Combining Gyroscope and Electromyogram Analysis for the Detection of Resting Tremor and Muscle Activity in Parkinson's Disease

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Abstract:- In this paper, we focus on designing and implementing a wearable device for detecting Parkinson's disease (PD) symptoms by analyzing resting tremors and abnormal muscle activity which contribute to PD combining gyroscope and electromyogram(EMG) analysis. Using advanced sensor technology, real-time data about movement and muscle activity is captured by the device. Here, we outline a hardware framework for optimizing data acquisition by identifying sensors to be used, their placement and integration strategies. In order to analyze data, machine learning algorithms are used to distinguish between tremors and muscle activity that are specific to Parkinson's disease and normal movements using classification technique. By enabling proactive healthcare interventions and customized patient management strategies, the proposed device represents a promising tool for the detection of early-stage Parkinson's disease.

Keywords:- *Parkinson's Disease(PD), Resting Tremor, Muscle Activity, Gyroscope, Electromyogram(EMG).*

I. INTRODUCTION

A tremor is a rhythmic, involuntary , shaking movements of the body . Resting tremor is a type of tremor that occurs mainly at rest and not specifically engaged in any movement. Resting tremor is a very important symptom of PD[1,4].Worldwide, an estimated 7–10 million people are living with PD and its occurrence increases with age, being rare before age 50 and more common in men than in women[2,3]. The occurrence of PD increases with age and PD affects 1% of the population above 60 years of age. It typically involves movement of limbs , wrist or other parts of body. In most cases, it operates at a frequency between 2 and 6 Hz.

As with other tremors, there are fundamental differences between resting tremors associated with Parkinson's disease and other tremors, such as their characteristic frequency, their progression and pathophysiology. However , there are similarities in their appearance , occurrences which leads to misdiagnosis of resting tremor associated with PD and other tremors . Misdiagnosis occur regarding the symptoms that can mimic PD such as essential tremors , dystonic tremors or other neurological disorders[5] . Thus , due to overlapping of such symptoms ,a reliable and accurate diagnosis is needed . Moreover, misdiagnosis can lead to improper medications , ineffective treatement , progression of the disease to a more complicated stage. Despite these challenges , the accurate diagnosis is highly dependent on clinical expertise , specialist consultation , and also includes previous history and physical examination . Neuroimaging and DAT scans have been a potential option to diagnose PD[6,13].However, it takes a huge time for the whole procedure,which can pose serious threats to patients.

Methods combining gyroscope and electromyography (EMG) electrodes[8,9,10] is a subject of growing interests as they are readily available , non-invasive , cost-effective diagnostic tools . Combination of these provides a satisfactory accuracy and diagnosis of resting tremor and abnormal muscle activity associated with PD . However , accuracy is not enough for validation of the disease . It requires validation from physician or a clinical expert . In this work , we proposed of creating a smart wearable device by detecting tremor , muscle activity associated with PD using gyroscope and EMG analysis. Recently, the application of machine learning techniques has increased in healthcare monitoring systems. Here , we have utilized SVM – based classifier to classify resting tremor associated with PD and abnormal muscle activities. This can be used to accurately predict the occurance of the disease and can take actions accordingly.

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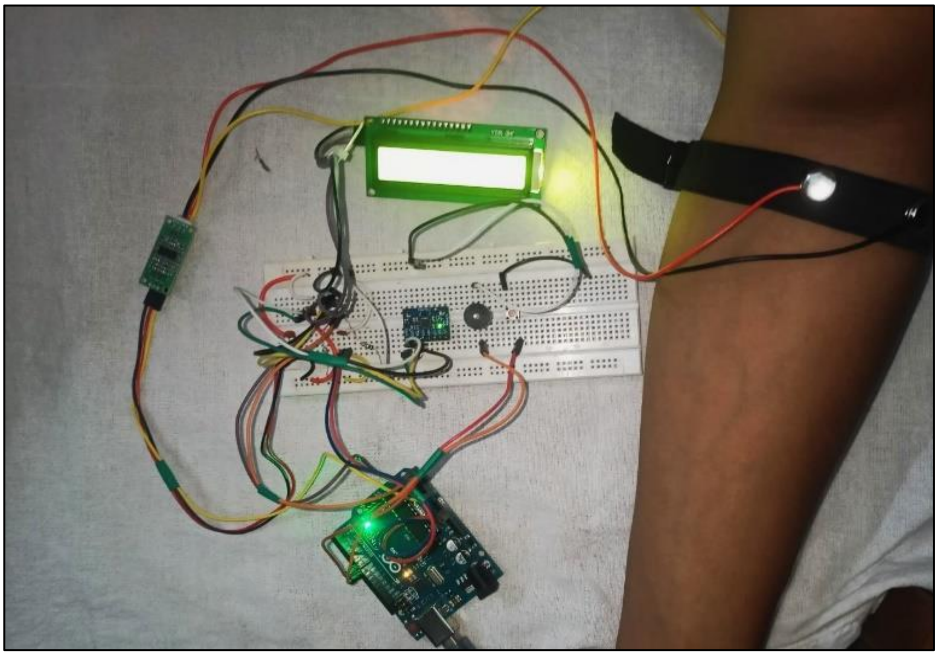

Fig. 1. Project Running Condition (Initally with Scattered Components)

II. METHODOLOGY

Our work comprises of the following steps : (1)hardware circuitry , (2)data acquisition , (3)data preprocessing ,(4)feature extraction , (5)dimensionality reduction and (6)classification . The schematic diagrams are provided below.

A. Hardware Circuitry

In this work , we used the following components : (1)arduino uno which acted as central processing unit and control interface , (2)EMG sensor and electrodes which helped in capturing muscle activity data , (3)Gyroscope sensor(GYROSCOPE) which helped detecting resting tremor and abnormal movements associated with PD , (4)buzzer which helped for real time monitoring feedback based on symptom detection ,(5)LCD which was used to display real-time data and system status. And finally used machine learning model on arduino to classify and analyze sensor data for detecting PD . User interacts with the device through a push button to start the monitoring process and upon pressing the button the device starts the data acquisition from EMG sensor and gyroscope .

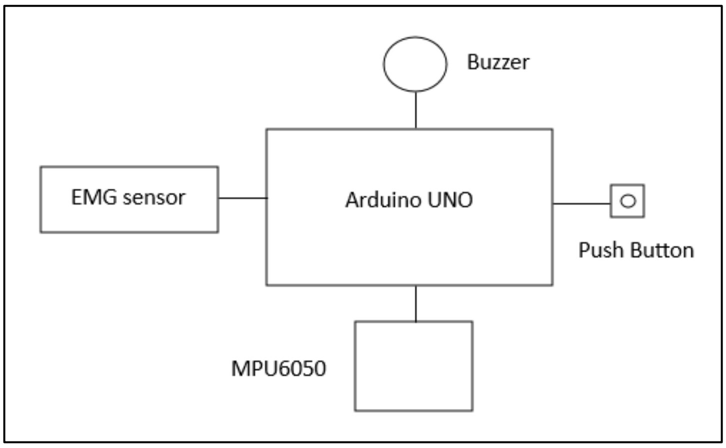

Fig. 2.Basic Block Diagram

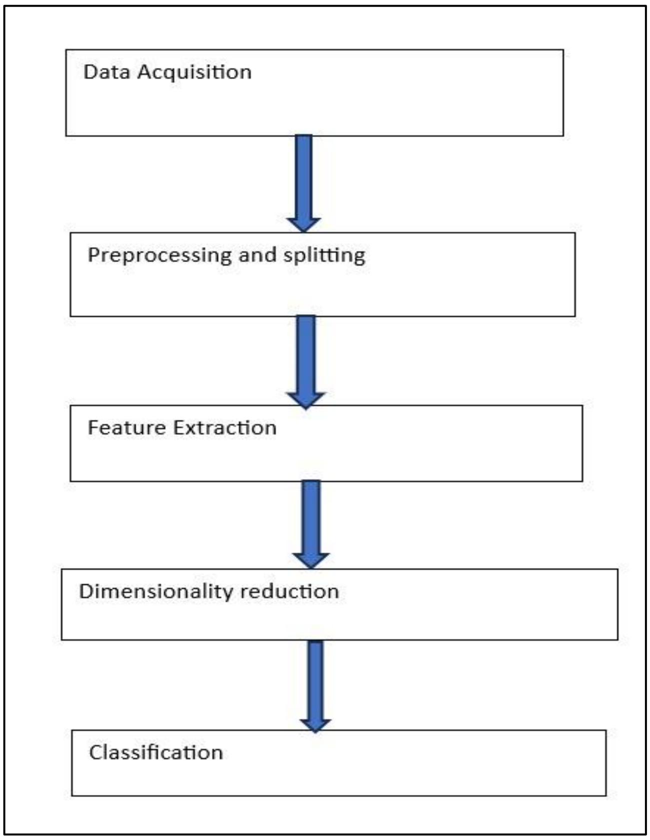

Fig. 3. Block Diagram of our Classification System

B. *Data Acquisition*

We have taken data from 81 patients among whom (1)36 normal patients who was not diagnosed with any resting tremor or abnormal muscle activity , (2)28 patients who were diagnosed with abnormal muscle activities but not tremor and finally(3)17 patients who were diagnosed with both resting tremor and abnormal muscle activities . For (3) many were detected with early-stage PD and for (2) some were diagnosed with PD not essentially having tremor . Data was collected through EMG sensor and gyroscope . EMG sensor continuously read EMG signals from muscles and also converted analog signals to digital for processing . Through gyroscope we collected data which detected resting tremor associated with PD.

The sensors were placed on different parts of the body particularly on wrist , limbs . The subjects were kept at resting position . Prior to sensor placement , the wrists and limbs were cleaned with ethanol and cotton . Three 30-seconds tests were performed for each patient. To discard artifacts and transitions from the recorded data, we considered only the signal from 10 to 25 seconds.

C. *Preprocessing and Splitting*

Raw sensor data went for a preprocessing to remove artifacts and high frequency components using low pass butterworth filter . Signals were filtered and normalised to enhance the symptom detection and model accuracy. We have split the data into test and train labels according to the sensor data and symptoms we were measuring for PD .

D. *Feature Extraction*

We used autoencoder technique for feature extraction which extracts relevant features from the sensor data . We have considered many layers for encoding and decoding . Mostly we have use rectifier linear unit(ReLU) as the activation functions rather than sigmoid for autoencoder as it gives better classification results . In the majority of tremor related patients, one side is more affected by the disease than the full body . Feature extraction is performed based on the most affected side of the patients in order to obtain more descriptive features.

E. *Dimensionality Reduction*

Dimensionality reduction was performed to reduce the dimensionality of the feature vector to avoid any interrupts in classification step . This is important as we have higher number of features and samples than the number of subjects . We achieved this by using principal component analysis(PCA)[14]. PCA actually projects the feature space into principal components in the direction of maximum variance. These new components make a feature space with reduced dimensionality. In our work, the number of components was optimized empirically in order to achieve a high classification performance.

F. *Classification*

For this work we have trained binary support vector machines (SVM)[15,20] classifier for the 2 classes : resting tremor and muscle activity . We used two kernels : radial basis function(RBF) and linear for the classification task . SVM consists of a cost parameter, which controls number of misclassifications of training examples. The RBF kernel has

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an additional parameter known as gamma, which controls how far the influence of a single training example reaches. We did a grid-search as a method of model selection to adjust the SVM parameters. The range of gamma was { 1, 0.1, 0.01, 0.001}. For better understanding of our device we also employed individual classification using SVM. To evaluate the performance we found out the accuracy[7] , and the performance metrics precision, recall , F1 score as in the classification report .

Table 1 Patient Characteristics

Details	Normal	RT and MA	MA
Number	36	17	28
Age(range)	30-70	50-80	35-65
Gender	M-18 ; F-18	M-12 ; F-5	M-16 ; F-12

RT – Resting tremor , MA – Muscle activity, M – Male, F- Female

III. RESULT

Accuracy was computed to check the performance of our device. As mentioned earlier we computed both individual and overall accuracy of our method. For individual computations , the best result came for muscle activity detection from EMG sensor of about 98% and for resting tremor detection we got accuracy approximately about 80% . The overall accuracy of our method to detect PD is approximately about 80%. Talking about the performance metrics (in individual cases) is given in TABLE II. We conducted tests under diverse environmental conditions and also measured response time from symptom onset to device alert activation that is of buzzer and LCD update displaying the results. During the work we encountered with various challenges , more particularly EMG sensor readings were initially affected by electrical noise and required adequate filtering techniques to enhance signal-to-noise ratio , and for gyroscope sensor which measures the angular rate that indicates changes in the orientation or rotation speed of the device that can further detect tremor activity and can be quantified. For this data, due to drift over time , it needed periodic calibrations to maintain the accuracy. We have taken the gyroscope data in terms of degrees/seconds which we converted further into hertz by using the formula :

$$Frequency(Hz) = \frac{(angular\ velocity)}{360}$$

We have taken the EMG sensor data in terms of microvolts(μV). This represents the amplitude of the electrical potential produced by the muscle contraction. We also performed model optimizations by tuning machine learning hyperparameters[19] to enhance model performance and reduce computational load on Arduino Uno.

IV. FUTURE ENHANCEMENTS AND CONCLUSION

This work provides potential benefits by early detection of PD enabling timely intervention . This helps the clinical professionals to track the disease progression and improve treatment efficiency. This device can be enhanced by incorporating more advanced sensors such as heart monitoring sensors , temperature sensors to detect more symptoms related to PD that can provide more details about this disease and can be more helpful for medical experts to diagnose PD[11,12] . More enhancements can be done by refining of machine learning (ML) algorithms by exploring more complex symptom recognition and classification[16,17] . Future developments and research could focus on remote monitoring and telemedicine integration by securely transmitting data to providers of healthcare . This also can provide personalized treatment adjustments through real-time data thereby helping in dosage management and required medications. Clinical trials and research could be done by standardizing tremor related metrics and providing high-resolution data for evaluating and introducing new therapies .

Currently , wearable technology is very important in healthcare monitoring particularly for chronic disease like PD [12,18]. Early detection of PD and timely monitoring is helpful for both patients and clinical professionals for improvement and treatment efficiency . This can potentially improve patient outcomes and quality of life. Further , enhancing the device's utility in both clinical practice and research can help paving the way for more effective management of PD.

TABLES

TABLE 2 DATA ACQUISITION TABLE

gx	gy	gz	EMG value	Resting tremor detected	Muscle Activity detected
504	328	90	71	0	0
495	203	87	779	0	1
497	172	85	670	0	1
1713	497	-596	716	1	1
607	-1670	-17	723	1	1

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478	165	107	564	0	1
295	292	78	91	0	0
-418	314	-69	58	0	0
511	138	105	81	0	0
493	181	88	778	0	1
1817	-1217	283	716	1	1
533	210	112	733	0	1
510	205	111	780	0	1
-657	-69	566	573	0	1
-627	-1707	456	657	1	1
496	227	84	352	0	0
519	184	89	128	0	0
628	182	114	438	0	0
-987	1564	1648	586	1	1

‘0’ – Not Detected ; ‘1’ – Detected ; gx , gy , gz : Gyroscope data

TABLE 3 EVALUATION TABLE

Classification	Accuracy	Precision	Recall	F1 score
Resting tremor	0.80	0.80	0.95	0.82
Muscle Activity	0.98	0.98	1.00	0.99

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