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Wearable Accelerometer and Gyroscope Sensors for Estimating the Severity of Essential Tremor

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Monash Health and RMIT University Human Research Ethics Committees under HREC Project No. 184981, and performed in line with the Human Experiments Helsinki Declaration (revised 2004).

ABSTRACT **Background:** Several validated clinical scales measure the severity of essential tremor (ET). Their assessments are subjective and can depend on familiarity and training with scoring systems. **Method:** We propose a multi-modal sensing using a wearable inertial measurement unit for estimating scores on the Fahn-Tolosa-Marin tremor rating scale (FTM) and determine the classification accuracy within the tremor type. 17 ET participants and 18 healthy controls were recruited for the study. Two movement disorder neurologists who were blinded to prior clinical information viewed video recordings and scored the FTM. Participants drew a guided Archimedes spiral while wearing an inertial measurement unit placed at the mid-point between the lateral epicondyle of the humerus and the anatomical snuff box. Acceleration and gyroscope recordings were analyzed. The ratio of the power spectral density between frequency bands 0.5-4 Hz and 4-12 Hz, and the sum of power spectrum density over the entire spectrum of 2-74 Hz, for both accelerometer and gyroscope data, were computed. FTM was estimated using regression model and classification using SVM was validated using the leave-one-out method. **Results:** Regression analysis showed a moderate to good correlation when individual features were used, while correlation was high ($r^2 = 0.818$) when suitable features of the gyro and accelerometer were combined. The accuracy for two-class classification of the combined features using SVM was 91.42% while for four-class it was 68.57%. **Conclusion:** Potential applications of this novel wearable sensing method using a wearable Inertial Measurement Unit (IMU) include monitoring of ET and clinical trials of new treatments for the disorder.

INDEX TERMS Essential tremor, Fahn-Tolosa-Marin tremor rating scale, wearables, inertial measurement unit.

I. INTRODUCTION

Essential tremor affects about 2% of the population, begin 5 to 10 times more prevalent compared with Parkinson's disease [1], [2]. While relatively mild forms of ET are common, the disorder does worsen over time and may cause significant disability in older individuals [3], [4], [5]. Two important developments have assisted ET clinical research in recent years. Better diagnostic criteria have been created to delineate ET and to help to separate it from other tremor disorders with which it can be confused [6]. Since 1993, a number of tremor rating scales have been validated.

Objective, reproducible assessments are needed to track the progression of ET and to facilitate clinical trials of therapeutic interventions, both pharmacological and non-pharmacological. These tools must perform well on tests of intra- and inter-rater reliability [7], and be sensitive to clinically meaningful changes in tremor severity.

The Fahn-Tolosa-Marin tremor rating scale (FTM) has a good track record with clinical observations of ET [8], [9]. While not developed specifically for ET, it comprises a range of observational, task-related and daily living assessments of tremor severity. A potential limitation of ceiling effect created by its definition of severe tremor amplitude is offset by a weighting for features that commonly accompany the progression of ET appearance of rest tremor, worsening kinetic tremor and spread of tremor to multiple body regions [10]. As with other clinimetric instruments for tremor, the ratings are subjective, and reliability can depend on assessors' familiarity and training with the scale.

Technological measurements of ET that could augment or even supplant the clinical scales would be advantageous. Recent advances in electronics have led to the development of compact, portable, wireless, low power and inexpensive devices for the measurement of movement [11]. Many smartwatches and armband fitness monitors contain accelerometer and gyroscopes [12]. Wearable accelerometers have been used to study activities of daily living [13], [14], [15], [16], inferring metabolic energy expenditure [17], [18], [19], measuring gait parameters [20] and predicting falls [21]. They have also been used for the detection of tremor [22], and for the assessment of tremor amplitude and frequency in ET [23].

Gyroscopes are commonly built into consumer wearable devices such as smart watches and smartphones. They are used in customised devices for clinical applications such as quantification of tremor [24] and bradykinesia [25], [26] in Parkinson's disease, and the recording of hand tapping angular movement [27]. Elble et al. [28] investigated the use of accelerometers and gyroscopes for measuring head tremors and found gyroscopes to be more effective. Multi-modal sensing combinations accelerometers with electrocardiograms [29]; accelerometers with microphones [30]; and accelerometers with gyroscopes [31], [32], [33], have shown promise for activity monitoring in various healthcare applications [34], [35]. Gyroscopes in combination with accelerometers have the advantage that both linear and angular motion is recorded [36], [37], reducing calibration biases. Haubenberger et al. [38] in reviewing the use of sensors to measure tremor severity, highlighted both advantages and limitations of the technology. While sensors are very sensitive to tremor amplitude and frequency, they may not be superior to clinical scales in detecting changes that exceed random variability in tremor amplitude.

The frequency of ET is typically in the vicinity of 8 cps. Voluntary movement tends to occupy a lower frequency range but there is overlap in freely moving individuals, some of whose actions could be rapid or jerky. When using sensors to measure ET, it is therefore desirable to select voluntary tasks that are relatively slow, without pronounced acceleration peaks and troughs [39]. Ideally, the chosen task should also accentuate the tremor. Spiral drawing, often used by clinicians as a pen-and-paper assessment of tremor disorders [40], is well-suited to the study of electronic recording of ET [41]. Several validated tremor rating scales, including the FTM, include specific scoring domains for the drawing of Archimedes spirals. Tremor classification studies using machine learning methods with the feature sets established from the acceleration signals [42]. Hand tremor classification using bi-spectrum analysis of acceleration signals and back-propagation neural network [43]. More recently using the combination of sEMG and accelerometer signals a quantitative classification of Essential and Parkinson's tremor using wavelet transform and artificial neural network [44] and support vector machines [45] is performed. A list of various classification studies for tremor diagnosis using wearable sensors is tabulated in Table 1.

This study extends our previous work on the electronic measurement of ET, using the FTM as the clinical yardstick. We previously reported a moderate correlation between the spectral parameters of the accelerometer and FTM score [46]. In this study we have proposed the combined use of accelerometer and gyroscope in ET to improve the estimation of tremor severity according to the FTM. Mild or localized ET consists largely of cycles of linear acceleration-deceleration. As ET progresses, its oscillations may propagate across multiple upper limb joints, introducing significant angular acceleration. Wearable IMU with accelerometer and gyroscopes were placed on the forearm while participants executed spiral drawings. Regression analysis was conducted for the FTM score with four features: the ratios of the power spectral density (PSD) of accelerometer (A_R) and gyroscope (G_R) between the frequency ranges of 0.5-4Hz and 4-12Hz, and summed PSD for the frequency band of 2Hz to 74Hz of the accelerometer (A_S), and gyroscope (G_S). Subsequently, a sensor based FTM estimation model was developed and validated. SVM analysis was performed using leave-one-out cross validation method using the combined features of the sensor data to identify the accuracy within and between the ET types.

II. METHODOLOGY

A. PARTICIPANTS

Seventeen participants (eight male) diagnosed with ET were recruited from the Movement Disorders service at Monash Health. Their mean age was 67.28 $\pm$ 13.39 years, with mean tremor duration of ET 22.94 $\pm$ 19.65 years. Eighteen healthy age-matched individuals (eight male; mean age 62.8 $\pm$ 11.6 years) were Age Matched Controls (AMC) for the drawing task studies. All ET participants compiled with the Axis 1 definition of ET in the 2018 Consensus Statement on the Classification of Tremors [54]. No participant with ET met any of the Axis 1 exclusion criteria for ET and ET plus.

B. CLINICAL ASSESSMENTS

Two movement disorders neurologists, who were blinded to prior clinical information, scored the FTM from videotapes, writing and drawing records, and a summary of a structured clinical interview. Mean total scores were obtained for each subject. They then classified the ET disorder as defined in Axis 1 of the Consensus Statement, which addresses the complexity of ET syndromes with its ET plus category. Patients were classified as ET plus by the presence of any of the following features: impaired tandem gait, questionable

TABLE 1. The review of wearable sensors used for clinical diagnosis.

Publication Source	Type of Sensor	Task Performed	Position of Sensor	Data Set	Amp/Freq	Performance
Kathleen E Norman *et.al.* (1999) [47]	Acc and sEMG	Horizontal movement	Acc: Dorsum of the index Finger sEMG: extensor digitorum communis	8 Controls and 6 PD	4-6 Hz	(r≥0.96 in amplitude measures in displacement, velocity and acceleration)
Otakar Sprdlik *et.al.* (2010) [48]	Acc	Rest/ Postural	Wrist	29 Controls and 30 ET	3.5 Hz to 12 Hz	79.9%
Xiaochen Zheng *et.al.* (2017) [49]	Smart Watch (Acc) / Smart Phone	Rest/ Postural	Wrist	8 ET	4 Hz to 12 Hz	-
N. H. Ghassemi *et.al.* (2016)[50]	Acc and sEMG	Resting, Holding, Carrying Weight	Dorsal Side of both hands	11 ET and 13 PD	Butterworth low pass filter with a cut of freq. of 70Hz.	83%
Soma Chakraborty *et.al.* (2017)[51]	Acc	Rest, Postural	Dorsa-palmar	30 Controls and 34 ET	2 Hz to 15 Hz	PT, bilateral coherence (97% of subjects), ET the prevalence was comparable for resting (54%) and postural (49%–57%) position.
S.M. Rissanen *et.al.* (2008)[52]	Acc and sEMG	Palms up at 90◦	Biceps and Parlmer wrist	33 healthy, 26 healthy old and 42 PD	High pass at 2Hz and Freq. band of (0 - 50)Hz.	Cluster, Control (90%), Subject (76%)
Rodger J. Elbel *et.al.* (1990) (Clinical)[53]	Acc, Tablet and sEMG	Archimedes Spiral	Dorsum of the hand between the second and third metacarpal bones	ET and Dystonia	All patients exhibited a severe 5-7-Hz tremor during the acts of writing and drawing	-

dystonic posturing, memory impairment, mildly impaired goal-directed coordination of unknown significance, mildly impaired rapid alternating movement of unknown significance, tremor at rest. For each participant, a neurologist familiar with the case also phenotyped the tremor disorder from the videotape. A majority classification was then obtained on the presence or absence of plus features, and on the number of plus features documented. Six subjects fulfilled the Consensus Axis 1 definition of ET (ET-0). Eleven subjects were classified as ET plus; 5 had 1 plus feature (ET+1) and 6 had 2 plus features (ET+2). The study was conducted following the human experiments Helsinki Declaration (revised 2004) and approved by the Monash Health and RMIT University Human Research Ethics Committees (HREC Project Number: 184981).

All participants gave their written informed consent before participating in the study. The patient data used in this study has also been reported in our earlier work [55].

C. EQUIPMENT AND DATA RECORDING

Figure 1 shows the experimental setup of data recording during the spiral drawing task and shows the anatomical placement of a wearable sensor at the mid-point of a line connecting the lateral epicondyle of the humerus with the anatomical snuff box [56]. The wearable Inertial Measurement Unit (IMU) sensor, Trigno (Delsys Trigno, USA), contains an inbuilt three-axis accelerometer and gyroscope used for recording the tremor data. The suitable location of the sensors has been reported in our previous study, selected experimentally based on the highest performance in detecting the tremor during spiral drawin [46]. In our experience, this location gives less chance of false positive detection of tremor when compared with the wrist.

The participants were asked to draw the spiral at their comfortable speed on a paper placed on a digital tablet (Wacom Intuos Pro Large, A3 sized) with a pressure-sensor mounted ink-pen. Customized software integrated the digital tablet and Delsys Trigno IMU signals. Pen-tip pressure was used to identify the start of the activity. Pen movements with pressure = 0 were labelled as 'pen-up' strokes, a 'pen-down' stoke was any movement while pressure was > 0. The accelerometer and gyroscope data were recorded at 148.1 samples/sec and stored in a.csv file format.

III. DATA ANALYSIS

The three recordings each from the accelerometer and gyroscope were segmented to remove the sections before and after the sketching task using the tablet's pen-up and pen-down data. To overcome sensor placement variation from geometrical differences, two scalars were derived from the raw acceleration and gyroscope such that $A(n) = \sqrt{a_x^2 + a_y^2 + a_z^2}$, $G(n) = \sqrt{g_x^2 + g_y^2 + g_z^2}$ [57], [58].

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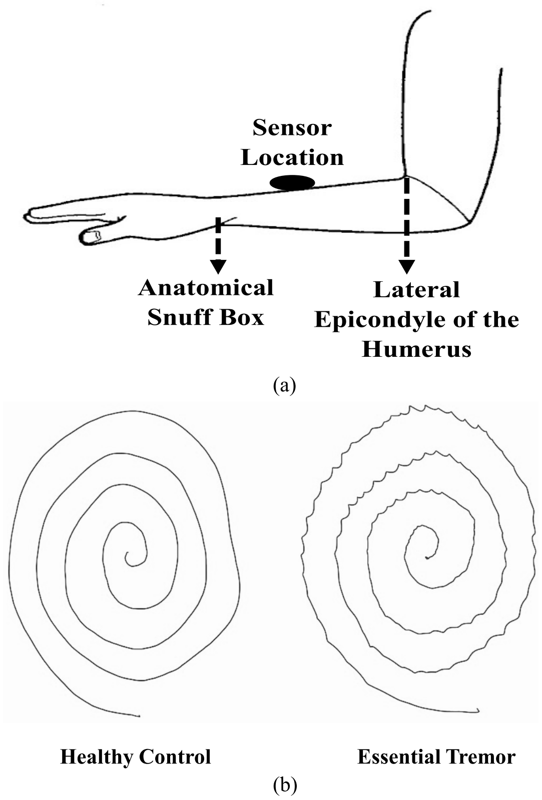

FIGURE 1. (a) Position of the wearable sensor placement, best suited for the data collection mounted on the upper limb. (b) Examples of spiral drawing by study participants. Note the 4 o'clock – 10 o'clock tremor axis typical of left-handed spirals produced in essential tremor.

The scalar of both accelerometer and gyroscope, i.e. A(n) and G(n), were high-pass filtered using 4^{th} order Butterworth filter with 3dB cut-off = 0.5 Hz. ET is associated with heightened activity in the frequency range of 4-12 Hz; in healthy people, the 0-4 Hz band is dominant [49], [59].

As a first step, the PSD was calculated for separate frequency bands 4-12Hz and 0.5-4Hz using welch periodogram for both acceleration A(n) and gyro G(n) with a window size of 2 seconds and a step frequency resolution of 0.5 Hz. The ratio of the PSD over the frequency bands 4-12 to 0.5-4 Hz, for acceleration (A_R), and for Gyro (G_R), were computed. It is hypothesised that people with ET have a higher PSD ratio compared with AMC. The recordings were first pre-processed using a 4^{th}-order notch filter (50Hz) in accordance Donald and Joseph [60]. For computing the summed PSD over the frequency band of 2Hz to 74Hz (S), the scalar A(n) and G(n) were filtered using a 4^{th}-orderButterworth bandpass filter (low cut off frequency = 2Hz, high cut-off frequency = 74Hz). The PSD was calculated using the welch periodogram method. The PSD sum over a frequency range of 2Hz to 74Hz (S) was obtained for acceleration (A_s), and for gyro (G_s).

A. STATISTICAL ANALYSIS

Shapiro-Wilk test was conducted to check for the normality distribution of the accelerometer and gyrometer parameters [61] and it showed a non-Gaussian distribution. Statistical analysis was performed using the non-parametric Mann-Whitney U test to determine the statistical significance of differences between ET and AMC groups for all the computed sensor parameters.

B. REGRESSION ANALYSIS

To determine the strength of correlation between the sensor features and the clinical FTM score, coefficient of determination R-squared was calculated. Linear regression analysis using the least-squares method was performed to find the relationship between the clinical FTM score and the individual IMU sensor features A_R, G_R, A_S and G_S and the total task time, T_t. The dependent variable for the analysis was the clinical FTM score, and the independent variables are the IMU sensor and time features.

A multiple regression analysis was performed to estimate the FTM score. Highly correlated sensor features of the accelerometer and gyro were used as the independent variables and the dependent variable was the FTM score. The validation of the estimated FTM score with the clinical FTM score was performed. All the computation, including statistical analysis, was performed using Python 3.8.

C. SVM CLASSIFIER

Studies have supported the Leave-One-Out Cross-Validation (LOOCV) for a more reliable performance for small datasets [62]. However, to ensure comparison with other works in literature, both, LOOCV and 5-fold Cross-validation (5-fold CV) were performed. A support vector machine (SVM) classifier using both LOOCV and 5-fold CV was used. The input to the SVM was the data set of the features of the acceleration and gyro: A_R, A_S, G_R, G_S. In the LOOCV technique, the number of folds equals the number of instances in the data set as it applies once for each person's data. All the samples are selected once, single-item test is performed and the average of all samples is reported as the overall accuracy. In this study, there were total of 35 people and thus the folds were repeated 35 times. This was repeated for both the binary classification of ET vs AMC and between the ET types; Controls, ET-0, ET+1, ET+2. Both, linear and radial basis function kernels were used, and the best classification accuracy was chosen from these two kernels.

IV. RESULTS

Table 2 shows demographic and clinical information for the 35 participants (17 ET, 18 AMC) with analyzable sensor recordings. The inter-rater analysis for FTM scored by the two blinded clinical assessors showed a very strong correlation of $r^2 = 0.95$, supporting the choice of the FTM score as the clinical severity standard for this study. Figure 2 displays box plots of the sensor features of ET and AMC groups. Table 2 also shows that, for all computerized features, mean values are significantly higher for the ET than the AMC group.

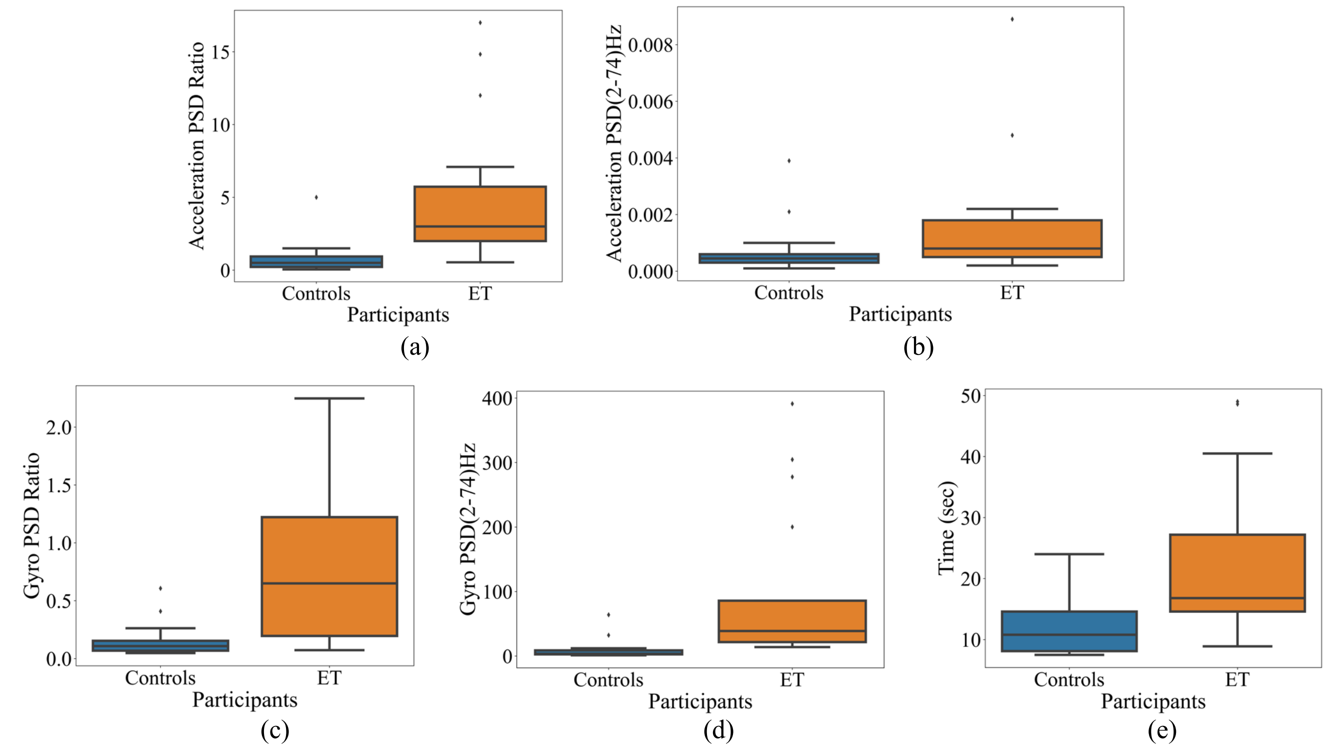

FIGURE 2. Comparison plot of Controls and ET participants for five parameters, 2.(a) A_R, 2.(b) A_S, 2.(c) G_R, 2.(d) G_S, 2.(e) T_t.

TABLE 2. The demographic, clinical and average IMU sensor features of ET and controls.

	Controls	ET	P-value
Clinical Features			
Number	18	17	–
M:F	8:10	8:9	–
Age	62.8 ± 11.6	67.28 ± 13.39	–
Age at tremor onset	–	43.88 ± 19.75	–
Tremor duration	–	22.94 ± 19.65	–
FTM score	–	24.44 ± 12.68	–
Sensor Features			
A_R	0.79 ± 1.12	4.98 ± 5.00	0.000
A_S	0.74 ± 0.90 (10^{-3})	1.58 ± 2.19 (10^{-3})	0.041
G_R	0.16 ± 0.15	0.78 ± 0.67	0.000
G_S	9.46 ± 15.43	95.64 ± 119.49	0.000
T_t	12.64 ± 5.53	22.58 ± 12.66	0.001

A. REGRESSION OF SENSOR FEATURES VS FTM

Linear regression analysis was performed to determine the relationship between the ET sensor features and FTM clinical score. The low ranked features were manually selected and removed, a technique that is suitable when the size of the dataset and number of features are small. The dependent variable is the FTM clinical score and the independent variable for each of the cases was ET A_R, ET G_R, ET A_S, ET G_S and T_t. Analysis was performed using all observations from the 17 ET participants, and the coefficient of determination r^2 values appear in Table 3. Figure 3 shows the regression analysis performed for the ET participants for the sensor features with respect to the FTM clinical score. The r^2 value indicated strong correlations between ET A_R and FTM clinical score ($r^2 = 0.50$), between ET A_S and FTM clinical core ($r^2 = 0.5684$), and between ET G_S and FTM clinical score ($r^2 = 0.612$). There was moderate to good correlation between ET G_R and FTM clinical score ($r^2 = 0.4791$). The correlation between T_t the FTM clinical score was moderate to low ($r^2 = 0.0018$). On that basis, T_t was not considered for the model to estimate FTM.

B. DETERMINATION OF MULTICOLLINEAR VARIABLE

Regression analysis was applied to sensor features A_R, G_R, A_S, G_S and T_t to determine any redundant multicollinear variables, and those r^2 values can be seen in Table 4. When two independent variables are highly correlated, these is redundancy and only one should be used in multiple regression analysis. Based on the r^2 values, it was found that A_R and A_S for ET had high correlation ($r^2 = 0.6838$), there was moderate to good correlation between G_S and A_S for ET ($r^2 = 0.4679$), while correlations between other parameters

TABLE 3. Regression analysis with respect to the FTM.

	FTM vs A_R	FTM vs A_S	FTM vs G_R	FTM vs G_S	FTM vs T_t (Acceleration, Gyro.)
Coefficient of determination (r-squared)	0.50	0.5684	0.4791	0.612	0.0018
Root Mean Square Error (RMSE)	8.7891	8.0854	8.8825	7.666	12.2961

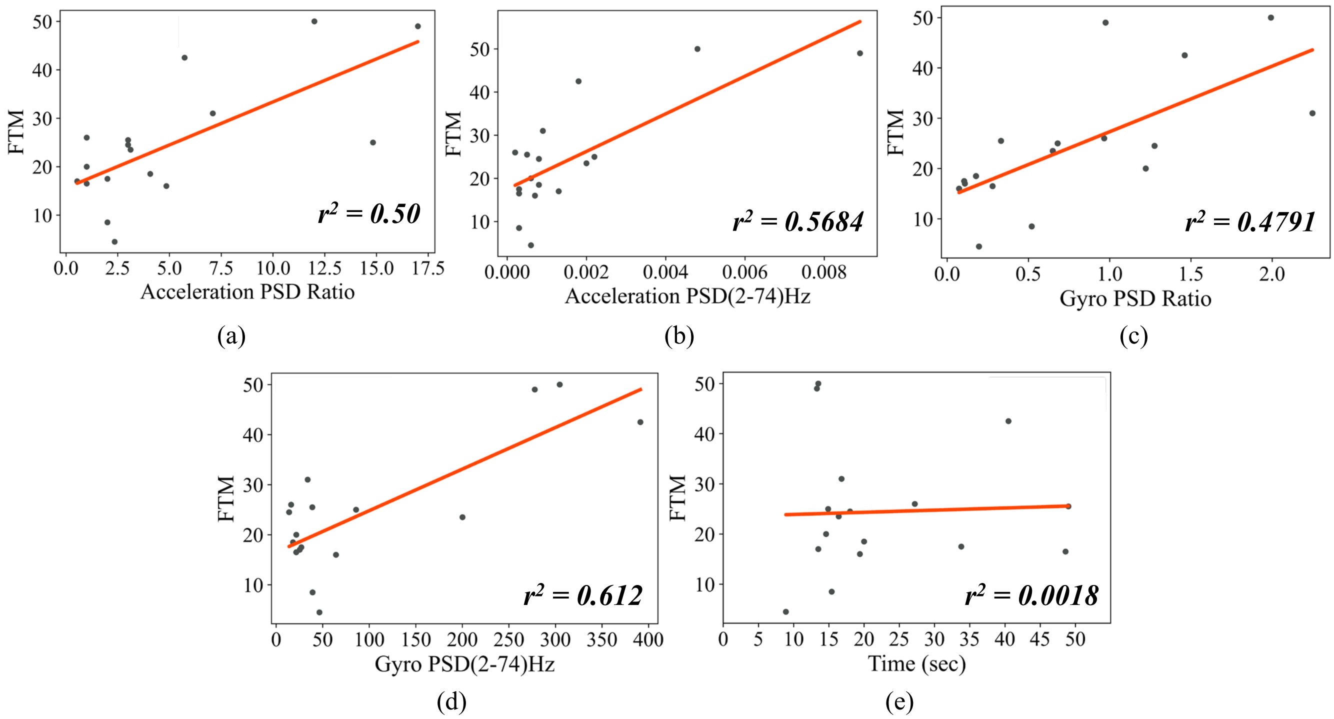

FIGURE 3. The regression plot of the ET sensors features vs FTM, 3.(a) ET AR vs FTM, 3.(b) ET AS vs FTM, 3.(c) ET GR vs FTM, 3.(d) ET GS vs FTM, 3.(e) ET Tt vs FTM.

were weaker. A_S was therefore identified to be redundant and not considered for the model to estimate FTM.

C. WEARABLE SENSORS FTM ESTIMATION

The multiple regression analysis using the least-square method was performed to estimate the FTM score from the sensor features. Based on Table 3 and 4, A_R, G_R and G_S were found to be the suitable features for the FTM estimation. The dependent variable was the FTM clinical score and the three independent variables were A_R, G_R and G_S. The regression analysis resulted in a model equation (1).

$$y = (10.6101 + (0.7461^* A_R) + (7.1881^* G_R) + (0.0472^* G_S)). \tag{1}$$

The estimation model has an $r^2 = 0.818$ and RMSE $= 5.25$. From the equation (1), the estimated FTM scores were validated and compared with the clinical FTM score, as shown in Table 5. Figure 4 is the comparison plot between the clinically obtained FTM and the estimated FTM using the wearable sensor for each of the ET participants.

D. WEARABLE SENSORS ET CLASSIFICATION

SVM Classifier showed a high accuracy of 91.42% for the 2-class ET and AMC in the following combination of the features (A_S, G_S), (A_S, G_S, G_R), (A_R, G_R, T_t) and (A_R, G_R, A_S, G_S). The other combination of the features showed an accuracy of 74.28% in (A_S, G_R) and 80% in (A_R, G_S, T_t), (A_S, G_S, T_t) and 82.85% in (A_S, G_R, T_t) and 85.71% in (A_R, G_R, A_S, G_S), (A_R, G_R, A_S) and 88.57% in (A_R, G_R), (A_R, G_S), (A_R, G_R, G_S), (A_S, G_S, A_R).

When considering the 4-class problem with the classes being ET-0, ET+1, ET+2 and AMC, the best SVM classification mean accuracy was 68.57% using combination of three features: A_S, G_S, T_t. The SVM classification accuracy for the different combination of features is shown in Table 6. The performance measured using two methods- LOOCV and

TABLE 4. Regression analysis within the sensor features.

	A_R vs A_S	A_R vs G_R	G_S vs A_R	A_S vs G_R	G_S vs A_S	G_S vs G_R
Coefficient of determination (r-squared)	0.6838	0.1527	0.3342	0.0996	0.4679	0.1939
Root Mean Square Error (RMSE)	2.7271	0.6015	3.9573	0.62	0.0016	0.5866

TABLE 5. The clinical vs estimated FTM.

Clinical FTM	Estimated FTM
42.5	43.85
49	43.41
17.5	14.13
26	19.06
31	33.66
50	48.26
4.5	15.97
25.5	17.06
18.5	15.78
16	17.79
8.5	17.69
16.5	14.38
20	21.16
24.5	22.68
17	12.99
23.5	27.06
25	30.61

TABLE 6. SVM classification accuracy for different inputs.

					LOOCV		5-fold CV	
					2 Class (ET and AMC)	4 Class (ET-0, ET+1, ET+2 and AMC)	2 Class (ET and AMC)	4 Class (ET-0, ET+1, ET+2 and AMC)
A_R	G_R	-	-	-	88.6	54.4	88.6	54.3
A_S	G_S	-	-	-	91.4	62.9	91.4	65.7
A_R	G_S	-	-	-	88.6	57.1	88.6	54.3
A_S	G_R	-	-	-	74.3	65.7	77.1	62.9
A_R	G_R	A_S	-	-	85.7	54.3	91.4	54.3
A_R	G_R	G_S	-	-	88.6	51.4	88.6	60.0
A_S	G_S	A_R	-	-	88.6	57.1	88.6	54.3
A_S	G_S	G_R	-	-	91.4	57.1	91.4	60.0
A_R	G_R	T_t	-	-	91.4	57.1	91.4	62.9
A_S	G_S	T_t	-	-	80.0	68.6	85.7	68.6
A_R	G_S	T_t	-	-	80.0	60.0	80.0	62.9
A_S	G_R	T_t	-	-	82.9	62.9	77.1	62.9
A_R	G_R	A_S	G_S	-	91.4	48.6	88.6	60.0
A_R	G_R	A_S	G_S	T_t	85.7	57.1	88.6	65.7

5-fold CV are presented to facilitate comparison with other similar works. The table shows that both the cross-validation methods show very similar classification accuracy for both, 2-class and 4-class problems.

V. DISCUSSION

Regression analysis identifies relationships between dependent and independent variables and generates models that can be used to estimate the dependent variables. The principle has been used to examine various clinical aspects of ET [63]. Regression analyses can also yield models for estimating clinical scores of neurological disability from data obtained from wearable accelerometer [64] and surface electromyogram (sEMG) [65] sensors. A study that investigated the use of accelerometer output for estimating the FTM in ET showed a moderate correlation (r $= 0.80$), equating to an approximate model [49].

In this study, we have aimed to improve the estimation of FTM scores in ET by combining accelerometer and gyroscope sensors. After identifying the redundant parameters by regression analysis of PSD features of the two sensors, multivariate regression between the FTM clinical score and the sensor features showed high correlation ($r^2 = 0.818$). From the observed regression coefficients of the sensor variables, gyro coefficients add considerable value to models based on accelerometer data alone [13], [14]. In our developed regression model of wearable IMU sensors that best estimated the FTM, correlations were high for G_R and moderate for A_R and G_S.

It has been previously shown that the spectral analysis of accelerometer signals can effectively discriminate between ET and healthy controls [66]. ET is dominant over the frequency range of 4-12 Hz, while normal voluntary movement usually generates frequencies ranging from 0 to 4 Hz [49], [67]. Thus, the ratio of the PSD computed over the two frequency bands 4-12Hz and 0.5-4 Hz, for both accelerometer (A_R) and gyro (G_R), is an obvious choice. We found a statistically significant difference between ET and controls for both these features, as is seen in Table 2. Regression analysis shows that A_R and G_R correlate with the FTM score.

The total PSD in ET is higher than for controls [68], suggesting that, when performing similar tasks, people with ET have increased overall motor activity. This is confirmed by our study, which shows that the PSD of accelerometer (A_S) and gyro (G_S), computed over the entire frequency range of 2Hz to 74Hz, shows statistically significant differences between ET and healthy controls (Table2). Much of this difference is explained by the tremor itself within its dominant frequency range. There may also be changes in the lower frequencies of voluntary movement from compensatory or adaptive motor strategies to minimise loss of accuracy during the spiral drawing task. For accelerometers, the PSD sum A_S and ratio A_R features showed strong correlation, with the redundant sum feature being omitted from the final model. The summed gyro activity G_S across frequencies 2Hz to 74Hz did, on the other hand, enhance the discriminative properties of our model, and appears as a term in its equation.

It is essential that sensors have a frequency range appropriate to the recording of tremor. Those used in this study had sampling rate of 148.1 samples/sec, sufficient to capture ET frequencies in the range 4-12 Hz [49] [58]. We employed a wireless IMU device that was small (size of case dimension 27 × 37 × 15 mm), lightweight (14.7 grams) and well-secured by mounting straps; none of the participants reported that it impeded their actions. These attributes, plus durability and long battery life, are suited to remote and long-term monitoring [12]. With high accuracy and repeatability, and relatively low price, the sensors have advantages over devices such as smartphones [69]. We believe that a standard motor task rather than freestyle movement allows better device-assisted measurement of the severity in ET, and that spiral drawing is particularly suitable.

The combination of accelerometer and gyro features of improved the accuracy for differentiating between two classes, i.e ET and control and between four classes, i.e. Controls, ET, ET+1 and ET+2 compared with the use of the use of only the accelerometer. In the two-class problem, it improved from 85% (reported in our previous study) to 91.42%, while it improved from 57.14% to 68.57% for the four-class problem. This is in line with the works of other researchers who have reported similar improvements but for movement analysis among healthy people only [31], [32], [33]. While this has potential for being used for measuring the difference between ET and controls, further improvement for the four class problem is necessary.

VI. CONCLUSION

This study has shown that by combining accelerometer and gyroscope data from IMUs placed on the forearm, the FTM score for people with ET can accurately be estimated. Regression analysis identified the ratio of PSD in the frequency bands, 0.5-4 Hz and 4-12 Hz for accelerometer and gyroscope scalars and the total PSD of gyroscope as the most relevant features ($r^2 = 0.818$). Classification of the combined features of accelerometer and gyro using SVM, the two-class ET and controls achieved an accuracy of 91.42% using the features of A_S, G_S, and the four class ET-0, ET+1, ET+2, Controls achieved a classification accuracy of 68.57% using the features of A_G, G_S, T_t. The accuracy of classification using the combination was better than when using accelerometer alone. The proposed study has potential for assessment and monitoring of ET patients, and for use in clinical trials using commercially available IMU.

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