RESUSCITATION 137 (2019) 183–189

Available online at www.sciencedirect.com

Resuscitation

journal homepage: www.elsevier.com/locate/resuscitation

Development of a novel cardiopulmonary resuscitation measurement tool using real-time feedback from wearable wireless instrumentation

Sarah R. Ward, Bronwyn C. Scott, David M. Rubin, Adam Pantanowitz *

Biomedical Engineering Research Group, School of Electrical & Information Engineering, University of the Witwatersrand, Johannesburg, Private Bag 3, 2050 Johannesburg, South Africa

Abstract

Aim: The design and implementation of a wearable training device to improve cardiopulmonary resuscitation (CPR) is presented.

Methods: The MYO contains both Electromyography (EMG) and Inertial Measurement Unit (IMU) sensors which are used to detect effective CPR, and the four common incorrect hand and arm positions viz. relaxed fingers; hands too low on the sternum; patient too close; or patient too far. The device determines the rate and depth of compressions calculated using a Fourier transform and dual-quaternions respectively. In addition, common positional mistakes are determined using classification algorithms (six machine learning algorithms are considered and tested). Feedback via Graphical User Interface (GUI) and audio is integrated.

Results: The system is tested by performing CPR on a mannequin and comparing real-time results to theoretical values. Tests show that although the classification algorithm performed well in testing (98%), in real time, it had low accuracy for certain categories (60%), which are attributable to the MYO calibration, sampling rate and misclassification of similar hand positions. Combining these similar incorrect positions into more general categories significantly improves accuracy, and produces the same improved outcome of improved CPR. The rate and depth measures have a general accuracy of 97%.

Conclusion: The system allows for portable, real-time feedback for use in training and in the field, and shows promise toward classifying and improving the administration of CPR.

Keywords: Cardiopulmonary resuscitation (CPR), Quality, Dual-quaternions, Electromyogram (EMG), Inertial Measurement Unit (IMU), MYO, Machine learning

1 Introduction

Improving the quality of CPR improves survival outcomes.[1] To achieve improved quality, researchers have considered various measurements, interventions and methods, including techniques for use in training and for use at scene, in transport, and in-hospital.[2–4]

It is estimated that a significant proportion of CPR is performed with poor technique,[5] with substantial clinical consequence.[6,7] This is, in part, attributable to high student-trainer ratios often encountered in CPR training, and training and awareness is a critical aspect of CPR.[8,9] In the field, defibrillation survival rates would be improved if the CPR process could be committed to muscle memory so that a care-giver is capable of performing effective CPR even under stress or in the field.[10,11]

The CPR standards set by the American Heart Association[12] provide a baseline by which to judge the effectiveness of CPR in terms of rate and depth of compressions as well as ensuring sufficient recoil

* Corresponding author.
E-mail address: adam.pantanowitz@wits.ac.za (A. Pantanowitz).

https://doi.org/10.1016/j.resuscitation.2019.02.019
Received 19 August 2018; Received in revised form 31 January 2019; Accepted 11 February 2019
Available online xxx

to allow the heart to refill.[12,13] Incorrect rate and depth significantly reduce the chances of survival of the patient.[14,15]

Training intervention systems have shown promise in improving training,[16] but require specialised equipment, and the translation of improvement into the field is only through applying the techniques. Real-time feedback is shown to be useful in the field, and is an active area of research.[3,17,18,2] However, these promising CPR quality interventions cannot be easily translated into the field context due to the equipment not being field appropriate, or the setup taking too long in a time critical context.

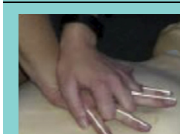
We propose a novel CPR quality measurement system which uses a wearable device, wireless transmission, classification of the CPR quality through machine learning, and real-time feedback. This system may be used both in training and in the field to train, assess, and improve quality of CPR. Through this feedback, we can improve quality similarly to the results in 17. This significantly extends the variety of measurements and portability of the work proposed by Aase and Myklebust[19] and González-Otero et al.,[2] which are most similar in principle to this work.

2 Methods

CPR position and most common positional mistakes are presented with photographs in Table 1 as determined through consultation with an expert from emergency medicine. Correcting these can result in improved outcomes.[20] We attempt to address these by using a real-time non-intrusive measurement system which can be used both in training and in the field.

We do so by providing real-time feedback through acquisition of real-time data from a wearable device comprising an accelerometer and electromyogram (EMG), worn by the practitioner, to which machine learning is applied to classify the quality of CPR delivery.

Table 1 – Correct and incorrect CPR hand and arm positions and the resulting effects. (Photographs by authors.)

Figure	Position	Result
	Palm flat on patient with fingers flexed	Correct CPR
	Fingers curled	Shallow compressions
	Palm facing sideways due to the hands being too low on the chest	Fractured ribs
	Arms perpendicular to the chest of the patient	Correct CPR
	Angle between the arms and the patient $<90^\circ$ due to having the patient too close	Insufficient recoil
	Angle between the arms and the patient $>90^\circ$ due to having the patient too far away	Shallow compressions and rapid fatigue

2.1 Approach

Our CPR quality measurement system uses the Myo™ armband which is worn on the forearm and transmits wireless information to a portable computer. The computer provides real-time audio (or visual) feedback.

The system utilises signal processing techniques including root mean squared (RMS) values, Fourier transforms, and zero-crossing to extract important features of the CPR to determine the rate and depth of the compressions. Furthermore machine learning techniques are used to identify common mistakes in hand and arm positioning on the patient.

2.2 Equipment/hardware

The Myo contains eight EMG sensors spaced evenly around the forearm.[21] An electromyogram (EMG) is a device that measures the strength of electric signals within muscle groups: contracted muscles result in more electrical activity than relaxed muscles.[22] The EMG sensors allow identification of which muscle groups are activated in the forearm and hand, particularly in the flexor and extensor groups. The Myo also has a nine-axis IMU sensor comprising three accelerometers (for the X, Y, and Z planes), three gyroscopes (for roll pitch and yaw), and three magnetometers to assess positions.

The Myo has been used extensively for sample applications due to the availability of a free software development kit.[23] Currently, most work done with the Myo has involved gaming and computer control applications.[23] Potential for medical applications are numerous, and to date include interfacing with a prosthetic arm.[24] The Myo was chosen for use in this project as it is easily transportable, non-invasive, has no wires to interfere with CPR application (non-intrusive), and allows CPR to be performed without attaching any equipment to the patient. A standard spring-based CPR mannequin is also used.

2.3 Software

The software subsystem can be divided into three main sections: the user interface; a signal processing component; and a machine learning component. All code for signal processing and machine learning is written in C++ due to its computation speed. The Graphical User Interface (GUI) is a Windows Forms application with a python server. An overview of how these three components interact is provided in Fig. 1. The components and actions performed by the system are split into three threads that are required to run all necessary simultaneous tasks. Thread 1 manages visual feedback in the form of updates to the GUI; thread 2 runs feature extraction and the classification algorithm; and thread 3 plays audible feedback. Data is encrypted using the SHA2 algorithm.

2.3.1 GUI

A simple GUI allows for interaction and feedback. This displays data in real-time relating to the user's CPR performance and provides audible feedback by sounding descriptions of the incorrect positions. The practitioner will thus be verbally informed of incorrect hand positions without the distraction of having to look at a display, thus allowing the user to correct their technique while continuing to focus on the patient to align to desired compression rate and form.

2.3.2 Signal processing

Supplementary documentation is included for more detail on the mathematical methods used in this work.

The signal processing comprises four tasks: Calculating the root mean squared (RMS) values of the EMG channels (which is generally proportional to the force of muscle contraction); and from the IMU;

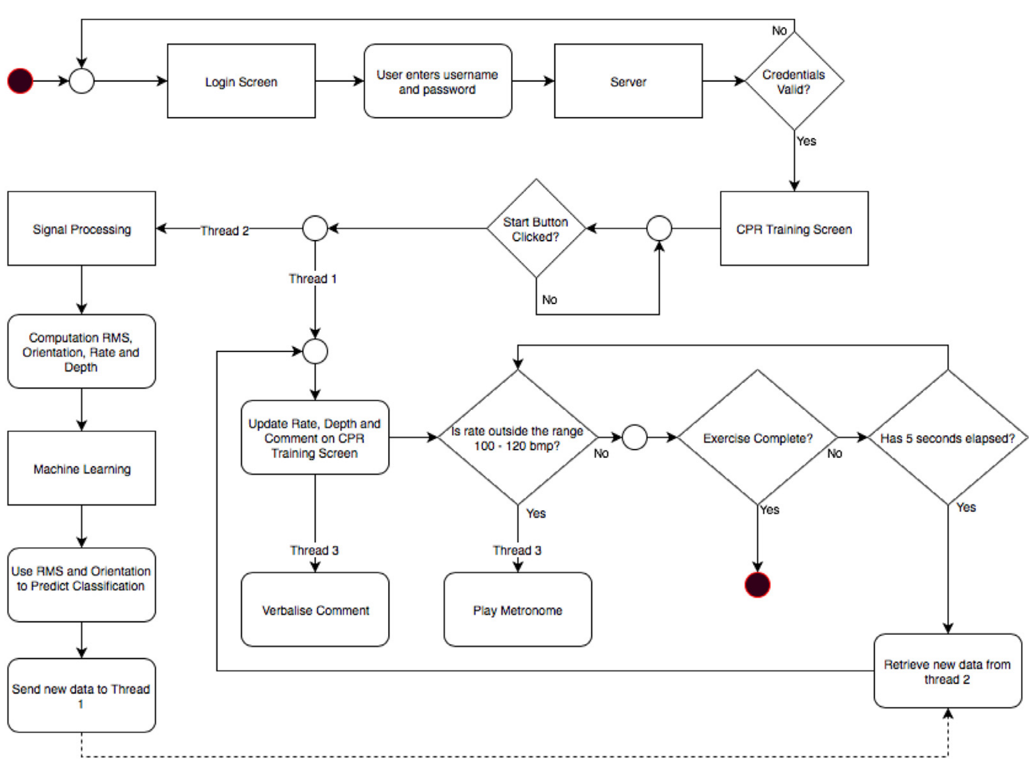


Fig. 1 – System overview.

extracting and calculating the roll, pitch and yaw; determining depth; and obtaining rate. RMS values and orientation data are used for machine learning. Rate and depth factors are independent of the machine learning. The RMS values are calculated for each of the eight EMG channels on the Myo. The ratio between each pair of channels is determined and is particularly important as it renders the magnitude of the EMG signals independent of the muscle strength of the user. The RMS produces a total of 36 values which form part of the machine learning feature vector. Another set of features is extracted as the orientation.

2.3.3 Rate

Compression direction/displacement during CPR are directed down the forearm into the palm, the rate of which is determined along this axis which corresponds to the x-axis acceleration of the Myo. Associated engineering detail is provided in supplemental material (http://dept.eie.wits.ac.za/~pantanowitz/research/cpr-quality/data).

2.3.4 Depth

Depth is calculated using dual-quaternions which are formulated by the Myo SDK, and more information is included in the supplemental material.

2.3.5 Machine learning algorithm selection

Machine learning is a general term for the iterative process of building up a model by experimentation, starting with a preliminary model, followed by iterative model refinement,[25] without explicit programming. Machine learning is often used in classification type problems. The algorithm is designed to learn to distinguish between correct and incorrectly-performed CPR from a set of training examples, using data which was collected from correctly and incorrectly performed CPR on the mannequin. Thereafter, unseen test examples are used to analyse the accuracy of the developed model.

Accuracy is selected as the metric by which to benchmark the machine learning algorithms.

Algorithms tested for this application include Random Forest,[26,27] Boosted Forest,[28] Multilayer Perceptron,[29] K-Nearest Neighbours,[30] Normal Bayes,[31] and Support Vector Machines.[32] Further information on these algorithms is provided in the additional material.

To determine the best-suited classification model, algorithms are trained and tested offline (with data split 80:20) using the feature vector of 47 features (IMU, EMG data) extracted across over 4800 CPR measurements. The Boosted Forest is found to be the most accurate algorithm with 98.7% accuracy on testing data with the specified data ratio.

A validation process is used to identify model parameters and prevent overfitting by ensuring that the model's accuracy is not restricted to the test set. Thus the data is split into three sets, namely the training, validation, and test sets in a ratio of 60:20:20. A grid search of the parameter values is then used with the algorithm being trained and tested on the validation set with each combination of parameters. The model is then verified on the test set in order to ensure that it has not been overfit. The parameters that are tuned are the depth of the decision trees (i.e. how many decisions are in each tree), the number of trees used, and the trim rate (i.e. how many of the least accurate trees are removed from the model). Using this process, an accuracy of 99.2% was achieved on the test set with a depth of 5 decisions, 50 decision trees, and a trim rate of 0.8. The output of validation can be found in the additional documentation.

The specified boosted forest classifier is thus selected for deployment as an online model for real-time classification due to the time-sensitive nature of CPR.

The GUI updates every five seconds and classification occurs approximately every half a second. Thus the most common classification over the five second interval is displayed when the GUI updates. This has the secondary effect of improving accuracy as it eliminates rare classifications within a time interval and results in the most significant mistake being identified while transient mistakes are disregarded.

3 Results

CPR measurements were taken on six hours of CPR activity over several days. The measurements were taken on two different CPR-trained practitioners in an attempt to obtain a better measure of general accuracy. A summary of the results are provided below.

In order to test the system, data were recorded for the various correct/incorrect hand positions and labelled accordingly. Accuracy of the system is defined as the fractional value of correctly classified hand positions. Hand positions that are mislabelled/misclassified lower the accuracy measured for the system. While there are other potential metrics to determine classification of the system, accuracy is deemed to be the most intuitive and relevant metric, as it is a critical metric of each class classification (for example, “hands too low on sternum” and “resting fingers on the patient” each constitute their own class, rather than being bundled into “effective” or “poor” CPR. This gives more insight into what is going wrong in the CPR process. As such, we are less interested in precision and recall, than in selecting a classifier that determines each class optimally. Accuracy is defined as the proportion of correctly classified data instances, relative to the total number of samples considered, and is defined mathematically in the supplemental material.

3.1 Rate and depth

Rate measurements were taken by performing CPR in time with a metronome and comparing the calculated rate to the actual rate determined by the metronome. From these results the accuracy, repeatability (in terms of variance), resolution, range, span, and hysteresis (in terms of percentage change when approaching a point from above versus from below) were determined. In addition the accuracy at the top and bottom of the accepted range was calculated. These are summarised in Table 2 .

The rate measurements are accurate across the entire range. In addition the repeatability of 0 indicates that there is no variance

Table 2 – Summary of rate measurement.

Measurand	Result
Range (bpm)	95–125
Span (bpm)	30
Resolution (bpm)	3
Repeatability (bpm)	0
Accuracy – centre of range (%)	100
Accuracy – top of range (%)	97.60
Accuracy – bottom of range (%)	96.85
Hysteresis (%)	3.28

Table 3 – Classification confusion matrix and performance analytics.

	Effective	Too Far	Too Forward	Fingers on patient	Too low on sternum
TP	159	156	125	144	230
FP	19	4	0	6	7
TN	669	688	720	688	599
FN	3	2	5	2	14
Accuracy (%)	97.41	99.29	99.41	99.10	97.53
Specificity (%)	99.55	99.71	99.31	99.71	97.72
Precision (%)	89.33	97.50	100.00	96.00	97.05

between rate measurements at the same rate and repeatability is consistently high. Although hysteresis is present, its effect is not significant as it is below 5% of the actual rate value.

Depth measurements were taken by moving the Myo exactly 5cm between two fixed objects and recording the calculated depth. Measurements were also taken at the limits of the accepted rate range and the accuracy calculated. Table 4 summarises the results of the measurements.

Although the accuracy of the depth measurement is very high in the centre of the rate range, it rapidly declines as the rate tends towards the limits of the accepted range. This shows an undesirable dependence on rate. In addition the standard deviation is 0.8cm which is 40% of the range of the measurements (2cm) indicating that repeatability is not ideal.

3.2 Classification algorithm

In order to assess the accuracy of the classification algorithms, the accuracy on the test set was measured. This provides the off-line test accuracy calculated on data collected for training and testing purposes. The most accurate algorithm was boosted trees with an off-line test accuracy of 99.2%.

Real-time accuracy is determined by performing CPR using the developed system and comparing predicted classification to actual hand and arm positions. The real-time accuracy is 60%. Three classes are classified 100% correctly, but reduced real-time accuracy arises as two classes are consistently classified incorrectly. CPR performed while too far from the patient is classified as “hands too low on the sternum”, and CPR performed while leaning too far over the patient is classified as “resting fingers on the patient”. The incorrect classifications are understandable, as placing hands too low on the sternum often results in a bent elbow, producing an angle at the wrist that is similar to that found when too far from the patient. In addition, being too close to the patient often results in resting fingers on the patient's chest to help the CPR practitioner balance. Combining these incorrectly classified classes significantly drives up the real-time accuracy.

Table 4 – Summary of depth measurement.

Measurand	Result
Range (cm)	4–6
Span (cm)	2
Repeatability (cm)	0.8
Accuracy – range centre (%)	97.00
Accuracy – range max (120bpm) (%)	71.80
Accuracy – range min (100 bpm) (%)	76.15

A confusion matrix on the off-line test data is used to determine the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) classifications for each class in the test set (850 data points). This is then further used to calculate the accuracy, specificity and precision for each class. The results are summarised in Table 3 .

4 Discussion

As a trainer is not able to observe all trainees at once, a CPR training device that provides constant accurate feedback to the CPR practitioner even without a trainer's supervision is useful to ensure that only correct technique is committed to muscle memory (similar to work in 16,19,2). Our proposed solution is less invasive, less costly, and wearable on the body of the practitioner rather than being built into the training mannequin, facilitating its use on less expensive, non-specialised mannequins. A quantitative study of performance would be useful for future work.

Given the findings in 1 regarding debriefing, it may be interesting to consider a post-CPR debriefing via the GUI, potentially with motion playback, to augment the debriefing process.

Uniquely, the proposed system is fully portable and can to be used both for training and in the field in emergency situations, without interfering with the performance of the practitioner. Both a graphical user interface (GUI) and audio feedback provide results of CPR performance, allowing the user to focus on performing CPR without distraction. This is similar in concept to 18, but our system does not require the setup of the equipment in advance.

The system provides verbal and visual feedback on CPR rate and depth, and classifies hand and arm position, successfully providing feedback of real-time CPR quality. The rate measurement is very accurate. However, the system suffers from some accuracy issues with respect to the depth measurement and the hand position classification. Possible causes and solutions for this lack of accuracy, and possible improvements are discussed below. Future work would allow for better characterisation of the system.

It is important to note that should the real-time incorrect classification of hand positions persist, these can be combined into a single error class (in the field), to improve classification accuracy to approximately the same as the offline accuracy. The system thus shows promise in the contexts of both training and emergency field use.

The depth measurement inaccuracy is caused by oversensitivity of the IMU readings. This causes the values to vary noticeably even when no movement is occurring. The Myo currently places many restrictions on the system since it has a low sampling rate and high sensitivity.

By performing numerous experiments with the Myo placed in slightly different positions on the forearm, and by removing the Myo between measurements, two possible reasons for the low classification accuracy in real time were revealed. Moving the Myo as little as half a centimetre up or down the forearm, or rotating it by half a centimetre causes the relative magnitude of EMG readings on each channel to change significantly. In addition, removing the Myo and putting it back in the same position still results in a slight shift in the relative EMG readings. Thus the source of the inaccuracy is in the placement of the Myo and the calibration when the Myo is removed and then replaced.

Greater research in characterising the device and establishing measurement errors, is required for future work. In order to improve system positioning and calibration, a program that helps position the Myo in exactly the same place on the forearm could be implemented, or alternatively, an external calibration system such as 18 could be used. In addition a custom calibration algorithm could be implemented to remove the inaccuracy due to poor calibration and to normalise the EMG values. The fact that two hand positions are always misclassified as similar positions suggests that the choice of the positions requiring classification may need to be reconsidered, as if these are combined into a single error class, the results would be significantly higher (in the order of the off-line test data).

Aside from correcting the inaccuracy for real-time (or combining error classes), we proposed other improvements including: allowing input of patient details (age, height range, and weight range) so that more precise feedback can be given; storing historical data in a database so that CPR performance can be tracked over weeks or months; developing a mobile version of the application to improve portability when being utilised in a real emergency situation.

The design could be improved by using a different device with a sampling rate of over 1 kHz, with Kalman filtering to create the quaternions and RSSI smoothing for the EMG in order to reduce the effects of the sensitivity of the device.

5 Conclusion

The system described in this paper offers a solution to improve CPR quality in both training and in the field. This is achieved by providing real-time feedback, and accurately measuring the depth of compressions. Depth and classification inaccuracy can be resolved by implementing a Kalman filter or integration with other devices as suggested, and by creating a custom positioning and calibration algorithm for the Myo. The system has nearly perfect accuracy in classifying proper vs improper CPR, however greater characterisation of this is required.

Ethical considerations

Ethical clearance was obtained from the University of the Witwatersrand, Johannesburg Medical Ethics Committee.

Conflict of interest

The authors declare a provisional patent over this work, and declare no further conflicts of interest.

Acknowledgement

This work was supported by research funds from the University of the Witwatersrand, Johannesburg. The authors would like to thank and acknowledge Professor Efraim Kramer, Werner Vermaak and the training staff at ER24 whose assistance and insight into this work were crucial to its development.

REFERENCES

1.. Dine CJ, Gersh RE, Leary M, Riegel BJ, Bellini LM, Abella BS. Improving cardiopulmonary resuscitation quality and resuscitation training by combining audiovisual feedback and debriefing. Crit Care Med 2008;36(10):2817–22.
2.. González-Otero DM, de Gauna SR, Ruiz JM, Gutiérrez JJ, Saiz P, Leturiondo M. Audiovisual feedback devices for chest compression quality during CPR. Resuscitation aspects. InTech 2017.
3.. Abella BS, Edelson DP, Kim S, et al. CPR quality improvement during in-hospital cardiac arrest using a real-time audiovisual feedback system. Resuscitation 2007;73(1):54–61.
4.. Cheskes S, Byers A, Zhan C, et al. CPR quality during out-of-hospital cardiac arrest transport. Resuscitation 2017;114:34–9.
5.. Bossaert L, Van Hoeywegen R, Group CRS, et al. Evaluation of cardiopulmonary resuscitation (CPR) techniques. Resuscitation 1989;17:S99–S109.
6.. Van Hoeyweghen RJ, Bossaert LL, Mullie A, et al. Quality and efficiency of bystander CPR. Resuscitation 1993;26(1):47–52.
7.. Wik L, Steen PA, Bircher NG. Quality of bystander cardiopulmonary resuscitation influences outcome after prehospital cardiac arrest. Resuscitation 1994;28(3):195–203.
8.. Beskind DL, Stolz U, Thiede R, et al. Viewing an ultra-brief chest compression only video improves some measures of bystander CPR performance and responsiveness at a mass gathering event. Resuscitation 2017;118:96–100.
9.. The American National Red Cross. Basic life support for healthcare providers. StayWell; 2015.
10.. Anderson R, Sebaldt A, Lin Y, Cheng A. Optimal training frequency for acquisition and retention of high-quality CPR skills: a randomized trial. Resuscitation 2018.
11.. Rasmussen SE, Nebsbjerg MA, Krogh LQ, et al. A novel protocol for dispatcher assisted CPR improves CPR quality and motivation among rescuers—a randomized controlled simulation study. Resuscitation 2017;110:74–80.
12.. American Heart Association. Circulation. American Heart Association Guidelines for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care; 2010. p. 5640–56.
13.. Harris AW, Kudenchuk PJ. Cardiopulmonary resuscitation: the science behind the hands. Heart 2018;104(13):1056–61, doi:http://dx.doi.org/10.1136/heartjnl-2017-312696.
14.. Travers A, Rea T, Bobrow B, et al. Part 4: CPR overview: 2010 American Heart Association guidelines for cardiopulmonary resuscitation and emergency cardiovascular care. American Heart Association Guidelines for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care Science; 2010.
15.. Birchak J, Abdul-Kafi O, Pham T, et al. Prolonged pauses in cardiopulmonary resuscitation are associated with poor survival during in-hospital cardiac arrest. J Am Coll Cardiol 2018;71(11):A459.
16.. Kong S, Shin S, Song K, et al. 25 effect of instructor's real-time feedback using QCPR-classroom device during layperson cardiopulmonary resuscitation (CPR) training on quality of CPR performances: a prospective cluster-randomised trial. 2018.
17.. Baldi E, Cornara S, Contri E, et al. Real-time visual feedback during training improves laypersons' CPR quality: a randomized controlled manikin study. Can J Emerg Med 2017;19(6):480–7.

18.. Wang JC, Tsai SH, Chen YH, Chen YL, Chu SJ, Liao WI. Kinect-based real-time audiovisual feedback device improves CPR quality of lower-body-weight rescuers. Am J Emerg Med 2018;36(4):577–82.
19.. Aase SO, Myklebust H. Compression depth estimation for CPR quality assessment using DSP on accelerometer signals. IEEE Trans Biomed Eng 2002;49(3):263–8.
20.. Yeung J, Meeks R, Edelson D, Gao F, Soar J, Perkins GD. The use of CPR feedback/prompt devices during training and CPR performance: a systematic review. Resuscitation 2009;80(7):743–51.
21.. Thalmic Labs. Myo– Tech Spec. 2018 (Accessed 17 August 2018, at https://www.thalmic.com/myo/techspecs).
22.. WebMD. Electromyogram (EMG) and Nerve Conduction Studies. 2018 (Accessed 16 August 2018, at http://www.webmd.com/brain/electromyogram-emg-and-nerve-conduction-studies).
23.. Thalmic Labs Inc. Myo Market. 2015 (Accessed 16 August 2018, at https://market.myo.com/).
24.. Li C, Ren J, Huang H, Wang B, Zhu Y, Hu H. PCA and deep learning based myoelectric grasping control of a prosthetic hand. BioMedical Engineering OnLine 2018;17(1):107, doi:http://dx.doi.org/10.1186/s12938-018-0539-8.
25.. Schapire R. COS511: theoretical machine learning. 2008 (Accessed 18 August 2018, at http://www.cs.princeton.edu/courses/archive/spr08/cos511/scribe_notes/0204.pdf).
26.. Hurwicz L. Decision trees. 2008 (Accessed 18 August 2018, at http://vserver1.cscs.lsa.umich.edu/spage/ONLINECOURSE/R4Decision.pdf).
27.. Kalisch M. Random Forest Applied Multivariant Statistics. 2012 (Accessed 18 August 2018, at https://stat.ethz.ch/education/semesters/ss2012/ams/slides/v10.2.pdf).
28.. OpenCV. Boosting. 2015 (Accessed 18 August 2018, at http://docs.opencv.org/3.0-beta/modules/ml/doc/boosting.html).
29.. Bourland H, Morgan N. Multilayer perceptron. Connectionist speech recognition: a hybrid method approach. New York: Springer Science and Business Media; 2012. p. 59–70.
30.. Sayad S. K nearest neighbors– classification. 2015 (Accessed 18 August 2018, at http://www.saedsayad.com/k_nearest_neighbors.htm).
31.. Bradski G, Kaehler A. Naive/normal Bayes classifier. 2008.
32.. Abe S. Support vector machines for pattern classification. second ed. Springer Science and Business Media; 2010.