Motion Artifact Detection Model using Machine Learning Technique for Classifying Abnormalities in Human Being

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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. The motion artifact signal is established to resemble similar to an additive noise. 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 research challenges, this manuscript present a novel hybrid approach for detection of artifacts. Firstly, this work present an accurate SpO2 measurement model. Secondly, present an adaptive filter and adaptive threshold model to detect artifact and obtain derivative of correlation coefficient (CC) for labelling artifacts respectively. Lastly, Enhanced Support Vector Machine (ESVM) Model is presented to perform classification. Experiment are conducted on both real-time and simulated dataset set. Our hybrid approach attain significant performance in term of accuracy, sensitivity, specificity and positive prediction.

Keywords: Artifact detection, Machine learning, PPG, SVM.

I. INTRODUCTION

Photoplethysmographic (PPG) signals are some of the main physiological signals used for assessing oxygen carrying hemoglobin level in Heart Rate (HR) and blood [1]. The SpO2 value given by the pulse oximeter shall be used in measuring or showing some symptoms [2] such as hypoxemia [3], pulmonary embolism (PE) [4], congenital heart disease (CTD) [5], lower extremity arterial disease (LEAD) [6], acute heart failure (CTF) [7], and chronic obstructive pulmonary disease (COPD) [8]. Other than measuring the symptoms, the pulse oximeter shall be possibly used in assessing testicular torsion (TT) [9] and pulp vitality (PV) [10] also.

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For obtaining these signals (oxygen carrying hemoglobin level in heart rate and blood), the. ultimate modest, cost effective and broadly used noninvasive method is pulse oximetry. By means of this method, PPG signals are acquired by using a minor wearable device which is easily adjustable on forehead or on the finger tips. LED light of particular wavelength is brightened on one side of the wearer’s finger. As the light travels through the finger, some of the light is captivated in the skin tissues whereas the left over is sensed by a sensor on another side of the device. As the captivated light’s power is reliant on the blood flow. The capacity of blood in the arteries fluctuates along with the heart pulse, therefore the light sensed by the sensor also differs resulting in a periodic signal that is used to measure HR. As PPG signals are extremely prone to motion artifact because of body movement, so even a smallest change sensed by these devices can misrepresent the PPG signal which affects hemoglobin level in blood and HR information [11].

To identify and remove mild motion artifacts from multiple signal processing units, a new algorithm is developed and processed, and use of in which finger movements sensed or a minor glitch in body position are stored [12], [13] Likewise, in [12] modified active adaptive noise filtering algorithm is used for eliminating motion artifacts, however it is reliant on the selection of listed signals. Independent component analysis (ICA) described in [14] is relatively similar in effecting eliminating motion artifacts. Other than verifying from patients HR, with the research on PPG signals from various data sets and doctors review PPG signals are extremely adaptive to motion artifact because of human body instability. Due to that a micro distortion sensed by the embedded system(device) can misrepresent PPG signals and that affects the hemoglobin level in blood and HR information [11].

Numerous methods [15], [16] are been explained in the literature for extraction of respiratory rate (RR) and heart rate (HR) and from Photoplethysmographic signals. But then again signal and ecological artifacts cause falsifications in Photoplethysmographic signal, which makes inaccurate assessment of respiratory rate and heart rate. It is mandatory to have complete mechanized embedded system, it is vital to make an extra module which permits to sense sections which are not functional for valuation due to artifacts noise/distortions. These two methods for controlling motion artifacts has offered by the state of work.
Primary one was to build based on filtering means which is adaptive in nature mechanism [17], empirical mode decomposition technique [18], and wavelet transformation method [19]. These approaches have great computational difficulty. They are restricted to boundaries of performance since there is no static model existing both for Photoplethysmographic or artifacts. Even bad, valuable info regarding respiratory and heart contraction and relaxation activities can be skipped when introducing filters, even if it is a sanitized portion of Photoplethysmographic. Signal of rich quality metrics are considered and allocated to pulses such that only worthy pulses are stored. Classification based models that cumulate multiple signal morphology structures are utilized in [20], that includes examining signals and wave’s morphology and assigning to multiple pulse signal in rich quality metrics, but, the approaches need huge demonstrative labeled database for testing and training problems. They appears barely possible for the real objective as of great difference amid prospect and ambiance methods as well extended period of time required for expert to tag signals, additional strategy is based on DT (decision tree) and predetermined thresholds and later used to choose if particular signal/pulse matched to referral value by formulating the Euclidean space. Numerous predetermined threshold are later used to opt a particular signal/pulse can be considered or declined. These technique are unable to be combined in stand-alone method as layout and thresholds are physically secured. Besides, research offered doesn’t take under consideration of HR fluctuation with respect to SpO2 that has a straight result/consequences on the pulse shape.

All the stated means are beneficial but they have more or less other drawback. That is, they consume higher computation time and computational cost, and suffers from eradicating of motion artifacts. The drive of this study is to offer an effective process of eliminating motion artifacts, in which concurrent three-axis acceleration data is attained and are utilized for calculating time and level of motion artifact in Photoplethysmographic signal and efficiently screen SpO2 and heart rate in intense exercise (12-15 km/hr) that is running by the subject.

To overcome the research challenges, this work firstly present an accurate 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, ESVM model is presented which takes these input feature with labelled class for training. Lastly, ESVM perform classification considering various kind of data.

The Contribution of research work is as follows:

- This work presented an accurate SpO2 measurement.
- Further presented adaptive filter and adaptive threshold model for identifying artifact and obtain derivative of correlation coefficient for labelling artifacts respectively.
- This manuscript presented a novel classification method namely ESVM for artifact detection, ambulatory monitoring and sleep disorder detection.
- Our model attain superior performance in terms of Accuracy, specificity, sensitivity, and positive prediction.

The rest of the paper is organized as follows. In section II, the proposed hybrid motion artifacts detection model using enhance support vector machine classifier is presented. In penultimate section experimental study is carried out. The conclusion and future work is described in last section.

II. HYBRID MOTION ARTIFACT DETECTION MODEL USING ENHANCED SUPPORT VECTOR MACHINE CLASSIFIER

The exiting methodology shows that motion artifact impacts the measurement of pulse oximetry and affect clinical research leading to false alarm [22], [23], and [24]. However, these model were tested using commercial software (i.e., using proprietary signal processing algorithms). 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 presence of MA on pulse oximetry interpretations. The exiting SpO2 measure model are designed without considering error mitigation technique due presence of artifacts. This work firstly present an accurate 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, ESVM model is presented which takes these input feature with labelled class for training. Lastly, ESVM perform classification considering various kind of data. The architecture of proposed hybrid architecture for artifact detection on PPG signal using Enhanced Support Vector Machine Model is shown in Fig. 1.
Fig. 1. Hybrid Architecture For Artifact Detection On PPG Signal Using Enhanced Support Vector Machine Model.

**a) SPO2 computation optimization considering the presence motion artifact:**

The arterial oxygen saturation can be derived using [25] and normalized optical density ratio or ratio of absorbance [26] is obtained as follows

\[
R_{ed} = \frac{AC_g/DC_g}{AC_c/DC_c}
\]

(1)

where \( DC \) and \( AC \) are amplitudes of direct current component and alternating current components respectively, \( R \) and \( J \) 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

\[
R_{ed} = \frac{Q_{f,n} e^{j\gamma f,n}}{Q_{f,hr} e^{j\gamma f,hr}}
\]

(2)

where \( e_{hr} \) is frequency per beat corresponding to harmonic, \( Q_{f,n} e^{j\gamma f,n} \) and \( Q_{f,hr} e^{j\gamma f,hr} \) are signal power at frequency \( e_{hr} \). The relationship of \( e_{hr} \) with respect to SpO2 calculation is obtained as follows

\[
Z = h R_{e_{hr}}
\]

(3)

where \( h \) depicts linear fitted calibration curve (LFCC).

The photoplethysmography signal has been designed as combination of motion artifact affected signal and clean signal [27], [28], and [29]. These design are considered to correct but are far from accurate considering real-time object (person) specific environment. As a result, the spectrum of good photoplethysmography signals and the control of these photoplethysmography signals primarily allocates in the initial set of harmonics (three harmonic sets) of the HR frequency. Thus, it shows that it can obtain extra perfect and exact spectrum computation or estimates by using a parametric spectrum methodology.

This work considers a empirical signal method in which the interference are of following three classes are describes below. Firstly, abnormal or arbitrary motion artifacts that causes non-periodic interferences, secondly, normal motion artifacts that resembles periodic interference and lastly, unavoidable Gaussian noise (GN) when fluid parameter (i.e., passage of fluid through tissue) is less. The PPG signal model is derived based on the conventions considered by the researcher in [27], [30]. Here, they considered that the non-pulsating and pulsating segments has been considered to possess dissimilar/varied optical absorption rate (OAR) \( s_b \) and \( s_w \). Based on the model presented in [27] the infrared component \( J \) and Red component \( R \) are measured as follows

\[
J = S + M
\]

(4)

\[
R = S_b * S + s_w + M
\]

(5)

where \( S \) represent signal and \( M \) represent motion. However, our approach considers PPG (heart rate specific Spo2) harmonic components for modelling signal which is obtained as follows

\[
g = b \cos 2\pi gu + \beta
\]

(6)

where \( b, \beta \), 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

\[
M = M_{\text{normal}} + M_{\text{abnormal}}
\]

(7)

\[
= \sum_{i=Q+1}^{N+Q} i g[i] \beta[i] + nu
\]

(8)

where \( nu \) depicts abnormal motion. This work further normalizes the model by relaxing the component in motion possess same \( s_b \) and component in signal possess same \( s_w \) due to the presence of colored noises, every abnormal motion artifacts/harmonic set has specific respective \( s_i \) in our approach. Let consider that that the both signal is composed of white noise \( xu \) with same power \( \alpha^2 \), the signal in our approach can be estimated as follows

\[
J = \sum_{i=1}^{Q} s[i] g[i] \beta[i] + \sum_{i=Q+1}^{N+Q} s[i] g[i] \beta[i] + xu + nu
\]

(9)

\[
R = \sum_{i=1}^{Q} i g[i] \beta[i] + \sum_{i=Q+1}^{N+Q} i g[i] \beta[i] + s_{Q+N+1} nu +
\]

(10)

**b) 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 to are simplified based on least mean error
The expected reference signal of motion artifacts signal is used for filtering purposes. The stochastic gradient descent are obtained as follows

\[
vo = (vo, vo - 1 \ldots vo - n + 1)^T \\
0 + 1 = io + \delta t o vo \\
en o - i_0.
\]

where \( vo, fo, eo \) are input, error induced signal and expected output respectively. Whereas \( \delta \) depicts step length to be used in adaptive filter and \( io \) is the weights of the computed filter. The \( \delta \) defines how adaptive filter coverages that is directly related on weight optimization. Larger the size of \( \delta \) is choosed, the gradient decent with respect to weight will result in high amplitude wavering near optimal parameter, that result in less accuracy and higher mean square error or vice versa. Therefore, optimization to bring good tradeoff for computing coefficient using an arbitrary PPG signal with minimum undesirable noise is expressed as follows

\[
zDo = x^o o, vo : Output construction \\
fo = eozDo Error computation:
\]

\[
vo + 1 = wo + \delta vD' o : Weight optimization
\]

In Eq. (12), \( d^o_j \) depicts coefficient of computed filter for optimization. Now stability and convergence are impacted by the reference signal \( v^o_0 \) with delay incurred with respect to both forward paths [31], One of the parameter of these filter is used for adaptive filtering block.

**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 \( t \) is obtained as follows

\[
S_n = \sum_{t=x}^{t=y} v^t
\]

If \( v^t > 0 \) then \( v^t \) is set as follows

\[
v^n = v^t
\]

If \( v^t < 0 \) then \( v^t \) is set as follows

\[
v^n = 0
\]

where \( v^t \) 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 [32]. 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.

**Research methodology:**

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 [33] and [34], 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 [35] which composed of PPG signals. 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 \( U_p \) 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 \( g_\nu \). To overcome error corresponding to local determined upper limits due to diastolic peak (distortion) [36], 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 \( y_a \) which is computed as follows

\[
y_a = \frac{1}{2} y^{o-x-1} + \cdots + y^o + \cdots + y^o-x-1
\]

where \( o \) is the signal features size, \( \chi = \frac{v^o_p}{2} \) is the window size of the moving average, and \( y \) depicts the size of PPG signal. The pulse maxima is a minimum parameter of \( y_0 \) in each segment due to delay incurred by moving average. Therefore, the pulse extracted are maximum with respect to \( v^o_0 \).

**Batch or template construction:** In each window, pulse batch \( \mathcal{P} \) is constructed by averaging entire pulses obtained from considered window. The CC \( C_\nu \) among each pulse \( \mathcal{P}_o \) and \( \mathcal{P}_T \) 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 \( C_\nu \).

**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 \( \frac{v^o_0}{U_p} \) samples, where \( U_p \) is the size of batch. The \( C \) is then computed among batch and the segment of these pulses. When motion artifacts arises, the \( C \) of these pulse is impacted and has low parameter values than those of clean signal. For computing these \( C \) variation derivative.
$\mathcal{D}_i$ 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 $\mathcal{D}_i$ for pulse $l$ and considers $\mathcal{D}_i = \mathcal{D}_i^0 + y_l \sim 0, \alpha^2$ and $\mathcal{D}_i^0$ is the true $\mathcal{D}_i$. Further checks $|\mathcal{D}_i^0| \leq T$ over $|\mathcal{D}_i^0| > T$, i.e., if $|\mathcal{D}_i| > Q$, then $L_d = 1$, presence of artifact (17) if $|\mathcal{D}_i| \leq Q$, then $L_d = 0$, no presence of artifacts (18)

Where $Q$ is threshold which can be obtained as follows

$Q = Q \alpha \gamma$ (19)

In which $\gamma, n$ is the adaptive solution to Eq. (16), $\alpha$ is the variance of the additive noise, $\omega$ is false alarm rate, and $T$ is the tolerance.

Classifier construction using enhanced support vector machine:

The enhanced support vector machine first extract features of normal PPG data and PPG with artifacts as training parameter which are labeled (without Artifact: 0, and with Artifact: 1). The support vector machine then trains the model utilizing labelled feature sets and collects support vector among features sets that maximize the distance among different set of classes considered. Then, the support vector machine builds a decision boundary from the obtained support vectors. If the estimated result from the decision boundary is dissimilar from its trained set label, the outcome is said to be as training error. For addressing such 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 parameter is introduced. For evaluating support vector using ESVM model is obtained as follows

$$\min \sum_{i=1}^{m} \mu_i + \frac{1}{2} \langle u, u \rangle,$$ (20)

Such that $u_i \langle u, z \rangle + c_i \geq 1$ for $z = 1, 2, 3, ..., D$, and $\mu_i \geq 0$

Where $\mathbb{D}$ is the number of vectors, $\mu_i$ is the slack parameter, $\mathbb{D}$ is regulation variable, $u$ is the weight vector, and $\langle u, \cdot \rangle$ is the inner product function. $u_i$ is the $z^{th}$ target parameter, $c_i$ is the bias, and $z$ is the $z^{th}$ input parameter. The support vector machine $\mathbb{G}$ is described as

$$\mathbb{G} = \langle u, z \rangle + c_i = 0$$ (21)

where $z$ is the input feature, $u_1$ is the weight vector, and $c_i$ depicts bias parameter. By exchanging the $z$ and $z$ term to $z \rightarrow z$ and $z \rightarrow z$, the non-linear SVM (NL-SVM) (i.e., the ESVM) can be transformed to linear based SVM as follows

$$\mathbb{G} = \langle u_0, z \rangle + c_i \geq 1$$ (22)

Further, to make classification using ESVM, a kernel function $\mathbb{G}_k(z, z')$, which is a dot-product in the transpired feature vector space is described as

$$\mathbb{G}_k(z, z') = (z_\mu, z_\nu)$$ (23)

where $z_\mu = 1, 2, ..., D$.

Further, the ESVM model is assessed using different PPG data which is consist of signal data of different motion specific data. The ESCM based approach can efficiently classify these signal when compared with existing approach which is proven experimentally in below section.

### III. RESULT AND ANALYSIS

This section present experiment analysis of proposed motion artifact detection model performance using ESVM classifier over exiting classifier model [38-43]. The system environment used for experiment analysis is Windows 10 enterprises edition, Intel Pentium I-7 class Quad core processor, 16 GB RAM, and NVIDIA CUDA enabled GPU. The ESCM model is implemented using C# library and Python 3. The performances is evaluated in terms of Accuracy ($A_c$), Sensitivity ($S_n$), Specificity ($S_p$) and Positive Prediction ($P_p$). The Accuracy is calculated as follows

$$\text{Accuracy} A_c = \frac{TP+TN}{TP+TN+FP+FN}$$ (24)

The specificity is calculated as follows

$$\text{Specificity} S_p = \frac{TN}{TN+FP}$$ (25)

The sensitivity is calculated as follows

$$\text{Sensitivity} S_n = \frac{TP}{TP+FN}$$ (26)

The positive prediction is calculated as follows

$$\text{Positive Prediction} P_p = \frac{TP}{TP+FP}$$ (27)

For experiment analysis the database is obtained from [35] 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 [37] with a pass band between 0.05 - 5 Hz [37]. Further, we collect sample of different individual IR and R value using pulse oximeter. The Signal is composed of both with artifacts and without artifacts. Person age, BMI information are added and labeling of artifact and without artifact is done manually.

a) Performance evaluation considering varied experiments in terms of Accuracy, Specificity, Sensitivity and Positive Prediction:

The Figure 1, depicts the outcome attained by proposed model in identifying, detecting motion artifact and eliminating motion and obtain clean PPG signal. The blue signal depicts PPG signal with motion artifacts and the blue signal is the clean PPG signal obtained by proposed design. These result are fed into ESVM classifier for automatic and accurate detection and classification of motion artifact and various kind of diseases and deficiencies. This work further compares proposed outcome over exiting model.
In [38] performed classification of sleep apnea and sleep hypopnea conditions using varied categorizations based on rigorousness of SDB using SVM. The classification outcome attained by these model shows are evaluated in terms of sensitivity and positivity prediction. A sensitivity performances improvement of 74.2% and 87.5% is attained considering apnea and hypopnea, respectively. Then, positive prediction performance improvement of 87.5% and 63.4% for apnea and hypopnea, respectively. Similarly, considering both apnea + hypopnea, a sensitivity and positive prediction performance improvement of 92.4% and 92.8% is attained, respectively. In [39] showed Apnea Hypopnea Index describes the rigorousness of sleep apnea hypopnea symptoms utilizing the signals acquired using Polysomnography. The results show an Accuracy, Specificity, Sensitivity of 88.61%, 64.29% 93.85% using Least Square SVM. In [40] performed classification and analysis of pulse oximetry readings to forecast obtrusive sleep apnea rigorousness in kids. An accuracy of 85.255 is attained. In [41] presented a fusion model and attained an accuracy of 75.46%, 83.35%, 81.56% considering varied experiment for SpO2 and heart rate detection. In [42] 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 93.0% respectively. In [43] their model attained a mean specificity performance of 85.8%, 80.5%, and 80.0% for the minor, modest, and worst (rigorous) conditions, respectively. Then, attained a mean sensitivity 72.5%, 74.2%, and 71.5% for the minor, modest, and worst (rigorous) conditions, respectively. Similarly, attain a mean accuracy performance of 70.3%, 77.1%, and 71.9% for the minor, modest, and worst (rigorous) conditions, respectively. In our model we attained accuracy of 95.97%, sensitivity of 94.6%, specificity of 97.5% and positive prediction of 98.57% performance is attained. The future work we would consider performance evaluation considering varied dataset and further enhance the classification model.

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<th>Table.1 Performance Evaluation Over State of art Technique</th>
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<td><strong>Accuracy</strong></td>
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<td>Our approach</td>
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**IV. CONCLUSION**

Motion and noise artifacts enforce constraint on the usability of the Photoplethysmographic, predominantly in the setting of ambulatory observation and sleep disorder detection. Motion and noise artifacts can affect/falsify Photoplethysmographic, resulting inaccurate estimate of physiological information’s such as SpO2 and HR. In this manuscript, the work presented a new hybrid method for detection of artifacts. Firstly, this work present an accurate SpO2 measurement model. Secondly, present an adaptive filter and adaptive threshold model to detect artifact and obtain derivative of correlation coefficient for labelling artifacts respectively. Lastly, Enhanced Support Vector Machine (ESVM) Model is presented to perform classification. Experiment are conducted on both real-time and simulated dataset set. Our hybrid approach attain significant performance in term of accuracy of 95.97%, sensitivity of 94.6%, specificity of 97.5% and positive perdition of 98.57% is attained. The future work we would consider performance evaluation considering varied dataset and further enhance the classification model.

**REFERENCES**


