A Pre-Study on Tremor Classification During Activities of Daily Living

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Abstract: Motor impairments, such as tremors, are often measured with specific tests or rating scales. As these have some disadvantages, like an inter-rater reliability and a lack of representation of the everyday life, a sensor-based continuous and objective monitoring of activities of daily living could be a suitable alternative. According to the literature, the use of inertial measurement units attached to the tremor-dominant arm in combination with support vector machines or neural networks seem to be promising. However, many approaches have to be adapted individually. Therefore, we conducted a preliminary study with ten healthy participants, who were asked to perform conventional and simulated tremor movements during five different activities related to eating. These movements were recorded with inertial measurement units. We identified four different parameters calculated from the recorded data, that we used to train multiple support vector machines for a non-individualized approach. The overall median accuracy score was 0.75, which is comparable to the results reported in the literature. This shows that support vector machines may be a non-individualized approach for differentiating between tremor and non-tremor movements during activities of daily living.

1 INTRODUCTION

Motor impairment is an important indicator for the early detection and monitoring of disease progression in a number of conditions, including Parkinson's disease, stroke, or multiple sclerosis. These motor impairments are measured in a medical context, for example, to either detecting them or determining the degree of impairment. There are multiple tests for measuring these impairments. The Action Research Arm Test (ARAT), for example, is a standardized tool for measuring the arm motor status in individuals who have experienced a stroke (Yozbatiran et al., 2008). The Unified Parkinson's Disease Rating Scale (UPDRS) is frequently used for assessing the severity of Parkinson's disease (Goetz et al., 2008).

Even though these tests are used very frequently and have many advantages, they come with a few disadvantages. These tests are unable to reflect possible fluctuations throughout the day, as they are not a continuous measurement (Heldman et al., 2011). Furthermore, the test results may be biased due to inter-rater reliability, with the clinician potentially influencing the output (Heldman et al., 2011). In addition, it is uncertain whether the test accurately reflects the limitations encountered in everyday life. On the one hand, the individuals may perform to a higher standard in a test situation than they would in their everyday lives. On the other hand, the exercises included in the test may not fully cover the individually important everyday movements of the individuals being tested.

As sensorimotor impairments correlate with activities of daily living (ADLs) (Shamay et al., 2011), particularly eating, which is one of the most affected activities by a tremor (Heldman et al., 2011; Feys et al., 2004), measurements during ADLs, especially eating, could counteract some of the aforementioned disadvantages. To enable continuous and objective monitoring, measurements could be conducted via sensors. Soran et al. achieved an accuracy of 95.4% in the detection of tremors using a camera as a sensor and a support vector machine (SVM) for training purposes (Soran et al., 2012). In the context of everyday live, cameras could have two potential disadvantages: firstly, that they are stationary, and secondly, that they may violate the anonymity of individuals. In contrast, inertial measurement units (IMUs) have the advantage of mobility and greater anonymity. As IMUs

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can capture the kinematics during ADLs in healthy adults (Aguirre, 2016), they could be useful sensors for monitoring. Additionally, IMUs can be used to estimate upper limb impairments after a stroke in ADLs (Oubre and Lee, 2022). Furthermore, Thorp et al. suggested that IMUs could be a promising approach for detecting tremor in in-home settings (Thorp et al., 2018).

There are multiple studies using IMUs or similar sensors to monitor ADLs: As demonstrated by Schmidle et al., the analysis of IMU data during ADLs can lead to conclusions regarding the frailty status of the elderly (Schmidle et al., 2020). Gulde et al. used an accelerometer, gyroscope, and pedometer during daily routines of stroke patients, for obtaining information of stroke-related laterality (Gulde et al., 2024). Heldman et al. used an IMU on the index finger during the everyday live to detect and classify tremors and to quantify tremor severity (Heldman et al., 2011). Nevertheless, it is unclear whether the placement of the sensor on the index finger is an optimal choice. As the sensor must not interfere with the performance of the ADLs (Thorp et al., 2018). Skaramagkas et al. demonstrated that training a SVM on features derived from accelerometer data to distinguish between essential tremor, Parkinson's tremor, and no tremor works best on poses and movements that are similar to ADL (Skaramagkas et al., 2021). In their literature review, Thorp et al. also concluded that Parkinson's disease symptoms can be classified using movement and muscle activity sensors with machine learning. They found that IMU sensors in combination with neural networks appear to be particularly promising for this purpose (Thorp et al., 2018).

Many algorithms need to be customized for each individual, which is a major challenge for clinical use (Thorp et al., 2018). Therefore, the aim of this paper is to check whether a non-individualized approach can be used across multiple individuals. This will be demonstrated through the analysis of tremor/ no tremor classification in ADLs using an IMU sensor on the potential affected arm. For this purpose, a prestudy will be conducted with healthy subjects simulating tremor and moving in a conventional manner while performing various eating activities, testing two distinct IMU positions.

2 METHODS

2.1 Study Design

To generate a dataset containing both tremor and conventional movements, we conducted a study with 10 healthy and young subjects (7 male, 3 female). The subjects were seated in front of a table and performed five different exercises. Each exercise was initially performed in a conventional manner and then with a simulated tremor in the dominant arm. For all subjects, the dominant arm was the right arm. The five exercises were as follows:

1. Hold an apple in the hand and bite into it.
2. Grasp a piece of cake with a fork and then eat it.
3. Cut a slice of bread with a knife.
4. Imitate to spread butter on a slice of bread with a knife.
5. Consume soup with a spoon.

For the tremor condition, participants were instructed to shake their dominant arm at a consistent frequency while performing the exercise. Subsequent analysis confirmed that the maximum frequency of 75% of the recorded simulated tremors was between 4 and 12 Hz, which is consistent with the typical frequency range for postural and kinetic tremors (Heldman et al., 2011).

The subjects were equipped with two inertial measurement units (Move4, Movisens). As stated in (Thorp et al., 2018), the sensors should be positioned on the (tremor-)dominant arm. Accordingly, one sensor was attached to the upper arm and another to the lower arm enabling a comparison of these two positions. Each IMU recorded data from an accelerometer and a gyroscope at a frequency of 64 Hz. In addition, the subjects were filmed by a camera (Azure Kinect DK, Microsoft). An illustration of the study setup is shown in Figure 1.

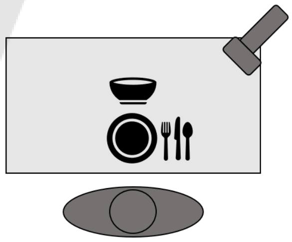


Figure 1: Illustration of the study setup. The participant was seated at a table with the eating utensils positioned in front of them. The camera was filming the scene from an angle.

The study was approved by the local ethics committee (ethical vote: Carl von Ossietzky Universität Oldenburg (Drs.EK/2024/022), and conducted in accordance with the Declaration of Helsinki.

2.2 Software Used

All data processing (data preprocessing, parameter calculation, and analysis) was done on the same computer using Python (version 3.12.7). The most important used packages were numpy (version 1.26.4), pandas (version 2.2.2), scikit-learn (version 1.5.1), and matplotlib (version 3.9.2).

2.3 Data Preprocessing

Prior to data analysis, it was necessary to preprocess the data. First, each exercise in the video data was visually labeled. This was necessary in order to analyze each exercise separately. As the start time was known from both the videos and the IMU data, the labeled time spans could be transferred to the IMU data. However, the IMU data and the video data were not recorded by the same computer, and the computer clocks were not synchronized. Consequently, the time spans must be shifted by seven seconds. To verify the correct assignment of time spans, each subject's IMU data was visually compared to the video data.

The IMU data was then loaded into Python, with each exercise correctly assigned to the data. Both the accelerometer and gyroscope sensors provide data for three axes separately. Therefore, the Euclidean norm was calculated to obtain the total acceleration and angular velocity. Additionally, the offset observed in each sensor (along with the 1 g of gravity) was subtracted from the data. These offsets were determined prior to analysis.

2.4 Parameter Calculation

In order to detect a difference between a conventional manner and a tremor, a number of parameters derived from the accelerometer and gyroscope data were calculated. There are multiple parameters found in the literature, that are used for analyzing activities of daily living. These include parameters to detect stroke-related laterality (Gulde et al., 2024), to measure the frailty status (Schmidle et al., 2020) or to get an upper limb functional status (Nam et al., 2022). As it was unclear if these parameters could be used to distinguish between tremors and conventional movements, we decided to test multiple found parameters. A list of the calculated parameters is provided in the appendix (Table 3).

To identify the most important parameters, an SVM with radial basis function as the kernel was trained multiple times, with one participant left out as test set for each SVM on the data of the upper arm. The most important features were determined for each run using the *permutation_importance* method, that determines the contribution of each feature to the performance of the SVM. Subsequently, the four most prominent features were identified across all runs. The four parameters that were used in the following analysis for both sensor positions are ”Peak Ratio Acceleration”, ”Relative Activity Acceleration”, ”Peak Ratio Angular Rate”, ”Number Peaks Angular Rate”.

The ”Peak Ratio Acceleration” (see (Schmidle et al., 2020)) was defined as the ratio between the number of peaks having a prominence of 0.2 $\frac{\mathrm{m}}{\mathrm{s}^2}$ or higher and the total number of peaks found in the acceleration data. This parameter was calculated with the scikit-learn method *find_peaks*:

$$\text{PeakRatioAcc} = \frac{\left|\{i \mid \text{prominence}(\text{acc}_i) \geq 0.2\frac{\mathrm{m}}{\mathrm{s}^2}\}\right|}{|\{i \mid i \text{ is a peak in acc}\}|} \tag{1}$$

The ”Relative Activity Acceleration” (see (Schmidle et al., 2020)) was defined as the number of acceleration data points, where the absolute data points are greater than 0.2 $\frac{\mathrm{m}}{\mathrm{s}^2}$ in relation to the total number of data points:

$$\text{RelativeActivityAcc} = \frac{\left|\{z \in \text{acc} \mid |z| > 0.2\frac{\mathrm{m}}{\mathrm{s}^2}\}\right|}{|\text{acc}|} \tag{2}$$

The ”Peak Ratio Angular Rate” (see (Gulde et al., 2024)) represented the signal-to-noise ratio of the angular velocity signal. It was calculated by the number of peaks having a minimum prominence of 0.17 $\frac{\circ}{s}$ divided by the total number of peaks of the angular velocity data. This parameter was also calculated using the scikit-learn method *find_peaks*:

$$\text{PeakRatioGyro} = \frac{\left|\{i \mid \text{prominence}(\text{gyro}_i) \geq 0.17\frac{\circ}{s}\}\right|}{|\{i \mid i \text{ is a peak in gyro}\}|} \tag{3}$$

The ”Number Peaks Angular Rate” was defined as the ratio of all peaks in angular rate data having a minimum height of 1.05 $\frac{\circ}{s}$ and all data points. This calculation used the scikit-learn method *find_peaks*:

$$\text{NumberPeaksGyro} = \frac{\left|\{i \mid \text{height}(\text{gyro}_i) \geq 1.05\frac{\circ}{s}\}\right|}{|\text{gyro}|} \tag{4}$$

The used thresholds for each parameter were primarily derived from existing literature. After identifying these four parameters, we attempted to optimize the thresholds using Bayesian optimization. As the results of the SVMs using the optimized thresholds are comparable, we employed the aforementioned thresholds from the literature for the subsequent analysis.

2.5 Analysis

The aim of this paper is to classify the calculated parameters into two distinct categories: conventional movements and tremor movements. Initially, all parameters were visually analyzed to identify a potential threshold that might separate data from tremor and conventional movements. This was conducted for each calculated parameter and for all used sensors. In addition, we analyzed the distribution of various parameters for each individual participant and for each exercise.

In a second step, we applied machine learning for the purpose of classification. Given the limited size of the dataset, we have decided not to use neural networks. In the existing literature, SVMs were used frequently (Soran et al., 2012; Skaramagkas et al., 2021). Therefore, we trained multiple SVMs. In addition, we attempted to train multiple Random Forest Classifiers. However, the results were slightly worse than those obtained from the trained SVMs, and thus we concentrated our analysis on the SVMs. For training the multiple SVMs, the identified four most important parameters (see Section 2.4) were used. The SVMs were trained using scikit-learn SVC. For each sensor, we trained SVMs, with four different kernels: linear, radial basis function (rbf), polynomial (poly), and sigmoid. All other SVC parameters were set to their default values. For each SVM, cross-validation was employed for training, using a *StratifiedKFold* with ten splits and shuffle, and with accuracy serving as the scoring metric as the accuracy was also given as results in the literature (Soran et al., 2012; Skaramagkas et al., 2021). For each kernel, multiple SVMs were trained with distinct train and test sets. The data of two participants was consistently designated as the testing set, while the remaining participants' data served as the training set. This process was repeated for every possible combination of participants. The performance of the SVMs was evaluated based on the accuracy, recall, precision, and F1 scores obtained from all runs of each used kernel.

All analysis steps were done on both sensors, upper and lower arm, to compare these two positions.

3 RESULTS

Due to the malfunction of the camera during the video recording of one participant, which made it impossible to recognize the different exercises, the data from nine participants could be evaluated. In addition, one participant did not perform the cutting exercise (exercise 3) with a simulated tremor. Therefore, the dataset contained 45 conventional exercise performances and 44 simulated tremor exercise performances.

As described in Section 2.5, we analyzed all parameter values visually to determine whether the tremor and conventional movements could be distinguished. Figure 2 shows the four parameters from Equations 1 to 4 that were used for training the SVM, calculated for the right upper arm. The parameter values for all nine participants and all five exercises (resulting in 45 and 44 values for conventional movement and simulated tremor, respectively) are shown. No clear threshold could be identified for the individual parameters to separate conventional and simulated tremor data. This behavior was observed consistently across all other parameters and sensor positions.

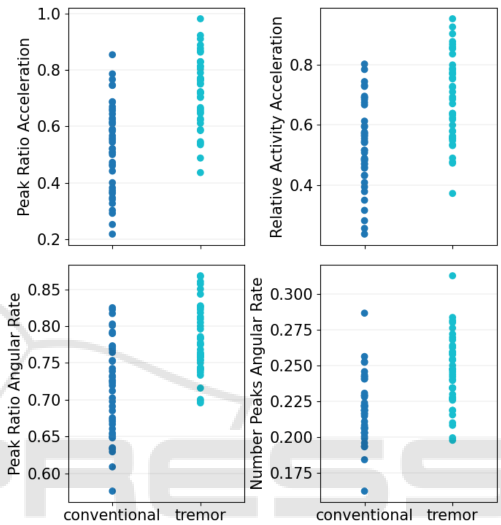


Figure 2: The parameter values for all four used parameters, divided for conventional manner and simulated tremor. The plotted data represent the values for all participants and all exercises. The data are presented for the upper arm.

Furthermore, the distribution of two out of the four used parameters for each exercise and each participant, calculated on the upper arm data, is shown in Figure 3 and Figure 4, respectively. Figure 3 shows that some conventional performances (represented by a cross) of exercises eating an apple (1) and cutting bread (3) were distributed more in the cluster representing the tremor performances (represented by a circle). Figure 4a shows that some performances of participant 0 with a simulated tremor were closely aligned with the cluster representing conventional movements (depicted by blue circles on the left). In addition, the conventional movements of participant 5 (illustrated by brown crosses in Figure 4b) tended towards higher parameter values than the other participants.

Furthermore, multiple SVMs were trained for four different kernels and different train and test sets. Table 1 shows the minimum, maximum, median, and standard deviation of accuracy, recall, precision, and F1 scores for all four kernels, calculated on all splits

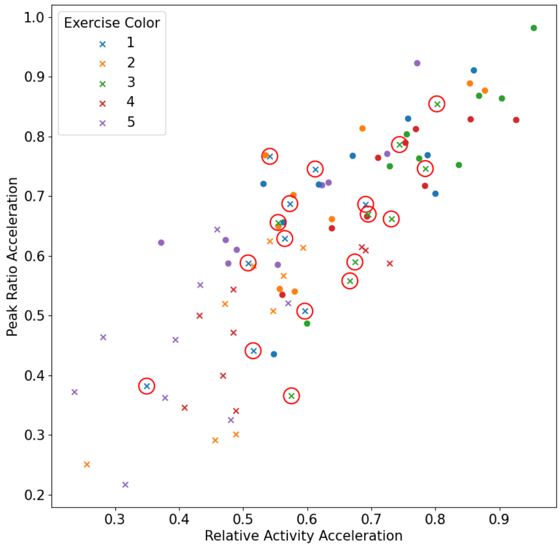


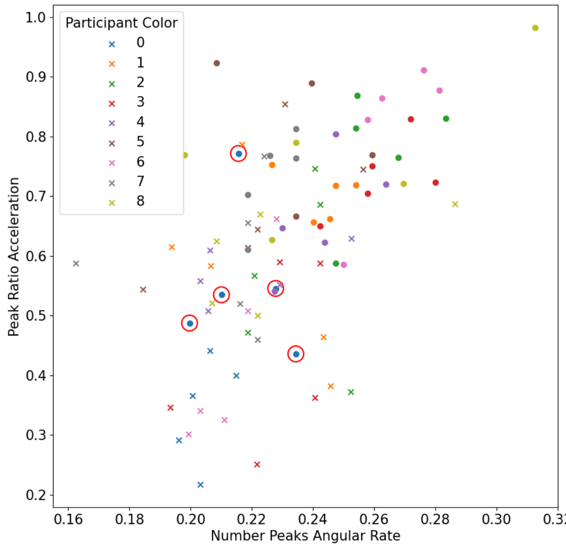
Figure 3: Scatter plot of two out of the four used parameters. The color represents the five different exercises eating an apple (1), eating with a fork (2), cutting a bread (3), spreading butter (4), and eating soup (5). A cross represents a performance in a conventional manner while a circle represents a performance with a simulated tremor. Red circles highlight performances of exercises 1 and 3 with conventional movements. The data are presented for the upper arm.

of the train and test sets. These values are for the sensor attached to the upper arm. The median accuracy was 0.75 for all kernels, while the median F1 score ranged from 0.72 (sigmoid) to 0.79 (poly). In comparison, the metrics for the lower arm are shown in Table 2. Here, the median accuracy ranged from 0.60 (poly) to 0.65 (linear and rbf), while the median F1 score ranged from 0.63 (rbf and poly) to 0.67 (linear and sigmoid).

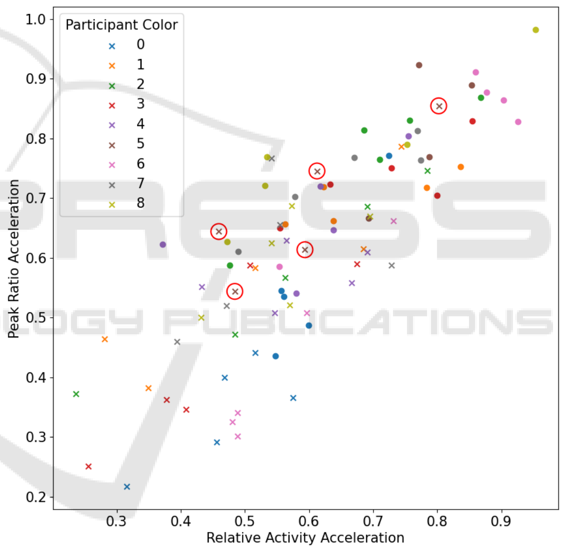
4 DISCUSSION

Upon visual analysis of the parameter values, we could not identify thresholds that would differentiate the values between conventional movements and movements with a simulated tremor. Therefore, there does not seem to be a clear distinction between the two behaviors across all participants. The distribution of the individual participants across the parameters in Figure 4 also demonstrated that there are differences between individuals. These observations align with those of Thorp et al., indicating that most algorithms require individual thresholds for individual persons (Thorp et al., 2018).

The trained SVMs showed that a distinction between conventional movements and tremor yielded to better outcome when a sensor was positioned at the upper arm in comparison to the lower arm. This



(a) Red circles highlight performances of participant 0 with a simulated tremor.



(b) Red circles highlight performances of participant 5 with conventional movements.

Figure 4: Two scatter plots, each showing two out of the four used parameters. The color represents the nine different participants. A cross represents a performance in a conventional manner while a circle represents a performance with a simulated tremor. The data are presented for the upper arm.

is particularly interesting, as the videos indicate that the participants tended to present more noticeable tremors in their lower arms than in their upper arms.

Given the considerable discrepancy in scores between the different splits of train and test sets, we have conducted a more detailed analysis of the test sets with accuracy scores below or equal to 0.6. It is striking that participant 5 had primarily recall scores

Table 1: The minimum (Min), maximum (Max), median, and standard deviation (Std) of the accuracy, recall, precision, and F1 scores for all test sets of the trained support vector machines separated by the four different kernel types linear, rbf, poly, and sigmoid. The data are presented for the upper arm.

		SVM kernel			
		linear	rbf	poly	sigmoid
Accuracy	Min	0.58	0.58	**0.63**	0.55
	Max	**0.95**	**0.95**	0.90	0.90
	Median	**0.75**	**0.75**	**0.75**	**0.75**
	Std	0.09	0.10	**0.06**	0.08
Recall	Min	0.40	0.40	**0.70**	0.30
	Max	**1.00**	**1.00**	**1.00**	**1.00**
	Median	0.80	0.80	**1.00**	0.70
	Std	0.18	0.19	**0.08**	0.19
Precision	Min	0.54	0.55	0.56	**0.57**
	Max	**1.00**	**1.00**	0.9	**1.00**
	Median	0.75	**0.78**	0.67	0.75
	Std	0.11	0.12	**0.07**	0.11
F1	Min	0.50	0.50	**0.72**	0.40
	Max	**0.95**	**0.95**	0.90	0.90
	Median	0.76	0.75	**0.79**	0.72
	Std	0.11	0.12	**0.04**	0.11

Table 2: The minimum (Min), maximum (Max), median, and standard deviation (Std) of the accuracy, recall, precision, and F1 scores for all test sets of the trained support vector machines separated by the four different kernel types linear, rbf, poly, and sigmoid. The data are presented for the lower arm.

		SVM kernel			
		linear	rbf	poly	sigmoid
Accuracy	Min	0.37	0.42	**0.47**	0.45
	Max	**0.90**	0.85	**0.90**	0.85
	Median	**0.65**	**0.65**	0.60	0.62
	Std	0.11	0.11	**0.10**	0.11
Recall	Min	**0.20**	0.10	0.00	**0.20**
	Max	**1.00**	**1.00**	**1.00**	**1.00**
	Median	0.70	0.60	0.63	**0.78**
	Std	0.24	0.22	0.27	**0.19**
Precision	Min	0.40	**0.43**	0.00	0.40
	Max	**1.00**	**1.00**	**1.00**	0.89
	Median	0.64	**0.68**	0.63	0.58
	Std	0.13	0.14	0.18	**0.12**
F1	Min	**0.29**	0.17	0.00	0.27
	Max	**0.91**	0.86	0.90	0.86
	Median	**0.67**	0.63	0.63	**0.67**
	Std	0.15	0.16	0.18	**0.13**

of 0.75 or 1.0 and precision scores of 0.5, indicating that numerous conventional movements were detected as simulated tremors. Upon inspection of the video, it became evident that this participant seemed to experience involuntary tremors on occasional basis. This is observable between the exercises during periods of rest. It is possible that this participant also experienced tremors while performing the exercises in a conventional manner, which could have resulted in the detection as a simulated tremor. In contrast, participant 8 often showed recall and precision scores of 0.6, with three correct and two incorrect exercises of each type of movement. This behavior cannot be explained at first glance, as the videos indicate clear differences between the participants conventional and tremor movements. Participant 0 is also noticeable, with a recall score of only 0.2 and a precision score of 1.0 for the majority of the exercises, as all exercises were usually classified as "conventional". In comparison to other participants, this participant seems to simulate a slightly lighter tremor, which could be the source of these results. These scores align with the results presented in Figure 4. This shows that, on the one hand, a slight natural tremor movement can be detected as tremor while on the other hand, slight simulated tremor movements can be classified as conventional movements. This needs to get investigated further in the future.

The overall results of the trained SVMs on the upper arm with a median accuracy of 0.75 for every kernel indicate that it may be feasible to detect a tremor during ADLs with a non-individualized approach. Skaramagkas et al. show success rates between 56.9% and 96.5%, with an average of 75.66% for data recorded at the forearm (Skaramagkas et al., 2021). These findings are comparable to our results. It should be noted that a distinction was made between three classes (essential tremor, Parkinson's tremor, and no tremor) and not between two classes, as is the case in our study. It is also important to note that a separate classifier was trained for each exercise, rather than a single classifier for different movements combined. As shown in Figure 3, the distributions of parameters may vary in different activities, potentially influencing the results. Our results were not as good as those reported by Soran et al. (accuracy of 95.4%) (Soran et al., 2012), although it is important to note that they used a camera, which is a different sensor system than our used IMUs. The study's findings indicate the presence of differences among the participants, primarily due to the absence of a clear threshold for distinguishing between the movements and the presence of variability in the precision and recall scores of the individual participants. Nevertheless, a non-individualized approach was implemented, enabling the differentiation of tremor from conventional movements with a median accuracy of 0.75.

It should be noted that the data set is relatively small, with only nine participants and five exercises. Additionally, the participants did not experience an actual tremor, but rather simulated one. Nevertheless, the overall results appear promising, suggesting that the study should be repeated with a larger sample size in the future. This should include participants with and without actual tremor performing different exercises to verify that machine learning algorithms like SVM can effectively differentiate between individuals with and without tremor in ADLs. With a larger data set, it is also possible to test whether neural networks, such as LSTM, deliver better results than an SVM. Additionally, a more detailed evaluation of the other calculated parameters could be conducted in the future, as it is possible that the *permutation_feature* method may discard relevant parameters if they appear to correlate with other parameters.

5 CONCLUSION

In conclusion, we trained a SVM as a non-individualized approach to distinguish between a tremor and conventional movements during ADLs with a median accuracy of 0.75. Therefore, in addition to the tests and rating scores used to quantify impairments, data could be recorded in everyday life to identify possible fluctuations throughout the day, generate more objective measurements, and enhance the recognition of actual effects on everyday life. However, this requires further confirmation through a more detailed study.

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APPENDIX

Table 3: All calculated parameters.

Parameter Name	Explanation of parameter
Mean Acceleration	Mean of acceleration; found in (Aguirre, 2016)
Maximal Jerk	Maximum of jerk; found in (Aguirre, 2016)
Mean Jerk	Mean of jerk
Mean Absolute Jerk	Mean of absolute jerk values
Mean Amplitude Deviation Acceleration (MAD)	The mean of the distances to the mean acceleration; based on (Gulde et al., 2024)
90th Percentile of Mean Amplitude Deviation	the 90th percentile of the distances to the mean acceleration; based on (Gulde et al., 2024)
Physical Activity Level	The ratio of the time with an absolute distance to the mean acceleration greater 0.1 g and the total time; based on (Gulde et al., 2024)
Maximum Angular Velocity	The maximum of angular velocity; based on (Gulde et al., 2024)
Mean Angular Velocity	The mean of angular velocity; based on (Gulde et al., 2024)
Standard Deviation Angular Velocity	The standard deviation of angular velocity; based on (Gulde et al., 2024)
Peak Ratio Angular Rate	The ratio of the number of peaks in angular velocity with a prominence of 0.17 $\frac{\circ}{s}$ and the number of all peaks in angular velocity; based on (Gulde et al., 2024)
Number Angular Velocity Peaks per 360°	The number of peaks in angular velocity per 360°; based on (Gulde et al., 2024)
Mean Height Angular Velocity Peaks	The mean of the heights of all peaks in angular velocity; based on (Gulde et al., 2024)
Mean Standard Deviation Angular Velocity Peaks	The standard deviation of the heights of all peaks in angular velocity; based on (Gulde et al., 2024)
Standard Deviation Acceleration	Standard deviation of the acceleration data; found in (Song et al., 2022)
Relative Activity Acceleration	”Period of time in which the absolute acceleration signal exceeded 0.2 $\frac{m}{s^2}$ related to [duration]” (Schmidle et al., 2020)
Peak Standard Deviation Acceleration	”Standard deviation of all acceleration peaks (maxima) in $\frac{m}{s^2}$” (Schmidle et al., 2020)
Peaks Per Second Acceleration	”Number of acceleration peaks per second” (Schmidle et al., 2020)
Peak Ratio Acceleration	”Ratio between the number of acceleration peaks with a minimum prominence of 0.2 $\frac{m}{s^2}$ and the total number of acceleration peaks” (Schmidle et al., 2020)
Mean Peak Acceleration	”Mean of acceleration peaks” (Schmidle et al., 2020)
Signal to Noise Ratio Acceleration	”Ratio of the sum of the frequency spectrum [of the acceleration data] by a fast Fourier transformation from 0.01 to 3 Hz and from 0.01 to 50 Hz” (Schmidle et al., 2020)
Frequency Spectrum 0-3 Hz	Sum of the frequency spectrum of the acceleration data from 0.01 to 3 Hz
Frequency Spectrum 3-50 Hz	Sum of the frequency spectrum of the acceleration data from 3 to 50 Hz
Mean Variance Acceleration	Mean of the variance of every second of the acceleration data
Root Mean Square Acceleration	Root mean square of acceleration data
Root Mean Square Jerk	Root mean square of jerk data
Number Peaks Acceleration	Ratio of all peaks in acceleration data having a minimum hight of 1.05 g and all data points
Mean Variance Angular Rate	Mean of the variance of every second of the angular rate
Amplitude Angular Rate	Difference of maximum and minimum of angular rate
Number Peaks Angular Rate	Ratio of all peaks in angular rate data having a minimum hight of 1.05 $\frac{\circ}{s}$ and all data points