Target Detection by Combination of Odor Sensors and Artificial Intelligence Technologies

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Abstract

This study aims target detection by combination of odor sensors and Artificial Intelligence Technologies. Fuzzy Logic Approach has been preferred as Artificial Intelligence Technology here. The developed system is modeled using Simulink and Fuzzy Logic Toolbox under Matlab and then is analyzed. The system is able to distinguish odors through the control system that uses the fuzzy logic algorithm. Three type odors have been determined and they have been introduced to the control system. A small wheeled robot has been designed and it has been integrated with the developed control system. So, the robot has become sensitive to smell. In other words, no longer it is odor-sensitive and can be directed to the desired odor source. This is the first study on the topic and the further studies will be on the expansion of the study. The main goal is to develop an electronic dog nose and to use it instead of the real dog smell functions.

Key words: Fuzzy logic, odor sensors, artificial intelligence technologies, target detection of odor sensors, Fuzzy logic controller

1. Introduction

In the literature, many articles for odor sensor are located with artificial intelligence technologies. The studies include artificial intelligence technologies such as *neural networks* [1,2,3,4,5,8,12,24] , *genetic algorithms* [2], *PSO* (particle swarm optimization) [14,15,20,21] , *Swarm optimization* [22] , *FLVQ*(fuzzy learning vector quantization ,*SOM*(An artificial neural network is used for low-dimensional unsupervised learning.) algorithms have been developed to increase the availability.)

There is almost no literature on target detection by fuzzy logic controller with odor sensor. Different odor sensors have been represented by three membership functions. The output obtained from three odor sensor has been defined as five different fragrances. Fuzzy logic rule bases are composed in the form of a table indicating changes in the output values and in the input values used in microcontroller. Fuzzy logic is limited between 0-100 values entered to toolbox and therefore, the potentiometer has been set to measure the maximum 100 voltage values. The buttons prepared to select smell are based on the lower and upper values of member functions. These limits have been compared with the values in the table so that the potentiometer can be correctly adjusted. It is observed that the motor can be activated so that the robot goes to the desired direction.

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2. Overview of the Application

The case study is discussed in four main sections as shown in figure-1. The first part contains an overview for MATLAB fuzzy logic tool, fuzzy membership functions and its rules. In the second part of the application, the input and output values have been displayed in a table according to the specified values. As a next step, the use of peripherals is explained and the codes are given into table. Proteus simulation results are presented in the last part of the application.

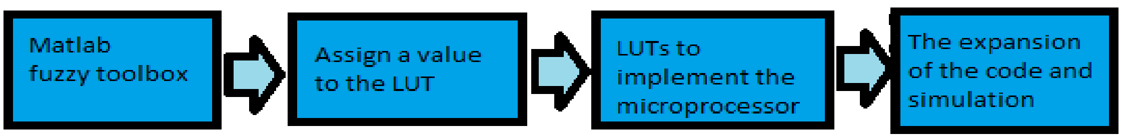

Figure1. Flow diagram

2.1. MATLAB Fuzzy Toolbox and an Overview of the Implementation of Article

Fuzzy logic is a form of many-valued logic or probabilistic logic; it deals with reasoning that is approximate rather than fixed and exact. When compared to traditional binary sets (here variables may take on true or false values) fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. The term "fuzzy logic" was introduced with the 1965 proposal of fuzzy set theory by Lotfi A. Zadeh. Fuzzy logic has been applied to many fields, from control theory to artificial intelligence. However, fuzzy logics had been studied since the 1920s as infinite-valued logics notably by Łukasiewicz and Tarski.[29]

In the system, the fuzzy logic has been used as control algorithm of which mathematical model isn't previously available and this case is an important privilege and advantage for the study. Suppose that smell is the essence of expert data.

Fragrances have been used to extract the structure of a three-way route. Five different membership functions for fragrances are generated at the output. Trapezoidal and triangular membership functions code of microprocessor for ease of operation in terms of the processing load would be more appropriate. The selected membership functions of the application are as in

Figure 2.1.1. The rules for the fuzzy logic control are shown in Figure 2.1.2. Figure 2.1.3's a representation of fuzzy logic control surfaces.

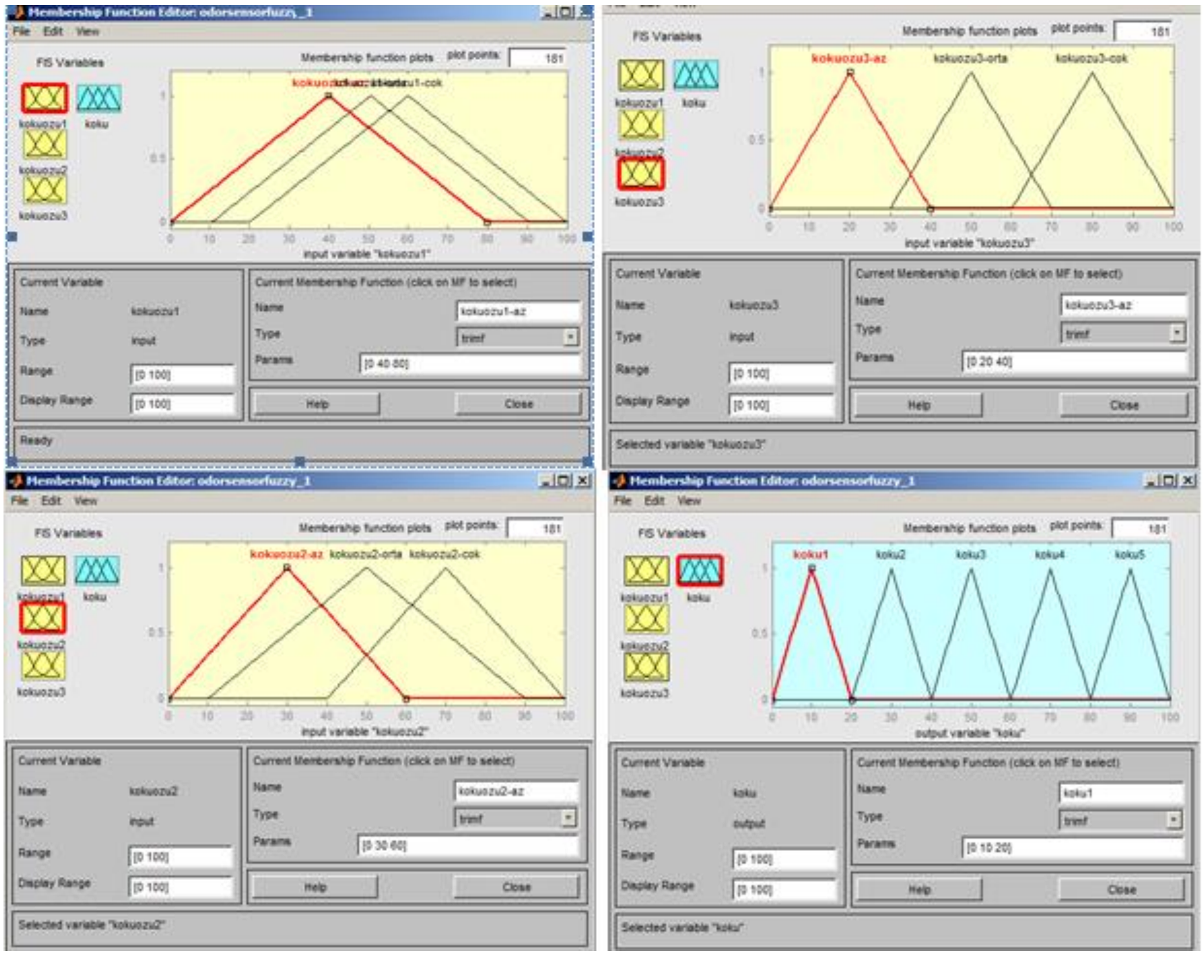

Figure2.1.1. Membership functions of the inputs and outputs

1. If (kokuozu1 is kokuozu1-az) and (kokuozu2 is kokuozu2-az) and (kokuozu3 is kokuozu3-az) then (koku is koku1) (1)
2. If (kokuozu1 is kokuozu1-orta) and (kokuozu2 is kokuozu2-orta) and (kokuozu3 is kokuozu3-az) then (koku is koku2) (1)
3. If (kokuozu1 is kokuozu1-orta) and (kokuozu2 is kokuozu2-orta) and (kokuozu3 is kokuozu3-orta) then (koku is koku3) (1)
4. If (kokuozu1 is kokuozu1-cok) and (kokuozu2 is kokuozu2-orta) and (kokuozu3 is kokuozu3-orta) then (koku is koku4) (1)
5. If (kokuozu1 is kokuozu1-cok) and (kokuozu2 is kokuozu2-cok) and (kokuozu3 is kokuozu3-cok) then (koku is koku5) (1)

Figure 2.1.2. The rules of the fuzzy logic controller

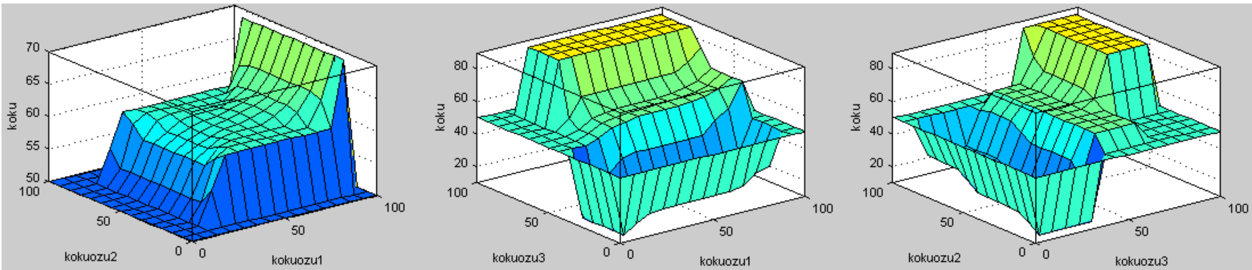

Figure 2.1.3. The surfaces of the fuzzy logic controller

2.2. Assign a Value to The LUT

Matlab fuzzy logic model also generate random values generated and applied to fuzzy logic controller. Input and output values are then converted into a table.

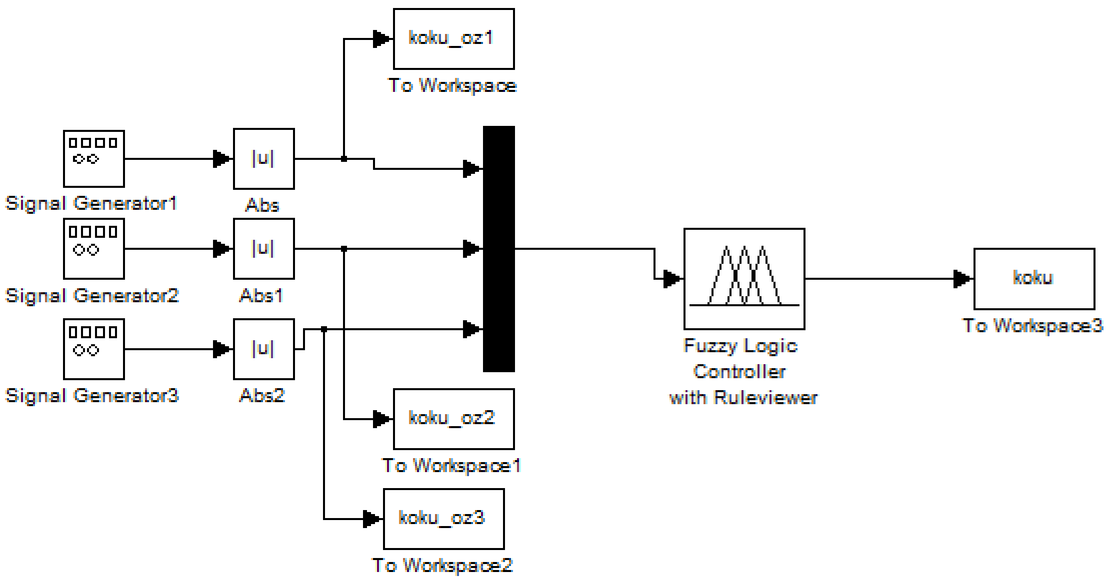

Figure 2.2.1. The fuzzy logic controller model

The input and output values are as follows:

koku_oz1[]={50,5,20,30,40,30,50,70,30,30,52,52};
koku_oz2[]={50,5,20,30,40,40,40,70,44,44,27,55};
koku_oz3[]={50,5,15,30,40,40,40,70,29,52,38,65};
koku[]   ={60,5,17,20,60,57,60,90,20,60,51,72};

2.3. LUTs To Implement The Microprocessor

The statements defining the microprocessor using the process variables are as follows:

```
int koku_oz1[]={50,5,20,30,40,30,50,70,30,30,52,52};
int koku_oz2[]={50,5,20,30,40,40,40,70,44,44,27,55};
int koku_oz3[]={50,5,15,30,40,40,40,70,29,52,38,65};
int koku[]    ={60,5,17,20,60,57,60,90,20,60,51,72};
```

Comparing the table values, the following code snippet determines the direction of smell coming from the sensor:

```
  for (j=0;j<12;j++){
  if((koku_oz1[j]==sensor1_1)&&(koku_oz2[j]==sensor1_2)&&(koku_oz3[j]==sensor1_3))
sol_koku=koku[j];
  if((koku_oz1[j]==sensor2_1)&&(koku_oz2[j]==sensor2_2)&&(koku_oz3[j]==sensor2_3))
orta_koku=koku[j];
  if((koku_oz1[j]==sensor3_1)&&(koku_oz2[j]==sensor3_2)&&(koku_oz3[j]==sensor3_3))
sag_koku=koku[j];
  }
```

The following code snippet, the direction of the motor is determined by comparing the value ranges and smell.

```
  if((ust_deger>sol_koku)&&(sol_koku>alt_deger))
{output_high(pin_D1);output_low(pin_D0);}
  if((ust_deger>orta_koku)&&(orta_koku>alt_deger))
{output_high(pin_D1);output_high(pin_D0);}
  if((ust_deger>sag_koku)&&(sag_koku>alt_deger))
{output_low(pin_D1);output_high(pin_D0);}
```

2.4. The Expansion of the Code and Simulation

The following code snippet determines odors using buttons and it show the minimum and maximum values on the LCD:

```
  putc(CLR);
  putc(I);
  putc(LINE2);
  if(input(pin_C0)) {printf("Koku :0-20");  tus=1;alt_deger=0;ust_deger=20;}
  if(input(pin_C1)) {printf("Koku :20-40"); tus=2;alt_deger=20;ust_deger=40;}
  if(input(pin_C2)) {printf("Koku :40-60"); tus=3;alt_deger=40;ust_deger=60;}
  if(input(pin_C3)) {printf("Koku :60-80"); tus=4;alt_deger=60;ust_deger=80;}
  if(input(pin_C4)) {printf("Koku :80-100");tus=5;alt_deger=80;ust_deger=100;}
```

Odor extracts to be between 0-100 ;if 5V-255 then x V-100 gets the value of . As a result,x=1.96V.1.96 V input, potentiometer 100 is determined as the maximum value. Analog-to-digital conversion in the following code specifies the values of the essence of smell.

```
set_adc_channel(0);
delay_us(20);
sensor1_1=read_adc();
putc(CLR);
putc(I);
putc(LINE1);
printf("Sensor1_1=%d",sensor1_1);
delay_ms(300);
```

Simulation results are as shown in Figure 2.4

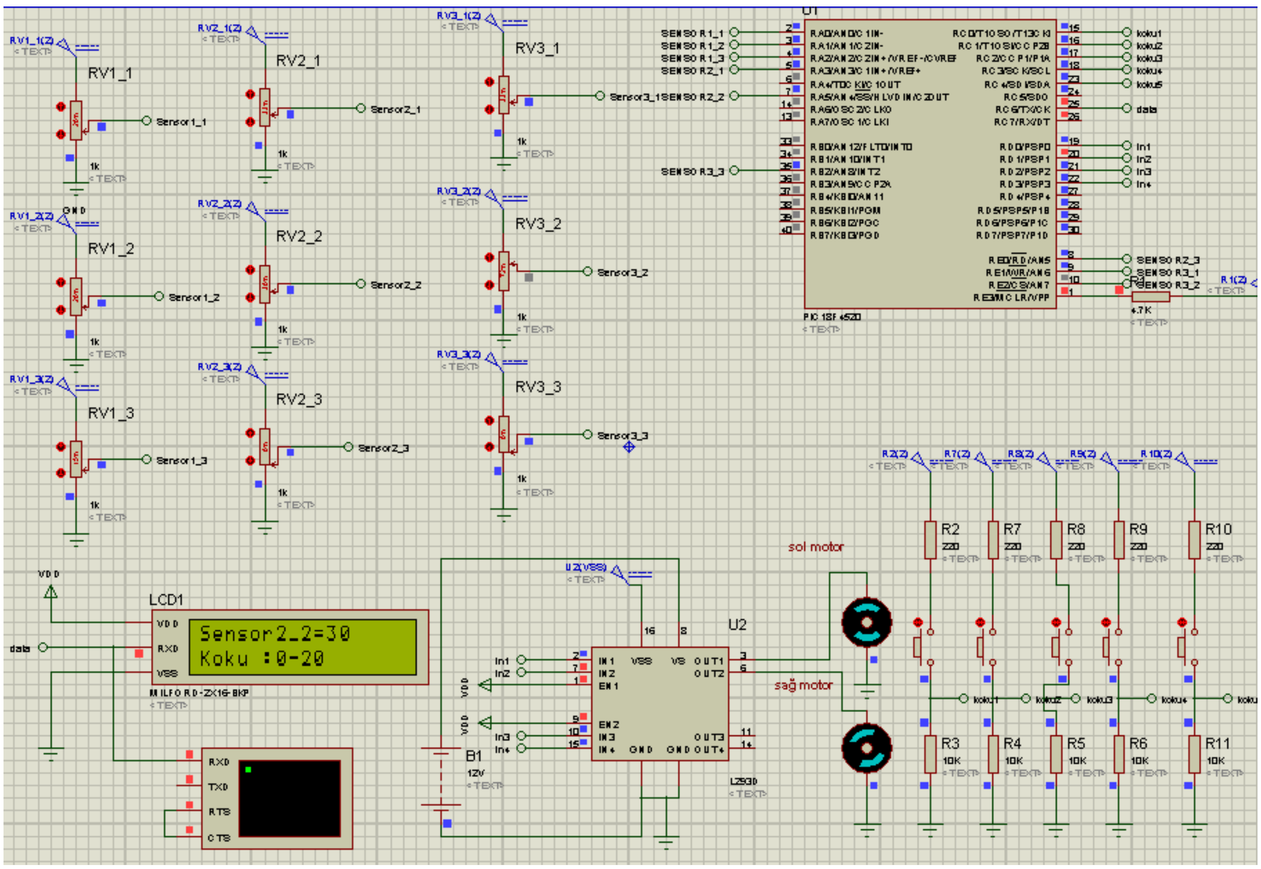

Figure 2.4. Simulation result

Conclusions

In this paper, target detection by combination of odor sensors and Artificial Intelligence Technologies has been demonstrated. With this study, a fuzzy logic controller chosen is designed to extract three different odor. The activity of the motor has been observed when the direction according to odor is determined. Thus, in a continuous cycle, target detection and target tracking can be performed. In the literature, there are a few publications on combination of fuzzy logic controller and target detection and monitoring applications. This is essentially a different study conducted on odor sensor technology and artificial intelligence. It is hoped that the preliminary results presented in this paper will open a door to develop an electronic dog nose and to use it instead of the real dog smell functions.

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