Driving Motorized Assistive Device Using Patterns Generated by RBFN Neural Network

T.Srinivas Sirish, Ashmi.M and Dr.K.S.Sivanandan

Abstract: The population of the elderly people is increasing and it is to be expected that 10% of people in total population having the age of sixty five years old and over in 2015. With the present eating habits and living conditions people with disabilities are increasing day by day. In order to assist them an assistive device is designed. The device developed helps the user to lock and unlock his knee during stance and swing phase of gait respectively. A radial basis function network (RBFN) Neural network is used to send signal to drive the lock according to the knee joint angle of the user. The RBFN Neural network is trained with a large set of knee joint angle data during stance and swing phase of gait. The data is collected from subjects with different anthropological data i.e. weight and height. The result shows that RBFN Neural network can be effectively used to classify the knee joint angles i.e. stance and swing phase of gait, which will be effectively used in triggering the driving circuits used in motorized assistive device based on patterns generated (0-locking, 1-unlocking). The simulation result shows that about 99.9% of data are classified correctly.

Keywords: **Gait, RBFN Neural Network, Stepper motor, Assistive device.**

I. INTRODUCTION

With the present eating habits people with muscles weakness are increasing day by day. For people with weakness or paralysis, a standard knee ankle foot orthosis (KAFO) is required to support the limb during locomotion. Human locomotion involves the dynamics of two legs which includes the locking of first leg knee joint (stance phase), unlocking of the knee of the second leg (swing phase) and dynamics of both legs during their unlock condition. When the first leg knee joint is locked and second leg knee is unlocked its dynamics begins for a finite period of time or for a fixed angular displacement whichever is desired. At the end of the dynamics of second leg the first leg knee joint has to be unlocked along with the locking of the second leg knee joint, both operations (locking of second leg knee joint and unlocking of first leg knee joint) should occur simultaneously. The moment the first leg knee joint unlocks its dynamics must start in the similar manner as that of second leg knee joint. The above process has to repeat periodically during the complete gait cycle.

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In connection to this many of exciting KAFO's support the limb by locking the knee in full extension throughout the gait cycle to prevent the leg from collapsing while weight bearing. During swing phase, KAFO users must adapt unnatural gait strategies. Lack of knee flexion during foot strike causes abrupt initial loading and disrupts the smooth progression of the center of mass of the body [5]. Abnormal gait patterns can lead to soft tissue and joint dysfunction of the hip and lower back, causing pain and loss of motion [6]. As well, walking with a fixed knee can decrease gait efficiency by 24 percent [7] and increases vertical displacement of the center of mass of the body by up to 65 percent [8]. The associated muscular effort can lead to higher energy expenditure [1]. Kenton R. Kaufman and et.all [1] and [2-4] improved KAFO by providing an articulated knee joint system that reduces the metabolic energy requirements during gait. This orthosis provides knee stability during stance while allowing free knee motion during the swing phase of gait. The ability to freely move the leg during the swing phase of gait results in more energy efficient ambulation. The robot dynamic modeling based on beam theories [10] and fuzzy based control for micro robot [11] deals with robotic application.

The observations from the exciting models are some locks only in full knee extension, bulky, heavy, noisy and expensive. The goal of the paper is to introduce to the novel method for knee locking mechanism during stance phase of gait which helps users to do their daily activities in a smarter way and safely. A smart system for us is a system which can support up to users needs during their motion. The main objective of the paper is to design and control the locking mechanism of knee automatically during locomotion with the use of the patterns classified using RBFN Neural network. This paper explains to provide lock and unlock mechanism in a motorized assistive device without using the biological signals. It uses only the signals generated by RBFN Neural network as patterns by classifying the knee angle data.

II. GENERATION OF DATABASE

For the generation of data base subjects with different anthropological data are considered and database is created by taking readings using digital camera. For the analysis purpose the subject is asked to walk on the floor for a considerable period of time with speed 3m/sec. The complete period is captured with the help of digital camera. The captured video is classified into different frames for the measurement of knee angle (to calculate stance and swing phase of gait). Using Frames shot software each sec is divided into 40 frames (each frame 25ms).

Firstly the human locomotion analysis (normal walking) using video approach is done and readings are tabulated as shown in Table 1. In the table the locking and unlocking time for a finite period for subject 1 is shown in appendix A.

We can conclude from the above table.

1 second = 40 frames, so each frame 25 ms.

Knee lock for 32 frames i.e. 800ms.

Knee unlocks for 21 frames i.e. 525ms.

Total gait cycle 53 frames i.e. 1325ms.

The readings obtained from our analysis conclude that 60% is stance phase and 40% is swing phase of total gait cycle and the total gait cycle is 1.3 sec.

The results of our analysis matches with the existing work in this area. So our analysis is validated.

III. RBFN NEURAL NETWORK

Radial basis function network consists of three layers, an input layer, hidden layer and output layer. RBF emerged as a variant of artificial neural network in late 80's. However the roots are entrenched in much older pattern recognition techniques as for example potential functions, clustering, function approximation, spline interpolation and mixture models. RBF's are embedded into two layer neural network, where each hidden unit implements a radial activation function. The output units implement a weighted sum of hidden unit outputs. The input into an RBF network is non linear while the output is linear. Due to their non linear approximation properties, RBF networks are able to model complex mappings.

In order to use a RBFN we need to specify the hidden unit activation functions, the number of processing units, a criterion for modeling a given task and a training algorithm for finding the parameters of the network. Finding the RBF weights is called network training. If we have at hand a set of input-output pairs, called training set, we optimize the network parameters in order to fit the network outputs to the given inputs. The fit is evaluated by means of a cost function, usually assumed to be the mean square error. After training, the RBF network can be used with data whose underlying statistics is similar to that of the training set. RBF network have been successfully applied to motion estimation and moving object segmentation [12].

A. Network Topology

Radial basis function are embedded into a two layer feed forward neural network. Such a network is characterized by a set of outputs. In between the inputs and outputs there is a layer of processing units called hidden units as shown in fig 1[13]

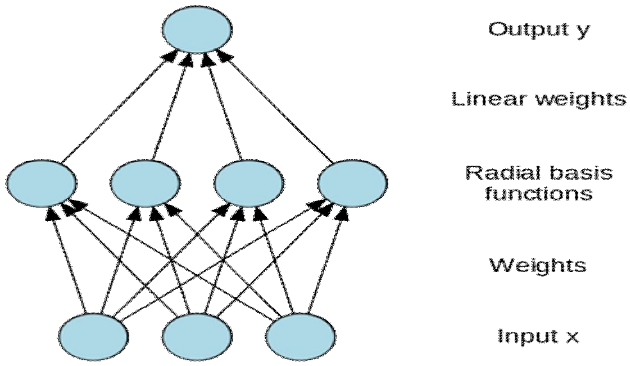

Fig 1 RBFN Topology

Each of them implements a radial basis function. The radial basis function in the hidden layer produces a significant non zero response only when the input falls within a small localized region of the input space. Each hidden unit has its own reception field in input space. An input vector Xi which lies in the receptive field for center Cj, would activate Cj and by proper choice of weights the target output is obtained. The output is given as [13]

$$Y = \sum_{j=1}^{h} \phi j \, wj \, , \phi j = (\|X\text{-}Cj\|) \qquad \text{--------(1)}$$

Wj: weight of j^{th} center, some radial function. The most popular radial function is Gaussian activation function. $(Z) = e^{-Z2/2\sigma 2}$ here Z=||X-Cj||

B. Learning in RBFN

Training of RBFN requires optimal selection of the parameter vectors Ci and Wi, i=1, 2…h. both layers are optimized using different techniques and in different time scales. Following techniques are used to update the weights and centers of a RBFN.

- Pseudo-inverse technique (offline)
- Gradient descent learning (online)
- Hybrid learning (online)

By means of training, the neural network models the underlying function of a certain mapping. In order to model such a mapping we have to find the network weights and topology. There are two categories of training algorithms: supervised and unsupervised. RBFN networks are used mainly in supervised applications. In a supervised application we are provided with a set of data samples called training set for which the corresponding network outputs are known. In this case the network parameters are found such that they minimize a cost function [12].

$$\min \sum_{i=1}^{q} \left(Yk(Xi) - Fk(Xi)\right)' \left(Yk(Xi) - Fk(Xi)\right)$$

where q is the total number of vectors from the training set, Yk (Xi) denotes the RBF output vector and Fk(Xi) represents the output vector associated with the data sample Xi from the training set. In unsupervised training the output assignment is not available for the given set.

IV. SIMULATION USING MATLAB

Radial basis networks can be used to approximate functions. NEWRB adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal [14].

NEWRB (P, T, GOAL, SPREAD, MN, DF) takes these arguments,

P - RxQ matrix of Q input vectors.

T - SxQ matrix of Q target class vectors.

GOAL - Mean squared error goal, default = 0.0.

SPREAD - Spread of radial basis functions, default = 1.0.

MN - Maximum number of neurons, default is Q.

DF - Number of neurons to add between displays, default = 25.

and returns a new radial basis network.

The larger that SPREAD is the smoother the function approximation will be. Too large a spread means a lot of neurons will be required to fit a fast changing function. Too small a spread means many neurons will be required to fit a smooth function, and the network may not generalize well. Call NEWRB with different spreads to find the best value for a given problem.

A. Algorithm

NEWRB creates a two layer network. The first layer has RADBAS neurons, and calculates its weighted inputs with DIST, and its net input with NETPROD. The second layer has PURELIN neurons, calculates its weighted input with DOTPROD and its net inputs with NETSUM. Both layers have biases. Initially the RADBAS layer has no neurons. The following steps are repeated until the network's mean squared error falls below GOAL or the maximum number of neurons are reached:

1) The network is simulated

2) The input vector with the greatest error is found

3) A RADBAS neuron is added with weights equal to that vector.

4) The PURELIN layer weights are redesigned to minimize error.

B. Experimental results

In the following we show the capabilities of the RBF network. We implement an RBF classifier on the set of knee joint angle data shown in table 1. We consider the knee joint angle grouped into two classes. The distributions are shown in table 2. Knee joint angle 180^0 corresponds to stance phase of gait so the knee should be locked, we classify this as "0" and any other knee joint angle corresponds to swing phase of gait so the knee should be unlock for free movement during gait, we classify this as "1".

The RBFN neural network is trained with the data classified as shown in table 2 in Appendix A. After successful training the network is simulated to check the performance by giving testing set of data from the training set and outside the training set. The output is correctly classified according to the knee joint angle. The output thus obtained can be used as a triggering pulse for driving the motor of the motorized assistive device to lock and unlock the knee during gait. Figure 2 below shows the training of RBFN Neural network.

After training the RBFN Neural network it is simulated with testing data, fig 3 shows the error plot between the known output and output obtained after training the network. From the error fig it can be concluded that almost 99.9% of knee joint angle data has been classifies correctly

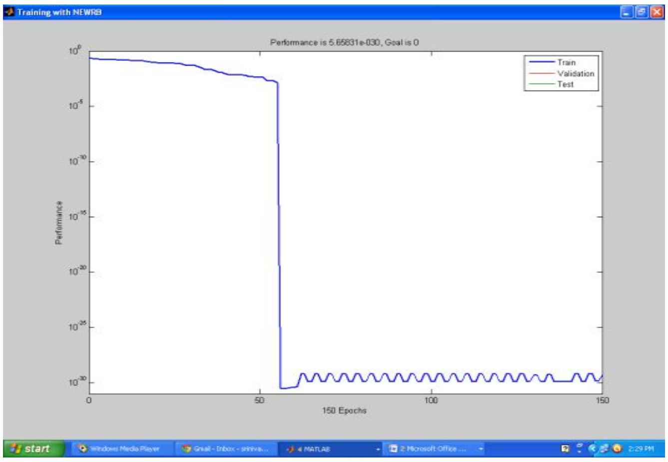

Fig 2 Training of RBFN

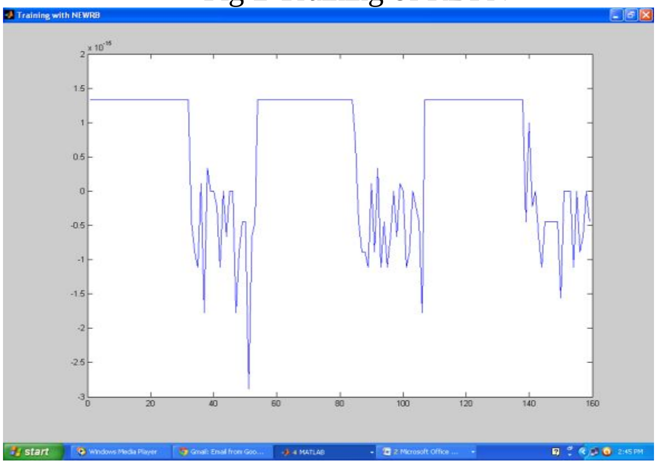

Fig 3 Error Plot

V. APPLICATION

The patterns generated by RBFN Neural network using knee joint angle database can be used as a triggering pulse for locking and unlocking the motorized assistive device. The output of the RBFN Neural Network can be given as pulse to two stepper motor for driving the lock to lock and unlock position with the help of PIC.

The hardware setup for the proposed driving circuit consists of the following
I. Minimum Hardware connections of PIC18F452
II. Bridge rectifiers, Regulators and driver circuit
The bridge rectifiers, Regulators and driver circuits used to convert 230V Ac to 12V DC and 5V DC to give as input to the stepper motor and the PIC controller. The complete driver circuit hardware setup is shown in fig 4.

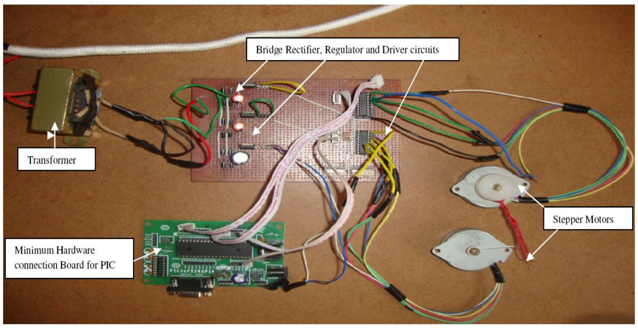

Fig 4 Hardware setup of the Electronic control circuit

The hardware setup for the proposed Mechanical lock consists of the following and is as shown in fig 5.

I. Aluminum lock
II. Cam-Shaft Arrangement

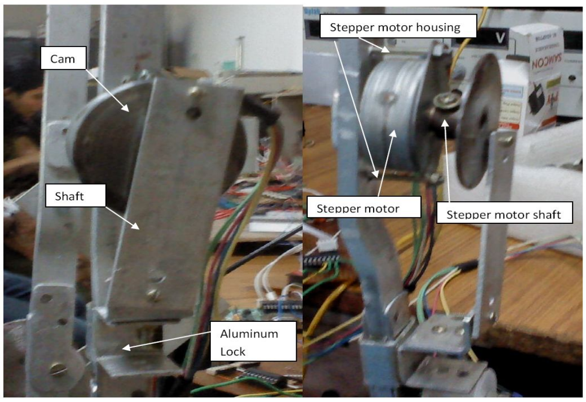

Fig 5. Hardware Setup of the Mechanical Lock

VI. Conclusion

For assisting people with profound muscle weakness an assistive device is required. The device designed should assist the user during his locomotion by providing strength to his lower limbs by locking and unlocking the knee during stance and swing phase of gait respectively. The assistive device will lock and unlock with the help of stepper motors. The actuating signal to stepper motor for performing the operation is obtained by binary patterns i.e. 0's and 1's generated by RBFN Neural network. Data base is created by performing an experiment on different subjects, after collecting data RBFN NN is trained with the data so collected and performance of the RBFN NN as a classifier is checked by simulating the NN with testing data. From the simulated results we can conclude that RBFN NN classifies about 99.9% correctly. This motivates us to use the RBFN for providing trigger pulse to driver circuits of the assistive device.

Appendix

Frame	Angle	Frame	Angle	Frame	Angle	Frame	Angle
1	180	41	126	81	180	121	180
2	180	42	125	82	180	122	180
3	180	43	128	83	180	123	180
4	180	44	130	84	180	124	180
5	180	45	135	85	164	125	180
6	180	46	135	86	158	126	180
7	180	47	142	87	155	127	180
8	180	48	152	88	152	128	180
9	180	49	158	89	150	129	180
10	180	50	158	90	145	130	180
11	180	51	165	91	140	131	180
12	180	52	174	92	132	132	180
13	180	53	175	93	125	133	180
14	180	54	180	94	123	134	180
15	180	55	180	95	125	135	180
16	180	56	180	96	130	136	180
17	180	57	180	97	128	137	180
18	180	58	180	98	130	138	180
19	180	59	180	99	134	139	158
20	180	60	180	100	135	140	157
21	180	61	180	101	138	141	151
22	180	62	180	102	140	142	135
23	180	63	180	103	148	143	130
24	180	64	180	104	154	144	125
25	180	65	180	105	163	145	123
26	180	66	180	106	172	146	123
27	180	67	180	107	180	147	123
28	180	68	180	108	180	148	123
29	180	69	180	109	180	149	123
30	180	70	180	110	180	150	124
31	180	71	180	111	180	151	128
32	180	72	180	112	180	152	135
33	158	73	180	113	180	153	135
34	152	74	180	114	180	154	138
35	150	75	180	115	180	155	148
36	145	76	180	116	180	156	155
37	142	77	180	117	180	157	162
38	132	78	180	118	180	158	171
39	128	79	180	119	180	159	176
40	128	80	180	120	180	160	180

Table 1 knee joint angle of Human locomotion

Knee joint angle	Stance “0”/ swing “1”	Knee joint angle	Stance “0”/ swing “1”	Knee joint angle	Stance “0”/ swing “1”	Knee joint angle	Stance “0”/ swing “1”	Knee joint angle	Stance “0”/ swing “1”
180	0	180	0	142	1	180	0	180	0
180	0	180	0	132	1	180	0	180	0
180	0	180	0	128	1	180	0	180	0
180	0	180	0	128	1	180	0	180	0
180	0	180	0	126	1	180	0	180	0
180	0	180	0	125	1	180	0	180	0
180	0	180	0	128	1	180	0	180	0
180	0	180	0	130	1	180	0	180	0
180	0	180	0	135	1	180	0	180	0
180	0	180	0	135	1	180	0	180	0
180	0	180	0	142	1	180	0	180	0

180	0	180	0	152	1	180	0	180	0
180	0	180	0	158	1	180	0	164	1
180	0	180	0	158	1	180	0	158	1
180	0	158	1	165	1	180	0	155	1
180	0	152	1	174	1	180	0	152	1
180	0	150	1	175	1	180	0	150	1
180	0	145	1	180	0	180	0	145	1

Table 2 Training sets

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