Applied Fuzzy C-means Clustering to Operation Evaluation for Gastric Cancer Patients

Hang Zettervall, Elisabeth Rakus-Andersson
Department of Mathematics and Science
Blekinge Institute of Technology
37179 Karlskrona, Sweden
Hang.Zettervall@bth.se
Elisabeth.Andersson@bth.se

Henrik Forssell
Blekinge Competence Center
37181 Karlskrona, Sweden
Henrik.Forssell@ltblekinge.se

***Abstract*—Like data analysis, pattern recognition and data mining, fuzzy clustering also has been applied widely, and successful applications have been reported. In this paper we aim to employ the technique of fuzzy c-means (FCM) cluster to prognosticate the operation possibility on gastric cancer patients. Our purpose is to partition some clinical data in two fuzzy clusters. One of them considers patients who have a chance for successful surgery whereas the other cluster contains the patients without a view for surgery. Each patient is given by characteristic biological markers. The initial values of membership degrees taking place in the partition matrix are usually determined randomly. In this work we will use particularly designed membership functions to calculate the degrees of membership.**

Keywords–fuzzy C-means clustering analysis; fuzzy partition; operation decision

I. INTRODUCTION

Nowadays we are living in an era of the rapid development of information technology. A large number of information is sent and received every day. Therefore, finding some data processing methods to discover the partial structure in a data set and to utilize useful information to solve efficiently daily issues becomes of vital importance.

A lot of approaches in this domain have been put forward. Cluster analysis is one of them. This method involves the task of dividing data points into homogeneous classes or clusters so that items in the same class are as similar as possible and items in different classes are as dissimilar as possible [1]. Moreover, some successful applications in clustering analysis have been presented. Among clustering approaches the fuzzy c-means clustering (FCM) is regarded as well-known and efficient [2–4].

In hard clustering, data points are divided into crisp clusters, where each data point belongs to exactly one cluster [5]. In many situations, boundary data points can be difficult to be allocated. Therefore, the realistic picture of the data structure may not be correctly presented by the crisp clustering. However, fuzzy partition can make up the flaw, due to the advantage that data points are allowed to belong to more than one cluster.

The application of fuzzy c-means cluster in medical diagnosis with respect to the operation possibility evaluation is the focal point of this paper. We attempt to utilize the FCM algorithms in order to divide a clinical data set into two clusters, where one presents the positive prognosis for "operation" and the other samples patients-vectors classified for "none operation".

The construction of this paper is organized as follows. In Section 2 the fuzzy c-means clustering algorithm is presented. In Section 3 we generate the methods for calculating the membership degrees to initialize the cluster matrix. Further, we provide a reader with the practical medical study resulting in operation decision in Section 4 to make conclusions concerning the application in Section 5.

II. DESCRIPTION OF FUZZY C-MEANS CLUSTERING ALGORITHM

Let us suppose that $X = \{x_1, \dots, x_n\}$ is a finite data set. Each data point $x_k = \left(x_{k_1}, \dots, x_{k_p}\right), k = 1, \dots, n$, is a pattern vector in R^p. Fuzzy C-means algorithm tries to partition X in a collection of S_i subsets, $2 \le i \le c$, called fuzzy clusters. By running the algorithm repeatedly, a list of v_i cluster centers and a partition matrix U are returned.

The fuzzy c-means algorithm is based on minimizing the objective function J with respect to the membership values $\mu_{S_i}(x_k)$ and the distance $d(\mathrm{v}_i, x_k)$ [2], where

$$J = \sum_{k=1}^{n} \sum_{i=1}^{c} \left(\mu_{S_i}(x_k)\right)^m \cdot d(\mathrm{v}_i, x_k). \tag{1}$$

In (1) n is the number of data points and c is the number of clusters. The value of $\mu_{S_i}(x_k)$ or μ_{ik} represents the value of membership degree of x_k in cluster S_i. Moreover, the sum of the membership degrees for each x_k sample in all clusters is equal to 1. The notation of $d(\mathrm{v}_i, x_k)$ indicates the Euclidean distance between the cluster center v_i and x_k. The constant $m > 1$ is called weighting exponent, which determines the fuzziness of the resulting clusters.

A linguistic description of the FCM algorithm is presented by the following steps:

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1) Select the number of clusters c, initialize the value of fuzzy parameter m $(2 \le m < \infty)$ and the termination tolerance ϵ.
2) Set $l = 0$.
3) Determine the initial values of membership degrees in partition matrix U^l.
4) Calculate cluster centers $\mathrm{v}_i^l, i = 1, \dots, c$, due to [2], as

$$\mathrm{v}_i^l = \frac{\sum_{k=1}^{n}\left(\left(\mu_{ik}^l\right)^m \cdot x_k\right)}{\sum_{k=1}^{n}(\mu_{ik}^l)^m}. \tag{2}$$

5) Calculate the updated partition matrix U^{l+1} by using v_i^l in formula

$$\mu_{ik}^{l+1} = \frac{\left(\frac{1}{d(x_k, \mathrm{v}_i^l)}\right)^{1/_{m-1}}}{\sum_{j=1}^{c}\left(\frac{1}{d\left(x_k, \mathrm{v}_j^l\right)}\right)^{1/_{m-1}}}. \tag{3}$$

6) If $\|U^{l+1} - U^l\| \ge \epsilon$, then set $l = l + 1$, and go to step 4. If $\|U^{l+1} - U^l\| \le \epsilon$, then stop the procedure. Matrix U^{l+1} is the most optimal distribution of membership degrees of x_k in clusters S_i.

The prior determination of the membership degrees of x_k in S_i plays a crucial role in this algorithm, as their choice not only can affect the convergence speed, but also may have a direct impact on the results of the classification [6].

The initial cluster centers are just prototypes and unstable. Therefore, they need to be iteratively updated. Every iteration guarantees an improvement of the coordinates of clustering centers. The updating procedure continues until two adjacent membership matrices cease to change. In Section 4 we wish to demonstrate how FCM algorithm has been applied in operation evaluations for gastric cancer patients.

Furthermore, the calculation of clustering centers depends on the values of initial membership degrees in the partition matrix. To avoid inaccuracy in final results we will discuss the own technique of calculation of membership degrees to avoid guessing at their values intuitively.

III. An Approach to Determining the Initial Membership Degrees in the Partition Matrix

The ccurate evaluation of the membership of x_k in S_i can improve the iteration time and the convergence speed. In this article, the *s*-class membership function is adopted for the further calculations due to [7–9]. We recall the formula of the s-function as

$$s(z, \alpha, \beta, \gamma) = \begin{cases} 0 & \text{for} \quad z \le \alpha, \\ 2\left(\frac{z-\alpha}{\gamma-\alpha}\right)^2 & \text{for} \quad \alpha \le z \le \beta, \\ 2\left(\frac{z-\gamma}{\gamma-\alpha}\right)^2 & \text{for} \quad \beta \le z \le \gamma, \\ 1 & \text{for} \quad z \ge \gamma. \end{cases} \tag{4}$$

The curve, implemented as a graph of (4), starts with point $(0, \alpha)$ and ends with $(\gamma, 1)$, whereas β is the arithmetic mean value of α and γ.

By referring to the most decisive medical factors, such as the patient's age, weight and *crp*-values (C-reactive proteins), operation prognoses usually can be expressed by "operation" and "none operation". The possibilities of the decision evaluation can be described by some linguistic terms.

Let us suppose that $L = \{L_1, \dots, L_\omega\}$ is a linguistic list consisting of ω words. Each word is associated with a fuzzy set. In compliance with [8–10], ω is a positive odd integer. Furthermore, let E be the length of a common reference set R, designed for all restrictions characterizing the fuzzy sets from L, provided that $z \in R$. We now wish to divide the linguistic terms into three groups recognized as a left group, a middle group and a right group.

The membership functions assigned to the leftmost terms are parametric functions, which are presented by (5) as

$$\mu_{L_t}(z) = \begin{cases} 1 \text{ for } z \le \frac{E(\omega-1)}{2(\omega+1)}\delta(t), \\ 1 - 2\left(\frac{z - \frac{E(\omega-1)}{2(\omega+1)}\delta(t)}{\frac{E(\omega-1)}{\omega(\omega+1)}\delta(t)}\right)^2 \\ \text{for } \frac{E(\omega-1)}{2(\omega+1)}\delta(t) \le z \le \frac{E(\omega-1)}{2\omega}\delta(t), \\ 2\left(\frac{z - \frac{E(\omega-1)(\omega+2)}{2\omega(\omega+1)}\delta(t)}{\frac{E(\omega-1)}{\omega(\omega+1)}\delta(t)}\right)^2 \\ \text{for } \frac{E(\omega-1)}{2\omega}\delta(t) \le z \le \frac{E(\omega-1)(\omega+2)}{2\omega(\omega+1)}\delta(t), \\ 0 \text{ for } z \ge \frac{E(\omega-1)(\omega+2)}{2\omega(\omega+1)}\delta(t), \end{cases} \tag{5}$$

where $\delta(t) = \frac{2t}{\omega-1}, t = 1, \dots, \frac{\omega-1}{2}$ is a parametric function depending on left function number t. When t is equal to 1, the formula implies the first leftmost membership function. If t takes the value of $\frac{\omega-1}{2}$, then we will obtain the last left membership function.

The membership function in the middle has the form of a clock. It is given by (6) in the form of

$$\mu_{L_{\frac{\omega+1}{2}}}(z) =$$

$$\begin{cases} 0 & \text{for} \quad z \le \frac{E(\omega-2)}{2\omega}, \\ 2\left(\frac{z-\frac{E(\omega-2)}{2\omega}}{\frac{E}{\omega}}\right)^2 & \text{for} \quad \frac{E(\omega-2)}{2\omega} \le z \le \frac{E(\omega-1)}{2\omega}, \\ 1-2\left(\frac{z-\frac{E}{2}}{\frac{E}{\omega}}\right)^2 & \text{for} \quad \frac{E(\omega-1)}{2\omega} \le z \le \frac{E}{2}, \\ 1-2\left(\frac{z-\frac{E}{2}}{\frac{E}{\omega}}\right)^2 & \text{for} \quad \frac{E}{2} \le z \le \frac{E(\omega+1)}{2\omega}, \\ 2\left(\frac{z-\frac{E(\omega+2)}{2\omega}}{\frac{E}{\omega}}\right)^2 & \text{for} \quad \frac{E(\omega+1)}{2\omega} \le z \le \frac{E(\omega+2)}{2\omega}, \\ 0 & \text{for} \quad z \ge \frac{E(\omega+2)}{2\omega}. \end{cases} \tag{6}$$

Finally, the membership functions on the right-hand side can be expressed by (7) as

$$\mu_{L_{\frac{\omega+3}{2}+t-1}}(z) =$$

$$\begin{cases} 0 \text{ for } z \le E - \frac{E(\omega-1)(\omega+2)}{2\omega(\omega+1)} \cdot \varepsilon(t), \\ 1-2\left(\frac{z-\left(E-\frac{E(\omega-1)(\omega+2)}{2\omega(\omega+1)}\cdot\varepsilon(t)\right)}{\frac{E(\omega-1)}{\omega(\omega+1)}\cdot\varepsilon(t)}\right)^2 \\ \text{for } E - \frac{E(\omega-1)(\omega+2)}{2\omega(\omega+1)} \cdot \varepsilon(t) \le z \le E - \frac{E(\omega-1)}{2\omega} \cdot \varepsilon(t), \\ 2\left(\frac{z-\left(E-\frac{E(\omega-1)}{2(\omega+1)}\cdot\varepsilon(t)\right)}{\frac{E(\omega-1)}{\omega(\omega+1)}\cdot\varepsilon(t)}\right)^2 \\ \text{for } E - \frac{E(\omega-1)}{2\omega} \cdot \varepsilon(t) \le z \le E - \frac{E(\omega-1)}{2(\omega+1)} \cdot \varepsilon(t), \\ 1 \text{ for } z \ge E - \frac{E(\omega-1)}{2(\omega+1)} \cdot \varepsilon(t). \end{cases} \tag{7}$$

A new function $\varepsilon(t) = 1 - \frac{2(t-1)}{\omega-1}, t = 1, \dots, \frac{\omega-1}{2}$ allows generating all rightmost functions one by one when setting t-values in (7).

IV. CASE STUDY

To make a decision "operate" contra "do not operate", concerning an individual patient in accordance with his/her biological markers' values, we have to involve the medical experience in the decision process. To facilitate a conversation with a physician we have prepared a linguistic list named "The primary judgment concerning possibility that a physician recommends "operation" opposite to "none operation"" = L = $\{L_1 = \text{"none"}, L_2 = \text{"little"}, L_3 = \text{"medium"}, L_4 = \text{"large"}, L_5 = \text{"total"}\}$.

TABLE I. THE DATA SET OF 25 GASTRIC CANCER PATIENTS

Patient x_k	Attribute-vectors and operation possibilities		
	Attribute-vectors (Age, weight, crp)	***Operation cluster S_1***	***None Operation cluster S_2***
x_1	(71, 85, 1)	Total	Little
x_2	(81, 70, 9)	Medium	Large
x_3	(50, 67, 4)	Large	Medium
x_4	(64, 84, 13)	Large	Little
x_5	(41, 95, 4)	Large	Little
…	…	…	…
x_{25}	(54, 49, 36)	None	Large

The excerpt of the data set, shown in TABLE I, consists of the patients' clinical records and primary judgments of operation possibilities made by the medical expert. The total medical report contains 25 gastric cancer patients randomly selected.

Two surgery states "operation" and "none operation" assist two clusters S_1 and S_2 respectively. By selecting words from the list the experienced surgeon makes the primary graded decision about possibilities of operating or not operating on the patient.

Each verbal expression, being the term of L, is associated with a fuzzy set. L_1 and L_2 represent two left fuzzy sets, L_3 is the fuzzy set in the middle, whereas L_4 and L_5 constitute two rightmost fuzzy sets. Unfortunately, these linguistic items do not provide us with any information about membership degrees expected in matrix U^0 as primary recommendation states of "operation" or "none operation". Therefore we adopted the following technique to assign numerical substitutes to verbal expressions from the list.

By inserting E = 100 (the length of the reference set R = [0,100] – typical of density measures in medical investigations), ω = 5 and t = 1, 2, in (5), we obtain the membership functions of the first two fuzzy sets, namely, $L_1 = \text{"none"}$ given as

$$\mu_{L_1}(z) = \begin{cases} 1 & \text{for} \quad z \le 16.7, \\ 1-2\left(\frac{z-16.7}{6.6}\right)^2 & \text{for} \quad 16.7 \le z \le 20, \\ 2\left(\frac{z-23.3}{6.6}\right)^2 & \text{for} \quad 20 \le z \le 23.3, \\ 0 & \text{for} \quad z \ge 23.3 \end{cases} \tag{8}$$

and $L_2 = \text{"little"}$ prepared as

$$\mu_{L_2}(z) = \begin{cases} 1 & \text{for} \quad z \leq 33.3, \\ 1 - 2\left(\dfrac{z - 33.3}{13.4}\right)^2 & \text{for} \quad 33.3 \leq z \leq 40, \\ 2\left(\dfrac{z - 46.7}{13.4}\right)^2 & \text{for} \quad 40 \leq z \leq 46.7, \\ 0 & \text{for} \quad z \geq 46.7\,. \end{cases} \tag{9}$$

By substituting E = 100 and ω = 5 in (6), the membership function of $L_3 =$ "middle" is given as the structure

$$\mu_{L_3}(z) = \begin{cases} 0 & \text{for} \quad z \leq 30, \\ 2\left(\dfrac{z - 40}{10}\right)^2 & \text{for} \quad 30 \leq z \leq 40, \\ 1 - 2\left(\dfrac{z - 50}{10}\right)^2 & \text{for} \quad 40 \leq z \leq 50, \\ 1 - 2\left(\dfrac{z - 50}{10}\right)^2 & \text{for} \quad 50 \leq z \leq 60, \\ 2\left(\dfrac{z - 60}{10}\right)^2 & \text{for} \quad 60 \leq z \leq 70, \\ 0 & \text{for} \quad z \geq 70. \end{cases} \tag{10}$$

Finally, for E = 100, ω = 5 and t = 1, 2, inserted in (7), we get the membership functions of $L_4 =$ "large" in the form of

$$\mu_{L_4}(z) = \begin{cases} 0 & \text{for} \quad z \leq 53.3, \\ 1 - 2\left(\dfrac{z - 53.3}{13.4}\right)^2 & \text{for} \quad 53.4 \leq z \leq 60, \\ 2\left(\dfrac{z - 66.7}{13.4}\right)^2 & \text{for} \quad 60 \leq z \leq 66.7, \\ 1 & \text{for} \quad z \geq 66.7 \end{cases} \tag{11}$$

and $L_5 =$ "total" as

$$\mu_{L_5}(z) = \begin{cases} 0 & \text{for} \quad z \leq 76.7, \\ 1 - 2\left(\dfrac{z - 76.7}{6.6}\right)^2 & \text{for} \quad 76.7 \leq z \leq 80, \\ 2\left(\dfrac{z - 66.7}{6.6}\right)^2 & \text{for} \quad 80 \leq z \leq 83.3, \\ 1 & \text{for} \quad z \geq 83.3\,. \end{cases} \tag{12}$$

When substituting $\alpha = 0, \beta = 50$ and $\gamma = 100$ in a new s-function impacted over set R we determine

$$\mu_R(z) = s(z, 0{,}50{,}100) =$$

$$\begin{cases} 0 & \text{for} \quad z \leq 0, \\ 2\left(\dfrac{z}{100}\right)^2 & \text{for} \quad 0 \leq z \leq 50, \\ 2\left(\dfrac{z - 100}{100}\right)^2 & \text{for} \quad 50 \leq z \leq 100 \\ 1 & \text{for} \quad z \geq 100. \end{cases} \tag{13}$$

After sampling all membership functions (8)–(13) in Figure 1, we aim at evaluating the membership degrees taking place in the first partition matrix U^0.

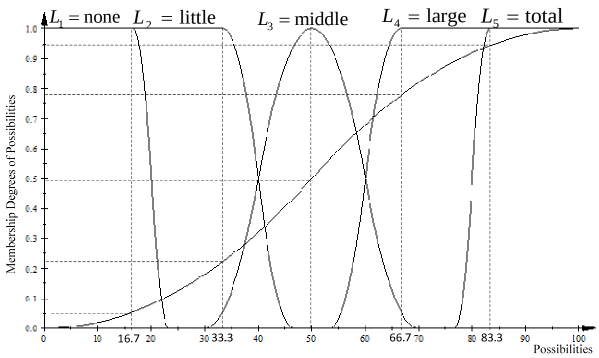

Figure. 1. The collection of all the membership functions.

In the interval [0, 16.7], the membership degree of $L_1 =$ "none" equals 1, which means that the possibility of none operation is the highest in this region. As the membership degrees decrease from 1 to 0 over (16.7, 23.3], then z = 16.7 will become a natural border for sure members in L_1. In (13), $z = 16.7 \in [0, 50]$. From the formula of membership function (13), which is lying over the interval [0, 100], we choose the segment $2\left(\frac{z}{100}\right)^2$ in which we set z = 16.7 to obtain $\mu_R(16.7) = 0.056$. This represents numerically L_1 in TABLE II which is a mathematical adaptation of TABLE I.

We apply the procedure to the second fuzzy set $L_2 =$ "little", where we select z = 33.3 for calculating its membership degree by employing (13) to get $\mu_R(33.3) = 0.22$. For the third fuzzy set $L_3 =$ "middle" the membership value is specified to be $\mu_R(50) = 0.50$. The last fuzzy sets $L_4 =$ "large" and $L_5 =$ "total" are represented by $\mu_R(66.7) = 0.78$ and $\mu_R(88.3) = 0.944$, respectively.

After the data arrangement, the linguistic words in TABLE 1 are replaced by numerical values put in TABLE II.

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TABLE II. DATA SET WITH INITIAL MEMBERSHIP VALUES

Patient x_k	**Attribute-vectors and operation possibilities**		
	Attribute-vectors (Age, weight, crp)	$\mu_{S_1}(x_k)$	$\mu_{S_2}(x_k)$
x_1	(71, 85, 1)	0.944	0.22
x_2	(81, 70, 9)	0.5	0.78
x_3	(50, 67, 4)	0.78	0.5
x_4	(64, 84, 13)	0.78	0.22
x_5	(41, 95, 4)	0.78	0.22
…	…	…	…
x_{25}	(54, 49, 36)	0.056	0.78

It is assumed that the sum of membership grades in clusters S_1 and S_2 should be equal to 1 for each x_k, k = 1,…,25. It can happen that the distinct sums differ from 1. In such cases some adjustments need to be made; therefore the following techniques are applied.

Case 1: $\mu_{S_1}(x_k) + \mu_{S_2}(x_k) > 1$.
If the sum is greater than 1, we calculate a quotient q_1, designed as

$$q_1 = \frac{\mu_{S_1}(x_k) + \mu_{S_2}(x_k) - 1}{2}.$$

Hence, two adjusted membership degrees are given by the following formulations:

$$\mu'_{S_1}(x_k) = \mu_{S_1}(x_k) - q_1 \text{ and } \mu'_{S_2}(x_k) = \mu_{S_2}(x_k) - q_1.$$

Proof:

$$\mu'_{S_1}(x_k) + \mu'_{S_2}(x_k) = \mu_{S_1}(x_k) + \mu_{S_2}(x_k) - 2q_1 =$$
$$\mu_{S_1}(x_k) + \mu_{S_2}(x_k) - 2 \cdot \frac{\mu_{S_1}(x_k) + \mu_{S_2}(x_k) - 1}{2} =$$
$$\mu_{S_1}(x_k) + \mu_{S_2}(x_k) - \mu_{S_1}(x_k) - \mu_{S_2}(x_k) + 1 = 1.$$

In contrast with Case 1, Case 2 handles the situation that the sum is less than 1.

Case 2: $\mu_{S_1}(x_k) + \mu_{S_2}(x_k) < 1$.
We now have to derive another fraction q_2, given by

$$q_2 = \frac{1 - \mu_{S_1}(x_k) - \mu_{S_2}(x_k)}{2}.$$

Membership values typical of Case 2 are verified by

$$\mu'_{S_1}(x_k) = \mu_{S_1}(x_k) + q_2 \text{ and } \mu'_{S_2}(x_k) = \mu_{S_2}(x_k) + q_2$$

Proof:

$$\mu'_{S_1}(x_k) + \mu'_{S_2}(x_k) = \mu_{S_1}(x_k) + \mu_{S_2}(x_k) + 2q_2 =$$
$$\mu_{S_1}(x_k) + \mu_{S_2}(x_k) + 2 \cdot \frac{1 - \mu_{S_1}(x_k) - \mu_{S_2}(x_k)}{2} =$$
$$\mu_{S_1}(x_k) + \mu_{S_2}(x_k) + 1 - \mu_{S_1}(x_k) - \mu_{S_2}(x_k) = 1.$$

After revising the membership degrees due to Case 1 or Case 2 we rearrange the last two columns of TABLE II to renew it as TABLE III.

TABLE III. DATA SET WITH VERIFIED MEMBERSHIP GRADES

Patient x_k	**Attribute-vectors and operation possibilities**		
	Attribute-vectors (Age, weight, crp)	$\mu'_{S_1}(x_k)$	$\mu'_{S_2}(x_k)$
x_1	(71, 85, 1)	0.862	0.138
x_2	(81, 70, 9)	0.36	0.64
x_3	(50, 67, 4)	0.64	0.36
x_4	(64, 84, 13)	0.78	0.22
x_5	(41, 95, 4)	0.78	0.22
…	…	…	…
x_{25}	(54, 49, 36)	0.138	0.862

The entries of the initial partition matrix U^0 consist of the values coming from the last two columns in Table III. U^0 is a 2x25 matrix given by

$$U^0 = \begin{array}{c c} & \begin{array}{ccccc} x_1 & x_2 & x_3 & \cdots & x_{25} \end{array} \\ \begin{array}{c} S_1 \\ S_2 \end{array} & \begin{bmatrix} 0.862 & 0.36 & 0.64 & \cdots & 0.138 \\ 0.138 & 0.64 & 0.36 & \ldots & 0.862 \end{bmatrix}_{2x25} \end{array}.$$

The numerical values in the first row in matrix U^0 propose membership degrees for patients $x_k, k = 1, \ldots, 25$, in cluster S_1. And the second row suggests the membership values for patients $x_k, k = 1, \cdots, 25$, in cluster S_2. The sum of membership degrees in each column is equal to one.

If we go back to the FCM algorithm and let l = 0, m = 3 and $\epsilon = 10^{-8}$ then, by using Matlab after 31 iterations, the cluster centers become stable and do not change their coordinates due to $\|U^{31} - U^{30}\| = 9.93692 \times 10^{-9} < 10^{-8}$. The last two partition matrices and the optimal cluster centers are listed in the patterns

$$U^{30} = \begin{array}{c c} & \begin{array}{ccc} x_1 & \cdots & x_{25} \end{array} \\ \begin{array}{c} S_1 \\ S_2 \end{array} & \begin{bmatrix} 0.74366062 & \cdots & 0.39447229 \\ 0.25633938 & \ldots & 0.60552771 \end{bmatrix}_{2x25} \end{array}$$

and

$$U^{31} = \begin{array}{c c} & \begin{array}{ccc} x_1 & \cdots & x_{25} \end{array} \\ \begin{array}{c} S_1 \\ S_2 \end{array} & \begin{bmatrix} 0.74366062 & \cdots & 0.39447229 \\ 0.25633938 & \ldots & 0.60552771 \end{bmatrix}_{2x25} \end{array},$$

as well as

$$v_1^{31} = (65.9704, 74.2257, 6.50373)$$

and

$$v_2^{31} = (70.4353, 69.735, 35.8068).$$

The final membership degrees for 25 patients, classified in S_1 and S_2, are depicted in Figure 2. In this manner the primary operation hypotheses, formulated by verbal structures, have been secondarily confirmed or denied by the strength of corresponding membership degrees in both clusters.

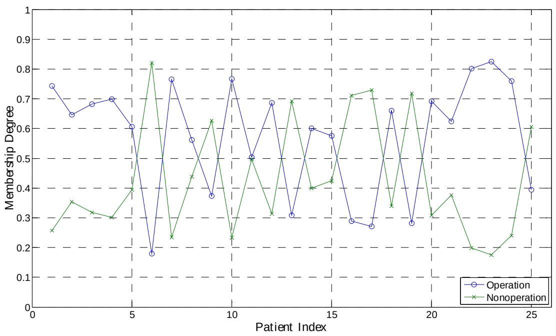

Figure 2. The final cluster membership degrees.

V. CONCLUSION

In this study we have adopted fuzzy 2-means clustering analysis to partition a patient data set, containing clinical records of 25 gastric cancer patients, in two fuzzy clusters. These reveal the numerical decision of states "operation" and "none operation" by the values of membership degrees due to the rule: the higher the degree is the more certain decision should be made with respect to the cluster considered.

We notice that the patients' original clinical marker quantities lead to higher membership degrees in the initial partition matrix when comparing them to the lower values in the final matrix. This phenomenon can be explained by the fact that the decision for an individual patient has been made by the assistance of all data filling the data set. This means that the medical knowledge provided in the form of the collective information, reset numerically, could decide "softer" decisions, which have not deprive the patient of a chance for surgery. We have engaged a new form of experience performed as computerized experience constituting a database.

The obtained results converge to cautious expertise made by physicians who want the patient to survive as well as possible without any unnecessary risks. Therefore, fuzzy c-means cluster analysis can be seen as one of the approaches that would assist medical operation diagnosis. The method can be applied for a large number of patients.

Lastly, we wish to emphasize that the adaptation of membership function families to the purpose of determining the initial membership degrees in the partition matrix has been an efficient tool in the algorithm. The functions, furnished with parameters, allow constructing arbitrary linguistic lists containing many verbal judgments. The mathematical translation of words to numbers has been done systematically without predetermining any casual values. This has improved definitely the convergence speed of the algorithm.

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