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Neuro-fuzzy controller for active ankle foot orthosis☆

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Summary The ankle foot orthosis (AFO) is as an assistive device used in foot disability for gait improvement. The objective of this paper was to design a neuro fuzzy controller for an AFO. Adaptive neuro fuzzy inference system (ANFIS) was selected after a detailed study of existing neuro-fuzzy architectures. Data of gait pattern was collected with the help of analog gyro sensors. This data was fed to the ANFIS and a fuzzy rule base was created to complete the neuro-fuzzy system which was used to control the gait pattern. Angular velocity and angle of feet served as inputs to the controller and the output was actuation. The results obtained showed sigmoidal membership functions for the various inputs and outputs due to their close resemblance with the normal human gait. Output of the ANFIS showcased the initial data which was fed to the system; the modified data; changed membership functions and error after training.

Introduction

Neuro-fuzzy controllers are a combination of neural and fuzzy controllers. This combination reduces the limitations of the two control systems while magnifying the advantages of both systems. Determination of rule base of the fuzzy logic is tedious and laborious and this is handled by the neural network. Once trained, the neural network can predict rule bases for the fuzzy logic. As a result, a fuzzy inference system is able to take linguistic information from not only from human experts, but also adapt it using numerical data (input/output pairs) to achieve better performance. This gives fuzzy inference system an edge over neural networks, which cannot take linguistic information directly (Jang and Sun, 1995; Zurada, 1992; Yen and Langari, 1998). There are several neural architectures which exist, each with its advantages and disadvantages (Vieira et al., 2004). Adaptive Neuro Fuzzy Inference System (ANFIS) is selected after a detailed study of existing neuro-fuzzy architectures. The ANFIS (Jang and Sun, 1995) implements a Takagi Sugeno fuzzy inference system and it has five layers. The first hidden layer is responsible for the mapping of the input variable relatively to each membership functions. The operator T-norm is applied in the second hidden layer to calculate the antecedents of the rules. The third hidden layer normalizes the rules strengths followed by the fourth hidden layer

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where the consequents of the rules are determined. The output layer calculates the global output as the summation of all the signals that arrive to this layer. ANFIS uses back-propagation learning to determine the input membership functions parameters and the least mean square method to determine the consequent parameters. Each step of the iterative learning algorithm has two parts. In the first part, the input patterns are propagated and the parameters of the consequents are calculated using the iterative minimum squared method algorithm, while the parameters of the premises are considered fixed. In the second part, the input patterns are propagated again. The learning algorithm back propagation is used in the each iteration to modify the parameters of the premises, while the consequents remain fixed.

The active ankle foot orthosis is an aid for correcting the gait deviation (drop foot gait) for the patients suffering from hemiparesis (Blaya et al., 2002; Hwang et al., 2006). The AFO requires a control system to control the foot movements. Several approaches for controlling the AFO have been developed (Dollar and Herr, 2008; Shorter et al., 2011). But limitations still exists. There is a need for a control system which can train by itself, adapt to the situations to support the proper gait movements. Neuro-fuzzy control is gaining importance in several fields (Kharola and Gupta, 2014; Tyagi and Sharma, 2014; Kaur and Dhindsa, 2014; Vastrad, 2014). A gait event prediction method is developed using ANFIS (Vastrad, 2014). The ANFIS is capable of predicting the seven phases of gait with high degree of accuracy and repeatability, invariant of the level of motor impairment. Thus, use of neuro-fuzzy networks can prove to be a viable option for correcting gait pattern of an affected patient. The paper proposes a method which can be used to control the active ankle foot orthosis using neuro-fuzzy logic. Data of gait pattern was collected with the help of analog gyro sensors LPY530AL which was interfaced with NI DAQ6221. This data was fed to the ANFIS and a fuzzy rule base was created to complete the neuro-fuzzy system to control the gait pattern. The membership functions of the fuzzy inference system (FIS) changed according to the data and correspondingly, different outputs were obtained for different inputs. Angular velocity and angle of feet served as inputs to the controller and the output is actuation. The results obtained showed sigmoidal membership functions for the various inputs and outputs due to their close resemblance with the normal human gait. Output of the ANFIS showcased the initial data which is fed to the system; the modified data changed membership functions and error after training.

Methodology

The proposed control system was fed with crisp input in the form of numerical values, where it got fuzzified. These fuzzified values were then fed into the membership functions of the fuzzy part through the neural network where they were then fed into the fuzzy inference engine. The fuzzy inference engine is a decision making device which makes use of an existing rule base which is initially designed by a human expert and depending on the membership function (MF) value which serves as the input to the inference engine, a fuzzified value is obtained as the output. This value was then fed into the neural network after which it was defuzzified to get the crisp numerical output of the controller. Sigmoidal MF's were used to better approximate the shape of inputs and outputs. The advantages of sigmoidal MF's over triangular MF's include better ''shoulders'' and hence better approximation through due to tapering edges. A sigmoidal membership is defined by equation 1.

$$Sigmoid(x; a, c) = \frac{1}{(1 + \exp[-a(x - c)])} \tag{1}$$

where 'a' controls the slope at the crossover point $x = c$. Sigmoidal functions of this kind are employed widely as activation function of artificial neural networks (Jang and Sun, 1995). Therefore, for a neural network to simulate the behaviour of a fuzzy inference system, the first problem is of synthesizing a close MF through a sigmoidal function. There are two best ways to achieve this: one is to take the product of two sigmoidal MF's; the other is to take the absolute difference of two sigmoidal MF's.

Development of membership functions

Using gyro sensors, the corresponding gait patterns were achieved as shown in Fig. 1. It was assumed that the left foot needs to be provided actuation based on the inputs from the right foot. The sensor read the angular velocity of the test subject in degree/second (deg/s) and the angle in degrees (deg). Using a reference from a normal person, ie. a person not suffering from foot drop, the actuation to the left foot was provided in deg/s. The angular velocity and actuation ideally replicate a sinusoidal curve. Using this graph and using the properties of sinusoidal curves, the membership functions were plotted in the region of the graph with the dense grids, ie approximately two gait cycles. The membership functions were as plotted in Table 1.

Table 1 List of membership functions.

Velocity	Angle	Actuation
V1 [−220,−180]	Ang1 [−50,−30]	Act1 [−200,−100]
V2 [−200,−150]	Ang2 [−40,−25]	Act2 [−110,−30]
V3 [−160,−120]	Ang3 [−30,−20]	Act3 [−40,−25]
V4 [−140,−110]	Ang4 [−25,−10]	Act4 [−35,−20]
V5 [−120,−90]	Ang5 [−15,0]	Act5 [−25,−10]
V6 [−100,−60]	Ang6 [0]	Act6 [−15,−5]
V7 [−70,−30]	Ang7 [0,15]	Act7 [−10,−0]
V8 [−35,−10]	Ang8 [10,25]	Act8 [0]
V9 [−15,0]	Ang9 [20,30]	Act9 [0,10]
V10 [0]	Ang10 [25,40]	Act10 [5,15]
V11 [0,15]	Ang11 [30,50]	Act11 [10,25]
V12 [10,35]		Act12 [20,35]
V13 [30,70]		Act13 [30,60]
V14 [60,100]		Act14 [50,120]
V15 [90,120]		Act15 [70,150]
V16 [110,140]		Act16 [120,180]
V17 [120,160]		Act17 [170,225]

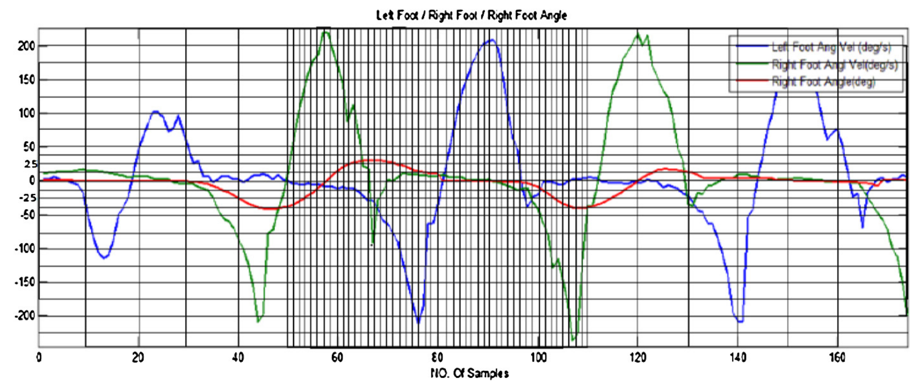

Figure 1 Human gait pattern.

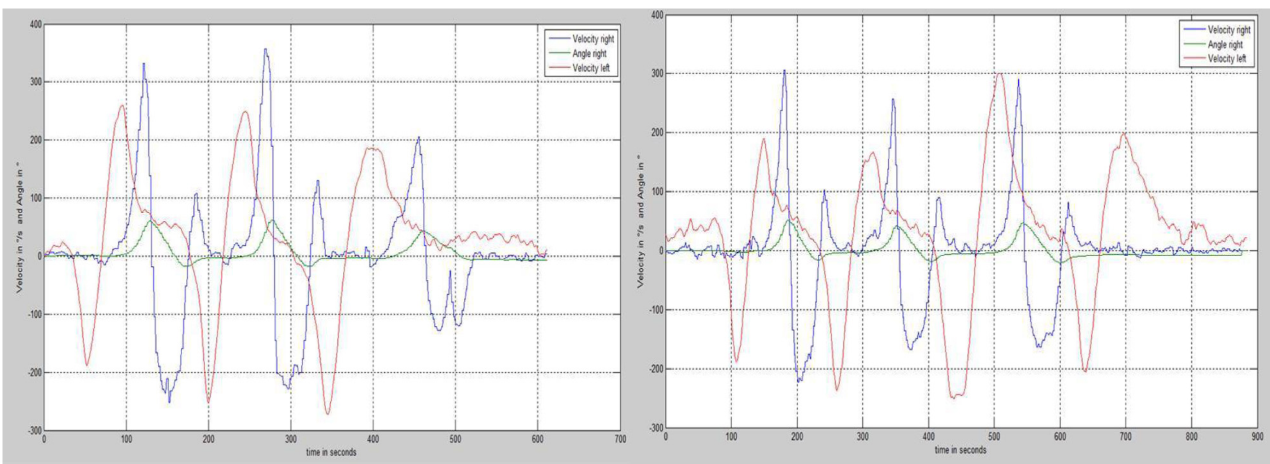

Figure 2 Data sets for gait pattern.

Designing the neuro fuzzy controller with ANFIS toolbox

Using the membership functions given in Table 1, it was required to design an initial rule base with fuzzy parameters. The rule base would replicate the sinusoidal patterns of actuation in terms of angular velocity corresponding to the given angle and angular velocity of the foot. This was done using the same values of the graph and the properties of the sinusoidal curve. The rule base that was achieved is as given in Table 2. Data points were collected from the gait patterns plotted in MATLAB, as shown in Fig. 2. The data points for approximately two gait cycle were fed as inputs to the ANFIS toolbox. Number of epochs for training was set

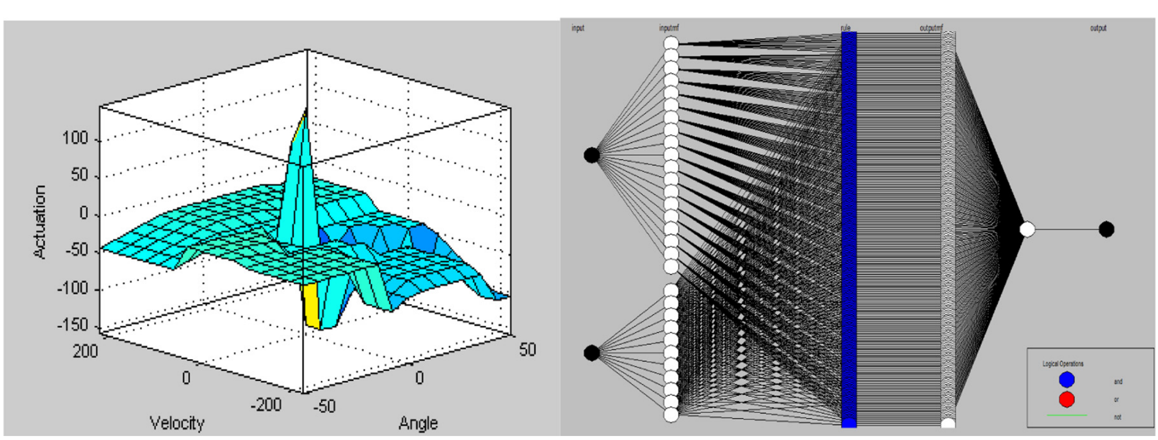

Figure 3 (a) The output of fuzzy rule base. The output is visible when mapped against the two inputs and (b) neural network structure.

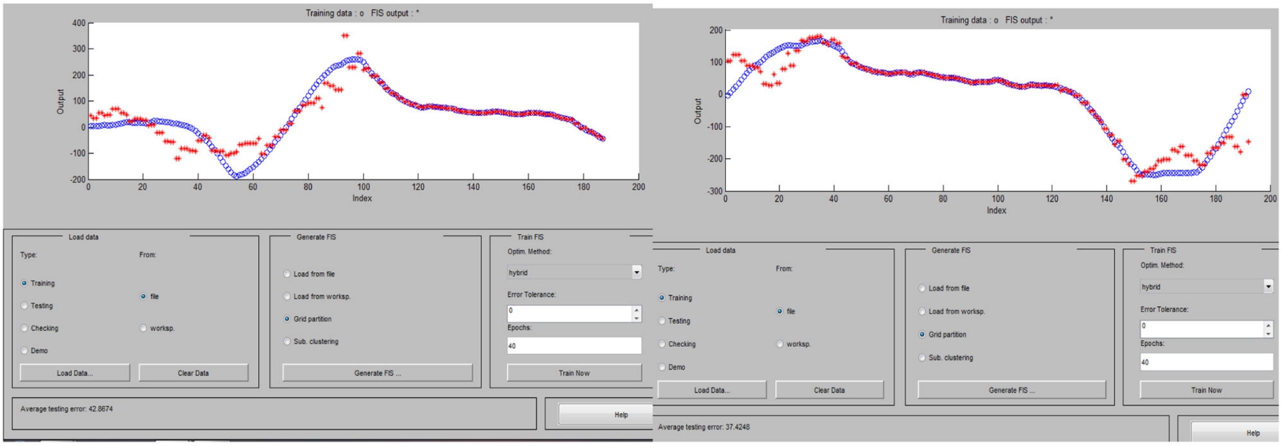

Figure 4 (a) Modification of first data set after training. Error reduces from 47 to 42.8. Blue circles mark the initial data which is fed to ANFIS for training and red crosses denote the same data after it has been changed by ANFIS training. (b) Modification of 2nd data set after training. Error reduces from 41 to 37.4. Blue circles mark the initial data which is fed to ANFIS for training and red crosses denote the same data after it has been changed by ANFIS training.

Table 2 Rule base.

Angle	Velocity	Actuation
An2	V11	Act7
An10	V11	Act4
An2	V12	Act7
An10	V12	Act4
An2	V13	Act7
An10	V13	Act4
An2	V14	Act7
An10	V14	Act5
An2	V15	Act7
An10	V15	Act5
An3	V16	Act7
An11	V16	Act6
An3	V17	Act7
An11	V17	Act6
An4	V18	Act7
An8	V18	Act7
An5	V19	Act7
An7	V19	Act7
An6	V10	Act17
An9	V10	Act2
An6	V9	Act17
An10	V9	Act3
An5	V8	Act5

to 40 and the error tolerance was set to 0. Hybrid type of training was used for ANFIS training and type of membership functions was set to constant.

Fig. 3(a) shows the 3-D surface obtained as the output of the fuzzy system and Fig. 3(b) shows the final neural network structure of the ANFIS architecture common to all the data sets. Two distinct crisp inputs angular velocity and angle are available at the beginning. These inputs were then mapped onto membership functions. There are 19 and 11 membership functions respectively for each input namely angular velocity and angle. The membership functions were then transformed into output membership functions using a rule base, to which values of each input membership functions were sent. The output membership functions were then summed together to give the final crisp output. It is visible in the structure that only AND rules were used to connect the MFs and make the rules.

Result analysis

The gait data was fed into ANFIS toolbox. This data was the set of angular velocity, angle and actuation triplets from the actual gait patterns and were crisp inputs. Each of these data sets was then compared with the rule base of Fig. 3(a) and based on the difference between the fed data and the output, the membership functions and crisp data itself was changed after each epoch of the ANFIS training. Initial error was computed between the input data and the surface of Fig. 3(a) and then decreased based on the training. Fig. 4 shows the input data to the ANFIS, before and after training. The results clearly depict that the rule base closely mimics the human gait pattern since it is sinusoidal. There is a sharp transition at the apex of the output on the positive side. The error in training of data sets varies from 37 to 42 after the data has been trained. The modification of values of membership functions and the data fed as input to the ANFIS is clearly visible.

Conclusion and future work

The neuro-fuzzy controller for the active ankle foot orthosis was designed for correction of gait pattern. The simulation for the same has been done using various data sets as inputs. Possible neural network schemes have been explored and ANFIS was selected as the best possible scheme for implementation of current project. Future work involves reducing the error in the rule base by implementing more number of membership functions. The first step to increasing the number of membership functions reduces the error obtained in ANFIS output, but if the number is too high, MATLAB displays a run time error. A possible trade-off between the numbers of MFs and the error needs to be arrived at the next step is to develop a system which is capable of using Mamdani type of output in the data set. ANFIS allows only Sugeno type of output in its FIS, but using other neuro-fuzzy schemes, Mamdani type of output can be implemented, which gives better replication of human gait pattern since it is continuous and not discrete like Sugeno type. ANFIS is the only neuro-fuzzy scheme which can be implemented easily in MATLAB as of now. Possible future work could explore more neuro-fuzzy techniques which could accept more kinds of inputs and overcome the rule and parameter sharing problem of ANFIS. Finally, future work might include a hardware implementation of the neuro fuzzy controller and the actual hardware to correct human gait pattern based on the MATLAB simulation of the same which has been carried out.

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