Legged Robot Trajectory Generation using Evolved Fuzzy Machine for IoT Environments

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IoT 환경을 위한 진화된 퍼지머신을 이용한 로봇의 궤적생성

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Abstract The Internet of Things (IoT) era, in which all items used in daily life are equipped with a network connection function, and they are closely linked to increase the convenience of life and work, has opened wide. Robots also need to develop according to the IoT environment. A use of new type of evolved fuzzy machine (EFM) for generating legged robot trajectory in IoT enviornmentms is discussed in this paper. Fuzzy system has been widely used for describing nonlinear systems. In fuzzy system, determination of antecedent and consequent structures of fuzzy model has been one of the most important problems. EFM is described which carries out evolving antecedent and consequent structure of fuzzy system for legged robot. To generate the robot trajectory, parameters of each structure in the fuzzy system are tuned automatically by the EFM. The results demonstrate the performance of the proposed approach for the legged robot.

Key Words : IoT Enviornment, Evolved Fuzzy Machine, Robot Trajectory

요 약 일상에서 이용하는 모든 물건들이 네트워크 접속 기능을 갖추고, 이들이 긴밀하게 연동하면서 생활 및 업무의 편의성을 높이는 IoT(사물인터넷) 시대가 활짝 열렸다. 로봇도 IoT 환경에 맞춰 발전해야 하는 상황이다. 논문에서는 IoT 환경을 위한 다리가 있는 로봇 궤적을 생성하기 위해 새로운 형태의 EFM (진화 퍼지 머신)을 사용하는 방법에 대하여 다룬다. 퍼지 시스템은 비선형 시스템을 묘사하는 데 널리 사용되고 있다. 퍼지 시스템에서 퍼지 모델의 전반부 및 후반부 구조를 결정하는 것은 매우 중요한 문제이다. EFM은 다리가 달린 로봇을 위해 퍼지 시스템의 전반부 및 후반부 구조를 진화시켜 효율적으로 구조를 개선한다. 퍼지 시스템에서 각 구조의 로봇 궤적 매개 변수를 생성하고 EFM에 의해 자동으로 조정된다. 제안된 접근 방식은 다리가 있는 로봇에 적용하여 성능을 살펴본다.

주제어 : IoT 환경, 진화된 퍼지 머신, 로봇 궤적

1. Introduction

The Internet of Things (IoT) era, in which all items used in daily life are equipped with a network connection function, and they are closely linked to increase the convenience of life and work, has opened wide. Robots also need to develop according to the IoT environment.

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Legged robots have recently evolved into an active area of research and development with the creation of several robot systems. The robots can be used as proxies or service providers to humans in performing tasks in real world environments including rough terrain, steep stairs, and obstacles. To realize human-like walking robots, stable and reliable biped walking which is fundamental issue should be carried out. But dynamics in the robot is very complex so we can not handle the robot easily. Regarding system modeling, The problem of system modeling has been studied for a long time in various fields such as pattern recognition, signal processing, and communication. However, it is difficult to present a realistically clear modeling method for a complex nonlinear system with many input variables. Because, as the number of input variables related to the system increases, the computational complexity and execution time of the system increase, and the memory space becomes insufficient. This problem can be solved by selecting an optimal input variable group. However, the problem of selecting the optimal input variable group is one of the very difficult tasks. In previous studies, it is common to select input variables using a fuzzy system or statistical technique that mainly reflects the opinions of experts. Similarily, we can use an approach of system modeling to handle complexity of the robot in the IoT environment. As for the indexes for legged robot to maintain its dynamical balance, zero moment point (ZMP) was introduced by Vukobratovic[2-4]. The ZMP has been very commonly used for the gait planning of biped robot[1-4,14]. This paper proposes that trajectory of legged robot based on the ZMP can be achieved by developing new evolved fuzzy machine (EFM) which can identify nonlinearity and uncertainty in the robot walking.

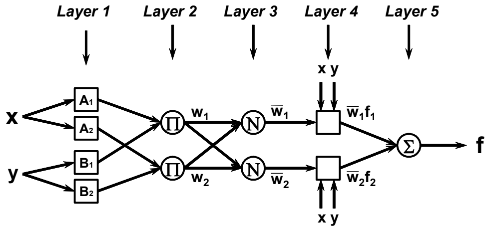
2. Evolved Fuzzy Machine

The fuzzy inference system (FIS)[5-10] is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. In this paper, we use the Sugeno-type fuzzy model in which since each rule has a crisp output, the overall output is obtained via weighted average, thus avoiding the time-consuming process of defuzzification. For simplicity, the nonlinear system to be identified is assumed to have two input variables and each input variables has two fuzzy set, respectively. And ssume there are two fuzzy if-then rules as belows.

Rule 1: $\textit{If } x \textit{ is } A_1 \textit{ and } y \textit{ is } B_1, \textit{ then } f_1 = p_1x + q_1y + r_1.$

Rule 2: $\textit{If } x \textit{ is } A_2 \textit{ and } y \textit{ is } B_2, \textit{ then } f_2 = p_2x + q_2y + r_2.$

Fig. 1 is an equivalent architecture to a two-input Sugeno-type fuzzy model with two rules, where each input assumed to have two associated membership functions (MFs).



[Fig. 1] Structure of fuzzy system

Description of each layer in Fig. 1 is as follows.

[Layer 1] All input variables become fuzzy variables including the membership of the fuzzy set. In other words,

$$O_i^1 = \mu_{Ai}(x)$$

Here, O_i^1 is the output for node i of layer 1, and the membership of the MF A is calculated.

[Layer 2] It calculates the fit, and is the product operation for the output value on the first layer, and is as follows.

$$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \ \ i = 1, \ 2$$

[Layer 3] The ith node of this layer calculates the ration of the rules' firing strength to the sum of all rules' firing strength

$$O_i^3 = \overline{w}_i = \frac{w_i}{w1 + w2}, \ i = 1,2$$

[Layer 4] The operation at the I node is as follows.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$$

$\overline{w_i}$ is output from previous layer and p, q, r are parameters of consequent part in fuzzy rules.

[Layer 5] A node that calculates the final output value. The output value is as follows.

$$O_1^5 = overall\ output, f = \sum_i \overline{w}_i f_i = \frac{\sum_i \overline{w}_i f_i}{\sum_i \overline{w}_i}$$

The genetic algorithm introduced by[6-9,12,13] is a computational model that solves complex real-world problems by simulating the evolution of the natural world based on the principle of survival of the fittest. These genetic algorithms express possible solutions to the problem to be solved in chromosomes, and then gradually transform them through genetic operators such as Selection, Crossover, and Mutation operators. Produce better solutions. Each possible solution is called an individual, and a set of individuals is called a population. Genetic algorithms can search for these populations iteratively to find a global solution rather than a local minima. Fig. 2 shows how this genetic algorithm finds an optimal solution.

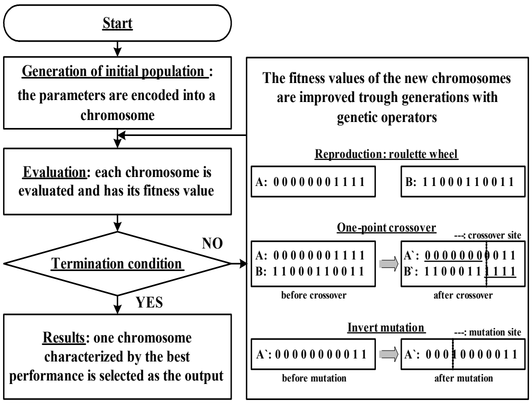
The overall sequence of operations of the genetic algorithm[11-13] is as follows.

Step 1: Form the first population.

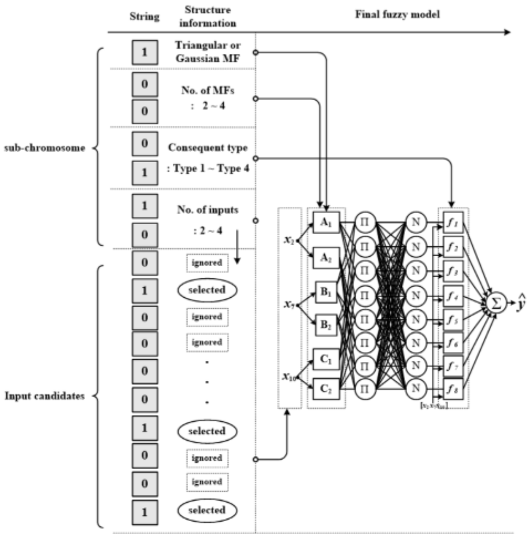
Step 2: To extract the dominant individuals, all individuals in the initial population are evaluated by a fitness function.

Step 3: When the desired level of solution is found, the execution stops. Otherwise, the dominant entity extracted by the fitness function generates the next generation population by genetic operators (selection, crossover, mutation).

Step 4: If the evolutionary generation is at its maximum, stop running the genetic algorithm. Otherwise, go to Step 2 and repeat the above process. Through the same execution process as above, the genetic algorithm generates the optimal solution.



[Fig. 2]. Structure of evoluationary algorithm



[Fig. 3] Evolved fuzzy machine through the genetic algorithms

To get optimal parameters in fuzzy system, we designed the structure of an evolved fuzzy machine and evolution strateges as shown in Fig. 3. Sugeno-type fuzzy rules[5] are used and for the evolution strategy we employ binary coding for the available design specifications which are the proper type of membership function(MF), number of MF, type of consequent polynomial, set of input variables, and dominant inputs among input candidates. These candidate solutions are encoded as chromosomes which are made of 5 sub-chromosomes. The first one has one bit and presents type of membership function. Two types of MF, Triangular and Gaussian MF, are used as the MF candidates. Each is represented by a bit 0 and 1. If the gene in the first sub-chromosome contains 0, the corresponding type of MF is Triangular type. If it contains 1, the MF is Gaussian type. The second sub-chromosome has two bits for number of MF. If many number of MF is selected for certain input variables then fuzzy rules and computational complex can be increased. So we constrain the number of MF to vary only between 2 and 4 for each input variable. We use a rule structure that has fuzzy antecedent and functional consequent parts. To avoid time consuming and heavy structure of fuzzy system, number of input variables to be selected is restricted under four. Input variables as many as the number represented in the 4th sub-chromosome are selected among all input candidates which are depicted by the fifth sub-chromosome. The number of genes in the fifth sub-chromosome is same as the whole candidates of input variables in legged robot system. The gene in the fifth sub-chromosome means the corresponding input variables. If a gene contains 1, the corresponding variable is selected and used as an input variable of the fuzzy system. If it contains 0, the variable is ignored and not used. In this way, the dominant input selection is done. Finally, evolved structure of fuzzy machine has two Gaussian MFs in the antecedent part and linear quadratic function with three inputs, in the consequent part for 8 fuzzy rules.

The design procedures of evolved fuzzy machine can be summarized as follows.

[Step 1] The population of the parent generation, the first generation, is formed by genetic algorithm. As shown in Fig. 2, each entity in the population consists of 10 strings, and each string can have a value of 1 or 0. Here, 1 means selection of the corresponding input variable, and 0 means deletion of the corresponding input variable. In this paper, each generation has 10 individuals.

[Step 2] The variable selected by Step 1 is applied as an input variable of fuzzy system to evaluate its performance.

[Step 3] The objects evaluated by Step 2 are selected by sorting by ranking selection method according to the result value.

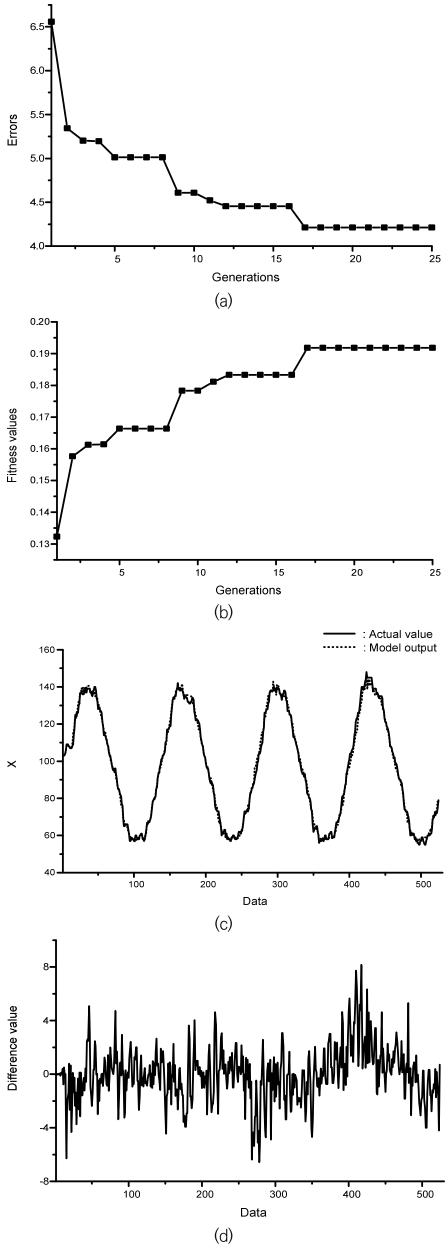
[Step 4] If the object selected by Step 3 satisfies the termination condition, the algorithm is terminated. Otherwise, a new population is created by the genetic operator and the above process is repeated again from Step 2. Here, the termination condition is a case in which the error value converges within the tolerance range or the number of evolutionary generations reaches the maximum target value.

In this way, the optimal input variable is selected by the genetic algorithm, and the evaluation of the selected input variable is confirmed through the fuzzy system.

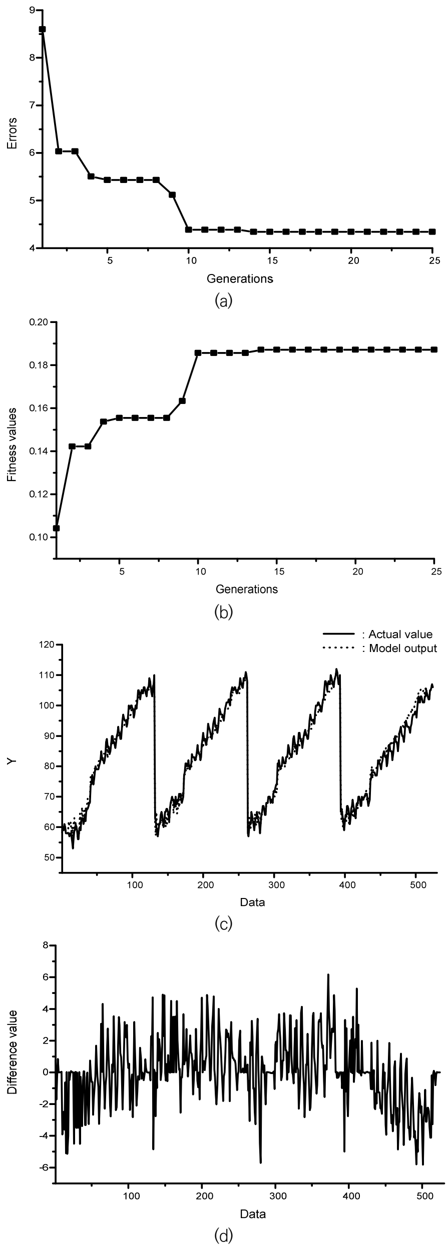
3. Legged robot

The legged robot has 19 joints[14]. Height and weight are 380 mm and 2700 g, respectively. Each joint is driven by an RC servomotor, which consists of a DC motor, gear, and a simple controller. Each RC servomotor is mounted on the link structure. We considered 10 joint locations in two legs of the robot as input variables of the robot for walking. Two joints for each hip, one for each knee, and two for each ankle are assigned for two legs of the robot. For numbering input variables, yaw and pitch of the left hip are the 1st and 2nd input variables. Left knee is the 3rd input. Pitch and yaw of the left ankle will be the 4th and 5th input variables. As same method, the input 6th to 10th are also defined. Four force sensors (FlexiForce sensor A201) are mounted at the four corners of the sole plate of the robot feet and measurements are carried out in real time. The foot pressure is obtained by summing the force signals. By using the force sensor data, it is easy to calculate the actual ZMP data.

Figure 4-5 show results of the evolved fuzzy system applied to x-y coordinates of walking humanoid robot on a flat floor. We set design parameters for evolutionary procedures. 30 chromosomes are generated and evolved gradually according to 0.85 of crossover rate and 0.05 of mutation rate during 25 generations, where each chromosome in the population is defined. All chromosomes are evaluated by the fitness function based on the mean square error (MSE) and ranked according to their fitness value. When the evolved fuzzy machine is applied to x-coordinate of legged robot, the best chromosome selected in the population is [1, 4, 4, 4 : 2, 4, 7, 8]. It means Gaussian MF is selected as type of membership function from 1st sub-chromosome, # of MF is determined as 4 from 2nd sub-chromosome, type of consequent polynomial is also determined from 3rd sub-chromosome, # of inputs and corresponding inputs are 4 and second, fourth, seventh, eighth input from 4th sub-chromosome and 5th sub-chromosome, respectively.



[Fig. 4] x-coordinate of the robot: (a)-MSE according to generations, (b)-fitness function values according to generations, (c)-actual values and model output, (d)-difference between actual values and model output.



[Fig. 5] y-coordinate of the robot: (a)-MSE according to generations, (b)-fitness function values according to generations, (c)-actual values and model output, (d)-difference between actual values and model output.

Finally the MSE of the best chromosome is 4.213. For the y-coordinate of legged robot, the best chromosome selected in the population is [0, 4, 3, 4 : 2, 7, 8, 9] which means triangular MF, 4 MFs, and 4 inputs such as second, seventh, eighth, ninth input are determined by evolutionary procedure. The MSE of this chromosome is 4.3428. According to the x-y coordinates of the robot, the final walking trajectory from the evolved fuzzy machine is generated.

4. Conclusion

This paper has presented evolved fuzzy machine for legged robot trajectory. As fuzzy system, type of membership function (MF), no. of MF, type of consequent polynomial in the fuzzy rule, no. of inputs, and dominant input selection are determined automatically. As evolutionary algorithm, binary string type genetic algorithm is used and consisted of five sub-chromosomes. Each sub-chromosome has one or two strings and 5th sub-chromosome is 10 bits which depicts whole input candidates of the legged robot. Finally, legged robot trajectory from evolved fuzzy machine is produced and it looks like very smooth.

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