Plastic Surgery Facial Image Correspondence: A Near Set Approach

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ABSTRACT
This article introduces perceptual resemblance of plastic surgery facial images using near sets. Near sets are disjoint sets that resemble each other. Near sets facilitate measurement of similarity between objects (digital images) based on features values (obtained by probe functions) that describe the objects. Resemblance between disjoint sets occurs whenever there are observable similarities between the objects in the sets. Each list of feature values defines an object's description. Objects that are perceived as similar based on their descriptions are grouped together. These groups of similar objects can provide information and reveal patterns about objects of interest in the disjoint sets. The practical application of near set theory on the pre and post plastic surgery facial images to extract resemblance between them was introduced in this article. Facial plastic surgery can be reconstructive to correct facial feature anomalies or cosmetic to improve the appearance. Both corrective as well as cosmetic surgeries alter the original facial information to a great extent thereby posing a great challenge for face recognition algorithms. The main aim of this article is to measure the degree of resemblance of facial images before and after plastic surgery. Blepharoplasty (Eyelid surgery) and Rhinoplasty (Nose surgery) is being considered for this research work due to the maximum number of individuals and easy to differentiate faces before and after plastic surgery .tHD ,tNM and tHM is being used to measure the degree of resemblances between plastic surgery images. tHD measure shows around 100% nearness as compared to tNM and tHM for all features . These measures can also be used in increasing the efficiency of any face recognition system containing plastic surgery images.

General Terms
Plastic Surgery, Resemblance, Blepharoplasty, Rhinoplasty, Tolerance nearness measure, Disjoint sets.

Keywords
Near sets, Rough sets, Resemblance, Plastic Surgery, Tolerance Near sets.

1. INTRODUCTION
Plastic surgery is a sophisticated operational technique that is used across the world for improving the facial appearance. For instance to remove acne scars, to become white, to remove dark circles and many more. Plastic surgery can be broadly classified in two different categories such as global plastic surgery and local plastic surgery. Global surgery changes the complete facial structure whereas in local plastic surgery certain parts of faces are changed. To recognize a face after plastic surgery might lead to rejection of genuine users or acceptance of impostors. To this challenge yet much literature is not available. Very few researchers till now have contributed in this field. In [3] authors have shown the comparative study of different face recognition algorithms for plastic surgery. Based on the experimentation carried out by authors it has been concluded that face recognition algorithms such as PCA, FDA, GF, LLA, LBP and GNN have shown recognition rate not more than 40% for local plastic surgery. Moreover, for global surgery it was merely up to 10%. Among all the algorithms, geometrical feature based approach has proven to a great extent comparatively for local plastic surgery. This article introduces perceptual resemblance of plastic surgery facial images using near sets . Near sets were introduced by James Peters in 2006[10] and formally defined in 2007[11] and elaborated in [12]. Near sets result from a generalization of rough set theory. One set X is near another set Y to the extent that the description of at least one of the objects in X matches the description of at least one of the objects in Y. The hallmark of near set theory is object description and the classification of objects by means of features [13]. Rough sets were introduced by Zdzisław Pawlak during the early 1980s [14][15] and provide a basis for perception of objects viewed on the level of classes rather than the level of individual objects. A fundamental basis for near set as well as rough set theory is the approximation of one set by another set considered in the context of approximation spaces. It was observed by Ewa Orłowska in 1982 that approximation spaces serve as a formal counterpart of perception, or observation [16].

The contribution of this article is a framework for measuring the degree of resemblances between plastic surgery facial images using tolerance nearness measure(tNM) and tolerance Hausdorff distance measure(tHD).A brief introduction to near sets is given in Sec.2 , Sec 3 elaborates about the tNM and tHD , Sec 4 discusses about facial plastic surgery especially Blepharoplasty (Eyelid surgery) and Rhinoplasty (Nose surgery) is being considered because of the presence of maximum number of individuals and easy to differentiate faces before and after plastic surgery , Sec 5 shows the results and discussions followed by the conclusion in Sec.6.

2. NEAR SETS

Let $X, Y \subseteq O, B \subseteq F$ .Set X is near Y if and only if there exists $x \in X$, $y \in Y$, $\phi_i \in B$ such that $x \cong_{B,\varepsilon} y$.
Object recognition problems, especially in adaptive learning and images [1] and the problem of the nearness of objects have motivated the introduction of near sets[10,11,12].

2.1 Tolerance Nearness Relation (TNR):

Let $\langle O, F \rangle$ be a perceptual system and let $X, Y \subseteq O, \varepsilon \in R$ .A set X is near to a set Y within perceptual system $\langle O, F \rangle$ iff there exists $x \in X$ and $y \in Y$ and there is $B \subseteq F$ such that $x \cong_{B,\varepsilon} y$.

2.2 Weak Perceptual Tolerance Relation (WPTR):

Let $\langle O, F \rangle$ be a perceptual system and let $\varepsilon \in R$, $\phi_i \in F$,Then the weak perceptual tolerance relation $\cong_{B,\varepsilon}$ is defined as follows:

$$\cong_{B,\varepsilon} = \{(x, y) \in O \times O : \exists \phi_i \in F . |\phi_i(x) - \phi_i(y)| \le \varepsilon\}$$

(a)

Fig. 1(a) Covering of two sets showing no relationship between two sets.

2.3Tolerance Near Sets(TNS):Let $\langle O, F \rangle$ be a perceptual system and let $\varepsilon \in R$, $B \subseteq F$,Further ,let $X, Y \subseteq O$ denotes disjoint sets with covering determined by the tolerance relation $\cong_{B,\varepsilon}$,and let $H_{\cong_{B,\varepsilon}}(X)$, $H_{\cong_{B,\varepsilon}}(Y)$ denote the set of tolerance classes for X, Y respectively. Sets X, Y are tolerance near sets iff there are tolerance classes $A \in H_{\cong_{B,\varepsilon}}(X)$, $B \in H_{\cong_{B,\varepsilon}}(Y)$ such that A is near to B.

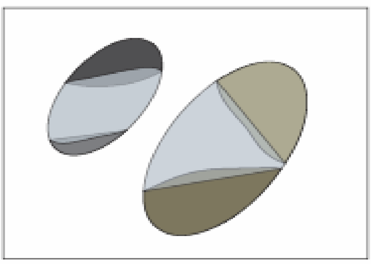
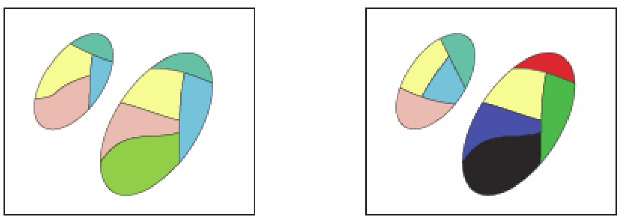


Fig. 1(b) Covering created using WPTR showing a relationship between two sets.

Observe that two sets $X, Y \subseteq O$ are tolerance near sets, if they satisfy the tolerance nearness relation. Also, notice that Tolerance near sets are a variation of the original definition of near sets using the indiscernibility relation [10]. The perceptual tolerance relation could produce a covering as given in Fig.1(a) (where each colour represents a difference tolerance class), indicating these two sets of objects, representing some perceptual information in the original problem domain, are not related to each other. An example of tolerance near sets is given in Fig.1(b), where the colours represent different tolerance classes, and classes with the same colour represent the situation where A./FB .

3. NEARNESS MEASURE

The nearness measure was created out of a need to determine the degree that near sets resemble each other, a need which arose during the application of near set theory to the practical applications of image correspondence and content-based image retrieval. Specifically, the nearness measure was introduced by Henry and Peters in [18]. The nearness measure presents a systematic approach to determining the degree of similarity between a pair of disjoint sets, an idea that can be visualized by asking “which pair of sets in Fig.2 are more similar?” The nearness measure was first proposed in working with the indiscernibility relation and equivalence classes. The approach was that the degree of nearness of sets in a perceptual system is determined by the cardinalities of the equivalence classes that have the same description .For sets that are considered “more similar” as in Fig.2(a) , there should be more pairs of equivalence classes (from the respective sets) that have matching descriptions. Consequently, the nearness measure is determined by counting the number of objects in equivalence classes that have matching descriptions. Thus, the sets in Fig.2 (a) are closer (more near) to each other in terms of their descriptions than the sets in Fig.2 (b). Moreover, this notion can be generalized to tolerance classes as is the case in the following definition.



(a) (b)

Fig. 2 (a) High degree of nearness (b) Low degree of nearness Tolerance Nearness Measure (tNM).

3.1Nearness Measure: Let $\langle O, F \rangle$ be a perceptual system and let $\varepsilon \in R$, $B \subseteq F$, Furthermore let X and Y be two disjoint sets and let $Z = X \cup Y$ then a nearness between two sets is given by:

$$tNM_{\cong_{B,\varepsilon}}(X,Y) = \left(\sum_{C \in H_{\cong_{B,\varepsilon}}(Z)} |C| \right)^{-1} \cdot \sum_{C \in H_{\cong_{B,\varepsilon}}(Z)} |C| \frac{\min(|C \cap X|, |C \cap Y|)}{\max(|C \cap X|, |C \cap Y|)}$$

The idea behind nearness measure is that similar sets should produce equivalence classes with matching descriptions. However, the addition of the perceptual tolerance relations subtly adds to the complexity of calculating the measure. The main idea stays the same, namely, similar sets should produce classes that are evenly divided between the two sets X and Y. It is the approach to calculating the measure that is important with the addition of the tolerance relation. For instance, using the indiscernibility relation it is simply a matter of determining the equivalence classes of objects in both sets and then comparing the description of each equivalence class in set X to the description of each equivalence class in set Y. In contrast, the process of calculating the measure under the perceptual tolerance relation involves first finding the tolerance classes of all objects in the union of X and Y . This approach is best because of the fact that all objects within a tolerance class must satisfy the tolerance relation. Because of this fact, a comparison of two tolerance classes cannot be made directly without comparing all the objects in one class with all the objects in the other class. As a result, a more efficient approach is to find the tolerance classes of the union of X and Y , and then determine which portion of each tolerance class (form the covering of Z) belongs to X and Y , which is why C is intersected with X and Y in above equation. In any event, the measure is calculated by counting the number of objects that belong to sets X and Y for each tolerance class, and then comparing these counts as a proper fraction (guaranteed by the min and max functions). Then, the final value of the measure is simply a weighted average of all the fractions. A weighted average was selected to give preference to larger tolerance classes with the idea that a larger tolerance class contains more perceptually relevant information. The nearness measure produces values in the interval [0, 1], where, for a pair of sets X, Y, a value of 0 represents no resemblance in terms of the probe functions in B, and a value of 1 indicates the sets X, Y completely resemble each other, a fact that can be seen by calculating the nearness measure on a single set, *i.e.* $tNM_{\cong_{B,\varepsilon}}(X,X)=1$

3.2Hausdorff Distance: The Hausdorff distance is used to measure the distance between sets in a metric space [19], and is defined as

$$d_H(X,Y)=\max\left\{\sup_{x\in X}\inf_{y\in Y} d(x,y), \sup_{y\in Y}\inf_{x\in X} d(x,y)\right\}$$

where sup and inf refer to the supremum and infimum, and d(x, y) is the distance metric (in this case it is the L2 norm). The distance is calculated by considering the distance from a single element in a set X to every element of set Y , and the shortest distance is selected as the infimum (see, *e.g.*, Fig. 3).

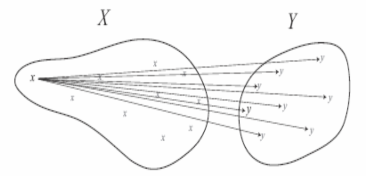


Fig.3 Hausdorff distance between two sets.

This process is repeated for every $x \in X$ and the largest distance (supremum) is selected as the Hausdorff distance of the set X to the set Y . This process is then repeated for the set Y because the two distances will not necessarily be the same. Keeping this in mind, the measure tHD [18] is defined as

$$tHD_{\cong_{B,\varepsilon}}(X,Y)=\left(\sum_{C\in H_{B,\varepsilon}(Z)}|C|\right)^{-1}\cdot\sum_{C\in H_{B,\varepsilon}(Z)}|C|(\sqrt{l}-d_H(C\cap X, C\cap Y)$$

Observe, that low values of the Hausdorff distance correspond to a higher degree of resemblance than larger distances. Consequently, the distance is subtracted from the largest distance $\sqrt{l}$. Also, notice that the performance of the Hausdorff distance is poor for low values of ε , since, as tolerance classes start to become equivalence classes (*i.e.* as $\varepsilon \to 0$), the Hausdorff distance approaches 0 as well. Thus, if each tolerance class is close to an equivalence class, the resulting distance will be zero, and consequently the measure will produce a value near to 1, even if the images are not alike. In contrast, as " increases, the members of classes tend to become separated in feature space, and, as a result, only classes with objects that have objects in X that are close to objects in Y will produce a distance close to zero. What does this imply? If for a larger value of ε , relatively speaking, the set of objects $Z = X \cup Y$ still produces tolerance classes with objects that are tightly clustered, then this measure will produce a high measure value. Notice, that this distinction is only made possible if ε is relaxed. Otherwise, all tolerance classes will be tightly clustered. The Hausdorff distance is a natural choice for comparison with the tNM nearness measure because it measures the distance between sets in a metric space. Recall, that tolerance classes are sets of objects with descriptions in l-dimensional feature space. The nearness measure evaluates the split of a tolerance class between sets X and Y, where the idea is that a tolerance class should be evenly divided between X and Y, if the two sets are similar (or the same). In contrast, the Hausdorff distance measures the distance between two sets. Here the distance being measured is between the portions of a tolerance class in sets X and Y. Thus, two different measures can be used on the same data, namely the tolerance classes obtained from the union of X and Y.

3.3Hamming Measure: The Hamming measure introduced in this section was inspired by the Hamming measure in [103], and since the Hamming measure is not defined in terms of sets, it was modified to give the following

$$tHM_{\cong_B}(X,Y)=\frac{1}{|H_{\cong_B}(Z)|}\cdot\sum_{C\in H_{\cong_B}(C)}1.(\|avgn|(C\cap X)-avgn(C\cap Y)\|_2\le th)$$

where $1(\cdot)$ is the indicator function and avgn ($C\cap X$)is the average feature vector used to describe objects in $C\cap X$. For example, the average feature vector can be calculated by adding all the values for a specific feature in the feature vector in $C\cap X$, and then dividing by the number of objects. The idea behind this measure is that, for similar sets, the average feature vector of the portion of a tolerance class (obtained from $Z = X \cup Y$ that lies in X should have values similar to the average feature vector of the portion of the tolerance class that lies in Y . Observe, that if $th = \varepsilon$, this function will simply count the number of classes that are not singletons, *i.e.* classes that contain more than one element, since all objects have descriptions whose distances are less than ε . If th $= \varepsilon$, than this measure will perform best for low levels of ε , since only sets that resemble each other will contain classes with cardinality greater than one. Otherwise, this measure will perform in a similar manner to tHD, namely, this measure will produce high values for classes which have objects in X that are close to objects in Y with respect to *th*.

4. PLASTIC SURGERY IMAGE CORRESPONDENCE

Plastic surgery is generally used for improving the facial appearance, for example, removing birth marks, moles, scars and correcting disfiguring defects. When an individual undergoes plastic surgery, the facial features are reconstructed either globally or locally. In general, this process changes the appearance. Plastic surgery, results being long lasting or even permanent, provide an easy and robust way to evade law and security mechanism. Local plastic surgery would be surgery for correcting jaw and teeth structure, nose structure, chin, forehead and eyelids etc. Apart from local plastic surgery, plastic surgery can be performed to completely change the facial structure known as global plastic surgery.

The problem considered in this paper is how to measure the degree of resemblance of facial images before and after plastic surgery. This will also help the face recognition system to improve its performance as far as recognition capability is concerned. Blepharoplasty (Eyelid surgery) and Rhinoplasty (Nose surgery) is being considered for this research work due to the maximum number of individuals(see table 1) and easy to differentiate faces before and after plastic surgery. Blepharoplasty is surgical modification of the eyelid. Excess tissue such as skin and fat are removed or repositioned, and surrounding muscles and tendons may be reinforced. It can be both a functional and cosmetic reasons. Rhinoplasty , also *nose job*, is a plastic surgery procedure for correcting and reconstructing the form, restoring the functions, and aesthetically enhancing the nose by resolving nasal trauma(blunt, penetrating, blast), congenital defect, respiratory impediment, and a failed primary Rhinoplasty.

Table 1 Plastic surgery database [9]

Type of Plastic Surgery	No. of Individuals
Rhinoplasty (Nose surgery)	71
Blepharoplasty (Eyelid	67
Skin peeling (Skin	57
Brow lift (Forehead surgery)	54
Rhytidectomy (Face lift)	49
Liposhaving (Facial	44
Mentoplasty (Chin surgery)	29
Otoplasty (Ear surgery)	26
Malar augmentation (Cheek	21
Others(Craniofacial, Dermabrasion,Lip augmentation, Melasma etc)	88

Blepharoplasty is surgical modification of the eyelid. Excess tissue such as skin and fat are removed or repositioned, and surrounding muscles and tendons may be reinforced. It can be both a functional and cosmetic reasons. It is often done as an elective surgery for cosmetics reasons. Lower eyelid blepharoplasty is almost always done for cosmetic reasons, to improve puffy lower eyelid "bags" and reduce the wrinkling of skin. *Asian blepharoplasty* or *double eyelid surgery* is a special type of blepharoplasty that creates a crease in the upper eyelid. his "supratarsal fold" is common in many races but absent in about half of Asians. Surgery can artificially create this crease and make a 'single-lidded' patient appear 'double-lidded'.

1(a) 1(b) 2(a) 2(b)

Fig.4 Blepharoplasty: 1(a)Before Plastic Surgery(upper eyelid), 1(b)After Plastic Surgery(upper eyelid) ,2(a) Before Plastic Surgery(upper eyelid) ,2(b) After Plastic Surgery(lower eyelid)It is the most popular form of cosmetic surgery among those of east and southeast Asian background.

Blepharoplasty is sometimes needed for functional reasons. When an advanced amount of upper eyelid skin is present, the skin may protrude over the eyelashes and causes a loss of peripheral vision. The outer and upper parts of the visual field are most commonly affected and the condition may cause difficulty with activities such as driving or reading. In this circumstance, upper eyelid blepharoplasty is performed to improve peripheral vision. There are the following conditions for eyelid surgery:-

• Excess skin obscuring the natural fold of the upper eyelids.

• Loose skin hanging down from the upper eyelids, perhaps impairing vision.

• A puffy appearance to the upper eyelids, making the eyes look tired.

• Excess skin and fine, “crepe paper type” wrinkles of the lower eyelids.

• Bags and dark circles under the eyes.

• Lower eyelid droopiness.

Rhinoplasty is a plastic surgery procedure for correcting and reconstructing the form, restoring the functions, and aesthetically enhancing the nose by resolving nasal trauma(blunt, penetrating, blast), congenital defect, respiratory impediment, and a failed primary rhinoplasty. Surgery to reshape the nose (Rhinoplasty) is one of the more common plastic surgery procedures and is performed to improve the external appearance and/or internal breathing, which may have been a result of birth deformity, trauma, genetic influences, infection, aging, tumours or other diseases. The procedure is:

- Change the size or shape of your nose
- Remove an unwanted hump
- Alter the shape of the tip or bridge of your nose
- Narrow or expand the width of your nostrils.
- Improve symmetry
- Change the angle between your nose and upper lip
- Improve breathing

- Improve the profile or augmentation of the dorsum of the nose – augmentation rhinoplasty / nasal implant / nasal augmentation.

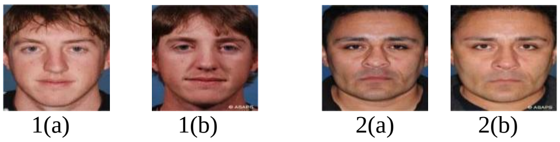


Fig.5 Rhinoplasty: 1(a) Before Plastic Surgery,1(b) After Plastic Surgery, 2(a) Before Plastic Surgery, 2(b) After Plastic Surgery.

4.1TNMR (Tolerance Nearness Measure Resemblance) Algorithm

Input-*Z=X , Y*
Output- *tNM ,tHD, tHM*
Initialize C← 0

1. Take two images X and Y.
2. Divide the images X and Y into sub-images of sizes p×q and m x n respectively.
3. Extract tolerance classes $H \cong_{B,\varepsilon} (Z)$ that depends upon different features i.e average grey, normalized R, normalized G, normalized B and Shanon entropy.
4. For each tolerance class repeat step 5 –step 6
5. Count the number of pixels of sub-images X and Y.
6. Add to C.
7. Calculate a tolerance class ratio r is equal to the minimum values/maximum values (of the sub-images X and Y).
8. Multiply r to C.
9. For each tolerance class ratio repeat step 7-step 8 and then add values to the previous values of step 8.
10. Calculate

$$tNM_{\cong_{B,\varepsilon}}(X,Y)=\left(\sum_{C\in H_{\cong_{B,\varepsilon}}(Z)}|C|\right)^{-1}\cdot\sum_{C\in H_{\cong_{B,\varepsilon}}(Z)}|C|\frac{\min(|C\cap X|,|C\cap Y|)}{\max(|C\cap X|,|C\cap Y|)}$$

$$tHD_{\cong_{B,\varepsilon}}(X,Y)=\left(\sum_{C\in H_{B,\varepsilon}(Z)}|C|\right)^{-1}\cdot\sum_{C\in H_{B,\varepsilon}(Z)}|C|(\sqrt{l}-d_H(C\cap X,C\cap Y))$$

$$tHM_{\cong_B}(X,Y)=\frac{1}{|H_{\cong_B}(Z)|}\cdot\sum_{C\in H_{\cong_B}(C)}1.(\|avgn|(C\cap X)-avgn(C\cap Y)\|_2\le th)$$

5. RESULTS AND DISCUSSIONS

Fig.6 Before and after upper eyelid plastic surgery images

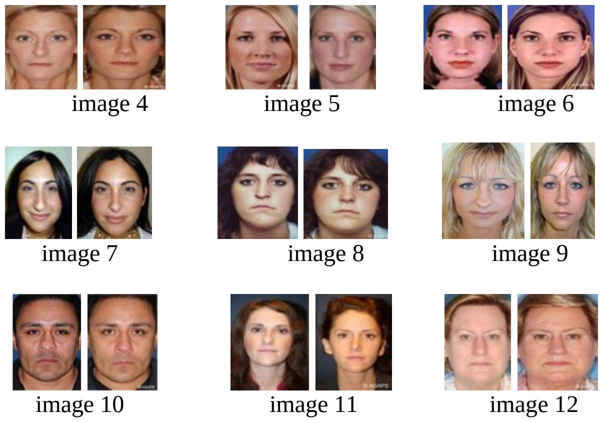


Fig.7 Before and after nose plastic surgery images

Total twelve upper eyelid i.e Blepharoplasty and Rhinoplasty (Nose surgery) images (see Fig.6,Fig.7 before and after plastic surgery images i.e image1 to image12) were considered for three nearness measures (tNM,tHD,tHM) having five different features(Average Grey, Normalized R, Normalized G, Normalized B and Shanon's Entropy).Assuming that the image dimensions must be same before and after plastic surgery.

Table 2(a) Tolerance Nearness Measures for tolerance=0.1(Rhinoplasty)

Feature	tNM	tHD	tHM
Avg.Grey	0.6714	0.9958	0.5553
Normalized R	0.8180	0.9975	0.5478
Normalized G	0.8441	0.9990	0.4625
Normalized B	0.7927	0.9980	0.6259
Shannon's Entropy	0.8123	0.9980	0.6660

Table 2(b) Tolerance Nearness Measures for tolerance=0.01(Rhinoplasty)

Feature	tNM	tHD	tHM
Avg.Grey	0.7091	0.9964	0.5834
Normalized R	0.7348	0.9982	0.3571
Normalized G	0.8131	0.9983	0.2458
Normalized B	0.7039	0.9975	0.3019
Shannon's Entropy	0.8168	0.9978	0.5855

Table 3(a) Tolerance Nearness Measures for tolerance=0.1(Blepharoplasty)

Feature	tNM	tHD	tHM
Avg.Grey	0.4555	0.9967	0.0143
Normalized R	0.5008	0.9978	0.0086
Normalized G	0.5276	0.9985	0.0151
Normalized B	0.5004	0.9980	0.0379
Shannon's Entropy	0.5548	0.9972	0.0106

Table 3(b) Tolerance Nearness Measures for tolerance=0.01(Blepharoplasty)

Feature	tNM	tHD	tHM
Avg.Grey	0.5056	0.9978	0.0323
Normalized R	0.5008	0.9978	0.0086
Normalized G	0.5276	0.9985	0.0151
Normalized B	0.5004	0.9980	0.0379
Shannon's Entropy	0.5548	0.9972	0.0106

The sub-image size was set to 25 and epsilon ε=0.1 and 0.01.Table 2(a) and 2(b) shows the nearness measure for ε=0.1 and 0.01 respectively. It has been observed that Tolerance Hausdroff distance (tHD) measures are high (very close to 1) than tolerance nearness measure (tNM) and tolerance hamming measure (tHM) .Values for six images were shown in the tables.

Above 70% resemblance was found for both Rhinoplasty and Blepharoplasty images (see table 2(a) and 3(a) when ε=0.1 and ε=0.01)using tNM and 50% to 60% resemblance for ε=0.01 (see table 2(b) and 3(b))and ε=0.1respectively using tNM. similarly around 100% resemblance was found when tHD was used as shown in tables from 2(a) to 3(b). As tolerance decreases the nearness measure also decreases because the number of tolerance classes decreases. tHD is one of the possible metric which can be used to measure the resemblances between before and plastic surgery images as compared to tNM and tHM. These measure can also be used in increasing the efficiency of any face recognition system containing plastic surgery images.

6. CONCLUSION

The practical application of near set theory on the pre and post plastic surgery facial images to extract resemblance between them was introduced in this article. Facial plastic surgery can be reconstructive to correct facial feature anomalies or cosmetic to improve the appearance. Both corrective as well as cosmetic surgeries alter the original facial information to a great extent thereby posing a great challenge for face recognition algorithms. The main aim of this article is to measure the degree of resemblance of facial images before and after plastic surgery. Blepharoplasty (Eyelid surgery) and Rhinoplasty (Nose surgery) is being considered for this purpose due to the availability of maximum number of individuals and it is easy to differentiate faces before and after plastic surgery. tHd ,tNM and tHM is being used to measure the degree of resemblances between plastic surgery images. tHD measure shows around 100% nearness as compared to tNM and tHM for all features . More features can be considered like Pal's Entropy, Zernike Moments etc to analyze the resemblances between images, similarly we can use other metrics also to measure the distances . These measure can also be used in increasing the efficiency of any face recognition system containing normal facial images and plastic surgery images.

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