Determining Human Activity Through ECG Motion Artifacts

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Abstract

Remote wearable single-lead electrocardiograms (ECGs) can contain motion artifacts (MA), caused by day-to-day human activity, making it difficult to identify QRS complexes and compute R-R intervals. This issue requires the development of complex signal processing techniques or the use of multi-sensor fusion modalities to eliminate MAs which increase the computational power needs of small battery-powered devices. This work proposes an exploration of embedded friendly machine learning (ML) models in the classification of capacitive electrode-based ECGs that contains MAs in the form of different types of human movements. Adult capacitive-electrode based ECGs (n=5) are obtained under different upper-limb movements. 48 statistical features are extracted from the original ECG signals and its wavelet coefficients. The Ensemble-based KNN approach is shown to provide the highest accuracy of 96% and sensitivity of 95% in binary classification between ECGs with movements and ECGs with no activity. While SVM showed the highest accuracy of 68% in multi label classification between unilateral, bilateral, and no activity. This work is a preliminary step in the investigation of explainable AI (XAI) techniques to identify different human activities solely from MA noise information presented in dry electrode-based ECGs.

1. Introduction

Remote single-lead ECG monitoring technologies are becoming candidate unobtrusive tools for heart health monitoring during day-to-day activities. This tool can provide the user insights about their overall cardiac function through heart rate, and heart-variability measurements. This technology can improve the wellbeing of individuals through preventative healthcare measures. The other benefit revolves around the use of ECG wearables in detecting cardiac abnormalities assisting physicians in identifying arrythmias.

Many medical wearables can perform remote ECG monitoring. For example, Holter monitors can be worn by the individual for up to five days that record up to 12-lead ECGs depending on the number of wet electrodes attached to the body using wires. This process allows for in-depth information of the heart but is not comfortable for longer term placement leading to low patient compliance. The wet electrodes are not suitable for day-to-day wear where sweat and activity impacts the ECG signal quality, limiting its usefulness and requiring computationally complex and power intensive signal processing algorithms to eliminate MA noise present [1]. This concept in turn limits the Holter's battery capacity leading to low continuous monitoring time up to 7+ days which is not suitable for post-operative cardiac monitoring of 30+ days [2]. These disadvantages lead researchers to examine different types of dry and capacitive electrodes for single-lead ECG to increase patient compliance and increase wear comfortability, allowing for longer continuous monitoring.

Dry electrodes are transducers that do not require a wet medium to acquire ECG. Dry electrode types include soft, hard, and fabric materials. Soft/flexible electrodes are used to conform with skin utilizing maximum skin electrode contact such as flexible metals, cotton, conductive polymers and foams. However, these sensors are delicate and are worn with time which is not appropriate for long-term continuous operation. In turn researchers examined capacitive electrodes to integrate into smart homes for continuous monitoring through multiple short-term contact with inanimate objects in the house. Capacitive electrodes use pre-amplifiers and circuitry to create a high input impedance that allows electrical activity to be recorded through a thin medium such as clothing for contactless based remote ECG monitoring yielding an increase in user compliance [3].

Lessard-Tremblay et. al developed contactless capacitive flexible printed electrodes using printed electronics to eliminate air gaps present between surface and electrode contact. Their work did not examine MAs but assumed their novel sensor will not be sensitive to MA due to its conformity [4]. On the other hand, Chen et. al examined active capacitive electrode design to mitigate environmental noises such as EMI and PLI noise and Mas [5]. Both works examined analog circuit designs to mitigate MA which can yield to an increase in power consumption for low-power wearable devices.

Also, digital signal processing (DSP) techniques are provided to further suppress MA noise such as using filter banks, wavelet transform, bling signal separation techniques such as empirical mode decomposition and ML and deep learning algorithms [6]. Most of the above-

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mentioned techniques except for wavelet and filter banks are computationally complex and require high computational power making it not suitable for wearables.

Furthermore, sensor fusion models using other types of sensors are offered to provide more information about MA which can assist with determining the appropriate DSP technique to be used in MA suppression. Meghrazi et. al used multichannel ECG recordings from noisy textile electrodes. The authors can detect R-peaks accurately in different activity scenarios [7].

To the best of our knowledge a gap between the use of sensor fusion and ML models for MA detection in capacitive electrode-based ECG signals is evident. Furthermore, the lack of literature in identifying different types of MA from ECG signals warrants us to further investigate this concept with the use of embedded friendly explainable AI (xAI) models. Our proposed work is the first of its kind to examine the use of ML models in detecting MA present in chest-based ECGs acquired using capacitive electrodes under different physical activities. It is important to note that this study is proof of concept work to determine the applicability and feasibility of the use of ML models in detecting MA.

This article is structured as follows; Methods offer an in-depth analysis into the dataset, features, and ML models used in MA detection. This section is followed by the results of the proof-of-concept investigation. The discussion explores the results and determines the appropriateness of ML models in MA detection. The conclusion offers concluding remarks for the study.

2. Methods

2.1. Dataset

25 Single-lead ECG signals from 5 adult subjects are used in creating the ML models outlined in this work. The signals, with a sampling frequency of 1 kHz, are collected using capacitive and gel electrodes located at the chest area, collecting Lead-I based ECGs as shown in Figure 1. The signals undergo x10 amplification and 0.5 Hz – 40 Hz bandpass filtering. This pre-processing is performed to remove baseline wander and ensure that low frequency MAs above 0.5 Hz are present during ECG acquisition which will be later used in signal noise classification. Each subject provides five ECG signals containing different types of ECG MA noise including subject at rest, wing motion, running, punching and upper body twists as shown in Figure 2. The subjects performed each motion for 2 minutes continuously and each signal is recorded separately. This dataset is approved by Auckland University of Technology ethics committee, application 22/383 [3].

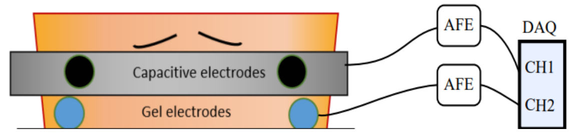

Figure 1: Chest electrode placement and ECG acquisition

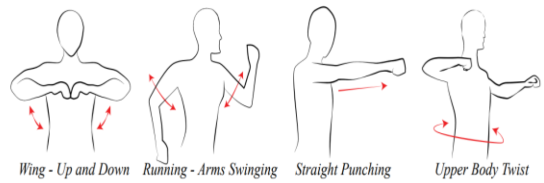

Figure 2: Upper-body movements

To examine ML models in classifying the type of MA noise in ECG, the different artifacts are categorized into unilateral and bilateral types of motions. Unilateral motion is defined as one side of the body performing the action while the other side is at rest or performs the opposite action. This type of motion includes body twists, punching and running. Bilateral motion is defined as both sides of the body performing the same action in unison such as presented in wing flapping.

2.2. Feature Selection

The goal of the work is to examine ML models that can classify MA types in real-time through on-chip computing for remote wearable-based applications such as monitoring during exercising. To this end, computational efficient features are utilized to ensure real-time applicability such as statistical and wavelet-based features. Third level wavelet decomposition using db4 is performed on the original raw ECG signals obtaining different levels of detail wavelet coefficients; cd1, cd2, and cd3. These coefficients are used to extract statistical features in conjunction with the raw original signal. These statistical features include skewness, kurtosis, variance, standard deviation, standard deviation error, minimum, maximum, root mean square, peak to peak, peak to root-mean square (RMS), zero crossing rate, and signal power. In total 48 statistical features are obtained from the original ECG signal. This information is presented in a 25x48 feature matrix where each row vector of the matrix represents the type of movement and its respective features.

2.3. ML Selection and Classification

Certain ML models are considered in this study due to their real-time and hardware friendly capabilities. The models examined include SVM, Naïve Bayes, KNN, and Ensemble techniques. These models were chosen due to their power efficient approach and can be embedded into microcontroller friendly programming in C. These models also can be created with efficient algorithmic optimization lowering memory usage for resource constrained devices.

Two classification approaches are examined to determine the appropriate pathway for MA recognition. The first approach includes a binary classification step that classifies all types of MA noise together separately from no action/movement ECG signals. This binary classification model training is performed with 10-fold cross validation and full dataset. This process is performed to ensure that the chosen ML models are feasible to separate the signals accordingly.

The second classification approach requires the development of a multi-label classification model to classify unilateral, bilateral and no movements apart based on the features. The same training conditions are performed for both classification models.

3. Preliminary Results

ECG MA binary classification is performed using multiple xAI ML models including SVM, Ensemble technique, and Naïve Bayes. MA classification using a KNN-based ensemble technique showed the highest accuracy in labelling MA versus no MA as shown in Table 1. The technique provided 96% accuracy in detecting no MA from MA with 95% sensitivity and 60% specificity as shown in Table 2. This ensemble technique utilized a subset of KNN classifiers and majority voting to determine the most appropriate prediction value for classification. Ensemble with KNN classifiers is followed by SVM with 88% accuracy utilizing either cubic or quadratic kernel functions. This binary classification process shows that xAI hardware friendly ML models can be suitable for detecting MA versus no MA which can offset the need for an accelerometer sensor fusion algorithm for MA detection.

Table 1: ML Approaches' binary classification accuracy

ML Approach	Accuracy (%)
Ensemble (KNN)	96
SVM	88
Naïve Bayes	84
Ensemble (Bagged Trees)	84

Table 2: Confusion Matrix of binary classification for Ensemble (KNN)

	Predicted No MA	Predicted MA	total
True No MA	3 (0.6)	2 (0.4)	60%
True MA	1 (0.05)	19 (0.95)	95%
total	75%	90.5%	

The second step involved multi-label classification which included the same ML models mentioned above. The most accurate models included SVM, and KNN. Both models showed 68% accuracy with 65% sensitivity and 40% specificity for detecting unilateral movements from bilateral and no MA data as shown in Table 3. However, this accuracy is skewed because no bilateral movement was identified in the models as shown in Table 4. It is evident that multi-label classification using xAI ML models especially SVM, KNN and ensemble techniques are lacking in separating unilateral, and bilateral motion artifacts present in capacitive ECG signals. It is important to note that the results of this study are preliminary, limited and require further investigation utilizing more data points and unique hand-crafted features for multi-label classification.

Table 3: ML Approaches' multi-label classification accuracy

ML Approach	Accuracy (%)
KNN	68
SVM	68
Ensemble (Boosted Trees)	60
Naïve Bayes	52

Table 4: Confusion Matrix of multi-label classification for KNN

	Predicted No MA	Predicted Unilateral	Predicted Bilateral
True No Movement	2 (0.4)	3 (0.6)	
True Unilateral		15 (1.0)	
True Bilateral		5 (1.0)	

4. Discussion

The purpose of this investigation is to determine the feasibility and usability of embedded friendly ML models; SVM, KNN, Ensemble and Naïve Bayes in classifying MA noise present in capacitive ECG signals using statistical and wavelet coefficients features for real-time classification. Firstly, binary classification of MA noise presence is performed. An ensemble technique with KNN modules showed the highest accuracy, 96%, followed by SVM, 88%, in this type of classification which shows that statistical features for the raw ECG signal and its wavelet coefficients suffice to perform initial no MA and MA separation. For KNN, the above-mentioned features can be clustered effectively with a voting scheme for classification. Both models are appropriate for long-term remote monitoring using capacitive electrodes. These models can differentiate segments of the ECG signals which contain high MA noise, allowing ECG wearable developers to remove these ECG strands from the original signal. The real-time nature of these algorithms allows for automatic excision by classification of MA noise induced ECG sections which can yield to an autonomous approach in labelling noises present in ECG eliminating MA noise more effectively. This approach is suitable for point of care applications where ECG wearable users can have more reliable ECG acquisition depending on their physical activity without the need for sensor fusion models or complex signal processing algorithms.

On the other hand, the multi-label classification using the above-mentioned algorithms showed low accuracies in classifying unilateral, bilateral, and no MA. The most accurate ML models are SVM and KNN offering 68% accuracy. However, these results are skewed because the algorithms were not able to differentiate between the unilateral and bilateral movements as shown in Table 4. The outcomes for multi-label classification provide an indication of the limitations of statistical and wavelet coefficient features in further separating unilateral from bilateral movements. Furthermore, the small dataset problem is further amplified with its imbalanced label issue for multi-label classification where the entire 25 vector dataset is split into 60%, 20% and 20% for unilateral, bilateral, and no MA signals. This limitation can be alleviated with the addition of more ECGs. This investigation is performed to show that although the same features are optimal for binary classification, multi-labelling requires a larger dataset and the study of other features. Other features that should be explored including non-linear and morphological ECG features. Improving the pipeline for feature extraction is paramount to improve ML model training parameters and in turn its accuracy in MA classification. It is important to note that this study is a proof of concept to show that ECG MA classification using ECG signals alone with ML classification models is suitable for the identification of MA. However, the models cannot identify the type of MA present. Future works should examine the small dataset problem, other features, and perform real-time and computational analysis of the ML models presented in this work. Other ML models should be further developed for cloud computing remote monitoring applications. With future microelectronic development, and optimized algorithmic deployment on microcontrollers, classification models are realizable for MA detection in ECGs in real-time for low-power single-lead ECG wearables based on capacitive electrodes.

5. Conclusion

ECG MA detection is performed on a small dataset of MA tainted ECGs with different MA types collected using chest-based capacitive electrodes. Thirty-six statistical features obtained from the raw ECG signals and its computer wavelet coefficients are used to develop ML models for binary and multi-label classification of MA noises. KNN and SVM showed high accuracies in binary classification. This exemplifies that ML models are suitable for binary classification which can become a candidate for general MA identification in wearable environments. While KNN and SVM did not perform well with multi-label classification of grouped activities of unilateral, bilateral and no MA states. These models identify the limitations of statistical features and the examined ML models in multi-label classification. This concept warrants further investigation of other features, addition of more data, and performing algorithmic power computational analysis to determine its suitability in embedded real-time applications. Overall, this work can act as an explorative study in the use of ML models in MA identification and classification for the purposes of enhancing MA recognition in real-time and develop future long-term monitoring solutions.

References

[1] A. Abdou and S. Krishnan, "Horizons in Single-lead ECG Analysis from Devices to Data," *Front. Signal Process.*, Mar. 2022, doi: 10.3389/frsip.2022.866047.

[2] W. N. Kernan *et al.*, "Guidelines for the Prevention of Stroke in Patients With Stroke and Transient Ischemic Attack: A Guideline for Healthcare Professionals From the American Heart Association/American Stroke Association," *Stroke*, vol. 45, no. 7, pp. 2160–2236, Jul. 2014, doi: 10.1161/STR.0000000000000024.

[3] W. Hoffmann, A. Lowe, M. Wilson, and M. M. Y. Kuo, "Investigation of Non-contact Electrodes for Electrocardiogram Monitoring," in *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Sydney, Australia: IEEE, Jul. 2023, pp. 1–4. doi: 10.1109/EMBC40787.2023.10340699.

[4] M. Lessard-Tremblay, J. Weeks, L. Morelli, G. Cowan, G. Gagnon, and R. J. Zednik, "Contactless Capacitive Electrocardiography Using Hybrid Flexible Printed Electrodes," *Sensors (Basel)*, vol. 20, no. 18, p. 5156, Sep. 2020, doi: 10.3390/s20185156.

[5] C.-C. Chen, S.-Y. Lin, and W.-Y. Chang, "Novel Stable Capacitive Electrocardiogram Measurement System," *Sensors (Basel)*, vol. 21, no. 11, p. 3668, May 2021, doi: 10.3390/s21113668.

[6] M. Khalili, H. GholamHosseini, A. Lowe, and M. M. Y. Kuo, "Motion Artifacts in Capacitive ECG Monitoring Systems: A Review of Existing Models and Reduction Techniques," *Med Biol Eng Comput*, Jul. 2024, doi: 10.1007/s11517-024-03165-1.

[7] M. Alizadeh Meghrazi *et al.*, "Multichannel ECG Recording from Waist Using Textile Sensors," *BioMed Eng OnLine*, vol. 19, no. 1, p. 48, Dec. 2020, doi: 10.1186/s12938-020-00788-x.

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