

## On Threshold Relation & Their Application

\*\*L.N.M.Tawfiq

\* N.M.Niama

Date of acceptance 8/12/2005

### Abstract

In this paper, The notion of. Threshold relations by using resemblance relation are introduced. To get a similarity relation from a resemblance relation  $R$ , we must build the transitive closure  $\overset{\wedge}{R}$  of the relation  $R$ .

### Introduction

A fuzzy set  $\mu$  on a universe  $X$  is a mapping from  $X$  to the unit interval  $[0,1]$ , with the value  $\mu(x)$  of  $\mu$  in  $x$  of  $X$  the degree of membership of  $x$  in  $\mu$ .  $\mu(x) = 1$  means full membership,  $\mu(x) = 0$  means non-membership, and all values  $\mu(x)$  in  $(0,1)$  denote partial membership.[1]

In order to analyze a fuzzy set  $\mu$  in  $X$  at a particular membership degree  $\alpha \in [0,1]$ , we can "cut" the fuzzy set at the degree, and consider only the set of elements  $x$  of  $X$  that have a membership degree  $\mu(x)$  of at least  $\alpha$ . The crisp set constructed in this way is called the  $\alpha$ -cut of the fuzzy set  $\mu$  and denoted as  $\mu_\alpha$ . Just as a fuzzy set extends a classical or crisp set, a fuzzy relation then extends the concept of a crisp relation from  $X$  to  $Y$ .

The product  $X \times X$  is defined by the membership function.  $\mu_{X \times X}(x, y) = \mu(x) \wedge \mu(y)$  and a fuzzy relation  $R$  on  $X$  is a subset of  $X \times X$ , i.e.,  $\mu_R(x, y) \leq \mu_{X \times X}(x, y) \forall x, y \in X$ .

In this paper, we introduce a unifying point of view based on the theory of fuzzy sets [2] and, more particularly, fuzzy relations. We will then discover some new and very interesting properties.

We introduce and study threshold relation by using resemblance relation. We illustrate other programs, by using some results.

### Similarity Relation

The notion of "similarity" as defined in this paper is essentially a generalization of the notion of equivalence. The notion of a distance,  $d(x, y)$ , between objects  $x$  and  $y$  has long been used in many contexts as a measure of similarity or dissimilarity between elements of a set.

### Definition 1 [3],[4],[5]

A similarity relation  $R$ , is a fuzzy relation in  $X$  that is reflexive, Symmetric, and Transitive. Thus let  $x_i, x_j$  be elements of  $X$ , and let  $\mu_R(x_i, x_j)$  denoted the grade-membership of the order pair  $(x_i, x_j)$  in  $R$ . Then  $R$  is a similarity relation in  $X$  if and only if  $\forall x, y, z \in X$ :

$$1. \mu_R(x, x) = 1 \quad (\text{reflexive})$$

$$2. \mu_R(x, y) = \mu_R(y, x) \quad (\text{symmetric})$$

$$3. \mu_R(x, z) \geq \bigvee_{y \in X} (\mu_R(x, y) \wedge \mu_R(y, z)) \quad (\text{transitive})$$

$$$$

Now, we introduce the following definition

\*College of Science for Women, Baghdad University.

\*\*College of Education Ibn Al-Haitham, Baghdad University

**Definition 2 [4]**

Let  $\mu_R(x, y)$  be a resemblance relation. Then  $\mu_R^n(x, y)$  is called the n-purlicious relation, defined as

$$\mu_R^n(x, y) = \bigvee_{x_1, x_2, x_3, \dots, x_{n-1} \in X} [\mu_R(x, x_1) \wedge \mu_R(x_1, x_2) \wedge \mu_R(x_2, x_3) \wedge \dots \wedge \mu_R(x_{n-1}, y)]$$

for  $n = 2, 3, 4$

...since  $\mu_R^1(x, y) = \mu_R(x, y)$ .

Clearly we have

$$0 \leq \mu_R(x, y) \leq \mu_R^2(x, y) \leq \dots$$

$$\leq \mu_R^n(x, y) \leq \mu_R^{n+1}(x, y) \leq \dots \leq 1$$

since

$$\mu_R^{n+1}(x, y) = \bigvee_{x_1, x_2, \dots, x_n \in X} [\mu_R(x, x_1) \wedge \mu_R(x_1, x_2) \wedge \dots \wedge \mu_R(x_{n-1}, x_n) \wedge \mu_R(x_n, y)]$$

$$\begin{aligned} &\geq \bigvee_{x_1, x_2, \dots, x_{n-1} \in X} [\mu_R(x, x_1) \wedge \mu_R(x_1, x_2) \wedge \dots \wedge \mu_R(x_{n-1}, y) \wedge \mu_R(y, y)] \\ &= \bigvee_{x_1, x_2, \dots, x_{n-1} \in X} [\mu_R(x, x_1) \wedge \mu_R(x_1, x_2) \wedge \dots \wedge \mu_R(x_{n-1}, y) \wedge 1] \\ &= \mu_R^n(x, y). \end{aligned}$$

Clearly, the n-purlicious relation defined as:

$$\mu_R^n(x, y) = \bigvee_{\vec{x} \in \hat{X}} [\mu_R(x, x_1) \wedge \mu_R(x_1, x_2) \wedge \dots \wedge \mu_R(x_{n-1}, y)]$$

Where

$$\hat{X} = \bigwedge_{\vec{x} = (x_1, x_2, \dots, x_{n-1}) \in \hat{X}}$$

is the (n-1)-fold Cartesian product of  $X$  with itself where  $x, y \in X$  implies that for all  $x, y \in X$  and all  $n \geq 1$ .

$$0 \leq \mu_R^n(x, y) \leq \mu_R^{n+1}(x, y) \leq 1$$

Consequently

$$\lim_{n \rightarrow \infty} \mu_R^n(x, y) = \bar{\mu}_R(x, y)$$

exists by the monotone convergence principle, namely, for every  $\epsilon > 0$ , there is an integer  $N$  such that:

$$|\mu_R^n(x, y) - \bar{\mu}_R(x, y)| < \epsilon \text{ for } n > N.$$

Since the sequence is non-decreasing and is bounded from above and below we can conclude that the limit exists.

Now we introduce the following definition which we help to define threshold relation.

**Definition 3**

Let  $x$  and  $y$  be two elements of  $X$ , and

Let  $\mu_R^n(x, y)$  be the n-purlicious relation as defined above. Then we define the propinquity  $\bar{\mu}(x, y)$  in  $[0, 1]$  such that

$$\bar{\mu}_R(x, y) = \lim_{n \rightarrow \infty} \mu_R^n(x, y) \text{ or}$$

$$\bar{\mu}(x, y) = \lim_{n \rightarrow \infty} \mu_R^n(x, y)$$

**Definition 4**

Let  $x, y \in X$ . Then  $x$  and  $y$  are said to have

a threshold relation  $xR_T y$  if and only if  $\bar{\mu}_R(x, y) \geq T$ . It is easy to show that  $\forall x, y, z \in X$

we have

$$\bar{\mu}_R(x, z) \geq \bar{\mu}_R(x, y) \wedge \bar{\mu}_R(y, z)$$

Now we introduce the following theorems about threshold relation property

**Theorem 1**

The threshold relation is a similarity relation in  $X$ .

**Proof**

$$i [0, 1] \quad xR_T x \quad \forall T \in -$$

$$\text{since } 1 = \mu_R(x, x) \leq \bar{\mu}_R(x, x) \leq 1 \quad \forall x \in X$$

$$ii \quad xR_T y \quad \text{if and only if } yR_T x -$$

since

$$\lim_{n \rightarrow \infty} \mu_R^n(x, y) = \bar{\mu}_R(x, y) = \bar{\mu}_R(y, x) = \lim_{n \rightarrow \infty} \mu_R^n(y, x)$$

$$iii) x R_T y \wedge y R_T z \rightarrow x R_T z$$

$$\text{Since } \bar{\mu}_R(x, z) \geq \bar{\mu}_R(x, y) \wedge \bar{\mu}_R(y, z)$$

Clearly we can associate with every relation an appropriate matrix to represent the relation, and hence we can classify the set using the partition induced by the threshold relation .

The fuzzy matrix approach is a pictorial representation of a graph theoretic principle involving the selection of a threshold distance. Once the threshold distance  $d_0$  is selected, two elements are said to be in the same set if the distance between them is less than  $d_0$ .

Suppose that we pick a threshold value  $d_0$  and say that  $\alpha$  is similar to  $\beta$  if  $R(\alpha, \beta) > d_0$

$$R_{ij} = \begin{cases} 1 & \text{if } R(\alpha_i, \beta_j) > d_0 \quad i, j = 1, 2, \dots, n \\ 0 & \text{otherwise} \end{cases}$$

This matrix defines a similarity graph in which nodes correspond to points and an edge joins node  $i$  and node  $j$  if and only if  $R_{ij} = 1$  .

It is clear that if  $R_T$  is a threshold relation induced by  $\mu_R(x, y)$  and  $R'_T$  is a threshold relation induced by  $\mu'_R(x, y)$  and

$$\mu_R(x, y) \leq \mu'_R(x, y) \text{ for all } x, y \in X .$$

Then  $R_T$  refines  $R'_T$  .

It is our assumption that if  $x \neq y$  then  $(0, 1] \bar{\mu}_R(x, y) \in$  and thus the function  $\bar{\eta}_R(x, y) = 1 - \bar{\mu}_R(x, y)$  acts as a distance function. This is obvious, since

$$i. \bar{\eta}_R(x, y) > 0 \text{ for } x \neq y \text{ and } \bar{\eta}_R(x, x) = 0$$

$$ii. \bar{\eta}_R(x, y) = \bar{\eta}_R(y, x)$$

$$iii. \bar{\eta}_R(x, z) \leq \bar{\eta}_R(x, y) + \bar{\eta}_R(y, z)$$

as

$$\bar{\mu}_R(x, z) \geq \bar{\mu}_R(x, y) \wedge \bar{\mu}_R(y, z) \geq \bar{\mu}_R(x, y) + \bar{\mu}_R(y, z) - 1$$

We shall assume for simplicity of the analysis that we deal with only a finite number of sets, and hence we shall consider our threshold relation on finite sets only.

**Theorem 2**

Let  $x_1, x_2, x_3, \dots, x_n \in X$  where  $n$  is a finite number .

$$R_T = \bigcup_j (R_T^*)^j = (R_T^*)^{n-1} . \text{ Then}$$

$$x R_T^* y \text{ iff } \mu_R(x, y) \geq T \text{ and } \bigcup_j (R_T^*)^j = \sup_j (R_T^*)^j = \text{adj}(R_T^*)$$

**Proof**

i - clearly  $\bigcup_j (R_T^*)^j$  refines  $R_T$  since

$$\bigcup_j (R_T^*)^j = \sup_j (R_T^*)^j \text{ and if}$$

$$x [\bigcup_j (R_T^*)^j] y \text{ then}$$

$$\exists x_1, x_2, x_3, \dots, x_{n-1} \in X \text{ such that } \mu_R(x, x_1) \geq T, \mu_R(x_1, x_2) \geq T$$

$$\dots, \mu_R(x_{n-1}, y) \geq T$$

and hence

$$\mu_R^n(x, y) \geq \mu_R(x, x_1) \wedge$$

$$\mu_R(x_1, x_2) \wedge \dots \wedge \mu_R(x_{n-1}, y) \geq T$$

which implies that

$$\bar{\mu}_R(x, y) \geq \mu_R^n(x, y) \geq T$$

and thus  $x R_T y$

ii- Assume  $x R_T y$  then

$$\mu_R(x, y) = \mu_R^{n-1}(x, y)$$

$$= \bigvee_{x_1, x_2, \dots, x_{n-2} \in X} [(\mu_R(x, x_1) \wedge \mu_R(x_1, x_2) \wedge \dots \wedge \mu_R(x_{n-2}, y))] \geq T$$

Therefore  $\exists x_1, x_2, x_3, \dots, x_{n-2} \in X$  such that

$$\mu_R(x, x_1) \geq T, \mu_R(x_1, x_2) \geq T, \dots,$$

$$\mu_R(x_{n-2}, y) \geq T$$

and thus we have

$$x R_T^* x_1, x_1 R_T^* x_2, \dots,$$

$$x_{n-2} R_T^* y$$

$$\rightarrow x (R_T^*)^{n-1} y \text{ exists}$$

$$\rightarrow x [\bigcup_j (R_T^*)^j] y \text{ exists}$$

iii- Let  $R_T^* [P_{ij}]$ . The  $ij$  entry of

$$(R_T^*)^2 \text{ is } \sum_{k=1}^n P_{ik} P_{kj} \text{ and this term}$$

has a grade membership of  $\bigvee_k [P_{ik} \wedge P_{kj}]$

If there is a direct path between vertices  $i$  and  $j$  or there is a path from  $i$  to  $j$  through one intermediate vertex.

Extending this argument to  $(R_T^*)^i$  it is clear that no path requires more than  $n-2$  intermediate vertices, since there are only  $n$  vertices and internal loops are excluded. Hence the  $ij$  entry of  $(R_T^*)^{n-1}$  has a grade membership of

$$\bigvee_{\text{subterm}} \{ij \text{ terms of } (R_T^*)^{n-1}\}.$$

If and only if  $i$  and  $j$  are connected, namely  $(R_T^*)^{n-1} = \bigcup_j (R_T^*)^j$ .

**Corollary 3**

$R_T^* = \bigcup_j (R_T^*)^j$  if and only if  $(R_T^*)^2 = R_T^*$ .

**Proof**

$$R_T^* = \bigcup_j (R_T^*)^j = (R_T^*)^{n-1} \text{ by above theorem}$$

Now, if

$$R_T^* = \bigcup_j (R_T^*)^j \Rightarrow R_T^* = \bigcup_j (R_T^*)^j = (R_T^*)^{n-1} \Rightarrow n-1=1 \Rightarrow n=2 \Rightarrow \bigcup_j (R_T^*)^j = R_T^* \Rightarrow (R_T^*)^2 = R_T^*$$

Conversely if

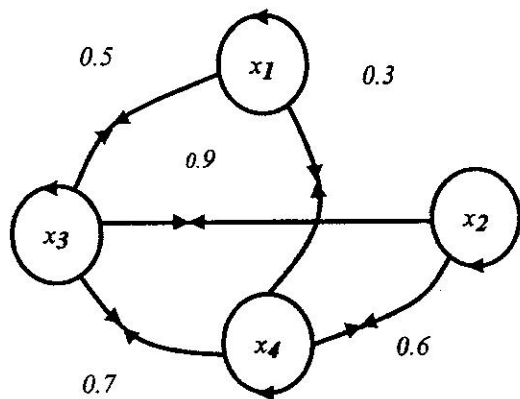
$$(R_T^*)^2 = R_T^* \Rightarrow \bigcup_j (R_T^*)^j = R_T^*$$

Now we introduce the following examples which clear above definitions and theorems :

**Example 1**

Let  $X = \{x_1, x_2, x_3, x_4\}$  and  $\mu_R(x_i, x_j)$   $i, j = 1, 2, 3, 4$  be as follows

$$R_T^* = \begin{matrix} & x_1 & x_2 & x_3 & x_4 \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0 & 0.5 & 0.3 \\ 0 & 1 & 0.9 & 0.6 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.3 & 0.6 & 0.7 & 1 \end{bmatrix} \end{matrix}$$



Then

$$\bigcup_j (R_T^*)^j = \begin{matrix} & x_1 & x_2 & x_3 & x_4 \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1 & 0.9 & 0.7 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.5 & 0.7 & 0.7 & 1 \end{bmatrix} \end{matrix} = (R_T^*)^2 = (R_T^*)^3$$

and we have the partitions

$$R_{T=1} = \{ [x_1], [x_2], [x_3], [x_4] \}$$

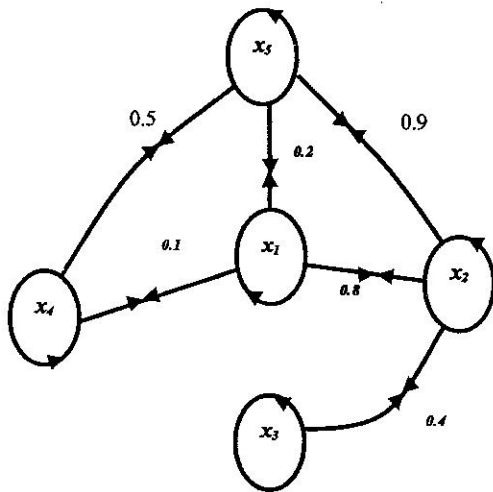
$$R_{0.7 < T \leq 0.9} = \{ [x_1], [x_2, x_3], [x_4] \}$$

$$R_{0.5 < T \leq 0.7} = \{ [x_2, x_3, x_4], [x_1] \}$$

$$R_{0 < T \leq 0.5} = \{ [x_1, x_2, x_3, x_4] \}$$

**Example 2**

$$R_T^* = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{matrix} & \begin{bmatrix} 1 & 0.8 & 0 & 0.1 & 0.2 \\ 0.8 & 1 & 0.4 & 0 & 0.9 \\ 0 & 0.4 & 1 & 0 & 0 \\ 0.1 & 0 & 0 & 1 & 0.5 \\ 0.2 & 0.9 & 0 & 0.5 & 1 \end{bmatrix} \end{matrix}$$



$$\bigcup_j (R_T^*)^j = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{matrix} & \begin{bmatrix} 1 & 0.8 & 0.4 & 0.5 & 0.8 \\ 0.8 & 1 & 0.4 & 0.5 & 0.9 \\ 0.4 & 0.4 & 1 & 0.4 & 0.4 \\ 0.5 & 0.5 & 0.4 & 1 & 0.5 \\ 0.8 & 0.9 & 0.4 & 0.5 & 1 \end{bmatrix} = (R_T^*)^4 \end{matrix}$$

Thus we have the partitions

$$R_{T=1} = \{ [x_1], [x_2], [x_3], [x_4], [x_5] \}$$

$$R_{1 > T > 0.8} = \{ [x_1], [x_2, x_5], [x_3], [x_4] \}$$

$$R_{0.8 \geq T > 0.5} = \{ [x_1, x_2, x_5], [x_3], [x_4] \}$$

$$R_{0.5 \geq T > 0.4} = \{ [x_1, x_2, x_4, x_5], [x_3] \}$$

$$R_{0.4 \geq T \geq 0} = \{ [x_1, x_2, x_3, x_4, x_5] \}$$

Now, we introduce the following definitions and theorems which

represent some application about threshold relation .

**Definition 5**

A vertex  $x$  is said to be  $\in$ -reachable from another vertex  $y$ , for some  $0 < \epsilon \leq 1$  if and only if  $\mu_{\bigcup_j (R_T^*)^j} (x, y) \geq \epsilon$

The reachability matrix of  $R_T^*$  denoted  $\cdot \bigcup_j (R_T^*)^j$  The  $\in$ -reachability matrix of

$$R_T^* \text{ denoted by } \left( \bigcup_j (R_T^*)^j \right)^\epsilon \text{ is}$$

obtained from  $\bigcup_j (R_T^*)^j$  such that

$$\mu_{\left( \bigcup_j (R_T^*)^j \right)^\epsilon} (x, y) = 1 \text{ if and only if } \geq \epsilon \mu_{\bigcup_j (R_T^*)^j} (x, y).$$

**Definition 6**

A relation  $R_T^*$  is called strongly  $\in$ -connected if and only if every pair of nodes are mutually  $\in$ -reachable.  $R_T^*$  is said to be initial  $\in$ -connected if and only if there exists  $x \in X$  such that every node  $y$  in  $R_T^*$  is  $\in$ -reachable from  $x$ .

A maximal strongly  $\in$ -connected sub relation (MS- $\in$ CS) of  $R_T^*$  is a strongly  $\in$ -connected sub graph not property contained in any other Ms- $\in$ CS. It is easily seen that strongly  $\in$ -connectedness implies initial  $\in$ -connectedness .

Also, the following result is straight forward.

**Theorem 4**

A fuzzy relation  $R_T^*$  is strongly  $\epsilon$ -connected if and only if there exists a node  $x$  such that for any other node  $y$  in  $\bigcup_j (R_T^*)^j(x, y) \geq \epsilon$ ,  $R_T^*$ .

**Example 3**

Let  $R_T^*$  given in Figure (1.a), and  $\left(\bigcup_j (R_T^*)^j\right)^{0.8}$  is given in Figure (1.b)

$$R_T^* = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0 & 0.5 & 0.3 \\ 0 & 1 & 0.9 & 0.6 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.3 & 0.6 & 0.7 & 1 \end{bmatrix} \end{matrix},$$

$$\bigcup_j (R_T^*)^j = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1 & 0.9 & 0.7 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.5 & 0.7 & 0.7 & 1 \end{bmatrix} \end{matrix}$$

(Figure 1.a)

$$\left(\bigcup_j (R_T^*)^j\right)^{0.8} = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{matrix}$$

Figure (1. b)

We see that the MS.8-CS'S of  $R_T^*$  contain the following nodes sets  $\{x_1\}, \{x_2, x_3\}, \{x_4\}$ , respectively.

The previous result is now applied to clustering analysis we assume that a data is given, where  $X$  is a set of data and  $(\mu_{R_T^*}(x, y))$  is a quantitative measure of the similarity of the two data items

$x$  and  $y$ . For  $0 < \epsilon \leq 1$  an  $\epsilon$ -cluster in  $X$  is a maximal subset  $Y$  of  $X$  such that each pair of elements in  $Y$  is  $\epsilon$ -cluster of  $X$  is tantamount of finding all maximal strongly  $\epsilon$ -connected sub relation of  $R_T^*$

**Example 4**

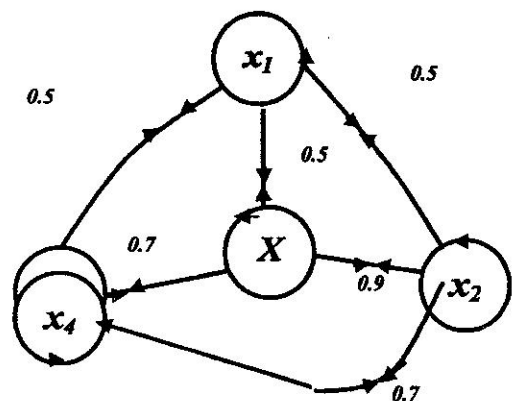
Let

$$R_T^* = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0 & 0.5 & 0.3 \\ 0 & 1 & 0.9 & 0.6 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.3 & 0.6 & 0.7 & 1 \end{bmatrix} \end{matrix}, (R_T^*)^2 =$$

$$(R_T^*)^2 = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1 & 0.9 & 0.7 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.5 & 0.7 & 0.7 & 1 \end{bmatrix} \end{matrix} = (R_T^*)^3 = (R_T^*)^4$$

Let

$$S = \sum_{j=1}^{\infty} (R_T^*)^j = \begin{matrix} & \begin{matrix} x_1 & x_2 & x_3 & x_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{matrix} & \begin{bmatrix} 1 & 0.5 & 0.5 & 0.5 \\ 0.5 & 1 & 0.9 & 0.7 \\ 0.5 & 0.9 & 1 & 0.7 \\ 0.5 & 0.7 & 0.7 & 1 \end{bmatrix} \end{matrix} = R_T^* \vee (R_T^*)^2$$



clear that  $S$  is reflexive and symmetric and transitive since  $(S)^2 = S$ ,  $V = \{x_1, x_2, x_3, x_4\}$   
 $F_{0.8}^S = \{k \subseteq V \mid (\forall x \in V)[x \in k \leftrightarrow (\forall y \in k)(\mu_S(x, y) \geq 0.8)]\}$   
 $= [\{x_1\}, \{x_2, x_3\}, \{x_4\}]$

Then, each element in  $F_{\in}^S$  is an  $\in$ -cluster we may also define an  $\in$ -cluster in  $X$  as a maximal subset  $Y$  of  $X$  such that every element of  $Y$  is  $\in$ -reachable from a special element  $y$  in  $Y$ . In this case, the construction of  $\in$ -clusters is equivalent to finding all maximal initial  $\in$ -connected.

Another application is the use of  $R_T^*$ ,

$$\bigcup_j (R_T^*)^j$$

to model information net works.[6], [7].

## References

1- George, J. k, 1997, "Fuzzy Set Theory Foundations And Applications", Ute St. Clair, Bo Yuan.

2- zadeh , L.A., 1980, Fuzzy Relations, Fuzzy Sets And Systems.

3- Kim, K., Mladen A., And David F. M. , 2002 , Fault – Tolerant Software Vaters Based On Fuzzy

Equivalence Relations, North Carolina State University, Raleigh, NC 27695–8206 (919) 515–6014.

4- Kandel, A., 1982, "Fuzzy Techniques In Pattern Recognition", The Florida State University, Tallahassee.

5- Tunstel, E., Lippincott T., And Jamshidi M., 2002, Introduction To Fuzzy Logic Control With Application To Mobile Robotics, NASA Center For Autonomous Control Engineering, University of New Mexico, Albuquerque, NM 87131.

6- Axler, S., G, Hring F. W., and Ribet K. A., 2001, " Gradute Texts in Mathematics, Graph Theory", Second Edition.

7- Da Ruan, 2000, Intelligent Hybrid Systems: Fuzzy Logic, Neural Networks, And Genetic Algorithms, Belgian Nuclear Research Centre (Sck. Cen) Mol, Belgium.

## حول علاقة العتبة وتطبيقاتها

نغم موسى نعمة\*\*

لمى ناجي محمد توفيق\*

\* دكتوراه-جامعة بغداد-كلية التربية ابن الهيثم

\*\* جامعة بغداد - كلية العلوم للبنات

## المستخلص

في هذا البحث عرفنا علاقة العتبة باستخدام العلاقة المتماثلة وللحصول على علاقة متجانسة من علاقة متماثلة  $R$  يجب أن ننشأ انغلاق التعدي للعلاقة  $R$ .