Artificial Neural Network Based Bionic Leg for Upper Knee Leg Amputation

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***Abstract*— Amputation of the leg is a common factor in military accident cases. Mainly leg amputations can be divided into two broad categories - minor amputations and major amputations. Minor amputations generally refer to the amputation of digits. Major amputations are commonly referred to as below-knee amputation and upper-knee amputation.**

Most of the commercial bionic legs are act on the electromyography (EMG) signals that detect from the thigh muscles. If the amputation happens in the upper knee by causing damage on thigh muscles such as military accidents made difficult to detect EMG signals. So, human who faced leg amputation with having damaged or inactive of thigh muscles, current commercial bionic legs are unable to use. Therefore, this research produces the active bionic leg which was controlled by the movement of human arm using Artificial neural network (ANN) for leg amputees with having inactive muscles of thigh.

The Model based technique such as artificial neural network (ANN) will be a pragmatic solution for this kind of randomness inherited cases. Generally, ANN is acting as the function to make relationship between input and corresponding output. This paper discusses a novel approach for developing a bionic leg which controlled by upper limb motion using artificial neural network model. This research focusses on analyzing the arm swing pattern related to the human gait cycle and develop an ANN model using upper limb motion (arm swing motion) related to the lower limb motion (leg motion). ANN model for whole system was validated using a prototype. According to the citation for results of healthy person, average gait cycle time was 1070 milliseconds. Bionic leg has a capability to be predict the corresponding knee joint angle using human arm swinging pattern around the 13 milliseconds with reference to the general human gait cycle time of 1070 milliseconds. This execution time is added to the general gate cycle time to complete full gate cycle for disable person. As a result of, gait cycle with bionic leg may have a time delay deviation by 1.21% between human gait cycle of normal healthy person and a disable person who wearing the bionic leg

Keywords—Active bionic leg, Artificial neural network, Human gait cycle time

I. INTRODUCTION

Below knee leg amputation can be solve using mechanical prosthetic leg without any sophisticated controlling parts. In point of view of major knee amputation, knee motion rehabilitation was the challenged in active prosthetic legs with having advanced controlling parts. Mechanical passive prosthetic legs are supported to the static stability for the disabled persons.

According to the literature review, most kind of passive prosthetic legs were developed for the below knee (BK, transtibial) mode [2]. But its unable to use against body dynamic balance during the bipedal walking [2, 3, 16, 22]. Active bionic legs come to solve this problem with more cutting edge technologies [19, 20, 21]. When discuss about concepts on current commercial active bionics legs, more sensitivity was included for the control signals using advanced controlling method including the locomotion of knee joint in bionic leg [4, 13].

Human who faced the leg amputation with having damaged of inactive muscles of the thigh, current commercial bionic leg was unable to use due to difficulty of gathering of the EMG signal on the thigh. This research discusses the design and implementation of a bionic leg based on the pre-trained model using Artificial Neural Networks (ANN) to predict the knee motion according to the arm swinging signal.

ANN is used as a random function approximation tool. This help to estimate the most effective and ideal methods for arriving at solutions while defining computing functions or distributions [5]. Training an artificial neural network involves choosing from allowed models for which there are several associated algorithms. The movement of arm are maintained by the muscles group in the human body and can be recognized using electromyography (EMG). This arm movement also can be tracked using the motor signal which generated in human brain and central pattern generator. But rhythmic pattern of the human body, like arm swinging was unable to detect properly using EEG. In this research project, Motion of the arm can be obtained as direct measurements using (Inertial Measurement Unit) IMU sensor. IMU sensor can be mount on surface of human arm and it never communicate with muscle to obtain the angle data. movement of the human limbs can be tracked using special purpose sensor and muscle activity based active limbs are best solution for the amputation for the human limbs. Active bionic limbs use these methods to get corresponding input from human body.

Vastus muscles and Rectus femoris muscles in human thigh [1, 6, 7] were damaged against the upper knee leg amputation with huge damaged of the thigh. In this case, Existing bionic leg products were difficult to use because of acquisition of the EMG signals from the inactive or damaged muscles is more difficult. Furthermore, exact signal pattern was unable to find for the particular task in walking gait cycle by the sensor on inactive muscles. Also more signal processing concepts and pattern recognition algorithms make slow response for the bionic leg [8].

Every human swing their arms to make the gait stability during the bipedal walking. The Central pattern generator of the human body concerned that gait stability by making the motion of arm corresponding walking patterns. [9, 10, 11, 16]. This bionic leg has capability to predict knee motion according to the arm movement during the bipedal walking of human.

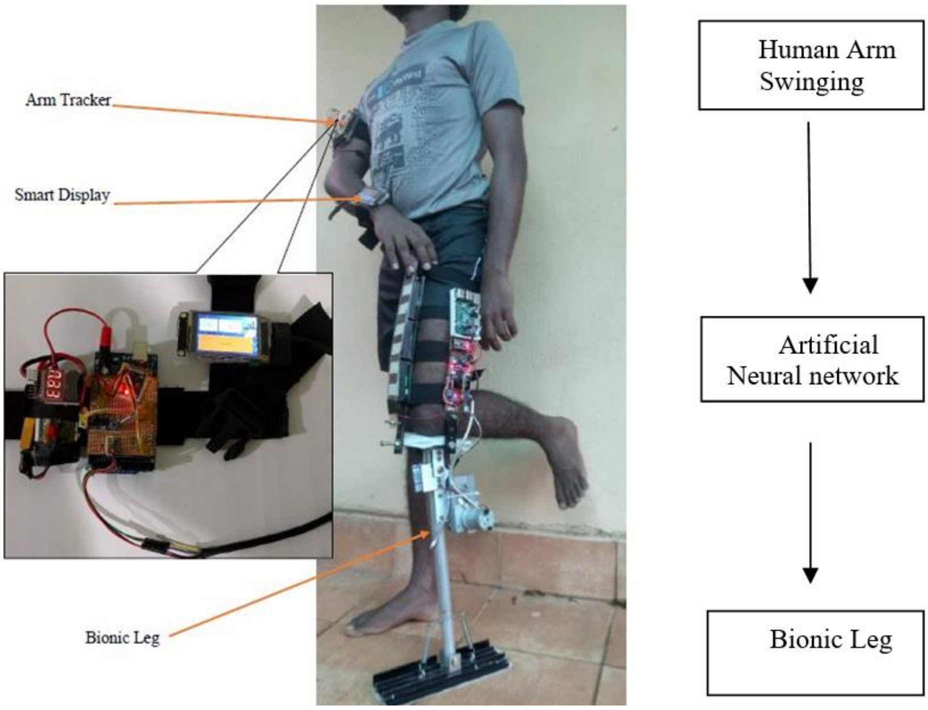

Fig. 1 ANN based bionic leg model

Figure 1 shows the major parts of the bionic leg with the (ANN) which was developed as the execution software. Arm swing pattern was grasped using arm tracker shown in Figure 1. The obtained arm swing pattern fed in to the pre-trained

Artificial Neural Network model and ANN has capability to predict the corresponding knee angle for the bionic leg. The predicted knee angle by ANN was the desired input for the knee motion controller of the bionic leg and knee motion controller make the knee position similar to the desired input (Predicted knee angle by ANN according to the arm swing patterns).

II. Methodology

The development of the bionic leg is carried out in two stages. Also, this ANN based bionic leg can predict the knee motion in related to the arm motion of human during bipedal walking. The main challenge of this project was the eliminate the knee motion for the unwanted arm movement. This problem was solved by using the ANN by considering the rate of change of arm angle during the bipedal walking. The multilayer ANN was trained under the backpropagation method. Initially Artificial Neural Network was developed and then fabricated the bionic leg according to the results of ANN. Human arm swinging data was tracked by the sensors and corresponding lower limb data such as thigh angle and knee angle were tracked in same time during the bipedal walking in natural speed by using wearable sensors as Figure 1. Second stage was validating present concept using the development of bionic leg Prototype using mechanical engineering, control engineering theories and practices [14, 15, 17, 18]. The model will be developed only for the walking on the flat surface. For this study Artificial Neural Network model was developed for healthy persons.

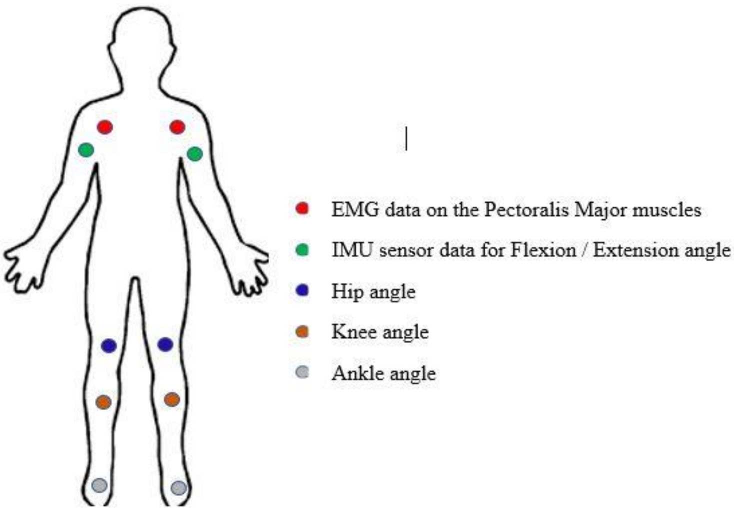

Fig. 2. Wearable sensor attachment on human body for the Data acquisition

A. Data acquisition

Data acquisition system contribute to make training data using EMG Sensors and accelerometer IMU Sensor by contacting the specific areas of the human body to make the data for train Artificial Neural Network. Figure 2 represent the attachment of the wearable sensors which combination of the IMU sensors and EMG sensors. data acquisition system

was programmed by using microcontroller and sensorized data should be processed using computer with data processing algorithm. EMG sensor and IMU sensor were attached to the microcontrollers because of the response of the data acquisition should be expedite during the bipedal walking. Microcontroller and microcontroller's boot loading platform are based on the Arduino Mega that powered by ATmega2560 AVR (AVR is a family of microcontrollers developed by Atmel beginning in 1996) Microcontroller with 16 MIPS CPU speed at 16 MHz and operates between 4.5-5.5 volts. Data acquisition part was executed on selected microcontroller with combination of the EMG sensor and number of 8 IMU sensors that comes from the one wire data bus.

adjusted for each application using the weight factor with having Exponential term.

III. Artificial Neural Network model

A. ANN Architecture

Four inputs and one output were existed on the neural network to operate the bionic leg's knee. Inputs of the ANN In01, In02, In03 and In04 as shown in Figure 4 are represented the body weights, body height, moving rate of change of Arm and IMU Angle value on the Arm respectively during the walking. Generally, Body weight and Body height are the constant value for the specific human also moving rate values and Angle values on Arm were changed with time during the walking with arm swinging.

Providing the above mentioned inputs during the walking with arm swinging, Trained Artificial Neural Network was capable to predict the output of knee angle of the bionic leg. These output were feed to the PID controller of bionic leg to operate the leg movement using arm swinging pattern using the above Artificial Neural Network architecture shown in Figure 4.

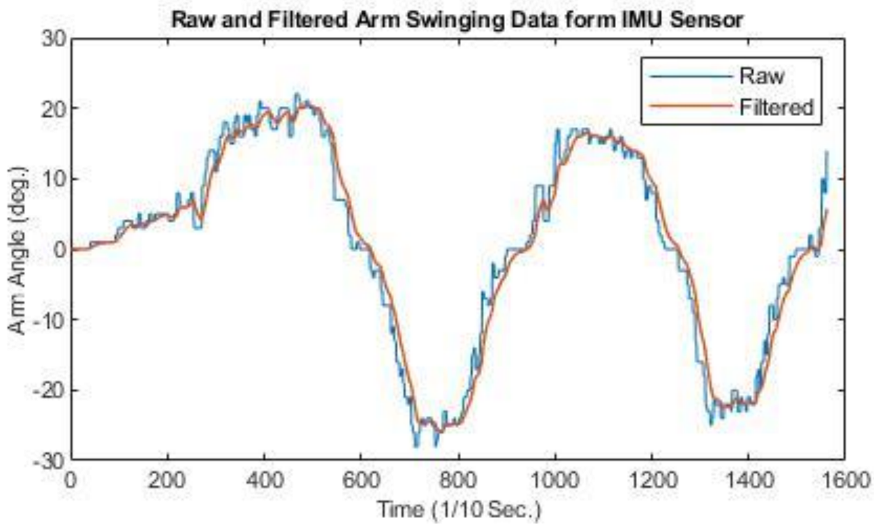

Fig. 3 Raw data and filtered data - Arm swinging

During the acquisition part of the signal form IMU sensors and EMG sensor, the smoothness of the signal was important factor to prepare the input output data for the neural network development.

The Exponential filter is a recursive filter. A recursive filter is just one that calculates a new, smoothed value by using the last smoothed value and a new measurement [12]. Two successive data sample is used to filter the data in the exponential filter algorithm.

Filtered data (Figure 3) can be gathered simultaneously during the real time data acquisition process. The small execution delay for the filtering process between raw data and filtered data was existed by using the Exponential filter algorithm. Delay time of the filtering process was eliminated by using exponential filter and filtering smoothness can be

Proposed Artificial Neural Network which was summarized in the Figure 4 was developed using the "Python" Programming language under the "Google TensorFlow™" Machine learning tool library. Supervised learning method was used to train the Neural Network. Multilayer flat (2D) ANN was trained using backpropagation method.

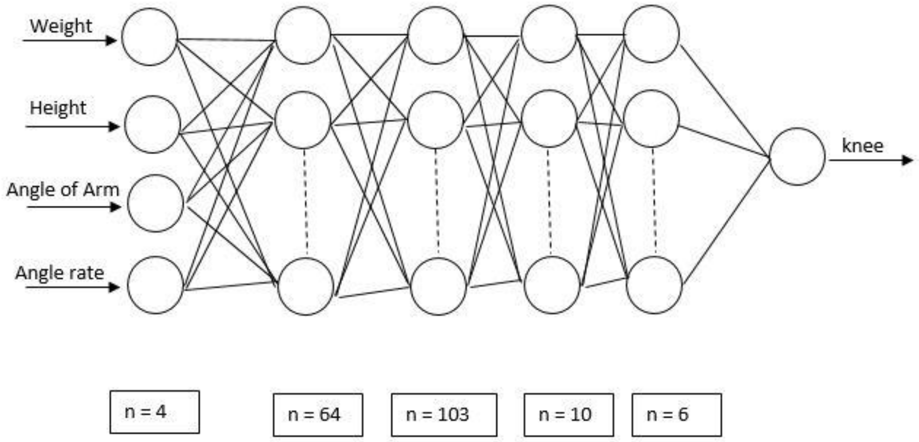

Fig. 4 ANN Architecture with 4 inputs and 1 outputs

B. *Accuracy and loss optimization*

After the developed an Artificial Neural Network by using the random architecture with having random Hyper-parameters (Weights, Bias, Layers etc.), architecture was optimized to obtain the good accuracy variation and less number of loss variation.

Fluctuated accuracy variation and loss function variation was represented in first attempt of training. After the adjustment of the number of Hidden Layers and Neurons on each layers, accuracy and loss was smoothed without any fluctuation. Currently, Artificial Neural Network has around 66% accuracy and around 26% loss value for the Number of three Hidden layers and with having architecture earlier. Also accuracy and loss values can be improved after the more adjustment of the Hyper-parameters of the Artificial Neural Network. Furthermore, Final accuracy of the ANN was obtained 97% for the architecture which was represented in Figure 4.

C. *ANN Validation*

The K-Fold Cross-Validation method was the kind of cross validation which was used in this research. The data set is separated into two sets, called the training set and the testing set. The function approximation tool fits a function using the training set only. Then the function approximation tool is asked to predict the output values for the data in the testing set (it has never seen these output values before). The errors it makes are accumulated as before to give the mean absolute test set error, which is used to evaluate the model. The advantage of this method is that it is usually preferable to the residual method and takes no longer to compute. However, its evaluation can have a high variance. The evaluation may depend heavily on which data points end up in the training set and which end up in the test set, and thus the evaluation may be significantly different depending on how the division is made. In this case, data was split into 70% training and 30% Testing along four number of training event for the k-Fold cross validation. (K = 4 training event).

IV. RESULTS

Terminal Stance and Pre-Swing phase in human gait cycle were represented with the movement of bionic leg during the gait cycle in Figure 5(a) and Figure 5(b) respectively.

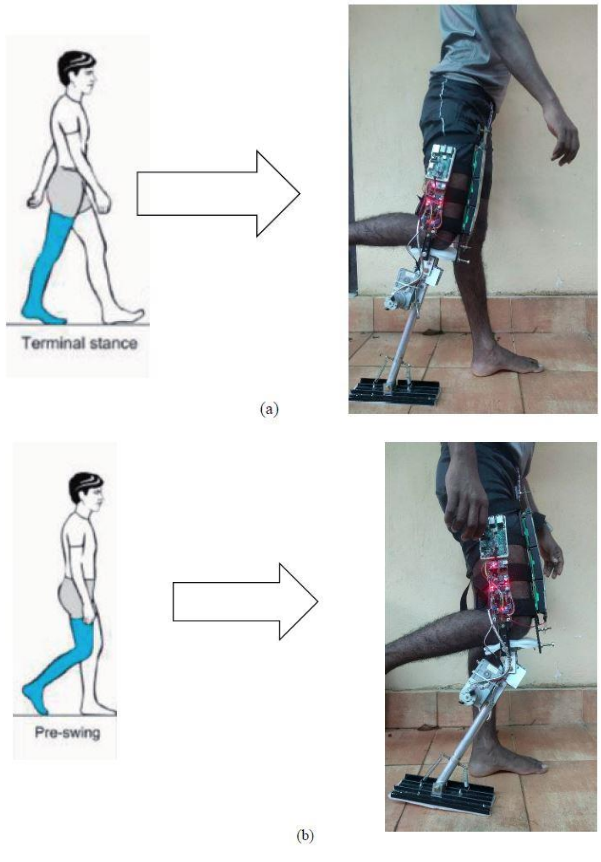

Fig. 5 Human walking pattern in special phases in Human gait cycle

Average gait cycle time of healthy human (young male) were 980 to 1070 milliseconds [23]. According to this literature, Average gait cycle time of 1070 milliseconds can be considered as the reference in this research for the analysis.

Gait cycle time (BL) = Gait cycle time (Human) +
Soft. Execution delay + Communication delay + PID
(1) *Control delay*

By considering the numerical data which were obtained in this research on Equation 1, Gait cycle time (Human), Software execution delay with communication delay and PID control execution delay were 1070, 5 and 8.17 milliseconds respectively. It seems additional 13.17 milliseconds ware added to average gait cycle time of human. Then gait cycle time of the bionic leg was around 1083 milliseconds.

Terminal Stance and Pre-Swing phase in human gait cycle were represented with the movement of bionic leg during the gait cycle in Figure 6. Arm data curve was displayed with corresponding actual knee motion (Actual. Knee) during the gait cycle and predicted data form the Artificial Neural Network (ANN) (ANN.knee), furthermore knee motion form the Knee motion PID controller in the Bionic Leg (BioLeg.Knee). According to the graph in Figure 6, Root Mean Square Error (RMSE) between actual knee (Actual.Knee) angle and knee angle in Bionic Leg (BioLeg.Knee) was 0.4826. Data on the Figure 6 was collected by the number of 50 working cycles including the slandered deviation for the data variance of arm, actual knee, predicted knee and Bionic leg knee as 1.764, 1.882, 1.837 and 1.934 degrees respectively.

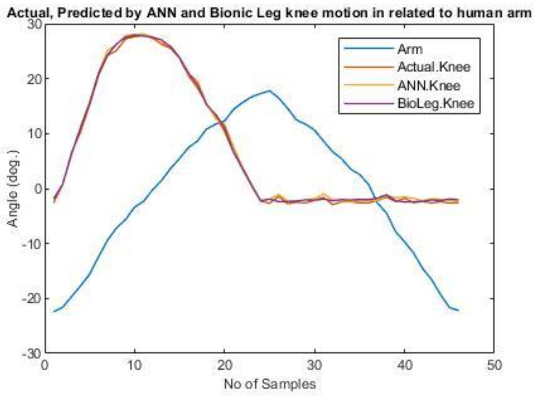

Fig. 6 Terminal Stance and Pre-Swing phase in gait cycle for Bionic Leg, collected data and Predicted Data

V. CONCLUSION

Instead of current bionic leg development for the amputation of leg above the knee joint, this model was developed for the amputation of above knee, in case of, having inactive muscles. Current development of commercial bionic leg unable to detect any data from inactive muscle using EMG. Some others introduced EEG based bionic development to fulfil this problem but using of EEG is not user-friendly due to difficulties of the signal detection and signal conditioning also human bipedal walking is rhythmic activity that control form the CPG (Central Pattern Generator) of the body. This project expected to develop the Artificial Neural Network model to rehabilitate lower-limb gait pattern using bionic leg. Artificial Neural Network model was intelligent to predict the lower-limb gait pattern for the person's arm swinging pattern. In this attempt, Introduced the data analysis part to train the Artificial Neural Network model by using effective sensor modules and expressed proper data types as the features of the model. At the end of this research project, bionic leg prototype was developed using the Artificial Neural network (ANN) model and knee joint control algorithm. to control knee joint according to arm swinging pattern. According to the results, bionic leg has a capability to be predict the corresponding knee joint angle using human arm swinging pattern around execution delay 13 milliseconds. As a result of, gait cycle with bionic leg may have a time delay deviation by 1.21% with healthy human

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