Biometric Systems
Lesson 14: Gallery Entropy and its uses
Use of Demographics

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Definition of Gallery Entropy and applications to biometrics

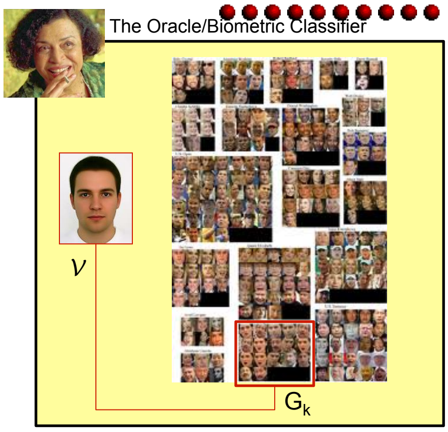
Entropy Based Template Anlaysis

The Oracle

We are interested in measuring the representativeness of G_k and how v alters it.

Assuming that an oracle has assigned the template v to its corresponding identity k, the score $s_{i,v}$ can be interpreted as the probability that template v conforms to $g_{i,k}$.

$$\mathrm{s}_{\mathrm{i,v}} = p\left(v \approx g_{i,k}\right)$$



In order for $s_{i,v}$ to represent such a probability, it must range in the interval [0,1], and the sum over all templates in G_k must be 1, therefore, each $s_{i,v}$ is normalized with respect to $\Sigma_i(s_{i,v})$.

N.T.: we do not question about the correct assignment of v to G_k;

Entropy Based Template Anlaysis

The Entropy Function

The entropy of a whole gallery G_k with respect to a probe v can be defined as:

$$H(G_k, v) = -\boxed{\frac{1}{\log_2(|G_k|)}} \sum_{i=1}^{|G_k|} s_{i,v} \log_2(s_{i,v})$$

N.T.: $1/\log_2(|G_k|)$ is a normalization factor and corresponds to the maximum entropy, which is obtained when $s_{i,v}$ has the same value for all the templates in G_k.

The entropy for the gallery G_k is computed by considering each gallery template $g_{j,k}$ in turn as a probe v.

Given Q the set of pairs $q_{i,j}=(g_{i,k}, g_{j,k})$ of elements in G_k such that $s_{i,j}>0$, the entropy for the gallery is defined as:

$$H(G_k) = -\frac{1}{\log(|Q|)} \sum_{q_{i,j} \in Q} s_{i,j} \log_2(s_{i,j})$$

Entropy Based Template Anlaysis

Entopy-Based Ordering

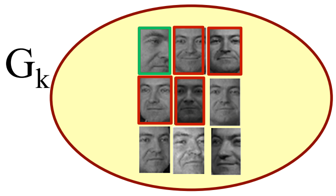
The proposed procedure takes a gallery G_k as input, and starting from it computes a similarity matrix M_k and the value for $H(G_k)$.

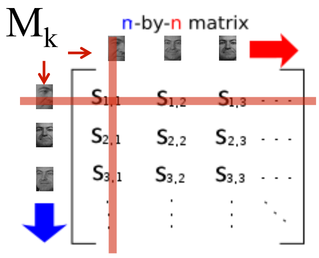
M_k is computed by applying the similarity measure d to all pairs of templates in G_k,
i.e. $M_k(i,j)=d(g_{i,k}, g_{j,k})$, $\forall\, g_{i,k}$ and $g_{j,k} \in G_k$.

For each $g_{i,k} \in G_k$, the matrix M_k is used to compute the value of $H(G_k \setminus \{g_{i,k}\})$

The sample $g_{i,k}$ achieving the minimum difference $f(G_k, g_{i,k})=H(G_k)- H(G_k \setminus \{g_{i,k}\})$ is selected.

The matrix M_k is updated by deleting the i-th row and column, and the process is repeated, until all elements of G_k have been selected.

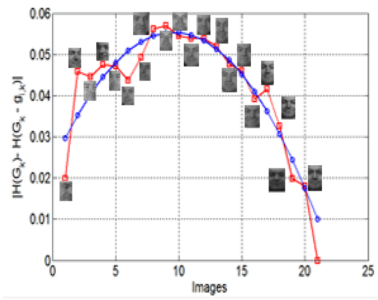




Entropy Based Template Anlaysis

Entopy-Based Ordering

- In practice, we first select the most representative samples → those causing the lower entropy (representativeness) decrease.
- In this way, the minimum entropy difference tends to increase, as expected. However, from a certain point, it tends to decrease again due to the much lower number of samples which are involved in the computation.
- We empirically identified the parabola as the simplest curve to approximate this behavior with sufficient accuracy.

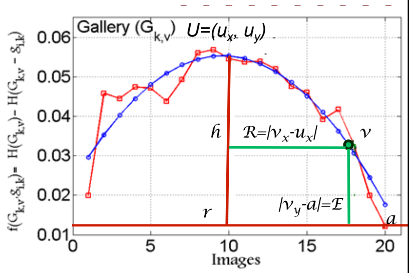


Entropy Based Template Anlaysis

Entropy-Based Classification

For each registered subject k, the algorithm:

- builds the new gallery $G_{k,v}=G_k \cup \{v\}$;
- sorts samples $g_{i,k}$ according to function $f(G_{k,v}, g_{i,k})$;
- computes the parabola which approximates the function $f(G_{k,v}, g_{i,k})=H(G_{k,v})- H(G_{k,v} \setminus \{g_{i,k}\})$.



Let be r the line parallel to the x-axis and passing through the minimum value a of function $f(G_{k,v}, g_{i,k})$.

h equals to the distance between the vertex $U=(u_x, u_y)$ of the parabola and the line r .

R represents the distance between the sample v and the axis of the parabola $(v_x - u_x)$.

E corresponds to the distance between sample v and line r, that is (v_y-a).

The similarity function for sample v with respect to gallery G_k is expressed by the following formula:

$$s_{v,k} = \frac{1}{2}\left[\frac{R}{\left(\left|G_{v,k}\right| - u_x\right)} + \frac{E}{h}\right]$$

the relative distance from the most "typical" templates
the relative representativeness of sample v.

Entropy Based Template Anlaysis

Wolf detection

The new similarity function we introduced shows two desirable properties compared to the existing ones:

- It relates the probe template with the elements in the gallery instead of just calculating a global distance.

- It is able to detect wolves [*] (people who could replace one or more persons registered in the system).

[*] G. Doddington, W. Liggett, A. Martin, M. Przybocki and D. Reynolds, Sheep, Goats, Lambs and Wolves: A Statistical Analysis of Speaker Performance in the NIST 1998 Speaker Recognition Evaluation, Proc. of International Conference on Spoken Language Processing (ICSLP), vol. 4, 1998, pp. 1351-1354.

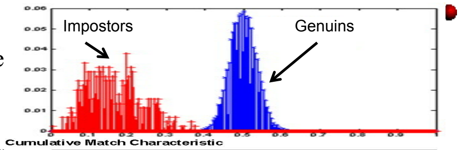
Entropy Based Template Anlaysis

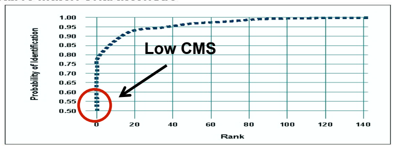
Wolf Detection

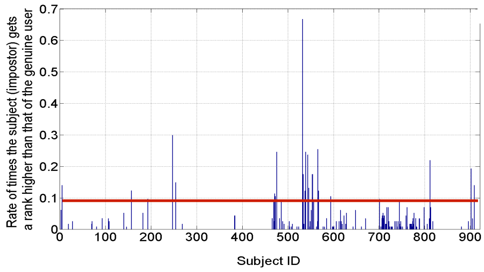
Experimentally we observed that:

- genuine and impostors score distributions are sufficiently different to guarantee acceptable values of Equal Error Rate (EER)

- the graph of Cumulative Match Curve (CMC) starts quite low; however, it reaches very quickly a satisfying height for a certain small value of the rank.







Some few subjects tend to be often returned at the first positions in the system answer list though being impostors.

Impostor subjects identified for a genuine one are most often come from the same subset.

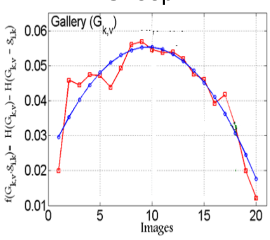
[*] G. Doddington, W. Liggett, A. Martin, M. Przybocki and D. Reynolds, Sheep, Goats, Lambs and Wolves: A Statistical Analysis of Speaker Performance in the NIST 1998 Speaker Recognition Evaluation, Proc. of International Conference on Spoken Language Processing (ICSLP), vol. 4, 1998, pp. 1351-1354.

Entropy Based Template Anlaysis

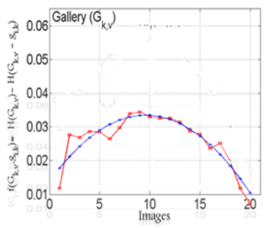
Wolf Detection

We experimentally observed that wolves present a much lower value for the area below the function $f(G_k, g_{i,k})$.

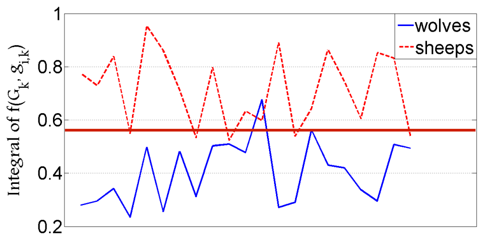
Sheep



Wolf



Looking at the following picture, it comes out that a threshold can be defined to well separate sheeps from wolves.



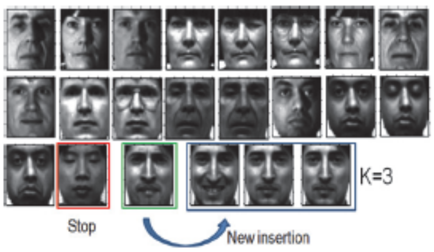
Entropy Based Template Anlaysis

Entropy-Based Clustering

```
CLUSTER LIST(G)
Input: gallery G
Output: list C of clusters
obtain an ordered list L by Order_Gallery (G).
repeat
    create a new cluster C_i with the last m elements of L
    update L by discarding all elements now in C_i
    consider the elements of L backwards
       repeat
         compute correlation of last item on L and those in C_i
         if at least 30% comparisons >= 0.8
             discard current element from L and insert into C_i
       until an item does not meet the correlation condition
    update G by discarding all elements now in C_i
    repeat ordering by Order_Gallery (G)
until G is empty
```

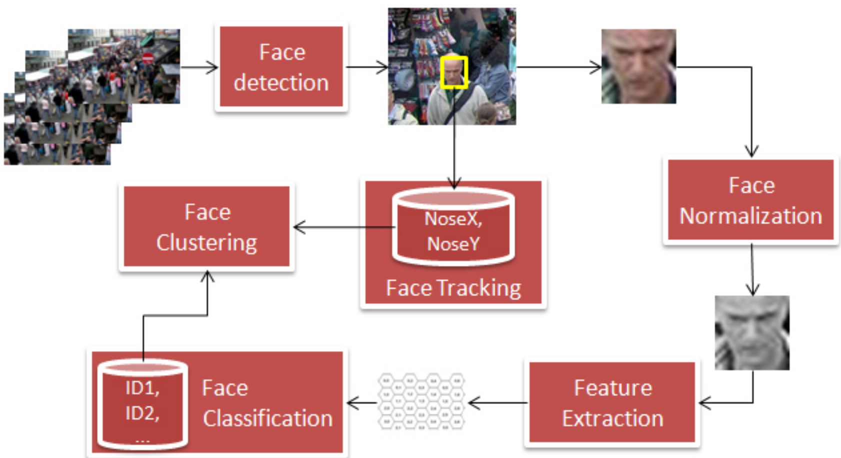
```
AGGREGATE CLUSTERS(C)
Input: list C of clusters
Output: updated list C of clusters
repeat
    for each pair of clusters C_h and C_k
       compute Correlation Matrix CM:
       CM(i,j)= corr(t_i,t_j), ∀ t_i ∈ C_h and t_j ∈ C_k
       if (percentage of entries >= 0.8 in CM) > threshold τ
            merge clusters C_h and C_k
until no pair of clusters can be further merged.
```

We obtain results comparable to k-means without fixing k in advance



Entropy Based Template Anlaysis

Surveillance System



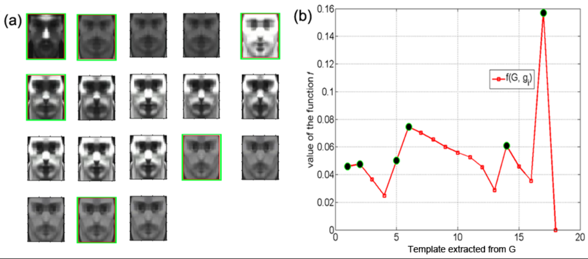
Entropy Based Template Anlaysis

Gallery Updating

An important aspect in the process of identity handling is represented by the choice of when the gallery is to be restructured. In case of failure, the temporary set becomes the gallery of a new permanent identity; we can consider two different pruning strategies:

Prune while merging (PWM): the restructuring operation is delayed until merging; as soon as two sets of templates are fused, the whole resulting gallery will be restructured.

Prune then merge (PTM): as soon as no more face samples are found for a temporary identity, its collected set is pruned, before trying the merging.



Entropy at BIPLAB

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M. De Marsico, M. Nappi, D. Riccio. Entropy in Biometric Face Template Analysis. Proceedings of International Conference on Image Analysis and Recognition – ICIAR 2012, Aveiro, Portugal, June 25-27, 2012, Lecture Notes in Computer Science, 2012, Volume 7325/2012, pp. 72-79.

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Use of demographics and EGA dataset

Ethnicity, Gender and Age

Motivations

A number of works have investigated the impact of face categorization on recognition performance.

It is difficult to appropriately set up related experiments, since available datasets are not organized according to any categorization.

Most of the existing face dataset are lacking in both the number and heterogeneity of subjects.

They cannot be further updated or extended.

Ethnicity, Gender and Age

Related Issues

The underlying core idea is to integrate into a single dataset face images from different databases, and to organize images according to individual features such as ethnicity, gender and age.

Problems:

a) most datasets are released after an agreement to not redistribute them;
b) acquisition condition, image format and quality are not uniform.

Solutions:

a) EGA has been conceived as a set of links to files previously processed by appropriate scripts, available at http://biplab.unisa.it/EGA.html.
   Each user can ask and obtain on its own the original datasets with the images needed to build EGA.

b) We tried to limit some distortions, such as illumination, pose, expression and occlusions, since large and sufficiently representative datasets are already available to test performance on them.

Ethnicity, Gender and Age

The Original Datasets

At present, EGA v1.0 is the union of images from six different datasets:

CASIA-Face V5

- 500 subjects;
- 2,500 images;
- a single session by an USB camera.
- image resolution is 640×480, 16bit color.
- subjects are mostly young and of Eastern ethnicity.

FEI

-200 subjects (100 male and 100 female);
-2,800 images (14 images per subject);
-Age ranging from 19 to 40 years;
-Latin ethnicity.
-colour images resolution is 640×480.

JAFFE

-10 subjects (all females);
-2130 images of 10
-Image resolution 256×256, 8bit;
-Japanese ethnicity;
-age seems to be uniform.

Ethnicity, Gender and Age

The Original Datasets

At present, EGA v1.0 is the union of images from six different datasets:

FERET

-1,199 subjects;
-14,126 images;
-heterogeneous with respect to ethnicity, gender and age;
-15 sessions;
-Image resolution 256×384, 8bits.

FRGC

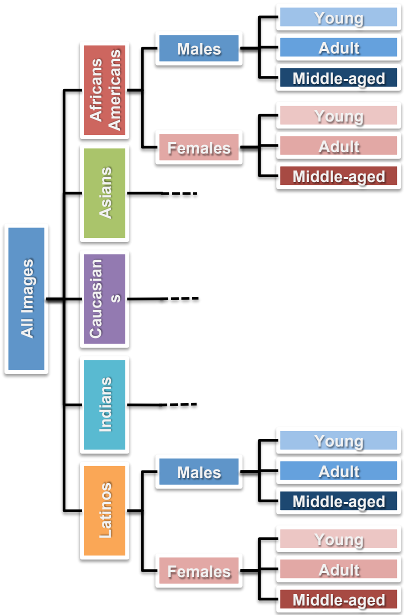
-less than 500 subjects;
-50,000 images;
-homogeneous with respect to ethnicity, gender and age;
-4,003 subject sessions;
-Image resolution 1704×2272, 24bits.

Indian Face Database

-40 subjects;
-male and female;
-Indian ethnicity;
-Image resolution 640×480, 8bits.

Ethnicity, Gender and Age

The EGA Structure



We considered five ethnicities:
a) African-American;
b) Asian;
c) Caucasian;
d) Indian;
e) Latin.

For each of them, subjects were divided into two genders:
a) male;
b) female.

These two subgroups have been further divided into three age ranges:
a) young;
b) adult;
c) middle-aged.

Ethnicity, Gender and Age

The EGA Structure

Ethnicity		Gender		Age	
African American	53	Males	20	Young	3
				Adult	13
				Middle-Aged	4
		Females	33	Young	16
				Adult	11
				Middle-Aged	6
Asian	111	Males	54	Young	34
				Adult	14
				Middle-Aged	6
		Females	57	Young	33
				Adult	19
				Middle-Aged	5
Caucasian	162	Males	89	Young	25
				Adult	50
				Middle-Aged	14
		Females	73	Young	20
				Adult	33
				Middle-Aged	20
Indian	75	Males	49	Young	3
				Adult	37
				Middle-Aged	9
		Females	26	Young	4
				Adult	15
				Middle-Aged	7
Latinos	68	Males	34	Young	7
				Adult	19
				Middle-Aged	8
		Females	34	Young	8
				Adult	16
				Middle-Aged	10

We can observe that the number of Afro-American subjects is limited with respect to subjects of Caucasian or Asian ethnicity.

Indians and Latinos are slightly more numerous.

EGA dataset is balanced with respect to subject gender with
52,4% male
47,6% female.

It is slightly less balanced with respect to age with
32,6% young,
48,5% adult.
18,9% middle-aged.

Ethnicity, Gender and Age

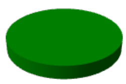
The EGA Structure

- CASIA-Face V5
- FEI
- FERET
- FRGC
- JAFFE
- Indian Face DB

Observation I: Some datasets contribute for only one ethnicity.

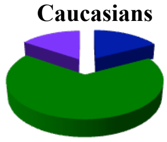
Observation II: Asian ethnicity is the one taking form the largest number of source datasets.

Africans-Americans



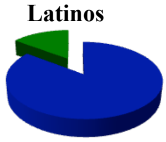
Asians

Caucasians



Indians

Latinos



Observation III: Datasets such as FERET and FRGC provide a more or less significant contribution for most ethnicities.

Ethnicity, Gender and Age

The EGA Structure

The nomenclature of individual files is structured in five parts, each conveying a different information. A filename is of the form **dd**-**ee**-**gg**-**aa**-**nnnn**-**mmmmm**.

dd – source dataset.
It is an integer value between 00 and 99:
01 – CASIA-Face V5;
02 – FEI;
03 – FERET;
04 – FRGC;
05 – JAFFE;
06 – Indian Face Database.

ee – ethnicity of the subject.
It is an integer value between 00 and 99:
01 – Africans-Americans;
02 – Asians;
03 – Caucasians;
04 – Indians;
05 – Latinos.

gg – the gender of the subject.
At present only two values:
01 – male;
02 – female.

aa – age range of the subject.
Subjects have been categorized in three ranges:
01 – young;
02 – adult;
03 – middle-aged.

nnnn – id of the subject.
Each subject has a unique id in the dataset, which is represented by a four-digit integer value.

mmmmm – id of the image.
Each subject can have more images. Thanks to this id, each image pertaining to a certain subject can be univocally identified.

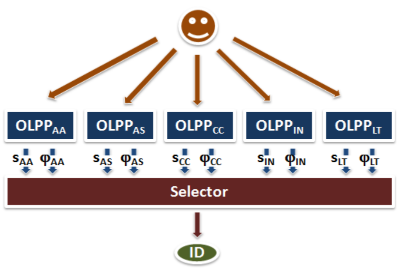
Ethnicity, Gender and Age

The EGA test-application

We explored feasible strategies to fully automate the process of demographics pre-selection. Multiple classifiers are trained, each on a specific demographic feature and any human intervention is avoided during normal system operations.
We tested two different ways to achieve this:

A Priori Demographics Selection (APrDS): a system recognizes relevant demographic features, and each probe image is submitted to the corresponding classifier. Using EGA, the selection of ethnicity of a probe image can be simulated by exploiting the metadata provided by the nomenclature of the dataset.

A Posteriori Demographics Selection (APoDS): the probe image is inputted to all the classifiers; to complete the recognition process, it is necessary to adopt a criterion for the selection of the global best answer.



BIPLAB Activities

References

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M. De Marsico, M. Nappi, D. Riccio, H. Wechsler. Demographics versus Biometric Automatic Interoperability. International Conference on Image Analysis and Processing (ICIAP 2013), Napoli (Italy, September 11-13 2013, LNCS 8156, pp.472-481.

Questions?????