A Novel Face Recognition Measure using Normalized Unmatched Points

Aditya Nigam
Supervisor: Dr. Phalguni Gupta

Department of Computer Science and Engineering
Indian Institute of Technology Kanpur

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Table of contents

Problem Definition

- Face picture acquisition under the same physical conditions is not always possible.
- Different face recognition algorithms perform poorly in typical varying environments.
- Varying illumination, poses, lighting conditions, expressions, backgrounds, scales causes a lot of variation in pixels intensities, and hence different algorithms performance got severely affected.
- So we require an algorithm that is robust enough to small amount of such variations.

Motivation

- Edge images are less affected by illumination variations, but they don't carry overall facial appearance "*they contains primarily the structure of the faces*".
- Gray images can't be used directly as they are affected by this illumination variation.
- *NUP* measure can compare the gray images and is found to be robust to slight variation in pose, expression and illumination.

Hausdorff Distance (*HD*)

- Conventional Hausdorff distance is dissimilarity between two set of points.
- 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:

$$HD(A, B) = HD(B, A) = max(hd(A, B), hd(B, A))$$

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

Directed hd

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

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

HD Example

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: Example hd(A,B)

PHD

- *HD* measure does not work well when some part of the object is occluded or missing.
- For partial matching partial Hausdorff distance *PHD* was introduced.
- Undirected *PHD* is defined as:

$$PHD(A,B) = PHD(B,A) = max(phd(A,B), phd(B,A))$$

here *phd(A,B)* is the directed *PHD*, which is defined by:

Directed phd

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

- Both *HD* and *PHD* works on edge map and can tolerate small amount of local and non-rigid distortion.

MHD

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

$$MHD(A,B) = MHD(B,A) = max(mhd(A,B), mhd(B,A))$$

here *mhd(A,B)* is the directed *MHD*, which is defined by:

Directed mhd

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

Where N_a is the number of points in set A.

M2HD

- *MHD* is improved to *M2HD* [10] by adding 3 more parameters :

Parameters

Neighborhood function ($\boldsymbol{N_B^a}$) N'hood 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 directed *M2HD* is defined as:

Directed m2hd

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

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

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

SWHD and *SW2HD*

- For better discriminative power *HD* and *M2HD* measures were 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 and are given more importance than others.
- Directed *SWHD* and *SW2HD* [11] were defined as:

Directed swhd and sw2hd

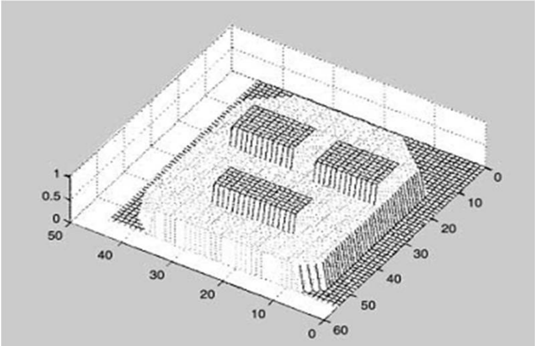
$$\begin{aligned} swhd(A,B) &= \max_{a\in A}\left[w(b)\cdot \min_{b\in B}\|a-b\|\right] \\ sw2hd(A,B) &= \frac{1}{N_a}\sum_{a\in N_a}\left[w(b)\cdot \min_{b\in B}\|a-b\|\right] \end{aligned}$$

Spatial Weighing Function

Where $w(x)$ is defined as:

Weighing Function

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



SEWHD and *SEW2HD*

- Rough estimation of facial features cannot fully reflect the exact structure of human face.
- Regions where the difference among the training images is large, the corresponding regions at the eigenfaces will have large magnitude.
- 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 in the eigenfaces will have large magnitude.

Eigen Weighing

Eigen faces can be used as weighing function because they represents the most significant variations in the set of training face images.

Eigen Faces

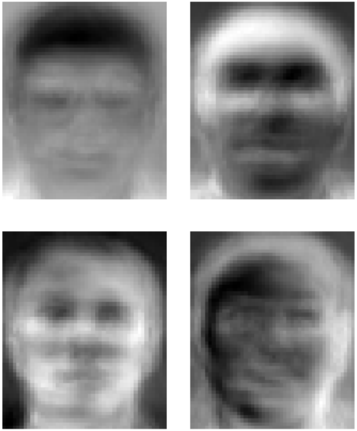


Figure: Eigenfaces

Defining *SEWHD* and *SEW2HD*

- Proposed *SEWHD* and *SEW2HD* [12] are defined as:

Directed sewhd and sew2hd

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

where $w_e(x)$ is defined as:

$w_e(x) =$ Eigen weight function generated by the first eigen vector

H_g and H_{pg}

- Edge images loose most of the important facial features, which are very useful for facial discrimination.
- H_g and H_{pg} [13] measures works on quantized images and are found robust to slight variation in poses, expressions and illumination.

Quantized Images

Images with $n \geq 5$ retains the perceptual appearance and the intrinsic facial feature information that resides in gray values (as shown in Figure below).

Figure: Quantized-faces

Defining H_g and H_{pg}

- H_g and H_{pg} are defined on quantized gray images as :

Directed h_g and h_{pg}

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

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

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

A_i and B_i are the set of pixels in quantized images A and B having quantized gray value i.

NUP Measure

NUP

- *NUP* measure can be applied on *gt*-transformed images obtained from gray-scale facial images.
- *NUP* measure is similar to the *HD* based measures but is computationally less expensive and more accurate.
- *NUP* also shows robustness against slight variation in pose, expression and illumination.

Transformation

- A pixel's relative gray value in its neighborhood can be more stable than its own gray value.
- *SK*-transformation [14] provides some robustness against illumination variation and local non-rigid distortions by converting gray scale images into transformed images that preserve intensity distribution.
- 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.

Property of *SK-transformed images*

Gray value of pixels are being changed in different poses of the same subject but their corresponding vector do not change by a great extent.

Example

Gray values

12	122	26
170	170	178
82	220	211

Sign of first-order derivative

-1	-1	-1
0	X	1
-1	1	1

0	-1	-1	-1	1	1	1	-1

Transformed vector

Problem

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

Observation

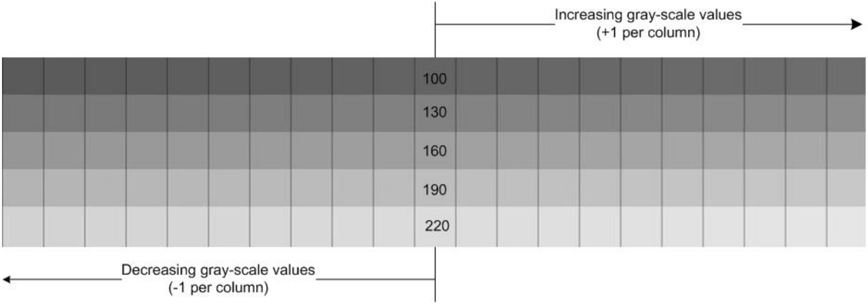


Figure: Gray-value spectrum.

Gray levels are hardly distinguishable (Similar) within a range of ± 5 units.

Improvement

- Basic Comparator

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

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

- *gt*-Comparator

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

Improvement

- Basic Comparator

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

- *gt*-Comparator

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

Where

- gt is gray value tolerance, $gt \geq 0$.
- X is a gray level *not merely a number*.
- Gray level X is neither greater than gray level $(X - 1)$ nor less than gray level $(X + 1)$; ideally they should be considered as similar.

Diagrammatically

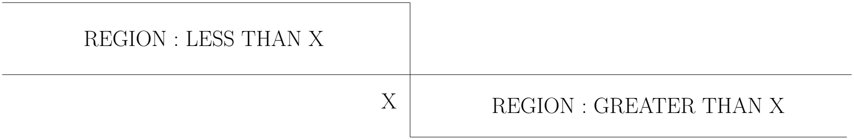


Figure: Basic Comparator

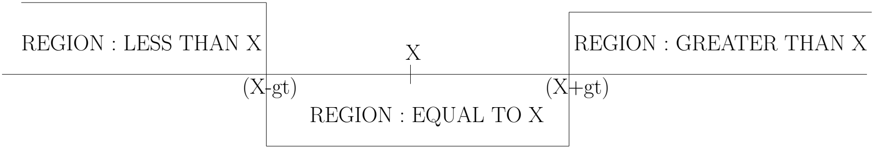


Figure: *gt*-Comparator

gt-Transformation

- Any pixel 'a' is represented by an 8-element vector $V(a)$ whose elements are drawn from the set $\{0, 1, 2\}$.
- The decimal equivalent of the $V(a)$ is called the transformed value of the pixel a, ranging from 0 to 6560 ($= 3^8 - 1$).

Stability

In typical varying environment transformed value of a pixel remains more stable than its corresponding gray value.

gt-Transformed Images

Encoding

Less Than $<$ *RED i.e.*[0], Equal To $=$ *BLUE i.e* [1], Greater Than $>$ *GREEN i.e.* [2].

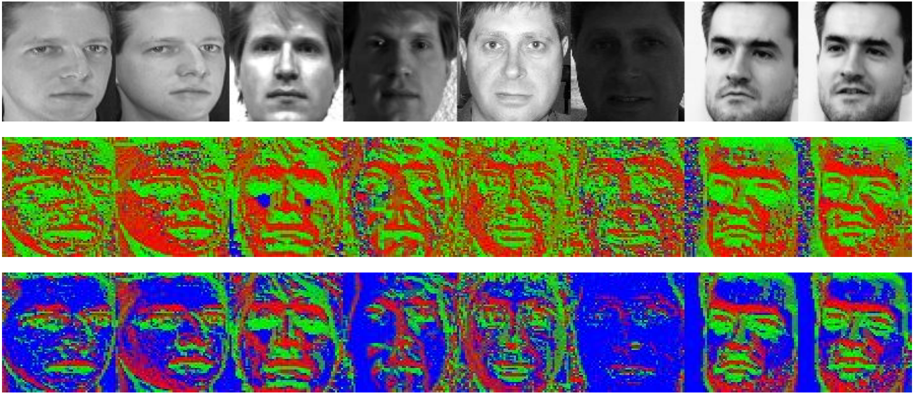


Figure: gt-Transformed images

Notations

Parameter Description

Parameter	Description
$\boldsymbol{A} \mid \boldsymbol{B}$	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;
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;

Defining N_B^a

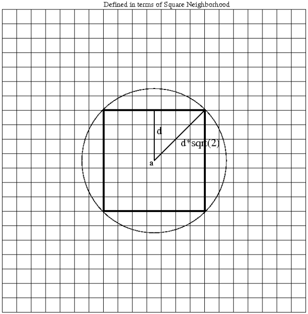
- Neighborhood of pixel a in image B
- Pixel's within a distance of $d\sqrt{2}$ from pixel a is considered to be in its neighborhood.

Neighborhood

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

Circular Neighborhood

Defined in terms of Square Neighborhood



Defining $Compare(A, B)$ and N^U_{AB}

- $Compare(A, B)$ compares two *gt*-transformed images A and B.
- **Returns** N^U_{AB} (*i.e.* Total number of unmatched pixels of A, when A is compared with B), defined as:

Unmatched Points

$$N^U_{AB} = \sum_{a \in A} (1 - Match(a, B))$$

Defining *Match*(a, B)

- *Match*(a, B) matches a pixel a with a gt-transformed image B.
- **Returns** 1 if there is a pixel within the neighborhood of a in image B, having same gt-transformed value (*i.e.* Matched),
  Else **Returns** 0 (*i.e.* Unmatched).
- *Match*(a, B) can be defined as:

Matching

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

Defining $NUP(A, B)$ and $nup(A, B)$

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

Undirected NUP

$$NUP(A, B) = \|\langle nup(A, B), nup(B, A)\rangle\|_p$$

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

Directed nup

$$nup(A, B) = \frac{N^U_{AB}}{N_a}$$

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

Some Properties of *NUP* and *nup*

Properties

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.

Efficient *Match(a,B)*

- Computing $NUP(A, B)$ using naive method requires $O(r^2c^2)$ time , which is prohibitively computationally intensive.
- Performing $Match(a, B)$ operation efficiently an array of pointers to linked list BLIST is created.

BLIST

It has 3^8 elements such 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].

Date-Structure BLIST

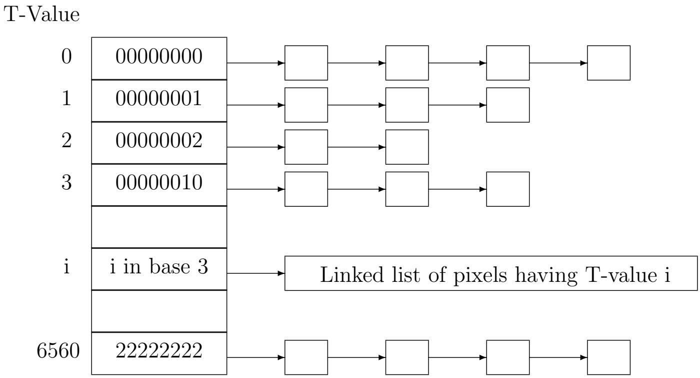


Figure: Data Structure: BLIST

Time Complexity

Preprocessing

- Gray scale images sized $r \times c$ transformed into *gt*-Transformed images. It is done once and single scan of the whole image is sufficient.
- Time complexity is $O(rc)$.

Processing

- Constructing data structure BLIST require $O(rc)$ time.
- *Match* function involves linear search of a linked list of pixels.
- Time taken by *Match* depends on the length of the list. Assuming that k is the length of the largest linked list.
- Computing *NUP(A,B)*, $Match(a, B)$ function has to be called $2rc$ times, therefore time required to compute *NUP* will be $O(krc)$.

Setup

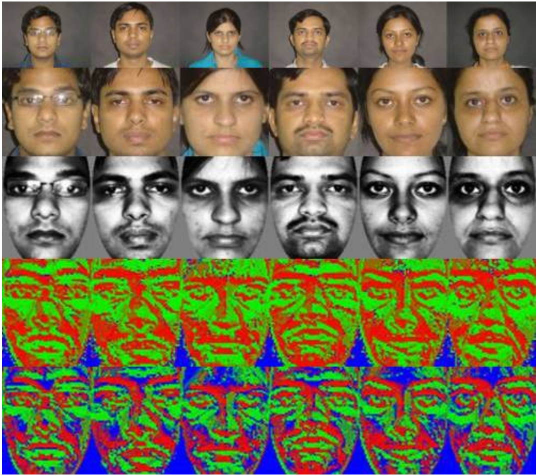


Figure: Images produced after various phases

Testing Strategy

- Whole database is treated as the testing set, then each image of the testing set is matched with all other images excluding itself. Finally top n best matches are reported.
- Match is announced if and only if a subject's image got matched with another pose of himself/herself.

Recognition Rate

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

Parameterized Analysis

Parameters

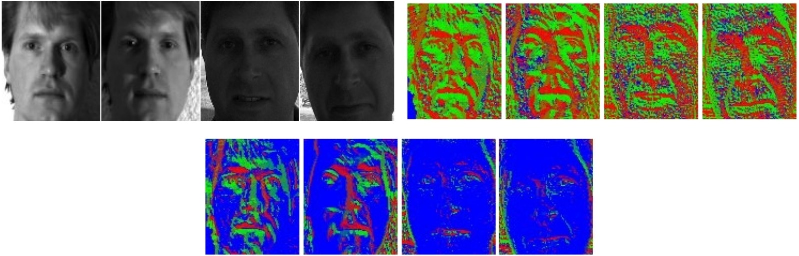
- *NUP* measure is parameterized primarily by two parameters gt and d, the third parameter p (order of norm) is set to 20 for this work.
- Gray value Tolerance gt can vary within range $[0, 5]$.
- Neighborhood parameter d can vary within range $[1, 15]$.

Databases Vs Parameters

Db,Nor	S,P,T	Time	gt,d,RR% [top1]	gt,d,RR% [top5]	Varying
ORL,N	40, 10, 400	1.8	5, 8, 99.75	5, 10, 90.15	Poses and Expressions
YALE,Y	15, 11, 165	1.2	1, 1, 92.75	0, 2, 85.57	Illumination and Expressions
BERN,N	30, 10, 300	1.6	5, 5, 98.66	5, 8, 75.80	Poses and Expressions
CALTECH,Y	17, 20, 340	1.6	1, 2, 98.23	0, 2, 95.64	Poses and Illumination
IITK,N	149, 10, 1490	4.6	5, 5, 99.73	4, 5, 99.58	Poses and Scale

Table: Databases vs Parameters

Big Illumination Variation [use $gt = 0$]

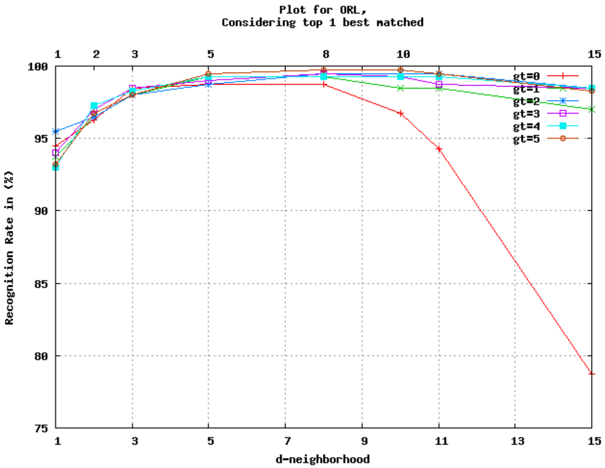


Effect of High gt values under heavy illumination variation

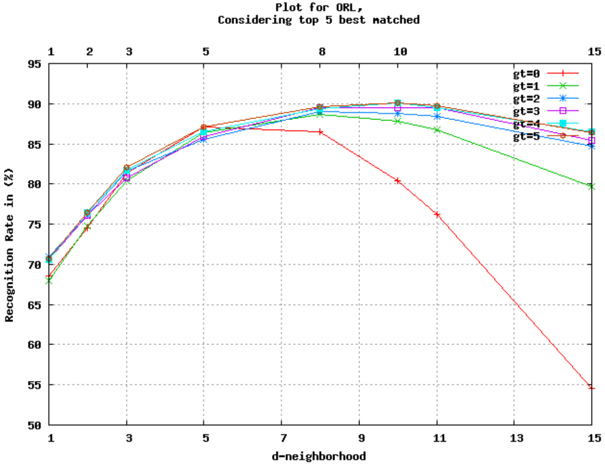
- With higher gt values more and more elements of $V(a)$ start acquiring value 1.
- This will boost the blue value of pixels in the gt-transformed images.
- Directional lights and heavy illumination condition variations may further lift up the blue value upto an extent that blue color starts dominating in gt-transformed image.

ORL:Pose and Expression Variations

ORL:top 1 [$gt = 5, d = 8, RR = 99.75\%$]

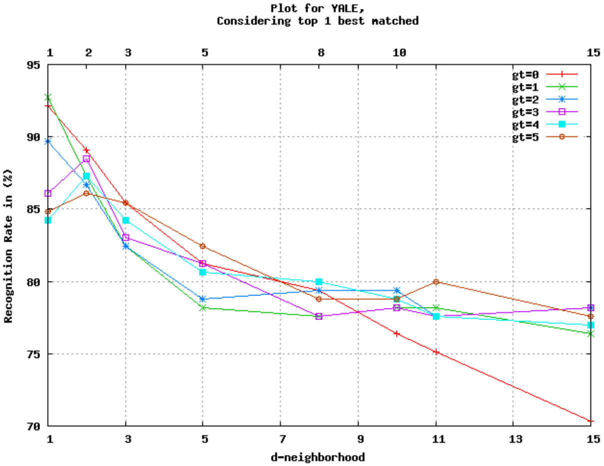


ORL:top 5 [$gt = 5, d = 10, RR = 90.15\%$]

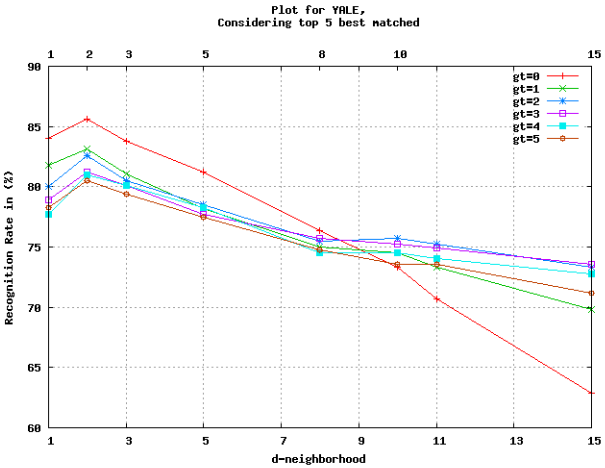


YALE:Illumination and Expression Variations

YALE:top 1 [$gt = 1, d = 1, RR = 92.75\%$]

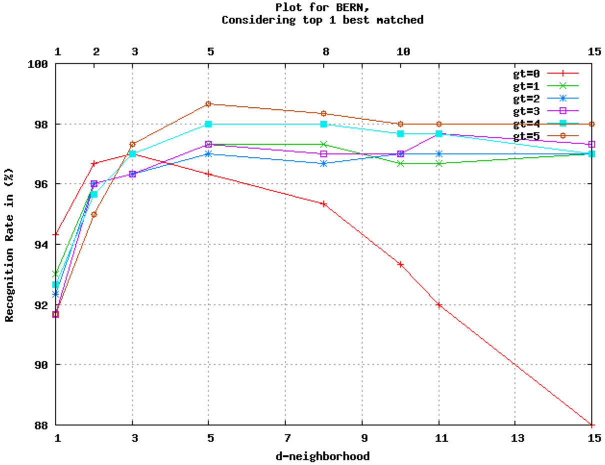


YALE:top 5 [$gt = 0, d = 2, RR = 85.57\%$]

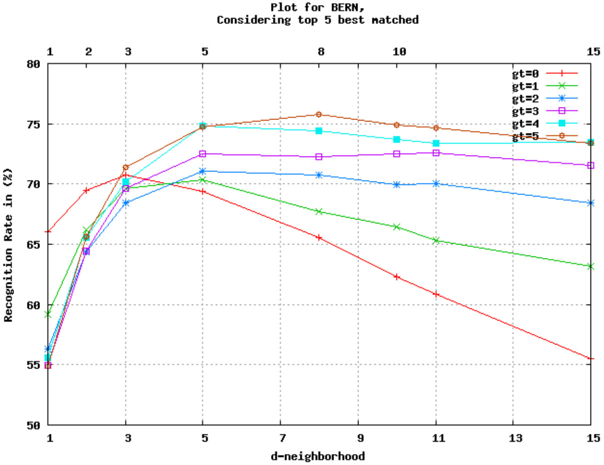


BERN:Big Pose and Expression Variations

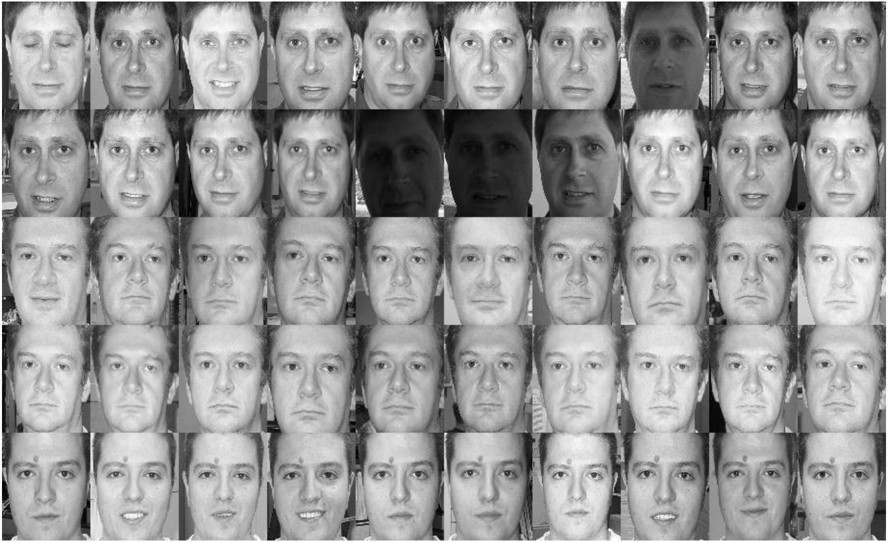
BERN:top 1 [$gt = 5, d = 5, RR = 98.66\%$]



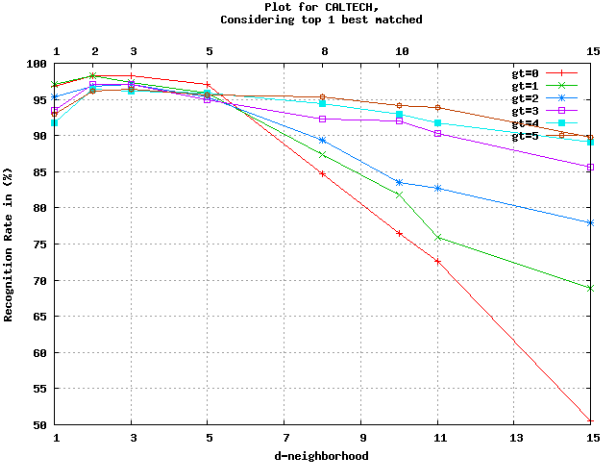
BERN:top 5 $[gt = 5, d = 8, RR = 75.80\%]$



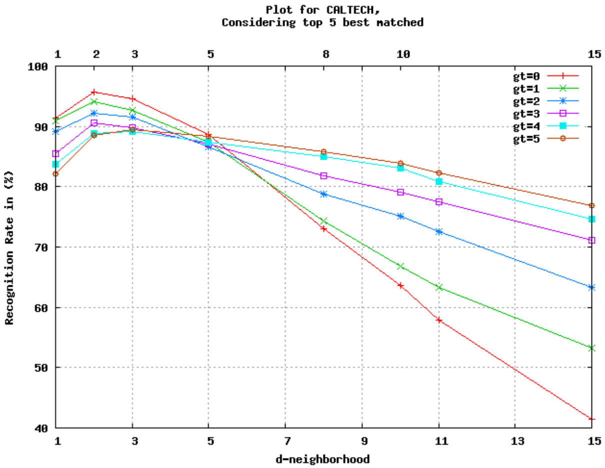
CALTECH:Small Pose, Expression, Illumination and Background Variation



CALTECH:top 1 [$gt = 1, d = 2, RR = 98.23\%$]

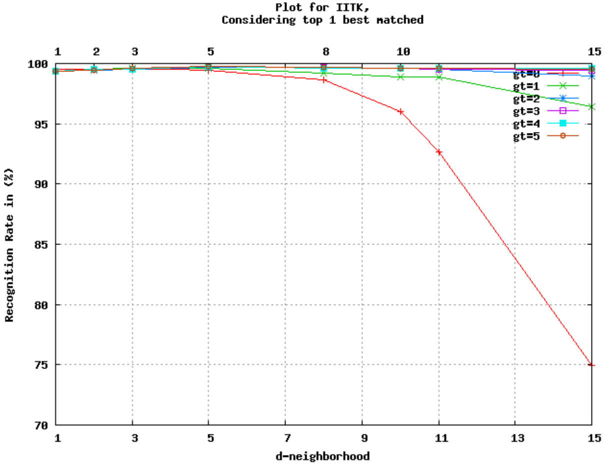


CALTECH:top 5 [$gt = 0, d = 2, RR = 95.64\%$]

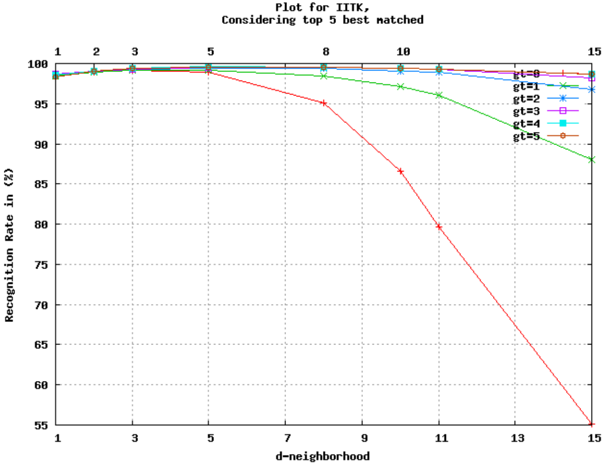


IITK:Very Small Expression and Pose Variations

IITK:top 1 [$gt = 5, d = 5, RR = 99.73\%$]



IITK:top 5 $[gt = 4, d = 5, RR = 99.58\%]$



Comparative Analysis

ORL and *YALE*

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

Comparative Analysis

BERN

Test Faces	Recognition rate (%)			
	PHD ($f = 0.85$)	LEM	H_{pg}	**NUP** ($gt = 5, d = 5$)
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: Comparative study on BERN database when considering *top* 1 best match

Overall Analysis

Overall

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

Overall Analysis

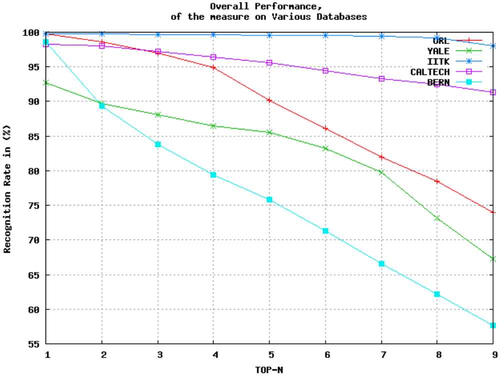


Figure: NUP measure on different face databases, *top n* best matches.

Future Work

- In constrained environment which is uniformly well illuminated *NUP* measure could also be used for video surveillance, scene segmentation in videos, face detection, face authentication.

Fast First Level Scanner

For recognition in complex varying environments with big images it can also be used as fast first level scanner, working on under sampled images providing assistance to the higher levels.

- It can also be extended to other biometric traits as iris and ear.

Conclusion

- Normalized Unmatched Points (*NUP*) measure proposed is different from existing Hausdorff distance based methods as it works on *gt*-transformed images.
- It is computationally inexpensive and provides good performance.
- Parameters gt, d, p are set taking into account the illumination variation and the nature of the images.

Discriminative Power

It has shown tolerance to varying poses, expressions and illumination conditions and can achieve a higher recognition rate than HD, PHD, MHD, M2HD, SWHD, SW2HD, SEWHD, SEW2HD, H_g and H_{pg}.

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