Available online at: https://ijact.in

Date of Submission	05/02/2020
Date of Acceptance	20/02/2020
Date of Publication	30/03/2020
Page numbers	3590-3595 (6 Pages)

Cite This Paper: Khalida AB Mohd. Zailan, Mohd. Hilmi BH, Gunawan W. Comparative analysis of machine learning algorithms for optimizing variable step-size least mean square in motion artifact reduction, 9(3), COMPUSOFT, An International Journal of Advanced Computer Technology. PP. 3590-3595.

ISSN:2320-0790

An International Journal of Advanced Computer Technology

COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR OPTIMIZING VARIABLE STEP-SIZE LEAST MEAN SQUARE IN MOTION ARTIFACT REDUCTION

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Abstract: Optical sensor like Photoplethysmographs (PPG), is widely used in generating real time information such as current heart rate. Existing studies on PPG demonstrated that the weakness of this technology is the sensor will capture the motion artifact reading when there is excessive motion exerts on the sensor. Numerous algorithms had been developed to reduce the motion artifact on PPG and increase the accuracy of the health monitoring device reading. However, these existing solutions using least mean square (LMS) algorithm failed to achieve high accuracy of heart rate reading. This paper presents and compares three types of machine learning algorithms that are widely used in classification of wearable signals, which are support vector machine (SVM), artificial neural network (ANN) and random forest (RF). The machine learning algorithms optimize variable step-size LMS (VSSLMS) accuracy by classifying the speed of the motion and giving suitable step size values based on the classification. The result shows that SVM is the best machine learning algorithm in classifying the speed category of the heart rate to eventually get the suitable step size value for VSSLMS.

Keywords: Variable step-size least mean square, support vector machine, artificial neural network, random forest, motion artifact reduction.

I. INTRODUCTION

Motion artifact is widely known in wearable health monitoring device because of the movement that we make when we move. The motion artifact would cause the reading to be inaccurate because of the movement between skin and sensor [1] and when motion exists on the sensor, the reading will capture the motion artifact reading [2-4]. The inaccurate system will cause false alarm for the user.

Algorithms to reduce motion artifact had been researched by many researchers, yet there are rooms for improvement especially for Least Mean Square (LMS) algorithm which one of widely used algorithm in adaptive filtering algorithm.

LMS is basically an adaptive filtering algorithm which focuses on the step size measurement adjustment that represents the adjustment between the speed of adaption and the noise in steady state. LMS also had been improvised into few versions, which in this research, the most suitable LMS is Variable Step-Size Least Mean Square (VSSLMS). Original LMS algorithm may not work well in high motion activities since the algorithm is based on fixed step size measurement adjustment, meanwhile every motion produced by the users have different step-size measurement adjustment [2-5].

Therefore, this paper will investigate suitable machine learning for optimizing with VSSLMS since VSSLMS have a problem in getting the suitable step size value for reducing motion artifact in three type of motions which are slow, normal and high-speed.

II. LITERATURE REVIEW

A. *Machine Learning*

Machine learning is a new problem solver in this new era where the computer or machine will learn things without being specifically programmed [6]. The algorithm will set the rules which the computer will react to, based on the rules. In machine learning, there are three main classification of machine learning algorithm which are supervised, unsupervised and reinforcement [6-9]. The supervised learning is where each data is labelled based on the set of examples [7] and require collection of desired training data responses [9], so that the algorithm able to make a prediction about future data [8]. Vice versa from supervised, unsupervised learning is unlabeled data which could organize the data in some way or describe its structure [8] and avoiding the need of desired response [9]. Lastly, reinforcement learning is used to analyse and learn [9] by optimizing the characteristic of an agent on the respond from the environment [7] without precise input-output available [9].

There are two types of supervised and unsupervised learning. Supervised learning can be divided into three types which are classification, pattern recognition and regression meanwhile for unsupervised it can also be divided into two types which are clustering and dimension reduction [7]. Supervised learning is more direct in comparison to unsupervised learning where supervised learning could develop a predictive model based on both input and output. The classification in supervised learning means that it has clear target output in prediction by binary classification mean; regression in supervised learning could determine the statistical relationship between two or more variables where a change in dependent variable will affect the independent variable [10]. While for an unsupervised learning is not rigid in getting the outcome but focusing more on the input by finding similar and cluster it into a group. Clustering could classify similar set of observations and group it into particular cluster by teaching the algorithm to classify either certain relationship exists between two data entries and group them accordingly [11].

Roy et al. [12] proposed two technique using ANN where the first technique is by using Artificial Neural Network (ANN) to evaluate PPG beat quality using six hidden layer perceptron-neural network (MLP-NN) classifier and generating the reference beat template for each subject. This first technique is for training purposes in getting the global reference template and recalibration. To avoid over or under fitting of the neural network, six folds cross validation and drop-out technique were used. Meanwhile the second technique for feature extraction also using MLP-NN but combined with deep auto-encoder (DAE) to extract effective features from a high-dimensional data in an unsupervised manner.

Two stages of random forest are proposed in this research by Ye et al. [13] to estimate heart rate from corrupted motion artifact in PPG signal. The first stage of the algorithm consists of hybrid method by combining two motion artifact removal algorithms with low computational complexity using accurate binary decision algorithm which will decide to execute the second motion artifact removal algorithm. The robust random forest-based was proposed as the second stage using spectral peak-tracking algorithm. The random forest-based spectral peak-tracking will detect the spectral peak that corresponds to heart rate which lead to formulate a pattern classification problem based on the problem of spectral peak tracking. Mainly the machine learning part for this research is on the random forest-based classifier training, where the algorithm will train ten-fold cross-validation method to estimate the generalization performance of the classifier for both first and second stages.

Zhang et al. [14] implemented a few machine learning algorithms in order to filter out automatically the motion artifact and detect the heartbeat and Sp02 such as support vector machine (SVM), dynamic time warping (DTW), K-medoids clustering method and histogram triangle-based method. There are three stages of signal processing and heartbeat/blood pressure estimation algorithm which are supervised learning of heartbeat identification in the first stage, unsupervised learning of signal quality labelling and signal purification and lastly heart rate estimation and supervised learning of blood pressure estimation. The first machine learning used was SVM, to identify raw heartbeat identification in the first stage of the process. Then, it was continued with unsupervised learning algorithms in the second stage whereby DTW generated the heartbeat-specific signal quality indices and performed PPG heartbeat purification; K-medoids clustering method was then applied to learn the high-quality heartbeat pattern and lastly the histogram triangle-based method was to learn the distort threshold. In the third stage, regression model learning was used to determine one suitable blood pressure reading.

Zhang et al. [15] proposed a novel machine learning-enabled framework which consists of two stages, which are heart rate identification and refinement. During the heart rate identification stage, a threshold-based auto-segmentation approach used to select out the heart rate candidates, and only twenty-six features extracted from the heart rate candidates. Then, the features evaluated by Support Vector Machine (SVM) to select out ten critical features only. Once the trained data used the selected features, the next process will continue to find heart rate from a huge number of candidates based on the selected features only. During heart rate refinement stage, enhancing the estimation of instantaneous heart rate (IHR) by removing the outliers and heart rate interpolation.

As shown in the Table I, most used machine learning classification in motion artifact reduction is supervised learning since this machine learning classification could classify and predict the data. Supervised learning can be divided into three techniques which are classification, pattern recognition and regression [7, 17]. For this research, we chose classifying since the VSSLMS will be improved by classify the signal into few classifications and based from that classification, we could come out with specific step size adjustment measurement to reduce the motion artifact. Classification in machine learning is a type of supervised machine learning by classifying new observation from labelled data which the algorithm learned from [17].

TABLE 1: PREVIOUS STUDY ON EXISTING MACHINE LEARNING IN MOTION ARTIFACT REDUCTION ALGORITHM

Title	Type of ML	Type of Classification	Function
Y. Ye, W. He, Y. Cheng, W. Huang, and Z. Zhan 2017 [13]	Random forest	Supervised	the algorithm will train ten-fold cross-validation method to estimate the generalization performance of the classifier for both first and second stages
M. S. Roy, R. Gupta, J. K. Chandra, K. D. Sharma, and A. Talukdar 2018 [12]	Artificial Neural Network	Supervised	Evaluate PPG beat quality and generating the reference beat template for each subject
Q. Zhang, X. Zeng, W. Hu, and D. Zhou 2017 [14]	Support vector machine	Supervised	identify raw heart beat identification in the first stage of the process
	Dynamic time warping	Unsupervised	generate the heart beat-specific signal quality indices and perform PPG heart beat purification
	K-Medoids clustering method	Unsupervised	learn the high-quality heart beat pattern
	Histogram triangle-based method	Unsupervised	learn distort threshold
Neha, R. Kanawade, S. Tewary, and H. K. Sardana 2019 [2]	Support vector machine	Supervised	constructs a hyper-plane for differentiating two classes
Q. Zhang, D. Zhou, and X. Zeng 2016 [15]	Support vector machine	Supervised	to select out ten critical features only

1) *Random Forest*

Random forest is a type of machine learning under supervised learning by using decision tree category [6] which uses branching method to find the possible output of a decision by unveiling a significant performance improvement compared another tree-based algorithm [13]. Decision tree can be controlled both in diagnosis process and determine the best predictors of health risk [11]. Random forest could adjust the parameter by an intelligent classifier [13]. to achieve better generalization and robustness; and could get more formalized rules. Plus, random forest-based binary decision algorithm is a low computational complexity which could cater the high computational complexity algorithm [6,13], fast and easy to train [6]. Random forest-based binary decision algorithm also could detect nonlinear relationship using the correlation coefficient as one feature. The higher correlation coefficient, the higher motion artifact value in the signal. One of the disadvantages for this machine learning type is that it might take longer time to get output prediction and the prediction is not easy to be interpreted [7].

2) *Artificial Neural Network*

Artificial Neural Network (ANN) is one of the most famous machine learning for classification of signals in speech, control system and vision, which look like the networked structure of neurons in the brain [17,20]. ANN each layer consists of number of units called neurons which have three layers which are input, hidden and output layer [2]. Deep learning also used ANN fundamental concept which use neurons in solving problem, just deep learning using several layers of neural networks assembled on each other [6]. ANN can learn from given labelled data which then it can be trained to classify data, forecast future event and recognize pattern [17,20]. ANN have a complex architecture which makes it very slow to train the signal especially for high number of neurons used [6]. The higher complex of the tasks, the higher time taken to train the model and need a lot of power.

3) *Support Vector Machine*

Support vector machine (SVM) is also a machine learning algorithm under supervised classification [7]. It is the most popular classification algorithm because of its advantages of convex optimization and regularization [16]. Based on cheat sheet stated that SVM usually used for output data which focuses more on accuracy and easy to implement since the parameters are easy to tune and perform well [7]. SVM easily used to clean cut on the classification of the data which is why it is good to identify the accuracy of the data. This is the reasons why these papers [14,15] were using this algorithm to identify and classify the data in the early stage of the project in order to get accurate data before proceeding with the next steps.

4) *Machine Learning Comparative Analysis*

As stated in the Table 2, comparison between supervised learning. Support vector machine is chosen as the machine learning for this research due to convincing discussion as per below.

TABLE 2: COMPARISON STUDY BETWEEN SUPERVISED LEARNING

Features	SVM	Random Forest	ANN

Application	Classification	Yes [2,7]	Yes [7]	Yes [12,17]
Efficiency	Accuracy	High [2,7]	High [7]	Yes [2]
	Time	Fast [7]	Quite slow [6]	Very slow [6]

Support vector machine is chosen for this research because of the flexibility that is suitable for accuracy and easy to implement since the parameters are easy to be tuned for classification. The support vector machine will firstly train the test dataset to classify the motion pattern of the signal that affects the reading of heart rate and motion artifact. Once the motion pattern had been classified, suitable step size value will be determined to continue VSSLMS calculation.

B. *Metrics*

Confusion is a widely used method in machine learning to describe the performance of a classification method. Confusion matrix will be used for this research to visualize the performance of the algorithm using precision, recall, F1 score and accuracy equations. The result of the confusion matrix will return in boxes which represents true positive, false positive, true negative and false negative respectively. The evaluation would be obtained by using these following equations [2]:

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \quad (1)$$

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \quad (2)$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$

III. RESULTS AND FINDINGS

This section will discuss on the result from VSSLMS which is the main algorithm for this research without the machine learning optimization. This chapter will outline the dataset that will be used throughout this research and results from VSSLMS algorithm without machine learning application.

A. *Dataset*

The dataset will be the PPG dataset given for 2015 IEEE Signal Processing Cup [18]. The dataset consists of three technologies. Firstly, two-channel PPG signals recorded from the two pulse oximeters, continue with tri-axis accelerometer signals recorded from tri-axis accelerometer and an ECG signal recorded from the chest. Ground truth of heart rate also provided by the dataset, calculated simultaneously with ECG signal for performance evaluation.

The datasets included 22 recordings collected from various range of age of subjects. The first 12 of 22 datasets and the action based on slow, normal and high-speed motion on a treadmill. The rest 10 of 22 datasets, each of the subjects performed random actions, including various upper arm and forearm exercises, jump and push-up, running, which the motion artifact is higher than the first 12 datasets [18].

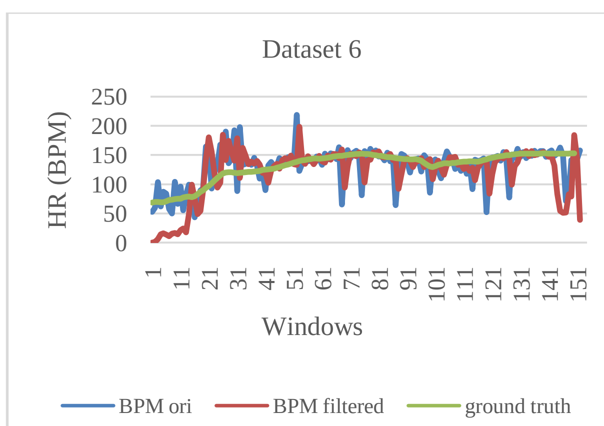
B. *Results from VSSLMS without Machine Learning algorithm*

For this pre-processing process, All PPG and accelerometer signals are processed by an infinite impulse response (IIR) response bandpass filter with a low cut-off frequency and a high cut-off frequency of 0.4 Hz and 4.0 Hz. As for VSSLMS, we used step-size μ=0.05 as it is the most stable step size value for normal speed activities [19].

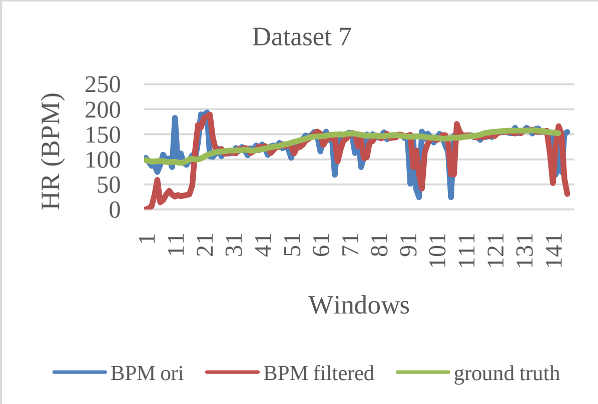
Table 3 shows all the results of average absolute error (AAE) for 12 datasets at 125 Hz sampling frequency. Dataset 6 is the result for AAE in BPM, 20.61 with 19% of average absolute error percentage (AAEP). Meanwhile in dataset 7 is the result for AAE in BPM is 20.38 with 17.82% of AEP and dataset 9 is the result for AAE in BPM is 17.81 with 16.33% of AAEP. Dataset 6, 7 and 9 are the most accurate compared to another dataset since other datasets have higher AAEP. Figure 1 shows the example results from dataset 6 (a) and 7 (b) between original BPM, filtered BPM and ground truth.

TABLE 3: THE AAE AND AAEP RESULTS OF 12 DATASETS AT 125 HZ SAMPLING FREQUENCY

Dataset	**1**	**2**	**3**	**4**	**5**	**6**
AAE	40.70	34.68	33.68	48.54	28.34	20.61
AAEP (%)	32.54	30.30	25.90	40.38	21.21	19.01
Dataset	**7**	**8**	**9**	**10**	**11**	**12**
AAE	20.38	24.68	17.81	44.35	22.63	36.03
AAEP (%)	17.82	21.33	16.33	28.06	16.56	26.98



(a)



(b)

Fig 1: The results from dataset 6 (a) and 7 (b) between original BPM, filtered BPM and ground truth

IV. CONCLUSION

This paper had been comparing three types of machine learning algorithms in classification, which are support vector machine (SVM), artificial neural network (ANN) and random forest (RF). The result shows that SVM is the best machine learning algorithm in classifying. This paper shows that VSSLMS algorithm still have room for improvements in improvising the accuracy of the output reading of the heart rate by optimizing SVM to improvise the VSSLMS algorithm. The SVM will classify movement speeds based on the signals which are slow, normal or fast movement; where every classification has their own step size value.

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