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Author(s)	Setiono, Felix Yustian; Elibol, Armagan; Chong, Nak Young
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Description	

Human Emotional State Estimation Evaluation using Heart Rate Variability and Activity Data

Felix Yustian Setiono, Armagan Elibol, and Nak-Young Chong

Abstract—**Human-Robot Interaction (HRI) is one of the most rapidly emerging fields in robotic applications over the years. One direction of the improvements in the HRI field is by adding the capability of emotional understanding as a fundamental part of human-human interaction necessities. Human emotion understanding has been studied through the well-known Heart Rate Variability (HRV) analysis recently. In this paper, two different methods of classification are proposed to find the relations between activity, heart rate, and emotional states. Two individual k-Nearest Neighborhood (kNN)-based classifications used in the first method and implemented for each dataset of pre-processed accelerometer data and HRV data where both aim to estimate the user's emotion and activity data at the same time. The features of the frequency domain-based HRV data and the user's activity data are combined into a new dataset and two different classifiers of Multilayer Perceptron (MLP) and Support Vector Machines (SVM) were used in the experimental evaluations. Performance comparisons are presented to show the efficiency. Results from both methods are analyzed and reported in this paper.**

I. INTRODUCTION

Human-Robot Interaction (HRI) as part of robot-human interactions could be improved by involving a personal emotion understanding. There are many irregular and inconsistent factors either internally or externally affecting emotional states such as age factors, health conditions, environmental changes, and many more have to become the main problem when dealing with human emotion.

There is a possibility of involving human physiological data as one indicator for estimating the human emotional states. One of them is through the human user's heart rate data since the heart rate has a direct correlation with the emotional states [1], [2], where this heart rate signal is processed and analyzed into some values by a method named Heart Rate Variability (HRV). Some previous works under this domain [2]–[4] were using neural network-based classification and reported to estimate the emotional state with reasonable accuracy scores for up to 80-89%.

In [5]–[9], emotions have been estimated using classification methods (e.g., Support Vector Machines (SVM) and others) where the features are raw heart rate, HRV, skin conductance data; to estimate a limited number (e.g., 3 to 5) of kinds of emotional states and having accuracy varying 57-84%. Up to our knowledge, all the previous works are used the stimulated-user method through emotion-induced videos and or music during the experimental tests; and some have a period of data measurement from 3 hours up to 2 weeks.

A new feature based on personal activity information is added to improve the performance of the human emotional state estimation system since the human movement correlated indirectly with the emotional states through the heart rate management mechanism and differs by activity based on the medical perspective [10]. Two kinds of methods are proposed in this paper to find the effect of this mechanism. In the first proposed method, two individual classification systems are conducted for each dataset of accelerometer data and the frequency domain-based HRV data to finds the base information of the emotional state estimation system. And for the second proposed system involves the relation of the activity, heart rate, and emotional states to improve the accuracy of the emotion estimation through the fusion of the frequency domain-based HRV analysis and the pre-processed accelerometer data. The data for both of the proposed methods obtained from a smart band under certain specific conditions in approximately 5 minutes of recording times.

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All authors are with the School of Information Science, Japan Advanced Institute of Science and Technology (JAIST), Nomi, Ishikawa, Japan `e-mail: felix.setiono, aelibol, nakyoung at jaist.ac.jp`

II. HEART RATE VARIABILITY

The frequency-domain based HRV analysis method [11] is used on this paper where irregular or very small fluctuations in the heart rate series data could be identified.

HRV analysis components in the frequency domain for the short-term recording could be divided into several categories such as:

- Very Low Frequency (VLF) components could be used as a representation of negative emotions, worry, and others [11], [12] and the range is ≤ 0.04 Hz
- Low Frequency (LF) components shows the increased sympathetic response in the human autonomous nerve systems [11], [12] where the range is $0.04 \sim 0.15$ Hz
- Normalized LF (LFnu) components is the normalized unit of the Low Frequency (LF) components
- High Frequency (HF) components shows the parasympathetic response and fluctuations caused by spontaneous respiration called Respiratory Sinus Arrhythmia (RSA) where the range is $0.15 \sim 0.4$ Hz
- Normalized HF (HFnu) components is the normalized unit of the High Frequency (HF) components
- LF/HF ratio shows the overall balance between the sympathetic and parasympathetic systems in the Autonomic Nerve System (ANS) where a high value means there is

a change in the emotional state and a lower value means there is little or no change in the emotional state [13]

Based on the references and standards [11]–[16]; the minimum time windowing for the heart rate monitoring under HRV analysis is approximately 5 minutes and can be up to 24 hours.

III. DATA RECORDING AND PROCESSING

A. Heart Rate and Accelerometer Data Recording

The ECG and accelerometer sensors of Bluetooth-connected Empatica E4 [17] smart band are employed for data recording where the data recording, processing, and combined features dataset-based classification scheme are shown in Fig. 2 and connected to a Personal Computer through a SiliconLabs BlueGiga BLED112-v1 BLE module [18] with the Empatica BLE Server [19] to record the one-second interval heart rate series and each axis acceleration data for a predefined time run by a Python-based data recording program under Transfer Control Protocol Internet Protocol (TCP-IP) interfaces.

The HRVAnalysis API [20] is used to retrieve the HRV values and the Inter-Beat Intervals (IBI) data recorded from the smart band. This analysis tool produces the HRV analysis results in two domains; the time-domain and the frequency-domain. The frequency-domain analysis used in the analysis tool is based on Welchs method [11] and acquired several features used in the classification as the HRV-based dataset; such are LF/HF ratio, VLF value, LF value, normalized LF (LFnu), HF value, and normalized HF (HFnu) value.

The procedures of the data recording are realized under specific conditions to limit the effects of the external factors from the environment. All the data are obtained from 15 participants (10 male and 5 female aged from 28 to 35 years old) doing the three activities of Sitting, Standing, and Walking under the influences of the four emotional states of Happy, Neutral, Worry, and Sad, where all participants were situated in the same conditioned rooms with temperatures around 24 to 26 degrees Celsius in the activities of Sitting and Standing.

In the activity of Sitting, the participants are sitting in one direction or free moving left or right as long as still in the sitting position. The participants are standstill or pretend to have phone calls in the activity of Standing. In the activity of Walking, the participants are free to move without changing altitudes. The defined condition in the activity of Walking is the outdoor environment with temperatures of around 31 to 32 degrees Celsius with some emotional-related movie scenes and or music proposed by each participant based on each emotional state used as inducements.

All accelerometer and IBI-based data are recorded with a smart band for each participant data in the above-explained conditions under a 5-minutes of the interval by each combined activity and emotional state.

B. Classification Method under Known Activity and Emotional State Label

From the accelerometer data recording process, the raw data of each axis are processed under specific conditions:

- The raw data by each axis is processed to find the Mean Absolute Derivation (MAD) values, by using the formula:

$$\mathrm{MAD}_{(\mathrm{x})} = \frac{\sum_{i=1}^{n} |x_{i+1} - x_i|}{n} \tag{1}$$

  This MAD equation applies to the raw acceleration values in y-axis and z-axis data also.
- The minimum and maximum values of the accelerometer data by each x, y, z-axis; in example for x-axis data are $\mathrm{x}_{\mathrm{min}}$ and $\mathrm{x}_{\mathrm{max}}$.

These data are used as the features for the accelerometer-based (ACC-based) dataset.

The 12 classes used are based on each activity (Walking, Sitting and Standing) combined with each emotional state (Happy, Worry, Sad and Neutral) such as Sitting and Happy, Standing and Neutral, Walking and Worry, and others.

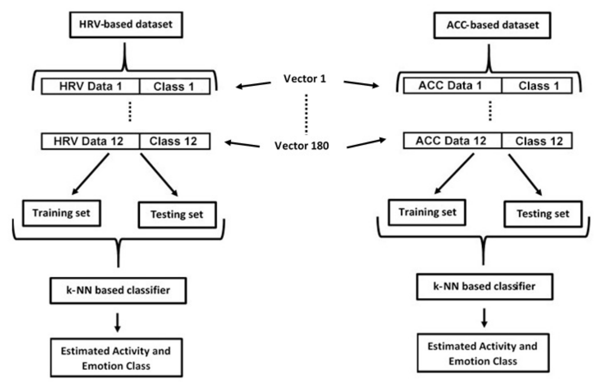

Fig. 1. Individual classification for each sensor data to find the relation of the activity and the heart rate

As the first classification system, two individual k-Nearest Neighborhood (kNN) classifiers are used to find the best estimation of the combined activity and emotional states by using only a single sensor-based dataset as the input features. In the beginning, each sensor-based dataset features are extracted, then it divided randomly by the train-test split method into 70% of the training set and 30% of the testing set then they are used to train by the pre-defined kNN parameters with the randomly selected number of neighbors 5 using the algorithm of *KDTree*.

C. Classification Method on Combined Accelerometer and Heart Rate Variability-based Dataset

The next step is combining the two datasets of pre-processed accelerometer and the frequency domain-based HRV data into one dataset based on the same known. The feature vector of the combined dataset is represented by their respective features and the corresponding class by using two supervised classification method of Multi-Layer Perceptron (MLP) and Support Vector Machines (SVM).

In the Multi-Layer Perceptron (MLP) classification, the number of the classes used is the same as the first proposed method where a single hidden layer with the sizes of 2,700

TABLE I
CLASSIFICATION RESULTS USING MLP

No.	Features as Inputs	Mean Accuracy Score (%)
1	All 15 features (9 ACC-based and 6 HRV-based features) - *P1*	87.20
2	(6 HRV-based features only) - *P2*	80.53
3	(9 ACC-based features only) - *P3*	17.20
4	(MAD of *x-axis*, MAD of *y-axis*, MAD of *z-axis*, *vlf*, *lf*, *hf*) - *P4*	84.95
5	(*x-min*, *x-max*, *y-min*, *y-max*, *z-min*, *z-max*, *vlf*, *lf*, *hf*) - *P5*	80
6	(MAD of *x-axis*, MAD of *y-axis*, MAD of *z-axis*, *lf-hf*) - *P6*	67.18
7	(*x-min*, *x-max*, *y-min*, *y-max*, *z-min*, *z-max*, *lf-hf*) - *P7*	43.85

neurons and *lbfgs* solver is used in the classifier and validation by a 10-fold validation technique is also carried out.

The second classification method used is the Support Vector Machines (SVM) with Linear SVM-based kernel and the same feature selections as the MLP classification by the implementation of minimum-maximum normalization for the features first.

IV. EXPERIMENTAL RESULTS

A. Classification Method under Known Activity and Emotional State Label

The accuracy score of the kNN-based classification on using only ACC-based features is approximately 22.22% with the most frequent estimated class is Walking and Worry since this class has the highest differences in the ACC-based features. While the accuracy score for the second kNN-based classifier on the only HRV-based features is around 75.93% with the most frequent estimated classes are either Standing and Sad, Sitting and Happy, or Walking and Sad show the balanced high and low relations on these classes between activity and heart rate conditions.

From these results; the activity states of the person under certain kinds of emotional states are influenced by the heart rate condition also since the ACC-based features only result are very low. This classification results defined as the base value results of the classification for the combined estimated emotional and activity states.

B. Combined Accelerometer and Heart Rate Variability-based Dataset Classification

1) Multilayer Perceptron Classification: The results of the MLP-based classification results are shown in table I, where several cases of features-based removal are conducted also.

The next process, the dataset is divided based on each defined emotional state; such as Happy, Neutral, Worry, and Sad for each activity of Sitting, Standing, and Walking. The test data are re-classify by removing several features and find the average accuracy scores through the 10-fold cross-validation method. Specifically for the MLP-based classifier, a new model needs to be designed with the solver of *lbfgs* and the single hidden layer of 675 neurons come from 45 vector sets of the dataset multiply by 15 features since the dataset used is based on specific emotion only and different with the mixed emotions one.

- For emotion of Happy (category *A*):
  - All 15 features *(A1)*: 84.5%
  - All HRV-based data only *(A2)*: 71.5%
  - All ACC-based data only *(A3)*: 78%
- For emotion of Neutral (category *B*):
  - All 15 features *(B1)*: 70%
  - All HRV-based data only *(B2)*: 92%
  - All ACC-based data only *(B3)*: 53.5%
- For the emotion of Worry (category *C*):
  - All 15 features *(C1)*: 56%
  - All HRV-based data only *(C2)*: 73%
  - All ACC-based data only *(C3)*: 79.5%
- For the emotion of Sad (category *D*):
  - All 15 features *(D1)*: 63%
  - All HRV-based data only *(D2)*: 77.5%
  - All ACC-based data only *(D3)*: 79.5%

In conclusion, for detecting and/or classifying the emotion of Neutral, the classifier could be worked well by using only the HRV-based data as the features for the inputs. If all of the 15 features are used in the classification process under the emotion of Neutral only, the result of *P1* is 87.2% and still higher compared with the existing emotional state-based classification results (*A1*: 84.5%, *B1*: 70%, *C1*: 56%, and *D1*: 63%).

On the contrary, the result of *B3* is the lowest one compared with the results of *A3*, *C3*, and *D3*, since there are no significant changes in body movement in the emotion of Neutral.

The MLP-based classifier results are higher in emotion of Happy since the relation of the 15 features is found by the classifier. the results in the emotion of Neutral has the highest one since the classifier could find the relation between the HRV-based features

The result in the emotion of Neutral for the ACC-based features is the lowest one since the participants tend to having a slower pace movement. On contrast, the result for the emotion of Neutral in the HRV-based features is the the highest one meaning that the participants have differences in their heart rate data.

2) Support Vector Machines Classification: For SVM classification, the dataset is split into the two parts with the same method and ratio as the MLP classification used. All the procedures are also the same as the MLP classification.

- For emotion of Happy (category *E*):
  - All 15 features *(E1)*: 100%
  - All HRV-based data only *(E2)*: 89%
  - All ACC-based data only *(E3)*: 87%
- For emotion of Neutral (category *F*):
  - All 15 features *(F1)*: 100%

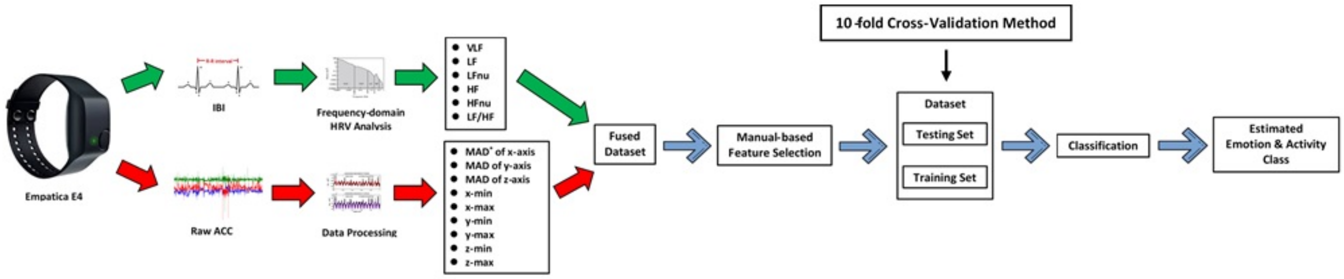

Fig. 2. The pipeline of the dataset combination and classification (*MAD: Mean Absolute Derivation)

TABLE II
CLASSIFICATION RESULTS USING SVM

No.	Features as Inputs	Mean Accuracy Score (%)
1	All 15 features (9 ACC-based and 6 HRV-based features) - *S1*	92.73
2	(6 HRV-based features only) - *S2*	60
3	(9 ACC-based features only) - *S3*	22.76
4	(MAD of *x-axis*, MAD of *y-axis*, MAD of *z-axis*, *vlf*, *lf*, *hf*) - *S4*	77.73
5	(*x-min*, *x-max*, *y-min*, *y-max*, *z-min*, *z-max*, *vlf*, *lf*, *hf*) - *S5*	71.06
6	(MAD of *x-axis*, MAD of *y-axis*, MAD of *z-axis*, *lf-hf*) - *S6*	46.65
7	(*x-min*, *x-max*, *y-min*, *y-max*, *z-min*, *z-max*, *lf-hf*) - *S7*	62.77

  - All HRV-based data only *(F2)*: 100%
  - All ACC-based data only *(F3)*: 66.5%
- For the emotion of Worry (category *G*):
  - All 15 features *(G1)*: 91%
  - All HRV-based data only *(G2)*: 52%
  - All ACC-based data only *(G3)*: 88.5%
- For the emotion of Sad (category *H*):
  - All 15 features *(H1)*: 91.5%
  - All HRV-based data only *(H2)*: 54%
  - All ACC-based data only *(H3)*: 88.5%

In the SVM-based classification, the results of *E1* and *F1* are 100% means the SVM-based classifier could find the differences on both the HRV-based and ACC-based features on these two emotions. And the result of *F2* is the highest one since the participants tend to move at slower pace; compared to *G2*, *H2*, and *E2*.

The accuracy scores of category *E* are higher compared to the category *A* because of the SVM-based classifier could find the differences between each feature vectors. In contrast, the results are higher in *H3* and *G3* since the participants tend to have a faster pace of movements means more differences shown up in their ACC-based features, where the results are also the same one with the HRV-based features.

In the case of the HRV-based features, the emotion of Neutral result is the highest one compared with others because of the slower pace movements of the participants. The same case also has seen in the MLP-based classification results. Since the accuracy scores in the emotions of Happy and Neutral are high enough made the HRV-based features could be used as the single feature inputs for these two emotional states.

The lowest HRV-based features result in the emotions of Worry and Sad showing the participants are having changes in both type of features. The result of *S2* is lower compared with *P2* shows that the MLP-based classifier is the best choice for the HRV-based features only classification.

And the accuracy scores in the ACC-based features results are the highest ones in the emotions of Happy, Worry, and Sad means the participants tend to have a faster pace of movement under these emotional states. On the other hand, the result in the emotion of Neutral is very low due to the effect of the slower pace of movements and made the SVM-based classifier the best option for the ACC-based features only.

3) Derived Feature Classification: A derived feature is proposed by using the ratio of *lfnu* and *hfnu*, called the LFnu/HFnu ratio to find out whether the LFnu and HFnu values affecting the emotion and activity also or not.

Two individual classifiers of MLP and SVM trained again by adding the *lfnu-hfnu* ratio and *vlf* as the HRV-based features combined with the different ACC-based features for each classification method based the previous experimental results, the selected ACC-based features perform better under each classifier; which are:

- in the MLP classification; MAD of *x-axis*, MAD of *y-axis*, and MAD of *z-axis* are used
- in the SVM classification; *x-min*, *x-max*, *y-min*, *y-max*, *z-min*, *z-max* are used

The results for both classification method are shown below:

- for MLP-based classification (category *I*):
  - for mixed class (activity and emotion data combined) (*I1*): 72.22%
  - for emotion of Happy class *(I2)*: 97.5%
  - for emotion of Neutral *(I3)*: 95.5%
  - for emotion of Worry *(I4)*: 52%
  - for emotion of Sad *(I5)*: 53.5%
- SVM-based classification (category *J*):
  - for mixed class (activity and emotion data combined) (*J1*): 85.54%
  - for emotion of Happy class *(J2)*: 98%

– for emotion of Neutral *(J3)*: 100%
– for emotion of Worry *(J4)*: 88.5%
– for emotion of Sad *(J5)*: 91%

The *J2* has close results with *E1* and the result of *A1* is lower than *I2* and as same as *E1* compared with *J2* concludes the LFnu/HFnu ratio predominantly affects the emotion of Happy. And the result of *J3* same as *F1* and the result of *I3* have better performance than *B1* shows the LFnu/HFnu ratio affects the emotion of Neutral also.

While the results of the emotion of Worry are close with the 15 features one in both classifiers similar with results of *G1*, *H1*, *J4*, and *J5*. And the SVM-based results in the emotion of Sad are closer to the 15 features one but lower with the MLP-based result similar to the results of *C1*, *D1*, *I4*, and *I5* showing that the LFnu/HFnu ratio doesn't affect these two emotions. By then, the SVM classifier performs better for the LFnu/HFnu ratio as shown on the results of category *J* are better compared with category *I*.

The ACC-based features found affecting the emotions also since two different kinds of features are used in each dataset. The ACC-based features of the minimum and maximum values of each axis used in the SVM-based classifier are found more effectively fused with the LFnu/HFnu ratio compared to the other ACC-based features of the MAD of each axis in the MLP-based classifier.

V. CONCLUSION AND FUTURE WORKS

The relation of activity, heart rate, and emotional states are discussed in every possible scenarios as described in experimental results above with additional a derived HRV-based feature mixed with an existing ACC-based feature is used as the features in the experimental test also.

The performances of the estimation system are improved by the adding of the activity-based features in both classifications. The kNN-based classification results are defined as the base value for this estimation system also. In conclusion, the MLP classifier performs better in the HRV-based features while the SVM classifier works best in the combined features one.

By then, it found that the MLP classifier found to perform better in the HRV-based features since the relation of the features is found. While in the SVM-based one, the results for the ACC-based features are perform better since the differences in the activity pattern features are found.

On the other hand, SVM-based classifier is perform better in the mixed HRV and ACC-based features because of the classifier could find the unique activity pattern between each person compared with the MLP-based classifier results.

Based on the findings above, the possible future work is to collect more data on these features based on the different categories; like age groups, more varied activities and emotions with the understanding of external emotional influences.

REFERENCES

[1] J. D. J. et al, "Heart rate variability analysis as an index of emotion regulation processes: Interest of the Analgesia Nociception Index (ANI)," *Proc. 34th Annual International Conference of the IEEE EMBS*, pp. 3432–3435, 2012.

[2] S. K. Y. et al, "Neural network-based emotion using heart rate variability and skin resistance," *Proc. of Advanced in Natural Computation part 1, ICNC 2005*, pp. 818–824, 2005.

[3] S.-N. Yu and S.-F. Chen, "Emotion state identification based on heart rate variability and genetic algorithm," *Proc. 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 538–541, 2015.

[4] Y. J. et al, *Emotion Recognition Through Cardiovascular Response in Daily Life Using KNN Classifier*, ser. Advances in Computer Science and Ubiquitous Computing. CUTE 2017, CSA 2017. Lecture Notes in Electrical Engineering. Singapore: Springer, 2018, vol. 474.

[5] H.-W. G. et al, "Heart rate variability signal features for emotion recognition by using principal component analysis and support vector machine," *Proc. 16th International Conference on Bioinformatics and Bioengineering*, pp. 274–277, 2012.

[6] N. T. N. et al, "A potential approach for emotion prediction using heart rate signal," *Proc 9th International Conference on Knowledge and System Engineering*, pp. 221–226, 2017.

[7] M. Ménard, P. Richard, H. Hamdi, B. Daucé, and T. Yamaguchi, "Emotion recognition based on heart rate and skin conductance," in *PhyCS*, 2015, pp. 26–32.

[8] A.-M. Brouwer, E. van Dam, J. B. Van Erp, D. P. Spangler, and J. R. Brooks, "Improving real-life estimates of emotion based on heart rate: a perspective on taking metabolic heart rate into account," *Frontiers in human neuroscience*, vol. 12, 2018.

[9] R. Rakshit, V. R. Reddy, and P. Deshpande, "Emotion detection and recognition using HRV features derived from photoplethysmogram signals," in *Proceedings of the 2nd workshop on Emotion Representations and Modelling for Companion Systems*. ACM, 2016, p. 2.

[10] B. K. et al, *Ganong's Review of Medical Physiology*, 23rd ed. McGrawHill Medical, 2010.

[11] T. Cui, "Spectrum analysis of Heart Rate Variability (HRV)," *student paper*, September 2013.

[12] T. F. of the European Society of Cardiology, the North American Society of Pacing, and Electrophysiology, "Heart rate variability: Standards of measurement, physiological interpretation, and clinical use," *European Heart Journal*, vol. 17, pp. 354–381, 1996.

[13] W. von Rosenberg et al, "Resolving ambiguities in the LF/HF ratio: LF-HF scatter plots for the categorization of mental and physical stress from HRV," *Frontiers in Physiology*, vol. 8, p. article 360, June 2017.

[14] S. Fred and J. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in Public Health*, vol. 5, p. 258, September 2017.

[15] K. Tom, *Methodological aspects of heart rate variability analysis: Heart Rate Variability (HRV) Signal Analysis*, ser. Heart Rate Variability (HRV) Signal Analysis. CRC Press, October 2012.

[16] G. D. Clifford, "Signal processing methods for heart rate variability," Ph.D. dissertation, Oxford University, 2002.

[17] "Empatica E4 product page," https://www.empatica.com/research/e4/ (January 2019).

[18] "SiliconLabs BlueGiga BLED112-v1 product page," https://www.silabs.com/products/wireless/bluetooth/bluetooth-low-energy-modules/bled112-bluetooth-smart-dongle (January 2019).

[19] "Empatica BLE server for Windows (beta) product page," http://developer.empatica.com/windows-ble-server.html (January 2019).

[20] R. Bartels, "Pythonic package for heart rate variability analysis version 0.2.3," https://github.com/rhenanbartels/hrv (January 2019).