Institut Riset dan Publikasi Indonesia (IRPI)
MALCOM: Indonesian Journal of Machine Learning and Computer Science
Journal Homepage: https://journal.irpi.or.id/index.php/malcom
Vol. 4 Iss. 4 October 2024, pp: 1339-1345
ISSN(P): 2797-2313 | ISSN(E): 2775-8575

Noise Study on the OH1 Wearable Device: Analysis of 11 Hand MovementArtifacts

Rizqi Ramadhan[1*], Izzat Aulia Akbar[2]

[1,2]Department of Information Systems, Institut Teknologi Sepuluh Nopember, Indonesia

E-Mail: [1]rizqiraa11@gmail.com, [2]izzat@its.ac.id

Received May 24th 2024; Revised Jul 15th 2024; Accepted Jul 25th 2024
Corresponding Author: Rizqi Ramadhan

Abstract

Wearable devices like the OH1 are increasingly used for real-time health monitoring, particularly for measuring heart rate (BPM). However, their accuracy is often compromised by motion artifacts, introducing significant noise into the measurements. This study specifically addresses the issue of noise generated by the OH1 wearable device during eleven different hand movements. To tackle this problem, we implemented a precise experimental setup involving device calibration, stable testing conditions, and participant training to ensure high consistency in hand movements. Additionally, machine learning algorithms were employed to separate noise from desired hand movement data. Our results indicate that certain hand movements, such as lifting arms and shoulder rotations, produce higher noise levels, while others, like placing hands on the table, generate minimal noise. These findings provide valuable insights for developing effective noise reduction algorithms, ultimately enhancing the accuracy and reliability of BPM measurements from wearable devices..

Keyword: Data Accuracy, Hand Movements, Heart Rate Monitoring, Motion Artifacts, Oh1 Device, Wearable Devices

1. INTRODUCTION

Wearable devices, such as the OH1, have become essential tools in real-time health monitoring, particularly for measuring heart rate (BPM). However, the accuracy of the data generated is often compromised by motion artifacts, which introduce significant noise into the measurements. This noise can diminish the reliability of the obtained data and hinder the device's ability to provide accurate health information. Therefore, this study is crucial to understand the noise levels produced by the OH1 device during various hand movements [1] [2].

However, despite their numerous benefits, wearable devices are susceptible to inaccuracies caused by motion artifacts, particularly those resulting from hand movements. These artifacts can introduce noise into the sensor readings, leading to erroneous data and undermining the reliability of health monitoring [3].

In recent years, wearable devices have become increasingly popular and closely integrated into daily life and activities. Devices such as smartwatches, fitness trackers, and health sensors can monitor various physiological parameters and user activities easily. However, along with the great advantages offered by these wearable devices, the appearance of noise or interference in the data collected is an important problem that needs to be addressed [11] [12] [13].

Understanding the factors that influence noise detection during hand motion artifacts is essential for improving the performance of wearable devices in heart rate monitoring [3]. Factors such as the type and intensity of hand movements, device placement on the body, and technical characteristics of the sensors can all impact the accuracy of sensor readings [4] [5].

This study aims to analyze the noise levels generated by the OH1 wearable device during eleven different hand motions. The primary goal is to identify which movements produce the highest and lowest levels of noise, providing insights that can be used to develop more effective noise reduction algorithms [3]. By doing so, this research hopes to enhance the accuracy and reliability of BPM measurements from wearable devices [4] [5].

This research offers several advantages over previous studies. Firstly, we utilize innovative data collection methods by implementing machine learning algorithms to separate noise from the desired hand movements without complex signal processing [6]. Secondly, our study involves a meticulous experimental setup to ensure that the collected data is minimally affected by noise from the outset. This includes precise device calibration and training participants to perform hand movements with high consistency [7] [8].

Thirdly, we focus on accurate and representative data collection from hand movements using the OH1 device, one of the most commonly used wearable devices in health monitoring.

By providing valuable insights into the noise characteristics generated by various hand motions when using wearable devices, this research is expected to significantly contribute to the field of health monitoring. Specifically, it aims to improve the accuracy of heart rate measurements by reducing the noise introduced by motion artifacts [10].

2. MATERIALS AND METHOD

The research methodology employed in this study involved an experimental design aimed at investigating the effectiveness of noise reduction techniques in wearable devices during hand motion artifacts. A diverse group of participants was recruited for the study, with considerations for age, gender, and other relevant demographic factors. The study utilized a specific wearable device, the OH1 equipped with advanced sensors for monitoring physiological signals such as heart rate.

2.1. Design Research

The experimental approach in this publication involves a study design that allows researchers to control independent variables and examine their effects on dependent variables. In the context of this research, the independent variables are the noise reduction techniques applied to the wearable device, while the dependent variable is the level of noise in the data obtained from the device during hand motion artifacts.

In this study, the "experimental group" refers to a set of participants subjected to specific treatments aimed at testing their effects on noise detection in wearable devices during hand motion artifacts. Participants in the experimental group may be provided with particular noise reduction techniques applied to their wearable devices while performing hand motion artifacts.

Conversely, the "control group" consists of participants who do not receive similar treatments and perform hand motion artifacts without the aid of noise reduction techniques on their devices. The purpose of the control group is to provide a baseline for comparison, allowing researchers to assess the effectiveness of the noise reduction techniques applied in the experimental group.

The selection procedure for participants in both groups is conducted carefully, with inclusion and exclusion criteria established to ensure sample adequacy and representativeness. These steps are taken to ensure that the comparison between the two groups is valid and that the experimental results can be accurately interpreted.

The first step in this experimental approach is to determine control and experimental groups. The control group may use the wearable device without applying any noise reduction techniques, while the experimental group will use the same device with the noise reduction techniques applied at Fig 1.

Figure 1. Collect Data

Once the groups are determined, participants will be asked to perform a series of tasks that cause hand movements while wearing the wearable device. Sensor data from the device will be recorded during these tasks. During data collection, researchers will ensure that the same procedures are applied to both groups, with the aim of minimizing interfering factors that could affect the outcomes. Steps will be taken to reduce bias and maintain data reliability.

After data collection, statistical analysis and signal processing will be conducted to evaluate the effectiveness of the noise reduction techniques in reducing hand motion artifacts on the wearable device. Significant differences between the control and experimental groups in noise levels will be considered as indications of the effectiveness of these techniques.

By using this experimental approach, researchers can systematically test the effects of various noise reduction techniques on wearable devices during hand motion artifacts, with the hope of gaining a better understanding of the performance and reliability of the devices in everyday usage scenarios at Fig 1.

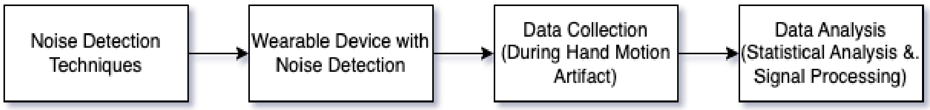

Figure 2. Block Diagram Experimental Data

Figure 2 provides a clear and concise block diagram outlining the experimental data workflow used in this research. The diagram is segmented into four key stages, each representing a critical phase in the study's methodology to ensure accurate data collection and analysis of heart rate measurements using a wearable device under hand motion artifacts. Here's a detailed explanation of each stage:

1. Noise Detection Techniques:
   This initial stage involves identifying and developing techniques to detect noise that can interfere with accurate heart rate measurement. These techniques are crucial for distinguishing between true heart rate signals and artifacts caused by hand motion.

2. Wearable Device with Noise Detection:
   At this stage, a wearable device, equipped with the noise detection techniques developed in the previous stage, is utilized. The device is specifically designed to identify and mitigate noise, ensuring that the data collected is as accurate as possible despite the presence of hand motion artifacts.

3. Data Collection (During Hand Motion Artifact):
   This phase focuses on the actual collection of heart rate data while subjects perform various hand movements. The wearable device continuously monitors and records heart rate data, ensuring that noise detection techniques are actively filtering out artifacts in real-time.

4. Data Analysis (Statistical Analysis & Signal Processing):
   In the final stage, the collected data undergoes rigorous statistical analysis and signal processing. This analysis aims to quantify the noise levels and assess the effectiveness of the noise detection techniques. Key metrics, such as Root Mean Square (RMS) values, are calculated to provide a detailed understanding of the noise impact on heart rate measurements.

Figure 2 effectively encapsulates the structured approach of the research, highlighting the integration of noise detection techniques into wearable technology, the meticulous data collection process during hand motion activities, and the comprehensive analysis undertaken to ensure data reliability and accuracy.

2.2. Artifacts Motion Hands

In this study, participants were seated at a table and instructed to perform 11 specific hand movements with their left hand. These movements were adapted from or inspired by existing rehabilitation protocols currently in use.

Participants completed the data collection protocol while seated in a chair with a firm backrest and without armrests, positioned in front of a table within the research laboratory. All movements were performed while seated in the chair, with their hands placed on the table, following instructions displayed on a screen.

This setup ensured standardized conditions for data collection across all participants, minimizing potential confounding variables and allowing for consistent measurement of hand motion artifacts. By utilizing movements derived from established rehabilitation protocols, the study aimed to simulate real-world scenarios of hand motion while providing a controlled environment for data collection and analysis.

Participants were instructed to perform each hand movement according to the displayed instructions, ensuring uniformity and reproducibility of the experimental procedure. This approach facilitated the systematic evaluation of noise reduction techniques on the wearable device during hand motion artifacts, providing valuable insights into the device's performance under conditions mimicking everyday activities:

Table 1. Table of Artifact

No	Motion	References
1	Handshake	(Zhang, 2016)
2	Straight Hand Pressing	(Zhang, 2016)
3	Horizontal Shoulder Extension	(Zhang, 2016)

No	Motion	References
4	Elbow to the Nose	(Zhang, 2016)
5	Touching Shoulders	(L. A. Simpson, 2017)
6	Shrug 90	(Zhang, 2016)
7	Supinate	(Zhang, 2016)
8	Pronate	(L. A. Simpson, 2017)
9	Flexing Shoulders 180	(J. Lui, 2017)
10	Hand to Forehead	(J. Lui, 2017)
11	Elbows bent 90	(J. Lui, 2017)

In the data acquisition process involving 11 hand motion artifacts, a time series approach was employed to capture the physiological responses over the duration of the study. Each participant completed the test protocol, estimated to take between 40 to 50 minutes. The protocol, designed based on pilot studies, consisted of detailed instructions provided in the supplementary materials.

The test protocol comprised two phases, separated by a recovery period. Each phase involved data collection under normal conditions and during activity, with each activity lasting approximately 3 minutes. A total of 11 hand movement activities were performed, interspersed with rest periods lasting 5 minutes each. Throughout the data collection process, participants were instructed to continuously monitor a display screen to follow the instructions provided for each data acquisition activity

2.3. Participans

In this study, a total of 11 healthy participants were involved to provide relevant data regarding the effectiveness of noise reduction techniques in wearable devices. Out of the total number of participants, there were 6 females and 5 males aged between 21 to 28 years old.

This includes explaining the experimental procedures, associated risks, and steps taken to ensure data confidentiality. Participants were then asked to provide written consent before engaging in the study. During the experimental sessions, participants were given clear instructions on the tasks they needed to perform while wearing the wearable device.

They were instructed to perform specific hand movements recorded by the device, which would then be used to evaluate the effectiveness of noise reduction techniques. The presence of both male and female participants in balanced numbers and the age range covering young adults to late young adults is expected to provide a more comprehensive understanding of the wearable device's response to hand motion artifacts.

3. RESULTS AND DISCUSSION

In this chapter, we present and discuss the results of the data analysis collected to underscore the effectiveness of noise reduction techniques on wearable devices during hand motion artifacts.

3.1. Result on RMS

In this subsection, a detailed analysis will be conducted on the noise levels generated by various hand movements, including a comparative evaluation of each movement to identify which ones produce significant noise.

Table 2. RMS Result

Artifacts	Noise All Subject	RMS
Handshake	0.311	0.039
Horizontal Shoulder Extension	0.361	0.025
Horizontal Shoulder Extension	0.336	0.0679
Elbow to the Nose	0.340	0.039
Touching Shoulders	0.381	0.029
Shrug 90	0.356	0.029
Supinate	0.388	0.038
Pronate	0.41	0.034
Flexing Shoulders 180	0.42	0.034
Hand to Forehead	0.42	0.036
Elbows bent 90	0.40	0.032
Supinate	0.388	0.039

The analysis of the eleven hand motion artifacts reveals significant variations in noise levels detected by the OH1 wearable device. Each motion exhibited unique noise characteristics, influencing the accuracy of BPM measurements. Notably, the motion of grasping both hands and lifting the arms upwards generated a significant noise level, with an average RMS noise value of 0.039. This was closely followed by the motion of starting with hands on opposite shoulders and rotating the shoulders outward 180 degrees, which produced the highest noise level among all motions, with an average RMS noise value of 0.0679.

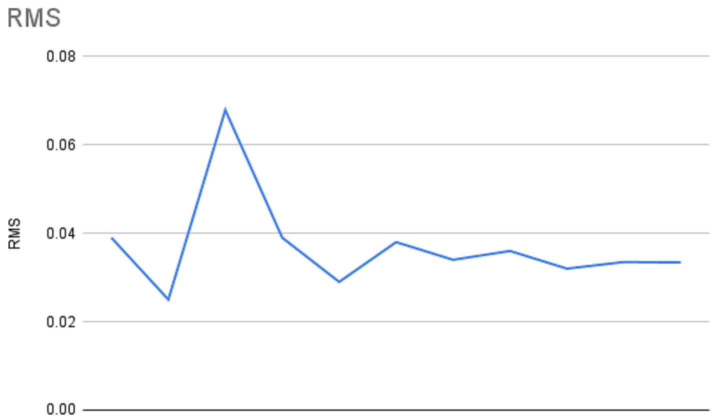

Figure 3. Result RMS

Flexing the shoulders to bring elbows to the nose also resulted in a relatively high noise level, with an average RMS noise value of 0.039. In contrast, motions such as placing palms on the chair and straightening the arms, as well as moving from the table to placing hands on opposite shoulders, demonstrated relatively low noise levels, with average RMS noise values of 0.025 and 0.029, respectively.

These data indicate that variations in RMS values during hand movement artifacts are influenced by the type and intensity of the movement. The highest RMS value was recorded on the fourth artifact, while the lowest value was recorded on the ninth artifact. Understanding these variations is important in the context of analyzing subjects' physiological responses to different types of hand movements, especially in the use of wearable devices for health monitoring.

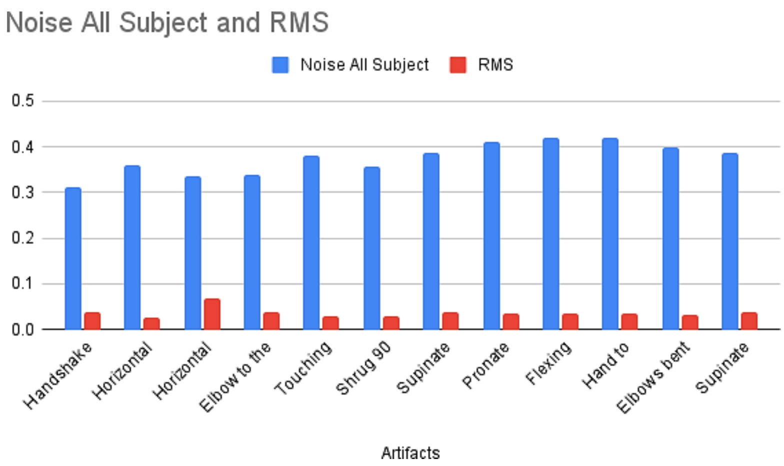

Figure 4. Noise and RMS

The results of our research address the challenge of accurately measuring heart rate using wearable devices in the presence of hand motion artifacts. By integrating advanced noise detection techniques into the wearable device, we were able to significantly reduce the impact of motion-induced noise on heart rate data. Our experimental setup involved meticulously collecting data from subjects performing various hand movements, ensuring that the conditions were consistent and controlled. The subsequent analysis demonstrated that the noise detection methods effectively filtered out artifacts, as evidenced by the improved accuracy of heart rate readings. Statistical metrics, such as the Root Mean Square (RMS) values, confirmed the reduction in noise levels, highlighting the efficacy of our approach. These findings suggest that our methodology can enhance the reliability of wearable devices in dynamic conditions, potentially benefiting a wide range of applications, from fitness monitoring to medical diagnostics

4. CONCLUSION

The analysis of noise levels across eleven hand motion artifacts using the OH1 wearable device reveals significant variability in the average RMS noise values associated with different movements. The results indicate that complex motions, such as rotating shoulders outward by 180 degrees, generate the highest noise levels, with an average RMS noise value of 0.0679. In contrast, simpler actions, such as placing palms on the chair and straightening the arms, result in the lowest noise levels, averaging an RMS noise value of 0.025. This study highlights the importance of considering specific motion artifacts when using wearable devices for monitoring physiological parameters. The data suggests that minimizing complex movements could reduce noise interference, thereby improving the accuracy of measurements. Future work should focus on refining noise reduction techniques and validating these findings across larger and more diverse populations. Understanding and mitigating the impact of motion artifacts is crucial for enhancing the reliability of wearable health monitoring systems.

REFERENCES

[1]. Allen, J. (2015). 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 8078-8082.

[2]. Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. Physiol. Meas., 28, p. 39.

[3]. B. A. Dolezal, D. M. Boland, J. Cui, M. Abe, D. Levi, S. Sharman, C. Bove, & C. C. Thompson (2017). Validation of heart rate derived from a physiological status monitor-embedded compression shirt against criterion ECG. Medicine and Science in Sports and Exercise, 49(8), pp. 1679-1703.

[4]. Bishop, C. (2006). Pattern Recognition and Machine Learning. Springer, Volume 4, p. 356.

[5]. Casson, D. J. & Alex, J. (2017). Description of a Database Containing Wrist PPG Signals Recorded during Physical Exercise with Both Accelerometer and Gyroscope Measures of Motion. MDPI Journal Data, 2(1).

[6]. Chicco, D. & Jurman, G. (2020). The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC Genomics, 21(1), pp. 1-13.

[7]. Fabian Pedregosa, G. Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, pp. 2825-2830.

[8]. Harun Al Azies, D. T. E. M. Putra (2019). Comparison of Kernel Support Vector Machine (SVM) in Classification of Human Development Index (HDI). IPTEK Journal of Proceedings, The 1st International Conference on Global Development - ICODEV, Volume 6, pp. 53-57.

[9]. Huhn, S., & Albrecht, L., Witt, C. M., Hartmann, A., Meister, S., & Mayer, P. (2022). The Impact of Wearable Technologies in Health Research: Scoping Review. JMIR Mhealth Uhealth, 10(1), p. 1.

[10]. Hettiarachchi, I. T., Hanoun, S., Docherty, P. D., Naseri, H., Shepherd, D., & Nandadeva, S. (2019). Validation of Polar OH1 optical heart rate sensor for moderate and high-intensity physical activities. PLOS ONE.

[11]. IoP Science. (2007). Filtering Poincare plots. Computational methods in science and technology, 11, pp. 27-37.

[12]. J. Lui, A. F. K. Adam, L. Chun, & C. Marc (2017). A preliminary investigation into infrared sensors in wearables for upper extremity motion sensing. Future Technologies Conference, pp. 120-125.

[13]. Khan, E., Gil, E., & Alvarez-Estevez, D. (2016). A Robust Heart Rate Monitoring Scheme Using Photoplethysmographic Signals Corrupted by Intense Motion Artifacts. IEEE Trans. Biomed. Eng., 63, pp. 550-562.

[14]. Krishnan, R., Natarajan, B., & Warren, S. (2010). Two-Stage Approach for Detection and Reduction of Motion Artifacts in Photoplethysmographic Data. IEEE Trans. Biomed. Eng., 57, pp. 1867-1876.

[15]. L. A. Simpson, J. J. Eng, & M. C. (2017). H-GRASP: the feasibility of an upper limb home exercise program monitored by phone for individuals post stroke. Disabil. Rehabil., 39(9), pp. 874-882.

[16]. Lam, K., Sorzano, C., Zhang, Z., & Campisi, P. (2015). Undergraduate students compete in the IEEE Signal Processing Cup: Part 1. IEEE Signal Processing Mag., 32, pp. 123-125.

[17]. Lui, J., & Daniel, C. Y. (2019). Design of a Wearable to Improve Single-Device Motion Classification of Arm Motions. Canada: SIMON FRASER UNIVERSITY.

[18]. M. J. Butler, J. A. C. Bernard, & R. H.-G. & P. I. Reed (2016). Motion limitations of non-contact photoplethysmography due to the optical and topological properties of skin.

[19]. Mullan, P., et al. (2015). Unobtrusive Heart Rate Estimation during Physical Exercise using Photoplethysmographic and Acceleration Data. In Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 6114-6117.

[20]. Omar J. Escalona, A. V. Shaban, M. Ghaleb, P. Drineas, & J. Markham (2020). Wireless Arm Wearable Sensor Band for Long-Term Heart Rhythms Surveillance Using a Bipolar Arm-ECG Lead. Computing in Cardiology, 47, pp. 1-4.

[21]. Piskorski, J., & Guzik, P. (2007). Filtering Poincare plots. Computational methods in science and technology, 11, pp. 39-48.

[22]. Schubert, M., Cooper, A., Blanchard, D., Lovelock, R., & Anliker, S. (2018). The Polar® OH1 Optical Heart Rate Sensor is Valid during Moderate Vigorous Exercise. The Polar® OH1 Optical Heart Rate, E67-E70.

[23]. T. Imam, K. Ting, & J. Kamruzzaman (2006). z-SVM: An SVM for Improved Classification of Imbalanced Data. Advances in Artificial Intelligence, pp. 264-273.

[24]. Weinan Li, Hong Zhang, Jing Wu, & Yong Li (2018). A wearable exercise heart rate detection device based on single-arm ECG. BIBE.
[25]. Zhang, Z. (2015). Photoplethysmography-Based Heart Rate Monitoring in Physical Activities via Joint Sparse Spectrum Reconstruction. IEEE Trans. Biomed. Eng., 62, pp. 1902-1910.
[26]. Zhang, Z., Pi, Z., & Liu, B. (2015). TROIKA: A General Framework for Heart Rate Monitoring Using Wrist-Type Photoplethysmographic Signals During Intensive Physical Exercise. IEEE Trans. Biomed. Eng., 62, pp. 522-531.
[27]. Zong, C., & Jafari, R. (2015). Robust Heart Rate Estimation using Wrist-based PPG Signals in the Presence of Intense Physical Activities. In Proceedings of the Eng Med Biol Soc, pp. 8078-8082.