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How Unique Is a Face: An Investigative Study

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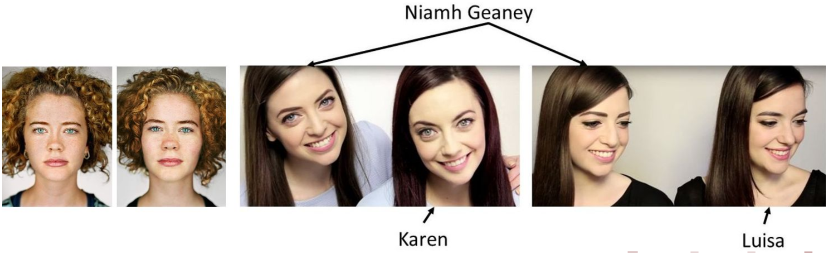


Uniqueness as Biometric Information

Five major properties of a biometric modality:

- universality
- uniqueness
- permanence
- measurability
- user-friendliness

Biometric uniqueness

- is the ability of a biometric modality to distinguish between individuals
- has been first quantified by Adler et al. [1] in terms of biometric information: "the decrease in uncertainty about the identity of a person due to a set of biometric measurements"

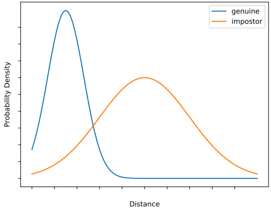
[1] Adler, Youmaran, Loyka: Towards a measure of biometric information. Canadian Conference on Electrical and Computer Engineering, IEEE, 2006

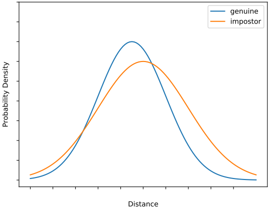
Biometric Information as a Divergence (1/3)

Takahashi et al. [2] show that biometric information can be approximated by the Kullback-Leibler divergence of genuine and impostor probability distributions

$$\text{biometric information} \approx D\left(P_G \middle\| P_I\right) = \sum_d P_G(d) \log \frac{P_G(d)}{P_I(d)} \qquad (1)$$

- d = distance (dissimilarity, comparison score) between a pair of observations
- $P_G(d)$ = probability of a genuine comparison score being equal to d
- $P_I(d)$ = probability of a impostor comparison score being equal to d
- is high if the distribution of genuine comparison scores is well separated from the distribution of impostor comparison scores
- is low if the genuine and impostor distributions significantly overlap





[2] Takahashi, Murakami: A measure of information gained through biometric systems. Image and Vision Computing, Elsevier, 2014

Biometric Information as a Divergence (2/3)

- Assume a dataset of persons and their observations.
- Every person splits this dataset into the sets of genuine G and impostor I observations. Intuitively $|G| < |I|$.
- Choose $I' \subseteq I$ of $|G| - 1$ random observations from I.
- Define $\delta_g(G)$ and $\delta_g(I')$ as the mean Euclidean norm between an observation $g \in G$ and all remaining observations in G and I'. Note that $|G \setminus \{g\}| = |I'|$.

Average norm estimator of the KL-divergence is defined by Sutcu et al. [3] as

$$D\left(P_G \middle\| P_I\right) \approx \hat{D}\left(G, I\right) = \frac{1}{|G|} \sum_{g \in G} \log \frac{\delta_g(I)}{\delta_g(G)} + \log \frac{|I|}{|G| - 1} \tag{2}$$

and substituting I' for I we get

$$\begin{aligned} \hat{D}\left(G, I'\right) &= \frac{1}{|G|} \sum_{g \in G} \log \frac{\delta_g(I')}{\delta_g(G)} + \log \frac{|G| - 1}{|G| - 1} \\ &= \frac{1}{|G|} \sum_{g \in G} \log \frac{\delta_g(I')}{\delta_g(G)} \end{aligned} \tag{3}$$

[3] Sutcu, Sencar, Memon: How to measure biometric information? International Conference on Pattern Recognition, IEEE, 2010.

Biometric Information as a Divergence (3/3)

- Recall the finite dataset S of c persons and their observations $\{S_1, \ldots, S_c\}$.
- Now we can calculate the divergence for a person $p \in \{1, \ldots, c\}$ using

$$\hat{D}\left(S_p, S \setminus \{S_p\}\right) = \frac{1}{|S_p|} \sum_{g \in S_p} \log \frac{\delta_g\left((S \setminus \{S_p\})'\right)}{\delta_g(S_p)} \tag{4}$$

- KL-divergence for the whole dataset S is the average $\hat{D}$ across all subjects

$$\bar{D}(S) = \frac{1}{c} \sum_{p=1}^{c} \hat{D}(S_p, S \setminus \{S_p\}) \tag{5}$$

- Finally, we sigmoid-normalize the total divergence into $(0, 1)$ and obtain uniqueness

$$\mathrm{U}(S) = \frac{1}{1 + \mathrm{e}^{-\bar{D}(S)}} \tag{6}$$

Datasets

AT&T Database of Faces (AT&T)

- face images acquired in the laboratory conditions
- 40 subjects and 400 images total

Labeled Faces in the Wild (LFW)

- collected from the web, highly unconstrained conditions
- 5,749 subjects and 13,233 images total
- we selected 9,164 images of 1,680 subjects with 2+ images

IMDb-Face (IMDb)

- a large-scale noise-controlled dataset
- $\sim$1.7M faces of $\sim$59K identities total
- manually cleaned subset of the original $\sim$2M raw images
- we selected 1,167,509 images of 10,347 subjects with 2+ images
- also contains gender and age annotations

ND-TWINS-2009-2010 (TWINS)

- twins at the Twins Days Festival
- under natural light in indoor and outdoor configurations
- 435 subjects and 23,762 images total

Evaluation (1/2)

Table: Uniqueness with resolution 224×224.

	AT&T	LFW	IMDb	TWINS
VGGFace	0.6710	0.5637	0.5420	0.5591
VGG16	0.6417	0.5364	0.5381	0.5339
ResNet50	0.6650	0.5364	0.5330	0.5574
InceptionV3	0.5915	0.5293	0.5272	0.5242
MobileNet	0.6204	0.5353	0.5299	0.5301
DenseNet121	0.6338	0.5302	0.5309	0.5268

Table: Uniqueness (and mean image entropy) with VGGFace feature extraction algorithm.

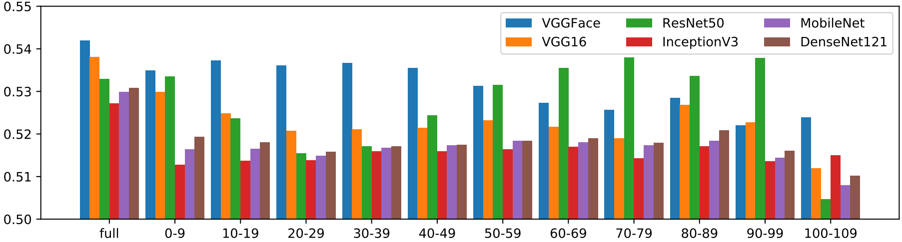
	AT&T	LFW	IMDb	TWINS
224×224	0.6710 (68.8)	0.5637 (87.4)	0.5420 (43.9)	0.5591 (27.8)
112×112	0.6725 (64.0)	0.5636 (70.1)	0.5418 (38.1)	0.5590 (25.3)
64×64	0.6620 (60.4)	0.5635 (59.3)	0.5405 (32.1)	0.5581 (23.3)
48×48	0.6485 (55.5)	0.5637 (34.4)	0.5385 (27.9)	0.5566 (21.9)
36×36	0.6241 (51.2)	0.5603 (19.0)	0.5345 (20.4)	0.5522 (19.7)

Evaluation (2/2)

Table: Uniqueness on IMDb with resolution 224×224 on full and two genders.

	full	female	male
VGGFace	0.542	0.535	0.532
VGG16	0.538	0.520	0.521
ResNet50	0.533	0.519	0.525
InceptionV3	0.527	0.511	0.514
MobileNet	0.530	0.514	0.516
DenseNet121	0.531	0.515	0.517

Figure: Uniqueness evaluated on full IMDb compared to its split into 10-year blocks.



Conclusions

- We introduced a new measure to quantify uniqueness of a biometric dataset to estimate the difficulty of recognition in the underlying environment.
- We provided an evidence of decrease in uniqueness with larger datasets, feature extractors trained on general objects, a specific gender and age group.
- We observed that image resolution has a negligible impact on uniqueness.
- Future work:
  - relations between uniqueness and entropy
  - How unique are other biometric modalities?

Thank you for attention!