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MEASUREMENT OF OBJECT RECOGNITION BY USING NORMALIZED UNMATCHED POINTS

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ABSTRACT

The object (Ex: human face) is the premier biometric in the field of object recognition, not only because of its easy acquisition but also since it has been extensively studied and several good algorithms exist for face recognition. However, there are several challenges in object recognition like different, backgrounds and illumination conditions to name a few, because of which the task becomes difficult. In this paper, we propose a new powerful measure called Normalized Unmatched Points (NUP) to compare grey images and discriminate facial images. Fundamentally, NUP works by counting the number of unmatched pixels between two images after they have been suitably pre-processed. An efficient algorithm for the computation of the NUP measure is also presented in this thesis. It has been shown that the NUP measure performs better than other existing similar variants on most of the databases.

KEYWORDS: Object Recognization

1. INTRODUCTION

Humans do face recognition on regular basis naturally and so effortlessly that we never think of what exactly we looked at in the face. Face is a three dimensional object that is subjected to varying illumination, poses, expressions and so on which has to be identified based on its two dimensional image. Hence, Face recognition is an intricate visual pattern recognition problem which can be operated in these modes

- Face Verification (or Authentication) that compares a query face image against a template face image whose identity is being claimed (i.e. one to one).
- Face Identification (or Recognition) that compares a query face image against all the template images in the database to determine the identity of the query face (i.e. One to many).
- Watch List that compares a query face image only to a list of suspects (i.e.one to few).

Most of the face recognition methods either rely on detecting local facial feature (feature extraction), within face as eyes, nose and mouth and use them for recognition or globally analysing a face as a whole for identifying the person. A face recognition system generally consists of four modules Face Detection, Face Normalization, Face Feature Extraction and Face Feature Matching.

Some of the conditions that should be accounted for when detecting faces are:

- **Occlusion:** face may be partially occluded by other objects
- **Presence or absence of structural components:** beards, moustaches and glasses
- **Facial expression:** face appearance is very much affected by a person's facial expression

- **Pose (Out-of Plane Rotation):** frontal, 45 degree, profile, upside down
- **Orientation (In Plane Rotation):** face appearance directly varies for different rotations about the camera's optical axis
- **Imaging conditions:** lighting (direction and intensity), camera characteristics, resolution

Face recognition is done after detection; some of the related problems include [23]:

- Face Localization
  - Determine face location in the image
  - Assume single face
- Face Feature Extraction
  - Determining location of various facial features as eyes, nose, nostrils, eyebrow, mouth, lips, ears, etc.
  - Assume single face
- Facial expression recognition
- Human pose estimation and tracking

Human face recognition finds application in a wide range of fields such as automatic video surveillance, criminal identification, credit cards and security systems to name just a few. The requirements of a good face recognition algorithm are high recognition rates, tolerance towards various environmental factors such as illumination, facial poses, facial expressions, image backgrounds, image scales, human ageing and also good computational and space complexity. The development of the field of face recognition can be found in [1, 2]. Initial approaches for face recognition of gray facial images involved the use of PCA [3], EBGM [4], Neural Networks [5], Support Vector Machines [6] and Hidden Markov Models [7]. However, these techniques are complex and computationally very expensive as they work on gray scale images and also do not provide too much tolerance to varying environment.

2. RELATED WORK

The conventional Hausdorff distance was defined on 2 set of points (say A and B) as:

"The minimum distance between any 2 points a and b such that $a \in A$ and $b \in B$."

Huttenlocher and Rucklidge et al [8] have proposed the Hausdorff Distance (HD) and Partial Hausdorff Distance (PHD) measures to compare images. The HD and PHD measures are not too computation intensive as they treat images as set of edge points. HD measure is found to be robust for small amount of local non rigid distortions. This property of Hausdorff distance makes it suitable for face recognition because such distortions occur frequently in facial images and are usually caused due to slight variation in poses and facial expressions.

Rucklidge [9] has used HD and PHD measures for object localization. HD has been modified by Dubuisson [15] to MHD, which was less sensitive to noise. The modified version of PHD named M2HD has been proposed by B.Takacs [10]. It uses the fact that facial images are assumed to be well cropped and normalized therefore corresponding points in edge images must be in a 'neighbourhood' [10]. Hence, M2HD penalizes points matched outside their 'neighbourhood'. Guo, Lam et al [11] have proposed SWHD and SW2HD which were also based on HD and M2HD. They give importance to vital facial feature points such as eyes, nose and mouth, which they approximate by rectangles. Lin, Lam et al [12] have improved SWHD and SW2HD to SEWHD and SEW2HD by using Eigenfaces as weighing functions because regions having larger variations are known to be important for facial discrimination.

The three-dimensional information of facial features plays vital role in discriminating faces. Unfortunately by creating edge maps we may lose most of this crucial information. HD and all its variant measures are defined on edge maps. They may work well for object detection and face recognition on some illumination- varying facial image databases. However their performance on pose-varying and expression-varying facial image databases is limited and cannot be improved be- yond a certain level since edge maps change drastically with pose and expression variance. Vivek and Sudha [13] have proposed Hg and Hpg measures which work directly on gray quantized images. These measures search for a correspondence between sets of pixels having the same quantized value from two images, where the distance measure itself being the distance between the worst correspondence.

2.1 HD and PHD

The Conventional Hausdorff distance is dissimilarity between two set of points. It can be applied on edge maps to compare shapes. This measures the proximity rather than exact superposition, Hence it can be calculated without explicit pairing up of points of two sets.

Let A = $\{a_1, a_2, a_3, a_4, .., am\}$ and B = {b1, b2 , b3, b4,..,bn } be two Set of points

Then, undirected Hausdorff distance [8] between A and B is defined as:

H D (A, B) = H D (B, A) = max (hd (A, B), hd (B, A))

Here hd (A,B) is the directed Hausdorff distance defined by:

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

and, $\| . \|$ is the norm of the vector.

Table 1: Example hd (A, B)

Pairs of Points	Distances	Min Value and Correspondence	Max Value
1-a	10	10(1-a) 1 corresponds to a	12(3-a) This is the worst correspondence [Most Dissimilar Points]
1-b	14		
2-a	8	8(2-a) 2 corresponds to a	
2-b	10		
3-a	12	12(3-a) 3 corresponds to a	
3-b	15		

Basically it is the maximum distance that one has to travel from any point of set A to any point of set B. It is a max min distance in which min estimates the best correspondence for each point, and max extracts the worst out of those. Hence, hd (A, B) is the distance between the worst correspondence pair (as shown in Figure 2.1).

HD measure does not work well when some part of the object is occluded or missing. This caused introduction of partial Hausdorff distance or PHD which is used for partial matching and is defined as:

$$Phd(A, B) = k^{th} \max_{a \in A} \min_{b \in B} \|a - b\|$$

HD and PHD do not solve point-to-point correspondence at all, and works on edge maps. Both of them can tolerate small amount of local and non-rigid distortion as well as illumination variations. But, the non-linear max and min functions make HD and PHD very sensitive to noise.

2.2 MHD and M2HD

Modified Hausdorff Distance MHD [15] has been introduced that uses averaging which is a linear function which makes it less sensitive to noise. MHD is defined as:

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

Where Na is the number of points in set A.

Further, MHD is improved to Doubly Modified Hausdorff Distance M2HD [10]

By adding 3 more parameters:

Neighbourhood function (N_B^a) Neighbourhood of the point a in set B

Indicator variable (I) I = 1 if a's corresponding point lie in (N_B^a) else I = 0

Associated penalty (P) if I = 0 penalize with this penalty and is defined as:

$$m2hd(A, B) = \frac{1}{N_a} \sum_{a \in A} d(a, b)$$

Where d(a,b) is defined as: $d(a,b) = \max[(I \cdot \min_{b \in (N_B^a)} \|a-b\|), ((1-I).P)]$

2.3 SWHD and SW2HD

To achieve better discriminative power HD and MHD measures were further improved by assigning the weights to every point according to its spatial information. Crucial facial feature points like eyes and mouth are approximated by the rectangular windows (as shown in Figure 2.2) and are given more importance than others. Hence, proposed Spatially Weighted Hausdorff Distance SWHD and Doubly Spatially Weighted Hausdorff Distance SW2HD [11] were defined as:

$$swhd(A, B) = \max_{a \in A} [w(b).\min_{b \in B} \|a - b\|]$$

$$sw2hd(A, B) = \frac{1}{N_a} \sum_{a \in N_a} [w(b).\min_{b \in B} \|a - b\|]$$

W(x) is defined as:

$$W(x) = \begin{cases} 1 & x \in \text{Important Facial Region,} \\ W & x \in \text{unimportant Facial Region} \\ 0 & x \in \text{background Region} \end{cases}$$

Where $W \leq 1$

2.4 SEWHD and SEW2HD

Rough estimation of facial features cannot fully reflect the exact structure of human face. Hence, further improvement is done by using eigenfaces as the weighing function because they represent the most significant variations in the set of training face images. Proposed Spatially Eigen Weighted Hausdorff Distance SE- WHD and Doubly Spatially Eigen Weighted Hausdorff Distance SEW2HD [12] are defined as:

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

$$sew2hd(A, B) = \frac{1}{N_a} \sum_{a \in N_a} [w(b).\min_{b \in B} \| a - b \|]$$

Where we (x) is defined as:

we (x) = The eigen weight function generated by the first eigen vector

Hg and Hpg

Till 2006 Hausdorff distance measure was being explored only on edge maps but unfortunately on edge images most of the important facial features are lost which are very useful for facial discrimination. Gray Hausdorff Distance Hg and Partial Gray Hausdorff Distance Hpg [13] measures works on quantized images and are found robust to slight variation in poses, expressions and illumination. It is seen that quantized image with $n \geq 5$ retains the perceptual appearance and the intrinsic facial feature information that resides in gray values

Hg and Hpg are defined as:

$$hg(A, B) = \max_{\substack{i=0..2n-1 \\ a \in Ai}} d(a, Bi)$$

$$hpg(A, B) = \underset{\substack{i=0..2n-1 \\ a \in Ai}}{K\text{ th}\max} \; d(a, Bi)$$

Where d (a, Bi) is defined as:

$$d(a, Bi) = \begin{cases} \min_{b \in B_i} \| a\text{-}b \| & \text{if } B_i \text{ is non-empty} \\ L & \text{otherwise} \end{cases}$$

Here, Ai and Bi are the set of pixels in A and B images having quantized gray value i. L is a large value can be$\sqrt{r2 + c2}$ +1 for r × c images. Both Hg and Hpg search for a correspondence between sets of pixels having the same quantized value from two images where the distance measure itself being the distance between the worst correspondence.

Efficient Computation of NUP:C ompare (A, B) and Match (a, B) operations are required to compute N U P (A, B). Both of these operations take O (rc) time for r × c sized images. Hence, computing N U P (A, B) using naive method requires O (r^2c^2) time, which is prohibitively computationally intensive. Hence an efficient algorithm is required to compute the NUP measure.

Algorithm: Flow Control of the Algorithm to compute NUP (A, B) (Algorithm 1) computes Normalized Unmatched Points measure between two gt-transformed images. It calls the function Compare (A, B) (Algorithm 2) that computes directional unmatched points, which itself calls Matched (a, B) (Algorithm 3) which only checks whether a pixel a got a Match in image B or not.

DISCUSSION OF THE ALGORITHMS

In Algorithm 1, two gt-transformed images are passed. Compare (A, B) function is called to calculate the directional unmatched points, which is further normalized by total number of pixels in the image.

To perform the M atch (a, B) operation efficiently an array of pointers to linked list BLIST is created. BLIST will have 3^8 elements such

Algorithm 1 N U P (A, B)

Require: gt-transformed images A and B

Ensure: Return N U P (A, B).

1: Load gt-transformed images A and B from the Disk;

2: nup(A, B) ← C om$\frac{\text{pare(A,B)}}{N_a}$;

3: nup(B, A) ← C om$\frac{\text{pare(B,A)}}{N_b}$;

4: N U P (A, B) ← ││<nup (A, B), nup (B, A)>k││p;

5: RETURN N U P (A, B);

that $\forall i \in [0, 3^8 - 1]$ the ith element points to a linked list of pixels having the transformed value i [14].

Computing BLIST data structure is a costly operation, and hence it is done once in Algorithm 2 and Match (a, B) i.e. Calculated using Algorithm 3 will use it. In Algorithm 2, all pixels of gt-transformed image A are checked that whether they got a match within their neighbourhood or not, using Algorithm 3.

Finally number of unmatched pixels is returned (i.e. Na_{AB}) with image A is compared with image B

Algorithm 2 C ompare (A, B)

Require: gt-transformed images A and B.

Ensure: Return NU_{AB} .

1: Construct BLIST (array of pointers to linked list) for B;

2: unmatched ← 0;

3: for i = 0 to (r − 3) do

4: for j = 0 to (c − 3) do

5: if Match (Aij, B) is 0 then

6: unmatched ← unmatched + 1;

7: end if

8: end for

9: end for

10: RETURN unmatched;

After the fore mentioned data structure BLIST is created for B in Algorithm 2, the Match (a, B) operation can be performed efficiently using Algorithm 3. Firstly, Calculate the transformed value tval_a of pixel a. BLIST [tval_a] will point to the linked list of pixels having the transformed value tval_a in image B .Then search the list BLIST [tval _a] linearly until a pixel is found which $\in N^a$. If such a pixel is found, return 1 else return 0.

Algorithm 3

Require: A pixel a and gt-Transformed image B

Ensure: If pixel a got matched then return 1, else return 0.

1: tval a ← gt-transformed value of pixel a;

2: Search linked list BLIST [tval_a], for a point $P \in N_B$ a;

3: if no point found in step 3.3.1 then

4: RETURN 0;

5: else

6: RETURN 1;

Time and Space Analysis

Pre-processing Conversion of gray scale images of size r × c into gt-Transformed images is done once for which a single scan of the whole image is sufficient. Hence time complexity is O (rc).

Processing Match function involves linear search of a linked list of pixels, therefore the time taken by this function depends on the length of the list. Let us assume that k is the length of the largest linked list. To compute NUP between two images, Compare function has to be called 2rc times, therefore time required to compute NUP will be O (krc). The worst case is when all the pixels in an image have the same transformed value. Then k = rc, which leads to the trivial O (r^2 c^2) time complexity. But, in face images and varying environment above condition will never occur.

Space requirement of a gray image is O (rc). The same space can be utilized for storing gt-transformed images as original images are not used for further computation.

The array of pointers to the linked list of pixels (BLIST) is of size (3^8). This is constant independence of image size. As all the pixels in both the images will be added once to lists of pixels the total memory used in constructing the data structure for the images is $2 \cdot (3^8 + rc)$ units.

Pre-Processing and Testing Strategy

After preprocessing, gt-transformed images are saved as colour images (in TIFF format), sized 90 × 110 (as shown in Figure 1). For testing any database we consider the whole database as the testing set and then each image of the testing set is matched with all other images excluding itself. Finally top n^* best matches are reported.

Experimental Results and Analysis

The performance evaluation of NUP measure was done on some standard bench- mark facial image databases such as ORL [17], YALE [18], BERN [19], CALTECH [20], and IITK (as shown in Table 4.1). Under varying lighting conditions, poses and expressions NUP measure has demonstrated very good recognition rates. A match is announced if and only if a subject's image got matched with another pose of himself/herself. Recognition rate is defined as:

$$\text{Recognition rate} = \frac{\text{number of matches}}{(\text{Total no.of images}) \times n}$$

This is used to analyse the performance of any measure.NUP is a dissimilarity measure and can tolerate small amount of variation in facial images of the same subject. In order to handle wide pose variations, we have to store templates of faces in different poses at the time of registration.

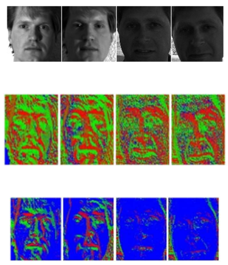

Figure 1: Effect of High gt Values under Heavy Illumination Variation

It is clear that more and more elements of V (a) start acquiring value 1 with higher gt values. This will boost the blue value of pixels in the gt-transformed images. In the presence of directional lights and heavy illumination condition variations some the facial regions becomes significantly dark. High gt values in these conditions may further lift up the blue value upto an extent that blue colour starts dominating in gt- transformed image (as shown in Figure 4.2). This results in deterioration of the performance.

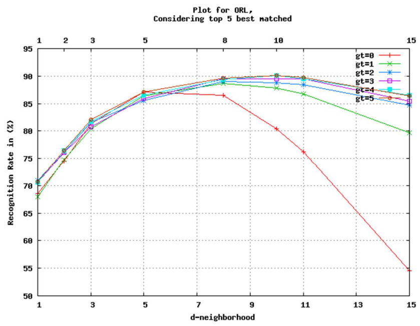

Figure 2: YALE, Considering Top 1 Best Matched

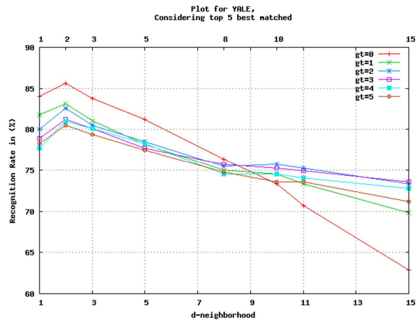

Figure 3: Yale, Considering Top 5 Best Matched

Table 2: Comparative Study on ORL and YALE Databases when Considering Top 1 Best Match

Distance Measure	Recognition Rate (%)	
	ORL	YALE
PCA	57	50
HD	56	76
PHD	72.08 (f = 0.85)	84 (f = 0.7)
M2HD	85	80
SEWHD	88	85
SEW2HD	91	89
H_{pg}	91.25	83.3 (f = 0.55)
NUP	99.75 (gt = 5, d =11)	92.73 (gt = 0, d = 1)1)

Table 3: Comparative Study on BERN Database when Considering Top 1 Best Match

Test Faces	Recognition Rate (%)			
	PHD (f = 0.85)	LEM	Hpg	NUP (gt = 5, d = 15)
Looks right/left	74.17	74.17	95.83	99.00
Looks up	43.33	70.00	90.00	99.00
Looks down	61.66	70.00	68.33	98.00
Average	58.75	72.09	87.50	98.66

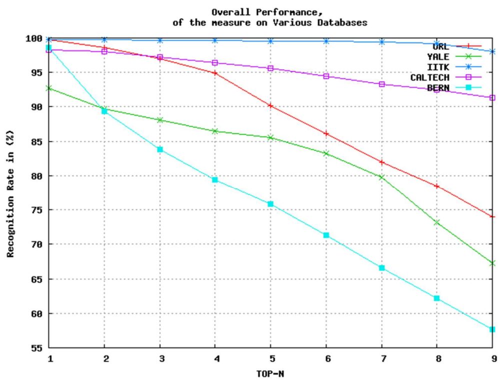

Figure 4: Results of NUP Based Face Recognition on Different Face Databases Considering Top n Best Matches

The overall performance of NUP is evaluated by testing it over various standard face databases with respect to n (as shown in Figure 4). For n = 1, 2 recognition rates are very good (as shown in Figure 4 and Table 4.4). With increasing n the recognition rate falls which is obvious.

Table 5: Overall Analysis

Top-n	ORL	YALE	CALTECH	BERN
1	99.75	92.72	98.23	98.66
2	98.63	89.7	98.08	89.33
3	97.10	88.11	97.25	83.77
4	94.87	86.51	96.40	79.41
5	90.15	85.57	95.64	75.80
6	86.13	83.23	94.46	71.33
7	82.10	79.74	93.27	66.57
8	78.50	73.11	92.42	62.12
9	74.01	67.20	91.30	57.70

CONCLUSIONS

In this work, a new measure Normalized Unmatched Points (NUP) has been pro- posed to compare gray facial images. The face recognition approach based on NUP measure is different from existing Hausdorff distance based methods as it works on gt-transformed images that are obtained from gray images rather than edge images. Thus, this approach can achieve the appearance based comparison of faces. An algorithm is also presented to efficiently compute the NUP measure.

Using the NUP measure, we have achieved recognition rates of 98.75% and90.35% on ORL, 94.547% and 86.75% on YALE, 98.25% and 95.64% on CAL- TECH, 98.66% and 75.8% on BERN face databases when top 1 and top 5 best matches are considered respectively, without normalizing with respect to any feature point. It has been shown that the NUP measure performs better than other existing similar variants on most of the databases.

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