A Novel Non-Parametric Approach Of Tremor Detection Using Wrist-Based Photoplethysmograph

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***Abstract*—Pervasive detection and quantification of tremor for Parkinson's Disease (PD) patients, using Commercial Off-the-self (COTS) wrist-wearable device is an important problem to investigate. Parkinsonian tremor is one of the earliest and major surrogate biomarker which indicates the progress or status of the disease for patients under treatment using drugs or deep brain stimulation (DBS) therapy. However, it is a challenging issue as tremor occurs at the minor extremities like fingers in some cases such as pill-rolling symptom, the effect of the same on a wrist-worn motion sensor system is not significant enough to be captured. In this paper, we explore the possibility of using the wrist-based photoplethysmography (PPG) as a novel sensor modality in detecting tremor at rest. Our preliminary results gathered from healthy cohorts performing simulations of Parkinsonian tremor elucidates the merit of the proposed method. Also, since PPG acquisition is power-hungry, we have leveraged a conceptual method of compressive sensing to reduce the overall power requirement of the application.**

***Index Terms*—Parkinson's Disease, Tremor, Photoplethysmogram (PPG), SSA, Compressive Sensing**

I. Introduction

Parkinsons Disease (PD) is a progressive neurodegenerative condition that manifests via motor and non-motor dysfunction. After Alzheimer's, PD is the most prevalent neurological disorder that approximately affected 10 million people worldwide [1]. It primarily affects the Basal Ganglia and causes the dopamine depletion which leads to the neuro-motor symptoms. The symptoms associated with PD are characterized by TRAP – Tremor, Rigidity(muscular stiffness), Akinesia (a movement disorder) and Postural instability. Tremor especially the rest tremor is the most cardinal symptom occurs in earlier stages of PD. It is defined as an involuntarily rhythmic movement persists on various part of the body (usually a hand or the fingers) at rest. Especially, in rest tremors, the fingers are majorly affected and posses a symptom called pill-rolling. In pill-rolling symptoms the index finger tends to get into contact with the thumb; it seems that people are trying to roll a pill or any small object between the thumb and index finger. A pill-rolling tremor is the most apparent tremor associated with PD. Despite widely ongoing research, there is no known cure of PD; hence, it is only a manageable disease at present. The treatment procedure relies on the medications which yield symptomatic relief. As the disease progresses, the effect of medications gradually diminishes and the severity of symptoms aggravate. According to the severity of the symptoms, the dose of medications needs to be altered. Presently, the quantitative assessment of the symptoms are ascertained by the various rating scales such as Unified Parkinsons Disease Rating Scale(UPDRS) [2] or Hoehn & Yahr scale. The UPDRS scale is the most widely used assessment procedure, accomplished in the clinical environment by expert neurologists. The patient is asked to perform certain tasks and based on their performance, the neurologist assigns values according to the rating scale.

The major shortcoming of this procedure is the recurring visit to the clinic for assessment. This incurs substantial cost and causes inconvenience to the patient. Moreover, as this procedure is only employed in the clinical environment, the expert has to rely on self-reporting for the patient's condition in their daily life. For most of the cases, this self-reporting is erroneous and does not provide adequate information to the physician. Therefore, continuous remote assessment of the symptoms can be very useful for the systematic management of PD.

With the advent of wearable technologies, Inertial Measurement Unit (IMU): accelerometer and gyroscope sensors gained popularity in the detection of tremor owing to its compact size, low cost and prevalence in wrist-based COTS system. Several research papers employed customized wrist-watch type wearable devices [3], [4] and explored various machine learning or deep learning [5] based algorithms for automatic assessment of Parkinsonian tremor. Interestingly, this papers [3], [4] deployed the accelerometer sensor on finger since the finger is greatly affected by rest tremor. However, the placement of the sensor on the finger or cumbersome glove form factor could cause inconvenience to the patient. It is to be noted that, since the intensity of the tremor at finger dies down on the wrist; thus sensing the finger tremor from the wrist is challenging.

Sensor Modality: PPG vs Accelerometer

Although the wrist-based accelerometer approaches are attractive, the sensor is inherently noisy in nature. Even when it is put rest condition, there is a substantial bias and high-frequency noise in the sensor signal. In specific cases, when the finger would possess a low-intensity vibration, the tremor could be buried in bias and noise floor. Specifically, in the case of pill-rolling tremor, this situation would be imperative. Another potential problem is the sensitivity of the accelerometer sensor towards the environmental effects such as tilt which has a high impact due to gravitational field shift with respect to the device coordinate system.

Acknowledging these issues, we have explored another sensor modality i.e photoplethysmograph. The photoplethysmograph (PPG) is an optical sensor system which measures the changes in blood flow volume at the microvascular bed of tissue of the human body. Conventionally, the PPG sensor is used to detect the heart rate [6], [7] or heart rate variability at peripheral sites (such as wrist) [8]. Nowadays, PPG is a very popular method, most of the smart-watches or fitness devices are embedded with the PPG sensor due to its unobtrusive approach and a high degree of usability. In the context of heart rate estimation, the most challenging issue is the quality of PPG. The PPG sensor is highly sensitive to the motion artefact; thus the slight movement of hand or vibration of the finger distorts PPG signal. This characteristics of PPG signal posses the true potential to be explored as a novel sensor modality for tremor.

Motivated by this finding, we have further investigated and addressed the two major challenges before preferring PPG as a new sensor modality. The two challenges are listed below:

- The acquired PPG signal combines of the tremor signal (motion artefact) and the true heart signal along with its harmonics. The imminent question is that how the tremor signal could be extracted and detected from PPG.
- Since the PPG sensor consumes more energy compare to accelerometer, how the energy could be conserved while using the PPG sensor.

In subsequent sections, we have elaborated our method and discussed some preliminary results from a lab study performed on volunteers.

II. Proposed Method

Essentially, the proposed method is conceptualized and formalized the plausible solution to address the issues mentioned in Section I. Figure 1 depicts the complete flow chart of the algorithm.

A. Tremor Signal Extraction Using Non-Parametric Approach

Inherently, the PPG signal consists of a slowly varying signal associated with cardiac rhythm. Considering the Heart Rate ranges $45 - 180$ BPM, the desired PPG signal's filter limits are usually 0.75 Hz-3 Hz. Notably, the range of Parkinson's tremor lies in 3 Hz-7 Hz. Thus, a conventional filtering method should be adequate to extract the tremor signal. However, this theory works appropriately until the harmonics of the heart rate signal gets overlapped with the tremor signal.
To overcome this, instead of only conventional filtering, a signal decomposition technique, Singular Spectrum Analysis(SSA) is employed for noise-cleaning. The comprehensive details of this SSA are described below:

1) Embedding: The first step of SSA is embedding, where the time series signal is mapped into a sequence of lagged vectors. Given the PPG signal $PPG_W = \{p_1, p_2, ..., p_N\}$ where N is the number of samples in a particular time window. The signal is converted into L lagged vectors. The L is denoted as the window length. It is worthwhile to mention that, for a meaningful projection, L must be chosen as $L < N/2$. The Trajectory matrix ($TPPG \in R^{L\times K}$) of the PPG window(PPG_W) is devised where $K = N - L + 1$.

$$PPG_W \Longrightarrow TPPG_{i,j} = \begin{bmatrix} p_1 & p_2 & \cdots & p_L \\ p_2 & p_3 & \cdots & p_{L+1} \\ \vdots & \vdots & \ddots & \vdots \\ p_K & p_{K+1} & \cdots & p_N \end{bmatrix}$$

2) Principal Component Analysis: Principal Component Analysis (PCA) is a statistical procedure that utilizes the orthogonal transforms and projects the signal into a meaningful basis that exploits the variation. Given the trajectory matrix $T \in \mathbb{R}^{L\times K}$; the projected matrix P is defined as: $\mathbf{P} = \mathbf{TE}$. Where $E \in \mathbb{R}^{K\times K}$ represents the eigenbasis matrix reckoned from the covariance matrix. The eigenbasis exploits the temporal covariance of the PPG signal, represented as lagged vectors in the trajectory matrix.

3) Signal Reconstruction using Diagonal Averaging : We have hypothesized that the major principal component denoted by the leading eigenvalue, represents the tremor component of the signal. It is imperative to note that, the rest tremor is the major component in PPG signal and posses a higher variance compares to the harmonics of heart signal or any other sensor noises. As PCA aims to learn the projection matrix by emphasizing the variance of the signal; implicitly, it could be stated the leading Principal components are associated with rest tremor.

To reconstruct the time series, the projection of the trajectory matrix on eigenbasis is inverted. This inversion operation is accomplished only using the leading principal component. The inverted projection is defined as $\mathbf{I} = \mathbf{P} * \mathbf{E}$. Where, $\mathbf{I}$ is the reconstructed components matrix and $\mathbf{P}$ is the Principal Components matrix. This leads to the reconstructed matrix $I \in R^{L\times K}$ which contains the time series signal only contributed by leading principal component. The anti-diagonal averaging is performed to reconstruct the elements in the time series window. If we consider $PPG_{RW}(n), n = 1, 2...N$ as the reconstructed time window, then the diagonal averaging process is defined by the following equation:

$$\mathbf{PPG_{RW}(n)} = \begin{cases} \frac{1}{n}\sum_{m=1}^{n} I(m, n-m+1) \forall 1 \leq n \leq L \\ \\ \frac{1}{L}\sum_{m=1}^{L} RC(m, n-m+1) \forall L \leq n \leq K \\ \\ \frac{1}{N-n+1}\sum_{m=(N-n+1)}^{L} I(m, n-m+1) \\ \forall (K+1) \leq n \leq N \end{cases} \tag{1}$$

B. Power Consumption using Compressive Sampling

The increased power consumption of the PPG based method is the major constraint while leveraging it. One widely used method for power management in PPG is duty cycling the LED operation by deploying the train of discrete pulses instead of continuous supply to the LED. However, to ensure the high signal to noise ratio, the LED switching frequency needs to be

Data: $PPG \in \mathbb{R}^{N\times 1}$ $PPGSignal$, WL
Result: $ReconsPPG \in \mathbb{R}^{N\times 1}$
begin
    $[T] \longleftarrow TrajectoryMatrix(PPG, WL)$;
    $[COVM] \longleftarrow CovarianceMatrix(T)$;
    $[EigVec, EigVal] \longleftarrow EigDecomp(COVM)$;
    $PPGPC \longleftarrow COVM * EigenVec$;
    $d \longleftarrow WL$;
    $x \longleftarrow 1$;
    $m \longleftarrow 1$;
    while *d>=(WL-2)* **do**
        $Buff \longleftarrow PPGPC(;, d) * EigenVec(:, d)$;
        $Buff \longleftarrow Buff(end : -1 : 1, :)$;
        for $x \in N$ **do**
            $RC(x, m) =$
            $mean(Diagonal(Buff, -(N-d+1)+x))$;
        end
        $d \longleftarrow d - 1$;
        $m \longleftarrow m + 1$;
    end
    $ReconsPPG \longleftarrow RC(:, 1) + RC(:, 2)$;
end

Algorithm 1: Tremor Identification using SSA.

higher than the Nyquist rate for heart-rate that is 3Hz. Lately, Compressive sensing (CS) has emerged as a new paradigm and offers a potential solution for acquiring the signal at a sub-Nyquist rate. The method of CS can directly optimize the power consumption by reducing the LED on time at a rate much lower than the Nyquist rate.

1) CS Theory and Implementation: Compressive Sensing (CS) is a new sensing modality, compresses the signal acquisition by obtaining the fewer random measurements compare to the Nyquist rate. By exploiting the sparsity of the signals, CS reconstruct the original signal back from these fewer measurements.Given few random measurements, the CS reconstruction model can be described mathematically by the following equation: $\mathbf{y} = \mathbf{A}\mathbf{x}$, where, $y \in \mathbb{R}^{m\times 1}$ is random measurement vector of size m contains the input signal; $x \in \mathbb{R}^{n\times 1}$ is the sparsified coefficient vector have very less number of non-zeros entries and $m << n$. $A \in \mathbb{R}^{m\times n}$ is the basis matrix where the signal is sparsified. This governing equation implies a undetermined system of linear equations and possess infinite number of possible solutions. To estimate the sparse vector x, the equation could be formulated as an l_0 optimization problem:

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{argmin} \left\|\mathbf{x}\right\|_{\mathbf{0}} \quad \text{s.t.} \quad \mathbf{y} = \mathbf{A}\mathbf{x} \tag{2}$$

Where, $\hat{x}$ is estimation of x. The l_0 optimization is an NP-hard problem, thus approximation is necessary to solve this equation. The equation could be solved using a greedy algorithm which offers the optimal choices locally and eventually finds the global optima in a heuristic manner. We have implemented the CoSaMP [9], a greedy algorithm to achieve faster performance. CoSaMP is based on orthogonal matching pursuit algorithm relies on the iterative approach for signal reconstruction. Since the tremor signal is quasi-periodic in nature; we have opted for DCT basis which is similar to DFT basis, but only includes the real-valued cosines functions. The PPG signal is sparse in the DCT domain, only a few coefficients are required to represent the signal. Each column of the DCT basis matrix represents one cosines basis of a particular frequency. Since the tremor ranges from 3 Hz to 7 Hz, the DCT basis columns associated with this frequency range only considered for reconstruction which enhances the speed of the algorithm. The reconstruction method of the CoSaMP algorithm is outlined in Algorithm 2.

input : Observation y, DCT basis A, Sparsity level s, Convergence criteria C
output: s-sparse approximation x of the observation y

Initialization:;
```
/* Initiate the Residual */
```
$r \leftarrow y$;
$x \leftarrow 0$;
while *C is not true* **do**
    $D \leftarrow A * r$;
```
    /* Identify the indexes of 2s large
       Coefficients */
```
    $T \leftarrow Max_{2s}(D)$;
    $K \leftarrow Union(T, K)$;
    $b \leftarrow pseudoinv(A(:, K)) * u$;
    $H \leftarrow Max_s(b)$;
    $T \leftarrow T(H)$;
    $x \leftarrow b(H)$;
    $r = y - A(:, T) * b$;
end

Algorithm 2: CoSaMP Reconstruction

We have attempted CS as a proof of concept because we envisage that the integration of this method in sensor design will optimize power consumption. However, the scope of this paper is limited and the sensor design part is not discussed here. Thus any analysis regarding the power consumption is not included here. In order to establish the concept, we acquired the PPG signal with a higher sampling rate (100 Hz), then employed the CS concept for further processing. Before applying the CS, the signal is preprocessed which includes basic filtering and normalization. As implemented, the CS method implies random sampling and selects only 100 random samples from the original PPG window of 1000 samples (10 Second window duration). Then by exploiting the spasticity of the tremor signal in the DCT domain, reconstructs the original 1000 sample back from these 100 samples. As mentioned earlier, If this method is integrated with sensor design; then only 100 samples will be acquired from the sensor and it would be enough for tremor detection. This could create a huge impact in terms of power consumption. Apart from power consumption, this could be advantageous for storage also. Here we have achieved the compression ratio of 10. Additionally, this will decrease the bandwidth if we try to transmit the data to other devices.

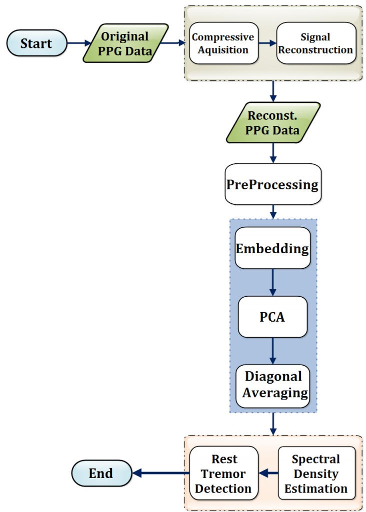

Fig. 1. Flow Chart Of the Complete Algorithm

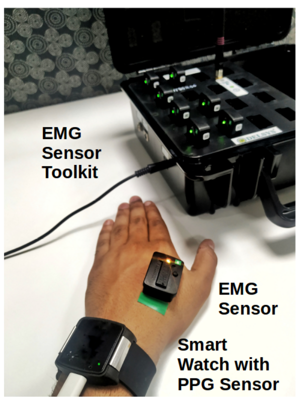

Fig. 2. The Experimental Setup

III. Evaluation

A. Experiment Design

To validate our hypothesis, we have carefully designed and generated a dataset for pill-rolling tremor using simulation. The unavailability of data from actual patients leads to the simulation where the participants were introduced to the basics of pill-rolling tremor symptoms and asked to mimic it. As the objective of this paper is only to detect the tremor, not to explore any further Parkinson disease-related analysis, it is expected to work quite satisfactorily with this simulated dataset. For the experiment, a COTS smartwatch equipped with an optical sensor is employed to acquire the PPG signal from the wrist. An industry-grade EMG Sensor from Delsys system [10] is used as a ground truth sensor to capture the signatures generated by the movement of muscles during the tremor. The EMG sensor transmits the collected data to the computer via internally built-in wifi, facilitated by Delsys system. The smartwatch is connected to the computer through a USB port to transmit the PPG data. The setup of the data collection procedure is illustrated in Figure 2.

B. Data Collection

The participant chosen for the experiment are healthy subjects and did not suffer from any disease. Firstly, the participants are made familiar with the pill-rolling tremor. Additionally, some videos are shown to them and explained the process for a better understanding. The participants are asked to wear the smartwatch on their preferred hand. The Delsys EMG sensor is placed on the same hand in between the muscles named Opponens Pollicis and Flexor Pollicis Brevis, near the index finger. This position has been chosen strategically, allowing no hindrance for the movement of the finger while mimicking the pill-rolling tremor. During experiments, the participants are asked to seat comfortably on a chair and put their hands in a completely relaxed position before the simulation.

We collected the data from eight participants with a mean average age of 27, the ages ranging from 23 to 42, approximately. Each participant was asked to mimic the pill-rolling symptom continuously for a window of 50 seconds. Each episodes containing one of such windows are collected and we have maintained a gap of approximately 3 minutes between each episode to ensure the fatigue-free collection of data for each episode.

C. Experimental Results & Analyis

Considering the oscillatory nature of the tremor signal, the spectral procedure is employed for the evaluation. The tremor signal is segmented into smaller windows of 10 seconds. The Fast Fourier Transform (FFT) is deployed as the spectrum estimation method and the dominant frequency obtained from the window of the EMG signal is considered as the reference parameter. Subsequently, it is compared with the dominant frequency of the corresponding window of the PPG or accelerometer spectrum. If the absolute difference does not cross the predefined threshold then the window is denoted as Right Window (RW) otherwise the window is considered as False Window (FW). The threshold is defined heuristically more than the frequency resolution of FFT (.1 Hz) and it is selected as .5 Hz. Simulation of tremor symptom and precisely generating the signal in the range of Parkinsonian tremor (3 Hz to 7 Hz) is quite an arduous task. Since we don't have any control over the frequency of movement; the tremor signal in the range of frequencies other than Parkinsonian tremor also gets generated. Thus to keep the analysis compact and precise, we have analyzed the EMG signal and discarded all the corresponding windows where the dominant frequency does not come in the range of parkinsonian tremor.

The experimental results regarding the different sensor modality are tabulated in Table I.

TABLE I
Experimental Results Tremor Detection Algorithm

Modality	**TW**	**RW**	**FW**	**Accuracy(%)**
CPPG	229	204	25	89.08
ACC	229	136	93	59.38
RPPG	229	186	43	81.20

With 10 seconds window duration and 5 seconds of overlap, a total of 229 windows (TW) are contemplated for evaluation. The first row of the table represents the performance of the tremor detection algorithm when the original PPG signal is leveraged. This PPG signal is acquired with a higher sampling

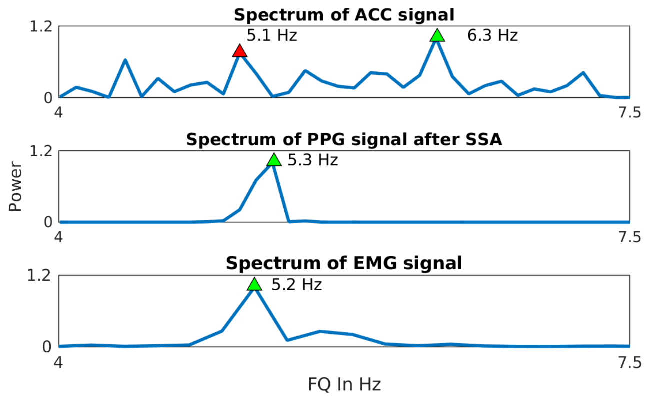

Fig. 3. Frequency Spectrum plot of Accelerometer, PPG and EMG signal

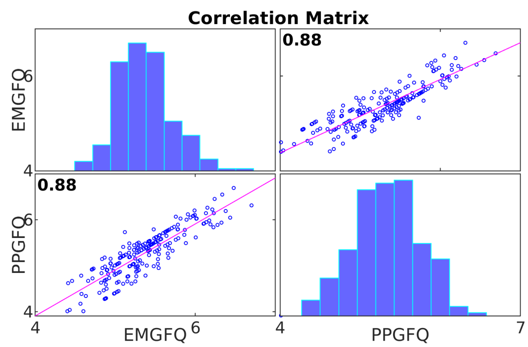

Fig. 4. Correlation Plot of Clean PPG and EMG signal

rate of 100Hz and then clean PPG (CPPG) signal is obtained after denoising it using SSA. The third row denotes the performance of the algorithm when reconstructed PPG (RPPG) is used for processing. The reconstructed PPG is estimated by the CS method from original PPG then SSA is implied for denoising. The second row indicates the performance of the accelerometer sensor. The resultant $\sqrt{x^2+y^2+z^2}$ of the accelerometer signal is considered for evaluation after preprocessing. It is quite evident from Table I that, the PPG sensor outperforms the accelerometer sensor with a significant margin. Although after utilizing the CS method the accuracy degrades compare to the original PPG but caters better accuracy than the accelerometer sensor.

For a particular window, the frequency spectrum of accelerometer, reconstructed PPG and EMG signal is depicted in Figure 3. It is apparent from the spectrum of accelerometer signal, that the original tremor signal (5.1 Hz) is cluttered with noises. The dominant peak is shown at 6.3 Hz which does not match with EMG dominant frequency (5.2 Hz). On the other hand, the spectrum of PPG signal is clean and the tremor signal (5.3 Hz) matches with EMG.

To have a visual perspective, a correlation plot of dominant frequencies of PPG (PPGFQ) and EMG spectrum (EMGFQ) for all windows is shown in Figure 4. This is a matrix plot, the associated histograms are also depicted here. Here, the linear correlation (Pearson Coefficient) is characterized as .88.

Discussions:

Despite the poor performance, interestingly, for some data file, the performance of the accelerometer sensor is comparable to PPG. This is a very intriguing observation. As we have investigated, it is observed that, in some cases, the simulation imparts a substantial effect on the acceleration signal. During the experiment, people make a conscious effort to simulate the tremor data which causes high-intensity vibration. Incidentally, for some cases of simulation, this phenomenon is inherent and makes the accelerometer significantly effective. This further justifies the improved performance of the accelerometer sensor. However, in the real scenario, this will be nullified as the real tremor data posses a low-intensity signal. It is also worthwhile to mention that, in simulation, if the PPG sensor fails to detect the tremor then the accelerometer sensor also fails.

IV. Conclusion

In this paper, we have provided some early study results on the feasibility of using the pulse photoplethysmogram signal for detecting Parkinsonian tremor and described the end-to-end signal processing pipeline for the same. To the best of our knowledge, this is the first kind of work where wrist-based photoplethysmograph is explored in the detection of rest tremor. As a next step, we plan to collect data from Parkinson's patients and further improve our method to correlate our tremor estimates with the UPDRS scale based assessment of Parkinson's patients.

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