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Optimized form of Data Representation of Odour Expressions in Human Beings

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Abstract: Odour expression of human being data is represented in various forms. The basic working which produce olfactory receptor among the users are discussed. This paper deals with data representation of olfactory receptor in digital form. The odour information is computed using neural network. Using neural network data is displayed in fuzzy number.

Keywords— digital data, fuzzy membership functions, neural network feed forward architecture

I. INTRODUCTION

Virtual reality is targeting towards sense of smell transformation through computers. With event of digital transformation we are able to transmit smell. This paper deals with evolution of olfactory receptor involving multimedia technology contributing a new path in the research and development of digital scent technology. Technology matches the database stored for smell identification and spray the essence on the generation of the image is the key features of this proposed research[1].

The digital scent technology converts the smell into digital form. The smell can be produced using a device called iSmell. ISmell is a peripheral device attached to the computer to spread the different flavours of the scents[2]. This technology is helpful in medical, entertainment, education, internet, communication and in e-commerce also.

In this paper we have proposed how to represent odour expression of human being in digital form and then coded in fuzzy membership function. Odours have complex chemical compositions and it is difficult to represent it in exact chemical form. Therefore, it may be more effective to represent an odour using database of each of the odours that the human being can perceive. Therefore, in this paper, we suggest a method of coding the feeling of a smell by mapping it to a predetermined expression factor. There are some adjective factors describing odours perceivable to human beings, so a large number of odours can be expressed by these adjective factors. The odours which are in digital form are then represented in different forms. The coded data can be represented using fuzzy membership function. Any coded data can be regained by determining a membership grade of a target odour which was represented using previously stored central values which was representative odours i.e. source odours. Individual human beings have various senses to an odour, these senses can be clustered by similarity, and a cluster which is the largest membership for the odour can be recognized.

In this paper digital encoded data is represented using k-means clustering algorithm[2]. The represented data are then encoded in the fuzzy number. Fuzzy membership function represents number in the range from 0 to 1 unlike binary number system in which the numbers are represented only in either true 1 or false 0 forms. The data is first represented in binary form which is then coded to fuzzy number.

Neural network feedforward architecture helps in optimization the data. The k-means result is applied on the feedforward architecture to get the optimized result.

II. REPRESENTATION OF BASIC ODOUR EXPRESSION

Table I shows the odour expression factors measured. For each odour expression factor a unique real number is assigned[3]. Following is a table which maps odour expression factor to a number. There are about 38 odour expression of human being are listed out.

Table 1: Odour Expression Factor Measurement

Number	Odour Expression Factor
1	Rich
2	Wild
3	Masculine
4	Violent
5	Fecal
6	Spoiled
7	Fishy
8	War
9	Animal
10	Ancient
11	Gunpowder-like
12	Luxurious
13	Green
14	Spermous
15	Coffee
16	Burnt
17	Harmful
18	Strong
19	Oxidizing

Number	Odour Expression Factor
20	Fresh
21	Fresh
22	Feminine
23	Peaceful
24	Floral
25	Gruity
26	Woday
27	Botanical
28	Modern
29	Pungent
30	Acidic
31	Metallic
32	Sharp
33	Mint
34	Sweet
35	Harmless
36	Oriental
37	Alcoholic
38	Disgusting

III. WORKING OF DATA REPRESENTATION

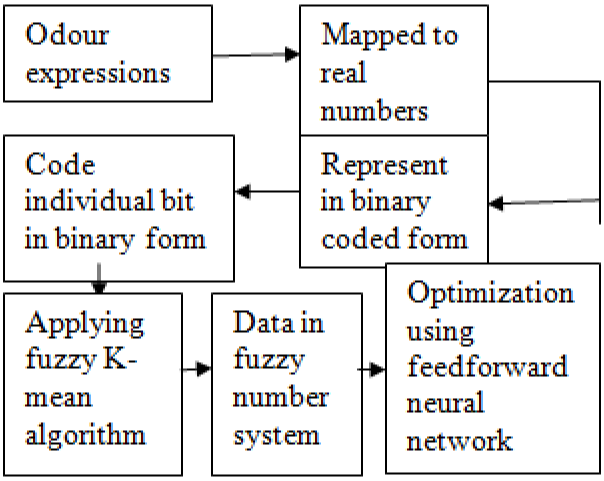

Figure.1. Methodology for odour detection

The odour expression of human being is mapped to a unique number. In this paper we have proposed the implementation of the unique number identified by human odour expression using neural network[4]. The methodology used here is that the odour expression of human being are coded in real unique numbers. Which then is represented in digital form using individual bit converter to binary form. Then k-means clustering algorithm is applied which is then forwarded to feedforward neural network. Her single layer Perceptron is used to get the optimized result. Fig1 [5]shows the overall methodology used in the system.

Table 2: Odour Expression Factor Represented In Binary Form

Odour	A	B	C	D	E	F
1	0	0	0	0	0	1
2	0	0	0	0	1	0
3	0	0	0	0	1	1
4	0	0	0	1	0	0
5	0	0	0	1	0	1
6	0	0	0	1	1	0
7	0	0	0	1	1	1
8	0	0	1	0	0	0
9	0	0	1	0	0	1
10	0	0	1	0	1	0
11	0	0	1	0	1	1
12	0	0	1	1	0	0
13	0	0	1	1	0	1
14	0	0	1	1	1	0
15	0	0	1	1	1	1
16	0	1	0	0	0	0
17	0	1	0	0	0	1
18	0	1	0	0	1	0
19	0	1	0	0	1	1
20	0	1	0	1	0	0
21	0	1	0	1	0	1
22	0	1	0	1	1	0
23	0	1	0	1	1	1
24	0	1	1	0	0	0
25	0	1	1	0	0	1
26	0	1	1	0	1	0
27	0	1	1	0	1	1
28	0	1	1	1	0	0
29	0	1	1	1	0	1
30	0	1	1	1	1	0
31	0	1	1	1	1	1
32	1	0	0	0	0	0
33	1	0	0	0	0	1
34	1	0	0	0	1	0
35	1	0	0	0	1	1
36	1	0	0	1	0	0
37	1	0	0	1	0	1
38	1	0	0	1	1	0

A

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24
25	26	27	28
29	30	31	32
33	34	35	36
37	38		

B

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24
25	26	27	28
29	30	31	32
33	34	35	36
37	38		

C

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24
25	26	27	28
29	30	31	32
33	34	35	36
37	38		

D

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24
25	26	27	28
29	30	31	32
33	34	35	36
37	38		

E

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24
25	26	27	28
29	30	31	32
33	34	35	36
37	38		

F

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16
17	18	19	20
21	22	23	24
25	26	27	28
29	30	31	32
33	34	35	36
37	38		

Table 2 shows the odour representation in binary form. Further tables A,B,C,D,E and F are the individual bit representation. Above are the various ways of data representation.

IV. FUZZY K-MEANS ALGORITHM

Fuzzy k-means clustering method is applied [6] on the data set to partition odour expression observations into k clusters in which each observation belongs to the cluster with the nearest mean. This results in a partitioning of the data space.

$$\sum_{i=1}^{k}\sum_{j=1}^{n}(X_i^j - \mu)^2$$

Where X is the number of observations

μ is mean of x

The data set now can be represented [7] as shown in table 3

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Table 3: Fuzzy k-means representation of data set

A	B	C	D	E	F
0.03393	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.177285	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.177285	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.177285	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.033934	0.33518	0.33518	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25
0.665513	0.177285	0.177285	0.25	0.25	0.25

Average K-means algorithm

0.150277	0.243767	0.243767	0.25	0.25	0.25

Table 3 shows k-means algorithm on the data set created.

V. IMPLEMENTATION USING NEURAL NETWORK

The data set which is available after k-means algorithm will be applied to neural network feedforward architecture for optimization. The following diagram shows how the data set is giving similar type of results.

$$X_j = \sum W_{ij} S_i + \Theta_j$$

Where W_{ij} is the weight from neuron i to j

Θ_j is the adjusting factor

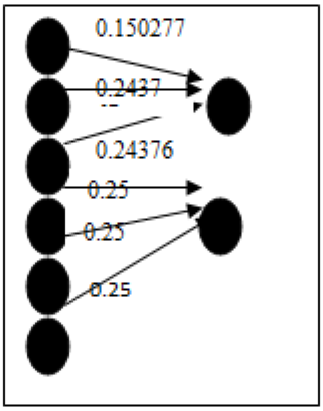

Figure 2. Single layer Feedforward neural network for optimization

VI. OBSERVATION

From the experiment we have observed that fuzzy k-means representation of data look quite similar as it grows. By the application of k-means algorithm the values turned into positive and the similar results are shown. Based on this information, we can forecast that the accuracy and the reliability of the data that has high k means value will be better than those of the data that has low k means value. For each smell, we have selected only a single data that has the highest average k means value to its repetition data to be the training data and to be the initial vectors for the k-means algorithm. Neural network feedforward architecture is applied on the data set to result in an optimized output.

VII. CONCLUSIONS

The paper deals with the data representation of odors expression in fuzzy form which helps in further analysis. We have implemented using neural network on the data set created so that the data can be better understood for the future applications. The result data in now optimized.

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