Application of Wearable Control Based on Feedforward Neural Network to Control Manipulator Arm of Field and Service Robot

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Abstract- Manipulator arm control in Field and Service Robot (FSR) which uses joystick as inputs is not easy and less efficient. Special training, and long study time for operators to be able to control precisely and quickly are needed. In this study, a wearable control device was used to replace joystick based on wearable control using Artificial Neural Network (ANN). The wearable control used is Myo Armband worn on the operator's right arm. This sensor consists of an electromyography sensor (EMG), 3-axis accelerometer, and 3-axis gyroscope. When the operator moves its arm, the operator's arm and arm position will be the command to move the 3D Manipulator Arm in MATLAB/Simulink. The operator's arm and arm position are read using the Inertial Measurement Unit (IMU) sensor found in the Myo Armband. Data acquisition from IMU is processed using ANN using the Feedforward Neural Network (FNN) method. The output of the user/operator arm angle of the FNN is used to drive the 3D Manipulator Arm model in the SimMechanics. Based on the result the FNN regression can be used successfully to drive the 3D animation of the manipulator's arm in real-time. With an accuracy value of R from training, validation, and testing 0.973, 0.967, and 0.982 respectively, and the overall R is 0.973 meaning the ANN works very well because all numbers exceed 0.950.

Keywords: wearable control, Myo Armband, artificial neural network, manipulator's arm.

I. Introduction

A field and service robot (FSR) is a robot created to help humans work both inside and outside the room. FSR replaces human position in a less secure condition or work area. FSR can be controlled remotely using wireless control [1]. FSR is usually equipped with a manipulator's arm to carry out its functions. This manipulator's arm is controlled using a joystick so that it is difficult and less efficient when controlled by the operator [2]. Operators need special training and a long time to become proficient at handling manipulator arms. In this research, wearable control is used to replace the joystick. Wearable control is expected to be easier and more efficient when used by operators. A wearable control device is worn on an operator's body, for example on the hands, arms, legs, thighs, head, and other limbs. The wearable control used in this research is the Myo Armband [3]. Myo Armband is worn on the operator's right arm. Myo Armband consists of sensors electromyography (EMG), inertial measurement unit (IMU). Research using the Myo Armband has been carried out to estimate arm movements [4]. The Myo Armband is often used by the EMG for control devices [5]. The use of EMG as a controller is one of them applied to manipulators [5][6]. The neural network has been implemented into the previous control system [7][8]. The system in this research will be carried out in MATLAB simulation as in [9]. Real-time system testing is used in simulations [10]. In this study, when the operator/user moves his/her arm, the movement and rotation angle of his arm becomes the command for the manipulator's arm. The manipulator's arm is modeled in 3D in MATLAB Simscape. The movement and position of the operator's arm are read by the IMU sensor on the Myo Armband. The signal from IMU is forwarded and processed using artificial neural network (ANN) regression with the feedforward neural network (FNN) method. The output of the FNN is used to control the 3D manipulator arm model in MATLAB/Simulink environment.

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II. PROPOSED ALGORITHM

A. IMU From Myo Armband

This research uses a wearable controller called the Myo Armband. Myo Armband produced by Thalmic Labs is a special arm bracelet worn on the user's arm. The used sensor of the Myo Armband consists of electromyography (EMG), a 3-axis accelerometer, and 3-axis gyroscope. In this study, the required signals from controlling the motion of the 3D virtual manipulator arm are inertial measuring unit (IMU) from the Myo Armband. IMU itself in the sensor consists of a 3-axis accelerometer sensor and a 3-axis gyroscope. The accelerometer is used to read the acceleration of the operator's arm translational acceleration motion on the x, y, and z axes. The Gyroscope functions to read the angular velocity of the rotating arm of the operator against the rotating axis x, y, and z. The signals from the accelerometer and gyroscope a Myo Armband are processed into three basic angular movements, like roll, pitch, and yaw. Accelerometer rate gyro (ARG) algorithm is employed for estimating the roll, pitch, and yaw angels of the Myo Armband using 3-axis acceleration and 3-axis angular velocity. The detailed ARG method for estimating the roll, pitch, and yaw angles can be seen in ref [11]. The ARG method is developed under MATLAB/Simulink environment. This processing method is performed in the MATLAB/Simulink environment which can be seen in Figure 1. In this research, only roll and pitch angle outputs are used. This roll and pitch will be used as control input on the Neural Network regression.

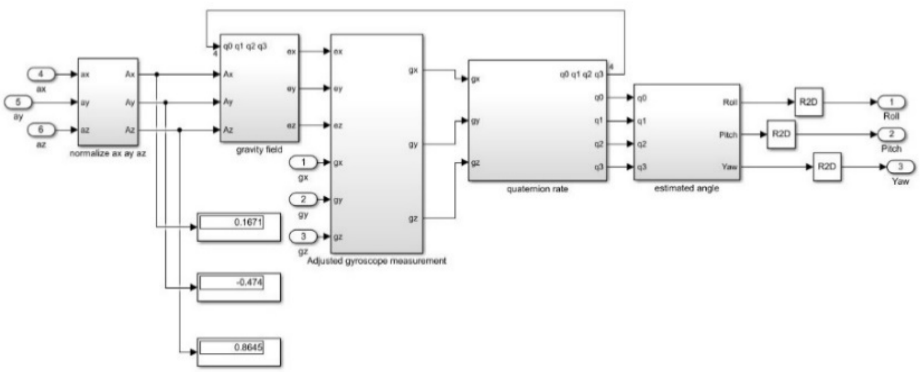

Figure 1. ARG method for roll, pitch, and yaw estimation

B. Artificial Neural Network

ANN [12] is used to process the input signal from the Myo Armband, so it becomes an output signal in the form of a command to control the 3D arm manipulator model. The ANN used in this research was FNN which has two inputs (roll and pitch), five hidden layers, and four joint angle outputs namely a_1, a_2, a_3, and a_4. These four outputs are used to be the control input of the 3D manipulator arm model. The structure of the FNN Simulink can be seen in Figure 2, while the training data for the input and output is shown in Figure 3.

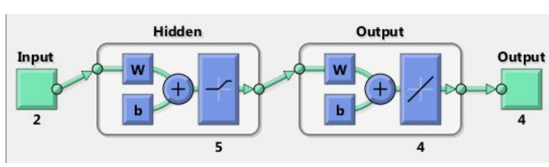

Figure 2. FNN structure in MATLAB Simulink

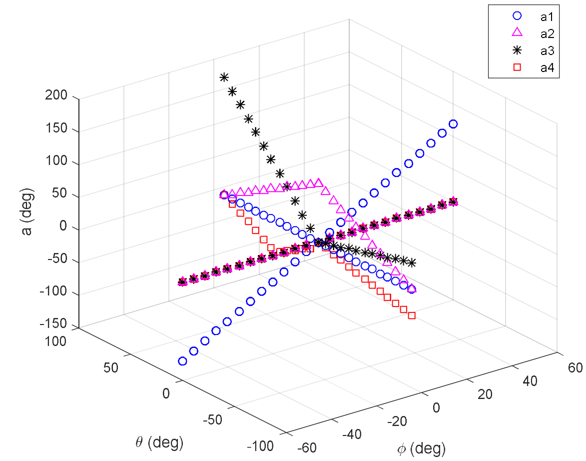

Figure 3. The training data for the input and output

Data retrieval is based on three variations of the roll and pitch inputs which affect the coefficients a_1, a_2, a_3, and a_4 with the results of 225 data. The three variations are: roll angle at zero while the pitch angle has non-zero values, pitch angle at zero while the roll angle has non-zero value, and when both the pitch and roll angles have non-zero values. The overall data are divided into three subsets such as training processes 70%, validation 15%, and testing 15% from 225 data. The training method in the FNN for regression uses the Levenberg-Marquardt Back-propagation method. Figure 4 shows the performance of the neural network for regression. The FNN reaches convergence value after 15 epochs. The best-resulted MSE value is 199,078 when it has performed 15 epochs.

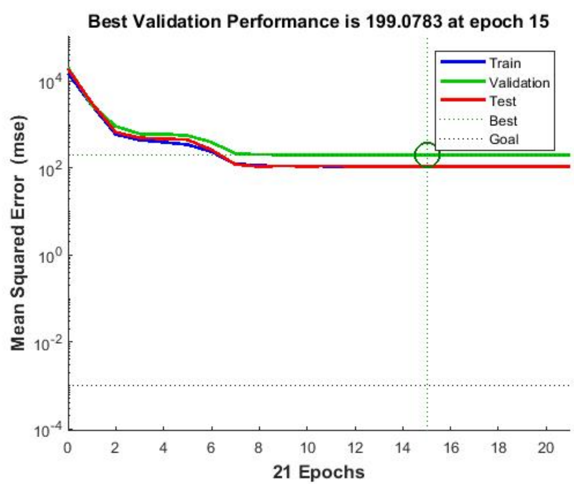

Figure 4. FNN Performance during training

The accuracy of the FNN results is shown in the Receiver Operating Characteristic (ROC) curve. The ROC curve is a two-dimensional plot with a false positive proportion (FP) on the X-axis and a true positive proportion (tp) on the Y axis, here are the results of the accuracy value R during training, validation, and testing are 0.973, 0.967, and 0.982 respectively, and the overall R is 0.973 as shown at Figure 5.

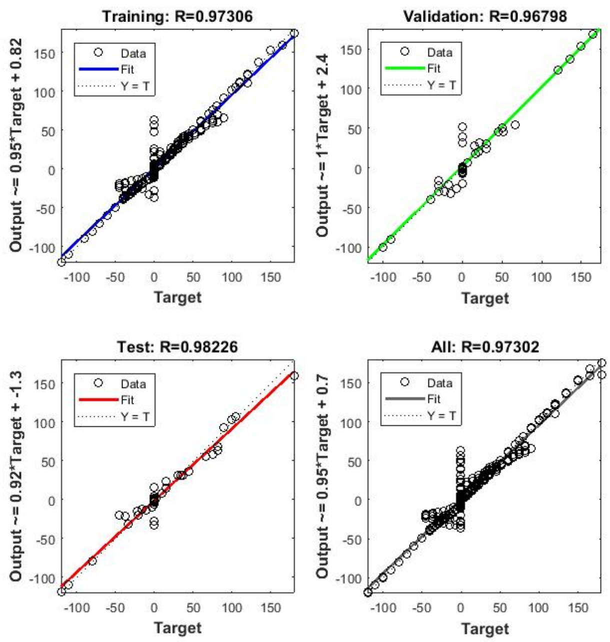

Figure 5. Receiver Operating Characteristic (ROC) curve of FNN

C. 3D Arm Manipulator Model

The manipulator arm modeled in 3D CAD has one base, four pivots, and four joints as shown in Figure 6. The four joint angles are a_1, a_2, a_3, and a_4. 3D computer-aided design (CAD) is then exported to SimMechanics 2nd generation under MATLAB/Simulink environment. The exported block diagram is shown in Figure 7. The inputs a_1, a_2, a_3, and a_4 are angular angle movements in degrees. The angles on the animation of the 3D manipulator's arm are depicted in Figure 6. The joint angles of the manipulator's arm are represented by the revolute joints in the SimMechanics block diagram.

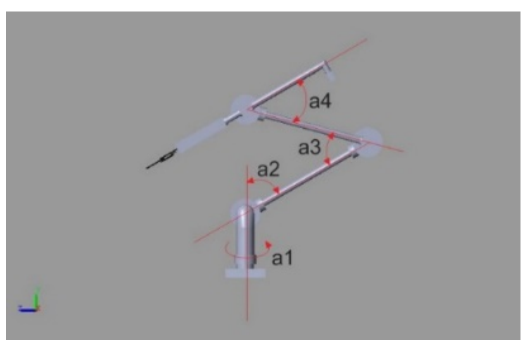

Figure 6. Arm manipulator model in SimMechanics 3D animation

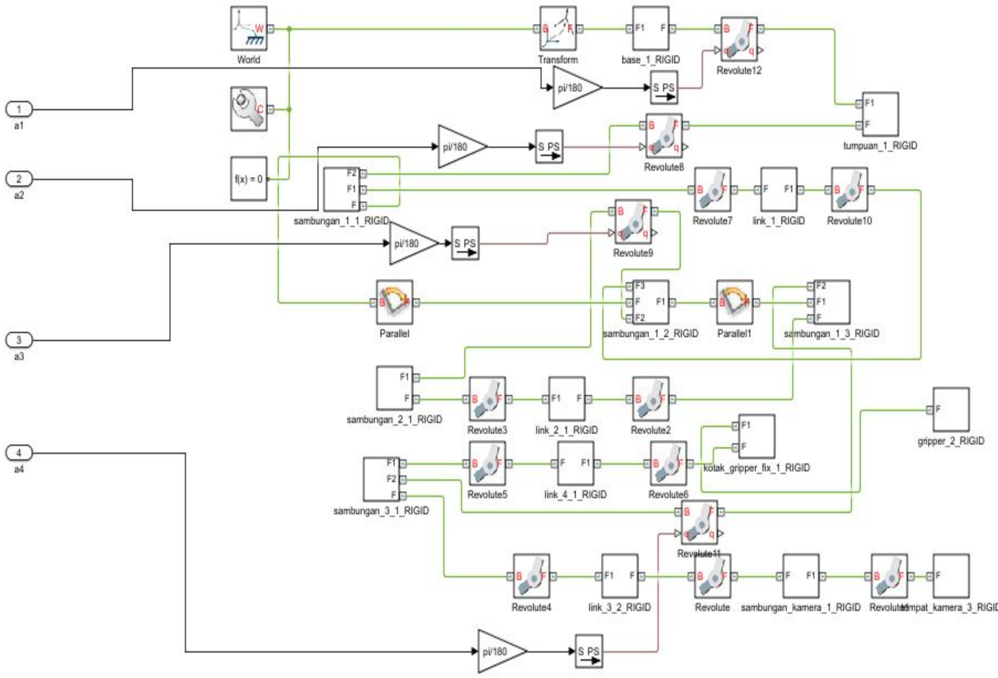

Figure 7. Manipulator arm model in Simulink

III. Experiment and Result

In this research, the operator/user wears a Myo Armband on his right arm. The pitch angle movement is in the form of moving the arm up, the roll motion can be performed by rotating the arm on the x-axis. The whole MATLAB/Simulink system can be seen in Figure 8. This system can run in real-time. Every movement carried out by the operator will move the 3D arm manipulator model as shown in Figure 9.

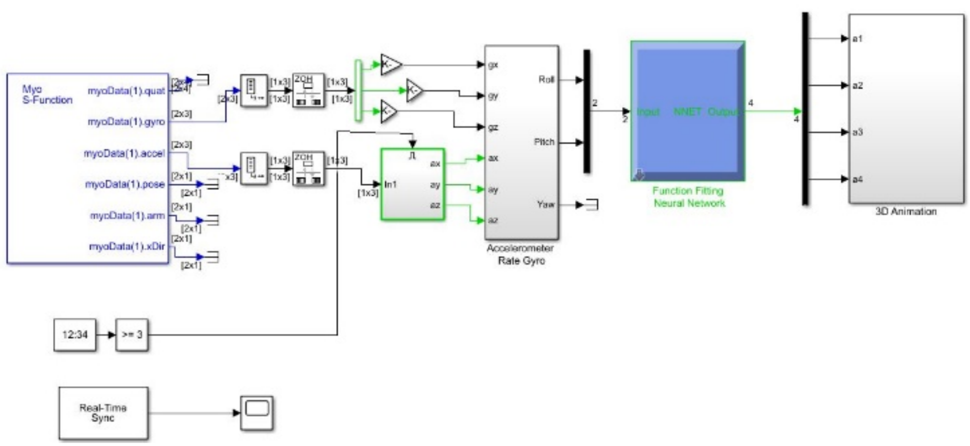

Figure 8. Overall block diagram of neural network with Myo Armband in Simulink

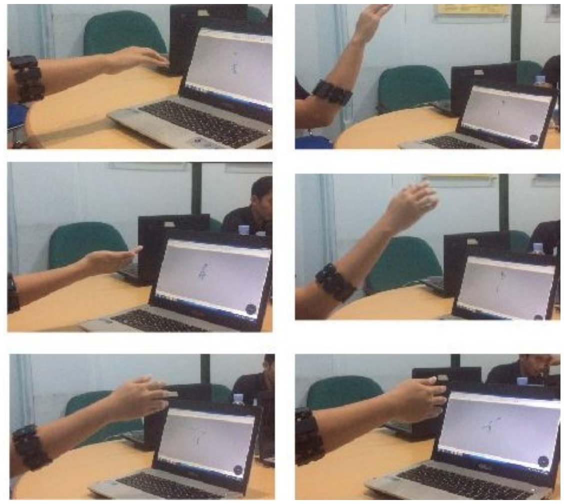

Figure 9. Test situation during controling arm manipulator model using Myo Armband

In this test, the user's arm is rotated in pitch motion from zero degrees to about 40 degrees, and then it rotates from zero degrees to about 40 degrees in roll motion. The angle inputs in the test are shown in Figure 10.

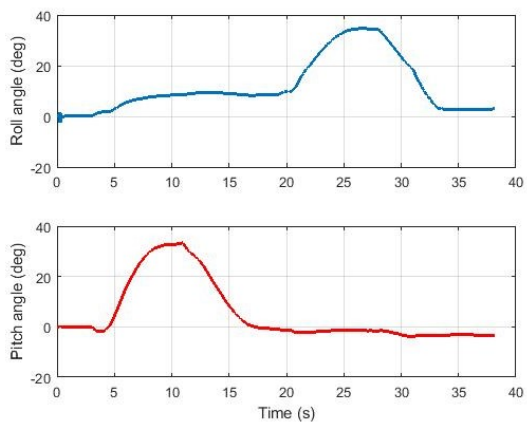

Figure 10. Input FNN Roll and Pitch angles

IV.CONCLUSION

Based on the ROC results, the obtained accuracy value of feedforward neural network regression (R) during training, validation, and testing are 0.973, 0.967, and 0.982 respectively, and the overall R is 0.973 that identifies the FNN works very well because all numbers exceed 0.950 and this indicates that the input can be properly regressed. As well as visually the movement of the 3D manipulator arm model in MATLAB/Simscape can follow the movement of commands from the operator's arm in real-time and at the right direction Fig.10.

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