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Quantitative Analysis of Dual Task Cost Based on Different Cognitive Difficulties

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Abstract: The impact of cognitive tasks on human movement is of practical significance; we hereby aim to demonstrate that a significant relationship exists between the dual task's cognitive demand and the disruption caused in hand movement, with the hope to extend this experiment to subjects with disorders (MS, CP, stroke patients) in future studies. By doing so, we hope to be able to develop a metric for evaluating their disease levels using our method and minimize clinical interventions. While previous research has predominantly focused on lower body activities, this study explores the effect of dual tasks on hand movements in healthy individuals.

A simulated finger-to-nose test combined with a standard reverse counting task, featuring four difficulty levels, was conducted. Utilizing SVM and decision tree classifiers, we analyzed various features to discern the impact of cognitive tasks on hand movements, including completed cycles and idle time at markers. Our findings reveal that features such as entropy and kurtosis effectively distinguish between task difficulty levels and hand movement disruption. The classifiers achieved accuracies of 70% and 74% for decision tree and SVM, respectively. We hope extending this research to diseased subjects could potentially provide a more accurate assessment of disease severity through the measurement of hand movements during cognitive tasks, offering a non-clinical alternative for disease evaluation.

Keywords: Hand Movement Analysis, Cognitive Task, Dual Tasks, Finger to Nose Test

1 Introduction

A variety of movement (mostly clinical) and cognitive tests are commonly used as identifiers of the type and severity of numerous diseases. Hand movement tests such as opening a jar of jam, writing down the number 8, finger tapping, finger to nose test, etc., are all examples of clinical tests which help physicians with their diagnosis, referred to as Chedoke Arm and Hand Activity Inventory (CAHAI) [1]. These tests are all qualitative examinations performed by physicians according to their professional preference and experience, and there is no gold standard for such practices. Patients are often scored on a scale of 1-5 based on their performance on these tests, with great variance between the opinions of physicians on how the patient performs. Apart from the lack of homogeneity in the named tests and the different scaling of patients by physicians, less experienced neurologists may easily miss small but highly indicative movement patterns. Such factors contribute to this area being prone to significant physical error [2]. The approach that researchers have obtained for dealing with these errors is the creation of a unified, quantitative test [3].

Many studies have pursued the goal of quantifying these commonly performed tests and creating new tests for such methods of diagnosis. Other researchers have aimed to create a valid tool that can serve as a gold-standard and reduce the errors in existing methods. The lack of such tools becomes more evident in the evaluation of patient rehabilitation outcomes. In one of

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such studies, Rodriguez et al. [4] tried to prove the effectiveness of the finger-to-nose test by studying endpoint performance (total movement time, trajectory straightness, and precision) and movement variability (joint rotations and inter-joint coordination). Their results demonstrate that the finger-to-nose test can be used as a valid indicator of upper limb coordination levels in stroke patients. In another study, Esteki et al. [5] looked at the effectiveness of Deep Brain Stimulation (DBS) on multiple sclerosis (MS) patients by simulating the finger-to-nose tests and studying the mean and deviation from the straight path of movement. The outcome of this study demonstrated the effectiveness of DBS on MS patients' hand vibration. Esmaeilpour et al. [6] complemented the above mentioned study by also analyzing non-linear features such as entropy, dominant frequency, mean, median, and standard deviation. Their results further strengthened the hypothesis presented by [4]. Another study by Lackzo et al. [7] analyzed inter-joint coordination deficits revealed in the decomposition of endpoint jerk during goal directed arm movement after stroke by calculating the smoothness of motion in a two-joint robot. Some researchers have performed more specific analyses using the quantification of movement for identifying the degree of disease in strokes[8, 9], Multiple Sclerosis[10], Ataxia[11, 12], and Parkinson disease[2]. Also, Krishna et al. conducted a study utilizing three clinical tests, including the FNT, to assess the severity of Cerebellar Ataxia (CA) and extract relevant features from hand movements. Their findings indicated that features such as acceleration serve as indicators of the disease, and the FNT demonstrated high accuracy and specificity in detecting CA [13]. Additionally, Khai et al. employed virtual reality (VR) technology to determine hand positions, simulating the Finger-to-Nose Test on 10 Cerebellar Stroke (CS) patients and 19 healthy subjects. Their research revealed that the reaching error was significantly higher in CS patients compared to age-matched controls across all conditions, suggesting its potential as an assessment tool for the severity of CS [14]. Similarly, Takayuki et al. utilized VR to simulate the Finger-to-Nose Test for evaluating the severity of cerebellar ataxia. Their study proposed an automated FNT measurement and evaluation system within the VR environment, demonstrating high accuracy and quantitative assessment capabilities [15].

Different approaches have been taken to detect cognitive patterns during movement. Some researchers have studied the interruptions that occur while performing two cognitive tasks concurrently, while others have looked at the effect of movement on the ability to perform cognitive tasks. According to the "limited capacity theory" attention, when a human performs two attention-demanding tasks simultaneously, one or both tasks will be disrupted [16]. For example, when we walk and text, our walking speed will unconsciously decrease, which is named the dual-task cost. Speciali et al. [17] studied simultaneous gait movements with cognitive tasks in Parkinson's patients in 2013. They detected a significant difference in patients when just walking, and walking while performing mathematical operations. In another study, Tsuyoshi Asai [18] analyzed the effect of cognitive tasks on body movement and gait in patients suffering from fear of falling, and demonstrated that simultaneous backward counting while walking increased the fluctuations in body movement. Pam Belluck [19] also studied the effect of cognitive tasks while walking on Alzheimer's patients by asking subjects to count backward from 50 while walking, and demonstrated that gait movement was disrupted when counting was in progress. Other studies have focused on standing and posture changes while performing cognitive tasks [20-26], while some groups have specifically studied the effect of cognitive tasks on lower limbs such as the ankle [27, 28].

Despite the aforementioned studies being conducted to analyze the effects of dual tasking, no studies have analyzed the effect of cognitive tasks on the hand movement of subjects. We hereby aim to demonstrate that a significant relationship exists between the dual task's cognitive demand and the disruption caused in hand movement, with the hope to extend this experiment to subjects with disorders (MS, CP, stroke patients) in future studies. By doing so, we hope to be able to develop a metric for evaluating their disease levels using our method and minimize clinical interventions.

2 Methods

2.1 Participants

The general goal of this experiment was to study the effects of cognitive tasks on hand movement as a basis for future studies. The signal from the movement task was recorded while the cognitive tasks were performed simultaneously. For this means, we aimed to form a representative group of participants that were in similar conditions. A group of 25 males, all right-handed and in the age range of 20-30 were recruited. Subjects were asked to fill out questionnaires to ensure they had no cognitive or movement disabilities. All tests were carried out in the morning to ensure similar test conditions. This precaution was applied because in preliminary experiments, it was observed that the focus and attention levels of individuals varied at different times of the day.

2.2 Apparatus

In this study, each subject's hand movement data is collected in three dimensions using an ultrasonic motion detector system (CMS10, manufactured by Zebris, Germany). Three sensors are used for this purpose, where two are used as the start and target points, and the third is placed on the subject's index finger as a pointer. WinData is used to acquire the signal, MATLAB is used for converting ASCII data to interpretable form and extracting signal properties, and SPSS is used for statistical analysis.

2.3 Movement task

As previously mentioned, the finger-to-nose test is one of the well-known tasks in order to detect movement disorders; also, it has already been proven as a valid indicator of upper limb coordination levels for patients suffering from diseases like stroke and Multiple Sclerosis [4-6, 13-15]. In order to simulate the finger-to-nose test, we placed two markers, hereafter referred to as the close and far targets on a table, and the third marker on the index finger of the subject's right hand. The close and far markers were placed 10cm and 40cm away from the subject, respectively. Subjects were then seated at a 90-degree angle behind the table, with the stable markers placed in front of them and on the anterior-posterior stretch (AP3). A still chair was used to prevent any extra movement, and all subjects were asked to remain in a relatively still position during the experiment. Each subject was asked to start moving between the two markers one second after the start of the experiment by repeatedly moving their finger between the close and far markers. This simulation of the finger-to-nose test is widely used by physicians for clinical studies. A camera was placed at the sagittal plane of the subject, where the ultrasound device captured 3D position at a frequency of 80 Hz in 20 seconds. The 20 second window was selected to ensure sufficient timing to capture all features, but also to keep the test short enough to prevent fatigue in the subjects. A schematic of the experimental setup is presented in Fig. 1.

Fig. 1. A schematic of the experiment setup. The red dots indicate the three markers. The distance between each marker and the subject is shown.

2.4 Cognitive Task

This test consisted of four different difficulty levels, categorized based on the level of difficulty of the second task accompanying the primary hand movement explained above. The difficulty levels were obtained from a survey of 30 people using the Likert Scale [29]. At the first level, subjects were asked only to perform the movement test without any extra cognitive tasks. In the following three levels, the subjects were asked to perform simple mathematical operations while performing the movement task. The mathematical operation consists of the subject performing subsequent negations from a specific number, and counting backward. At the second level, which is named the easy level, the subject was asked to negate 2 from a specific number each time. The third (moderate) and fourth (difficult) levels consist of the subject continuously negating 7 and 13 from a given number, respectively.

For each participant, the experiment was conducted and data was recorded three times on the same morning. Subjects were first engaged in a test round to familiarize them with the procedure. Subjects created multiple pauses during this test round to ask questions and confirm the procedures they were given. This caused the first-round data to be highly unstable; therefore, the data gathered in this round was discarded. The first period of the movement signals was also discarded because it included starting jerks and vibrations.

2.5 Signal Processing

The initial two markers serve the purpose of establishing both the starting and ending points of the hand movement trajectory, while the third marker is dedicated to tracking the hand's 3D path between these points. The 3D coordinates of this marker were recorded to generate three 2D planes, representing the hand's vibration, movement, and elevation. It is evident that distinct patterns of hand movement can be discerned within each dimension. Fig. 2 illustrates the hand movement patterns in the Y-X and Y-Z planes. These segregated signals hold potential for offering valuable insights and information, thus each plane (x, y, and z) was analyzed individually. In the pre-processing of the data, the following steps were taken: 1) the baseline signal was first removed, 2) the signal was mean removed, 3) interpolation was applied for the lost data, and 4) a 10 Hz low-pass filter was applied to remove noise. The data obtained after these steps was used for calculating movement features. A sample of hand movements in the sagittal and horizontal trajectories during a 20 second test without a cognitive task is depicted in Fig. 2a and 2b, respectively. After obtaining signals and applying data pre-processing, we computed some movement features which can be divided into statistical and non-linear features. In the statistical features, the following are evaluated: 1- Precision and accuracy: used as performance estimation metrics, obtained using the average movement of the hand and standard deviation; 2- The number of completed cycles: computed by counting the number of back and forth between the near and far markers; In the role of non-linear features, we had: 1- Cumulative power: obtained by calculating the area under the curve of the Fourier transform of the signal; 2- Index of curvature: used to calculate the straightness of the path, obtained using the ratio of the 3D distance traveled to the shortest distance between the two markers; 3- Skewness and kurtosis: measured as the third and fourth moment of probability distributed function calculating the asymmetry and tailedness of the PDF. Then, the approximate entropy and Shannon entropy are computed to compute the amount of irregularity and information in the signal. Also, the velocity of hand movement is computed as the average speed of the hand in the movement plane.

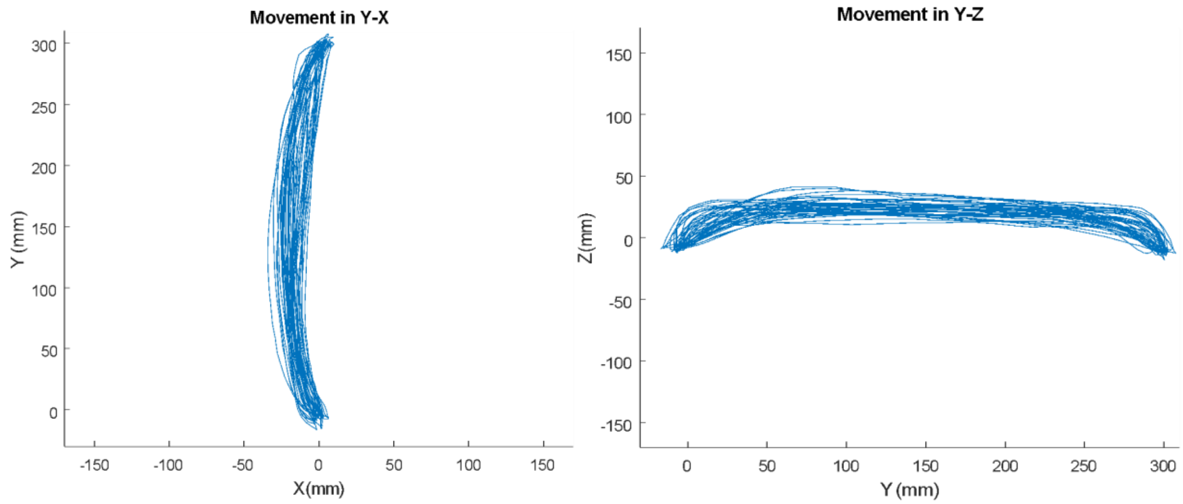

Fig. 2. Sample of hand movements during a 20 second finger to nose test in the sagittal and horizontal trajectories for a healthy subject without a cognitive task

2.6 Statistical Analysis

After calculating the features, statistical analysis was performed to determine the significance of each feature and determine to what extent each of the obtained features can predict the difficulty level. Since there was no independence within the groups, we used a Paired-T test to determine the difference between the two groups, and used a repeated measure test to test for statistical significance between the 4 classes (no cognitive task, easy, moderate, and difficult).

The selected features were then fed into a pattern classification algorithm to determine to what extent they were capable of determining the correct class of each signal. We used both support vector machines (SVM) and decision trees for this purpose, and constructed the confusion matrix using the results. From the confusion matrix, we obtained the true positive rate, false negative rate, positive predictive value and false discovery rate. All classifications were performed using MATLAB's classification learner. A linear SVM model with box constraint level set to 5, kernel scaling mode set to automatic, and all other parameters set as default was used. For the decision tree, a coarse tree was used with the maximum number of splits set to 4, and all other parameters set to default. The parameters for both the SVM and decision trees were selected through trial and error, where it was found that the selected parameters yielded the best results.

3 Results and Discussion

3.1 Feature selection

All experiment results presented in this section have been evaluated using five-fold cross-validation. Regarding the choice of statistical tests, we considered both parametric and non-parametric options. While parametric tests are typically used when data are normally distributed, non-parametric tests are more robust to deviations from normality and are suitable for data with non-normal distributions or smaller sample sizes. In this paper, we opted for parametric tests due to the nature of our data and the sample size. With a sample size of $n \geq 25$ and a skewness value close to zero, we determined that our data met the assumptions for using parametric tests. Experiment results for the repeated measure tests for Kurtosis, approximate entropy, and

Shannon entropy in the hand's movement plane are provided in Table 1. Table 1 shows that repeated measure tests determine a significant difference between the classes with an error rate of 5%. The first feature to consider is entropy, where the repeated measure test shows that the entropy can distinguish the 4 classes from one another with relatively high confidence. The best result comes from Shannon entropy as our first feature when the p-value equals 0.005. The next feature is kurtosis, where according to Table 1 it is able to distinguish between the classes with p-value equals to 0.001. Also, Cumulative power shows that it can distinguish four classes with a p-value of 0.001 in repeated measure test.

Table 1 The repeated measure test for Kurtosis, approximate entropy, and Shannon entropy in the hand's movement plane.

Index	P-value	F
Kurtosis	<0.001	7.009
Approximate entropy	0.018	4.28
Shannon entropy	0.005	4.62
Cumulative Power	<0.001	5.13

We also analyze the index of curvature, which looks at the ratio of distance traveled by the subject to the shortest distance between the two markers. It goes without saying that this metric will be increased once the subject is not able to follow the normal and optimal path between the markers. This feature can differentiate the primary and easy levels from the medium and hard levels with statistical significance, which can also be observed in Fig. 3. However, it could not determine a significant difference between the primary and easy levels, or between the moderate and difficult levels.

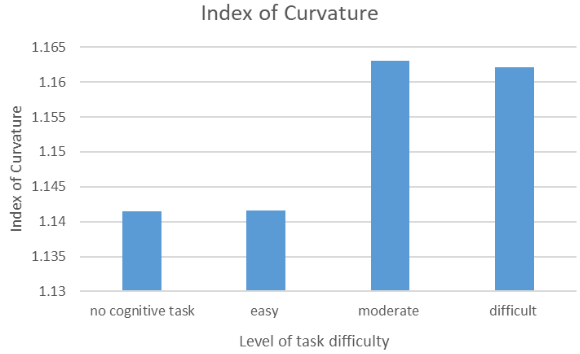

Fig. 3. Index of curvature for the four cognitive levels.

Additionally, Fig. 4 visually compares results for different task difficulties, and as it can be seen, kurtosis and the number of completed cycles are highest for the easy level compared to other levels. Conversely, idle times at both markers are lowest at both markers for the easy level. A Paired-T test is applied to the number of cycles and idle time at each marker to distinguish between the easy level and the other three levels (Table 2). Since, we have four classes and we want to compare these four classes two by two, we should use Bonferroni correction to normalize p value and make it comparable. So, the Bonferroni correction is applied and because we are comparing multiple groups (n=4), therefore a p value of 0.0125 is used. As shown in figure 4, there is a correlation between completed cycles, idle time at the near marker and idle time at the far marker. This is probably because subjects will have a higher number of completed cycles when they have shorter pauses at the markers. So, to have less redundancy, we only select completed cycles. Finally, kurtosis, cumulative power, Shannon entropy, index of curvature, and completed cycles were chosen to feed our classifiers.

Table 2 The Paired-T test for number of completed cycles, idle time in first marker and idle time in second marker in the hand's movement plane.

Index	Cognitive Level	P-value	T
Completed cycle	no cognitive task & easy level	<0.001	4.17
	Easy & moderate level	0.002	3.19
	Easy & difficult level	0.002	3.07
Idle time in first marker	no cognitive task & easy level	0.011	2.41
	Easy & moderate level	0.015	2.28
	Easy & difficult level	0.001	3.3
	Moderate & difficult level	0.302	0.52
Idle time in second marker	no cognitive task & easy level	0.007	2.6
	Easy & moderate level	0.006	2.68
	Easy & difficult level	<0.001	3.69
	Moderate & difficult level	0.197	0.86

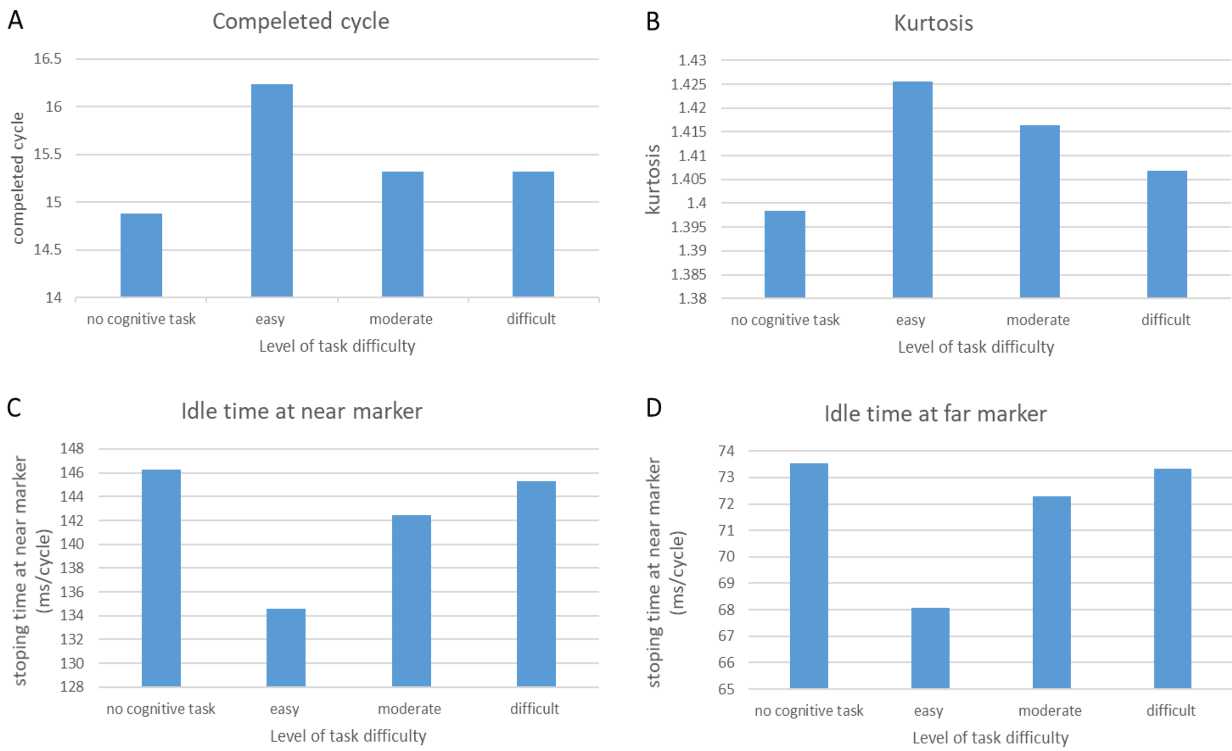

Fig. 4. (A) Completed cycles for the four cognitive levels; (B) Kurtosis for the four cognitive levels; (C) Idle time at the near marker for the four cognitive levels; (D) Idle time at the far marker for the four cognitive levels.

By looking at the confusion matrix of the decision tree and SVM classifiers (Figure 5), we obtain accuracies of 70% and 74%, respectively. Classes 1 and 2 demonstrate a high predictability value close to 80%, while this value drops to 52% and 68% for classes 3 and 4, respectively. By looking at the true positive rate of the classes, it is observed that the features were able to predict classes 1, 2 and 4 with an average accuracy close to 80%, whereas this figure dropped to approximately 50% for class 3. According to these results, our algorithms were easily able to distinguish between all classes except class 3, as the data demonstrated overlaps with the other classes.

Ground Truth	Prediction: no cognitive task	Easy level	Moderate level	Difficult level	**True positive rate**	**False negative rate**
no cognitive task	20	3	2	0	**80 %**	**20 %**
Easy level	2	19	4	0	**76 %**	**24 %**
Moderate level	2	2	12	9	**48 %**	**52 %**
Difficult level	0	1	5	19	**76 %**	**24 %**
Positive predictive values	**83 %**	**76 %**	**52 %**	**68 %**		
False discovery rate	**17 %**	**24 %**	**48 %**	**32 %**		

Ground Truth	Prediction: no cognitive task	Easy level	Moderate level	Difficult level	**True positive rate**	**False negative rate**
no cognitive task	21	2	2	0	**84 %**	**16 %**
Easy level	2	20	2	1	**80 %**	**20 %**
Moderate level	1	2	14	8	**56 %**	**44 %**
Difficult level	0	0	6	19	**76 %**	**24 %**
Positive predictive values	**88 %**	**83 %**	**58 %**	**68 %**		
False discovery rate	**12 %**	**17 %**	**42 %**	**32 %**		

Fig. 5. Confusion matrix for decision tree (left); confusion matrix for svm (right).

During the experiments, when we asked subjects to move their hands between the two markers without performing any cognitive tasks, they were able to do so easily and with full control over their movement. But when the counting task started, a decrease in movement control were observed. Subjects generally tried to compensate this decrease in control by increasing movement speed. Therefore, it was observed that after the start of the cognitive task, the number of cycles completed by each individual increased (Figure 4). Although this fact must be taken into account that at the easy level, the subjects do not require significant focus to perform the cognitive task as it is relatively simple. Therefore, they were able to increase their movement speed and thus complete more cycles quite easily. But during the next two levels and as the cognitive task became more difficult, subjects had to pay more attention to their counting. Therefore, it was observed that the number of cycles during these levels decreased once again, and kurtosis also decreased at both levels, more so for the hard level than the medium.

We also looked at the possibility of correlation between the number of cycles completed and the velocity of hand movement and idle time at the markers. By computing the idle time at the first marker (Figure 4), we found that idle time was significantly less for the easy level compared to the other levels. This re-confirms our theory that when the subject starts his cognitive task, a reduction in movement control occurs, and the subject tries to compensate for this with increased movement speed and less idle time. Once again, it is observed that the subject is only able to attempt this compensation when the cognitive task is simple to perform and requires minimal concentration, as this does not occur in the other two difficulty levels. Hence, idle time at the markers increases as the difficulty level increases (Figure 4). By applying a Paired-T test, it was found that this difference is significant between all classes except between the moderate and hard levels (Table 2). Classification results also confirmed that difficulty existed when distinguishing between the medium and hard levels. This does not overshadow our work since the goal was to determine whether it’s possible to distinguish between an individual state while performing a cognitively involved dual task and while not performing one. This problem could be dealt with by increasing the difference between difficulty levels in future research.

4 Conclusion

In this study, it was revealed that performing cognitive tasks can have a significant effect on the hand movements of healthy subjects, and that the difficulty of the task being performed is also effective. While the subjects were easily able to perform the movement tasks, they encountered problems once this task was coupled with a backward counting task. At easier levels of this task, subjects responded by increasing movement speed and decreasing idle time at each marker to compensate for disrupted movement. When the cognitive task became more difficult and demanded more concentration, they were forced to reduce speed to ensure correct movement. Our results also demonstrated that an increase in difficulty levels of the tests may be required to achieve statistically significant results. This work was conducted and completed in 2019 so we hope for many advancements since then in this field.

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