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An Efficient Motion and Noise Artifacts Removal Method using GAIT and Machine Learning Model

S. Pushpalatha , Shrishail Math

Abstract*— obtaining an exact measurement of oxygen saturation (SpO2) using a finger-probe based pulse oximeter is dependent on both artifact-free infrared (IR) and red (R) Photoplethysmographic signals. However, in actual real-time environment condition, these Photoplethysmographic signals are corrupted due to presence of motion artifact (MA) signal that is produced due to the movement/motion from either hand or finger. To address this motion artifacts interference, the cause of the contamination of Photoplethysmographic signals by the motion artifacts signal is observed using GAIT. Motion and noise artifacts enforce constraints on the usability of the Photoplethysmographic, predominantly in the setting of sleep disorder detection and ambulatory monitoring. Motion and noise artifacts can alter Photoplethysmographic, resulting wrong approximation of physiological factors such as arterial oxygen saturation and heart rate. For overcoming issues and problems, this manuscript presented a new approach for detection of artifacts. First, present an adaptive filter and adaptive threshold model to detect artifact and obtain derivative of correlation coefficient (CC) for labelling artifacts, respectively. Lastly, Improved Support Vector Machine Model is presented to perform classification. Experiment are conducted on real-time dataset. Our approach attain significant performance in term of accuracy, sensitivity, specificity and positive prediction.

Keywords*— Adaptive filter, Ambulatory monitoring, Gait analysis, Machine learning, Motion and noise artifacts, Obstructive sleep apnea..

I. INTRODUCTION

Wearable diagnostic devices can be used for enabling the scenario of real time remote PA (Physical Assessment) and military triage of miners, mountaineers, combatants and the other individuals which are operating in the hazardous environment. Moreover, this allows the front line medics and first responders to work under the stressful condition for prioritizing the medical intervention during the limited resource supply; hence, this provokes the effective care for the one, which is more urgent. However growing health concern in the world sleep disorder has been one of the underrated disease also known as OSA (obstructive sleep apnea) syndrome, it is highly prevalent and affects nearly 5-20% of the population.

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* Correspondence Author
S. Pushpalatha*, Research Scholar, Department of ISE, Dr. AIT Bengaluru, India. E-mail: pushpahemu@gmail.com,
Dr. Shrishail Math, Professor, Department Of CSE, SKIT, India. E-mail: Shri_math@yahoo.com,

Sleep fragmentation and CIH (Chronic intermittent hypoxia) are induced in OSA patients during the sleep, periodic upper airway collapses, and this phenomenon promotes the cerebrovascular and cardiovascular disease along with brain insult through the vascular inflammation [1], systemic and sympathetic activation. Moreover, the main dominating complaints are impaired function observed in the daily life and excessive sleepiness in daytime. The study of Neurocognitive shows the obstructive sleep apnea impact in various cognitive domain such as memory, attention/vigilance and executive functions [2]. Moreover, CPA (Continuous positive airway) pressure uses the pulse oximeter and it is one of the most effective which is widely used for the treatment and shows the significant growth in in the cognitive impairment [3]. Thus, Gait can be described as one of the automatic motor activity, which is independent from the CF (Cognitive Functions). In past few decades several reports has shown the effectiveness of executive function in the given gait control with the use of dual task[1], however this itself requires the particular subject for performing the attention demanding and cognitive task while walking. Through the analysis it shows that the interference of attention demanding ask rely on the given same functional sub-system, hence this phenomena suggest that even gait requires the attention. Through the study of substantial data, it is suggested that FEF has been involved completely in gait control [1], however there has not been any particular data that can show the effect of CPAP on the gait using the pulse oximeter in OSA patients. Moreover, by taking the advantage of the improvisation in FEF after CPAP treatment using the particular pulse oximeter [2] and the relationship between FEF [1] and gait, this research work hypothesizes the CPAP using the pulse oximeter and this led to the improvisation in gait parameters in obstructive sleep apnea patients.

It is found that obstructive sleep apnea has the adverse physical effects; moreover the more repetitive obstructive apneic minimizes the saturation of blood oxygen and surges in the blood pressure and heart rate after each apneic episode led to the arousal from sleep and it solely effects the sleep quality. Negligence in sleep apnea maximizes the hypertension risk, heart attack and cardiac arrhythmia and stroke [4]. IT also maximizes the motor vehicle collision risk [5], however individual are rarely aware about the disorder and this is one of the primary reason for negligence. Polysomnography (PSG) is the study of sleep apnea diagnosis, it involves the monitoring patient by overnight and analyzing the physiological signal such as peripheral oxygen saturation (SpO2), EMG (Electromyogram), Electrooculography (EOG) , ECG (electrocardiogram), EEG(Electroencephalogram) form the abdominal movement signal. Thoracic and pulse oximeter in the sleep lab. Moreover polysomnography is time consuming, costly and mostly inconvenient to the patient as the limited amount of labs, lab specialist for the treatment and diagnosis. The average waiting time for D & T (Diagnosis and Treatment) in the UK and US is nearly 7-60 and 2-10 months, respectively [6].

In the past few decades, there has been enormous growth of research in the developing easy to implement and cost effective method for detecting obstructive sleep apnea. Advancement in the several fields such as wireless communications, computing and embedded sensing has led the development of various cost effective wearable sensors, which is capable of gathering the various physiological signals such as respiration, SPO2 and ECG in the non-invasive manner. Several existing methodology has been discussed in the literature review section of this research work, many researchers have adopted feature extraction and classifiers, these methods used the data driven approach. At first various features were defined and then it is extracted from the given various physiological measurement signals such as SPO2 and ECG. Later the supervised learning were applied for the classification of the non-apneic and apneic data. However the main problem with these methods were that it totally depends on the sensor data in case of training and it depends on the particular type of feature extracted. All these methods consider the physiological signal as the independent data and then FE (Feature Extraction) is done for each signal individually whereas in reality they might be dependent on each other. Let's take for instance that ECG signal has the respiratory information and the PPG (photoplethysmogram) has information about heart rate as well as respiration rate [7] and SPO2 is also related to the given RS (respiration signal) [8].

Vital signs extraction along with the other physiological parameters, which is generated using the pulse oximetry, is already predicted on the given artifact free motion photoplethysmogram data. It is also known that photoplethysmogram signals are the high-sensitive data to the artifacts specially the one which is recorded when the patient were in motion [10] and this phenomena has the restricted use of the photoplethysmogram for application of ambulatory monitoring. Moreover, motion and noise artifacts also known as MNAs leads to the estimation of SPO2 and HR [10]. However the various sensors may be able to minimize the motion disturbance and it makes sure that sensor are placed securely and it is found that they are not enough capable for removing the MNA. Hence combating the MNAs in PPG data is one of the core focus for the researchers for several years. To overcome that various method has been proposed that can alleviate the effects of MNAs, however the solution remains on the unsatisfactory side. Few methods such as blind source techniques, power spectrum analysis, T&F (Time and Frequency) domain filtering and power spectrum analysis [11] [12]. The above mentioned technique helps in reconstructing the noise contaminated data of PPG such that reduced noise signal is available, however these reconstructed signals has the non-complete dynamic feature of the given uncorrupted PPG signal. Few methods were only able to capture only SPO2 and HR instead of the signal amplitude that are required for the computation of other physiological derivations [13]. This reconstruction algorithm also operates on the portion of clean PPG where the MNA minimization is not required, hence MNA algorithm needs to be designed that can differentiate between the clean portion and corrupted portion. Moreover it is required not to distort the data segments of non-corrupted one [14]. These MNA detection techniques are mainly based on the SQI (Signal Quality Index) that can quantify the various artifacts, some of the technique also computes the SQI using the filtered output[16] or the morphologies [15] whereas others computes SQI by using the hardware product such as electrocardiogram [17] and accelerometer. In case of some of the commercial available pulse oximeter the accelerometers is not given and also if it is available the raw data are non-feasible and they cannot employed for the cancellation, hence all these traditional approach for cancellation of MNAs does not give the satisfactory results.

For overcoming research challenges, this work first present an accurate SpO2 measurement model considering the impact of artifacts such as walking, running, random movement etc. Secondly present a data pre-processing model to obtain PPG signal with and without artifacts using adaptive filter model. Further present a batch or template selection model using adaptive threshold model to obtain derivative of correlation coefficient for labelling artifacts and without artifacts. Then, machine learning algorithm such as using neural network and support vector machine is presented which takes these input feature with labelled class for training. Lastly, machine learning model is used to perform classification considering various kind of dataprofile (min 100 word) along with photo should be included in the final paper/camera ready submission. It is be sure that contents of the paper are fine and satisfactory. Author (s) can make rectification in the final paper but after the final submission to the journal, rectification is not possible. In the formatted paper, volume no/ issue no will be in the right top corner of the paper. In the case of failure, the papers will be declined from the database of journal and publishing house. It is noted that: 1. Each author profile along with photo (min 100 word) has been included in the final paper. 2. Final paper is prepared as per journal the template. 3. Contents of the paper are fine and satisfactory. Author (s) can make rectification in the final paper but after the final submission to the journal, rectification is not possible.

The Contribution of research work is as follows:

- This work presented an efficient motion and noise artifact detection and removal technique for pulse oximeter using Gait analysis (i.e., using accelerometer and gyroscope).
- Experiment outcome shows the proposed method can classify motion and noise artifact and OSA more accurately when compared with existing method.

The rest of the paper is organized as follows. In section II the proposed motion and noise artifact detection method is presented. In penultimate section experimental study is carried out. The conclusion and future work is described in last section.

I. Motion And Noise Artifacts Removal Technique Method For Pulse Oximeter Using Gait Analysis

The exiting methodology shows that motion artifact impacts the measurement of pulse oximetry and affect clinical research leading to false alarm [18], [19], and [20]. However, these model were tested using commercial software. There exist measurement error considering various pulse oximetry signal processing methods, including template, averaging or bias correlation methods. This work considers more generic and adaptive design to underline the effects of motion artifacts on pulse oximetry readings. This work first present a SpO2 measurement model considering the impact of artifacts. Secondly present a **data preprocessing** model to obtain PPG signal with and without artifact using adaptive filter model. Further present a **batch or template selection model** using adaptive threshold model to obtain derivative of correlation coefficient for labelling artifact and without artifacts. Then, improved support vector machine model is presented which takes these input feature with labelled class for training. Lastly, improved support vector machine perform classification considering various kind of data. The architecture of proposed hybrid architecture for artifact detection on PPG signal using improved Support Vector Machine Model is shown in Fig. 1.

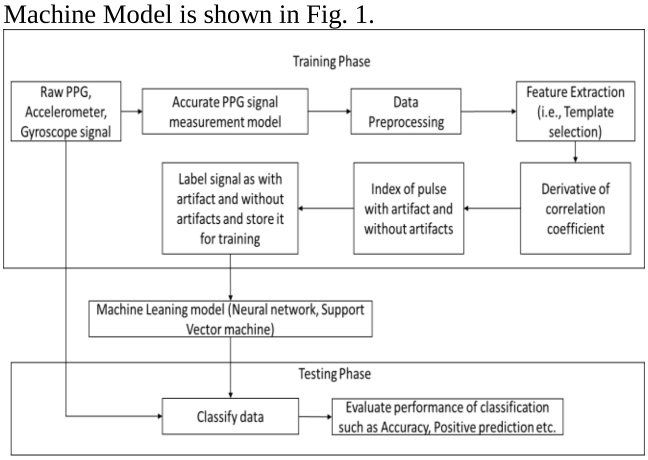

Figure I.1 The architecture for artifact detection on PPG signal using machine learning model.

a) SpO2 measurement, adaptive filter, and peak tracking model:

The arterial oxygen saturation can be derived using [21] and normalized optical density ratio or ratio of absorbance [22] is obtained as follows

$$\mathcal{R}_{rd} = \frac{\mathcal{AC}_{\mathcal{R}}/\mathcal{DC}_{\mathcal{R}}}{\mathcal{AC}_{\mathcal{I}}/\mathcal{DC}_{\mathcal{I}}} \tag{1}$$

where $\mathcal{DC}$ and $\mathcal{AC}$ are amplitudes of direct current component and alternating current components respectively, $\mathcal{R}$ and $\mathcal{I}$ depicts red light and infrared light channel respectively. This work considers frequency domain ratio of absorbance at heart beat rather than measuring at alternating current components which is obtained as follows

$$\mathcal{R}_{rd} = \frac{Q_{\mathcal{R}}(e_{hr})/\mathcal{DC}_{\mathcal{R}}}{Q_{\mathcal{I}}(e_{hr})/\mathcal{DC}_{\mathcal{I}}} \tag{2}$$

where e_{hr} is frequency per beat corresponding to harmonic, $Q_{\mathcal{R}}(e_{hr})$ and $Q_{\mathcal{I}}(e_{hr})$ are signal power at frequency e_{hr}. The relationship of e_{hr} with respect to SpO2 calculation is obtained as follows

$$SpO2 = h(\mathcal{R}(e_{hr}))$$

where h is the linear fitted calibration curve.

The photoplethysmography signal has been designed as combination of motion artifact affected signal and clean signal [23], [24], and [25]. These design are considered to correct but are far from accurate considering real-time object (person) specific environment. As a result, the spectrum of clean photoplethysmography signal, the power of the photoplethysmography signal primarily dispenses in the initial set of harmonics (three harmonic sets) of the HR frequency, which shows that we can obtain more perfect and accurate spectrum computation or estimates by applying a parametric spectrum methodology.

This work considers a empirical signal model, in which the interference are of following three classes such as, firstly, abnormal or arbitrary motion artifacts that causes non-periodic interferences, secondly, normal motion artifacts that resembles periodic interference and lastly, unavoidable additive white Gaussian noise when perfusion parameter is less. The PPG signal model is derived based on the case study considered made in [24], [26], in which the pulsatile segment and non-pulsatile segment are considered to possess diverse/dissimilar optical absorption ratio (OBR) s_b ands_w. Based on the method presented in [24] the infrared component $\mathcal{I}$ and Red component $\mathcal{R}$ are measured as follows

$$\mathcal{I} = \mathcal{S} + \mathcal{M} \tag{4}$$

$$\mathcal{R} = s_b * \mathcal{S} + s_w + \mathcal{M} \tag{5}$$

where $\mathcal{S}$ represent signal and $\mathcal{M}$ represent motion.

However, our approach considers PPG (heart rate specific Spo2) harmonic components for modelling signal which is obtained as follows

$$i(g, \beta) = b\cos(2\pi g u + \beta), \tag{6}$$

Where b , β , and g depicts the amplitude, phase, and frequency of the i respectively. Considering N motion harmonics and Q PPG sample (heart beat specific Spo2), the motion and signal related component is estimated as follows

$$\mathcal{M} = \mathcal{M}_{normal} + \mathcal{M}_{abnormal} \tag{7}$$

$$= \sum_{j=Q+1}^{N+Q} i_j(g_j, \beta_j) + n(u)$$

$$\mathcal{S} = \sum_{j=Q+1}^{N+Q} i_j(g_j, \beta_j) \tag{8}$$

Where $n(u)$ depicts abnormal motion.

Adaptive filter Model for detecting motion artifacts: For building an adaptive filters, this work considers using stochastic gradient decent (.i.e., here the filters coefficient$i(o)$ are simplified based on least mean error $f(o)$ at present instance of time) similar to Least mean squares (LMS) [27].

The expected reference signal of motion artifacts signal is used for filtering purposes. The stochastic gradient decent are obtained as follows

$$v(o) = [v(o), v(o-1) \dots v(o-n+1)]^U \tag{9}$$

$$i(o+1) = i(o) + \delta . f^{*}(o). v(o)$$

$$f(o) = e(o) - i^{I}(o). v(o)$$

where $v(o)$, $f(o)$, $e(o)$ are input, error induced signal and expected output respectively. Whereas δ depicts step length to be used in adaptive filter and $i(o)$ are the weights of the computed filter.

Signal peak and adaptive threshold modeling: Slope Sum Mechanism (SSM) is utilized for enhancing ascending segment of photoplethysmography signal while it decline descending segment of these signals. The, each signals is transpired further into a Slope Sum Method signals for identifying upper limits and track it utilizing proposed strategy which is adaptive in nature. The onset and offset of each signals is first established considering certain window size. Then upper limit are detected considering offset and onset of each and every signals. The SSM of a given instance of time u is obtained as follows

$$\mathbb{S}_u = \sum_{l=u-x}^{u} \varphi v_l \tag{10}$$

If $\varphi y_l > 0$ then φv_l is set as follows

$$\varphi v_l = \varphi y_l \tag{11}$$

If $\varphi y_l < 0$ then φv_l is set as follows

$$\varphi v_l = 0 \tag{12}$$

where φv_l depicts outcome of the low pass filter, and x depicts chosen window size. This work considers a window size of 3 seconds for peak tracking. Firstly, we measure the peak value of PPG keeping subject at rest for estimating initial threshold according to [28]. Utilizing these initial threshold, the forthcoming window upper limits is computed utilizing proposed threshold model which is adaptive in nature. In each windows iteration update, the threshold parameter is optimized and upper limits computation lasts till computation of all signals is completed. In scenario of lost upper limits, the preceding parameter is kept for aiding computing peak parameter of the missing or next window.

b) Motion and noise artifacts removal method:

By perceiving the morphology structure of a photoplethysmography waveforms, it can see slight variation in amplitude and shape and the pulse with identical forms. A pulse is a signal part among any two consecutive minima. In circumstance of presence of artifacts due to noise or motion, the shape of those pulses rapidly varies rapidly or abruptly. As shown in [29] and [30], using template/batch and comparing metrics of these batches aid in performance improvement. This work present a design to enhance automatic batch estimation and to perform comparative analysis among pulse and the template, this work use CC derivatives parameters, that follows the modification of pulse morphological structure. Lastly, we include arbitrary distortion testing to obtain optimal strategy for attaining adaptive threshold.

Data preprocessing: the database is obtained from [31] which composed of PPG signal. The data was collected with hand held fixed on a table top for 20 seconds and later certain movement is performed for another 20 second an PPG signals are collected. PPG signals are collected with selection ratio of thousand hertz and signal are filtered using proposed adaptive filter model presented in above section. **Pulse segmentation:** Pulse-to-pulse (P2P) session U_F is considered to be inverse of the heart frequency and it varies with respect to time. This frequency may match with determined upper limit of 0.5 to 3 Hertz when using Fourier transformation of the Photoplethysmographic. Then, window size (WS) of M is considered for estimation of local HR frequencies $g_{\mathcal{H}}$. To overcome error corresponding to local determined upper limits due to diastolic peak (distortion) [32], using moving average that depicts heart beats with respect to SpO2 areas, a block of interest are generated. Therefore, the block bounds are the minima of the corresponding signal $y_{\mathcal{A}}$ which is computed as follows.

$$y_{\mathcal{A}} = \frac{1}{\mathcal{X}}\left(y\left(\frac{o-x-1}{2}\right) + \cdots + y(o) + \cdots + y\left(\frac{o-x-1}{2}\right)\right)$$

where o is the signal features size, $\mathcal{X} = \frac{U_F}{2} = \frac{1}{2g_{\mathcal{H}}}$ is the window size of the moving average, and y depicts the size of PPG signal. The pulse maxima is a minimum parameter of $y(o)$ in each segment due to delay incurred by moving average. Therefore, the pulse extracted are maximum with respect to $\frac{U_F}{2}$. **Batch or template construction:** In each window, pulse batch $\mathcal{P}_{\mathcal{T}}$ is constructed by averaging entire pulses obtained from considered window. The CC $\mathcal{C}_j(o)$ among each pulse $\mathcal{P}(o)$ and $\mathcal{P}_{\mathcal{T}}$ of the considered window are computed. For attaining good accurateness performance, the pulse batch should be computed in most stable (adaptive) window. Then, the concluding pulse batch $\mathcal{P}$ is one with max average $\mathcal{C}_j$. **Artifact identification for labelling:** Post obtaining ideal $\mathcal{P}$, a comparative analysis among $\mathcal{P}$ and all pulses in batch list is performed. That is, considering a pulse of index or list, this work identify its upper limit with respect to the batch. From both direction of this upper limit, we chose $\frac{U_F}{2}$ samples, where U_F is the size of batch. The $\mathcal{C}$ is then computed among batch and the segment of these pulses. When motion artifacts arises, the $\mathcal{C}$ of these pulse is impacted and has low parameter values than those of clean signal. For computing these $\mathcal{C}$ variation derivative $\mathcal{DC}_l$ is used and thresholding is required for decision. But variation among different individual affects photoplethysmography features. As a result, having fixed threshold for all photoplethysmography signals is not practicable. To overcome, adaptive threshold modelling presented in above section is used. Further, to identify and label the signal are with artifact on without artifacts using adaptive threshold model. This work computes $\mathcal{DC}_l$ for pulse l and considers $\mathcal{DC}_l = \mathcal{DC}^0{}_l + y_l \sim O(0, \alpha^2)$ and $\mathcal{DC}^0{}_l$ is the true $\mathcal{DC}_l$. Further checks $|\mathcal{DC}^0{}_l| \leq \mathbb{T}$ over $|\mathcal{DC}^0{}_l| > \mathbb{T}$. i.e., if $|\mathcal{DC}_l| > \mathbb{Q}$, then

$$\mathcal{L}_{\mathcal{A}} = 1, presence\ of\ artifact \tag{14}$$

if $|\mathcal{DC}_l| \leq \mathbb{Q}$, then

$$\mathcal{L}_{\mathcal{A}} = 0, no\ presence\ of\ artifacts \quad (15)$$

where $\mathbb{Q}$ is threshold which can be obtained as follows

$$\mathbb{Q} = \alpha\gamma_{\omega}\left(\frac{\mathbb{T}}{\alpha}\right) \quad (16)$$

In which $\gamma_{\omega}(n)$ is the adaptive solution to Eq. (13), α is the variance of the additive noise, ω is false alarm rate, and $\mathbb{T}$ is the tolerance.

c) Improved machine learning classification model:

The improved support vector machine first extract features of normal PPG data and PPG with artifacts as training parameter which are labeled (withoutArtifact: 0, and withArtifact: 1). The support vector machine then trains the model utilizing labelled feature sets and collects support vector (SV) amongst features sets which exploits (i.e., maximizes) the space between different set of class set considered. Then, the support vector machine builds a decision constraint or boundaries (DB) utilizing the obtained SV's. If the estimated result using the decision boundary is dissimilar from its trained set class type. Then, the outcome is said to be as training inaccuracy or error. Thus, for addressing these circumstances, a soft-margin SVM is considered. This aid in fixing boundary even when the training set cannot be fragmented and are mixed. For minimizing training error and maximizing margin a slack parameters is introduced. For evaluating SV utilizing improved support vector machine method described using below equation

$$\min \mathbb{D} \sum_{z=1}^{\mathbb{O}} \mu_z + \frac{1}{2}\langle u_t, u_t \rangle, \quad (17)$$

Such that it meets following condition $\mathbb{U}_z(\langle u_t, z_z \rangle + \mathbb{c}_t) \geq 1 = \mu_z \ \forall z = 1,2,3, \dots, \mathbb{O}$, & $\mu_z \geq 0$

where $\mathbb{O}$ depicts the amount of vector utilized, $\boldsymbol{\mu_z}$ **is the slack parameter**, $\mathbb{D}$ is regulation variable, u_t is the threshold or weight vectors, and $<.,.>$ depicts inner product operation. The $\mathbb{U}_z$ depicts z^{th} target outcome value, $\mathbb{c}_t$ depicts biasing parameter, and z_z depicts z^{th} input param. The support vector machine DB $\mathbb{G}_z$ is described as

$$\mathbb{G}_z = \langle u_t^*, z \rangle + \mathbb{c}_t^* = 0 \quad (18)$$

where z is the input feature, u_t^* represent weight vector, and $\mathbb{c}_t^*$ depicts **bias paramete**r. By emerging the z_z and z term to $z_z \rightarrow (z_z)$ and $z \rightarrow (z)$, the improved support vector machine is converted to linear SVM classification model using following equation

$$\mathbb{U}_z(\langle u_t, (z_z) \rangle + \mathbb{c}_t) \geq 1 \quad (19)$$

Then, for performing classification or testing utilizing improved support vector machine, a kernel operation $\mathbb{L}_t(.,.)$ is introduced. The kernel operation is a dot-product (DP) in the transformed feature vector boundaries which is described using following equation

$$\mathbb{L}_t(z_z, z_{z'}) = \langle (z_z), (z_{z'}) \rangle \quad (20)$$

where $z_{z'} = 1,2, \dots, \mathbb{O}$.

Lastly, using improved support vector machine classification method is assessed using different PPG dataset that consist of signal data of dynamic motion specific information or dataset. The improved support vector machine based approach can efficiently classify these signal when compared with existing approach which is proven experimentally in below section.

II. SIMULATION RESULT AND ANALYSIS

This section presents experiment analysis of proposed motion artifact detection model performance using improved support vector machine classifier over exiting classifier model [4], [10], [33], [34], [35], and [36]. The system environment used for experiment analysis is Windows 10 enterprises edition, Intel Pentium I-7 class Quad core processor, 16 gigabits memory, and NVIDIA graphical processing unit that has CUDA compatibility. The improved support vector machine model is implemented using C# library and Python 3. The performances is evaluated in terms of accuracy, sensitivity, specificity and positive prediction. This work use accuracy, sensitivity, specificity and positive prediction to evaluate performance. The Accuracy is calculated as follows

$$Accuracy\,(A_c) = \frac{TP * TN}{TP + TN + FP + FN} \quad (21)$$

The specificity is calculated as follows

$$Specificity\ (S_p) = \frac{TN}{TN + FP} \quad (22)$$

The sensitivity is calculated as follows

$$Sensitivity\,(S_n) = \frac{TP}{TP + FN} \quad (23)$$

The positive prediction is calculated as follows

$$Positive\ Prediction\,(P_p) = \frac{TP}{TP + FP} \quad (24)$$

For experiment analysis the database is obtained from [31], [38] which composed of PPG signal. The data was collected with hand held fixed on a table top for 20 seconds and later certain movement is performed for another 20 second an PPG signals are collected. PPG signals are collected at a sampling rate of 1000 Hz and signals were filtered using as per Allen [37] with a pass band between 0.05 - 5 Hz [37] using first-order band-pass Butterworth filter. The First-Order Butterworth Filter whose frequency response is preferred as it is flat over the passband region. Low pass filter produces constant output from DC up to cutoff frequency and rejects all signals above the frequency

a) ROC performance evaluation:

The Fig. 2, depicts the outcome attained by proposed model in identifying, detecting motion artifacts and eliminating motion and obtain clean PPG signal where x-axis depicts time and y-axis depict ppg outcomes (mv). The blue signal depicts PPG signal with motion artifacts and the red signal is the clean PPG signal obtained by proposed design. These result are fed into improved SVM classifier for automatic and accurate detection and classification of motion artifacts and various kind of diseases and deficiencies. This work further compares proposed outcome over exiting model.

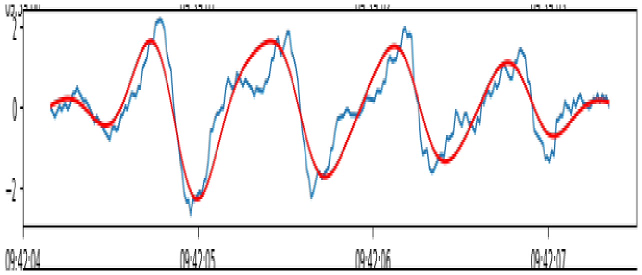

Fig. 2 Outcome attained by proposed model in identifying, detecting motion artifacts and eliminating motion and obtain clean PPG signal.

Experiments are conducted to detect and remove motion and noise artifact. In [4] presented a fusion model and attained a sensitivity performance of 75.46%, specificity performance of 83.35%, and accuracy performance of 81.56% considering experiment for SpO2 detection. In [10] presented a classifier model using SVM to distinguish between MNA-corrupted and MNA-free PPG data. The model attained accuracy, sensitivity, and specificity improvement of 92.0%, 93.0%, and 90.0% respectively. In our model we attained accuracy of 95.98%, sensitivity of 94.7%, specificity of 97.6% and positive perdition of 98.58% performance is attained. The experiment outcome of proposed and its comparison with state-of-art classification method is presented in Table 1. The overall result achieved demonstrates the efficiency of proposed hybrid design/method using improved support vector machine classification model over state-of-art technique.

Table 1 Performance evaluation overstate of art technique for detecting motion artifacts

Authors/Ref No.	Accuracy	Sensitivity	Specificity	Positive prediction
Gutta et al., [4]	81.56%	75.46	83.35%	-
Dao et al., [10]	92.00%	93.00%	90.00%	-
Our approach	**95.98%**	**94.70%**	**97.60%**	**98.58%**

Further, experiment is carried out to detect people suffering from sleep apnoea. For experiment analysis, classification of apnoea and its severity, similar setup as in [33], [34] is considered. In [33] performed classification task of detecting people suffering from sleep hypopnea and sleep apnea condition. For detecting both sleep hypopnea and sleep apnea condition they considered rigorousness of Sleep-disordered breathing (SDB). For performing classification they used SVM classification model to categorize or group severity (i.e., affected level) of SDB. The outcome attained shows a positivity predicted (PP) and sensitivity outcomes of 63.4%and 87.5% for performing classification of hypopnea, 87.5% and 74.2% for performing classification of apnea, and 92.8% and 92.4% for hypopnea + apnea, respectively. In [34] showed that utilizing Apnea Hypopnea Index it is better to classify the severe nature of SAHS (Sleep Apnea-Hypopnea Syndrome) utilizing Polysomnography signal information. The results show an Accuracy, Specificity, Sensitivity of 88.61%, 64.29% 93.85% using Least Square Support Vector Machines (LS-SVM). In [4] presented a fusion model and attained a sensitivity performance of 75.46%, specificity performance of 83.35%, and accuracy performance of 81.56% considering experiment for SpO2 detection. In our model we attained accuracy of 95.64%, sensitivity of 94.17%, specificity of 97.2% and positive perdition of 98.27% performance is attained for apnea classification. The experiment outcome of proposed and its comparison with state-of-art classification method is presented in Table 2. The overall result achieved demonstrates the efficiency of proposed hybrid method using improved support vector machine classification model over state-of-art technique for classifying sleep apnea.

Table 2 Performance evaluation over state-of-art technique for detecting sleep apnea

Authors/Ref No.	Accuracy	Sensitivity	Specificity	Positive prediction
Park et al. , [33]	-	84.73%	-	81.23%
Morales et al., [34]	88.61%	93.85%	64.29%	-
Gutierrez et al., [35]	85.255	-	-	-
Gutta et al., [4]	81.56%	75.46	83.35%	-
Er denebayar et al., [36]	74.47%	76.20%	76.39%	-
Our approach	**95.64%**	**94.17%**	**97.20%**	**98.27%**

III. CONCLUSION

MNA induces constraint on the applicability of the Photoplethysmograph especially in the case study of ubiquitous computing and ambulatory screening or observation, SAHS, SDB, and sleep disorder detection. MNA can affects the quality (i.e., induces noise) Photoplethysmograph. As a result, it induces inaccurate computation or quantification of physiological information SPO2 levels and HR. This, chapter studied and presented an efficient method for detection of artifacts. Firstly, this work present an adaptive filter and adaptive threshold model to detect artifact and obtain derivative of correlation coefficient for labelling artifacts respectively. Lastly, improved support vector machine Model is presented to perform classification. Experiment are conducted on both real-time and simulated dataset set. Our approach attain significant performance in term of accuracy of 95.98%, sensitivity of 94.7%, specificity of 97.6% and positive perdition of 98.58% is attained. Further, experiment are conducted to evaluate sleep apnea detection. The outcome shows the hybrid model attained accuracy of 95.64%, sensitivity of 94.17%, specificity of 97.2% and positive perdition of 98.27% performance is attained for apnea classification.

Future work would consider building low complexity gait analysis using deep learning technique (i.e., using RNN, CNN) for efficiently detecting user's motion artifacts such as walking, running etc. This will aid in providing efficient health care (i.e., detecting and diagnosis of OSA) service to user/patient remotely using smart phones.

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AUTHORS PROFILE

S.Pushpalatha is a Research Scholar from Dr.Ambedkar institute of Technology, Bengaluru. I have completed my M.Tech from VTU, presently pursuing research work in machine learning techniques, under the guidance of Dr. Shrishail Math, Prof at SKIT, Bengaluru.

Dr. Shrishail Math Prof from Sri Krishna Institute of Technology, Bengaluru. Presently guiding many students in Research areas like Computer Vision, computer forensicsand information security and assurance. He has presented and published many papers in many international journals. He is a life member for many professional bodies like ISTE(Indian Society for technical education), IAENG(International Association of Engineers), Internation Association of Computer science and information Technology(IACSIT).