Exploring Quality Scores for Workload Reduction in Biometric Identification

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Research topics
biometric indexing and privacy-enhancing technologies

Biometric Operation Modes

Verification — A biometric claim through one-to-one (1:1) biometric comparison.

Identification — A biometric probe is compared against all stored biometric references.

- ***one-to-many*** (1:N) biometric comparisons.
- Biometric feature vectors are typically ***high-dimensional***.
- Biometric data is ***fuzzy*** and has no ***inherent*** logical ordering (e.g. fingerprint instances).

Border control

Unique Identification Authority of India
Government of India
सत्यमेव जयते

Largest system: Aadhaar technology
(hundreds of millions or beyond a billion)

Global market value of biometric technologies
(Tens of billions of dollars)

Biometric Sample Quality

- Quality of a sample is defined as its ***utility*** for recognition (score computed by image quality assessment methods).
- ***Large variabilities*** may result in different utilities.
- Utility depends on ***character*** and ***fidelity*** of a sample.

= ?

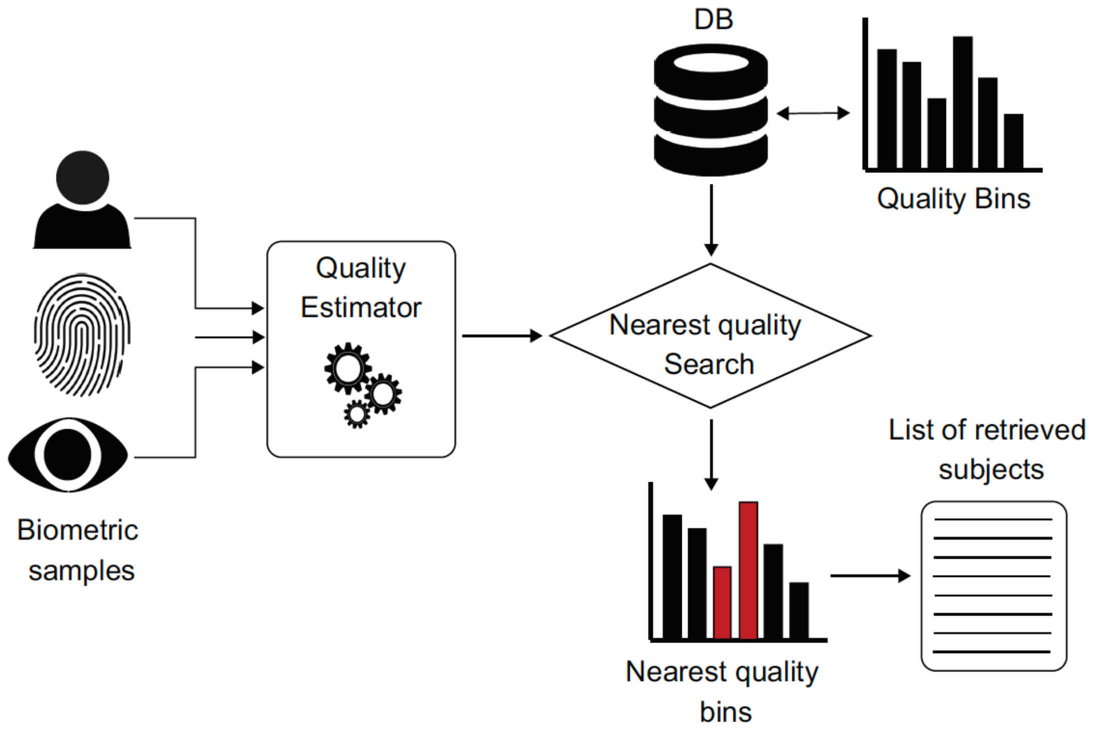
Fidelity of a sample

Character of a sample → ***Challenging scenario***

Workload-reduction

- Proposed search strategies which aim at computational workload reduction do not take into account the information of biometric sample quality (i.e. utility-based quality) during indexing.
- Search processes can take advantage of enrolled subjects that vary noticeably in quality.
- To what extent the quality scores resulting from different sample quality assessment methods can be suitable for identification.
- An indexing scheme ***agnostic*** w.r.t biometric modality (applied on Face, Iris, and Fingerprint).

Proposed system



1- Indexing based on quality scores.

2- Retrieval by nearest quality scores.

3- *Computational workload-reduction*.

$$W_{b_j}(s_p) = \begin{cases} \frac{|b_j|}{N} & \text{if } \exists s_i \in b_j : s_i = s_p \\ \frac{|b_j|}{N} + W_{b_{j-1}}(s_p) + W_{b_{j+1}}(s_p) & \text{otherwise.} \end{cases}$$

Experimental setup

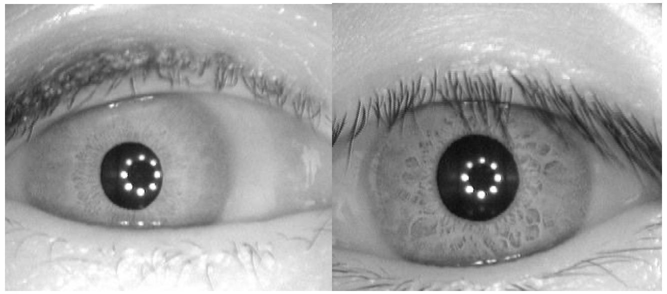
- Quality assessment methods applied on three well-known biometric characteristics:
  - ✓ FaceQnet v1, SER-FIQ, and MagFace applied on face.
  - ✓ NFIQ 2.0 applied on Fingerprint.
  - ✓ Visible iris area applied on Iris.
- Experiments conducted on the biometric identification mode: closed-set scenario.
- A single sample per subject was randomly selected as biometric reference and the remaining samples were used as probe samples in the search.
- Sub-sampling over 10 rounds is performed for all the experiments.
- Databases:
  - ✓ LFW (visible spectrum-based device).
  - ✓ MCYT (optical- and capacitive-based capture devices).
  - ✓ CASIA-IrisV3-Interval (near-infrared light spectrum-based devices).

Experimental setup

Visible spectrum-based devices

Optical-based devices

Capacitive-based devices



near-infrared-based devices

- Metrics:
  - ✓ Biometric performance is defined in terms of the number of comparisons and computational workload.
  - ✓ Penetration rate (PR).
  - ✓ Number of comparisons per identification transaction (# of comparisons) to find a match.
- Baseline:
  - ✓ A one-to-first search approximately 50%.

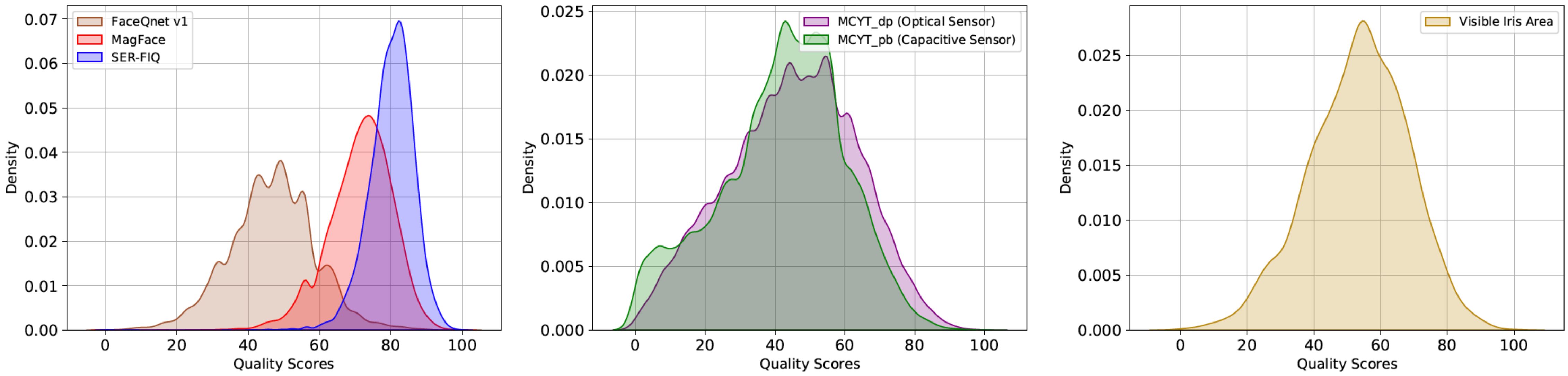
Experimental results

TABLE I: Average number of comparisons and its corresponding penetration rate averaged for a set of identification transactions retrieved by nearest quality score-based search. Results are shown with a 95% of confidence interval.

Biometric characteristic	Database	Sensor	Quality estimator	# of comparisons	PR(%)	# of enrolled subjects
Face	LFW	Visible spectrum	FaceQnet v1	631.43 ± 17.10	37.59	1,680
			SER-FIQ	659.11 ± 20.95	39.23	1,680
			MagFace	732.24 ± 18.04	43.59	1,680
Fingerprint	MCYT_dp	Optical	NFIQ2.0	898.13 ± 3.84	27.22	3,300
	MCYT_pb	Capacitive	NFIQ2.0	968.79 ± 2.96	29.36	3,300
Iris	CASIA	Near infrared	Visible Iris Area	118.67 ± 1.73	30.04	2,244

- ✓ Penetration rate is reduced w.r.t baseline (50%).
- ✓ Best results (PR < 31%) over Fingerprint and Iris.
- ✓ Low variability in terms of the number of comparisons (Fingerprint and Iris).
- ✓ Face achieves different penetration rates for different quality estimator.

Experimental results



(a) Face (b) Fingerprint (c) Iris

Fig. 3: Distribution of normalised quality scores from different quality estimators over face, fingerprint, and iris.

Experimental results

TABLE II: Statistical distribution of the enrolment sets organised for each biometric characteristic according to sensor and quality estimator. Statistical data are computed for a set of biometric transactions.

Biometric characteristic	Sensor	Quality estimator	Total bins	Maximum bin	Minimum bin	First bin (%)
Face	Visible spectrum	FaceQnet v1	70.40	80.50	1.0	4.34
		SER-FIQ	44.30	124.60	1.0	7.65
		MagFace	55.00	95.20	1.0	4.64
Fingerprint	Optical	NFIQ2.0	77.60	155.50	1.0	4.69
	Capacitive		69.50	156.50	1.0	5.04
Iris	Near Infrared	Visible Iris Area	68.10	25.30	1.0	5.84

Total bins: Number of non-empty bins (image quality scores).
Maximum bin: Average maximum number of subjects enrolled in bin.
Minimum bin: Average minimum number of subjects enrolled in bin.
First bin (%): Percentage of the number of subjects for which their match was found in the first searched bin.

- ✓ Bins with the same score quality.

Experimental results

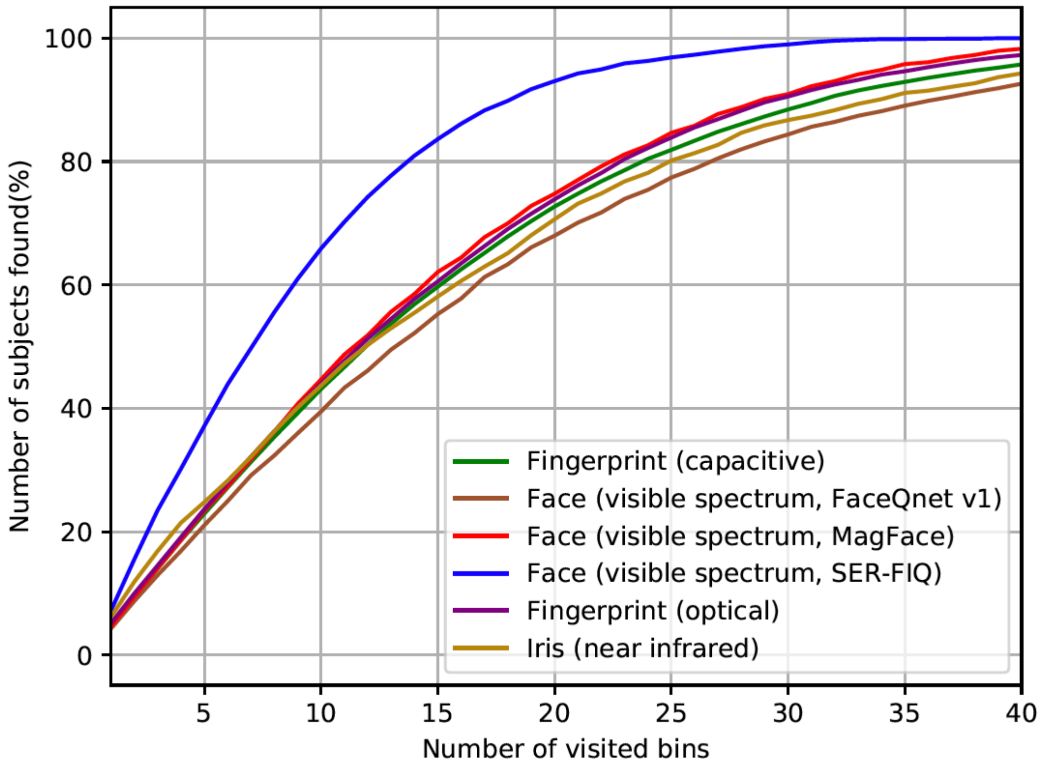


Fig. 4: Relation between the number of visited bins and the percentage of subjects found for a set of transactions per biometric characteristic.

- ✓ Quality estimators lead to priorities to find an earliest match.
- ✓ Impact of the quality bin organisations on the intelligent search.

Conclusions

✓ The variability of quality scores exhibited on different biometric characteristic types (face, iris, and fingerprint) was turned into an advantage for rapid indexing.

✓ Experimental results showed that the search space can be reduced significantly for each biometric characteristic, depending on the variation in terms of sample quality: face (<38%), fingerprint (<29%), and iris (<31%).

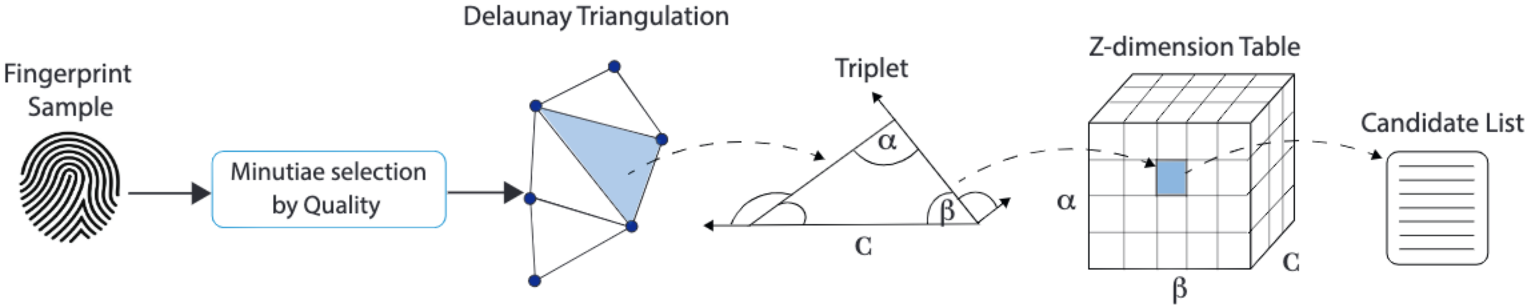
Future Work

✓ Work on large-scale databases analysing more quality factors.

✓ Experiments over realistic scenarios where the stop condition of the intelligent search would incorporate a decision threshold in open-set scenarios.

More about quality-indexing in Fingerprint!

BIOSIG Conference



Thank you !

Questions ?

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