIGURE 8. User test for data collection at University of Turkul.

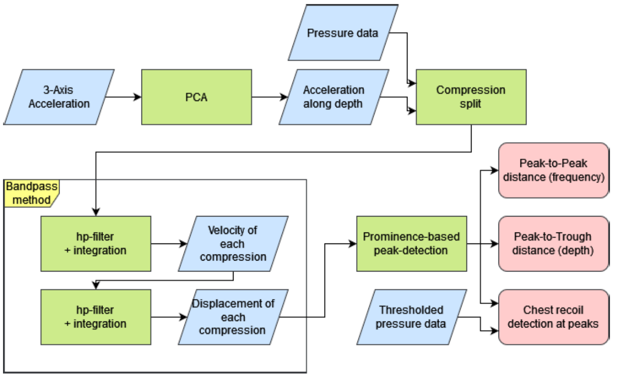


FIGURE 9. Flowchart of the applied detection method. The used portion of original bandpass method is highlighted. Blue rhomboids are descriptions of data at each step, while green rectangles portray the processing steps. Red, rounded rectangles portray the output of the method.

the accuracy of compression depth and rate detection. The IMU was attached to a glove worn on the left hand. All the sensors were connected to a single Arduino UNO Board to receive and safely obtain the data.

IV. DETECTION ALGORITHM

Chest compression monitoring usually focuses on the detection of the frequency and depth of each compression. As indicated in literature [31], the depth measurements are primarily done by integrating acceleration measurements. However, this may cause drift in the resulting signal where the mean of the estimated depth wanders to unreasonable values. This challenge can be dealt with through different methods, and based on a comparative study [31], we chose to augment the bandpass method [15]. The bandpass method is used to obtain displacement readings from 1-axis acceleration readings. Depth and frequency can then be read from the displacement. In our approach, outlined in Figure 9, acceleration measurements are complemented with pressure sensor input to properly consider the chest recoil, which is not possible with the bandpass method introduced in earlier works. Our overall approach then simply changes the method of compression splits while leveraging the depth estimates yielded by the bandpass method.

As both frequency and depth estimates require a certain time period of a signal to yield meaningful results, we used the pressure sensors to split the measurements into individual compressions. This happened via simple thresholding as the pressure sensor was configured to yield fixed output when hands are laid neutral on the chest, ready to begin CPR.

Within each of these compressions, we first applied principle component analysis (PCA) [55] to obtain the acceleration along the direction of the compressions from the first eigenvector. Earlier works, such as [15], aligned the compression depth with one of the acceleration axes, but this might not be possible in a glove scenario. We applied singular value decomposition (SVD), a type of PCA suitable for non-square matrices, from SciKit-Learn library [56]. SVD decomposed the matrix of acceleration data M into singular values Σ, and left and right singular vectors U, V: $M = U\Sigma V^T$. The right signular vector V was of particular interest here, as it corresponds to the rotation of the original data that aligns the first dimension towards the greatest variance. We assumed that the compressions themselves are the main source of variance in the data, so after applying our rotation $V \cdot M$ we had data along the direction of the compressions (equivalently, the data can be obtained via $U \cdot \Sigma$). This process has two additional benefits. First, data is always mean-centered before applying PCA, which eliminated the constant gravitational component along the compressions. Second, the noise that is not along the direction determined by the first singular vector, i.e. the compressions, is eliminated from the data.

Next, we obtained the displacement from the acceleration readings. When applying the bandpass method, the filter parameters should be reset between the compressions to combat drift due to the cyclical nature of the CPR. In the original bandpass method [15], the filter resetting is done at the zero-crossings of the velocity estimates. However, doing so will potentially mask scenarios where the chest is not allowed to fully recoil, and each compression is gradually deeper, i.e. the actual compression depth is drifting. Our modified method resets the filters based on the thresholded pressure readings instead, which remedies the issue. Outside of this and the application of PCA, we apply the bandpass method as described in [15]. The original bandpass method is built from two parts: a highpass filter to eliminate noise, and a lowpass filter in the form of integration. In our implementation, we chose a fourth-order Butterworth filter at 0.6 Hz, and cumulative trapezoids were used for the integration part.

Finally, we arrive at an estimate of the displacement during a single compression. However, the values of interest were frequency and pressure depth. As individual compressions were already obtained, we could measure the peak-to-peak depth within each press. The peaks were identified using prominence-based peak detection (prominence of 0.2 in a [0,1] normalized signal) in SciPy library [57]. Similarly, the time difference of zero points in pressure sensors yielded the compression frequency. Finally, the frequency and depth

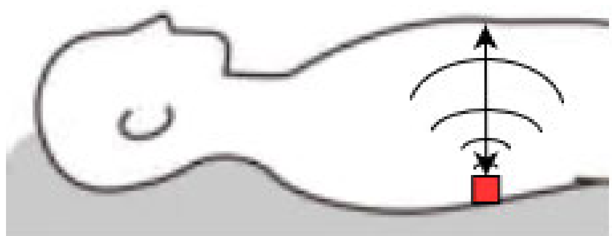


FIGURE 10. Placement of the ultrasound sensor to obtain ground truth from a CPR Manikin. The torso outline represents the Manikin, while the red box illustrates the location of the sensor measuring the distance indicated by the arrow.

estimates can be unstable due to noise when observing just a single compression. As is discussed in [15], a user does not necessarily require feedback for every compression. Hence we averaged the results over three previous compressions, similar to [15], to reduce the noise in the estimates.

V. EVALUATION

A. SETUP OF DATA COLLECTION

The CPR gloves prototype was evaluated in a pilot test in a simulation room at the University of Turku, Faculty of Medicine (Figure 8). Nine participants were instructed to perform CPR according to the ERC guidelines [58] while wearing the glove prototypes. Four of the participants were health professionals who have experience in providing high-quality CPR in accordance with the guidelines of the ERC while the remainder were lay rescuers. We provided them with details about the study, including the location and date/time of the demonstration, and only those who agreed to participate were given more information. We clarified that participation in the study was entirely voluntary and that they could withdraw at any time without giving a reason. Consent for participation in the study was assumed upon arrival at the University of Turku's simulation room.

The participants were given verbal feedback by a medical professional, based on the readings of the CPR manikin, on their performance to ensure the compression depth remained within 5 to 6 cm and the compression rate within 100 - 120 per minute. To minimise the effect of fatigue, each participant performed three sets of compressions (30 per set) with a break between each set. chest compressions were performed on Little Anne QCPR [49]. Data were collected from both gloves in real-time during the study. To determine a ground truth, i.e. the direct observation, for compression depth measurement, an ultrasonic sensor HC-SR04 was placed inside a training manikin just below the pressure area. The sensor was attached to the manikin's inner back plate to measure the distance so the manikin's inner chest plate as illustrated in Figure 10.

B. DATA SETS

We collected the simultaneous readings of the IMU attached to one glove, the 3 pressure sensors on the other glove, as well as the ultrasonic sensor placed inside the manikin. The pressure sensor readings were in arbitrary units describing the resistance in the sensor, which was not calibrated to real pressure readings. Accelerometer readings were readily available in the expected units, and gyroscope readings were not used for this study. The ultrasonic sensor readings given in milliseconds were converted to meters via multiplication with the speed of sound. To obtain relative distance for the compressions, these readings were centred around the first mode of the distribution.

The noisy ultrasound-based distance was processed by correcting outliers with linear interpolation (excluding outliers above 25cm), filtering noise with a 4th-order Butterworth lowpass filter at 3Hz, and identifying individual compression depths by analyzing peaks and troughs of the signal. The values for outlier detection and filtering were chosen based on the chest-to-back distance of the manikin (20cm) and the expected compression rate (<180 compressions per minute) respectively. The compression depth of the ground truth readings was determined from individual compressions.

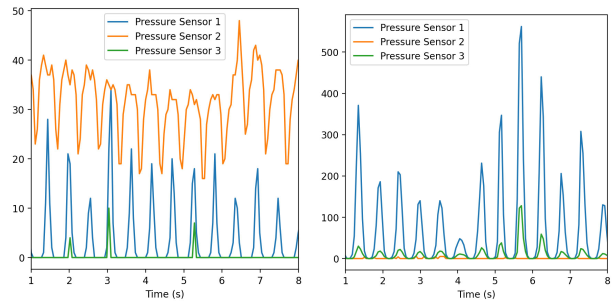
Using these methods, our data set was sized 8942 samples at an 18.5Hz sampling rate (8 minutes of compressions). The low sampling rate was due to the ultrasonic sensor, while the used IMU and pressure sensors would be able to offer higher time resolution. These 8 minutes of recordings included nine subjects with three compression sets each. As expected, the distribution of ultrasonic readings had two modes with approximately a 6cm difference, corresponding to the initial rest state and the compressed date of the CPR process. There was significant noise present even after the preprocessing: 99% of the data was found in the interval [-2.76, 16.45]cm. Accelerometer readings, on the other hand, were normally distributed for the three axes with means [4.29, −3.43, 7.98]ms^{-2} and standard deviations of [4.72, 4.41, 5.61]ms^{-2}. These values were within the expected ranges.

VI. FINDINGS

A. SENSOR LAYOUT

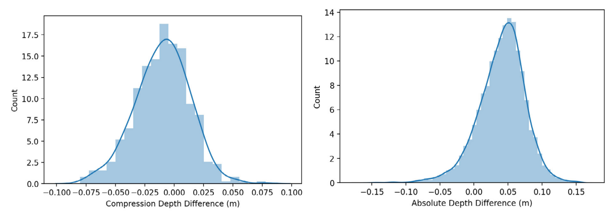
The prototyping process and the user study obtained data showed positive results regarding the feasibility of utilising a textile-based smart glove for CPR, and verified the design choices described in Section III.

Resistive pressure sensors applied on the palm were a suitable option to complement the acceleration data related to chest recoil, rate of compression, and interruptions between compressions. The obtained data suggest that even one pressure sensor placed on the outer side of the palm can be enough to provide the required additional data (Sensor 1 from Figure 6 and 11). Contrary to the pressure sensor layout test results, we observed that data from a sensor near the thumb does not provide reliable readings (Sensor 3 in the same figures). Sensor placement on the top of the palm (Sensor 2 in the figures), under locking fingers, seemed only reliable for practitioners who do use the locking finger posture. The final location on the outer side of the palm provided the most reliable readings of the compressions.



(a) Pressure sensor data with locked fingers pose (b) Pressure sensor data with open pose

FIGURE 11. Example of pressure data from two participants. Y-axis represents arbitrary units related to resistance from the pressure sensors.



(a) Depth estimate errors for individual compressions (b) Instantaneous depth errors.

FIGURE 12. Distribution of errors with the modified bandpass method, x-axis showing the errors in meters.

Figure 11 showcases the difference in pressure measurements from two participants applying different compression poses.

B. ACCURACY

For the accuracy of our approach, we provide the results along three different metrics: instantaneous depth error, depth estimate error, and frequency estimate error. Instantaneous depth error describes the positional error between our estimate and the ultrasonic ground truth at each time step, while the depth estimate error is the difference between the depth of compression estimates between the method and ultrasonic distance. Both of these distributions are displayed in Figure 12. We observed that focusing on individual compressions for depth indeed improves the estimation accuracy from the instantaneous error's $\mu = 0.04049, \sigma = 0.03487$ to $\mu = -0.00996, \sigma = 0.02337$. Thus, while our method was not appropriate for monitoring the instantaneous position of the hand during the compressions, it yielded reasonable results when assessing the compression depth.

Frequency estimates using the peak-to-peak difference were nearly perfect, with some outlier estimates present. We achieved a mean error of 8.162 Hz with IQR of 0. This is unsurprising as the main frequency is not affected by the data processing or filtering methods, and we are using the same peak-to-peak estimation method to calculate the frequency from both displacement and ultrasonic ground truth data.

In [31], the bandpass method from a wrist-worn device yielded median absolute difference (MAD) of 4.5mm (ours:

−8.7mm) with interquartile range of 2.3 - 7.8mm (ours: −25.0 - 5.6mm). Despite the difference being large, the results are comparable and give an indication of the potential performance of the model under an ideal scenario. The first of two factors influencing our results was the usage of an ultrasonic sensor on the ground truth measurements. The sensor yielded noisy results, and despite filtering, the comparisons of baseline and the ground truth were influenced by this. Especially the large interquartile range can be expected to be influenced by this. The second influencing factor was the usage of the sensors in two different hands. As the IMU was placed on the back of the upper hand, it was not as accurate in measuring the compression as a placement on the lower hand could be. We additionally observed the practitioners' hands occasionally bouncing due to the spring inside the Manikin. This would influence the MAD results obtained by our study. Overall, the resulting MAD indicates that the modified method is usable for monitoring CPR depth, providing additional information about the chest recoil.

C. USER EXPERIENCE

During the study, we observed that the usability, adaptability and comfort aspects were essential for reliable data collection besides technical functionality. Observations from the iterative development process of the proof-of-concept glove prototypes showed that the glove sizing affected the correct chest compression performance and data quality while training. We observed that although the pressure-sensitive glove fitted various hand sizes, wearing it on more extensive hands increased the risk of breaking the sensors due to fabric stretching. On the other hand, a loose glove could move during CPR, creating a displacement of the sensors and extra friction to the hand skin, which impacted lowering the intensity of the exercise.

Material choices were another major contributor to the comfortable use of the prototype. The polyamide fabric used for the glove proved to be suitable for maintaining the elasticity of the glove, allowing it to adapt to different hand sizes and hand movements. Nevertheless, the exercise was more intense than expected, causing sweating of the hands. The polyamide fabric did not absorb or move the sweat to the textile's outer surface, creating a humid environment. The study participants mentioned that it increased friction resulting in uncomfortable abrasion while performing CPR. This could also raise a hygienic concern and the necessity for frequent cleaning.

Finally, fabricating the pressure sensors from flexible materials enabled the creation of custom-made patches attached to the polyamide fabric. The sensors retained some of the materials' stretchability, although the multilayer construction was less flexible than the individual materials. The stiffness of the sensors limited the glove to adapting to the movements of the palm. The sensors' size also decreased the glove's fit as the laminated sensors and textile wires covered the whole palm area. As mentioned in section VI. the number of sensors could be reduced to one, besides which the results suggest the sensors could also be smaller while still producing necessary data for chest compression monitoring. Both modifications to the sensor layout would contribute to a more flexible glove.

VII. DISCUSSION AND CONCLUSION

This paper presented a development process and an evaluation of smart glove prototypes for CPR monitoring. The proposed solution can monitor four essential characteristics of high-quality chest compression: complete chest recoil, compression depth, compression rate and interruptions between compressions.

The study applied design methods such as fast prototyping and bandpass method, which allowed for simultaneously acknowledging requirements related to materials, technology, wearability, and accuracy throughout the process. A proof-of-concept glove prototype was achieved, highlighting the importance of applying both qualitative and quantitative evaluation methods to guide decision-making in different development phases. This section discusses the study findings more in-depth, proposes new avenues for further research, and addresses the methodological limitations.

Compared to the existing alternatives (e.g. [14], [27], [28]), our prototype is flexible, adapts to adult hands, and can be personalised to different hand sizes. This was due to the use of smart textiles, which allowed for harnessing the benefits of textile material properties and using textile production methods in circuit integration. The selected materials and methods also aided in the creation of a low-cost and accessible tool for CPR. Replicating the proposed prototype does not require access to advanced textile fabrication or lab facilities. On the contrary, the use of typical textile production techniques (sewing and lamination) lowers the barrier to producing such gloves. We believe this, together with using open-source hardware, could increase accessibility to wearable chest compression monitoring devices, enabling training to a broader audience. In addition, accessibility requires transparent knowledge transfer, for example, in the form of open-source instructions or DIY kits. To ensure it, the fabrication files, circuit schematics and algorithms will be made open-source once the project concludes.

The proof-of-concept prototype points directions for further design and development needs. We observed that the training setup, which included two smart gloves, was perceived as slightly invasive. Integrating the sensors in a single smart glove would interfere less with the CPR performance. In addition, the two-hands setup also increased noise in the measurements as the participants' hands were not continuously moving in sync. This indicates a need for better sensor layout design to improve the system's usability and measurement accuracy. Moreover, re-designing the sensor layout should be done in tandem with optimising the glove's other form and material factors. In terms of design, material selection and sewing pattern design need to consider comfortable use and wearability. For example, fabric with moisture-wicking properties [59] would help transport moisture outside the glove, thus decreasing friction while wearing the glove. In addition, more user studies should be conducted focusing on wearability to deeply study the user's response to the gloves.

Additionally, as shown in previous research on CPR monitoring, real-time feedback elements are typically embedded in the systems to aid the users in performing better. Thus, further research is needed to evaluate the most suitable feedback modalities for a smart glove, such as audio or haptic feedback.

On the technical side, the sensor fusion of pressure and acceleration into a single smart glove enables the monitoring of complete chest recoil. Using the presented algorithm, the glove can accurately monitor the frequency and depth of compressions to a reasonable extent, and the method can be expected to work when using different accelerometers or pressure sensors due to modeling the scenario mathematically. The combination of these three factors makes the glove a suitable tool for cardiopulmonary resuscitation training and lays the groundwork for a similar tool for real-life scenarios.

Our results yield reasonable accuracy on tracking the depth, and excellent accuracy on tracking the frequency of compressions. This also means that the splitting of individual compressions using our method is successful. Given that our modified bandpass method executes identically to the unmodified method after the compression split (Figure 9), we can expect similar accuracy in tracking depth when using the same data. In other words, despite the weaknesses in our tracking accuracy results, our algorithm should not be expected to influence the accuracy or precision of depth estimates and our focus is on monitoring the chest recoil as an additional feature.

Further research could focus on deepening the sensor fusion by combining well-calibrated pressure sensors into the depth estimates, instead of using them to segment the signal. This could lead to improvements in the accuracy of the depth estimates. The angles of approach here could be Extended Kalman Filter [60] style data integration, or machine learning methods like simple feedforward networks or shallow random forests [61]. Furthermore, including the gyroscope readings in the sensor fusion has the potential to further stabilize the compression direction in online scenarios and hence improve the precision.

Regarding the sensors, work should be done on the characterization and optimization of the sizes and shapes, and the hand position during the exercises should also be considered as a future perspective. Studies with a bigger number of participants need to be conducted to obtain outliers points of reference and more generalizable results.

A considerable limitation in our study was the quality of our ground truth measurements. Obtaining high-quality depth measurements from the manikin manufacturer would yield more reliable results but they were not available for our study. It could also enable pressure sensors to directly improve the depth measurements. While the pressure sensor shape and sensitivity remain a challenge, sensor fusion via machine learning methods has the potential to overcome these issues and improve the precision of the depth estimates. Conducting the study through a generative design process allowed running a user study with early phase prototypes to gain an initial understanding of the smart gloves' usability and electrical performance while exploring new design opportunities for smart textiles in CPR monitoring. On the other hand, these prototypes rely on hand-craft techniques and did not yet take into consideration industrial production, cost, scalability, or extended user comfort. A future design prototyping process needs to take these variables into account.

The presented study showed the design process and outcome of a novel CPR quality assessment wearable. We have outlined a design process that can be used for similar smart garments, showcased our prototype and its functionality, and elaborated on the inclusion of chest recoil monitoring in the modified bandpass algorithm. Chest recoil is an important aspect of CPR compressions and its monitoring and feedback will improve the quality of CPR. The design process and the prototype showcases how technology and user experience aspects influence and inform one another.

Our future research on the glove prototype will focus on refining the technology towards possibilities on manufacturing, system validation, and user testing. Further, we encourage researchers to study deeper sensor characterization on textile-based pressure sensors, multimodal monitor, and sensor fusion methods in the domain.

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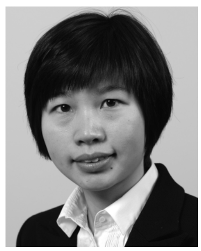

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