Development of Android Based Chest Compression Feedback Application Using the Accelerometer in Smartphone

Yeongtak Song, Youngjoon Chee

University of Ulsan, School of Electrical Engineering 93 Daehak-ro, Nam-gu, Ulsan, Republic of Korea yeongtaksong@gmail.com; yjchee@ulsan.ac.kr

Jaehoon Oh, Sanghyun Lee

Hanyang University, Department of Emergency Medicine 222 Wangsimni-ro, Seongdong- Gu, Seoul, Republic of Korea ojjai@hanmail.net; gagul81@gmail.com

Abstract - Chest compression depth (CCD) and rate (CCR) are important factors of cardiopulmonary resuscitation (CPR). To assist performing CPR by citizen, a number of CPR related applications are being developed on a smartphone application market. Most of apps provide procedure of CPR. In case of using accelerometer, it is possible to estimate CCD and CCR. In this study, we proposed an app which provides feedback of CCD and CCR. The proposed app provided feedback of CCD and CCR in real time through the calculated displacement using the acceleration signal which is obtained from the built-in accelerometer of smartphone. For the verification, nineteen CPR providers performed chest compressions on a manikin lying on two different surfaces (flat floor and foam mattress on a bed frame) with feedback from the app. We analysed CCD and CCR from the app and the manikin for each surface. When chest compressions were performed on the manikin lying on the flat floor, the mean (SD) of CCD from manikin and developed app were 55.16 (3.09) mm and 55.12 (3.64) mm (p>0.05). And when the manikin lying on the foam mattress, the mean (SD) of CCD were 52.68(4.18) mm and 57.90(2.59) (p=0.047). The CCR was no significant difference between manikin data and app data both surface (p>0.05). The proposed app provided suitable feedback of CCD and CCR for high quality CPR on the flat floor. However, because of the mattress compression depth the app overestimated CCD on foam mattress.

Keywords: Cardiopulmonary resuscitation, Chest compression, Smartphone, Accelerometer.

1. Introduction

Cardiopulmonary resuscitation (CPR) is an emergency procedure for manually preserving brain function until further measures to restore spontaneous blood circulation and breathing in a person who is in cardiac arrest. The main contents of CPR are chest compressions and rescue breathing, and it is important technique in the hospital, at home, and in the accident field. According to 2010 American Heart Association (AHA) Guidelines, high-quality CPR includes chest compressions of adequate rate (at least 100/minute) and depth (least 50 mm), allowing full chest recoil after each compression and minimizing interruptions in compressions (Berg R.A. et al., 2010). Chest compression depth (CCD) and chest compression rate (CCR) are important factors and it is related to survival rates of cardiac arrest (Berg R.A. et al., 2010, Edelson D.P. et al., 2006, Bellamy R.F. et al., 1984 and Christenson J. et al., 2009).

However, insufficient chest compression (CC) when compared with the current recommendation was observed during CPR in both out-of-hospital and in-hospital studies (Abella B.S. et al., 2005 and Wik L. et al., 2005). To reduce the insufficient CC, emergency medical participants are trained the basic life support (BLS) education periodically. In addition, they have used several devices which offer feedback of CCR and CCD (Gruber J. et al., 2012). These feedback devices calculate CCD from the accelerometer or

pressure sensor. Several studies have shown that these feedback devices improve CCD in simulated cardiac arrest (Perkins G.D. et al., 2005, Skorning M. et al., 2010 and Pozner C.N. et al., 2011).

Most of cardiac arrest patients are occurred in out-of-hospital. In this situation, the existence probability of feedback device is extremely low. In addition, most of the citizens do not receive periodic BLS training. According to Gartner, Inc., in the second quarter of 2013, worldwide smartphone sales to end users reached 225 million units, up 46.5 percent from the second quarter of 2012 (Web-1). A lot of smartphone applications (apps) are developed and registered on application market (Google Play Store) with increasing sales of smartphone. A number of CPR related apps are registered in Google Play Store. And most of these apps are guide the CPR procedures to provider using text and pictures or video. It could increase the survival rate of cardiac arrest patient if someone developed the app that has the feedback function.

There were no reports on estimation method of CCD with smartphone. In this study, we proposed a real time CCD and CCR feedback app (we called 'U-CPR') using android based smartphone which has a built in three-axis accelerometer and verified adequacy using manikin.

2. Methods

2. 1. Chest Compression Depth and Rate Estimation Algorithm Using the Smartphone's Accelerometer

Theoretically, as shown in Eqs. (1) by integrating the acceleration signal (a(t)) we can obtain velocity(v(t)), and by integrating again them the depth of compression(d(t)) can be obtained.

$$\vec{d}(t) = \int \vec{v}(t)dt + C_{v} = \iint \vec{a}(t)dtdt + C_{v}t + C_{a}$$
(1)

However, accumulation of errors due to integration constants (C_a, C_v) are considerable. Some devices use an additional pressure switch to detect the starting point of each compression to solve this problem (Aase S.O. et al., 2002), which cannot be implemented with a smartphone. Chest compression motion is a periodic reciprocation action. It means that positive-peak to negative-peak of distance data (peak-to-peak distance) is the only valid information. Using this information, we could estimate CCD (Song Y. et al., 2011).

Normally, the signal (raw data) from the accelerometer has noise. And the raw data were sampled for every event, which fires whenever the Android OS determines that the input signal of the accelerometer has changed. Due to the varying activity loads of the OS, this event is not fired regularly. Due to the irregular acquisition, it cannot be applied general filter. To remove the noise, we used to the weighted smoothing technique (Eqs. (2)) such as low pass filter, and for the drift remove, we used to the emphasizing transient components technique (Eqs. (3)) such as high pass filter (Milette G. et al., 2012). We also try the re-sampling, (sampling rate: 200Hz) it used to linear interpolation between two neighboring sample (one before and one after) and apply general band pass filter (frequency range: 0.5~20Hz), but there was no difference with our method. It takes more time for processing re-sampling so we use the techniques (transient components emphasizing, weighted smoothing) as stated above.

$$y[n] = ((1 - \beta) \times x[n - 1]) + (\beta \times x[n])$$
(2)

$$y[n] = \alpha \times (y[n-1] + x[n] + x[n-1])$$
(3)

Fig. 1. shows the flow chart used to determine the distance of one axis. To minimize sensor noise, we used the weighted smoothing technique as shown in Eqs. (2), where β is 0.7. We can obtain the velocity by integrating the filtered signal. The cumulative error occurs due to the bias, which is given by the integral constant. This error produces the drift effect on the waveform, as shown in Fig. 1. We used the

transient components emphasizing technique to reduce the slowly changing components, as shown in Eqs. (3), where α is 0.9. The velocity was integrated again to obtain the distance data. We estimated the CCD as the difference of the positive peak and negative peak in the distance data (Song Y. et al., 2011). Also, from these peaks, we could estimate the CCR. When we found distance of each axis, we can estimate the actual distance of moving in a three-dimensional space through the vector sum of three axes (Eqs. (4)). In Eqs. (4), d_x, d_y and d_z are the calculated distance from x, y and z axis of accelerometer respectively. d is the distance of movement in three-dimensional space.

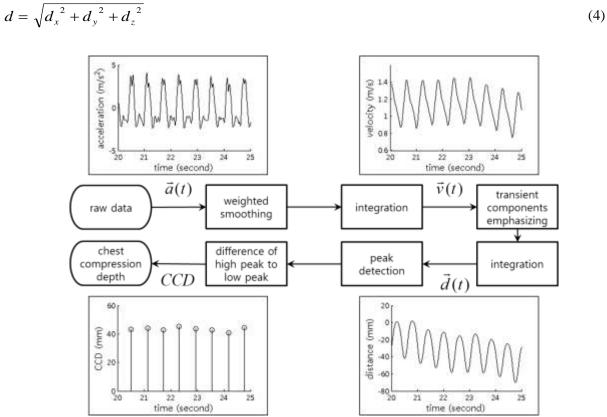


Fig. 1. Flowchart of chest compression depth estimation algorithm for the one axis.

2. 2. Experiment for Verification of Proposed Apps Feedback Function

For the verification of feedback function, nineteen American Heart Association (AHA) Basic Life Support (BLS) providers participated in this study. Each provider performed CCs on a manikin (Resusci Annie Modular System Skill Reporter® (Laerdal Medical, Orpington, UK)) placed on two different underlying surfaces with the app's visual feedback and metronome. One surface is flat floor like a situation of out of hospital and the other surface is foam mattress (660 X 1920 X 80 mm, soft foam with polyurethane coverage, Stryker Co., US) on a bed frame (Transport stretcher®, 760 X 2110mm, 228 kg, Stryker Co., US) like a situation of in hospital. Fig. 2. shows an example of app's feedback screen. Providers performed CCs according to this screen message. About 200 CCs were performed over two minutes in each instance with a five minutes break between instances. In each case, we calculated mean and standard deviation (SD) of CCD and CCR.

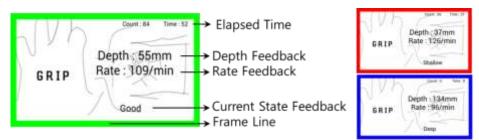


Fig. 2. Capture image of feedback screen.

The color of frame line changes according to current chest compression quality. (Green: adequate (left), Red: insufficient (upper right), Blue: excessive (bottom right))

3. Results

The CPR performers were all male with a median age of 31 years (range 25-37 years). The median performer weight was 77 kg (60-91 kg), and the median height was 172 cm (160-182 cm).

Table 1. shows the summarized results of the experiment which were mean (SD) of CCD and CCR from each device (manikin and U-CPR). As shown in Table. 1, when CCs were performed on flat floor, in terms of U-CPR, mean (SD) of CCD was 55.16 (3.09) mm, whereas manikin data was 55.12 (3.64) mm (p>0.05). In mattress surface case, U-CPR's and manikin's mean (SD) of CCD were 52.68 (4.18) mm and 57.90 (2.59) mm respectively (p=0.047). There were no significant difference between manikin's CCR and U-CPR's CCR in both surface (p>0.05).

		Surface	
		Floor	Mattress
Depth (mm)	Manikin	55.16(3.09)	52.68(4.18)
	U-CPR	55.12(3.64)	57.90(2.59)*
Rate (#/min)	Manikin	101.74(3.52)	100.84(3.20)
	U-CPR	101.41(2.71)	101.71(2.65)

Table 1. Chest compression depth and rate on two different surface.

Mean (SD) in mm. * p < 0.05 (Manikin vs. U-CPR, Two sample t-test)

4. Discussion

In this study, we suggest and analyse accuracy of chest compression depth estimation algorithm which is based on android smartphone. When estimate the distance from an accelerometer, there is a few errors because it is not measured distance directly. Suggested CCD and CCR feedback algorithm might be accurate on verification experiments. The CCR was no significant difference between manikin data and app data both surface (p>0.05) and it is suitable for high quality CPR.

When CCs were performed on foam mattress, the U-CPR overestimated CCD (p=0.047). The U-CPR can overestimate CCD because it estimate added value which are CCD and mattress compression depth (MCD) (Perkins G.D. et al., 2009). This limitation occurs when CCD estimated by using an accelerometer. In this case, using the backboard can reduce overestimation (Nishisaki A. et al., 2012). It's also a good idea that increasing CCD to at least 65 mm if the patient is lying on a mattress to compensate for MCD such as suggestion by Handley A.J. (2012). In addition, AHA guidelines recommended full chest recoil after each compression, but we cannot know about recoil because our algorithm utilized the assumption of full chest decompression (CDC).

We finished feasibility test of using the U-CPR. Additionally, we materialized metronome function. It makes the proper bit that is 100 times per minute and guide proper CCR to CC performer. Using the metronome is helpful for improve CC quality (Park S.O. et al., 2013). Our future plan is making the complete application by adding several functions.

5. Conclusion

In this study, we proposed a new CCD estimation algorithm using android based smartphone which has a built in accelerometer and verified proposed algorithm using the manikin. The proposed CCD estimation algorithm has a suitable level of accuracy for high quality CPR on flat floor. However, because of the mattress compression depth the app overestimated CCD on foam mattress. Through this app, we expect to increase survival rate by leading accurate CPR.

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References

- Aase S.O., Myklebust H. (2002). Compression depth estimation for CPR quality assessment using DSP on accelerometer signals. IEEE Transactions on Biomedical Engineering, 49(3), 263-8.
- Abella B.S., Alvarado J.P., Myklebust H., Edelson D.P., Barry A., O'Hearn N., Hoek T.L.V., Becker L.B. (2005). Quality of cardiopulmonary resuscitation during in-hospital cardiac arrest. JAMA: The Journal of the American Medical Association, 293(3), 305-10.
- Bellamy R.F., DeGuzman L.R., Pedersen D.C. (1984). Coronary blood flow during cardiopulmonary resuscitation in swine. Circulation, 69(1), 174-80.
- Berg R.A., Hemphill R., Abella B.S., Aufderheide T.P., Cave D.M., Hazinski M.F., Lerner E.B., Rea T.D., Sayre M.R., Swor R.A. (2010). Part 5: Adult basic life support 2010 american heart association guidelines for cardiopulmonary resuscitation and emergency cardiovascular care. Circulation, 122(18 suppl 3), S685-705.
- Christenson J., Andrusiek D., Everson-Stewart S., Kudenchuk P., Hostler D., Powell J., Callaway C.W., Bishop D., Vaillancourt C., Davis D. (2009). Chest compression fraction determines survival in patients with out-of-hospital ventricular fibrillation. Circulation, 120(13), 1241-7.
- Edelson D.P., Abella B.S., Kramer-Johansen J., Wik L., Myklebust H., Barry A.M., Merchant R.M., Hoek T.L.V, Steen P.A, Becker L.B. (2006). Effects of compression depth and pre-shock pauses predict defibrillation failure during cardiac arrest. Resuscitation, 71(2), 137-45.

Gruber J., Stumpf D., Zapletal B., Neuhold S., Fischer H. (2012). Real-time feedback systems in CPR. Trends in Anaesthesia and Critical Care, 2, 287-304.

- Handley A.J. (2012). In-hospital chest compressions—The patient on a bed. Resuscitation, 83(7), 795-6.
- Milette G., Stroud A. (2012). Professional android sensor programming: Chapter 6: Errors and sensor signal processing. John Wiely & Sons, Inc. 103-20.
- Nishisaki A., Maltese M.R., Niles D.E., Sutton R.M., Urbano J., Berg R.A., Nadkarni V.M. (2012). Backboards are important when chest compressions are provided on a soft mattress. Resuscitation, 83(8), 1013-20.
- Park S.O., Hong C.K., Shin D.H., Lee J.H., Hwang S.Y. (2013). Efficacy of metronome sound guidance via a phone speaker during dispatcher-assisted compression-only cardiopulmonary resuscitation by an untrained layperson: A randomised controlled simulation study using a manikin. Emerg Med J, 30(8), 657-61.
- Perkins G.D., Kocierz L., Smith S.C., McCulloch R.A., Davies R.P. (2009). Compression feedback devices over estimate chest compression depth when performed on a bed. Resuscitation, 80(1), 79-82.
- Perkins G.D., Augré C., Rogers H., Allan M., Thickett D.R. (2005). CPREzy[™]: An evaluation during simulated cardiac arrest on a hospital bed. Resuscitation, 64(1), 103-8.
- Pozner C.N., Almozlino A., Elmer J., Poole S., McNamara D., Barash D. (2011). Cardiopulmonary resuscitation feedback improves the quality of chest compression provided by hospital health care professionals. Am J Emerg Med, 29(6), 618-25.

Skorning M., Beckers S.K., Brokmann J.C., Rörtgen D., Bergrath S., Veiser T., Heussen N., Rossaint R. (2010). New visual feedback device improves performance of chest compressions by professionals in simulated cardiac arrest. Resuscitation, 81(1), 53-8.

Song Y., Chee Y. (2011). The development of feedback monitoring device for CPR. Engineering in medicine and biology society, EMBC, 2011 annual international conference of the IEEE. 3294-3297.

Wik L., Kramer-Johansen J., Myklebust H., Sørebø H., Svensson L., Fellows B., Steen P.A. (2005). Quality of cardiopulmonary resuscitation during out-of-hospital cardiac arrest. JAMA: The Journal of the American Medical Association, 293(3), 299-304..

Web sites:

Web-1: http://www.gartner.com/newsroom/id/2573415 consulted 20 March. 2014.