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RESEARCH ARTICLE

Full Hand Pose Recognition in Performing Daily Activities for Tele-Rehabilitation based on Decision Tree Algorithm

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ABSTRACT - The older population has the highest risk of getting a stroke, leading to a high healthcare cost and a heavy economic burden to the nation. Tele-rehabilitation aids to enhance the life of stroke survivors by allowing them to conduct the therapy from home, which helps the patient with low mobility and living far from the medical centers. This work focuses on the development of full hand pose recognition in performing daily activities for tele-rehabilitation treatment using Decision Tree algorithm under Machine Learning. Force sensor, flexible sensors and MPU6050 Micro Electro-Mechanical system (MEMS) are used for the data collection. All the sensors' readings act as the input to the Machine Learning algorithm and the type of hand pose acts as the output. Three hand gesture procedure are chosen in this study, which are grasping a glass, turning the pipe and switching on the plug. The procedure for data collection has been devised. The Decision Tree has been trained and tested using Python programming language on Jupyter Notebook, a web-based interactive computing platform. At this stage of study, tests are conducted with healthy subjects to validate the feasibility and effectiveness of the proposed recognition system. An accuracy of 94% for the hand pose recognition while performing the three daily activities has been achieved. This project will assist the medical staffs in delivering a better treatment for the patients and will lead to a faster recovery process.

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1.0 INTRODUCTION

Human hands are able to manipulate various objects, machines, tools and are also used to socialize with other humans. The hand actions involve a high mobility of the fingers. Rehabilitation treatment facilitates the patients who has lost their limb abilities to regains their functionality. Besides the current manual rehabilitation therapies, there are various robotic assisted rehabilitation therapies introduced and under study [1]- [2]. Tele-rehabilitation is a system that allows medical staff to assess and give treatment to the patients using communication technologies remotely from the hospitals. These systems may be helpful in the recovery of the motor function following stroke and injuries. Tele-rehabilitation is also a specialized field in telehealth that enables the implementation of therapeutic programs through a multimedia platform.

Tele-rehabilitation gives a higher level of satisfaction to the patient as they need less help from a family member during self-therapy at home compared to the conventional rehabilitation in improving upper limb functionality. Tele-rehabilitation is also suitable for patients who are having difficulties to travel to the clinic. It provides a cost-effective treatment, reduces the pain and improves treatment. Tele-rehabilitation benefits the patients by enabling the patients to carry out therapy at home and communicate via the Internet regarding the recovery process [3]. Health professionals can remotely monitor the patient's performance.

Machine learning is an artificial intelligence algorithm with the ability to learn. It works by getting input data from the user and analyzing the data. The data is used to identify the patterns of the input, which are then used to make the output prediction. There are three types of machine learning which are supervised learning, unsupervised learning and reinforcement learning. The decision tree is classified under supervised machine learning which is used in this study as it can be used for classification problems. This algorithm uses a branching method to illustrate every possible outcome of a decision. It takes decisions based on the answer to every condition.

This research presents a full hand pose recognition in performing daily activities for tele-rehabilitation using Decision Tree algorithm under machine learning. The contribution of this research is a new method of hand pose recognition while performing 3 selected activities of daily living, for tele-rehabilitation application, using flex sensors, force sensors and MPU6050 gyroscope by implementing the Decision Tree algorithm. The human hand movement, fingers motion and force data while performing the daily tasks on the manipulation rehabilitation board are collected. This board is used in Malaysian public hospitals for patients' rehabilitation treatment. The performance of the proposed system has been tested

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by hardware experimental tests. The rest of the paper is organized as follows: Section 2 describes the previous works on hand pose recognition, Section 3 outlines the methodology, including the data collection procedure and devices configuration. Results are discussed in Section 4 and finally conclusions are drawn in Section 5.

2.0 PREVIOUS WORKS ON HAND POSE RECOGNITION

In recent years, there are tremendous efforts by researchers to develop hand pose recognition systems for various applications such as sign language and tele-rehabilitation. Different methods and devices were deployed to achieve their research objectives. In this review, we focused on the data collecting devices and the machine-learn algorithm for hand pose recognition.

2.1 Data Collection Devices for Hand Pose Recognition System

Many devices like encoders, Electromyography (EMG) signals, inertial measuring units, flex sensors, optical fiber, have been used to measure human hand motions for hand pose recognition. Rogez et al. the formulated hand poses recognition task as a tracking problem, giving red, green and blue (RGB) sequence manual initialization [4]. A fully automated method in processing egocentric videos is challenging as there is only a limited view from the egocentric viewpoint. This causes the hands to move outside of camera frequently. According to Rashid and Hasan [5], physiotherapists uses goniometers for measuring hand angles, hand stretch dynamometers for hand grip force measurement and questionnaires to monitor the rehabilitation process, with the aim to identify the patients' ability to perform different tasks [5]. However, this method consumes a lot of time and energy for both patients and medical staff. Tian et al. works on gesture Control Armbands for hand pose recognition while performing daily activities [6]. The armband consists of Inertia Measurement Unit (IMU) and 8 surface EMG sensors including a Bluetooth receiver. The band is placed on the wrist for data collection. The sensor is portable and can recognize several features. However, the amount of data that can be recognized is limited, making it difficult for the application involving fine-finger motions. Rastogi et al. uses RGB and Leap motion sensors for the classification of hand gestures in sign language recognition [7]. However, the system involves a high computational cost and multiple cameras are needed to obtain robust results. In [8], sensors are incorporated on a glove to recognize the user's hand pose. The stretch sensors are placed on the glove to capture any deformation of the hand.

2.2 Machine Learning Algorithm for Recognition Systems

The accuracy of hand pose recognition depends on the machine learning algorithm and the quality of the data set. Several recognition problems have been solved using ML algorithms [9]-[10]. Deep learning also has developed rapidly in recent years and has been widely used for hand pose estimation. Convolutional Neural Networks is a type of traditional Artificial Neural Network (ANN) with a convolutional layer and dropout layer to avoid overfitting. Stephenson et al. implemented CNN to classify the upper limb's EMG signals of four healthy subjects. In recognizing the 12 poses, 94.9% accuracy is achieved [11]. A three-dimensional Convolutional Neural Networks (3D CNN) has been applied for hand gesture recognition using depth cameras in [12]. 50 healthy subjects perform 7 gestures to validate the system. A CNN based classifier has also been used to classify 11 hand poses for 18 healthy subject and 95% accuracy is achieved in the research [13]. Data mining has been implemented to identify the bandwidth of hand motion in [14]. CNN has also been used in recognising 24 letters [15]. A hierarchical decision has been programmed for hand gesture classifier based on the finger feature [16]. In the works in [17], a one-dimensional feature vector is generated and then fed into a one-vs-all nonlinear SVM classifier with Radial Basis Function (RBF) for gesture classification. A recognition accuracy of 93.3% has been achieved. Naglot and Kulkarni classify 26 American Sign Language (ASL) alphabets using ANN with the back-propagation algorithm and an accuracy of 96.2% has been achieved [18].

Medical staff and stroke patients need full hand pose recognizer for measuring the patient's recovery in performing important daily activities for tele-rehabilitation treatment that can be conducted outside the hospitals compound or rehabilitation centres. Many of the patients are facing difficulties to go to the medical centre for treatment due to high travelling time and cost and needing the help of others to assist them during the travel to the centres. The hand pose recognition in the previous study only focuses on the general movements of the upper limb. Relatively less studies have been conducted specifically on the hand poses while performing the activities on the manipulation rehabilitation boards that are used during rehabilitation therapies in Malaysian government hospitals as shown in Figure 1.

Figure 1. Manipulation Board used in the rehabilitation therapy in Malaysian hospitals

3.0 METHODOLOGY

An electrical circuit consisting of the flex sensors, force sensors and MPU6050 MEMS has been constructed for the hand pose recognition system while performing daily activities on the Manipulation Board. Data are collected using Arduino Uno and CoolTerm software applications. 30 participants aged 20 to 25 years old has participated in the data collection process since this study is still at preliminary stage. Some of the activities on the Manipulation Board used in Malaysia public hospitals have been included for the hand pose recognition, which are

1. Grasping the glass.
2. Switching on the plug.
3. Turning the pipe.

These three specific activities have been chosen in this study since they are among the common tasks performed in daily activities.At this stage of study, the data are collected from healthy subjects to check the feasibility of the proposed system before implementing it on real patients. Each of the subjects must wear a glove embedded with flex sensors, force sensors and MPU6050 MEMS, and repeat each task for three cycles, similar as the study in [9]. Decision Tree algorithm under machine learning has been used to identify the type of movement performed by the subjects. The algorithm has been implemented using Python programming language on Jupyter Notebook web-based interactive computing platform.

3.1 Procedure for Data Collection

Three hand gesture while performing daily tasks have been chosen in this study which are grasping a glass, turning the pipe and switching on the plug. The procedure for conducting these activities for data collection has been devised as follows:

1. The subject sits on a chair that is positioned in front of the table where the Manipulation Board is placed.
2. The subject's hand is placed on the table, near the Manipulation Board.
3. The subject starts to perform the required activities.
4. The sensors reading is collected when the hand starts to move.
5. The subject repeats each task for three times.
6. The experiment ends when the subjects have completed performing the three cycles of motion of all the three tasks.

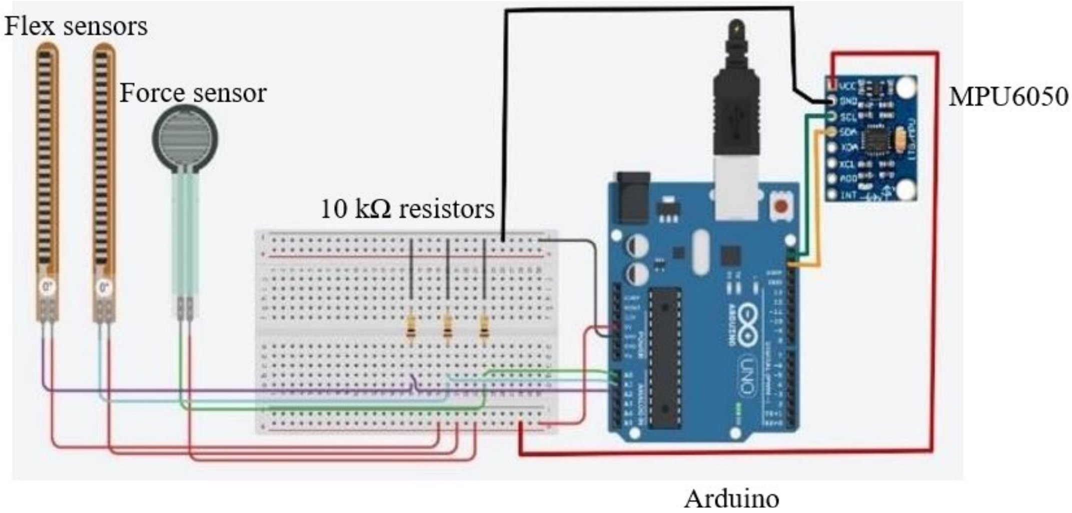
The collected data that acts as the input data to the Decision Tree algorithm includes the resistance of the flex sensors and force sensors, and acceleration and rotational angle from the MPU6050 Micro Electro-Mechanical system (MEMS).

3.2 Data Collection

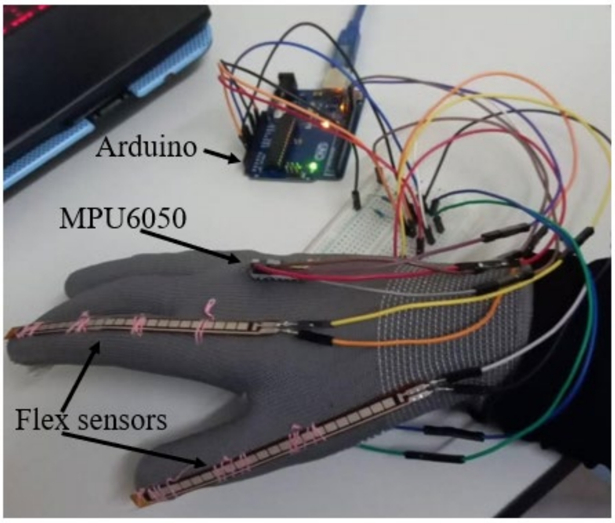
The components for data collection involve Arduino Uno, flex sensors, Force Sensitivity Resistor (FSR) and MPU6050 Micro Electro-mechanical system (MEMS). The flex sensor or bend sensor is used to measure the amount of finger deflection. Its resistance changes according to the bending angle. The force sensor or FSR is used to detect the amount of force exerted on the fingertip as the participants apply some pressure while performing the activities. This sensor exhibits changes in the resistance when pressure is applied to the sensing area. The resistance value is low if large pressure is applied and vice versa. The MPU6050 MEMS is equipped with a gyroscope and an accelerometer which enable the rotational angle and acceleration to be measured around three axes.

The electrical connections of the hand pose recognition system for tele-rehabilitation system consisting of the Arduino Uno, three 10 kΩ resistors, a force sensor, two flex sensors, an MPU6050 MEMS and jumper wires is illustrated in Figure 2 (a). The force sensor is placed at the index finger tip and connected to A0 analog pin of the Arduino Uno as depicted in

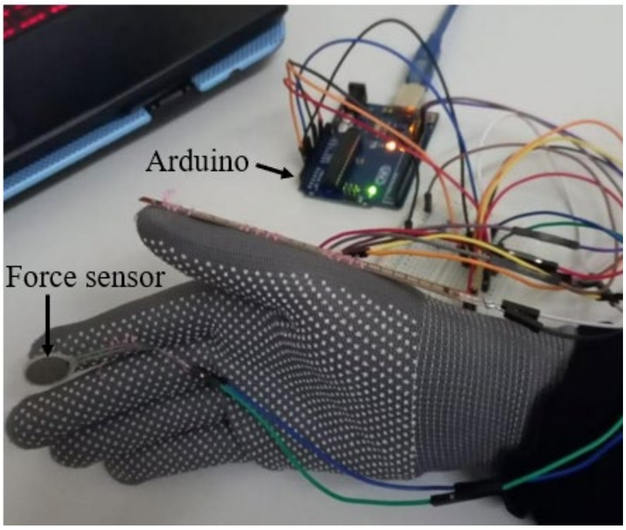
Figure 2 (b). MPU6050 is placed at the back of the hand to detect the acceleration and rotational angle of hand movement while performing the three activities. Two flex sensors are placed on the thumb and index finger as shown in Figure 2 (c) and they are connected to A1 and A2 analog pins of the Arduino Uno. Three 10 kΩ resistors are used in voltage divider circuit so that the resistance reading for sensors can be obtained.



(a)



(b)



(c)

Figure 2. (a) Electrical connection for data collection (b) Flex sensor configuration on the glove (c) Force sensor placement on the glove

3.3 Decision Tree

Decision Tree algorithm under the machine learning technique has been chosen to identify the correct hand pose while performing the selected Activities Daily Living (ADL) on the Manipulation Board for rehabilitation treatment. It has been chosen since it is easy to understand and interpret. Decision tree is a non-parametric supervised learning algorithm that implements a model with tree-like feature, consisting of the decision and possible consequences in solving classification and regression problems. It is easy to understand and highly intuitive. Further information on Decision Tree can be found in [19]- [20]. In this study, the input to the Decision Tree algorithm are the subject's flex sensor data, providing the movement of the thumb and index finger, force sensor reading that gives the amount of force exerted on the fingertip, and MPU6050 data that supply the information of the hand rotational movements and acceleration. The identified hand poses which are grasping a glass, turning the pipe and switching on the plug are set as the output for the model training purpose. Only the thumb and index finger data are used instead of all the 5 fingers since it is assumed that the movement of middle, ring and little fingers are similar to the index finger's motion. From the 30 healthy participants' data collected, 7272 data are used for training and 1818 data are utilized for testing purpose. The codes are written using Python programming language on Jupyter Notebook platform. This enables the data inspection to be easier compared to other code editors. The Decision Tree algorithm is available in a library called scikit-learn. Sklearn is a package that comes with a scikit-learn library. The module named "tree" in the Sklearn package comes with the Decision Tree classifier.

4.0 RESULTS AND DISCUSSION

The acceleration and rotation of the hand around x, y and z axes, force sensor and flex sensors reading for grasping a glass, turning the pipe and switching on the plug are depicted in Figures 3-6, Figures 7-10 and Figures 11-14 respectively. From Figures 3-6, it can be seen that the acceleration of the hand in z axis gives the highest variation compared to the other two axes while grasping a glass. The force sensor reading increases as pressure is applied as the hand holds the glass. The resistance of the flex sensor attached to the index finger shows a higher increment than the one measuring the thumb movement, which agrees to the natural hand motion when grasping a glass. Figures 9 show that 5800 kΩ force is exerted by the fingertip when the pipe is turned. The resistance of both flex sensors attached to the thumb and index fingers vary while turning the pipe as can be observed in Figure 10. For the last task, Figure 11 exhibits the highest variation of the hand acceleration occurs around y axis compared to x and z axes. The value of the flex sensor resistance for the index finger records a higher change compared to the thumb as can be seen in Figure 14 since the index finger is used to switch on the plug.

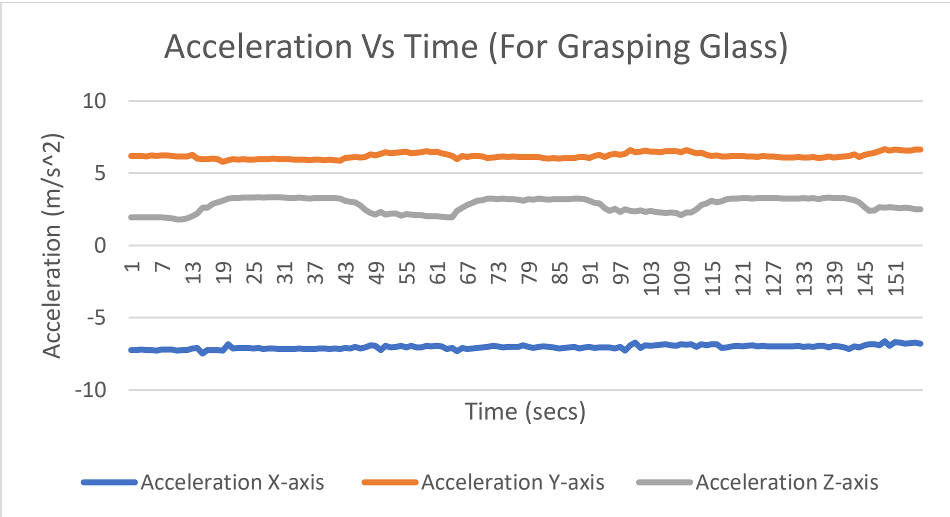


Figure 3. Acceleration of the hand around x, y and z axes while grasping a glass

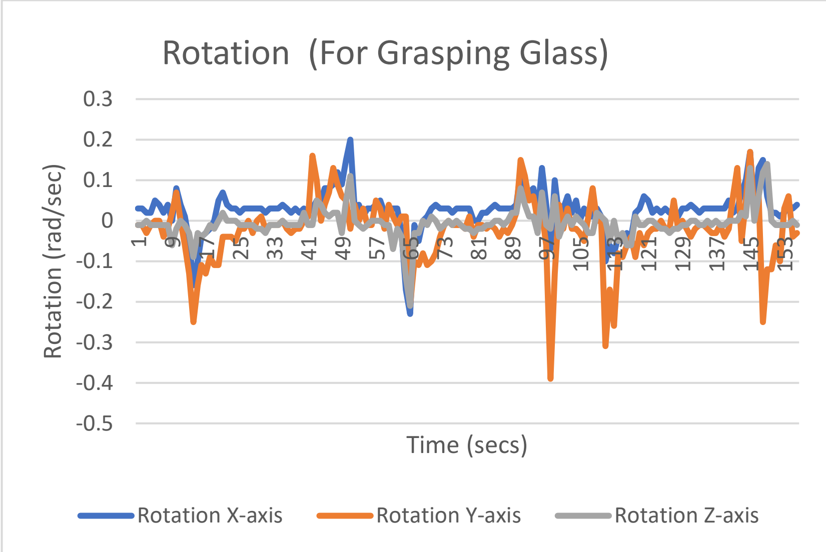


Figure 4. Rotation of the hand around x, y and z axes while grasping a glass

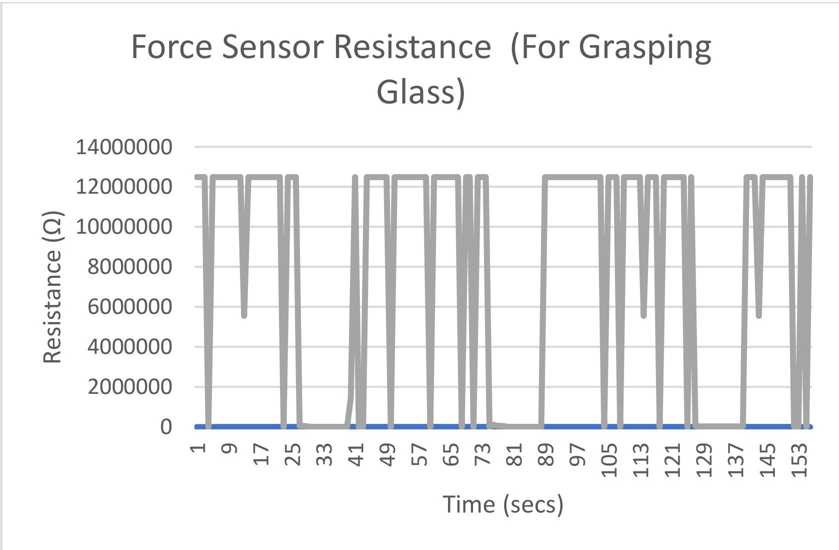


Figure 5. Force sensor reading while grasping a glass

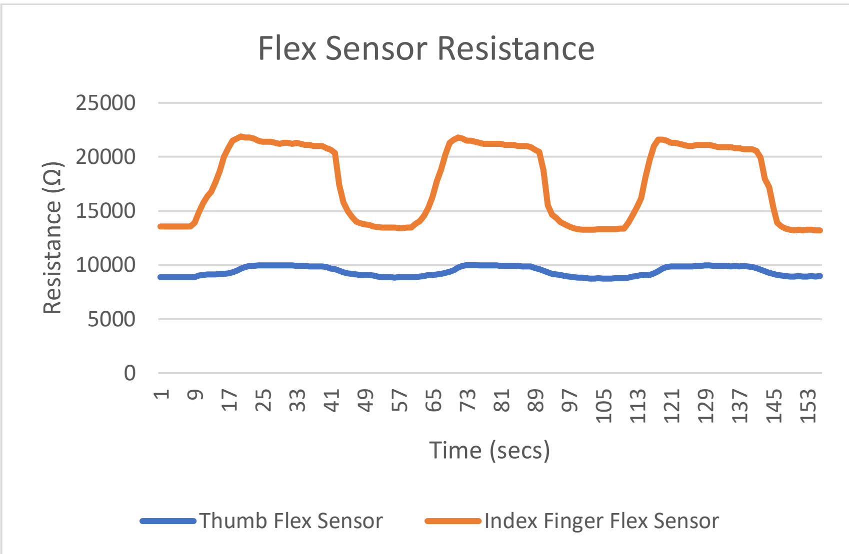


Figure 6. Flex sensor reading while grasping a glass

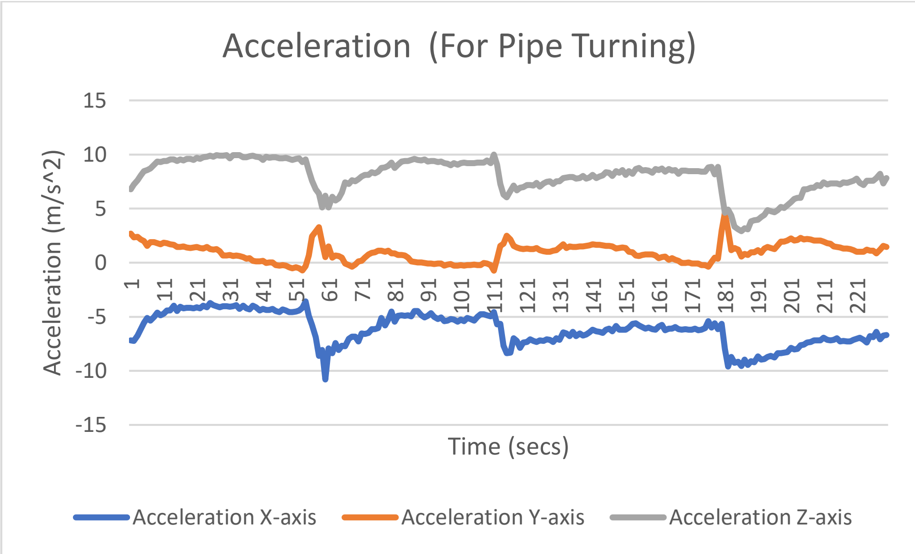


Figure 7. Acceleration of the hand around x, y and z axes while turning the pipe

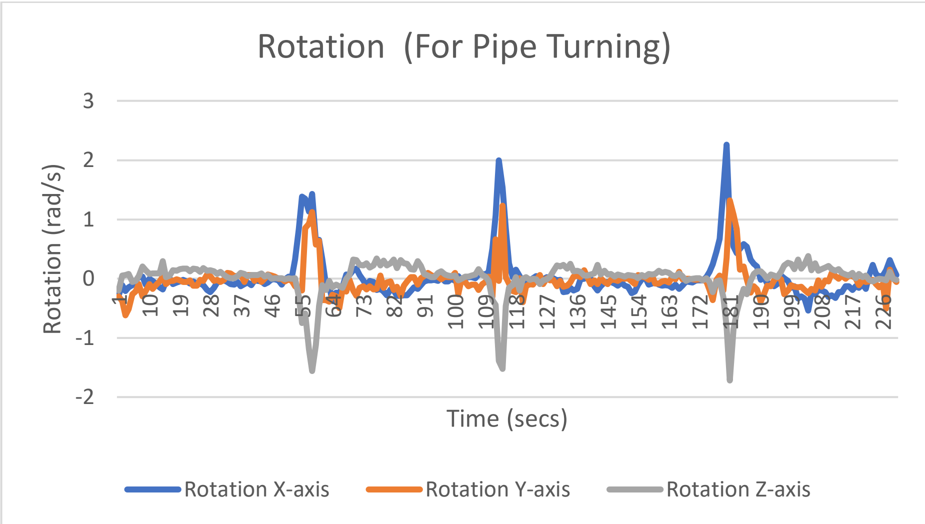


Figure 8. Acceleration of the hand around x, y and z axes while turning the pipe

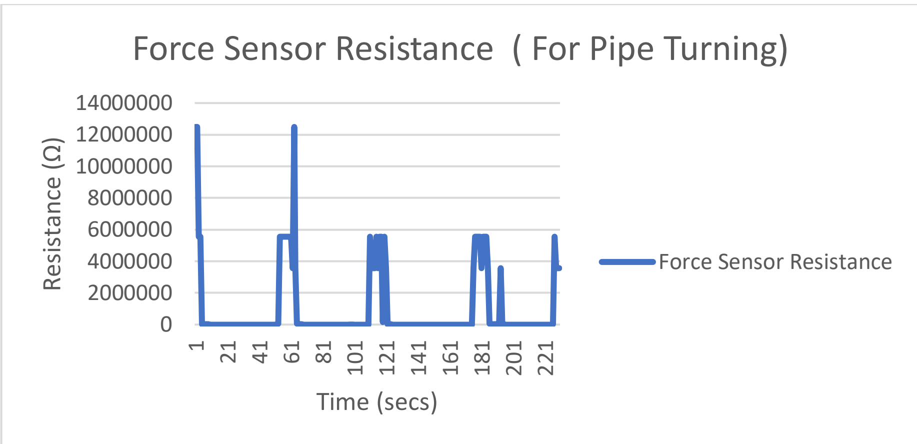


Figure 9. Force sensor reading while turning the pipe

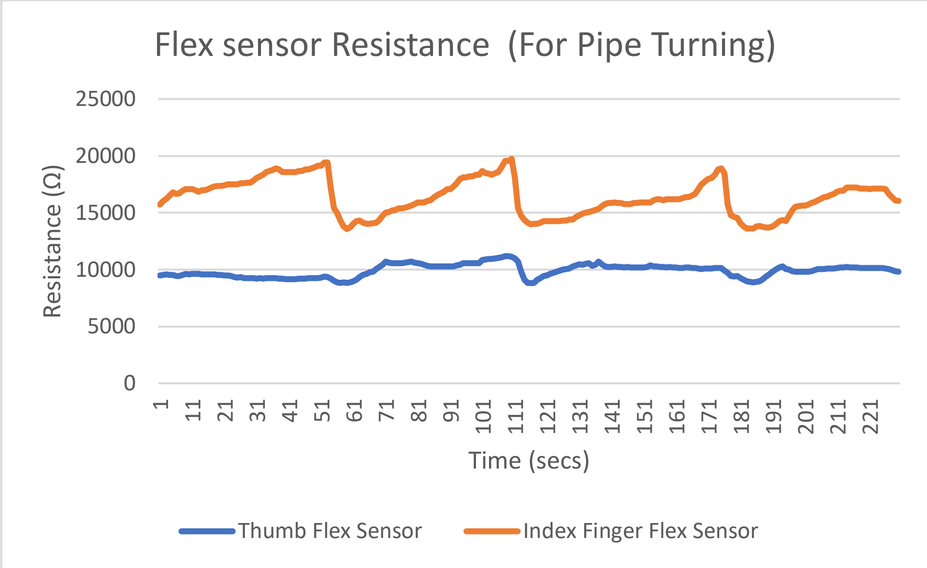


Figure 10. Flex sensors reading while turning the pipe

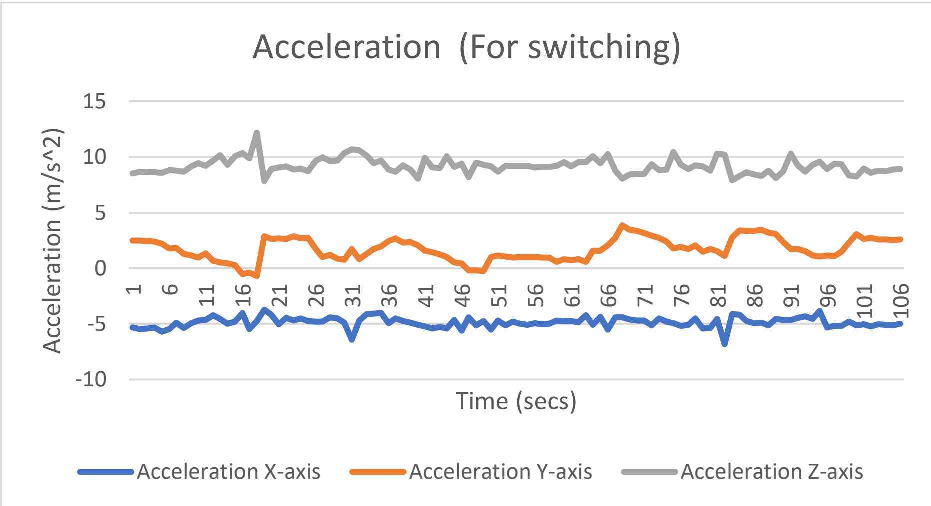


Figure 11. Acceleration of the hand around x, y and z axes while switching on the plug

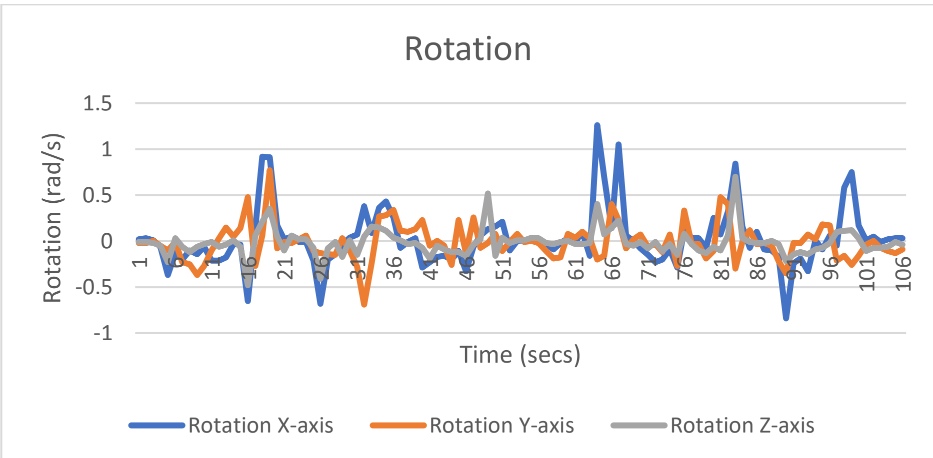


Figure 12. Rotation of the hand around x, y and z axes while switching on the plug

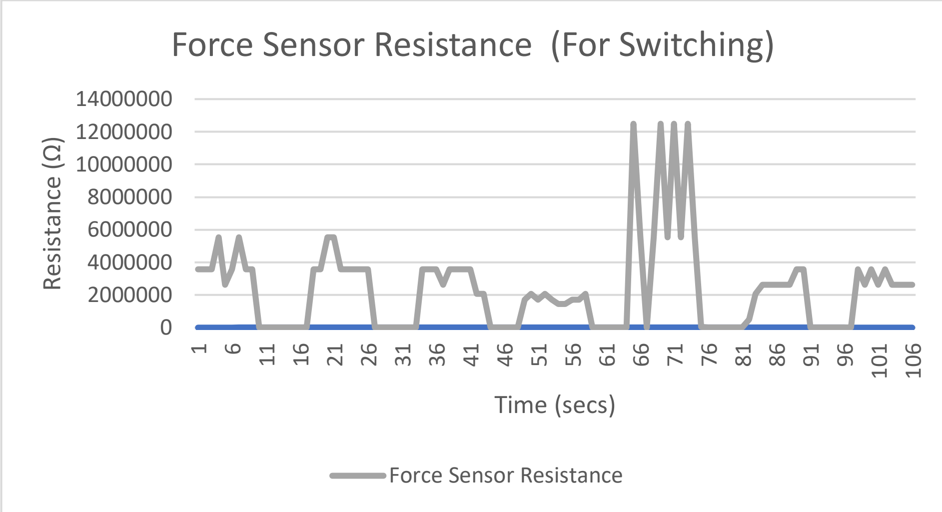


Figure 13. Force sensor reading while switching on the plug

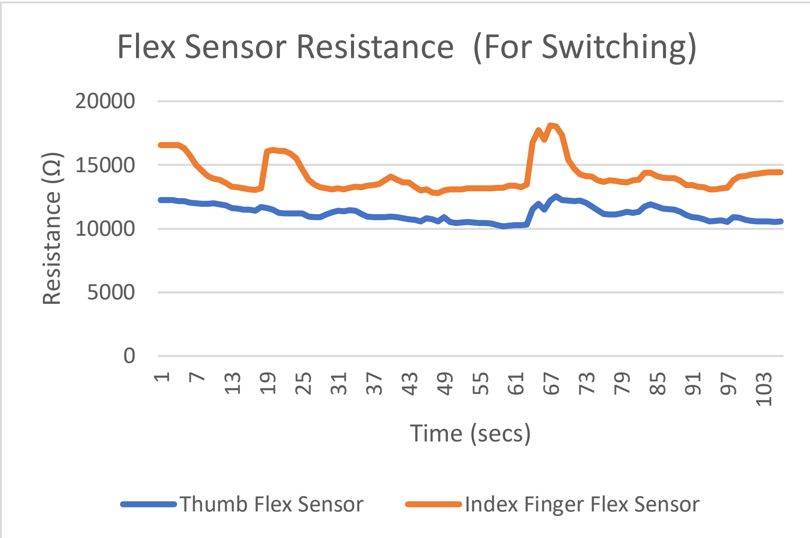


Figure 14. Flex sensor reading while switching on the plug

Figure 15 describes the resulting confusion matrix from the machine learning algorithm implemented. The system has achieved a prediction accuracy of 94%. The model has detected 745 data of grasping a glass hand pose correctly. For switching on the plug hand pose, the model has identified 462 data accurately. The model predicts 532 data of the hand pose while turning the pipe precisely. Other values in the confusion matrix represent wrongly classified values. There are 3 and 18 data of the grasping a glass wrongly predicted as the hand pose for switching on the plug and turning the pipe respectively. Switching on the plug hand pose have been recognized incorrectly as grasping the glass and turning the pipe for 4 and 16 data respectively. The system has inaccurately identified 16 data of turning the pipe as grasping the glass and 22 data as switching the plug. These results may be improved with the application of other machine learning algorithms and having more data for the training. Overall, it is evident from the results that the proposed system is able to recognize the full hand pose while performing these three activities in ADL, which is useful for tele-rehabilitation treatment.

		Predicted		
		Turning Pipe	Switching on Plug	Grasping Glass
Actual	Turning Pipe	745	3	18
	Switching on Plug	4	462	16
	Grasping Glass	16	22	532

Figure 15. The Confusion Matrix

5.0 CONCLUSION

The proposed hand poses recognition system based on Decision Tree algorithm while performing three daily activities, including two tasks as installed on the Manipulation Board for rehabilitation therapy in Malaysian government hospitals has been developed in this study. The system collects the human hand data using Arduino Uno, two flex sensors, a force sensor and an MPU6050. The inputs to the Decision Tree include the resistance of the flexible sensors and force sensors, and the acceleration and rotational angle readings from MPU6050 Micro Electro-Mechanical system (MEMS), whereas the hand poses while grasping a glass, switching on the plug and turning the pipe serve as the outputs. The experimental results with 30 subjects show an accuracy of 94%. However, at this stage of study, only the data from the healthy individuals aged 20-25 years old have been collected and used in the training and testing for simplicity. For future works, new data need to be collected from real patients. The training and testing of the Decision Tree algorithm will be repeated using these new data. Another limitation of this study is the low number of activities considered in the recognition problem. In future study, all the daily activities on the Manipulation Board may be included. The effect of utilizing other machine learning algorithms may also be investigated in the future. The real and practical tele-rehabilitation equipment and setting will be incorporated into the full hand pose recognition system while performing Activities of Daily Living (ADL). This research may contribute towards a more effective and convenient rehabilitation treatment that will lead to a faster recovery process and improve the patients' quality of lives.

6.0 ACKNOWLEDGEMENTS

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