Indexed Search Strategy for an Automated Biometric Identification System

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Abstract: Biometric Identification Systems capture biometric data i.e. face, fingerprint, iris, etc. images and store them in the database to form a Gallery. During an identification search, incoming biometric probe data is matched against all the images in the Gallery. A decision threshold is applied to these matches to obtain the potential match(es) in the Gallery for a particular probe. Typically the above approach works very well if the gallery size is up to few thousands. However, performance degrades rapidly when the gallery size grows to few hundred thousands or millions of biometric records. We present an approach to drastically reduce the performance degradation without degrading the accuracy of the overall system.

1 Introduction

Biometric Identification Systems are gaining popularity in variety of business applications, such as, in Banking, Healthcare, and Defense. The market for biometric applications is growing worldwide, and specifically in emerging economies, such as India [Ref: Aadhaar], where scalability is a huge challenge. As a result, there is a fundamental need for a underlying platform that can enable biometric searches over a very large database in real time without compromising accuracy. Furthermore, the platform much be inexpensive in order for the solution to be economically viable.

To improve the performance, we first identified the possible reasons for the poor performance in case of large gallery sizes in a biometric authentication system. Then as a next step we proposed an algorithm called Indexed Search Strategy to improve on the performance factors while also analyzing the accuracy impact due to the same to select the optimum values.

We performed experiments on a dataset comprising of 1894 identities. Each identity comprised of probe-record pair. Each probe/record contained the left and right Iris of the subject.

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2 Background

There are various approaches to store biometric data during enrolment process. Some of the approaches are outlined below:

Approach 1 – *Storing Biometric Images*: Initial approach suggests storing the captured biometric images in the gallery (Figure 1). During the matching process, the incoming probe image and the image selected for matching undergo a template extraction phase as the captured images are not suitable, as is, for biometric matching. Once the templates are extracted out of these two images, a matching is performed among these two templates.

The above approach has certain disadvantages as mentioned below:

- Storing images as is in the memory is an expensive process both in terms of storage and performance
- Before actual matching, the image should be converted into template which adds additional delay in the whole process. In this case, it is tough to achieve real-time performance unless the matching algorithm is very high performing in terms of extraction and matching timings.

Approach 2 – *Storing Biometric Templates*: Another approach (Figure 2) suggests storing the templates extracted from the captured biometric images in the database to form the Gallery. During the matching process, only the incoming probe image undergoes a template extraction phase and is then matched against the templates stored in the Gallery.

This approach overcomes the disadvantages of the previous approach. The size of a biometric template is much smaller than the actual image therefore storage is not as expensive as in the previous approach. Also, the delay due to template extraction in the matching process is eliminated as storing templates allows us to match them directly[1].

However, the above approach also has a major disadvantage as mentioned below:

- Due to the template storage, we have a limitation regarding vendor lock-in as the templates generated by a particular vendor algorithm is unique therefore for matching process you need the same vendor algorithm by which the template was extracted. This can be a serious limitation in some cases as the vendor algorithm may be available at the time of template extraction but may not be available when the actual matching happens.

Approach 3 – *Storing Biometric Images and Templates together*: To overcome the drawbacks of the above two approaches, the current approach (Figure 3) combines the two, and stores both the biometric images as well as their templates in the database. The downside of this approach is larger storage requirement but it is viable to use this approach if we look into the benefits mentioned below:

- Stored templates can be used for matching when the probe template is from the same vendor algorithm. Matching the templates saves time for extraction on the fly.
- Multiple stored templates can be used for pre-filtering, cascaded matching, parallel matching, etc.
- In the case when the probe template is not from the same vendor algorithm as the templates in the database, the template can be extracted on the fly to perform matching. Also, the template can be enrolled at the same time for future matches.
- Every time a new vendor algorithm is introduced, the templates for the images in the gallery can be added to their individual template profiles. This will help in future matching process for those samples.

3 Problem foundation

Regardless of the approach, performance becomes an issue when the gallery size increases. All these approaches work fine in terms of response time to find a match if the gallery consists of thousands or few hundred thousand records. But as the gallery size grows to a million or more, the search time grows dramatically. In this case, achieving a real-time biometric identification search becomes impossible due to the following reasons:

- Extracting a template for each image in the gallery is very time consuming, and it becomes even worse with the increasing size of the gallery[2].
- Matching a probe template against the stored templates in the gallery becomes time consuming, especially with a large gallery size, because the matching is done in a sequential manner where the probe template is first compared against the first stored template in the gallery followed by comparing it against the next stored template and so on until last stored template is matched., Identification search yields a list of identities that are considered to be similar to probe on basis of their match score.[2].

Because of the above reasons, the existing techniques for biometric authentication scale linearly with the number of entries in the biometric gallery. That is, the time to identify an individual based on his/her biometrics doubles/triples if the number of entries in the gallery doubles/triples.

Given N identities in a database, It is well-known that linear search algorithms are O(N). Consequently, the question arises, why aren't fast search algorithms that are O(logN) used for biometric search.

The answer is, fast search algorithms require the search database to be sorted in ascending or descending order, and it is not clear how one can sort "fingerprints" or "retina scans" or "facial images".

4 Our solution: Indexed Search Strategy

Our solution is based on a technique that converts biometrics into "meaningful" numbers that can be sorted and arranged in ascending or descending order so that a fast search algorithm can be used for the matching.

In order to perform fast search, index profiles needs to be created by identifying a suitable reference image set and then obtaining a match score by comparing each record in the gallery with reference image set.

4.1 Identifying a Reference Image Set and Matching Algorithm

Selecting a suitable reference image set to create an index profile is very important as the choice has a huge impact on the system's overall accuracy and performance. Therefore, selection of a reference image set should be based on the following criteria:

- Quality of the reference images
- Manual Inspection of the reference images
- Threshold value range for the reference images

We selected Iris for our analysis and experimentation since it is one of the most accurate modality in terms of biometric matching. A reference image set in our case consists of a Left Iris and Right Iris image. The SDK[3] used by us for the Iris image extraction and matching provided us six different quality metrics to be used for individual analysis of the images.

Quality	**Range**	**Min.**	**Max.**
Focus	0-100	0	40
Saturation	0-100	0	75
Signal to Noise Ratio(SNR)	0-100	45	100
Average Grey Level	0-250	80	200
Contrast	0-250	30	85
Occlusion	0-100	0	40

Table 1: Acceptable range of quality metrics provided by the SDK

An image whose quality metric values lie within the minimum and maximum range of each quality metric may be considered as a good reference image.

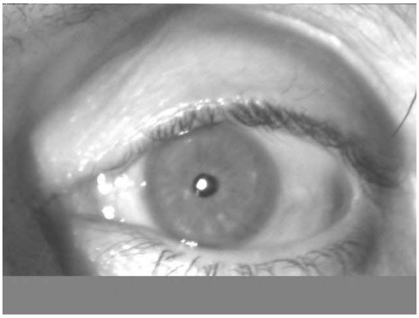
Meeting the quality metrics criteria alone doesn't guarantee the eligibility of an image to be a reference image. We found some cases where the quality metrics of an image met the acceptance criteria, but the image did not qualify to be a reference image. Let us explain a specific case to drive the point home. Consider the following image with the corresponding quality metrics:

Quality Metric	Value
Signal to Noise Ratio (SNR)	97
Contrast	32
Grey Level	132
Occlusion	0
Saturation	6
Focus	0

Figure 1: Partially-Captured Image and corresponding quality metrics

Note that all the quality metric values of the image are all within the desirable range; however the image (shown below) is partially captured, and as a result, it is unsuitable to be considered as a reference image. Other cases similar to the above can result from images with cuts, shadows and other impairments. Hence an image needs to be inspected manually before it is considered as a part of reference image set.

The matching algorithm also plays an important role in determining the overall performance of the system referred to as Index Search Strategy (ISS). An analysis performed in the context of a good-quality reference image explains the issue next:



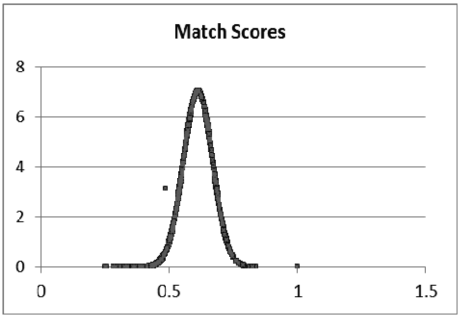


Figure 2: Good-Quality Reference Image and Normal distribution of match scores

The above image when considered as a reference image and matched with all the images in dataset gives the matching scores plotted in the Normal Distribution Curve. The x-axis corresponds to the match scores while the y-axis corresponds to the density of the match scores at specific values.

It is clear from the above graph that the maximum density corresponds to the match score of 0.6 approximately whereas the total range of match scores varies from 0.28 to 0.82. The scores between the range **0.28 to 0.4** and **0.8 to 0.82** are the outliers which are very small in number as their density is nearly zero. It can be stated that the wider the range of scores the matching algorithm provides for the non-matches, the more will be the benefit obtained out of index search strategy.

Another factor which is important to be considered is that a particular reference image that is suitable for a particular type of dataset may or may not be suitable for another type of dataset. In other words, two different datasets belonging to two different regions or races of people may have two different images as the appropriate reference images for the corresponding groups.

4.2 Index Profile Creation

The creation of index profile is explained below:

Assumption: There exists an algorithm A which given two images I_R(Reference Image) and I_S(Sample Image) can provide a match score M_{RS} between them on a scale of [0,1].

Given: A set of N images I_i where i = 1 to N

For each image in a reference image set repeat following steps to create an index:

Step-1: Pick a Reference Image I_R

Step-2: For i = 1 to N

Compute $M_{R,i}$ (Match Score of I_i with respect to Reference I_R)

Step-3: Sort the Images in Descending order based on the similarity score $M_{R,i}$

Step-4: Store in a database table, the sorted list of scores along with the unique IDs of the corresponding images in the gallery. This unique ID is generated for every image in the gallery in order to link it with its unique match scores stored in the database table.

This sorted list of match scores with respect to a specified reference image is referred to as the index profile of the gallery.

4.3 Performing Fast Search using ISS

Main aim of the indexed search strategy is to reduce the final search space in order to improve the performance of the system by reducing search time. Following are the high level steps to perform fast search using ISS.

1. Repeat following steps for each biometric image in the incoming probe
   a. Obtain a match score by comparing each image in the incoming probe with corresponding reference image and do a fast search (such as, binary search) to find the closest index in the gallery.
   b. Select additional entries from the gallery (other than the one corresponding to the closest index) based on a pre-defined threshold value, and discard the rest. The selected records are referred to as candidate list and threshold value is referred as Indexing threshold.
2. Above step will yield a candidate list corresponding to each biometric image in the probe. In order to obtain a single candidate list we need to fuse these multiple

candidate lists. One such fusing scheme is to use intersection of each candidate list to obtain the final candidate list. Intersection eradicates the records that are not present in both lists thus helping in further reducing the search space.

3. Perform actual biometric match of the probe with those in the candidate list.

5 Performance Benefits

In a traditional approach, an incoming probe is matched against each image in the gallery during an identification search. As a result when gallery size increases, performance of the system degrades linearly given the same hardware.

In contrast, when using ISS, the subset of the gallery that needs to be matched with an incoming probe for identification/de-duplication purposes depends on the incoming probe's quality and the list of match scores in the Index Profile table.. In fact, the ISS approach provides a huge performance gain over the traditional approach.

Filtering of the gallery for each identification search depends on the following factors:

- **Probe image's match score with respect to reference image:** This refers to the point where the score of the probe image lies on the normal distribution curve corresponding to the reference image. If this point lies in the less densely populated area, benefits will be more, because the number of potentially similar images will be less and the comparison will be done against a smaller set of images.

- **Probe image's quality score:** This score will decide the threshold window that can be used to filter the gallery. If this is high, the threshold window will be smaller resulting in improved performance as the comparison will be done against a smaller set of images. This ability to choose threshold window dynamically helps in maintaining higher accuracy of the system.

- **Threshold Window**: This value help obtain the final subset of the gallery to be used for 1:1 comparison with the probe. Smaller the range, more efficient is the process of comparison.

The benefits of using ISS over the traditional search approach are explained below with an example:

Images in the gallery = 3788
Threshold: 0.089121
Threshold Window: (0.089121 X 2) = 0.178242

When using Traditional approach, the images that need to be matched = **3788**
When using ISS, number of images in gallery that will be used for actual 1:1 match will vary. For simplicity let's assume that the quality of probes is high and the threshold

window is fixed. Following are some results for different probes having different match scores when matched with the reference image.

Approach	Indexing Threshold	Match Score	Filtered Gallery (out of total 3788 images)	% of Gallery used for Comparison
Traditional	-	-	3788	100%
ISS	0.178242	0.4	49	1.3%
		0.5	1185	31.7%
		0.6	3390	89.5%
		0.7	1998	52.7%
		0.8	109	2.8%

Table 2: Performance Gain with ISS over Traditional approach

The tables above show that the number of images used for actual comparison is *always* reduced when using ISS, and there are cases where the number of images used for comparison against the probe image is reduced by a factor of 100. Thus performance using ISS is always better compared to using traditional approach.

It can be deduced from the above analysis that the smaller is the amplitude of the distribution curve, the higher is the benefit of ISS. Also, an ideal SDK should provide a larger span of values between 0 and 1 to have a better distribution resulting in more benefit due to ISS.

In following sections we present the results obtained by running the tests related to Performance and Accuracy impact of ISS on the overall system.

5.1 Accuracy Metrics

The performance of any biometrics system is gauged by various statistics. The two most important accuracy metrics for any identification system are:

False Positive Identification Rate (FPIR): It is defined as fraction of identification transactions that were not enrolled in the system but were falsely identified by biometric system[5]. It can be represented using following equation 1:

$$FPIR = \frac{F_i}{T_i} \quad (1)$$

Where F_i is number of falsely identified transactions.
T_i is total number of identification transaction.

False Negative Identification Rate (FNIR): It is defined as fraction of identification transactions enrolled in the system but not identified by the biometric system [5]. It can be represented using following equation 2:

$$FNIR = \frac{N_i}{T_i} \qquad (2)$$

Where N_i is number of enrolled identification transactions that were not identified.
T_i is total number of identification transactions.

Our proposed approach basically tries to reduce the final search space and only pass the portion of whole gallery for actual matching. This will not affect FPIR, however it can contribute to FNIR. Hence it is sufficient to monitor only FNIR as accuracy metric during our performance evaluation.

5.2 Performance Gain Metrics

As already mentioned in the above sections, performance improvement of the system due to Indexed Search Strategy comes from the number of records filtered for each individual search. As we know for a linear search we have to match the probe with all the records in the gallery for a complete identification process. Whereas, using ISS we filter out majority of records before the actual matching is done in an identification search. Also, the number of filtered records depends on the threshold value and the index value of the particular probe.

To identify N_p number of probes in gallery of Size S, number of 1:1 match attempts M_t can be calculated using equation 3:

$$M_t = N_p \times S \qquad (3)$$

In our proposed approach 1:1 match attempts can be calculated using equation 4:

$$M_i = (N_p \times C) + (N_p \times N_s) \qquad (4)$$

Where M_i is 1:1 match attempts in our approach
C is Candidate List
N_s is number of sub modalities

Number of Candidate List C depends upon Indexing Threshold T and the Index Score I. Candidate List can be obtained using equation 5:

$$C = \left(\bigcup_{l=I-T}^{I+T} E_l\right) \bigcap \left(\bigcup_{r=I-T}^{I+T} E_r\right) \qquad (5)$$

Where E_l is index entry for left iris

E_r is index entry for right iris

Performance gain P of the proposed approach compared to traditional approach can be calculated using equation 6:

$$P = \frac{M_t - M_i}{M_t} \times 100 \quad (6)$$

5.3 Experiment Results

In order to carry out our experiments we performed analysis on test dataset comprising of 7972 iris images (Both left and right Irises). Out of which, 289 images were discarded as they failed during template extraction phase. Remaining images were then subjected to quality assessment and low quality images were further discarded. Finally we were left with 7576 images (1894 unique identities). For each identity, data was captured in two sessions. Data captured from one session was stored in database as a record while the other session data was used as a probe. A separate database table comprising of 1894 true match pairs was prepared to store the association of probe and record belonging to same identity.

We evaluated performance of Indexed Search strategy by comparing False Negative Identification Rate at various indexing thresholds. We also attempted to study the impact of reference images quality on the overall system performance and accuracy.

As discussed in previous sections we identified two sets of reference images. Each set contained a reference image for left and right iris. Before performing actual tests we created indices with help of match score obtained by comparing each record in database with respective reference image. In total we prepared four indices (left iris and right iris indices for each reference set). Quality assessment results of these two reference sets are shown in Table 3 and 4:

Modality	**Sub-Modality**	**Quality Metrics**					
		SNR	**Contrast**	**Occlusion**	**Grey Level**	**Focus**	**Saturation**
Iris	Left	57	40	0	137	20	6
Iris	Right	54	45	0	140	15	4

Table 3: Reference Image Set 1

Modality	**Sub-Modality**	**Quality Metrics**					
		SNR	**Contrast**	**Occlusion**	**Grey Level**	**Focus**	**Saturation**
Iris	Left	71	43	0	136	30	6

Iris	Right	70	51	0	138	35	3

Table 4: Reference Image Set 2

We performed multiple experiments by varying indexing threshold from 0.005 to 0.195 and using reference image sets mentioned above. The results w.r.t FNIR(%) and performance gain are shown in table 5:

Indexing Threshold	**Reference Image Set-1**		**Reference Image Set-2**	
	FNIR (%)	**Performance Gain (%)**	**FNIR (%)**	**Performance Gain (%)**
0.005	87.46065058	94.23081581	86.9884575	94.25429609
0.01	74.92130115	88.48728652	73.76705142	88.54679925
0.015	63.79853095	82.81997866	61.85729276	82.90522886
0.02	53.83001049	77.23269093	52.25603358	77.30660013
0.025	44.64847849	71.77345743	43.12696747	71.87024132
0.03	36.83105981	66.45045359	35.2570829	66.57501192
0.035	30.79748164	61.30730922	28.80377754	61.44419952
0.04	24.55403987	56.34936452	22.66526758	56.49723797
0.045	19.62224554	51.6278742	18.04826863	51.76575546
0.05	15.11017838	47.0961805	13.64113326	47.22073884
0.055	11.90975866	42.81035533	10.38824764	42.9383545
0.06	9.233997901	38.7810515	7.869884575	38.89107573
0.065	7.555089192	34.99973574	5.403987408	35.08559153
0.07	5.823714586	31.47009664	3.934942288	31.52746229
0.075	4.354669465	28.19012474	2.938090241	28.2262673
0.08	3.620146905	25.15048849	2.151101784	25.17052793
0.085	2.885624344	22.38080662	1.416579224	22.35102273
0.09	2.203567681	19.84119294	1.154249738	19.77336714
0.095	1.678908709	17.52168278	0.786988458	17.42371525
0.1	1.259181532	15.42491871	0.472193075	15.28805594
0.105	0.944386149	13.52637444	0.36726128	13.36528817
0.11	0.682056663	11.83967567	0.314795383	11.6354
0.115	0.524658972	10.30773203	0.157397692	10.08168274
0.12	0.419727177	8.97012692	0.157397692	8.69940179
0.125	0.314795383	7.772660258	0.104931794	7.485694372
0.13	0.262329486	6.715882578	0.104931794	6.406537482
0.135	0.157397692	5.785782788	0.104931794	5.45265462
0.14	0.104931794	4.978864997	0	4.627761892
0.145	0.104931794	4.277622221	0	3.912150177
0.15	0.104931794	3.660253312	0	3.288202385
0.155	0.104931794	3.127941916	0	2.756358944
0.16	0.104931794	2.676146129	0	2.305333904
0.165	0.052465897	2.283422648	0	1.918170818
0.17	0.052465897	1.945669994	0	1.588676175
0.175	0.052465897	1.660135497	0	1.307683584
0.18	0.052465897	1.420845863	0	1.072550481
0.185	0.052465897	1.213156883	0	0.873119513
0.19	0.052465897	1.037178667	0	0.71206077
0.195	0	0.890956817	0	0.573216077

Table 5: Performance Results for two different Reference datasets

After analyzing the above tables we found that results obtained by using reference Image set 2 are much better than those obtained by using reference image set 1. We can achieve performance gain of 25%-30% at FNIR of 2%-4% (acceptable in most of the biometric systems) by using reference image set 2. In case of applications where accuracy is of higher importance, performance gain of 5% can be achieved at 0% FNIR.

As seen from Tables 3 and 4, the overall quality of reference image set 2 is higher than that of reference image set 1. Specifically, the values of Focus and Signal to Noise Ratio (SNR) are much better in reference image set 2 compared to reference image set 1. The results shown in Table 8 combined with the fact that the quality of reference image set 2 is better than quality of reference image set 1 helps us deduce that quality of reference image plays a major role in overall performance of the system. Better the quality of reference image set, higher will be the performance gain without compromising the accuracy of the system.

6 Conclusion

In this paper, we presented the concept, implementation and experimental results of Indexed Search Strategy (ISS), and explained the criteria needed to be fulfilled by such system to derive the desired benefits. We performed several tests to identify a suitable reference image, and ran a set of tests to analyze the impact of threshold value and the quality of reference image set on performance improvements and accuracy.

Based on the tests performed, we observe that with a proper choice of reference image set, 25 to 30% performance gain can be achieved with FNIR of 2-4%. This translates to 25-30% reduction of the system's HW footprint for the same level of performance. For future work, this proposed approach can be further extended to other modalities.

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