

*Article*

## On Neutrosophic Graph

Shimaa Fathi <sup>1,\*</sup>, Hewayda ElGhawalby <sup>2</sup> and A.A. Salama <sup>3</sup>

<sup>1,2</sup> Physics and Engineering Mathematics Department, Faculty of Engineering, Port Said University Egypt; hewayda2011@eng.psu.edu.eg

<sup>3</sup> Department of Mathematics and Computer Science, Port Said University, Egypt; drsalama44@gmail.com

\* Correspondence: Shimaa\_f\_a@eng.psu.edu.eg.

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**Abstract:** This paper is devoted for presenting new neutrosophic similarity measures between neutrosophic graphs. We propose two ways to determine the neutrosophic distance between neutrosophic vertex graphs. The two neutrosophic distances are based on the Hausdorff distance, and a robust modified variant of the Hausdorff distance, moreover we show that they both satisfy the metric distance measure axioms. Furthermore, a similarity measure between neutrosophic edge graphs, that is based on a probabilistic variant of Hausdorff distance, is introduced. The aim is to use those measures for the purpose of matching neutrosophic graphs whose structure can be described in the neutrosophic domain.

**Keywords:** Neutrosophic Graphs, Hausdorff Distance, Graph Matching.

### 1. Introduction

Graphs are essential for encoding information, which may serve in several fields ranging from computational biology to computer vision. The notion of graph theory was first introduced by Euler in 1736, given a graph where vertices and edges represent pairwise interactions between entities [2, 5]. The past years have witnessed a high development in the areas of the applications of graphs of pattern recognition and computer vision, where graphs are the most powerful and handy tool used in representing both objects and concepts. The invariance properties, as well as the fact that graphs are well suited to model objects in terms of parts and their relations, make them very attractive for various applications. Hence, the theory of graph became an extremely useful tool for solving combinatorial problems in different areas such as geometry, algebra, number theory, topology, operations research, optimization and computer science [1]. In 1975, a fuzzy graph theory as a generalization of Euler's graph theory was introduced by Rosenfeld [7], based on the concepts of fuzzy set theory proposed by Zadeh in 1965 [19].

In a world full of indeterminacy, traditional crisp set with its boundaries of truth and false has not infused itself with the ability of reflecting the reality. Therefore, neutrosophic found its place into contemporary research as an alternative representation of the real world. Established by Florentin Smarandache [16], Neutrosophy was presented as the study of "the origin, nature, and scope of neutralities, as well as their interactions with different ideational spectra". The main idea was to consider an entity "A" in relation to its opposite "Non-A", and to that which is neither "A" nor "Non-A", denoted by "Neut-A". From then on, Neutrosophy became the basis of Neutrosophic Logic, Neutrosophic Probability, Neutrosophic Set Theory, and Neutrosophic Statistics. According to this theory every idea "A" tends to be neutralized and balanced by "neut-A" and "non-A" ideas - as a state of equilibrium. In a classical way "A", "neut-A", "anti-A" are disjoint two by two. But, since

in many cases the borders between notions are vague, imprecise or sorties, it is possible that "A", "neut-A" and "anti-A" have common parts two by two, or even all three of them as well. In [16, 17], Smarandache introduced the fundamental concepts of neutrosophic set, that had led Salama and Smarandache [15], to provide a mathematical treatment for the neutrosophic phenomena which already existed in our real world. Moreover the work of Salama and Smarandache[15,16,17] formed a starting point to construct new branches of neutrosophic mathematics. Hence, Neutrosophic set theory turned out to be a generalization of both the classical and fuzzy counterparts.

In [6,11,12,13], the authors gave a new dimension for the graph theory using the concept of neutrosophy, some study for different types of neutrosophic graphs were presented and some of their properties were investigated. The aim of this paper is to compute the dissimilarity between two graphs, our methodology is based on the Hausdorff distance, which is invariant to rotation. Whereas several neutrosophic distances were introduced in [4, 14], the authors constructed the neutrosophic distance between neutrosophic sets. The remaining of the paper is structured as follows: definitions of neutrosophic sets and graphs are presented in §2 and §3. Whereas, §4 introduces the idea behind the Hausdorff distance between two crisp sets. In §5.2 and §5.3, we propose two new neutrosophic dissimilarity measures between neutrosophic vertex graphs based on the classical and the modified Hausdorff distances. Furthermore, we investigate the metric axioms for the obtained distances. A neutrosophic similarity measure between neutrosophic edge graphs, based on a probabilistic variant of Hausdorff distance, is introduced in §5.3.

## 2. Neutrosophic Sets

let  $X$  be a space of points (objects), with a generic element in  $X$  denoted by  $x$ , a neutrosophic set  $A$  in  $X$  is characterized by a truth-membership function  $T$ , a indeterminacy-membership function  $I$  and a falsity-membership function  $F$  [15, 18], That is:  $T, I, F: x \rightarrow ]-0, 1+[$ .

Where  $T(x)$ ,  $I(x)$  and  $F(x)$  are real standard or non-standard subsets of  $] -0, 1+[$ .

In general if there is no restriction on the sum of  $T(x)$ ,  $I(x)$  and  $F(x)$ , so  $0^- \leq T(x) + I(x) + F(x) \leq 3^+$ .  $T, I, F$  are called neutrosophic components. In this paper we will restrict our work to use the standard unit interval  $[0, 1]$ .

## 3. Neutrosophic Graphs

In [6], the authors defined the neutrosophic graph, to be a graph  $G < V, E >$  combined with six mappings, written in the form  $G_N = < V, E, T_e, I_e, F_e, T_v, I_v, F_v >$ , where

$T_v: V \rightarrow [0,1]$ ,  $I_v: V \rightarrow [0,1]$ ,  $F_v: V \rightarrow [0,1]$  denoting the degree of membership, degree of indeterminacy and non-membership of the element  $v_i \in V$  respectively and  $0 \leq T_v(v_i) + I_v(v_i) + F_v(v_i) \leq 3$  for every  $v_i \in V, (i = 1, 2, \dots, n)$ , and

$T_e: V \times V \rightarrow [0,1]$ ,  $I_e: V \times V \rightarrow [0,1]$  and  $F_e: V \times V \rightarrow [0,1]$  are such that  $T_e(v_i, v_j) \leq \min(T_v(v_i), T_v(v_j))$ ,  $I_e(v_i, v_j) \leq \min(I_v(v_i), I_v(v_j))$  and  $F_e(v_i, v_j) \leq \min(F_v(v_i), F_v(v_j))$  and  $0 \leq T_e(v_i, v_j) + I_e(v_i, v_j) + F_e(v_i, v_j) \leq 3$  for every  $(v_i, v_j) \in E (i, j = 1, 2, 3, \dots, n)$ .

The concept of neutrosophic graph was used by several authors; nevertheless they took different points of view when describing the interpretation of graph neutrosophy. We constructed the following structure depending on the one given in [6, 12].

### 3.1. Neutrosophic Edge Graphs

A neutrosophic graph is defined as a graph combined with three mappings, written as  $G = (V, E, T_e, I_e, F_e)$ , where  $T_e: V \times V \rightarrow [0,1]$ ,  $I_e: V \times V \rightarrow [0,1]$  and  $F_e: V \times V \rightarrow [0,1]$  are such that  $T_e(v_i, v_j) \leq \min(T_v(v_i), T_v(v_j))$ ,  $I_e(v_i, v_j) \leq \min(I_v(v_i), I_v(v_j))$  and  $F_e(v_i, v_j) \leq \min(F_v(v_i), F_v(v_j))$  and  $0 \leq T_e(v_i, v_j) + I_e(v_i, v_j) + F_e(v_i, v_j) \leq 3$  for every  $(v_i, v_j) \in E (i, j = 1, 2, 3, \dots, n)$ .

### 3.2. Neutrosophic Vertex Graphs

The term neutrosophic vertex graph was used to define a graph of the form:

$G = (V, E, T_v, I_v, F_v)$  combined with three mappings, written as  $T_v: V \rightarrow [0,1]$ ,  $I_v: V \rightarrow [0,1]$ ,  $F_v: V \rightarrow [0,1]$  denoting the degree of membership, degree of indeterminacy and non-membership of the element  $v_i \in V$  respectively and  $0 \leq T_v(v_i) + I_v(v_i) + F_v(v_i) \leq 3$  for every  $v_i \in V$ , ( $i = 1, 2, \dots, n$ ).

### 4. Hausdorff distance

Since first introduced by Hausdorff in 1914 [8], the Hausdorff distance has been used in several areas including matching and recognition problems. It provides a means of computing the distance between sets of unordered observations when the correspondences between the individual items are unknown. In its most general setting, the Hausdorff distance measures how far two subsets of a metric space are from each other. It turns the set of non-empty compact subsets of a metric space into a metric space in its own right. Given two such sets, the closest point in the second set for each point in the first set is considered. Hence, the Hausdorff distance is the maximum over all these values. More formally, the classical Hausdorff distance (H D) [4, 10], between two finite point sets A and B is given by:

$$H(A,B) = \max(h(A,B), h(B,A))$$

Where the directed Hausdorff distance from A to B is defined to be:

$$h(A,B) = \max_{a \in A} \min_{b \in B} \|a - b\|$$

And  $\| \cdot \|$  is some underlying norm on the points of A and B (e.g., the  $L_2$  or Euclidean norm). Regardless of the norm, the Hausdorff metric captures the notion of the worst match between two objects. The computed value is the largest distance between a point in one set and a point in the other one. Several variants of the Hausdorff distance have been proposed as alternatives to the maximum of the minimum approach in the classical one, like Hausdorff fraction, Hausdorff quintile [10] and Spatially Coherent Matching [3].

A robust modified Hausdorff distance (MHD) based on the average distance value instead of the maximum value was proposed by Dubuisson and Jain [7], in this sense they defined the directed distance of the MHD as:

$$MH(A,B) = \frac{1}{N_A} \sum_{a \in A} \min_{b \in B} \|a - b\|$$

### 5. Neutrosophic Graph Similarity Measures

In this section, we introduce neutrosophic graph similarity measures, based on the concept of Hausdorff distance and some of its variants.

Firstly, we propose two new neutrosophic dissimilarity measures based on the classical and the modified Hausdorff distances [4, 6, 14]. Basically the neutrosophic dissimilarity measure is a triple: the first part is a dissimilarity measure of the true value of the neutrosophic object, the second part is a dissimilarity measure of the indeterminate value of the neutrosophic object, and the third part is a dissimilarity measure of the false value of the neutrosophic object; that is the opposite of the neutrosophic object. Secondly, we propose a new neutrosophic similarity measure based on the probabilistic Hausdorff distance [9]. With a similar structure, the neutrosophic similarity measure is also a triple as the explained in the neutrosophic dissimilarity measure. Obviously, if the indeterminate part does not exist (its measure is zero) and if the measure of the opposite object is ignored the suggested neutrosophic dissimilarity measure is reduced to the concept of Hausdorff distance in the fuzzy sense.

5.1 Neutrosophic Hausdorff Distance

To commence, we consider two neutrosophic vertex graphs

$G_1 = (V_1, E_1, T_{v1}, I_{v1}, F_{v1})$  and  $G_2 = (V_2, E_2, T_{v2}, I_{v2}, F_{v2})$ , where  $V_i, i = 1, 2$  are the sets of nodes,  $E_i$ , where  $i = 1, 2$  are the sets of edges and  $T_{vi}, I_{vi}, F_{vi}$ , where  $i = 1, 2$  are the matrices whose elements are the true, indeterminate and false values defined for each element of  $V_i, i = 1, 2$ , respectively. We can now write the distances between the two neutrosophic vertex graphs  $G_1, G_2$  as follows:

$$NGD(G_1, G_2) = (T_{NGD}(G_1, G_2), I_{NGD}(G_1, G_2), F_{NGD}(G_1, G_2))$$

Where,

$$T_{NGD}(G_1, G_2) = \max(T_{NGd}(G_1, G_2), T_{NGd}(G_2, G_1))$$

$$I_{NGD}(G_1, G_2) = \max(I_{NGd}(G_1, G_2), I_{NGd}(G_2, G_1))$$

$$F_{NGD}(G_1, G_2) = \max(F_{NGd}(G_1, G_2), F_{NGd}(G_2, G_1))$$

And

$$T_{NGd}(G_1, G_2) = \max_{i \in V_1} \max_{j \in V_1} \min_{l \in V_2} \min_{j \in V_2} \|T_{v_2}(l, j) - T_{v_1}(i, j)\|$$

$$I_{NGd}(G_1, G_2) = \max_{i \in V_1} \max_{j \in V_1} \frac{1}{|V_2| \times |V_2|} \sum_{l \in V_2} \sum_{j \in V_2} \|I_{v_2}(l, j) - I_{v_1}(i, j)\|$$

$$F_{NGd}(G_1, G_2) = \min_{i \in V_1} \min_{j \in V_1} \max_{l \in V_2} \max_{j \in V_2} \|F_{v_2}(l, j) - F_{v_1}(i, j)\|$$

$NGd(G_2, G_1)$  can be computed in a similar way.

*Proposition 1:* The Neutrosophic vertex graph distance NGD satisfies the metric distance measure axioms:

A1) (Symmetry):  $NGD(G_1, G_2) = NGD(G_2, G_1)$ ,

A2) (Non-negativity):  $NGD(G_1, G_2) \geq 0$ ,

A3) (Coincidence): if  $NGD(G_1, G_2) = 0$  then  $G_1 = G_2$ ,

A4) (Triangle Inequality): for any three neutrosophic vertex graphs  $G_1, G_2$  and  $G_3$  we have:  $NGD(G_1, G_2) \leq NGD(G_1, G_2) + NGD(G_2, G_3)$ .

Proof: A1 and A2 can easily be proven.

A3): When  $NGD(G_1, G_2) = (T_{NGD}(G_1, G_2), I_{NGD}(G_1, G_2), F_{NGD}(G_1, G_2)) = (0,0,0)$ , that is every component of the triple which is the maximum of two positive values is zero, the values of  $T_{NGd}(G_i, G_j), I_{NGd}(G_i, G_j)$  and  $F_{NGd}(G_i, G_j)$  for  $i, j = 1, 2$  are all zeros. Namely the maximum distance among the nearest nodes in both  $G_1, G_2$  is zero. That means that the distance between each element of  $V_1$  and its nearest element in the set  $V_2$  is zero. That is each element in  $V_1$  coincides with an element in  $V_2$  and vice versa; hence  $V_1 = V_2$ .

A4): Consider any three neutrosophic graphs  $G_1 = (V_1, E_1, T_1, I_1, F_1),$

$G_2 = (V_2, E_2, T_2, I_2, F_2)$  and  $G_3 = (V_3, E_3, T_3, I_3, F_3)$ . For any

$i_k, j_k \in V_k, k = 1, 2, 3,$  we can easily see that:

$$\|T_3(i_3, j_3) - T_1(i_1, j_1)\| \leq \|T_3(i_3, j_3) - T_2(i_2, j_2)\| + \|T_2(i_2, j_2) - T_1(i_1, j_1)\|$$

where the values  $T_K(i_k, j_k), K=1, 2, 3,$  lie in the interval  $[0, 1]$ . Consequently, one can show that:

$$\begin{aligned} & \max_{i_1 \in V_1} \max_{j_1 \in V_1} \min_{i_3 \in V_3} \min_{j_3 \in V_3} \|T_3(i_3, j_3) - T_1(i_1, j_1)\| \\ & \leq \max_{i_2 \in V_2} \max_{j_2 \in V_2} \min_{i_3 \in V_3} \min_{j_3 \in V_3} \|T_3(i_3, j_3) - T_2(i_2, j_2)\| \\ & + \max_{i_1 \in V_1} \max_{j_1 \in V_1} \min_{i_2 \in V_2} \min_{j_2 \in V_2} \|T_2(i_2, j_2) - T_1(i_1, j_1)\| \end{aligned}$$

That is:  $T_{NGd}(G_1, G_3) \leq T_{NGd}(G_2, G_3) + T_{NGd}(G_1, G_2)$  and similarly  $T_{NGd}(G_3, G_1) \leq T_{NGd}(G_3, G_2) + T_{NGd}(G_2, G_1)$

Hence,  $\max(T_{NGd}(G_1, G_3), T_{NGd}(G_3, G_1)) \leq \max(T_{NGd}(G_2, G_3), T_{NGd}(G_3, G_2)) + \max(T_{NGd}(G_1, G_2), T_{NGd}(G_2, G_1))$ . Then,  $T_{NGD}(G_1, G_3) \leq T_{NGD}(G_1, G_2) + T_{NGD}(G_2, G_3)$ .

The same procedure goes for both  $I_{NGD}$  and  $F_{NGD}$ . That leads to

$$NGD(G_1, G_3) \leq NGD(G_1, G_2) + NGD(G_2, G_3).$$

### 5.2 Modified Neutrosophic Hausdorff Distance

Consider two neutrosophic vertex graphs  $G_1 = (V_1, E_1, T_{v1}, I_{v1}, F_{v1})$  and  $G_2 = (V_2, E_2, T_{v2}, I_{v2}, F_{v2})$ , where  $V_i, i=1, 2$  are the sets of nodes,  $E_i$ , where  $i=1, 2$  are the sets of edges and  $T_{vi}, I_{vi}, F_{vi}$ , where  $i=1, 2$  are the matrices whose elements are the true, indeterminate and false values defined for each element of  $V_i, i=1, 2$ , respectively. We can now write the distances between the two neutrosophic vertex graphs  $G_1, G_2$  as follows:

$$MNGD(G_1, G_2) = (T_{MNGD}(G_1, G_2), I_{MNGD}(G_1, G_2), F_{MNGD}(G_1, G_2))$$

Where,

$$T_{MNGD}(G_1, G_2) = \max(T_{MNGd}(G_1, G_2), T_{MNGd}(G_2, G_1))$$

$$I_{MNGD}(G_1, G_2) = \max(I_{MNGd}(G_1, G_2), I_{MNGd}(G_2, G_1))$$

$$F_{MNGD}(G_1, G_2) = \max(F_{MNGd}(G_1, G_2), F_{MNGd}(G_2, G_1))$$

And,

$$T_{MNGd}(G_1, G_2) = \frac{1}{|V_1| \times |V_1|} \sum_{i \in V_1} \sum_{j \in V_1} \min_{i \in V_2} \min_{j \in V_2} \|T_2(I, J) - T_1(i, j)\|$$

$$I_{MNGd}(G_1, G_2) = \frac{1}{|V_1| \times |V_1|} \sum_{i \in V_1} \sum_{j \in V_1} \frac{1}{|V_2| \times |V_2|} \sum_{I \in V_2} \sum_{J \in V_2} \|T_2(I, J) - T_1(i, j)\|.$$

$$F_{MNGd}(G_1, G_2) = \frac{1}{|V_1| \times |V_1|} \sum_{i \in V_1} \sum_{j \in V_1} \max_{I \in V_2} \max_{J \in V_2} \|F_2(I, J) - F_1(i, j)\|$$

Similarly, we can find  $MNGd(G_2, G_1)$ .

*Proposition 2:* The Modified Neutrosophic vertex graph distance MNGD satisfies the metric distance measure axioms:

AA1) (symmetry):  $MNGD(G_1, G_2) = MNGD(G_2, G_1)$ ,

AA2) (non-negativity):  $MNGD(G_1, G_2) \geq 0$ ,

AA3) (coincidence): if  $MNGD(G_1, G_2) = 0$  then  $G_1 = G_2$ ,

AA4) (triangle inequality): for any three neutrosophic vertex graphs  $G_1, G_2$  and  $G_3$  we have:

$$MNGD(G_1, G_3) \leq MNGD(G_1, G_2) + MNGD(G_2, G_3).$$

Proof: Similar to the procedure used to prove Proposition 1.

### 5.3 Probabilistic Neutrosophic Hausdorff Distance

To overcome the robustness of both the classical and the modified Hausdorff distance, Hue and Hancock [9] have developed a probabilistic variant of the Hausdorff distance. This measure the similarity of the set of attributes rather than using defined set based distance measures. To commence, we recall two edge graphs  $G_1 = (V_1, E_1, T_{e1}, I_{e1}, F_{e1})$ ,  $G_2 = (V_2, E_2, T_{e2}, I_{e2}, F_{e2})$  as mentioned before, the set of all nodes connected to the node  $I \in G_2$  by an edge is defined as:

$C_I^2 = \{J | (I, J) \in E_2\}$ , and the corresponding set of nodes connected to the node  $i \in G_1$  by an edge  $C_i^1 = \{j | (i, j) \in E_1\}$ . A measure for the match of the graph  $G_2$  onto  $G_1$  is:

$$PNGD(G_1, G_2) = (T_{PNGD}(G_1, G_2), I_{PNGD}(G_1, G_2), F_{PNGD}(G_1, G_2))$$

where,  $T_{PNGD}(G_1, G_2) = \max(T_{PNGd}(G_1, G_2), T_{PNGd}(G_2, G_1))$

$$I_{PNGD}(G_1, G_2) = \max(I_{PNGd}(G_1, G_2), I_{PNGd}(G_2, G_1))$$

$$F_{PNGD}(G_1, G_2) = \max(F_{PNGd}(G_1, G_2), F_{PNGd}(G_2, G_1))$$

and,  $T_{PNGd}(G_1, G_2) = \frac{1}{|V_2| \times |V_1|} \sum_{i \in V_1} \sum_{j \in C_i^1} \max_{I \in V_2} \max_{J \in C_I^2} P((i, j) \rightarrow (I, J) | T_{e2}(I, J), T_{e1}(i, j))$

$$I_{PNGd}(G_1, G_2) = \frac{1}{|V_2| \times |V_1|} \sum_{i \in V_1} \sum_{j \in C_i^1} \max_{I \in V_2} \max_{J \in C_I^2} P((i, j) \rightarrow (I, J) | I_{e2}(I, J), I_{e1}(i, j))$$

$$F_{PNGd}(G_1, G_2) = \frac{1}{|V_2| \times |V_1|} \sum_{i \in V_1} \sum_{j \in C_i^1} \min_{I \in V_2} \min_{J \in C_I^2} P((i, j) \rightarrow (I, J) | F_{e2}(I, J), F_{e1}(i, j))$$

In this formula the posteriori probability  $P((i, j) \rightarrow (I, J) | T_{e2}(I, J), T_{e1}(i, j))$  represents the true value for the match of the  $G_2$  edge (I, J) onto the  $G_1$  edge (i, j) provided by the corresponding

pair of  $T_{e_2}(I, J)$  and  $T_{e_1}(i, j)$ . This similarity measure works as follows, it commence with finding the maximum probability over the nodes in  $C_i^2$  then averaging the edge compatibilities over the nodes  $C_i^1$ . Similarly we consider the maximum probability over the nodes in the graph  $G_2$  followed by averaging over the nodes in  $G_1$ . It worth mentioned here that unlike Neutrosophic Hausdorff distance this similarity measure does not satisfy the distance axioms. Moreover, while the true components of the Neutrosophic Hausdorff distance measures the maximum distance between two sets of observations, our measures here returns the maximum similarity. Back to the rest formulae of the posteriori probability which represent the indeterminacy value and the false value for the match of the  $G_2$  edge  $(I, J)$  onto the  $G_1$  edge  $(i, j)$  using similar procedure to the true value. We still need to compute the probabilities  $P((i, j) \rightarrow (I, J)|T_{e_2}(I, J), T_{e_1}(i, j))$ ,

$P((i, j) \rightarrow (I, J)|I_{e_2}(I, J), I_{e_1}(i, j))$  and  $P((i, j) \rightarrow (I, J)|F_{e_2}(I, J), F_{e_1}(i, j))$ . For that purpose we will use a robust weighting function:

$$P((i, j) \rightarrow (I, J)|T_{e_2}(I, J), T_{e_1}(i, j)) = \frac{\Gamma_\sigma(\|T_{e_2}(I, J), T_{e_1}(i, j)\|)}{\sum_{(I, J) \in E_2} \Gamma_\sigma(\|T_{e_2}(I, J), T_{e_1}(i, j)\|)}$$

$$P((i, j) \rightarrow (I, J)|I_{e_2}(I, J), I_{e_1}(i, j)) = \frac{\Gamma_\sigma(\|I_{e_2}(I, J), I_{e_1}(i, j)\|)}{\sum_{(I, J) \in E_2} \Gamma_\sigma(\|I_{e_2}(I, J), I_{e_1}(i, j)\|)}$$

$$P((i, j) \rightarrow (I, J)|F_{e_2}(I, J), F_{e_1}(i, j)) = \frac{\Gamma_\sigma(\|F_{e_2}(I, J), F_{e_1}(i, j)\|)}{\sum_{(I, J) \in E_2} \Gamma_\sigma(\|F_{e_2}(I, J), F_{e_1}(i, j)\|)}$$

Where  $\Gamma_\sigma(\cdot)$  is a distance weighting function. There are several alternative robust weighting functions. For instance, one may consider the Gaussian of the form

$$\Gamma_\sigma(p) = \exp\left(\frac{-\rho^2}{2\sigma^2}\right) \text{ where } \rho^2 = \left(T_{e_2}(I, J) - T_{e_1}(i, j)\right)^2 \text{ according to the true part,}$$

$\rho^2 = \left(I_{e_2}(I, J) - I_{e_1}(i, j)\right)^2$  according to the indeterminacy part and  $\rho^2 = \left(F_{e_2}(I, J) - F_{e_1}(i, j)\right)^2$  according to the false part, where  $\sigma$  is the standard deviation. The similarity measure can be viewed as an average pairwise attribute consistency measure.

## 6. Conclusion and Future Work

Graphs are the most powerful and handy tool used in representing objects and concepts. This paper is dedicated for presenting new neutrosophic similarity and dissimilarity measures between neutrosophic graphs. The proposed distance measures are based on the Hausdorff distance, a modified and a probabilistic variant of the Hausdorff distance, additionally we proved that the given Neutrosophic Hausdorff and the Neutrosophic Modified Hausdorff distances satisfy the metric distance measure axioms. The aim is to use those measures for the purpose of matching graphs whose structure is described in the neutrosophic domain. In our plan for the future we will consider using the deduced measurements in image processing applications, such as image clustering and segmentation.

## References

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