A Novel Face Recognition Approach using Normalized Unmatched Points Measure

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CERTIFICATE

This is to certify that the work contained in the thesis entitled "*A Novel Face Recognition Approach using Normalized Unmatched Points Measure*" by *Aditya Nigam* has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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Abstract

The human face is the premier biometric in the field of human 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 face recognition like different poses, expressions, backgrounds and illumination conditions to name a few, because of which the task becomes difficult.

In this work, we propose a new powerful measure called Normalized Unmatched Points (*NUP*) to compare gray 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.

Using the *NUP* measure, we have achieved recognition rates of 99.75% and 90.15% on ORL, 92.727% and 85.57% on YALE, 98.23% and 95.64% on CALTECH, 98.66% and 75.8% on BERN and 99.73% and 99.58% on IITK 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.

Chapter 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).

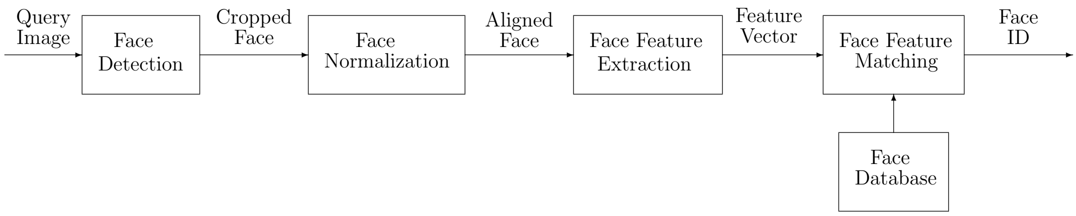


Figure 1.1: Face recognition system

1.1 Face Recognition System

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 analyzing a face as a whole for identifying the person. A face recognition system [23] generally consist of four modules (as shown in Figure 1.1): Face Detection, Face Normalization, Face Feature Extraction and Face Feature Matching.

Some of the conditions that should be accounted for when detecting faces are [22]:

1. Occlusion: face may be partially occluded by other objects
2. Presence or absence of structural components: beards, mustaches and glasses
3. Facial expression: face appearance is very much affected by a person's facial expression
4. Pose (Out-of Plane Rotation): frontal,45 degree,profile,upside down
5. Orientation (In Plane Rotation): face appearance directly varies for different rotations about the camera's optical axis

6. Imaging conditions: lighting (direction and intensity), camera characteristics, resolution

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

1. Face Localization
   (a) Determine face location in the image
   (b) Assume single face
2. Face Feature Extraction
   (a) Determining location of various facial features as eyes, nose, nostrils, eyebrow, mouth, lips, ears, *etc.*
   (b) Assume single face
3. Facial expression recognition
4. 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.

1.2 Motivation

Face recognition is becoming primary biometric technology because of rapid advancement in the technology such as digital cameras, the internet and mobile devices which in turn facilitates its acquisition. Artificially simulating face recognition is required to create intelligent autonomous machines. Face recognition by machine can contribute in various application in real life such as electronic and physical access control, biometric authentication, surveillance, human computer interaction, multimedia management to name just a few. Also, it has many advantages over other biometric traits as it requires least cooperation, non intrusive, easy to acquire and use.

1.3 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 'neighborhood' [10]. Hence, *M2HD* penalizes points matched outside their 'neighborhood'. 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 Eigen faces * (as shown in Figure 1.2) 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 beyond a certain level since edge maps change drastically with pose and expression variance. Vivek and Sudha [13] have proposed H_g and H_{pg} measures which work

*Eigenfaces appears as light and dark areas arranged in a specific pattern. Regions where the difference among the training images is large, the corresponding regions at the eigenfaces will have large magnitude.

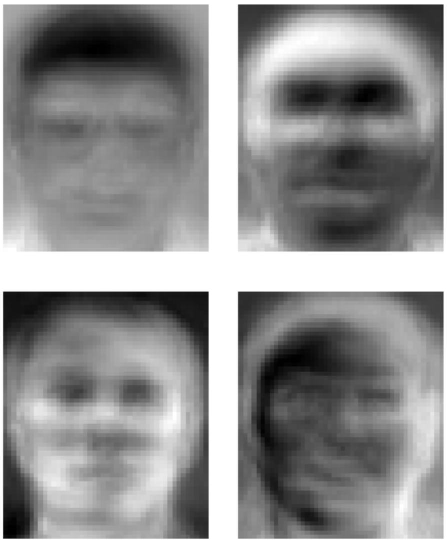


Figure 1.2: Eigenfaces

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.

1.4 Organization of the thesis

This thesis is divided into 5 chapters. A brief overview of the chapters is as follows:

- Chapter 2, discusses the conventional *HD* and its various variants.
- In Chapter 3, a novel *NUP* distance measure is described and an efficient algorithm for its computation is also presented.
- In Chapter 4, experimental results, its analysis and details of implementation is presented.

†In quantized gray-scale image only n ($n \leq 8$) most significant bits of the gray value are considered.

- In Chapter 5, future work is presented and conclusion is given.

Chapter 2

Literature Review

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 $A = \{a_1, a_2, a_3, a_4..a_m\}$ and $B = \{b_1, b_2, b_3, b_4..b_n\}$ be two Set of points then, undirected Hausdorff distance [8] between A and B is defined as:

$$HD(A, B) = HD(B, A) = max(hd(A, B), hd(B, A)) \tag{2.1}$$

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

$$hd(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\| \tag{2.2}$$

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

Pairs of Points	Distances	Min Value and Correspondance	Max Value
1-a	10	10(1-a) 1 corresponds to a	12(3-a) This is the worst correspondance [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		

Figure 2.1: Example hd(A,B)

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:

$$phd(A,B) = K^{th} \max_{a \in A} \min_{b \in B} \|a - b\| \tag{2.3}$$

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:

$$mhd(A, B) = \frac{1}{N_a} \sum_{a \in A} \min_{b \in B} \|a - b\| \tag{2.4}$$

Where N_a is the number of points in set A.

Further, *MHD* is improved to Doubly Modified Hausdorff Distance *M2HD* [10] by adding 3 more parameters :

Neighborhood function (N_B^a) Neighborhood 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:

$$m2hd(A, B) = \frac{1}{N_a} \sum_{a \in A} d(a, B) \tag{2.5}$$

Where *d(a,B)* is defined as:

$$d(a, B) = \max[(I \cdot \min_{b \in N_B^a} \|a - b\|), ((1 - I) \cdot P)] \tag{2.6}$$

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:

$$swhd(A,B) = \max_{a\in A}\left[w(b)\cdot\min_{b\in B}\|a-b\|\right] \tag{2.7}$$

$$sw2hd(A,B) = \frac{1}{N_a}\sum_{a\in N_a}\left[w(b)\cdot\min_{b\in B}\|a-b\|\right] \tag{2.8}$$

Where $w(x)$ is defined as:

$$w(x) = \begin{cases} 1 & x \in \text{Important facial region} \quad (2.9a) \\ W & x \in \text{Unimportant facial region} \quad (2.9b) \\ 0 & x \in \text{Background region} \quad (2.9c) \end{cases}$$

Here $W \leq 1$

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 weigh-

*Eigenfaces appears as light and dark areas arranged in a specific pattern (as shown in Figure 1.2). Regions where the difference among the training images is large, the corresponding regions at the eigenfaces will have large magnitude.

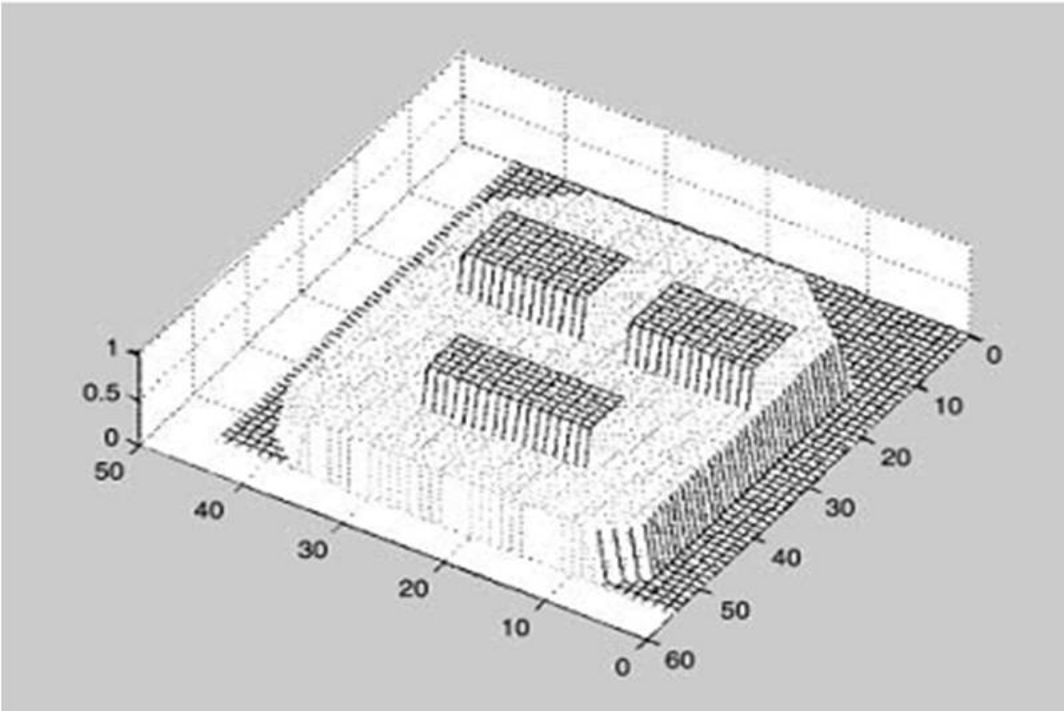


Figure 2.2: Spatial Weighing Function

ing function because they represents 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:

$$\begin{aligned} sewhd(A,B) &= \max_{a \in A}\left[w_e(b) \cdot \min_{b \in B}\|a-b\|\right] & (2.10)\\ sew2hd(A,B) &= \frac{1}{N_a}\sum_{a \in N_a}\left[w_e(b) \cdot \min_{b \in B}\|a-b\|\right] & (2.11) \end{aligned}$$

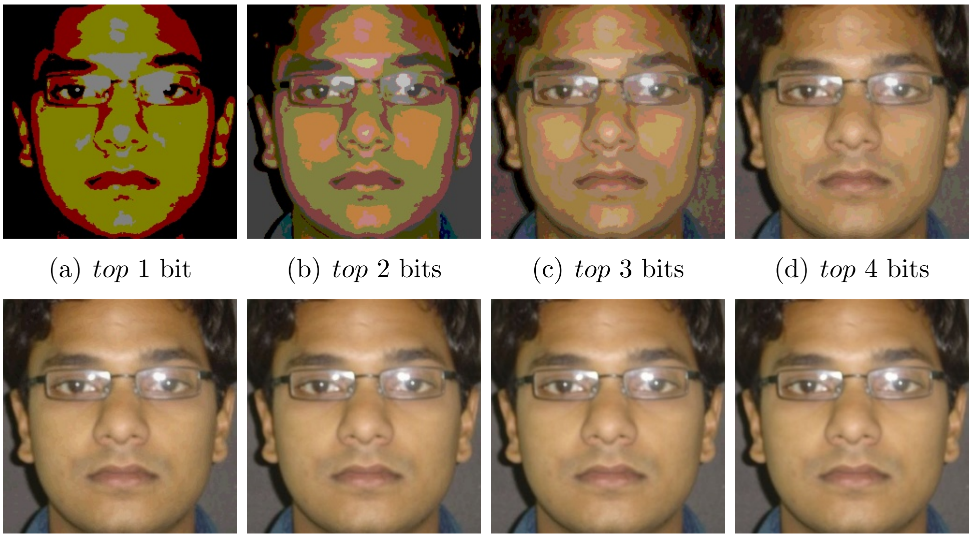
where $w_e(x)$ is defined as:

$$w_e(x) = \text{The eigen weight function generated by the first eigen vector} \quad (2.12)$$

2.5 H_g and H_{pg}

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 H_g and Partial Gray Hausdorff Distance H_{pg} [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 (as shown in Figure 2.3).

H_g and H_{pg} are defined as :



(a) *top* 1 bit (b) *top* 2 bits (c) *top* 3 bits (d) *top* 4 bits

(e) *top* 5 bits (f) *top* 6 bits (g) *top* 7 bits (h) *top* 8 bits

Figure 2.3: Quantized Images

$$h_g(A,B) = \max_{\substack{i=0..2^n-1 \\ a\in A_i}} d(a,B_i) \tag{2.13}$$

$$h_{pg}(A,B) = K^{th} \max_{\substack{i=0..2^n-1 \\ a\in A_i}} d(a,B_i) \tag{2.14}$$

where $d(a, B_i)$ is defined as :

$$d(a,B_i) = \begin{cases} \min_{b\in B_i} \|a-b\| & \text{if } B_i \text{ is non-empty} \quad (2.15a) \\ L & \text{otherwise} \quad (2.15b) \end{cases}$$

Here, A_i and B_i are the set of pixels in A and B images having quantized gray value i. L is a large value can be $\sqrt{r^2+c^2}+1$ for $r \times c$ images. Both H_g and H_{pg} 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.

2.6 Application in Face Recognition

All of the measures discussed before H_g and H_{pg} works on edge images. They treat an image as a set of edge points and then calculates the value of the measure using its mathematical formula as defined above (in their respective section).

H_g and H_{pg} works on quantized images. They treat a gray-scale image A as 256 sets of points (say $\{A_0, A_1, A_2, ..A_{255}\}$), where A_i is the set of pixels in image A having quantized gray value i. Then H_g and H_{pg} are calculated using its mathematical formula as defined above.

Chapter 3

The Proposed Approach and Implementation Details

We define a new Normalized Unmatched Points measure *NUP* that can be applied on gray-scale facial images. It is similar to the Hausdorff distance based measures but is computationally less expensive and more accurate. *NUP* also shows robustness against slight variation in poses, expressions and illumination.

In a gray-scale image, each pixel has an 8-bit gray value that lies in between 0 to 255 which is very sensitive to the environmental conditions. In varying uncontrolled environment, it becomes very difficult for a measure to capture any useful information about the image. Hence face recognition is very challenging using gray-scale images.

3.1 Transformation

Sudha and Wong [14] describe a transformation (referred hereafter as SK-transformation) which provides some robustness against illumination variation and local non-rigid distortions by converting gray scale images into transformed images that preserve intensity distribution.

A pixel's relative gray value in its neighborhood can be more stable than its own gray value. Hence in an SK-transformed image, every pixel is represented by an 8-element vector which in itself can store the sign of first-order derivative with respect to its 8-neighborhood. Each SK-transformed images hold a property that even if the gray value of the pixels are being changed in different poses of the same subject, their corresponding vector (*i.e.* its contribution in the transformed image) do not change by a great extent.

The above property holds when gray values of neighborhood pixels are not too close to each other. But usually, we have small variations in the gray values (*e.g.* in background, facial features *etc.*), where the above property *fails* to hold.

The problem is caused by our comparator function, which assumes for any gray level X that:

$$X \begin{cases} = X & (3.1a) \\ < \alpha \in (X, 255] & (3.1b) \\ > \alpha \in [0, X) & (3.1c) \end{cases}$$

where X is a gray level *not merely a number*.

Practically a gray level X is neither greater than gray level $(X-1)$ nor less than gray level $(X+1)$; ideally they should be considered as equal. Gray levels

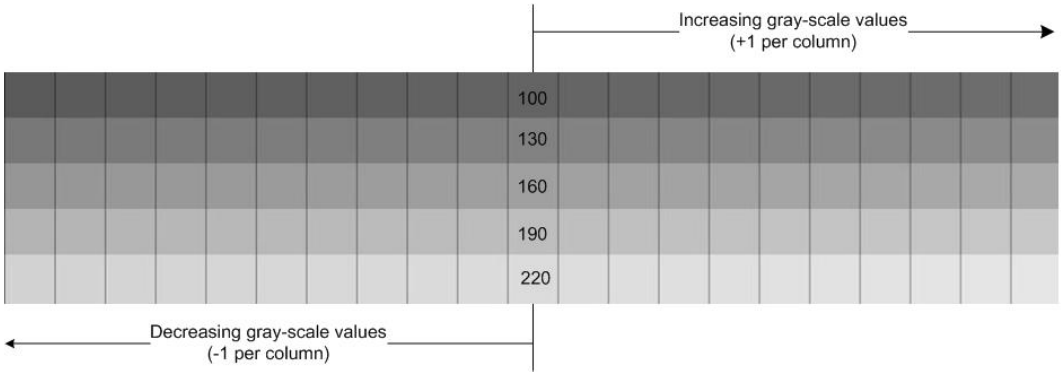


Figure 3.1: Gray-value spectrum.

are hardly distinguishable within a range of ± 5 units (as shown in Figure 3.1) . Quantization [13] can also be thought of as a solution to this problem however it too behaves similarly at the boundaries.

3.1.1 gt-Transformation

In order to solve this problem a new gt-transformation is introduced which uses gt-comparator function.

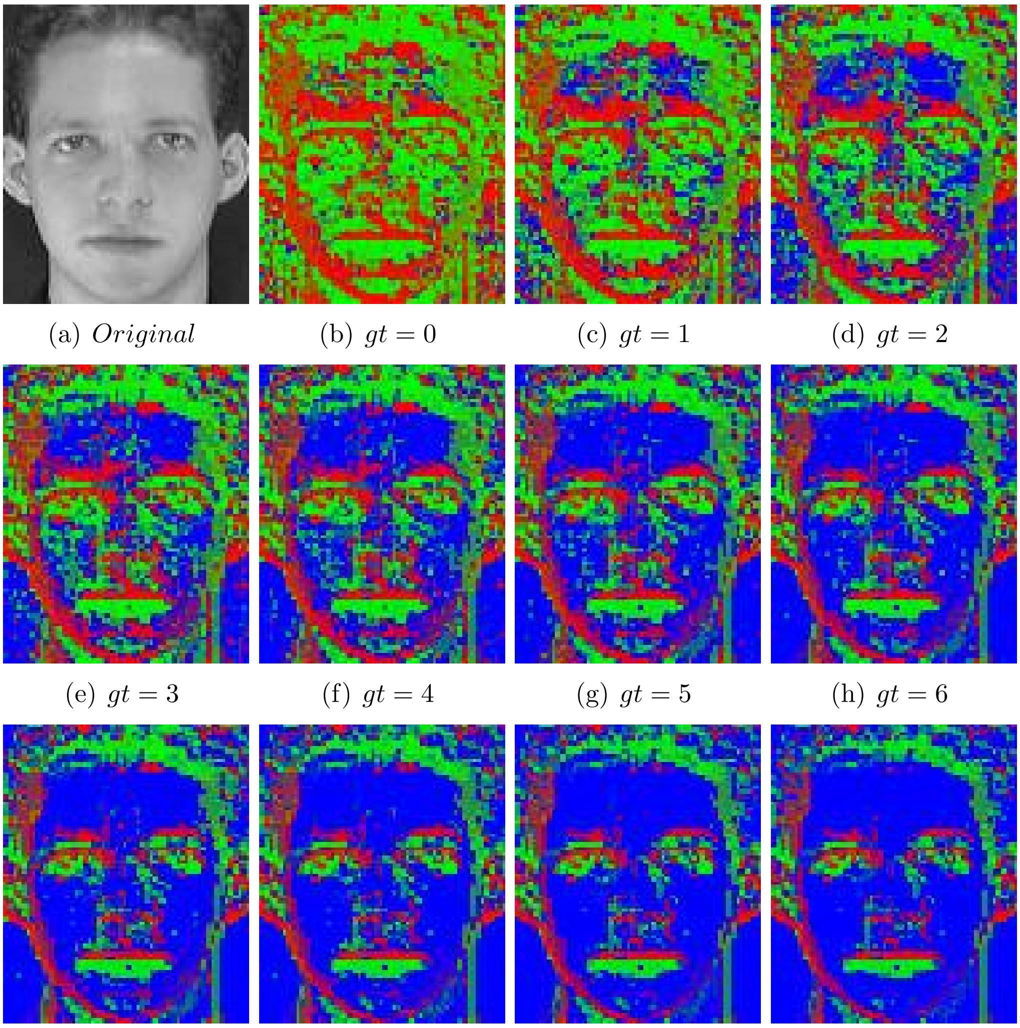
gt-Comparator

The gt-comparator function depends on parameter gt (gray value tolerance). It assumes for any gray level X that:

$$X \begin{cases} = \alpha \in [(X - gt), (X + gt)] & (3.2a) \\ < \alpha \in (X + gt, 255] & (3.2b) \\ > \alpha \in [0, X - gt) & (3.2c) \end{cases}$$

for $gt \geq 0$ where X is a gray level.

As shown in the Figure 3.2, with big gt values important facial features are lost.



(a) *Original* (b) $gt = 0$ (c) $gt = 1$ (d) $gt = 2$

(e) $gt = 3$ (f) $gt = 4$ (g) $gt = 5$ (h) $gt = 6$

(i) $gt = 7$ (j) $gt = 8$ (k) $gt = 9$ (l) $gt = 10$

Figure 3.2: gt-Transformed images

If there is limited variation in illumination and lighting conditions, then $gt = 5$ can be useful (as shown in Figure 3.1). The value of gt depends on the database that is being tested; however it cannot be chosen to be very large; otherwise performance may be adversely affected.

In SK-transformation, every pixel a is represented by an 8-element vector $V(a)$ whose elements are drawn from the set $\{-1, 0, 1\}$. In our gt-transformation, we choose this set of values to be $\{0, 1, 2\}$ so that every $V(a)$ can be represented as an 8-digit number in base 3. The decimal equivalent of the $V(a)$ is called the transformed value of the pixel a and has values ranging from 0 to 6560 $(= 3^8 - 1)$. Thus, every pixel now has a gray value as well as a transformed value. In typical varying environment transformed value of a pixel remains more stable than its corresponding gray value.

(a) Original images (taken 2 each from ORL,YALE,BERN,CALTECH databases)

(b) Corresponding transformed images (with gt=0)

(c) Corresponding transformed images (with gt=5)

Figure 3.3: gt-Transformed images

The result of gt-transformation can now be saved as colored RGB image. The R, G and B values of any pixel a captures the positions of 0,2 and 1 respectively in $V(a)$, where $V(a)$ is calculated using gt-comparator around pixel a in gray scale image (as shown in Figure 3.3).

3.2 Defining *NUP*

Some notations used for the computation of *NUP* measure are given in Table 3.1.

Parameter	Description
$\boldsymbol{A' \mid B'}$	Facial gray scale images of size $r \times c$;
$\boldsymbol{A \mid B}$	The corresponding *gt*-transformed images $(r-2)\times(c-2)$, boundary pixels are ignored;
$\boldsymbol{N_B^a}$	Neighborhood of pixel a in image B;
$\boldsymbol{V(a)}$	The 8-element vector at pixel a;
$\boldsymbol{tval\_a}$	The decimal equivalent of $V(a)$, *i.e.* the transformed value of pixel a;
$\boldsymbol{NUP(A,B)}$	Undirected Normalized Unmatched Points measure between A and B;
$\boldsymbol{nup(A,B)}$	Directed Normalized Unmatched Points measure, when A is compared with B;
$\boldsymbol{p}$	Order of the norm ;
$\boldsymbol{N_a}$	Total number of pixels in image A;
$\boldsymbol{N_{AB}^U}$	Total number of unmatched pixels of A, when A is compared with B;
$\boldsymbol{Compare(A,B)}$	Compares image A to image B, and returns N_{AB}^U;
$\boldsymbol{Match(a,B)}$	Matches a pixel a with B, and returns 1 if Matched or 0 if Unmatched;

Table 3.1: Notations

3.2.1 Definitions

Any pixel within a distance of $d\sqrt{2}$ with pixel a is considered to be in its neighborhood (as shown in the Figure 3.4). Neighborhood N_B^a of a pixel a in image B is defined using a parameter* d as:

* $d\sqrt{2}$ is the radius of circumcircle of $(2d+1)\times(2d+1)$ square neighborhood centered and around pixel a (as shown in Figure 3.4).

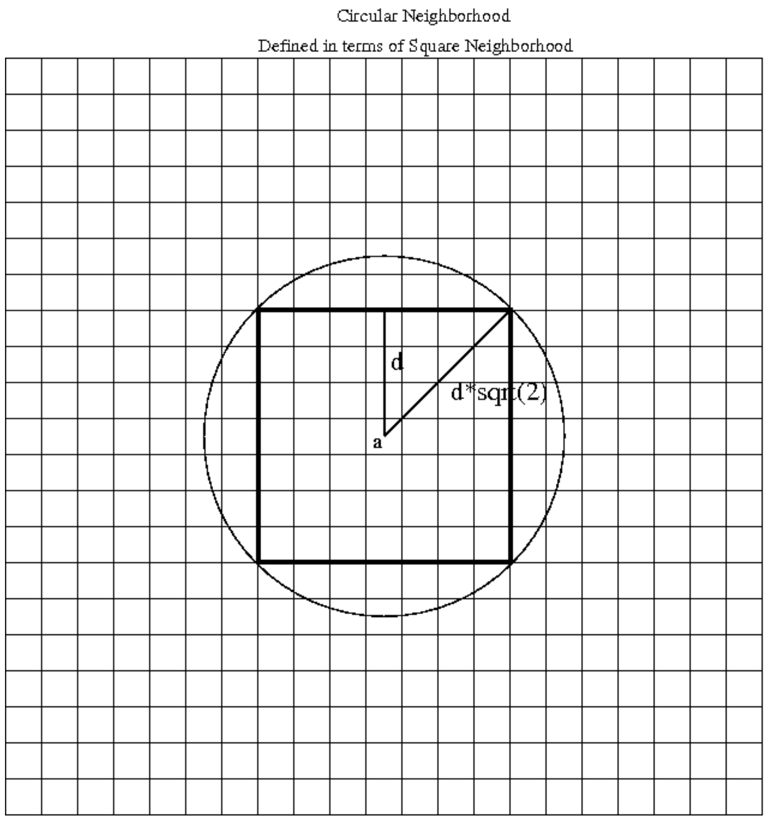


Figure 3.4: Circular Neighborhood

$$N_B^a = \{b \in B \mid \|a - b\| \leq d\sqrt{2}\} \tag{3.3}$$

$Compare(A, B)$ compares image A to image B, and returns N_{AB}^U (*i.e.* number of unmatched points), which can be defined as:

$$N_{AB}^U = \sum_{a \in A} (1 - Match(a, B)) \tag{3.4}$$

where $Match(a, B)$ can be defined as:

$$Match(a, B) = \begin{cases} 1 & \text{If } \exists_{b \in N_B^a} \ V(a) = V(b) \text{ [i.e. Matched]} \quad (3.5a) \\ 0 & \text{else} \quad (3.5b) \end{cases}$$

$Match(a, B)$ matches a pixel a with a *gt*-transformed image B. It returns 1 if there is a pixel within the neighborhood of a in image B, having same *gt*-transformed value (*i.e.* Matched), else it returns 0 (*i.e.* Unmatched).

Now $NUP(A, B)$ is defined as:

$$NUP(A, B) = \|\langle nup(A, B), nup(B, A)\rangle\|_p \tag{3.6}$$

where $nup(A, B)$ is defined as:

$$\begin{aligned} nup(A, B) &= \frac{\sum_{a \in A} (1 - Match(a, B))}{N_a} \\ &= \frac{N_{AB}^U}{N_a} \end{aligned} \tag{3.7}$$

and $\|.\|_p$ is the p^{th} norm.

Some Properties of *NUP* and *nup*

1. $NUP(A, B) = NUP(B, A)$.
2. If $nup(A, B) = K$, then $K \cdot N_a$ pixels of A do not have any pixel with same transformed value within its neighborhood in B.
3. $NUP(A, B)$ and $nup(A, B)$ are always positive and normalized between 0 and 1.

4. $NUP(A, B)$ and $nup(A, B)$ are parameterized by gt, d and p.

3.3 Efficient computation of *NUP*

$Compare(A, B)$ and $Match(a, B)$ operations are required to compute $NUP(A, B)$. Both of these operations take $O(rc)$ time for $r \times c$ sized images. Hence, computing $NUP(A, B)$ 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.

3.3.1 Algorithm

Flow Control of the Algorithm

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 $Match(a, B)$ operation efficiently an array of pointers to linked list BLIST (as shown in Figure 3.5) is created. BLIST will have 3^8 elements such

Algorithm 1 $NUP(A, B)$

Require: gt-transformed images A and B.
Ensure: Return $NUP(A, B)$.

Load gt-transformed images A and B from the Disk;
$nup(A, B) \leftarrow \frac{Compare(A,B)}{N_a}$;
$nup(B, A) \leftarrow \frac{Compare(B,A)}{N_b}$;
$NUP(A, B) \leftarrow \|\langle nup(A, B), nup(B, A)\rangle\|_p$;
RETURN $NUP(A, B)$;

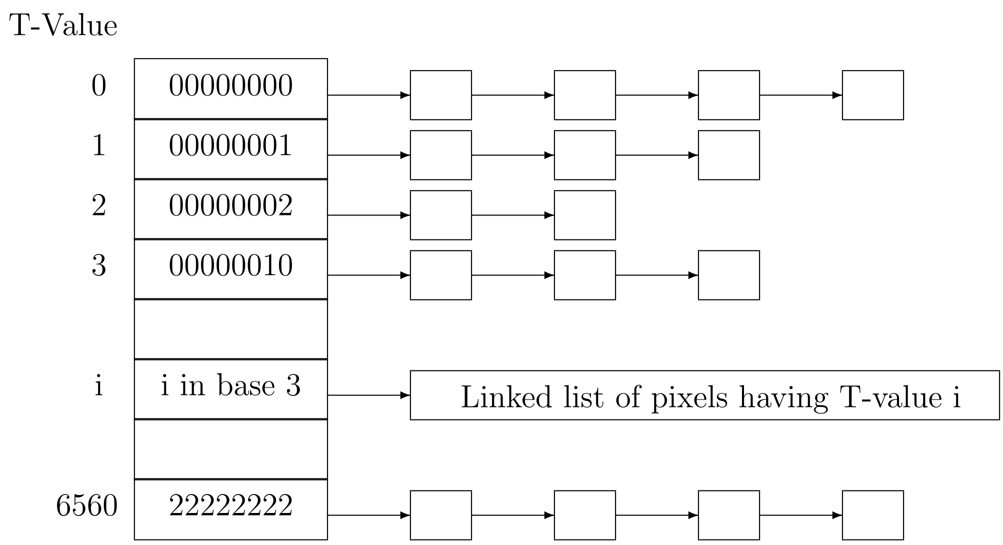


Figure 3.5: Data Structure: BLIST

that $\forall i \in [0, 3^8 - 1]$ the i^{th} 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 neighborhood or not, using Algorithm 3. Finally, number of unmatched pixels is returned (*i.e.* N^a_{AB}), when image A is compared with image B.

Algorithm 2 $Compare(A, B)$

Require: gt-transformed images A and B.
Ensure: Return N^U_{AB}.

Construct BLIST (array of pointers to linked list) for B;
$unmatched \leftarrow 0$;
for $i = 0$ to $(r - 3)$ **do**
    for $j = 0$ to $(c - 3)$ **do**
        if $Match(A_{ij}, B)$ is 0 **then**
            $unmatched \leftarrow unmatched + 1$;
        end if
    end for
end for
RETURN *unmatched*;

After the aforementioned 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 (as shown in the Figure 3.5). Then search the list BLIST[$tval\_a$] linearly until a pixel is found which $\in N^a_B$. If such a pixel is found, return 1 else return 0.

Algorithm 3 $Match(a, B)$

Require: A pixel a and gt-transformed image B.
Ensure: If pixel a got $Matched$ then return 1, else return 0.

$tval\_a \leftarrow gt$-transformed value of pixel a;
Search linked list BLIST[$tval\_a$], for a point $P \in N_B^a$;
if no point found in step 3.3.1 **then**
    RETURN 0;
else
    RETURN 1;
end if

3.3.2 Running Time Analysis

Preprocessing

Conversion of gray scale images of size $r \times c$ 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 $O(r^2c^2)$ time complexity. But, in face images and varying environment above condition will never occur.

3.3.3 Space Analysis

Space requirement of an 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 independent 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.

Chapter 4

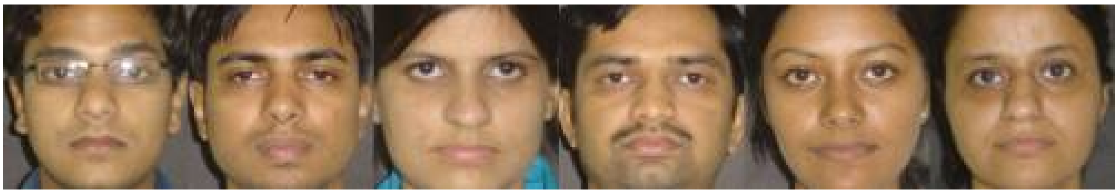
Experimental Results and Analysis

4.1 Setup for Face Recognition System

Our face recognition system consists of 3 phases. In first phase face detection is done, in second phase some preprocessing is performed (*i.e.* gt-transformation), and finally in third phase face comparison using NUP measure is performed.

In this system, face normalization is optional because for big databases a lot of manual work is required to gather the ground truth information. Neighborhood function will take care of this normalization. Also face feature extraction and matching is not required as suggested in Figure 1.1, because our approach relies on globally analysing a face as a whole for the recognition purpose.

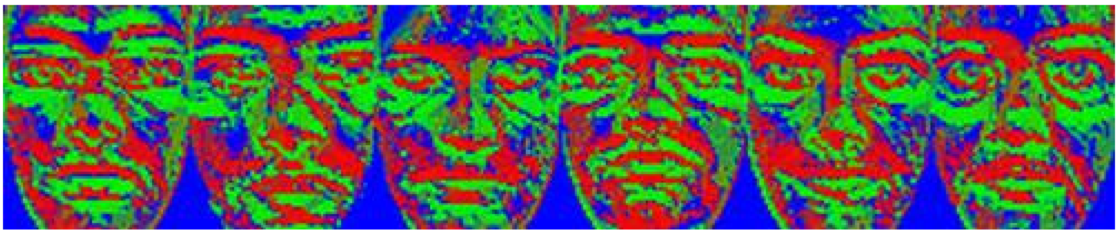
(a) Input Face images



(b) Cropped Face images

(c) Normalized Face images

(d) gt-Transformed images(gt=0)



(e) gt-Transformed images(gt=5)

Figure 4.1: Images produced after various phases

4.1.1 Face Detection

Faces are extracted using Haar cascades. Trained Haar cascades are used directly as available in OpenCV [25]. Cropped face are resized to the ORL standard size (*i.e.* 92×112 pixels) (as shown in Figure 4.1(b)).

4.1.2 Preprocessing and Testing Strategy

After preprocessing, *gt*-transformed images are saved as color images (in TIFF format), sized 90×110 (as shown in Figures 4.1(d) and 4.1(e)). 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.

4.1.3 Face image Comparison using *NUP* measure

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:

$$\text{Recognition rate} = \frac{\text{Number of matches}}{(\text{Total number of images}) \times n} \tag{4.1}$$

which is used to analyze 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.

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*The value of n can range from 1 to (Total number of poses per subject - 1).

Database	Subjects	Poses	Total Images	Varying
ORL	40	10	400	Poses and Expressions
YALE	15	11	165	Illumination and Expressions
BERN	30	10	300	Poses and Expressions
CALTECH	17	20	340	Poses and Illumination
IITK	149	10	1490	Poses and Scale

Table 4.1: Databases Information

4.2 Experimental Results

The performance evaluation of *NUP* measure was done on some standard benchmark 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.

4.2.1 Parameterized results of *NUP* based recognition on different facial databases

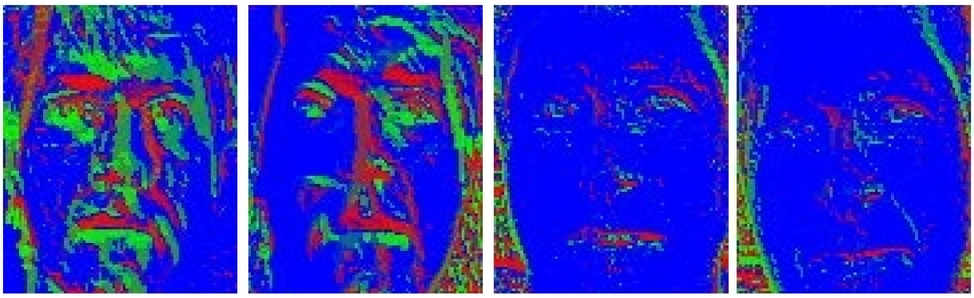
NUP measure is parameterized primarily by two parameters gt and d, the third parameter p (order of norm) is set to 20 for this work. Gray value Tolerance gt can vary within range $[0, 5]$ and Neighborhood parameter d can vary within range $[1, 15]$.

Discussion for gt (Gray Value Tolerance)

From the definition of gt (as shown in Equation 3.2a) 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 of the facial

(a) Original

(b) $gt = 0$



(c) $gt = 5$

Figure 4.2: Effect of High gt values under heavy illumination variation

regions becomes significantly dark. High gt values in these conditions may further lift up the blue value upto an extent that blue color starts dominating in gt-transformed image (as shown in Figure 4.2). This results in deterioration of the performance.

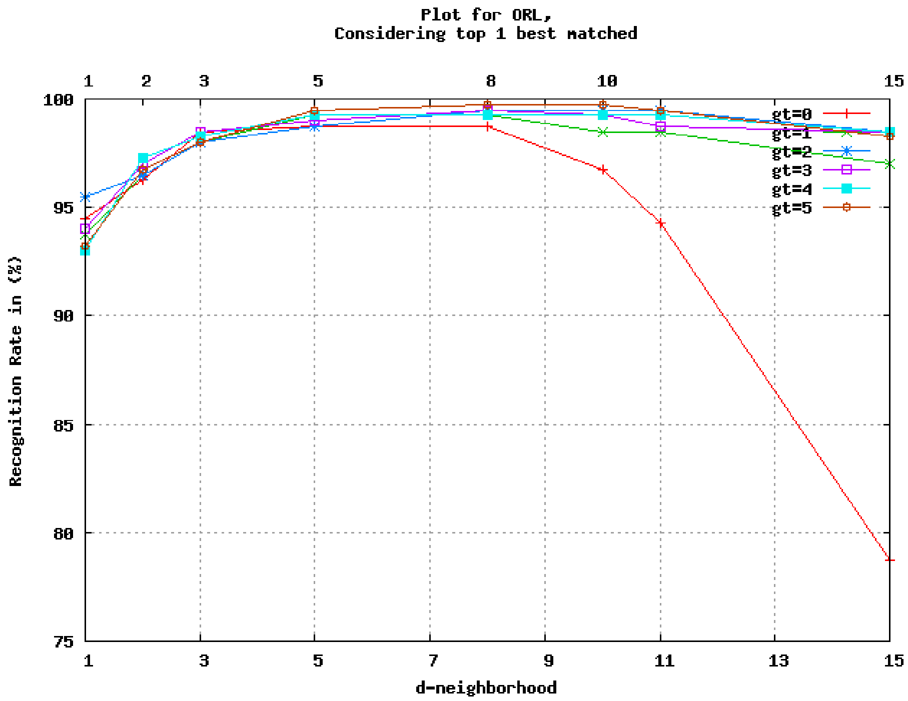
NUP measure performs well on illumination varying databases such as YALE and CALTECH (as shown in Table 4.1) with lower gt values (as shown in Figures 4.4 and 4.6). Databases like ORL, BERN and IITK where illumination is not varying too much and directional lighting is also absent, higher gt values will yield better discrimination (as shown in Figures 4.3, 4.5 and 4.7).

Discussion for d (Neighborhood parameter)

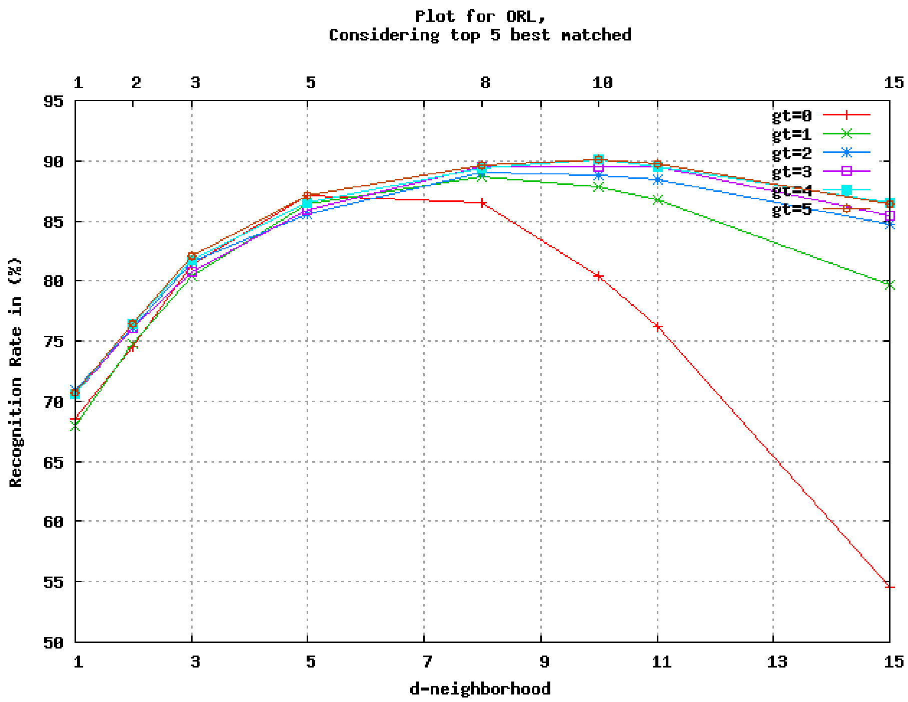
From the definition of d (as shown in Equation 3.3), on unnormalized [†], pose and expression varying images of ORL, BERN and IITK databases, bigger neighborhood yield good performance as also suggested by the plots (as shown in Figures 4.3, 4.5 and 4.7).

On databases like YALE and CALTECH smaller neighborhood is expected because they contain fairly normalized images without too much pose and expression variations (as shown in Table 4.1), as also suggested by the plots (as shown in Figures 4.4 and 4.6).

[†]Images not normalized with respect to any of the facial features.

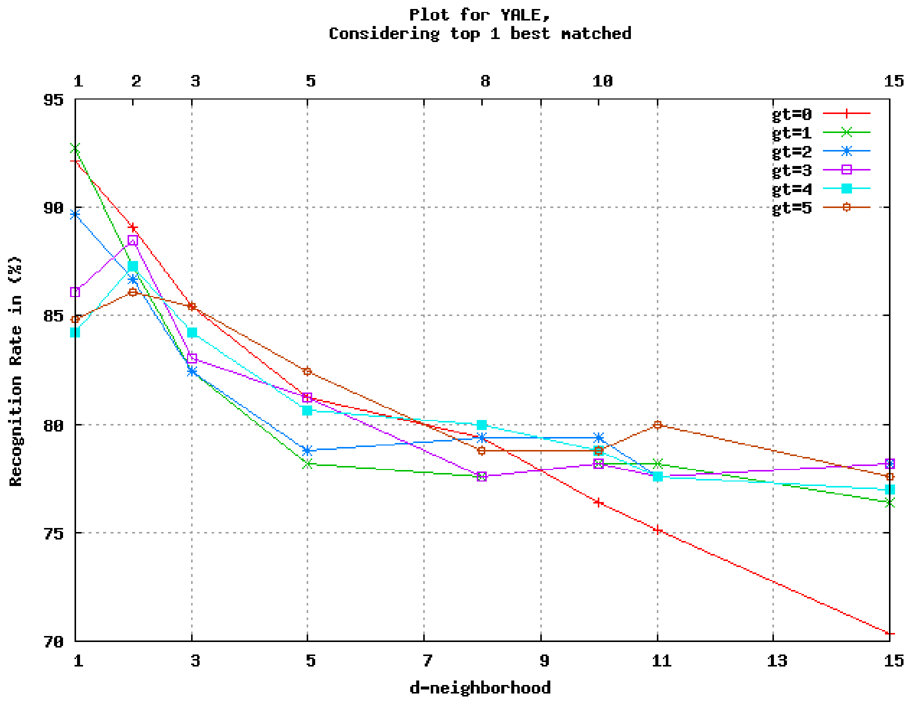


(a) ORL, Considering *top* 1 best matched

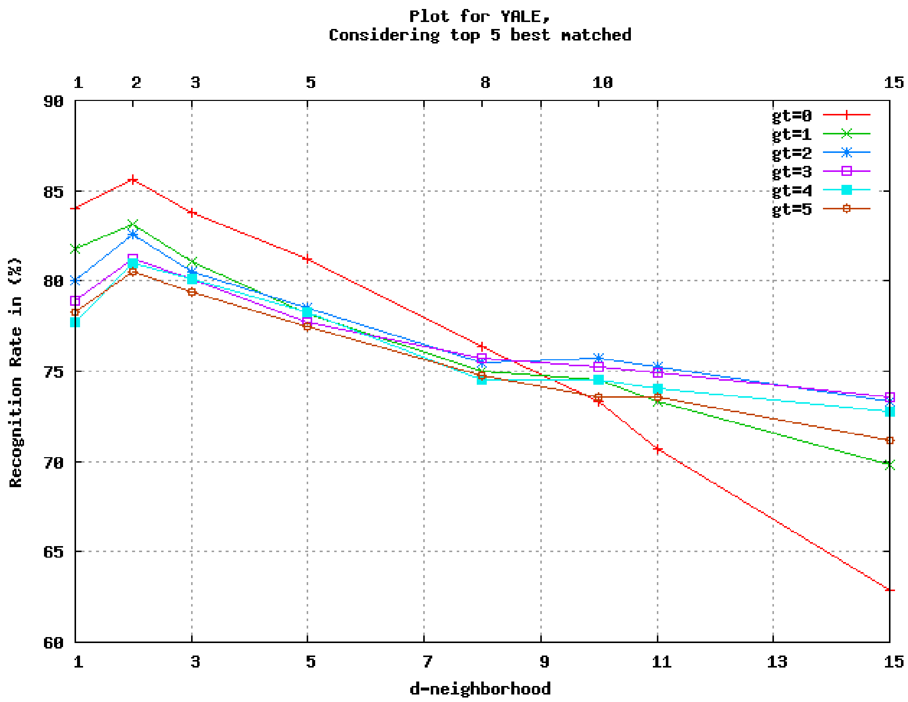


(b) ORL, Considering *top* 5 best matched

Figure 4.3: ORL Database Results

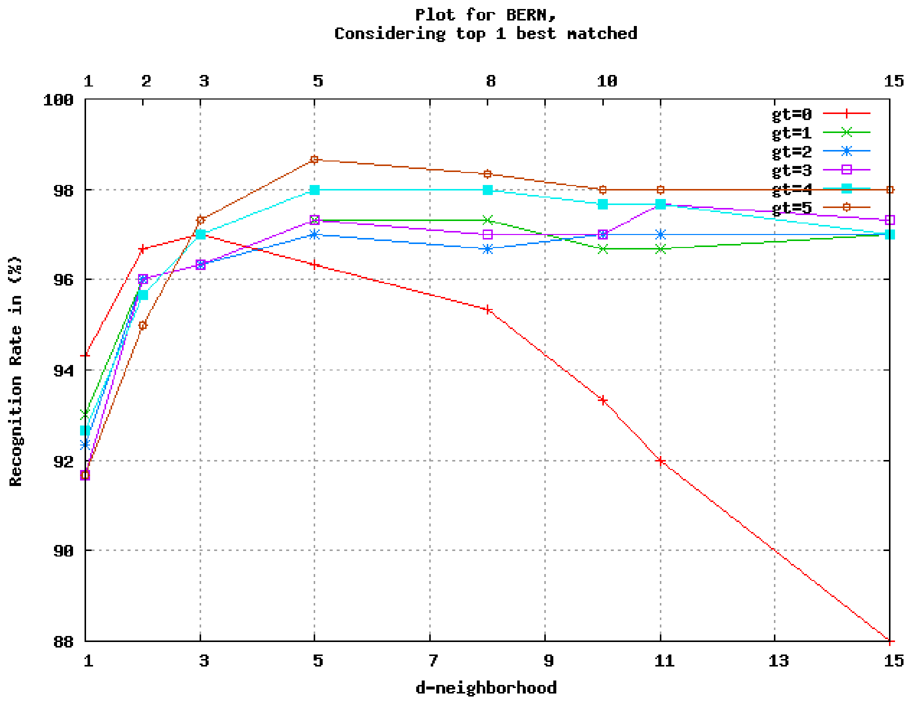


(a) YALE, Considering *top* 1 best matched

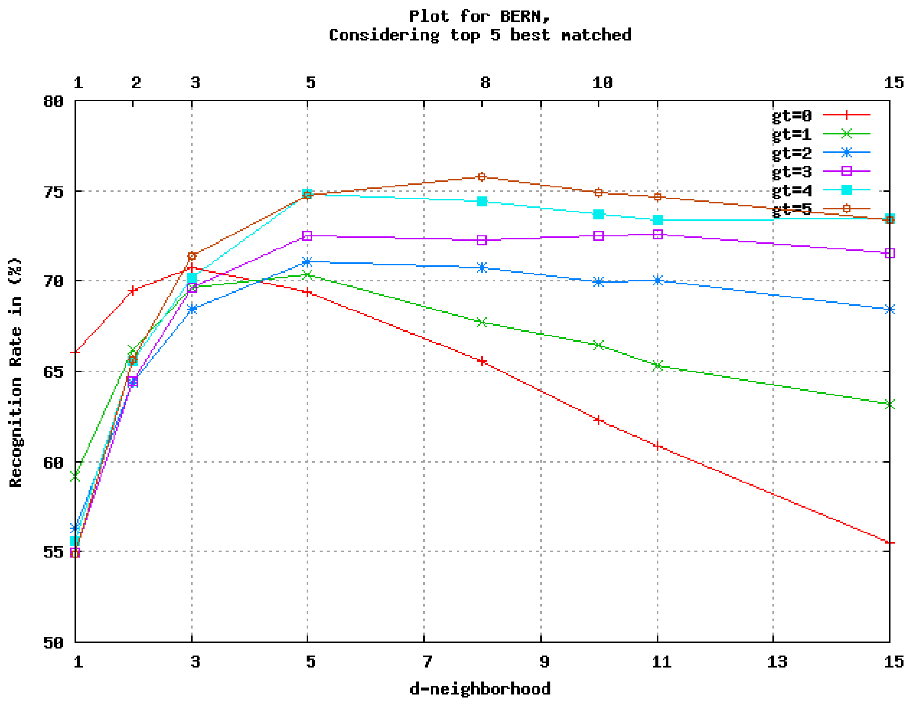


(b) YALE, Considering *top* 5 best matched

Figure 4.4: YALE Database Results

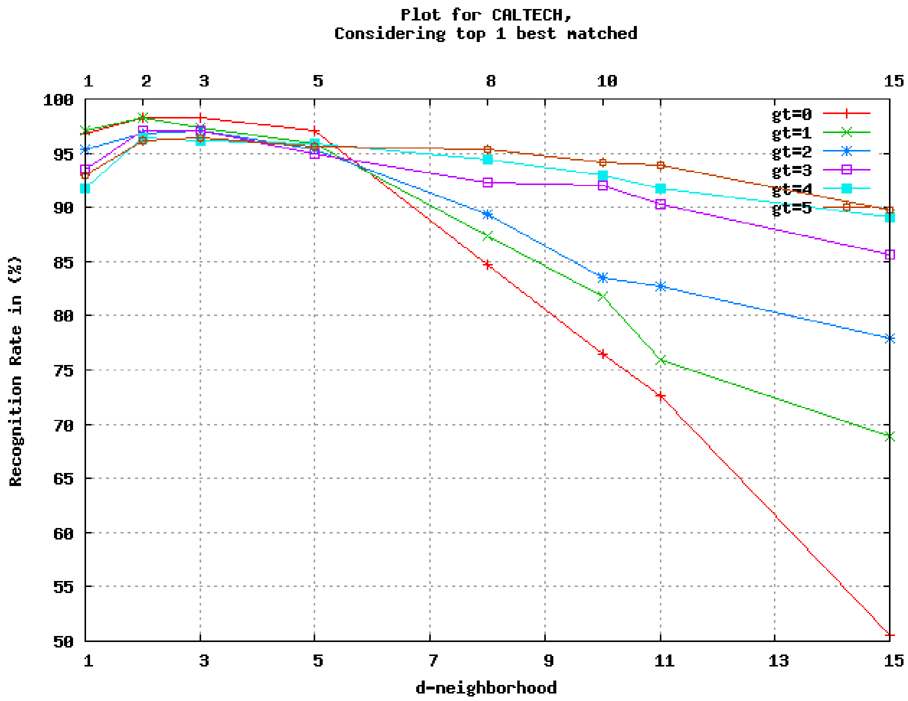


(a) BERN, Considering *top* 1 best matched

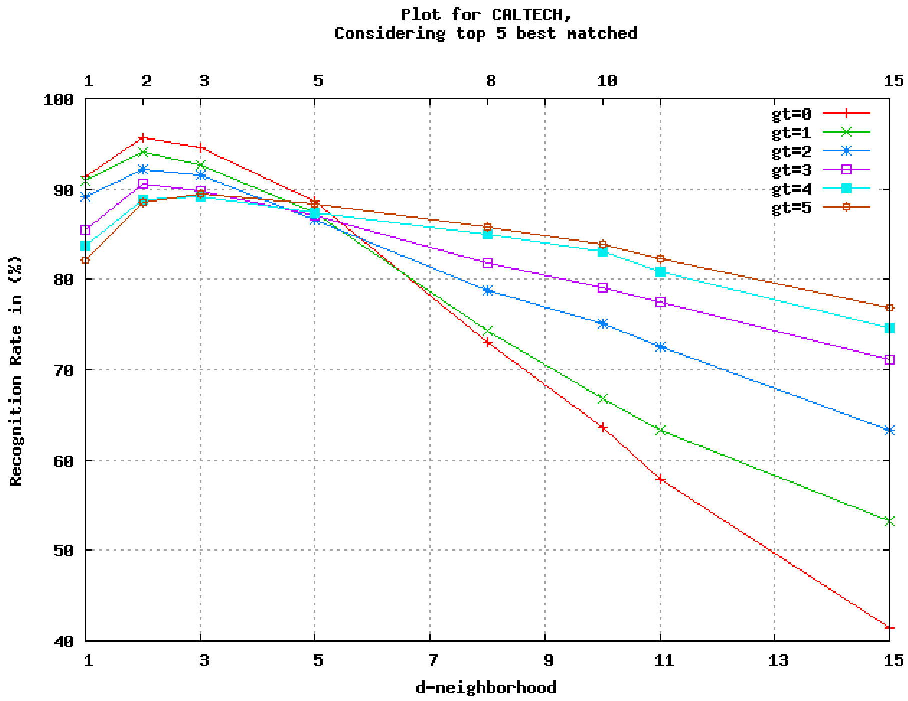


(b) BERN, Considering *top* 5 best matched

Figure 4.5: BERN Database Results

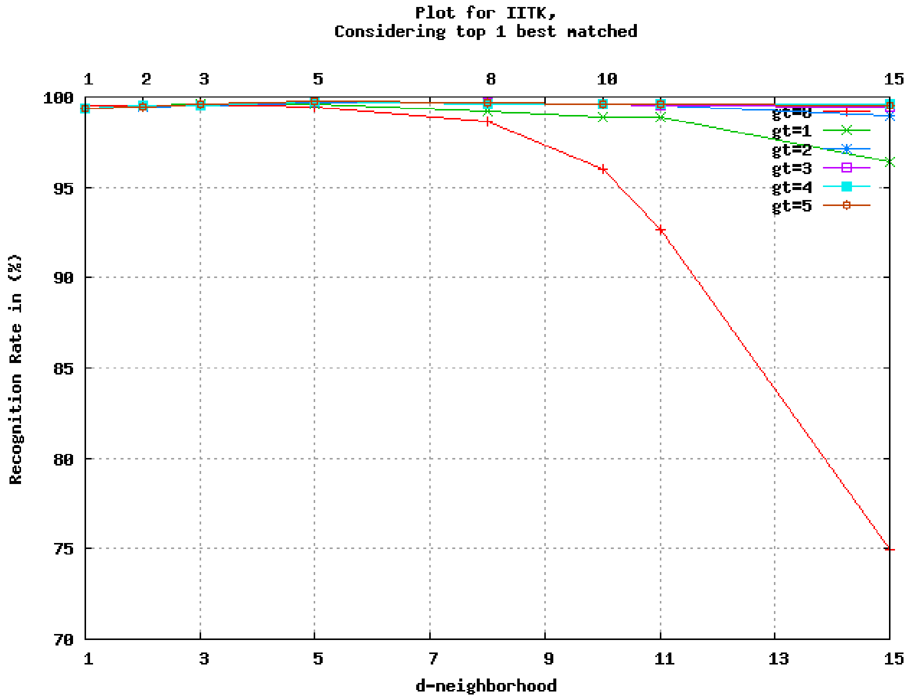


(a) CALTECH, Considering *top* 1 best matched

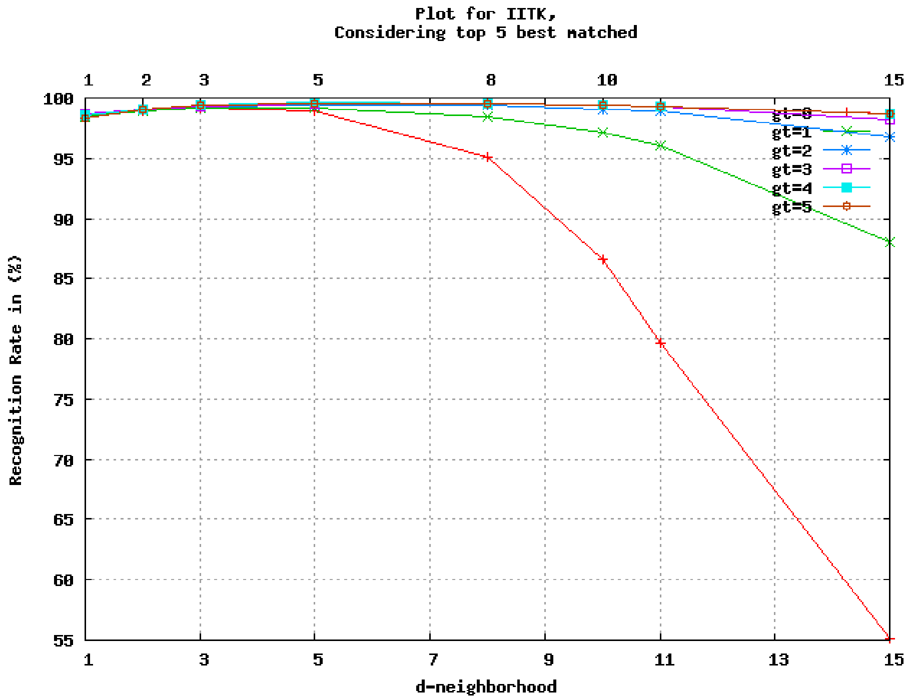


(b) CALTECH, Considering *top* 5 best matched

Figure 4.6: CALTECH Database Results



(a) IITK, Considering *top* 1 best matched



(b) IITK, Considering *top* 5 best matched

Figure 4.7: IITK Database Results

Distance Measure	Recognition rate (%) ORL	YALE
PCA	63	50
HD	46	66
PHD	72.08 ($f = 0.85$)	84 ($f = 0.7$)
M2HD	75	80
SWHD	82	82
SW2HD	88	83
SEWHD	88	85
SEW2HD	91	89
H_{pg}	91.25	83.3 ($f = 0.55$)
NUP	**99.75** ($gt = 5,\ d = 11$)	**92.73** ($gt = 0, d = 1$)

Table 4.2: Comparative study on ORL and YALE databases when considering *top* 1 best match

Test Faces	Recognition rate (%) PHD ($f = 0.85$)	LEM	H_{pg}	**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**

Table 4.3: Comparative study on BERN database when considering *top* 1 best match

4.2.2 Comparative Analysis

As shown in the Tables 4.2 and 4.3 it can be seen that *NUP* measure performed with a superior discriminative power than the other existing distance measures (for other existing distance measures refer Chapter 2).

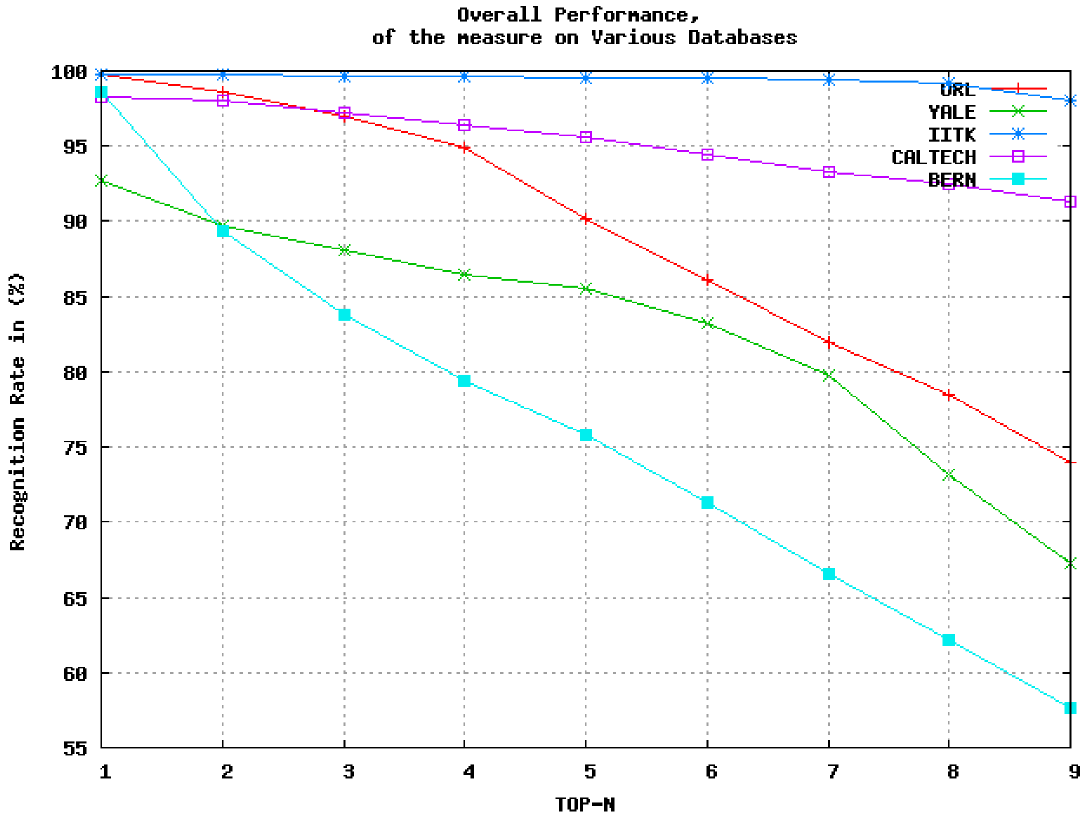


Figure 4.8: Results of NUP based face recognition on different face databases considering *top n* best matches.

4.2.3 Overall Analysis

The overall performance of *NUP* is evaluated by testing it over various standard face databases with respect to n (as shown in Figure 4.8). For $n = 1, 2$ recognition rates are very good(as shown in Figure 4.8 and Table 4.4). With increasing n the recognition rate falls which is obvious.

Top-n	ORL	YALE	CALTECH	BERN	IITK
1	99.75	92.72	98.23	98.66	99.73
2	98.63	89.7	98.08	89.33	99.73
3	97.10	88.11	97.25	83.77	99.66
4	94.87	86.51	96.40	79.41	99.63
5	90.15	85.57	95.64	75.80	99.58
6	86.13	83.23	94.46	71.33	99.55
7	82.10	79.74	93.27	66.57	99.41
8	78.50	73.11	92.42	62.12	99.14
9	74.01	67.20	91.30	57.70	98.05

Table 4.4: Overall Analysis (considering *top-n* best matched)

Chapter 5

Conclusion and Further Work

In this work, a new measure Normalized Unmatched Points (*NUP*) has been proposed 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.

The *NUP* measure is primarily controlled by two parameters, gt and d. The values for the parameters are set taking into account the illumination variation and the nature of the images in the face database. *NUP* measure has shown tolerance to varying poses, expressions and illumination conditions. Experiments on ORL, YALE, BERN and CALTECH benchmark face databases with the *NUP* measure have achieved recognition rates of 95% and above.

In a constrained environment which is uniformly well illuminated *NUP* measure could also be used for video surveillance, scene segmentation in videos, face detection, face authentication. The *NUP* measure is computationally inexpensive and provides good performance levels. For recognition in complex varying environments with big images it can also be used as fast first level scanner, working on re-sampled* images providing assistance to the higher levels. This measure can also be extended to other biometric traits as iris and ear.

Experimental results have shown that the *NUP* measure has a better discriminative power as it can achieve a higher recognition rate than HD, PHD, MHD, M2HD, SWHD, SW2HD, SEWHD, SEW2HD, H_g and H_{pg}.

*A $n \times n$ sized image can be re-sampled as considering every k^{th} scan line, and on it every l^{th} pixel. Hence $n \times n$ pixels, are reduced to only $\left[\frac{n^2}{k \cdot l}\right]$ pixels.

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