Automatic Subject Identification Using Scale-Based Ballistocardiogram Signals

Beren Semiz[1(✉)], M. Emre Gursoy[2], Md Mobashir Hasan Shandhi[3], Lara Orlandic[4], Vincent J. Mooney[5], and Omer T. Inan[5]

[1] Electrical and Electronics Engineering, Koc University, Istanbul, Turkey
besemiz@ku.edu.tr
[2] Computer Engineering, Koc University, Istanbul, Turkey
emregursoy@ku.edu.tr
[3] Biomedical Engineering, Duke University, Durham, NC, USA
mobashir.shandhi@duke.edu
[4] Electrical Engineering, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland
lara.orlandic@epfl.ch
[5] Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, USA
{mooney,omer.inan}@ece.gatech.edu

Abstract. Many electronic devices such as weighing scales, fitness equipment and medical devices are nowadays shared by multiple users. In such devices, automatic identification of device users becomes an important step towards improved user convenience and personalized service. In this paper, we propose a novel approach for subject identification using ballistocardiogram (BCG) signals collected unobtrusively from a modified weighing scale. Our approach first segments BCG signals into heartbeats using signal filtering and beat detection techniques, and averages beats to obtain smoother ensemble averaged BCG frames that are more robust to noise. Second, it extracts features related to subjects' cardiovascular performance and musculoskeletal system from their BCG frames. Finally, it trains a machine learning model for predicting the owner of an unlabeled BCG recording based on its features. We evaluated our approach through a pilot experimental study with subjects' BCG signals recorded at rest and following different physiological modulation. Our approach achieves up to 97% identification accuracy at rest conditions and incurs a 15–20% accuracy drop on average under physiological modulation.

Keywords: Subject identification · Ballistocardiography · Biometrics · Machine learning

X. Gao et al. (Eds.): MobiHealth 2021, LNICST 440, pp. 281–292, 2022.
https://doi.org/10.1007/978-3-031-06368-8_19

1 Introduction

Recent advancements have made it possible to embed various sensors into electronic devices such as electronic scales, fitness equipment, and hospital equipment, which enable unobtrusive and non-invasive collection of physiological signals. These devices are often shared by multiple users such as members of a family, athletes in a sports team, or patients in a hospital. It becomes desirable that these shared devices can automatically identify their users (subjects) based on collected signals, for improved user convenience, personalization of devices and services, as well as enabling safer and more secure systems through biometric authentication [6,13].

Currently, subject identification in most smart household devices such as smart scales rely either on simple biometrics such as weight and heart rate, or require the user to manually introduce themselves by entering their ID or pairing with a third party device (e.g., smartphone) at each time of use [4,5,21]. The main drawback of the state-of-the-art is that biometrics such as weight or heart rate are not subject-specific, i.e., they can change over time and different users may have similar weights. The drawback of the latter is its inconvenience, e.g., the user has to carry their smartphone or enter their ID to the smart scale every time. In contrast, automatic subject identification using physiological signals alleviates both drawbacks – physiological signals are naturally present in living individuals at all times and they often contain subject-specific features.

In this paper, we study subject identification using ballistocardiography (BCG), an important physiological signal that measures the recoil forces of the body in reaction to cardiac ejection of blood into the vascular tree [20]. With advances in sensor technology (e.g. accelerometers), it has become easier to measure BCG signals using pervasive accessories such as weighing scales, beds, chairs, and wearables [9,12,16]. In particular, we use a modified weighing scale in our setup, which has two main advantages. First is the popularity of weighing scales – more than 80% of American households own a scale, and emerging smart scales leverage advanced capabilities [11]. Second, subjects naturally stand up when using a scale, which ensures that the BCG measurements are completely longitudinal.

Our system for identifying scale users from their BCG signals has many practical applications in the real world. One pervasive application is in smart scales which are already equipped with sensors with capabilities exceeding weight measurement. As these devices nowadays support multiple users, e.g., the QardioBase 2 supports up to 5 users [2], Withings WS-50 and Aria 2 support up to 8 users [1,4] and Garmin Index Smart Scale supports up to 16 users [3], reliable subject identification methods other than manual subject selection, phone pairing or weight biometrics would be beneficial.

While there has been prior work in identifying subjects using certain physiological signals such as electrocardiogram (ECG), electroencephalogram (EEG) and photoplethysmogram (PPG) [14,17,23], subject identification with BCG signals has been less studied. Recent studies using BCG for subject identification suffer from certain limitations [8,9,16,22], which we aim to circumvent in this

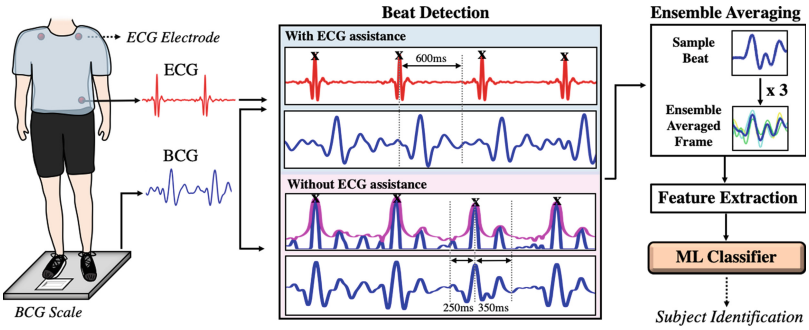


Fig. 1. Overview and steps of our approach

work. First, in most studies a wearable device (head-mounted or wrist-mounted) is needed to record the BCG signals [8,9,16,22], which may cause inconvenience to the user. In contrast, we rely on BCG signals collected from a modified weighing scale, without requiring wearables. Second, sensors on wearable devices only capture the local vibrations at specific locations in the body (head or wrist), whereas our scale can capture the longitudinal whole-body motions. Third, in existing studies BCG signals are collected while subjects are motionless in a specific posture without any external force or physiological modulation [8,22]. In contrast, we also study the effect of various physiological modulations such as Valsalva maneuver, exercise, and cold pressor. Finally, as discussed by Hernandez et al. [9], most studies require simultaneous electrocardiogram (ECG) recordings along with the BCG recordings [22], which can make it difficult to measure the effectiveness of BCG signals for subject identification in isolation. We propose and implement both ECG-assisted and non-assisted versions of our system, where the ECG-assisted version employs the simultaneous ECG signal only to improve beat detection and segmentation of BCG signals.

2 Methods

2.1 Hardware Setup

The overview of our study is provided in Fig. 1. Two types of physiological signals are recorded using our hardware setup: BCG and ECG. BCG signals are recorded using a modified weighing scale, the function of which was previously validated in [12]. The output of the scale is connected to the MP150 data acquisition system (BIOPAC System, Inc., Goleta, CA). ECG signals are recorded concurrently using BN-EL50 module (BIOPAC System, Inc., Goleta, CA) and transmitted wirelessly to the MP150. All signals are sampled at 2 kHz.

2.2 Experimental Protocol

This study was conducted under a protocol approved by the Georgia Institute of Technology Institutional Review Board and all subjects provided written con-

sent. 10 subjects without any known heart problems participated in the study (five females and five males, age: 22 ± 0.6, height: 172.3 ± 9.8 cm and weight: 65.4 ± 9.9 kg). This subject count is representative of the smart scale application scenario, as current smart scales in the market support up to 5–16 users.[1]

In the protocol, different non-invasive physiological modulation techniques (Valsalva maneuver, exercise and cold pressor test) were used to induce changes in the BCG and ECG signals, in addition to the data collected during an initial rest period. First, subjects were asked to stand on the BCG scale for five minutes. Then, they were asked to perform 20 s of Valsalva maneuver followed by a two-minute rest period. To increase the heart rate further, subjects performed two minutes of walking exercise on a treadmill at 4.8 km per hour (kph). This walking exercise was followed by 90 s of squatting exercise. Subjects were then asked to stand on the BCG scale again for five minutes. At the end of this recovery period, each subject's left hand was immersed into 4 °C water for 15 s, followed by two minutes of a final rest period. Physiological signals were collected throughout the protocol. In total, we collected 14 min of data from each subject: five minutes of initial rest, two minutes after the Valsalva maneuver, five minutes after exercise, and two minutes after the cold pressor.

2.3 Pre-processing and Beat Detection

After BCG and ECG signals are collected, they are filtered with finite impulse response (FIR) Kaiser-window band-pass filters (0.5–20 Hz and 0.5–40 Hz, respectively). We propose two options for beat detection (Fig. 1): with ECG assistance and without ECG assistance, one of which is chosen depending on whether simultaneously recorded ECG signals are available. If a simultaneous ECG signal is available, for each BCG-ECG pair, R-peaks are detected on the ECG signal and the BCG is segmented into beats using the R-peak locations. The beat length is determined to be 600ms as previously done in [19]. These BCG beats are then ensemble averaged to remove noise and reduce the impact of outlier beats. The moving window size is determined to be 3 beats/frame with an overlap of 2 beats between consecutive ensemble averaged frames. We empirically observed that larger window sizes are not desirable, as they decrease the total number of ensemble averaged frames in each recording.

If a simultaneously recorded ECG signal is not available, we use the J-peaks of the BCG signals as our reference points. J-peaks are the points having the highest amplitude and occurring approximately 250 ms after the beginning of each beat [12]. To detect J-peaks, the BCG portion where amplitude is greater than zero is taken on the BCG signal and the upper envelope is constructed. The local maxima points in this envelope correspond to the J-peaks, which are detected from the enveloped signal. A minimum distance of 400 ms between consecutive peaks is enforced to detect the local maxima, which corresponds to a heart rate of 150 beats/min [9]. This strategy minimizes the risk of missing beats even if the subject's heart rate is high. Also, using an envelope function

[1] Examples: QardioBase 2, Fitbit Aria 2, Garmin Index Smart Scale.

flattens the actual BCG signal by covering the less prominent smaller peaks and makes the J-peaks more explicit, so that misdetections are prevented. Once the J-peaks are located, we take the BCG signal segments that are 250 ms before and 350 ms after each J-peak location on the BCG recording (600 ms in total). We keep the portion before the J-peak shorter than the portion after it, since the J-peak typically occurs around 250 ms [9]. The detected beats are ensemble averaged into frames using a moving average window size of 3 beats/frame, identical to the above.

2.4 Feature Extraction

Following the formation of ensemble averaged BCG frames as explained in the previous section, our system extracts relevant features from these frames. In particular, we focus on the I-J-K waves of the frames, which have previously been found clinically useful in cardiovascular performance assessment [10]. These features are also driven by the underlying anatomical structure of the heart, vasculature, and musculoskeletal system for the person, and thus exhibit more inter-subject variability compared to intra-subject variability, even in the presence of changing cardiovascular health.

Our system extracts a total of 12 features from each ensemble averaged frame, including the amplitudes and locations of I, J, K-waves; the durations of I-J, J-K and I-J-K segments; the RMS power of the I-J-K complex; and the amplitudes of I-J and J-K waves. As a typical J-wave occurs approximately 250 ms after the beginning of a beat [15,24], it can be detected by taking the peak with the largest amplitude in between 150–400 ms of the frame. The I and K-waves are determined as the valleys before and after the J-wave, respectively. For consistency, the same features are extracted regardless of whether ECG recordings are available, i.e., no ECG-related feature (such as R-R interval) is included in our feature set.

2.5 Classifier Training and Prediction

We pose the subject identification problem as a multi-class classification task that can be solved via supervised machine learning. Let D denote the training data. Each instance in the training data corresponds to an ensemble averaged BCG frame, and is of the form: $(\mathbf{x}_i, y_i)$, where $\mathbf{x}_i = (x_{i,1}, x_{i,2}, ..., x_{i,12})$ are the 12 features extracted as described in the previous section, and y_i is the label equal to the unique subject identifier of the subject that the frame belongs to. The training dataset D is used to build a classifier denoted $\mathcal{M}$ that learns to predict the subject identifier of a frame usings its features, i.e., $\mathcal{M} : \mathbf{x} \rightarrow$ subject ID.

We use Support Vector Machine (SVM) to train our classifier model $\mathcal{M}$, which is a popular supervised learning method in biometrics and bioinformatics due to its accuracy, flexibility, and ability to deal with high-dimensional feature spaces [25], as well as high performance in physiological signal analysis [9,26]. SVM aims to construct a hyperplane or set of hyperplanes that separates points from different classes with largest margins. In addition to linear margins, SVM

can enforce non-linear margins through kernel functions [7,18] for capturing linear and non-linear relationships in the feature space. As such, we implemented SVM with *grid search* to automatically search for optimal hyperparameters, including the kernel function (linear or RBF), kernel coefficient γ (options ranging from 0.0001 to 1 in multiples of 10), and penalty parameter C (options ranging from 0.01 to 100 in multiples of 10). Our model supports multi-class classification through the one-vs-all strategy.

At prediction (test) time, an unlabeled BCG recording is provided to the system. This recording goes through the pre-processing, beat detection, ensemble averaging, and feature extraction process. At the end of the process, a set of *unlabeled* feature vectors are obtained: $\mathbf{X}^u = (\mathbf{x}_1^u, \mathbf{x}_2^u, ..., \mathbf{x}_n^u)$, where n is the number of ensemble averaged frames in the unlabeled recording. Each of the unlabeled feature vectors are provided to $\mathcal{M}$, and $\mathcal{M}$ predicts a label for each vector, collectively denoted by: $Y^u = (y_1^u, y_2^u, ..., y_n^u)$. Finally, our system predicts the subject of the whole test BCG recording using the label that is observed most number of times in Y^u. We denote this final output prediction by y_{pred}.

2.6 Confidence Measurement and Threshold

In our system, each prediction is associated with a *confidence* value, denoting how confident our system is in predicting that y_{pred} is the true subject ID of a test BCG recording. Prediction confidence is measured as:

$$\text{Confidence} = \frac{\#\text{ of occurrences of } y_{pred} \text{ in } Y^u}{|Y^u|} \tag{1}$$

We use a threshold τ such that for a test recording with confidence $< \tau$, our system outputs that subject identification was unsuccessful for that recording (i.e., "subject could not be found"), instead of making an unconfident prediction which has higher risk of being incorrect. If confidence $\geq \tau$, the system outputs y_{pred} as usual.

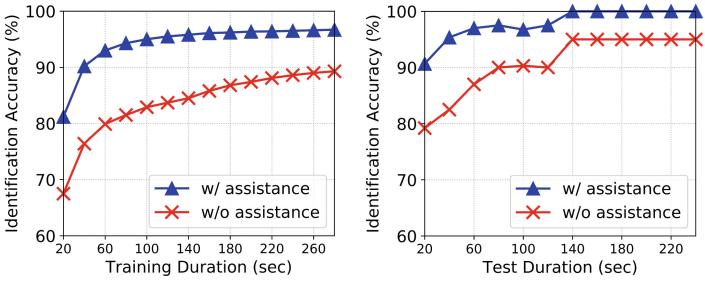
Our confidence-based thresholding approach has multiple advantages. When using a smart scale, if the scale is not sufficiently confident who the user is, it could be preferable that the user manually tells the scale who the user is, instead of the scale carrying a higher risk of misidentifying the user. Misidentifications may allow one scale user to view another user's data which could be sensitive (e.g., pregnant housemember), or misidentified user's readings may be saved under another user's name which may cause problems in long-term health tracking. Furthermore, in future BCG-based biometric authentication systems that grant access to classified environments, mispredictions and false positives should be avoided since they may grant access to unauthorized users. On the other hand, finding an appropriate value for the threshold parameter τ is worthy of investigation. By definition, $\tau \in [0, 1]$. Having a large τ has the desirable outcome that we prevent incorrect predictions, since incorrect predictions typically have lower confidence. However, if τ is too large, some correct predictions (true positives) which do not have as large confidence might be lost. We empirically study the impact of different τ in a variety of settings in Sect. 3.2.

3 Evaluation and Results

In the experiments, we operate in multiples of 20 s since it is a reasonable amount of time to stand on a smart scale for BMI, vital signs, and fat and water percentage measurement. To do so, we divide the continuous BCG and ECG signals into 20-s long segments to obtain multiple non-overlapping recordings per subject. We use leave-k-recordings-out cross-validation (LkRO-CV), i.e., we run multiple iterations where in each iteration we leave out k recordings of each subject (out of n total recordings per subject) from the training data. These k recordings constitute the test data, whereas the remaining $n - k$ recordings constitute the training data.

3.1 Subject Identification Accuracy

We measure the subject identification accuracy of our approach under two scenarios. First, we keep the test recording durations fixed and vary the total training data duration for each subject. Note here that training data does not need to be collected in one session; data from multiple sessions can be concatenated. Second, we keep the total training data duration fixed and vary the test recording durations for each subject. We report the results in Figs. 2a and 2b.



(a) Varying training duration (b) Varying test duration

Fig. 2. Subject identification accuracy of our approach with and without ECG assistance in beat detection. In (a), test recording duration is fixed to 20 s. In (b), total training data duration per subject is fixed to 1 min.

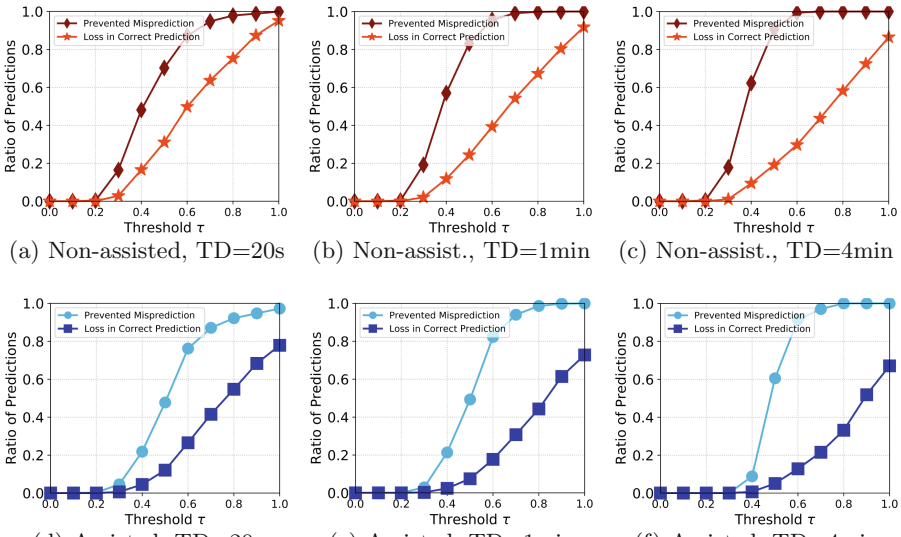
In Fig. 2a, the test recording duration is fixed to 20 s and we experiment with total training duration varying between 20 s and 280 s. Overall, we observe that ECG assistance in beat detection improves the subject identification accuracy of our system. Although the accuracy difference between the assisted and non-assisted versions is 14% when training durations are short (e.g., 20 s), the difference decreases as longer training data becomes available and becomes less than 7% when total training data duration is 4 min or longer. Furthermore, 1 min of training data is sufficient for our system to achieve 80% and 93% subject identification accuracy in the non-assisted and assisted cases, respectively.

This training data can be collected in 3 initial sessions of scale usage. Note that the accuracy of random prediction is only 10% (since we have 10 test subjects). Having more training data clearly improves accuracy, as shown by the accuracy becoming 97% with 4 min or more training data.

In Fig. 2b, the total training data duration is fixed to 1 min per subject and we experiment with test recording durations varying between 20 s and 240 s. We observe that subject identification is accurate even for 20 s of test recordings: 80% and 91% for non-assisted and assisted versions of our system. Accuracy increases substantially with longer test recordings and our system achieves 95% and 100% accuracy for the non-assisted and assisted cases, when test recordings are longer than 2 min.

3.2 Prediction Confidence

We vary the confidence threshold τ between 0 and 1 in increments of 0.1 and measure the mispredictions prevented as well as the correct predictions lost under different τ values. We report the results in Fig. 3 for three different training durations: 20 s, 1 min, and 4 min. In each setting, two lines are plotted: the ratio of mispredictions prevented and the ratio of correct predictions lost (due to a correct prediction not having sufficiently high confidence to meet τ). We observe that $\tau \leq 0.3$ causes little or no loss in correct predictions while being able to prevent some mispredictions. On the other hand, the value of τ which maximizes the difference between prevented mispredictions and loss of correct predictions is around $\tau \cong 0.6$ or 0.7 (our default value for the reported results).



(a) Non-assisted, TD=20s (b) Non-assist., TD=1min (c) Non-assist., TD=4min

(d) Assisted, TD=20s (e) Assisted, TD=1min (f) Assisted, TD=4min

Fig. 3. Impact of confidence threshold parameter τ under different total training data durations, with and without ECG assistance. (TD = Training Duration)

In addition, longer training durations not only increase confidence in correct predictions but also decrease confidence in mispredictions. For example, with $\tau = 0.6$, the loss in correct predictions is 0.26 in Fig. 3d, it is 0.18 in Fig. 3e, and 0.13 in Fig. 3f. The confidence values for correct predictions must have increased to lose fewer predictions under the same τ. Furthermore, in Fig. 3d the prevented misprediction ratio is 0.76, in Fig. 3e it is 0.82, and in Fig. 3f it is 0.91. Confidence values for mispredictions must have decreased to prevent more mispredictions under the same τ. Hence, we conclude that longer training durations have a dual positive impact on prediction confidence.

3.3 Experiments on Physiologically Modulated Signals

In the experiments so far, we trained and tested our system using BCG signals from subjects' fully rested (sedentary) conditions. While we expect this to be the common setting, in some cases it is also possible that subjects are involved in some form of physiological exercise before they step on the scale, which increases their heart rate and results in non-traditional BCG and ECG signals. These are called physiological modulations. Recalling Sect. 2.2, we collected data with three types of modulations: Valsalva maneuver, walking and squats exercise, and cold pressor. To evaluate the generalizability of our approach, we also measure subject identification under physiological modulation. We perform training using either 1 min or 4 min of rest data and measure accuracy using modulated BCG recordings as test data. Results are provided in Table 1.

Comparing Table 1 with Fig. 2, we observe that on average, the accuracy of modulated recordings is 15–20% lower than rest recordings. This drop is expected, considering that the training data does not contain any modulation, hence our model is not acquainted with modulated signals with different feature values. In particular, we would expect the location (duration) features to have different values depending on the existence of modulation, due to increased heart rates and shortened R-R intervals resulting from modulation. Note that the type of modulation is also important; for example, exercise and cold pressor typically cause higher accuracy loss than the Valsalva maneuver. On the other hand, considering that the accuracy of random prediction is 10%, our results in Table 1 show that our approach still has substantial identification ability.

Table 1. Impact of physiological modulation on accuracy.

	Train data	Test data	Accuracy
Our approach w/ECG assistance	Rest (1 min)	Valsalva	0.820
		Exercise	0.708
		Cold pressor	0.721
	Rest (4 min)	Valsalva	0.863
		Exercise	0.773
		Cold pressor	0.779
Our approach w/o ECG assistance	Rest (1 min)	Valsalva	0.696
		Exercise	0.632
		Cold pressor	0.623
	Rest (4 min)	Valsalva	0.717
		Exercise	0.697
		Cold pressor	0.638

4 Conclusion and Future Work

In this paper, we studied subject identification using BCG signals collected from a weighing scale. In future work, we will consider its applicability to bed-, chair-, and wearable-based BCG sensors; as well as fitness equipment for identifying athletes in sports teams and medical equipment for patient monitoring in hospitals and long-term care facilities. We will also focus on validating our approach with larger datasets with more subjects, as well as customize our system according to the detected modulation impact to render the overall approach less susceptible to modulation-related accuracy loss.

Acknowledgements. Research reported in this publication was supported in part by the National Heart, Lung and Blood Institute under R01HL130619. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

References

1. Fitbit aria 2 review & rating, pcmag.com (2017). https://www.pcmag.com/review/357402/fitbit-aria-2
2. Qardiobase 2 review & rating, pcmag.com (2017). https://www.pcmag.com/review/357255/qardiobase-2
3. Garmin index smart scale (2019). https://buy.garmin.com/en-US/US/p/530464
4. Smart body analyzer (ws-50) (2019). https://support.withings.com/hc/en-us/articles/201490007-Smart-Body-Analyzer-WS-50-Setting-up-the-scale-for-multiple-users
5. User guide for smart weigh digital BMI body fat bathroom scale (2019). https://www.betterbasics.com/guide/SW-SBS500

6. Bolle, R.M., Connell, J.H., Pankanti, S., Ratha, N.K., Senior, A.W.: Guide to Biometrics. Springer, Heidelberg (2013)
7. Cortes, C., Vapnik, V.: Support-vector networks. Mach. Learn. **20**(3), 273–297 (1995)
8. Hebert, J., Lewis, B., Cai, H., Venkatasubramanian, K.K., Provost, M., Charlebois, K.: Ballistocardiogram-based authentication using convolutional neural networks. arXiv preprint arXiv:1807.03216 (2018)
9. Hernandez, J., McDuff, D.J., Picard, R.W.: Bioinsights: extracting personal data from "still" wearable motion sensors. In: 2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN), pp. 1–6. IEEE (2015)
10. Inan, O.T., Etemadi, M., Wiard, R.M., Kovacs, G.T., Giovangrandi, L.: Non-invasive measurement of valsalva-induced hemodynamic changes on a bathroom scale ballistocardiograph. In: 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 674–677. IEEE (2008)
11. Inan, O.T., et al.: Ballistocardiography and seismocardiography: a review of recent advances. IEEE J. Biomed. Health Inform. **19**(4), 1414–1427 (2015)
12. Inan, O., Etemadi, M., Wiard, R., Giovangrandi, L., Kovacs, G.: Robust ballisto-cardiogram acquisition for home monitoring. Physiol. Meas. **30**(2), 169 (2009)
13. Jain, A.K., Bolle, R., Pankanti, S.: Biometrics: Personal Identification in Networked Society, vol. 479. Springer, Heidelberg (2006)
14. Karimian, N., Tehranipoor, M., Forte, D.: Non-fiducial ppg-based authentication for healthcare application. In: 2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), pp. 429–432. IEEE (2017)
15. Lindqvist, A., Pihlajamäki, K., Jalonen, J., Laaksonen, V., Alihanka, J.: Static-charge-sensitive bed ballistocardiography in cardiovascular monitoring. Clin. Physiol. **16**(1), 23–30 (1996)
16. McConville, R., Santos-Rodriguez, R., Twomey, N.: Person identification and discovery with wrist worn accelerometer data. In: Proceedings of the European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (2018)
17. Odinaka, I., Lai, P.H., Kaplan, A.D., O'Sullivan, J.A., Sirevaag, E.J., Rohrbaugh, J.W.: ECG biometric recognition: a comparative analysis. IEEE Trans. Inf. Forensics Secur. **7**(6), 1812–1824 (2012)
18. Schölkopf, B., Smola, A.J., Bach, F., et al.: Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. MIT Press, Cambridge (2002)
19. Shandhi, M.M.H., Semiz, B., Hersek, S., Goller, N., Ayazi, F., Inan, O.: Performance analysis of gyroscope and accelerometer sensors for seismocardiography-based wearable pre-ejection period estimation. IEEE J. Biomed. Health Inf. **23**, 2365–2374 (2019)
20. Starr, I., Rawson, A., Schroeder, H., Joseph, N.: Studies on the estimation of cardiac ouptut in man, and of abnormalities in cardiac function, from the heart's recoil and the blood's impacts; the ballistocardiogram. Am. J. Physiol.-Legacy Content **127**(1), 1–28 (1939)
21. Vhaduri, S., Poellabauer, C.: Multi-modal biometric-based implicit authentication of wearable device users. IEEE Trans. Inf. Forensics Secur. **14**, 3116–3125 (2019)
22. Vural, E., Simske, S., Schuckers, S.: Verification of individuals from accelerometer measures of cardiac chest movements. In: 2013 International Conference of the BIOSIG Special Interest Group (BIOSIG), pp. 1–8. IEEE (2013)

23. Wang, M., El-Fiqi, H., Hu, J., Abbass, H.A.: Convolutional neural networks using dynamic functional connectivity for EEG-based person identification in diverse human states. IEEE Trans. Inf. Forensics Secur. **14**, 3259–3272 (2019)
24. Wiens, A., Etemadi, M., Klein, L., Roy, S., Inan, O.T.: Wearable ballistocardiography: preliminary methods for mapping surface vibration measurements to whole body forces. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 5172–5175. IEEE (2014)
25. Witten, I.H., Frank, E., Hall, M.A., Pal, C.J.: Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann (2016)
26. Zakeri, V., Akhbardeh, A., Alamdari, N., Fazel-Rezai, R., Paukkunen, M., Tavakolian, K.: Analyzing seismocardiogram cycles to identify the respiratory phases. IEEE Trans. Biomed. Eng. **64**(8), 1786–1792 (2017)