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Control of a legged robot using brain computer interface

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ABSTRACT

This paper interprets neuron activity using Brain Robot interface (BRI) system, which identifies and classifies the signals using Genetic Algorithm based neural network methodology. A new line has been used as a classifier to recognize the imaginary signals, which is called as Genetic Algorithm. The genetic algorithm enables to choose the most representative features. The Genetic algorithm is applied to choose the best features. A Genetic algorithm is an evolutionary algorithm that its optimality has been approved in other fields, the computation complexity is low, and it is an appropriate method in real time problems. With this method, we can achieve the best accuracy of classification with the lowest amount of input data from the neural system to supply direct communication between the human brain and physical devices by translating different patterns of brain motion into commands in real time. The commands, which are identified is classified into signals and transmitted through data acquisition card to the LEGGED ROBOT.

KEY WORDS: Brain robot interface, Genetic algorithm.

1. INTRODUCTION

A brain-computer interface otherwise called Mind-Machine Interface (MMI) which has a direct communication between the brain and an external device. Here dry electrodes with conductivity gel have been used to obtain the brainwave signals. The obtained signals have been classified using genetic algorithm using artificial neural networks. A neural network consists of elements called neurons or otherwise called as units, cells, or nodes. Each neuron is associated with another neuron using directed communication links, each associated with different weight. A genetic algorithm is used as an identifier to classify the accurate signals by which they generate solutions, and it is also used to optimization problems using similar techniques such as crossover, mutation, and selection. The signal obtained from this process has been given to the controller. Here the controller will be a four legged robot.

2. METHEDOLOGY

a) Start
b) T1=0
c) Generate the population of p1(T1)
d) simulate and calculate the fitness value p1(T1)
e) T1=T1+1
f) Check if the termination criterion satisfies
g) If it satisfies go to step 11
h) Now select p1(T1) from p1(T1-1)
i) crossover both the populations p(T1)
j) Now go to step 3
k) output the best population and stop
l) End

Selection: Selection is a practice of choosing the best chromosome. Chromosomes are chosen based on the fitness function. The Fitness function is a methodology which drivers the average with about to the other members of the population. Each with high fitness function ends up with more number in the mating pool, so that they can generate more significant child chromosomes.

Crossover and Mutation: Crossover is the substitute of qualities which occurs between selected parents followed by mutation. In mutation, many genes may change randomly. As soon as the crossover and mutation operation occurs, the resulting child is undergone with the selection process and for a second time, it will generate parent chromosomes this process will replicate. A termination principle is used to specify until when GA should last.

Fitness Function: Fitness Function is the most efficient function to evaluate the mechanism of each string. The selection process of fitness function is preferred to be constantly positive. In this model, we have ranged the value of f as -5, which is the least value, so that we can add a value of 5 to each fitness bar samples. The Second approach is to find the minimum value of the fitness bar for each element in the population and adds its absolute value so that the value remains in the optimistic significantly.

EEG signals are collected from samples using electrodes kit. The signals which are obtained is at different frequencies so that the genetic algorithm identify and classify the signals accordingly. By implementing crossover technique, we can categorize the signals and identify the best case and the worst case. With the combination of the

best and worst case we can consider it as lucky case and with worst and medium cases, it can be the average case. The Lucky case would be the best selection to obtain the exact frequency.

Table.1.Comparison of Wave Groups

Name of the wave	Location	Frequency	Normal state
Delta	Frontally in adults, posterior in children	0.5 – 4 Hz	Deep sleep, Coma
Theta	Temporal cortex	4 – 8 Hz	Trance, Dreams
Alpha	Posterior regions of head, both sides, higher in amplitude on dominant side. Central sites (C3 – C4) at rest.	8 – 13 Hz	Relaxation with eyes closed but still awake
Mu	Sensorimotor cortex	8 – 12 Hz	They diminish with movement or the intention to move
Beta	Frontally evident on both sides, symmetrical Distribution	13 – 30 Hz	Beta 1: 13 – 20 Hz, Perception, Thinking, Mental Activity
			Beta 2: 20 – 30 Hz, Tension, Anxiety, Excitement
Gamma	prefrontal cortex and left temporal lobe	26 – 100 Hz	Stream of consciousness

Design of Legged Robot: Servo motor features

a) Weight: 9 g.
b) Dimension: 22.2 x 11.8 x 31 mm approx.
c) Stall torque: 1.8 kgf cm.
d) Operating speed: 0.1 s/60 degree.
e) Operating voltage: 4.8 V (~5V).
f) Dead band width: 10 s.
g) Temperature range: 0^0C 55^0C.

Design: The Base frame is designed such that we can fit four servo motors into this for the moment of the legs. The link is the part which connects the leg and the base frame. There will be another servo motor fixed between the link and the leg. The Link is attached to the base frame then we need to assemble leg with the link.leg is arranged in such a way that with the help of the servo motors it will navigate. By using servo motors legged robot has been designed. Here eight servo motors have been used, The neural network trained output signal is interfaced with this legged robot. The motion and the direction of the robot depend on the classified output.

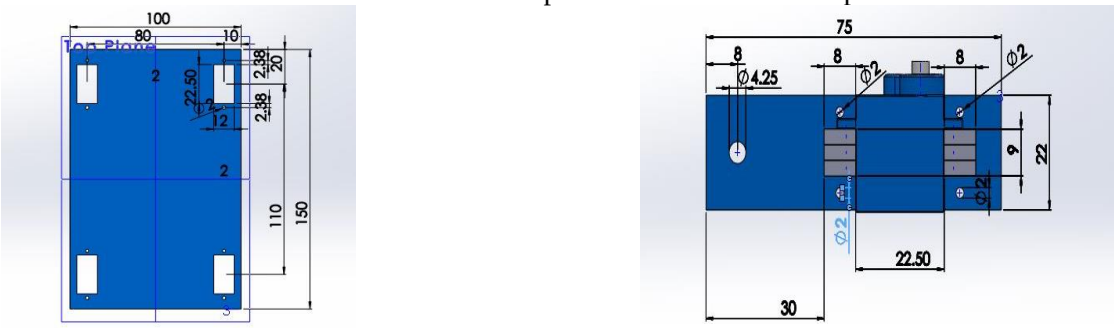

Fig.2. Base frame and Link

Fig.3. C section and Assembly

3. RESULTS

By using dry electrodes 200 brain frequency samples has been taken. These samples were classified according to their frequency with genetic algorithm methodology. According to the classification they are classified into three ranges which are namely best, worst and average. Within these signals the best case signals were been examined. Using Fitness function analyzer the best case signal is generated. The generated signal is transmitted to the controller. According to the neural signals the robot is being controlled.

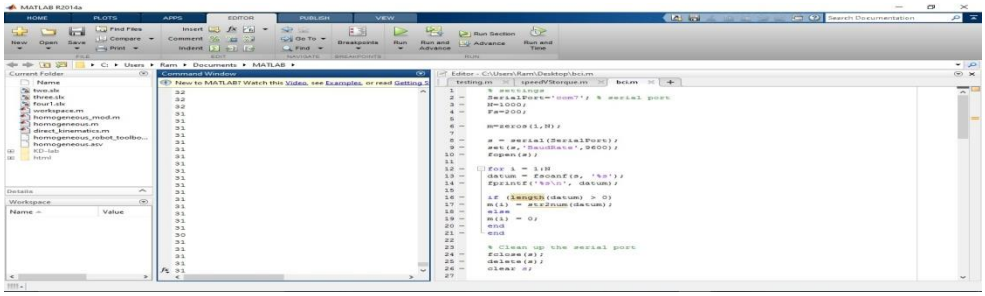

Fig.4. Frequency signals

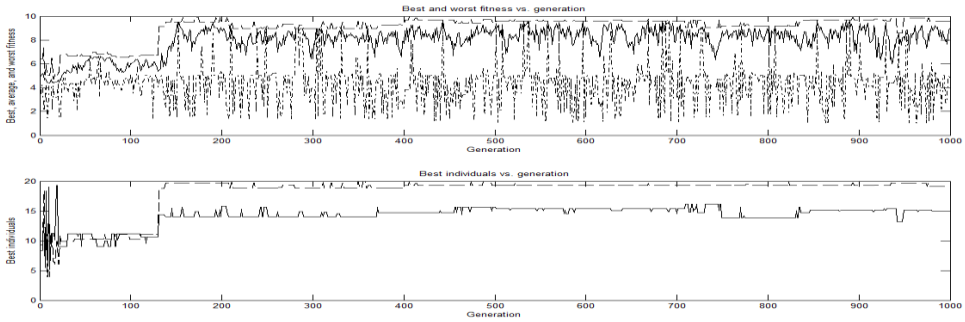

Fig.5. Classification of signals

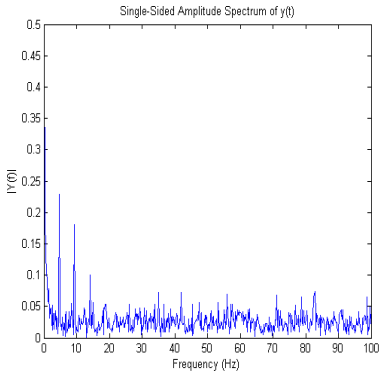

Fig.6. Single sided amplitude spectrum

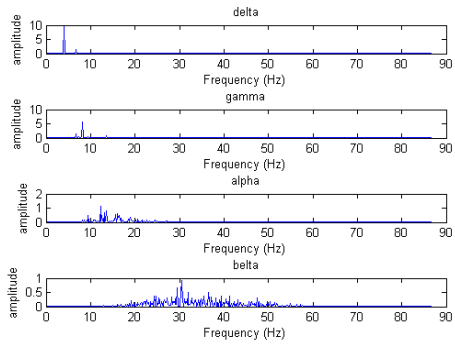

Fig.7. Amplitude vs Frequency

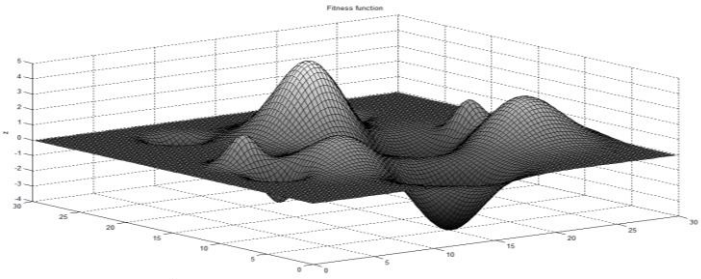

Fig.8. Fitness Function

4. CONCLUSION

Thus, for various input EEG signals, we repeated the experiment and the output were obtained which is the direction in which the robot has to move. The neural network was trained with a limited number of signals which can be improved by training it with much more signal. The degree convergence in the

output is remarkable. Then feature selection is now computed using a very small number of operations. Many features can make the decision accurate.

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