# Analysis of smart phone video footage classifies chest compression rate during simulated CPR: a pilot study

Adam Frisch, MD, MS [1]
Samarjit Das, PhD [2]
Joshua C. Reynolds, MD, MS [3]
Fernando De la Torre, PhD [2]
Jessica K. Hodgins, PhD [2]
Jestin N. Carlson, MD, MS [4, 5]

[1] Department of Emergency Medicine
Albany Medical Center
Albany, NY

[2] Robotics Institute
Carnegie Mellon University
Pittsburgh, PA

[3] Department of Emergency Medicine
Michigan State University College of Human Medicine
Grand Rapids, MI

[4] Department of Emergency Medicine
Saint Vincent Health System
Erie, PA

[5] Department of Emergency Medicine
University of Pittsburgh
Pittsburgh, PA

**Correspondence**:
Joshua C. Reynolds, MD, MS
15 Michigan Street NE, Suite 429 G
Grand Rapids, MI 49503
Phone: 616-234-2728
Fax: 616-458-4680
E-mail: reyno406@msu.edu

**Key Words**: heart arrest; CPR; simulation; cellular phone

**Word Count**: 1,447

Presented at National Association of EMS Physicians Annual Meeting 2013 in Bonita Springs, FL

My colleagues are Adam Frisch, MD; Samarjit Das, PhD; Fernando De la Torre, PhD; Jessica K. Hodgins, PhD; and Jestin N. Carlson. Our contributions are as follows:

Adam Frisch – study design, data collection/analysis, manuscript preparation and revision
Samarjit Das – study design, data collection/analysis, manuscript preparation and revision
Joshua C. Reynolds – study design, data collection/analysis, manuscript preparation and revision
Fernando De la Torre – study design, data analysis, manuscript revision
Jessica K. Hodgins – study design, data analysis, manuscript revision
Jestin Carlson – study design, data collection/analysis, manuscript preparation and revision

## Abstract

*Objective*

Real-time CPR feedback improves pre-hospital chest compression quality, but few tools are available for lay rescuers. Mobile applications utilizing the embedded accelerometer within smart phones offer CPR feedback, but require accessories to affix the phone to the rescuer or victim. In this pilot study, we tested whether repetitive body movements detected on smart phone video footage of rescuers performing simulated chest compressions classifies chest compression rate.

*Methods*

Six subjects performed 30-second bouts of simulated chest compressions at specified parameters: normal rate (100-120 compressions/minute), 'too fast' (>120 compressions/minute), and 'too slow' (<100 compressions/minute). A nearby smart phone camera recorded participants. Portable inertial measurement units affixed to subjects' hands determined actual compression rate. We extracted the oscillatory signal from the video footage representing the repetitious movement of chest compressions, and divided it into 2-second epochs. We calculated test performance characteristics within- and between-subjects with k-nearest neighbors.

*Results*

Extraction and analyses yielded 153 video segments with recorded chest compression rates ranging from 60-144 per minute. Test performance characteristics were mostly good

or excellent. Overall classification accuracy was 88% (95% CI 82%-92%) (within-subject) and 80% (95% CI 73%-85%) (between-subject).

*Conclusions*

Repetitive body movements identified on smart phone video footage of rescuers performing simulated chest compressions classifies chest compression rate with reasonable accuracy. Such video footage can be obtained by a stationary smart phone in close proximity to the rescuer.

## Introduction

Approximately 360,000 persons suffer out-of-hospital cardiac arrest (OHCA) annually in the United States. [1] Prompt, high-quality CPR is the cornerstone of prehospital cardiac arrest resuscitation. [2] Real-time feedback devices improve the quality of CPR [3], but are typically manufactured as an accessory to the monitor-defibrillator and are not readily available to the lay public. Instead, the lay public is taught to "push hard and fast" without any provision for real-time feedback to optimize chest compression performance. [4] Bystander CPR provides a key link in the chain of survival. [5] Communities that have increased rates of bystander CPR have enjoyed commensurate improvements in OHCA survival. [2, 6] For every 30 OHCA victims who receive bystander CPR, one additional life is saved. [7]

The current generation of smart phones house accelerometers and high-resolution video cameras, both of which are commonly integrated into mobile software applications. Several mobile applications commercially available to the lay public advertise chest compression feedback using the phone's accelerometer, but these applications require a means to affix the smart phone to the rescuer's hand via a strap, glove, case, or cradle. [8-14] These key accessories may or may not be available in the event of emergency necessitating bystander CPR. However, utilizing the built-in video camera may obviate the need for additional accessories by allowing the phone to simply be placed in proximity to the rescuer.

We hypothesized that the repetitive body movements identified on smart phone videos of rescuers performing chest compressions reflects the true chest compression rate. In this preliminary report, we demonstrate proof of concept that such videos can be obtained by a stationary smart phone in proximity to the rescuer, and that analysis of these videos can classify the rate of chest compressions with reasonable accuracy.

## Methods

The University of Pittsburgh Institutional Review Board approved this study. Each participant provided written informed consent.

*Study Design and Setting*: This was a prospective pilot study of smart phone video footage analysis to classify chest compression rates during simulated CPR. Subjects were recruited from a convenience sample of faculty and staff within the University of Pittsburgh Department of Emergency Medicine research offices. For this preliminary study, we selected subjects that were certified in CPR and had clinical experience performing CPR. Subjects performed 30-second bouts of chest compressions on a simulation manikin at three specified parameters: 'normal rate' (100-120 compressions/minute), 'too fast' (> 120 compressions/minute), and 'too slow' (< 100 compressions/minute). To allow for natural variation in compression rates between and within subjects, we did not provide instruction on the specific rate at which to perform 'too fast' or 'too slow' compressions. We used the 2010 ILCOR guidelines of 100-120 compressions/minute as the normal range. The order of the bouts of chest compressions was randomized via simple random number generator. To verify the actual chest compression rate, we affixed a portable, wireless inertial measurement device (APDM, Inc., Portland, OR) to each rescuer's hands. Chest compression rate measured by these devices served as the reference standard.

*Video Recording and Processing*: Subjects provided chest compressions while kneeling on the floor perpendicular to the manikin's torso. We placed a smart phone (iPhone 4, Apple Inc., Cupertino, CA) on the ground between the subjects' knees and the manikin. (Figure 1)

The extracted videos were stored in MPEG-4 (.mp4) format. The video frames were converted from colored to grey-level (back and white) for further processing.
We processed the video frames with image processing algorithms in MATLAB (MathWorks, Natick, MA). These algorithms generated unique features from the video frames that were used to 'learn' chest compression rate from the videos.

The periodic up-and-down movement pattern associated with chest compressions was captured in the videos. For each video frame, we extracted the grey-scale image and computed the integral image and sum of all pixel values. Since each video contained a periodic pattern of chest compressions, the sum of pixel values likewise varied periodically. This repetitive process yielded an oscillatory signal of the pixel sum. (Figure 2) For each 2-second segment of the pixel sum signal, we computed the chest compression rate with the dominant frequency component (e.g. correct rate, too fast, too slow) in the fast Fourier transform spectrum of the pixel sum signal. [15]

*Study Outcomes*: Our primary outcome was to demonstrate that capture of smart phone video footage is feasible and provides a method to determine chest compression rate. We calculated test performance characteristics and overall classification accuracy of chest compression rate determined by video analysis.

*Statistical Analyses*: We divided the compilation of 2-second epochs of video footage equally into a training test and test set for the video analysis software. We tested two different methods of dividing the epochs into test and training sets. To test performance characteristics within each subject, we first separated half of the video segments from each subject as a training set, and used the other half as a test set. To test performance characteristics between subjects, we separated all the video segments from half of the subjects as a training set, and used the other subjects as a test set. For each analysis, we used k-nearest neighbors to calculate test performance characteristics for classifying chest compression rate as too fast (> 120 compressions/minute), too slow (< 100 compressions/minute), and at the recommended rate (100 – 120 compressions/minute).

We selected k-nearest neighbors because the feature space has distinct inter-class variations in the frequency domain, and k-nearest neighbors carries a low computation burden suitable for application in mobile devices with limited computing power. We calculated sensitivity, specificity, positive predictive value, and negative predictive value for each binary classification of correct rate, too fast, and too slow, compared to the other two classifications. We also calculated overall classification accuracy for each mode of analysis (separating video segments into training and test sets within or between subjects).

## Results

The stationary smartphone easily captured high-quality video for subsequent analysis. Six subjects (median age 31 years; 83% male) provided 540 seconds. Of this, 306 seconds was suitable for analysis, yielding 153 two-second video segments. Recorded chest compression rates ranged from 60-144 per minute.

Test performance characteristics are presented in Table 1 for each type of analysis. Dividing video segments within each subject as training and test sets, the overall classification accuracy was 88% (95% CI 82% - 92%). Dividing video segments between subjects as training and tests sets, the overall classification accuracy was 80% (95% CI 73% - 85%).

## Discussion

In this preliminary report, we demonstrated proof of concept that a stationary smart phone placed on the ground between a simulated rescuer and manikin can record video footage that yields chest compression rate.  Furthermore, chest compression rate was accurately classified as 'correct', 'too fast', or 'too slow' 80% - 90% of the time in this small sample of subjects.  With additional training sets, the algorithm used to recognize oscillations may achieve improved accuracy.

Future directions for this work include assessment of chest compression depth and other quality measures with characteristics of the oscillatory signal extracted from the video footage.   Additionally, these algorithms embedded within a smart phone mobile application could test the accuracy and precision of chest compression monitoring aimed specifically at lay rescuers.  Such a mobile application could also support a mechanism of real-time feedback to vary chest compression rate and depth in order to achieve pre-specified parameters.  This mode of CPR quality feedback would not rely on extra accessories to affix the phone to the rescuer or victim.

Additionally, very little is known about the quality and makeup of bystander CPR.  In one of the few clinical studies of bystander CPR quality, Takei, et al. report EMS assessment of bystander CPR quality upon arrival to the scene. [16] Using subjective judgments about hand position, compression rate, and compression depth, bystander CPR was deemed acceptable in 81% of cases.  Acceptable quality was associated with earlier initiation by multiple non-family, non-elderly bystanders in an urban location. A mobile application that utilized video (+/- audio) recording could capture objective bystander CPR quality data and provide additional insight into patient care that occurs before EMS arrival.

This preliminary report represents a proof of concept that was limited to a small number of subjects that were mostly male, younger in age, and had medium builds. These analyses should be tested in rescuers of different height, size, habitus, ethnicity, as well as in different positions/postures and settings, in order to ensure reproducibility across a range of rescuer features and environmental conditions.

## Conclusion

Repetitive body movements identified on smart phone videos of rescuers performing simulated chest compressions classifies chest compression rate as ‘correct’, ‘too fast’, or ‘too slow’ with reasonable accuracy. Such videos can be obtained by a stationary smart phone in close proximity to the rescuer.

**Conflicts of Interest:**

| | |
|---|---|
| Frisch: | None |
| Das: | None |
| Reynolds: | None |
| De la Torre: | Supported by National Science Foundation grant (0931999) |
| Hodgins: | Supported by National Science Foundation grant (0931999) |
| Carlson: | None |

## References


1. Go AS, Mozaffarian D, Roger VL, Benjamin EJ, Berry JD, Borden WB, Bravata DM, Dai S, Ford ES, Fox CS, Franco S, Fullerton HJ, Gillespie C, Hailpern SM, Heit JA, Howard VJ, Huffman MD, Kissela BM, Kittner SJ, Lackland DT, Lichtman JH, Lisabeth LD, Magid D, Marcus GM, Marelli A, Matchar DB, McGuire DK, Mohler ER, Moy CS, Mussolino ME, Nichol G, Paynter NP, Schreiner PJ, Sorlie PD, Stein J, TuranT N, Virani SS, Wong ND, Woo D, Turner MB; on behalf of the American Heart Association Statistics Committee and Stroke Statistics Subcommittee.. Heart disease and stroke statistics–2013 update: a report from the American Heart Association. Circulation. 2013;127:e6–e245
2. Bobrow BJ, Spaite DW, Berg RA, Stolz U, Sanders AB, Kern KB, Vadeboncoeur TF, Clark LL, Gallagher JV, Stapczynski JS, LoVecchio F, Mullins TJ, Humble WO, Ewy GA. Chest compression-only CPR by lay rescuers and survival from out-of-hospital cardiac arrest. JAMA. 2010;304:1447-54.
3. Kirkbright S, Finn J, Tohira H, Bremner A, Jacobs I, Celenza A. Audiovisual feedback device use by health care professionals during CPR: A systematic review and meta-analysis of randomized and non-randomized trials. Resuscitation. 2013 Dec 21. [Epub ahead of print].
4. Mirza M, Brown TB, Saini D, Pepper TL, Nandigam HK, Kaza N, Cofield SS. Instructions to "push as hard as you can" improve average chest compression depth in dispatcher-assisted cardiopulmonary resuscitation. Resuscitation. 2008;79:97-102.

5. Sasson C, Meischke H, Abella BS, Berg RA, Bobrow BJ, Chan PS, Root ED, Heisler M, Levy JH, Link M, Masoudi F, Ong M, Sayre MR, Rumsfeld JS, Rea TD; American Heart Association Council on Quality of Care and Outcomes Research, Emergency Cardiovascular Care Committee, Council on Cardiopulmonary, Critical Care, Perioperative and Resuscitation, Council on Clinical Cardiology, and Council on Cardiovascular Surgery and Anesthesia. Increasing cardiopulmonary resuscitation provision in communities with low bystander cardiopulmonary resuscitation rates: a science advisory from the American Heart Association for healthcare providers, policymakers, public health departments, and community leaders. Circulation. 2013 Mar 26;127(12):1342-50.
6. Rea TD, Eisenberg MS, Becker LJ, Murray JA, Hearne T. Temporal trends in sudden cardiac arrest: a 25-year emergency medical services perspective.*Circulation.* 2003;107:2780–2785.
7. Sasson C, Rogers MA, Dahl J, Kellermann AL. Predictors of survival from out-of-hospital cardiac arrest: a systematic review and meta-analysis. Circ Cardiovasc Qual Outcomes. 2010;3:63–81
8. Semeraro F, Taggi F, Tammaro G, Imbriaco G, Marchetti L, Cerchiari EL. iCPR: a new application of high-quality cardiopulmonary resuscitation training. Resuscitation. 2011;82:436-41.
9. Kovic I, Lulic I. Mobile phone in the chain of survival. Resuscitation. 2011;82:776-9.
10. Ivor Kovic. CPR PRO App. Ivor Medical. URL: http://ivormedical.com/products/cpr-pro-app/ [accessed 13.01.11]. Archived at http://www.webcitation.org/5viP2oLIN.

11. iCPR – iPhone App for CPR training. D-Sign S.r.l. URL: http://www.icpr.it/ [accessed 13.01.11]. Archived athttp://www.webcitation.org/5viPE6JUZ.

12. PocketCPR – Your CPR Coach: PocketCPR for iPhone. Bio-Detek, Inc. URL:http://www.pocketcpr.com/iphone.html [accessed 13.01.11]. Archived at http://www.webcitation.org/5viPRP5yU.

13. iSkin – pulse. iSkin Inc. URL: http://www.iskin.com/pulse/details.tpl [accessed 13.01.11]. Archived athttp://www.webcitation.org/5viQlT47f.

14. Ivor Kovic. CPR PRO Cradle. Ivor Medical. URL: http://ivormedical.com/products/cpr-pro-cradle/ [accessed 13.01.11]. Archived at http://www.webcitation.org/5viQuLDUL.

15. Rabiner LR, Rader CM. Digital signal processing. New York: IEEE Press, 1972.

16. Takei Y, Nishi T, Matsubara H, Hashimoto M, Inaba H. Factors associated with quality of bystander CPR: The presence of multiple rescuers andbystander-initiated CPR without instruction. Resuscitation. 2014;85(4):492-8.

## Figure Legends

**Figure 1:** Placement of the subject, manikin, and smart phone.

**Figure 2:** Oscillatory pixel sum signal for representative video segments of 'correct rate', 'too fast', and 'too slow'.

Figure 1

**Figure 1:** Placement of the subject, manikin, and smart phone.

Figure 2

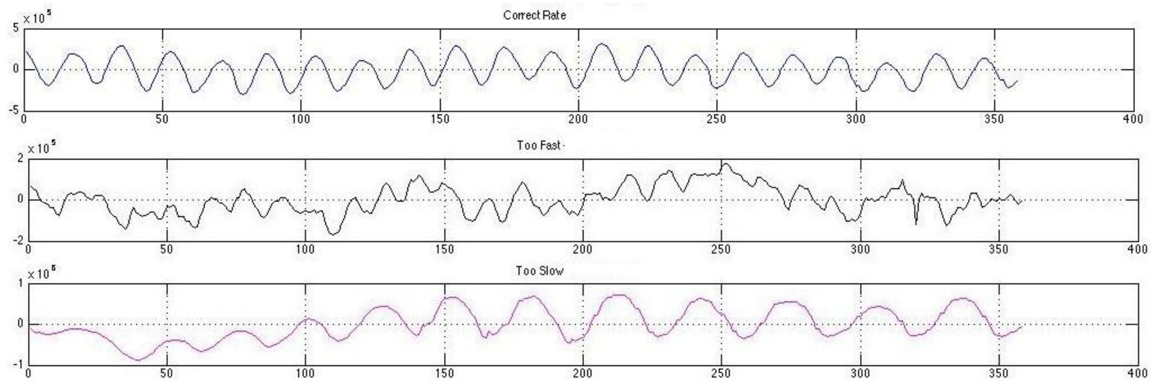


**Figure 2:** Oscillatory pixel sum signal for representative video segments of 'correct rate', 'too fast', and 'too slow'.

Table 1

| | Too slow (< 100 compressions/min) | Correct rate (100-120 compressions/min) | Too fast (> 120 compressions/min) |
|---|---|---|---|
| **Within-Subject Analysis** | | | |
| Sensitivity | 75.0% (46.8%, 91.1%) | 96.1% (86.8%, 98.9%) | 41.7% (24.5%, 61.2%) |
| Specificity | 95.4% (87.3%, 98.4%) | 76.9% (57.9%, 89.0%) | 100% (93.2%, 100%) |
| PPV | 75.0% (46.8%, 91.1%) | 89.1% (78.2%, 94.9%) | 100% (72.2%, 100%) |
| NPV | 95.4% (87.3%, 98.4%) | 90.9% (72.2%, 97.5%) | 79.1% (67.9%, 87.1%) |
| **Between-Subject Analysis** | | | |
| Sensitivity | 90.9% (62.3%, 98.4%) | 93.2% (81.8%, 97.7%) | 50.0% (30.7%, 69.3%) |
| Specificity | 92.4% (83.5%, 96.7%) | 72.7% (55.8, 84.9%) | 98.2% (90.4%, 99.7%) |
| PPV | 66.7% (41.7%, 84.8%) | 82.0% (69.2%, 90.2%) | 91.7% (64.6%, 98.5%) |
| NPV | 98.4% (91.4%, 99.7%) | 88.9% (71.9%, 96.1%) | 83.1% (72.2%, 90.3%) |

**Table 1**: Test performance characteristics (95% confidence intervals) for each binary classification of chest compression rate. **Within-Subject Analysis**: dividing video segments within each subject into training/test sets. **Between-Subject Analysis**: dividing video segments between subjects into training/test sets **PPV**: positive predictive value. **NPV**: negative predictive value.

**Table & Figure Legends**

**Figure 1:** Placement of the subject, manikin, and smart phone.

**Figure 2:** Oscillatory pixel sum signal for representative video segments of 'correct rate', 'too fast', and 'too slow'.

**Table 1**: Test performance characteristics (95% confidence intervals) for each binary classification of chest compression rate. **Within-Subject Analysis**: dividing video segments within each subject into training/test sets. **Between-Subject Analysis**: dividing video segments between subjects into training/test sets **PPV**: positive predictive value. **NPV**: negative predictive value.