Soft Comput (2006) 10: 1031–1042
DOI 10.1007/s00500-005-0030-x

ORIGINAL PAPER

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Flexible fuzzy OWA querying method for hemodialysis database

Published online: 5 November 2005

Abstract The hemodialysis quality contains the subjective opinions of the physicians. However, the range of good/bad quality of one physician's perspective usually differs from the others, so we use the fuzzy theory to solve this vague situation. This paper proposes the fuzzy ordered weighting average (OWA) technique to evaluate fuzzy database queries about linguistic or precise values, which can improve the crisp values' constrains of traditional database. Besides, we deal with the dynamical weighting problem more rationally and flexibly according to the situational parameter α value from the user's viewpoint. In this paper, we focus on hemodialysis adequacy and develop the query system of practical hemodialysis database for a regional hospital in Taiwan. From the experimental result, we can find the overall accuracy rate is better than other methods and our result is more matching the doctor's view. That is, the fuzzy OWA query is more flexible and more accurate.

Keywords Fuzzy OWA Operator · Fuzzy query · Fuzzy weight · Hemodialysis database · Similarity measures

1 Introduction

The human kidneys can continually filter the waste product and toxins in our blood. The main purpose of hemodialysis is to substitute the kidney's functionality of patients and help them for eliminating the uremic toxins inside their blood. In the healthcare, the "sufficient dialysis" means the most suitable dialysis dosage and it also decides the eliminated quantity of uremic toxins, and the "hemodialysis adequacy" means the least quantity of uremic toxins that we need to eliminate. But, the hemodialysis quality traditionally contains the subjective opinions of the physicians, and the range of good/bad quality of one physician's perspective usually differs from the others. The recent researches indicate that the patients may become ill or even die if they can't get enough hemodialysis dosage [18].

Traditionally, the database querying language usually only allows users to query crisp value. But, the Fuzzy query processing techniques can allow the database systems to deal with users' fuzzy queries in a more flexible and more intelligent manner. Flexible querying enables users to express preferences inside requirements and priorities inside compound queries [21]. The fuzzy sets theory offers a general framework for dealing with flexible queries.

In this paper, we focus on hemodialysis adequacy and develop the query system of practical hemodialysis database for a regional hospital in Taiwan. The hemodialysis adequacy contains multiple criteria, and how to get the relative weights in multi-criteria decision making (MCDM) problems is a very important issue [14]. For solving this problem, Yager [22, 23] introduced the concept of ordered weighting average (OWA) operators in 1988. The main objective of our research is to develop a fuzzy OWA technique to evaluate fuzzy database queries about linguistic or precise values, which can improve the crisp values' constrain of traditional databases.

The rest of this paper is organized as follows. In Sect. 2, basic theory and hemodialysis indices are introduced. In Sect. 3, a fuzzy OWA query method is developed. In Sect. 4, we describe briefly how the processing of the fuzzy OWA query method to implement, and we present some practical examples. The conclusions and future research are discussed in Sect. 5.

2 Preliminaries

In this section, we describe briefly about fuzzy set theory, linguistic variable, fuzzy query, OWA, etc.

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2.1 Fuzzy set theory

In 1965, Zadeh [25] proposed the theory of fuzzy sets. Today, many people apply it to many practice samples, and receive good results with more and more encomium. Some concepts are summarized here [25, 26, 31].

Definition 1 *The four fundamental operations of right triangular fuzzy number are given below* $\tilde{A} = (a_1, a_2, a_3)$ *and* $\tilde{B} = (b_1, b_2, b_3)$ *is defined by*

$$\tilde{A}(+)\tilde{B} : (a_1, a_2, a_3)(+)(b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{1}$$

$$\tilde{A}(-)\tilde{B} : (a_1, a_2, a_3)(-)(b_1, b_2, b_3) = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \tag{2}$$

$$\tilde{A}(\times)\tilde{B} : (a_1, a_2, a_3)(\times)(b_1, b_2, b_3) = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3) \tag{3}$$

$$\tilde{A}(\div)\tilde{B} : (a_1, a_2, a_3)(\div)(b_1, b_2, b_3) = (a_1 \div b_3, a_2 \div b_2, a_3 \div b_1) \tag{4}$$

Definition 2 *The union of the fuzzy sets* $\tilde{A}$ *and* $\tilde{B}$ *is denoted by* $\tilde{A} \cup \tilde{B}$ *and is defined by*

$$\tilde{A} \cup \tilde{B} = \{(u_i, f_{\tilde{A}\cup\tilde{B}}(u_i)) \mid f_{\tilde{A}\cup\tilde{B}}(u_i) = \mathrm{Max}(f_{\tilde{A}}(u_i), f_{\tilde{B}}(u_i)), u_i \in U\} \tag{5}$$

Definition 3 *The intersection of the fuzzy sets* $\tilde{A}$ *and* $\tilde{B}$ *is denoted by* $\tilde{A} \cap \tilde{B}$ *and is defined by*

$$\tilde{A} \cap \tilde{B} = \{(u_i, f_{\tilde{A}\cap\tilde{B}}(u_i)) \mid f_{\tilde{A}\cap\tilde{B}}(u_i) = \mathrm{Min}(f_{\tilde{A}}(u_i), f_{\tilde{B}}(u_i)), u_i \in U\} \tag{6}$$

Defuzzification

Defuzzification is the procedure that generates a crisp value out of one or more given fuzzy sets [2]. There are many defuzzification methods, such as extreme value method [left of maximum (LOM); right of maximum (ROM); center of maximum (COM)], centroid (center of area/center of gravity), mean of maxima (MOM), center of area (COA), etc. This paper uses the centroid method (center of gravity) to defuzzify the fuzzy sets, and the f value of Eq. (7) is the defuzzification result.

$$f = \frac{\sum g(x_i) \times f_{\tilde{A}}(x_i)}{\sum f_{\tilde{A}}(x_i)}, \tag{7}$$

where $\tilde{A}$ is fuzzy number, $f_A(x_i)$ is the $\tilde{A}$'s grade, $g(x_i)$ is the weighting value, and f is the centroid of membership function.

2.2 Linguistic variable and fuzzy term

In 1975, Zadeh [27–29] introduced the linguistic variable. The linguistic variable usually combines with linguistic qualifier, such as very, more or less. When executing fuzzy operations, we can use some operators such as fuzzy concentration and fuzzy dilation to deal with the linguistic qualifier, and the definitions of these operators are described below.

Definition 4 *The membership function of the fuzzy proposition "U is close to P" can be defined by [3]:*

$$f_{\text{close to p}}(u) = \frac{1}{1 + \left(\frac{u-p}{\beta}\right)^2} \tag{8}$$

where the larger of β*, the wider of the curve and the less of* β *the more narrow of the curve. Figure 1 shows the membership function of the fuzzy proposition "U is close to p".*

Definition 5 *If* $\tilde{A}_j$ *is a simple fuzzy term represented by a fuzzy number in the universe of discourse U, and* $f_{\tilde{A}}$ *as its membership function, where* $f_{\tilde{A}_j} : U \to [0, 1]$*, then,*

(1) *The concentration rule*

$$f_{\text{very}\tilde{A}_j}(u_i) = \left(f_{\tilde{A}_j}(u_i)\right)^2, \forall u_i \in U \tag{9}$$

(2) *The dilation rule*

$$f_{\text{more or less}\tilde{A}_j}(u_i) = \left(f_{\tilde{A}_j}(u_i)\right)^{1/2}, \forall u_i \in U \tag{10}$$

2.3 Fuzzy Query

Fuzzy query processing techniques can allow the database systems to deal with users' fuzzy queries in a more flexible and more intelligent manner [4, 5, 11, 12, 20, 21, 24, 30].

SELECT <Attribute>
FROM <Table>
WHERE <Condition>
RTV < Threshold value>

The above basic syntax is the same with SQL-syntax, and we define the word: RTV (Threshold value) to help the users declare the threshold of query. The threshold can extract the quantity of query data, or we can say that the higher the threshold, the more fitness of output data. So, the count of fitting data would be less if we declare threshold value higher, where threshold value is defined between 0 and 1.

In crisp queries we can make multi-criteria searching where we use the functions AND/OR to aggregate the predicates. Normally the minimum will be used as the AND aggregation and the maximum for the OR aggregation. For example:

SELECT < Attribute 1, ..., Attribute n>
FROM < Table >
WHERE < Attribute 1 and Attribute 2 and $\cdots$ Attribute n>

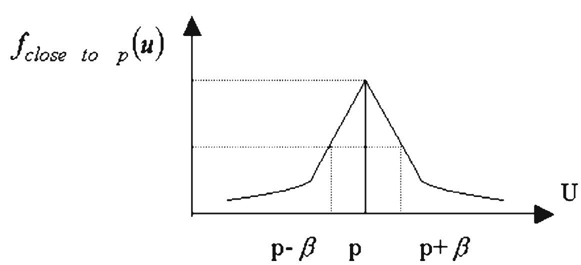

Fig. 1 The membership function of the fuzzy proposition "U is close to p"

2.4 OWA operator

The concept of OWA operators was first introduced by Yager [22] in 1988 . Many approaches have been proposed to calculate the weights based on OWA operators and apply this concept to many fields. In this section, we introduce the basic definition and some operations of OWA [7,22,23].

Definition 6 *An OWA operator of dimension n is a mapping F: $R^n \rightarrow R$, that has an associated weighting vector* $W = [w_1 w_2, \ldots, w_n]^T$ *of having the properties*

$$\sum_i w_i = 1, \forall w_i \in [0, 1], \quad i = 1, \ldots., n,$$

and such that

$$f(a_1, \ldots, a_n) = \sum_{j=1}^{n} w_j b_j \tag{11}$$

where b_j is the jth largest element of the collection of the aggregated objects $a_1, a_2, \ldots, a_n$.

Fuller and Majlender [9] use the method of Lagrange multipliers to transfer Eq. (12) to a polynomial equation, which can determine the optimal weighting vector. By their method, the associated weighting vector is easily obtained by Eqs. (13)–(18).

$$\text{Orness}(W) = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i \tag{13}$$

$$\text{Disp(W)} = -\sum_{i=1}^{n} w_i \ln w_i \tag{14}$$

$$\text{Maximize}\sum_{i=1}^{n} w_i \ln w_i, \quad \text{subject to } \alpha = \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i \tag{15}$$

$$\ln w_j = \frac{j-1}{n-1}\ln w_n + \frac{n-j}{n-1}\ln w_1 \Rightarrow w_j = \sqrt[n-1]{w_1^{n-j} w_n^{j-1}} \tag{16}$$

and

$$w_1[(n-1)\alpha + 1 - nw_1]^n = [(n-1)\alpha]^{n-1}[((n-1)\alpha - n)w_1 + 1] \tag{17}$$

If $w_1 = w_2 = \cdots = w_n = \frac{1}{n} \Rightarrow \text{disp}(W) = \ln n$

$$w_n = \frac{((n-1)\alpha - n)w_1 + 1}{(n-1)\alpha + 1 - nw_1} \tag{18}$$

Hence, the optimal value of w_1 should satisfy Eq. (17). When w_1 is computed, we can determine w_n from Eq. (18), and then the other weights are obtained from Eq. (16). In a special case, when $w_1 = w_2 = \cdots = w_n = \frac{1}{n} \Rightarrow \text{disp}(W) = \ln n$ which is the optimal solution for α= 0.5.

The parameter α can be treated as a magnifying lens for the optimistic decision makers to determine the most important attribute based on the sparest information (*i.e.*, optimistic and α=0 or 1) situation. On the other hand, when α=0.5 (moderate situation), this method can get the attributes' weights (equal weights of attributes) for the pessimistic decision makers based on maximal information (maximal entropy) [6]

2.5 The similarity function

The degree of similarity is to measure the "distance" between two fuzzy sets. Our approach selects some familiar similarity functions to compare the output data quantity of query procedure. After some simple experiments, the users can understand which method matches their querying objective. These three methods are described below.

2.5.1 Min-Max Method: [17]

Let $\tilde{A}$, $\tilde{B}$ are two fuzzy sets, defined as

$$\tilde{A} = f_{\tilde{A}}(X_1)/X_1 + f_{\tilde{A}}(X_2)/X_2 + \cdots + f_{\tilde{A}}(X_n)/X_n$$
$$\tilde{B} = f_{\tilde{B}}(X_1)/X_1 + f_{\tilde{B}}(X_2)/X_2 + \cdots + f_{\tilde{B}}(X_n)/X_n$$

Then the Eq. (19) is the similarity function, and we can get the matching degree of fuzzy sets $\tilde{A}$ and $\tilde{B}$.

$$S\left(\tilde{A}, \tilde{B}\right) = \frac{\left|\tilde{A} \cap \tilde{B}\right|}{\left|\tilde{A} \cup \tilde{B}\right|}, S\left(\tilde{A}, \tilde{B}\right) \in [0, 1] \tag{19}$$

where,

$$\left|\tilde{A} \cap \tilde{B}\right| = \text{Min}\left(f_{\tilde{A}}(X_1), f_{\tilde{B}}(X_1)\right) + \text{Min}\left(f_{\tilde{A}}(X_2), f_{\tilde{B}}(X_2)\right) + \cdots + \text{Min}\left(f_{\tilde{A}}(X_n), f_{\tilde{B}}(X_n)\right)$$

$$\left|\tilde{A} \cup \tilde{B}\right| = \text{Max}\left(f_{\tilde{A}}(X_1), f_{\tilde{B}}(X_1)\right) + \text{Max}\left(f_{\tilde{A}}(X_2), f_{\tilde{B}}(X_2)\right) + \cdots + \text{Max}\left(f_{\tilde{A}}(X_n), f_{\tilde{B}}(X_n)\right)$$

2.5.2 The degree of similarity of Euclidean distance $(\mathrm{N_E}\left(\tilde{A}, \tilde{B}\right))$ *[19]*

This method can calculate the degree of similarity of two fuzzy sets based on Euclidean distance. The more distance between two fuzzy sets the less degree of similarity of them; otherwise, the less distance between two sets the more degree of similarity of them. This approach also uses the concept of degree of similarity.

Let $\tilde{A}$, $\tilde{B}$ are two fuzzy sets, defined as

$$\tilde{A} = f_{\tilde{A}}(X_1)/X_1 + f_{\tilde{A}}(X_2)/X_2 + \cdots + f_{\tilde{A}}(X_n)/X_n$$
$$\tilde{B} = f_{\tilde{B}}(X_1)/X_1 + f_{\tilde{B}}(X_2)/X_2 + \cdots + f_{\tilde{B}}(X_n)/X_n$$

Then,

$$\text{Euclidean distance: } \varepsilon\left(\tilde{A}, \tilde{B}\right) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_{\tilde{A}}(x_i) - f_{\tilde{B}}(x_i)\right)^2} \quad (20)$$

$$\text{Degree of similarity: } \mathrm{N_E}\left(\tilde{A}, \tilde{B}\right) = 1 - \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_{\tilde{A}}(x_i) - f_{\tilde{B}}(x_i)\right)^2} \quad (21)$$

2.5.3 The degree of similarity of Hamming distance ($N_{\mathrm{H}}\left(\tilde{A}, \tilde{B}\right)$) [15]

The degree of similarity of Hamming distance can also reflect the similarity degree of two fuzzy sets.

Let $\tilde{A}$, $\tilde{B}$ are two fuzzy sets, defined as

$$\tilde{A} = f_{\tilde{A}}(X_1)/X_1 + f_{\tilde{A}}(X_2)/X_2 + \cdots + f_{\tilde{A}}(X_n)/X_n$$
$$\tilde{B} = f_{\tilde{B}}(X_1)/X_1 + f_{\tilde{B}}(X_2)/X_2 + \cdots + f_{\tilde{B}}(X_n)/X_n$$

Then,

$$\text{Hamming distance: } \delta\left(\tilde{A}, \tilde{B}\right) = \frac{1}{n}\sum_{i=1}^{n}\left|\mu_{\tilde{A}}(x_i) - \mu_{\tilde{B}}(x_i)\right| \quad (22)$$

$$\text{Degree of similarity: } \mathrm{N_H}\left(\tilde{A}, \tilde{B}\right) = 1 - \frac{1}{n}\sum_{i=1}^{n}\left|\mu_{\tilde{A}}(x_i) - \mu_{\tilde{B}}(x_i)\right| \quad (23)$$

2.6 Hemodialysis indices

Hemodialysis is a form of dialysis that uses an artificial kidney machine to remove excess fluids and waste products from the bloodstream. Kt/V and URR are common indices in hemodialysis adequacy [13]. Kt/V (pronounced Kt over V): The "K" stands for the urea clearance in milliliters per minute, the "t" is the dialysis time in minutes, and the "V" is the volume of distribution of urea in the body. URR stands for Urea reduction ratio, and the URR test measures how much urea was removed from your blood during one dialysis treatment. The actual formula is below:

$$URR\% = \frac{(\text{Pre } BUN - \text{Post } BUN)}{\text{Pre } BUN} \times 100 \quad (24)$$

Pre BUN: Serum level of BUN at the beginning of HD.

Post BUN: Serum level of BUN at the end of HD.

Research shows that patients feel better and will live longer when they receive enough dialysis. The findings all state that when people did not receive enough dialysis, they could get sick and die. A URR of 65 % and Kt/V of 1.2 are the minimum values for adequate dialysis [8,10,13].

Except for above two indices, there are two other familiar indices in hemodialysis adequacy where so called albumin and Hematocrit (Hct). Diseased kidneys sometimes lose large amounts of albumin into the urine faster than the liver can produce it. In malnutrition there is not enough protein in the patient's diet for the liver to make new albumin. The normal range of albumin concentrations in human blood is between 3.5 and 5.0 g/dL. The main functionality of Hematocrit (Hct) is to tell us (red blood cell count and) level of anemia. A low HCT is referred to as being anemic. The Hct is expressed as a percentage. The normal range of Hct is 30–36% [1,16].

3 A fuzzy OWA query method for hemodiclysis database

The main objective of our paper focuses on developing a fuzzy query system of the practical hemodialysis database for a regional hospital in Taiwan. And we use a new fuzzy OWA query method to evaluate fuzzy database queries about linguistic or precise values, which can improve the crisp values' constrain of traditional database. For this reason, this method has four advantages: (1) Use fuzzy OWA query method (2) Use actual hemodialysis database to verify our method (3) Provide an aid opinion for doctor (4) Develop a fuzzy query database system.

3.1 A new fuzzy OWA query model

In this section, we introduce the model (as Fig. 2) and main steps of proposed new fuzzy OWA query method.

The main components of our model are: (1) Fuzzy query; (2) Fuzzy weight and fuzzy OWA operator; (3) Similarity operators. The algorithm of this research is:

Step 1. Build the fuzzy membership function of hemodialysis indices. (The sub-steps are in Sect. 3.2)

Step 2. Preprocess the data of an actual fuzzy hemodialysis database.
This step contains (1) remove the outliers, (2) scaling, encoding, and selecting features of the data.

Step 3. Select fuzzy query's weighting method.
If the user doesn't need any weighting operator, execute Step 4. Else if the user selects the fuzzy OWA weighting method, this step must get the situation parameter's value (α) from the users. (its sub-steps are in Sect. 3.3) And, according to doctors'/experts' experiences, we can rank the degree of important of the indices.

Step 4. Select fuzzy query's similarity method.
The options contain (1) None (2) Min–Max method (3) similarity of Euclidean distance (4) Similarity of Hamming distance (Refer to Sect. 2.5)

Step 5. **If** match degree is greater than RTV **then** this tuple is selected.

3.2 Build the fuzzy membership function of hemodialysis indices

In this paper, we sent 12 expert's questionnaires (Appendix A), 10 responses were found to be complete and usable, and

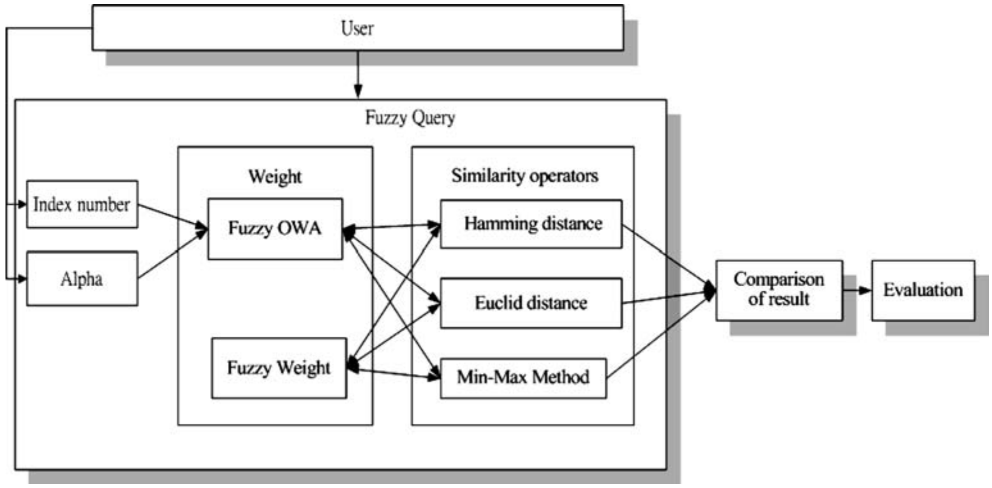

Fig. 2 Research model

gathers information on Kt/V, URR, Albumin, Hct, PCR, TAC and Cr. Therefore, the membership functions (MF) of four major indices are derived from ten expert's questionnaires, they are: (1)Kt/V (2)URR (3)Albumin (4)Hct, and every hemodialysis indices are composed of three scales: good, normal and bad. For simple explanation, we list three sub-steps of establish MF for hemodialysis indices in the following.

Step 1.1. From literature review, this paper finds the most two important hemodialysis indices (Kt/V, URR), and we add Albumin and Hct to establish membership functions through expert interview.

Step 1.2. This paper obtains the important degrees and their ranges for four hemodialysis indices by literature review [13] and the expert interviews. From aggregating experts' opinions, the crisp ranges of these four indices are as Table 1.

Step 1.3. To integrate expert opinions and use the mode and 80% confidence level to build fuzzy membership function (Appendix B). For example, the Kt/V's membership functions [Eqs. (25) – (28)] is shown in Fig. 3.

$$\mu_G(x) = \begin{cases} \frac{x-1}{0.3} & 1 \leqslant x < 1.3 \\ 1 & 1.3 \leqslant x < 1.4 \\ \frac{1.6-x}{0.2} & 1.4 \leqslant x < 1.6 \end{cases} \tag{25}$$

$$\mu_F(x) = \begin{cases} \frac{x-0.7}{0.3} & 0.7 \leqslant x < 1 \\ 1 & 1 \leqslant x < 1.1 \\ \frac{1.3-x}{0.2} & 1.1 \leqslant x < 1.3 \end{cases} \tag{26}$$

$$\mu_B^L(x) = \begin{cases} \frac{1-x}{0.2} & 0.8 \leqslant x < 1 \\ 1 & x < 0.8 \end{cases} \tag{27}$$

$$\mu_B^R(x) = \begin{cases} \frac{x-1.4}{0.2} & 1.4 \leqslant x \leqslant 1.6 \\ 1 & x > 1.6 \end{cases} \tag{28}$$

Table 1 The crisp range of four indices from aggregating experts' opinions

Index	Kt/V	Albumin	URR (%)	Hct (%)
Range	1.2–1.6	3.5–5.0	60–75	28–36

3.3 Fuzzy weight and fuzzy OWA operator

Miller [15] cited the best scale is 7 ± 2 for treating capability of human. Therefore, we use five scales: very unimportant (VU), unimportant (U), medium (M), important (I), very important (VI), and use triangular fuzzy numbers to represent relative importance linguistic terms. Linguistic value of relative importance and its triangular fuzzy numbers are shown in Table 2.

Step 3.1. Fuzzy weighting algorithm

Step 3.1.1. Normalize weight of the attribute:

$$\tilde{W}_i' = \tilde{W}_i / \sum_{i=1}^{n} \tilde{W}_i \tag{29}$$

where n is the number of criteria in the query, $\tilde{W}_i = i$th weight of fuzzy number

Step 3.1.2. Obtain fuzzy aggregative weight of attributes $\tilde{R}$ by Eq. (30).

$$\tilde{\mathrm{R}} = \mathrm{R}_1' \times \tilde{W}_n' + \cdots + \mathrm{R}_n' \times \tilde{W}_n' \tag{30}$$

where $\mathrm{R'}_\mathrm{i} = i$th match degree of query's attribute and record.

Step 3.1.3. Use Eq. (31) to defuzzify the fuzzy aggregative weight $\tilde{R}$.

Let $\tilde{R} = (a, b, c)$, then

$$De_i = (a + 2b + c)/4. \tag{31}$$

Step 3.1.4. To avoid aggregative result $D_i > 1$, we can use Eq. (32) to get constrain solution D_i.

$$D_i = \mathrm{Min}(1, De_i). \tag{32}$$

Step 3.2. Fuzzy OWA algorithm

Step 3.2.1. Obtain the query's attribute number n and situation parameter α.

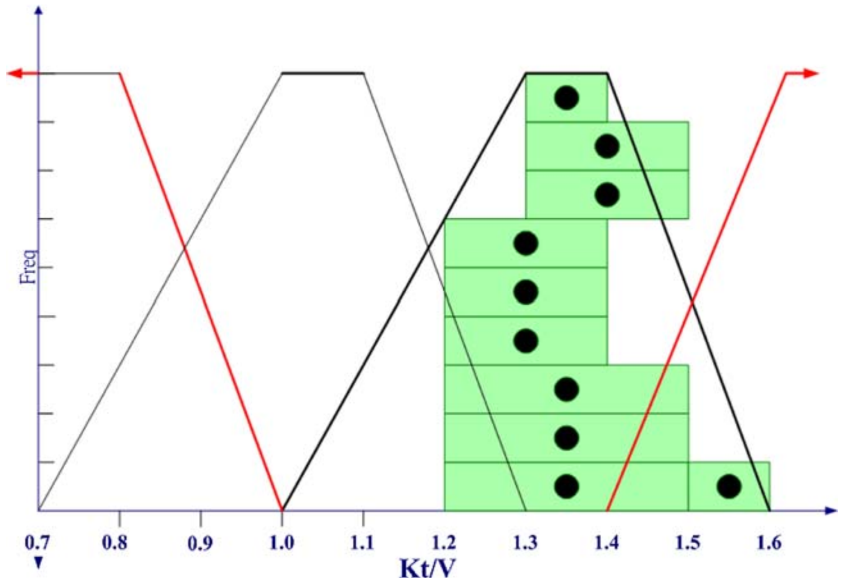

Fig. 3 Kt/V's membership function

Step 3.2.2. Rank the degree of important of query's attribute.

Step 3.2.3. From step 3.2.1, we can get the largest weight w_1 by Eq. (17).

Step 3.2.4. From step 3.2.3, we can obtain the smallest weight w_n by Eq. (18).

Step 3.2.5. When w_1 and w_n are known, we can get the other weights by Eq. (16).

Step 3.2.6. Calculate the aggregative weight of attributes by Eq. (29).

Step 3.2.7. Use Eq. (30) to defuzzify the fuzzy aggregative weight $\tilde{R}$.

Step 3.2.8. To avoid aggregative result $D_i > 1$, we can use Eq. (31) to get constrain solution $D_i > 1$.

3.4 An algorithm of fuzzy query analysis

For easy computing, we build an algorithm of fuzzy query analysis, and the flow chart is shown in Fig. 4.

Step 1. **If** query's attribute include weight attribute **then** step2. **Else** step 3.

Step 2. **If** weight attribute is fuzzy weight **then** retrieval important degree of query attribute
Else if weight attribute is fuzzy OWA weight **then** retrieval α value and query's attribute number.

Step 3. Integrate query's condition.

Step 4. Compute match degree of query's attribute and record.

Step 5. **If** match degree is greater than threshold value **then** choice and response to user

Else no responding.

Table 2 Linguistic terms of relative importance and its triangular fuzzy numbers

Linguistic terms	Triangular fuzzy numbers
Very unimportant (VUI)	(0.0,0.167,0.333)
Unimportant (UI)	(0.167,0.333,0.5)
Medium (M)	(0.333,0.5,0.667)
Important (I)	(0.5,0.667,0.833)
Very important (VI)	(0.667,0.833,1.0)

4 System development and verification

This research constructs a fuzzy OWA query method and adopts a hemodialysis database of a real region hospital to develop a system to demonstrate. There are totally 123 patient's dialysis data in this database. Borland C++ Builder and SQL Server 2000 are adopted to develop this system. Figure 5 is the screen of fuzzy OWA querying system. This chapter can be divided into two parts, Sect. 4.1 is the demonstration of actual example, and Sect. 4.2 is the comparison of methods.

4.1 The demonstration of actual example

In order to clear the results of this research, we list several examples of hemodialysis indicators query. Table 3 shows some data of the real database, which were used as illustration for the examples in this paragraph. Examples 1 and 2 just use the first five data (S001–S005), and the other examples use the last five data (S006–S010).

Example 1 (Basic fuzzy query in crisp database) Assume that the user's fuzzy query statement is "Find the patient's ID whose Kt/V index is good". The membership function of the linguistic term "Good" is shown as Eq. (25). Such as S004,

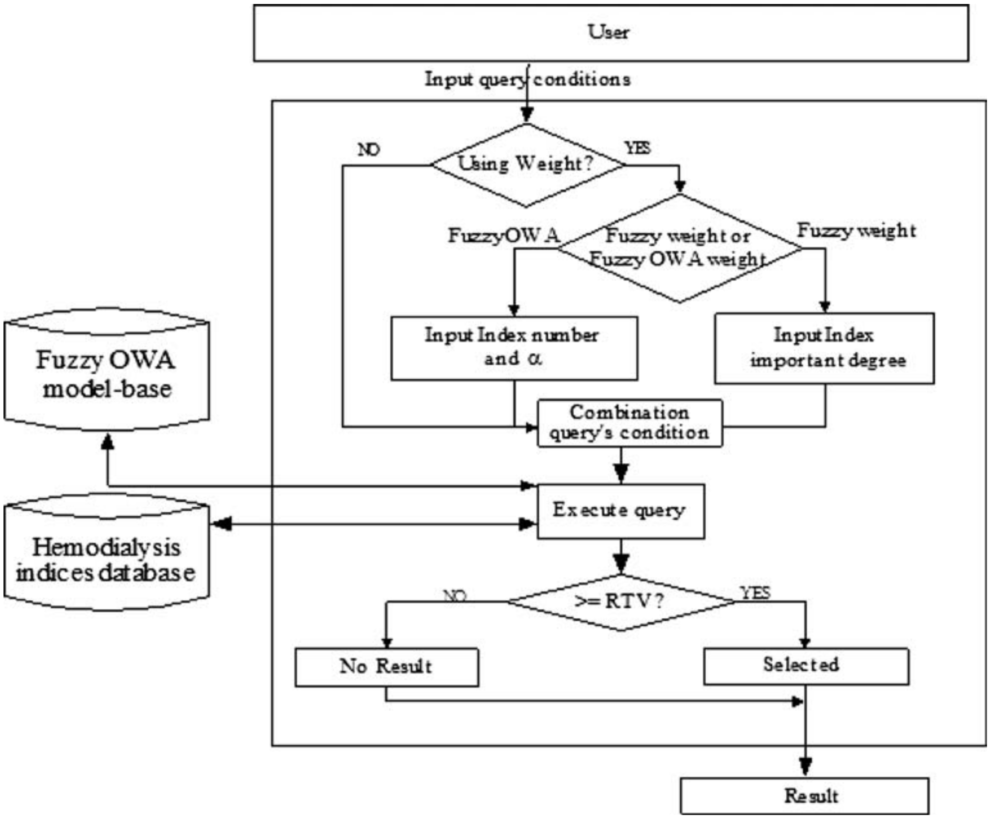

Fig. 4 A flow chart of fuzzy query analysis

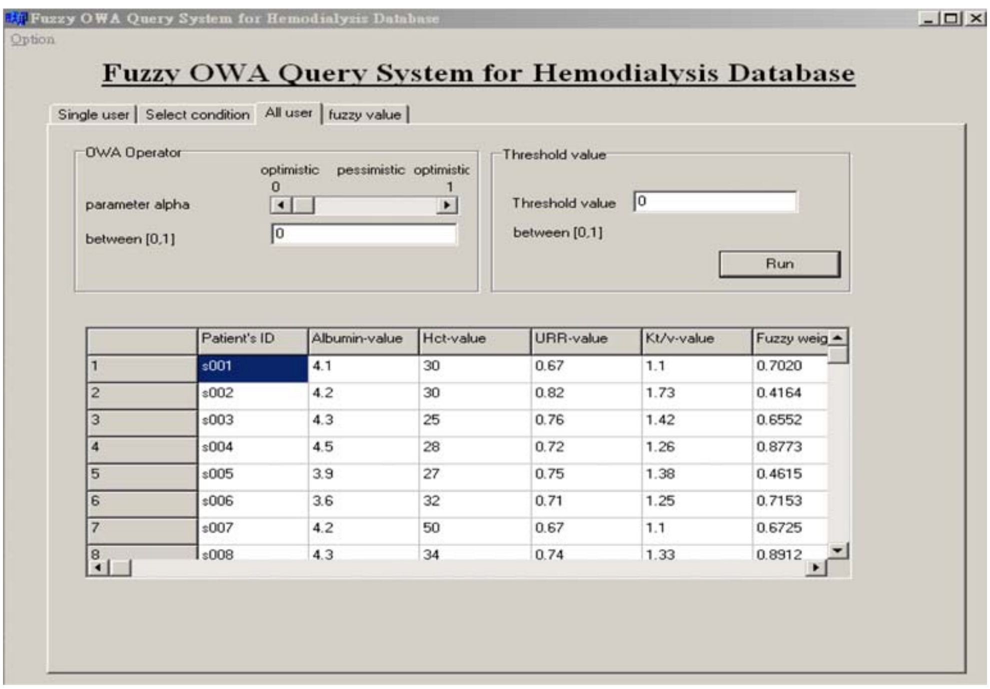

Fig. 5 The screen of fuzzy OWA querying system

we can see that $\mu_G(1.26)$=0.866, in other words, the matching degree of the record with respect to the user's query is 0.866. We can say the patient's Kt/V index is good and the degree is 0.866.

Example 2 (Fuzzy query in fuzzy database) Assume that record value is linguistic term (Table 4) and the user's fuzzy query statement is "Find the patient's ID whose Albumin index is good". We can use min–max method, Euclid distance, and Hamming distance to calculate the matching degrees of each record.

1. Min-Max Method:
   (a) Assume that the membership function of the fuzzy sets "Good" and "Medium" are shown as follows:

$$\begin{aligned}\mu_{\text{Good}} &= \frac{0}{1.0} + \cdots \frac{0.25}{3.9} + \frac{0.5}{4.0} + \frac{0.75}{4.1} + \frac{1}{4.2} \\ &\quad + \frac{1}{4.3} + \frac{1}{4.4} + \frac{1}{4.5} + \frac{1}{4.6} + \frac{1}{4.7} \\ &\quad + \frac{1}{4.8} + \frac{1}{4.9} + \frac{1}{5.0} \\ \mu_{\text{Medium}} &= \frac{0}{1} + \cdots + \frac{1}{3.5} + \frac{0.857}{3.6} + \frac{0.714}{3.7} \\ &\quad + \frac{0.571}{3.8} + \frac{0.429}{3.9} + \frac{0.286}{4.0} + \frac{0.413}{4.1}\end{aligned}$$

   (b) Based on the Min–Max method function (19), we can see that matching degree of the record with respect to the user's query is 0.0645.
2. Euclid distance $\varepsilon\left(\tilde{A}, \tilde{B}\right)$: Based on the Eq. (20), we can get Euclid distance $\varepsilon\left(\tilde{A}, \tilde{B}\right)$ =0.5172, then the matching degree (degree of similarity) of the record with respect to the user's query $\mathrm{N_E}\left(\tilde{A}, \tilde{B}\right)$=0.4828 [by Eq. (21)].
3. Hamming distance$\delta\left(\tilde{A}, \tilde{B}\right)$: Based on the Eq. (22), we can get Hamming distance $\delta\left(\tilde{A}, \tilde{B}\right)$=0.290, and then based on the Eq. (23), the matching degree (degree of similarity) $\mathrm{N_H}\left(\tilde{A}, \tilde{B}\right)$=0.710.

Example 3 (Fuzzy query with fuzzy weight) Assume that the user's fuzzy query statement is "Find the patient's ID whose Kt/V index is good, Albumin index is good, URR is good and Hct is good and Kt/V is VI Albumin is I URR is M Hct is UI." The execution steps of this query are as follows:

1. Table 3 shows the actual database table.
2. To obtain the matching degree of the record with respect to the user's query, such as Table 5.
3. Normalize weight of the attribute by Eq. (29).

$$\begin{aligned}\overline{W}_{Kt/V} &= (0.2223, 0.3571, 0.5999), \\ \overline{W}_{\text{Albumin}} &= (0.1667, 0.2859, 0.4997) \\ \overline{W}_{\text{URR}} &= (0.1110, 0.2143, 0.4001), \\ \overline{W}_{\text{Hct}} &= (0.0557, 0.14276, 0.2999)\end{aligned}$$

4. Calculate the aggregative weight of the attributes by Eq. (30). [In Table 6 (second column)].
5. Use Eq. (31) and (32) to defuzzify the value of aggregative weight. [In Table 6 (third column)].
6. Assume the threshold value is 0.8, and then the selected results are as Table 6 (fourth column).

Example 4 (Fuzzy query with fuzzy OWA) Assume that the user's fuzzy query statement is the same as Example 3, and use fuzzy OWA to query. The execution steps are as follows:

1. The actual database table is as Table 3.
2. Obtain matching degree of the record with respect to the user's query (as Table 5).
3. Computing weight W_1−−W_n by Eqs. (13)−(18), assume situation parameter α is 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0; the result is Table 7.

Table 3 The selected patient's dialysis data from this database

ID	Kt/V	Albumin	Urea reduction ratio (URR)	Hematocrit (Hct)
S001	1.1	4.1	0.67	30
S002	1.73	4.2	0.82	30
S003	1.42	4.3	0.76	25
S004	1.26	4.5	0.72	28
S005	1.38	3.9	0.75	27
S006	1.25	3.6	0.71	32
S007	1.1	4.2	0.67	50
S008	1.33	4.3	0.74	34
S009	1.15	4.4	0.68	30
S010	1.33	4	0.74	27

Table 4 The patient's attribute with linguistic term in database

ID	Albumin
...	...
S005	Medium
...	...

Table 5 The matching degree of the record with respect to the user's query

ID	Kt/V	Albumin	URR	Hct
S006	0.8330	0.0000	1.0000	1.0000
S007	0.3330	1.0000	1.0000	0.0000
S008	1.0000	1.0000	0.5000	0.5000
S009	0.5000	1.0000	1.0000	0.6670
S010	1.0000	0.5000	0.5000	0.0000
...	...	...	...	...

Table 6 The results of Example 3

ID	Aggregative weight	Min (1, defuzzify weight)	Result (RTV=0.8)
S006	(0.3519,0.6545,1.1998)	0.7151	
S007	(0.3517,0.6191,1.09958)	0.6724	
S008	(0.4723,0.8215,1.4496)	0.8912	Selected
S009	(0.4629,0.7739,1.3998)	0.8526	Selected
S010	(0.3612,0.6072,1.0498)	0.6563	
...	...	...	...

Table 7 The W_1–W_n values for different situation parameter value

	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1.0$
W_1	0.25	0.3475	0.4609	0.5965	0.7641	1
W_2	0.25	0.2722	0.2754	0.2521	0.1822	0
W_3	0.25	0.2133	0.1646	0.1065	0.0434	0
W_4	0.25	0.1671	0.0987	0.0450	0.0104	0

4. Calculate the aggregative weight of attribute by Eq. (30).
5. Use Eq. (31) and (32) to defuzzify step 4's result, the result is as Table 8.
6. Assume the threshold value is 0.8, then the query results are as Table 9.

4.2 The comparison of different similarity operators

In order to compare the differences between the three kinds of similarity operators (see Sect. 2.5), this paper utilize hemodialysis database of real region hospital. Example 5 uses the membership functions to translate the crisp value into fuzzy value.

Example 5 (Fuzzy query with different similarity operators in fuzzy database) Assume that the user's fuzzy query statement is "Find the patient's ID whose Kt/V index is Good". The results of randomly selected five patients' dialysis data are as Table 10.

Table 8 The defuzzified weight of each data

ID	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1.0$
S006	0.7083	0.6698	0.6472	0.6484	0.6903	0.8330
S007	0.5833	0.6011	0.5934	0.5572	0.4801	0.3330
S008	0.7500	0.8098	0.8680	0.9243	0.9732	1.0000
S009	0.7918	0.7706	0.7362	0.6869	0.6146	0.5000
S010	0.5000	0.5901	0.6809	0.7758	0.8769	1.0000
...	...	...	...	...	...	...

Table 9 The results of RTV ≥ 0.8

User situation indicator	Result (RTV ≥ 0.8)					
$\alpha = 0.5$	none					
$\alpha = 0.6$	S008					
$\alpha = 0.7$	S004	S008				
$\alpha = 0.8$	S004	S008				
$\alpha = 0.9$	S003	S004	S005	S008		
$\alpha = 1.0$	S003	S004	S005	S006	S008	S010

Table 10 The query results of Example 5

ID	Kt/V	Min–Max method	Euclid distance	Hamming distance
S021	Medium	0.1471	0.5428*	0.7456**
S029	Bad	0.0313	0.1173	0.1842
S071	Medium	0.1471	0.5428*	0.7456**
S083	Good	1.0000**	1.0000**	1.0000**
S115	Bad	0.0313	0.1173	0.1842

* Selected under RTV ≥ 0.5
** Selected under RTV ≥ 0.7

From Table 10, the Min–Max method just select S083 when RTV=0.5, but the other two methods can select S021, S071, and S083. Therefore, the Min–Max method may be easy losing information, while the degree of similarity of Euclid distance and Hamming distance are more reasonable and discriminate.

4.3 The results of different query methods

The traditional query method only can query crisp data so that often lose information. Flexible querying enables users to express preferences inside requirements and priorities inside compound queries. Therefore, this paper proposes a new fuzzy OWA query method to assist the decision makers to make more flexible and adaptive judgment. For example, the Kt/V of the patient S009 is 1.15 (Table 3), and the literatures suggest that the value of Kt/V $\geqslant 1.2$ is good. If these data are only identified by the doctor subjectivity, the quality of the patient's hemodialysis (by Kt/V) may be judged bad. The advantages of proposed method are clarified as follows.

In order to compare the advantages and disadvantages between fuzzy weight and fuzzy OWA more clearly, we use Examples 3 and 4 previously to make comprehensive comparison and show the results in Example 6.

Example 6 If the users want to select the patients of good hemodialysis, the user's fuzzy query statement is "Find the patient's ID whose Kt/V index is good, Albumin index is good, URR is good and Hct is good and Kt/V is VI Albumin is I, URR is M, Hct is UI, and RTV=0.7." However, the traditional crisp database only can query (in boolean logic form): "Find the patient's ID whose Kt/V index $\geqslant 1.2$, Albumin index is between 3.5 and 5.0, URR $\geqslant 0.65$, and Hct is between 30 and 36" (from Table 1). Their query results of different methods are listed in Table 11 and Fig. 6. In fuzzy OWA method, each user's situation parameter α=0.5, 0.6, 0.7, 0.8, 0.9, 1.0.

Comparison results

(1) From Table 11, we can find out that if the data are selected by crisp query method (ID = S004, S006, and S008), it must be selected by the fuzzy weight and fuzzy OWA method with different α values.
(2) In some cases, the fuzzy OWA weighting method can select the data where the other two methods can not select these data (such as ID=S005, Kt/V:1.38, Albumin: 3.9, URR: 0.75, Hct: 27). The experimental results verify that our proposed method is more flexible and adaptive than the other methods. Because the fuzzy OWA can adjust the degree of important between hemodialysis indices by user.
(3) The data could be selected by fuzzy weighting method (ID = S001, S003, S007, S009 and S010), fuzzy OWA method would be selected by the under the matched α's interval-values.
(4) The decision makers want to query (by Example 6's queries) the whole database with 123 patients, the comparison results of different methods are as Table 12 and

Table 11 The query results of different methods

ID	Crisp	Fuzzy weight	Fuzzy OWA					
			$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1$
S001		0.7020**	0.6875*	0.6446*	0.5905	0.5244	0.4417	0.3333
S002		0.4164	0.4167	0.3836	0.3412	0.2821	0.1891	0.0000
S003		0.6552*	0.4750	0.5849	0.6902*	0.7889**	0.8699**	0.9000**
S004	Selected	0.8774**	0.7167**	0.7866**	0.8394**	0.8756**	0.8879**	0.8667**
S005		0.4615	0.3125	0.4155	0.5298	0.6595*	0.8097**	1.0000**
S006	Selected	0.7151**	0.7083**	0.6698*	0.6472*	0.6484*	0.6903*	0.8330**
S007		0.6724*	0.5833	0.6011*	0.5934	0.5572	0.4801	0.3330
S008	Selected	0.8912**	0.7500**	0.8098**	0.8680**	0.9243**	0.9732**	1.0000**
S009		0.8249**	0.7918**	0.7706**	0.7362**	0.6869*	0.6146*	0.5000
S010		0.6563*	0.5000	0.5901	0.6809*	0.7758**	0.8769**	1.0000**
...		...	...	...	...	...	...	...

* Selected under RTV $\geq$ 0.6
** Selected under RTV $\geq$ 0.7

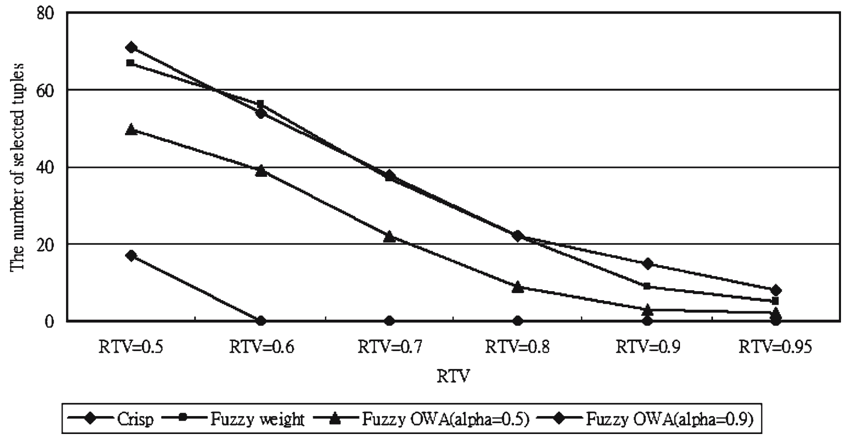

Fig. 6 The number of selected tuples for different methods under different RTV

Table 12 The number of selected tuples under different methods

RTV	Crisp	Fuzzy weight	Fuzzy OWA ($\alpha = 0.5$)	Fuzzy OWA ($\alpha = 0.9$)
0.5	17	67	50	71
0.6		56	39	54
0.7		37	22	38
0.8		22	9	22
0.9		9	3	15
0.95		5	2	8

Table 13 The doctor's diagnoses

ID	Kt/V	Albumin	URR	Hct	Hemodialysis quality
S001	1.1	4.1	0.67	30	Medium
S002	1.73	4.2	0.82	30	Good
S003	1.42	4.3	0.76	25	Medium
S004	1.26	4.5	0.72	28	Good
...	...	...	...	...	

Fig. 6. From Fig. 6, under different RTV's values, the fuzzy OWA method can select the number of tuples more flexible than the other two methods by user (except for RTV=0.6).

Table 14 The result compare with doctor by accuracy ratio (Single index, The threshold=0.5)

Single index	
K	0.557692
A	0.788462
U	0.5
H	0.403846*

* Accuracy rate <0.5
K Kt/V
U URR
A Albumin
H Hct

4.4 Evaluate the effectiveness of fuzzy OWA

In order to evaluate the effectiveness of fuzzy OWA, we compare the results with doctor's diagnoses. We query by fuzzy weight and fuzzy OWA to obtain the tuples' match degrees with the index is "Good". The tuple is selected when its match degrees $\geq$ 0.5. Secondly, we compare the effectiveness of fuzzy OWA with doctor's diagnoses by accuracy ratio, and the doctor's diagnoses are shown in Table 13.

$$\text{Accuracy rate} = |\upsilon \cap \omega| / |\omega| \tag{33}$$

Table 15 The result compare with doctor by accuracy ratio (Double indices, The threshold=0.5)

Double indices	Fuzzy weight	Fuzzy OWA					
		$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1$
KA	0.692308	0.788462	0.692308	0.75	0.75	0.75	0.557692
KU	0.557692	0.538462	0.576923	0.480769*	0.480769*	0.480769*	0.557692
AK	0.788462	0.788462	0.75	0.692308	0.692308	0.673077	0.788462
AU	0.788462	0.807692	0.788462	0.519231	0.538462	0.519231	0.788462
UK	0.480769*	0.538462	0.480769*	0.538462	0.538462	0.538462	0.5
UA	0.538462	0.807692	0.538462	0.769231	0.788462	0.769231	0.5

* Accuracy rate <0.5

Table 16 The result compare with doctor by accuracy ratio (Triple indices, The threshold=0.5)

Triple indices	Fuzzy weight	Fuzzy OWA					
		$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1$
KAU	0.692308	0.634615	0.653846	0.692308	0.692308	0.596154	0.557692
KUA	0.615385	0.634615	0.596154	0.615385	0.615385	0.576923	0.557692
AKU	0.730769	0.634615	0.711538	0.788462	0.75	0.75	0.788462
AUK	0.730769	0.634615	0.711538	0.788462	0.730769	0.730769	0.788462
UKA	0.519231	0.634615	0.480769*	0.480769*	0.480769*	0.461538*	0.5
UAK	0.634615	0.634615	0.615385	0.519231	0.519231	0.5	0.5

* Accuracy rate <0.5

where υ donates the tuples of match degree ≥ 0.5, ω denotes the tuples of hemodialysis quality is good by the doctor's diagnoses, and || donates the number of tuples.

In order to easily compare the result, we use single index, double indices, and triple indices to present. (1) Firstly, we let the threshold of accuracy rate =0.5, and delete the index does not fit this threshold. Then, we delete the index "H" (i.e. Hct) according to the Table 14. (2) Secondly, we pair-wise join other indices whose accuracy rate is above threshold, and the permutation in Table 15 (first column) implies the importance ordering of indices. For example, "KA" imply Kt/V is more important than Albumin. (3) Besides, there are three indices with accuracy rate $\geq$ 0.5 (i.e. "K", "A", and "U") in Table 14, so we just need to join these three indices and the results are shown in Table 15. In the next, we produce higher level combinations of indices according the concept of the second step until each index with accuracy rate ≥ 0.5 is joined. Then, Table 16 is produced because each row in Table 15 has at least one accuracy rate ≥ 0.5.

The fuzzy OWA deal with the dynamical weighting problem more rationally and flexibly according to the situational parameter α's value from the doctor's viewpoint. Note that, $\alpha = 0.5$ means equal weightage to all the indices, and $\alpha = 1$ means only using first index. From the result, we can see the overall accuracy rate of the triple indices "AKU" is better than others, so we suggest the default important ordering of indices is A>K>U. From Table 16, we can find the permutation of triple indices "AKU" more fit the doctor's view, and their performances are higher in fuzzy OWA when $\alpha = 0.7--0.9$ (accuracy rate is $0.75 - -0.788462$) than the highest accuracy rate by fuzzy weight (accuracy rate = 0.730769). That is, the fuzzy OWA is more flexibly and more accuracy than fuzzy weight querying method.

5 Conclusion

In this paper, we have developed the query system of practical hemodialysis database for a regional hospital in Taiwan, which can help the doctors to make more accurate decision in hemodialysis. Secondly, we build the fuzzy membership function of hemodialysis indices based on experts' interviews. Thirdly, we proposed a fuzzy OWA query method, and let the decision makers (doctors) just need to change the weights of attributes dynamical, then the proposed method can revise the weight of each attributes based on aggregation situation and the system will provide synthetic suggestions to the decision makers. Finally, the results show that this new method can evaluate fuzzy database queries about linguistic or precise values, which can improve the crisp values' constrain of traditional database. From the result, we also find that the doctor's preference is Albumin > Kt/V > URR > Hct. The future researches could apply the proposed method to the integration of querying and weighting operators in database. It can also improve the efficiency and effectiveness in the web query environment.

Appendix A. Questionnaire (briefly vision)

1. Please sort follows hemodialysis indices by the importance of degree. (Sort from important to unimportant by 1–5)
   () Kt/V
   () URR
   () Albumin
   () Hct

() Other: (Please write the hemodialysis index item in blank.) ____

☐ PCR: ____

☐ CR: ____

☐ TAC: ____

2. Please give the ranges for four hemodialysis indices by hemodialysis adequacy.

Kt/V:

0.7—0.8—0.9—1.0—1.1—1.2—1.3—1.4—1.5

URR:

50—55—60—65—70—75

Albumin:

3.0—3.5—4.0—4.5—5.0

Hct:

27—28—29—30—31—32—33—-34—35—36

Appendix B. The membership functions (MF) of the indices

Index	Term	Membership function	
URR	Good	$\mu_G(x) = \begin{cases} \frac{x-62}{5} & 62 \leqslant x < 67 \\ 1 & 67 \leqslant x < 73 \\ \frac{75-x}{2} & 73 \leqslant x < 75 \end{cases}$	(B1)
	Fair	$\mu_F(x) = \begin{cases} \frac{x-55}{5} & 55 \leqslant x < 60 \\ 1 & 60 \leqslant x < 62 \\ \frac{67-x}{5} & 62 \leqslant x < 67 \end{cases}$	(B2)
	Bad	$\mu_B^L(x) = \begin{cases} \frac{60-x}{5} & 55 \leqslant x < 60 \\ 1 & x < 55 \end{cases}$	(B3)
		$\mu_B^R(x) = \begin{cases} \frac{x-73}{2} & 73 \leqslant x \leqslant 75 \\ 1 & x > 75 \end{cases}$	(B4)
Albumin	Good	$\mu_G(x) = \begin{cases} \frac{x-3.8}{0.4} & 3.8 < x \leqslant 4.2 \\ 1 & x > 4.2 \end{cases}$	(B5)
	Fair	$\mu_F(x) = \begin{cases} \frac{x-3.2}{0.4} & 3.2 \leqslant x < 3.6 \\ 1 & 3.6 \leqslant x < 3.8 \\ \frac{4.2-x}{0.4} & 3.8 \leqslant x < 4.2 \end{cases}$	(B6)
	Bad	$\mu_B(x) = \begin{cases} \frac{3.6-x}{0.4} & 3.2 < x < 3.6 \\ 1 & x \leqslant 3.2 \end{cases}$	(B7)
Hct	Good	$\mu_G(x) = \begin{cases} \frac{x-28}{3} & 28 \leqslant x < 31 \\ 1 & 30 \leqslant x < 33 \\ \frac{35-x}{2} & 33 \leqslant x < 35 \end{cases}$	(B8)
	Fair	$\mu_F(x) = \begin{cases} \frac{x-27}{1} & 27 \leqslant x < 28 \\ 1 & 28 \leqslant x < 29 \\ \frac{31-x}{2} & 29 \leqslant x < 31 \end{cases}$	(B9)
	Bad	$\mu_B^L(x) = \begin{cases} \frac{28-x}{1} & 27 \leqslant x < 28 \\ 1 & x < 27 \end{cases}$	(B10)
		$\mu_B^R(x) = \begin{cases} \frac{x-33}{2} & 33 \leqslant x \leqslant 35 \\ 1 & x > 35 \end{cases}$	(B11)

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