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Size-Reduction Strategies for Iris Codes

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Abstract—Iris codes contain bits with different entropy. This work investigates different strategies to reduce the size of iris code templates with the aim of reducing storage requirements and computational demand in the matching process. Besides simple sub-sampling schemes, also a binary multi-resolution representation as used in the JBIG hierarchical coding mode is assessed. We find that iris code template size can be reduced significantly while maintaining recognition accuracy. Besides, we propose a two-stage identification approach, using small-sized iris code templates in a pre-selection stage, and full resolution templates for final identification, which shows promising recognition behaviour.

Keywords—Iris recognition, compact iris code, fast matching, best bits, pre-selection identification, two-stage identification.

I. Introduction

The human iris is emerging as the biometric of choice for high confidence authentication [1], [9]. Proposed approaches to iris recognition report recognition rates above 99% and equal error rates significantly less than 1%. Providing high accuracy iris recognition appears to be well suitable for access control systems managing large-scale user databases. Within identification systems, single iris-codes (probes) have to be matched against a database of iris-codes (gallery) requiring linear effort. In case databases comprise millions of iris-codes (as it is the case in UIDAI's Aadhaar endeavour), without choice, biometric identification will lead to long-lasting response times. That is, reducing the computational effort of iris-based identification systems represents a challenging issue [2].

Recent work of Hollingsworth *et al.* [3] has shown that distinct parts of iris textures reveal more constant features (bits in the iris-code) than others. In other words, distinct parts of iris-codes turn out to be more consistent than others. This is because some areas within iris textures are more likely to be occluded by eye lids or eye lashes. Additionally, parts of iris-codes which originate from analyzing the inner bands of iris textures are found to be more constant than parts which originate from analyzing the outer bands. The authors exploit this fact by ignoring user-specific "fragile" bits during matching, resulting in a significant gain in terms of recognition accuracy. In this context, it has been also shown that a well selected but low number of iris bits can lead to highly accurate recognition results [9].

Combinations of multiple iris algorithms operating on the same input instance may serve different purposes: On the one hand, this may aim at gaining recognition performance in biometric fusion scenarios at the cost of larger templates or more time-consuming comparison (e.g. [6], [10], [11]). On the other hand, the following approaches try to improve both, resource requirements (storage and/or time) and fusion recognition accuracy. Konrad *et al.* [4] combine a rotation invariant pre-selection algorithm and a traditional rotation compensating iris-code. The authors report improvements in recognition accuracy as well as computational effort. Rathgeb *et al.* [8] have recently presented an incremental approach to iris recognition using early rejection of unlikely matches during comparison to incrementally determine best-matching candidates in identification mode operating on reordered iris templates according to bit reliability (see [3]) of a single algorithm. Following a similar idea, Gentile et al. [2] suggested a two-stage iris recognition system, where so-called short length iris-codes (SLICs) preestimate a shortlist of candidates which are further processed. While SLICs exhibit only 8% of the original size of iris-codes the reduction of bits was limiting the true positive rate to about 93% for the overall system.

In this work, we investigate different means how to decrease the size of iris code templates while maintaining recognition accuracy. Specific focus is set on fast schemes, neither requiring several enrollment samples nor conducting expensive bit reliability investigations. Section II introduces several schemes, among them a proposal based on the JBIG binary hierarchical representation. In this section, we also propose a two-stage identification scheme, using lower-resolution templates for pre-selection into a "shortlist", while full resolution iris codes are used to identify the final match. Corresponding experiments are conducted in Section III, while Section IV concludes the paper.

II. Compacting Iris Codes

The size of iris biometric templates obviously has significant impact: First, it determines storage requirements of the gallery database and eventually critical storage requirements when probe templates are stored on smart cards or other memory critical devices. Second, the time complexity of the Hamming-distance based matching procedure is linear in the size of the template (which can get costly when using circular shifts). Thus we investigate strategies to reduce the size of the input data (iris code bits) considering two different approaches. Our first approach is based on observations made in the context of "sub-sampling" in iris codes. The second approach examines hierarchical feature extraction with different levels of depth based on the resolution reduction algorithm of the JBIG standard [1]. Additionally, we combine the two techniques.

A. Subsampling Strategies

The first approach for reducing the input data size is to sub-sample the iris code templates. We consider several different approaches for sub-sampling:

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[1] ITU-T Recommendation T.82 (1993)

- **Front**: The template is constructed by simply cutting off a given number of bits at the end of the 10240 bit binary string.
- **Back**: The template is constructed by simply cutting off a given number of bits at the beginning of the 10240 bit binary string.
- **Sub-n**: The template is constructed by using every n^{th} bit of the 10240 bit binary string e.g. if we set $n = 2$ then Sub-2 denotes that every second bit of the original 10240 bit binary string is used for template construction.

B. JBIG Hierarchical Representation

Joint **B**inary **I**mage Experts **G**roup is an ITU standard (ITU recommendation T.82) finalized in 1993 for compressing binary images and was meant to improve the fax compression standards of that time especially with respect to the coding of halftoned images. The standard is substantially based on a hierarchical progressive coding mode which relies on a hierarchical representation of binary image data (see [7] for using this representation for creating an efficient selective encryption scheme).

JBIGs core coding engine is a binary context-based adaptive arithmetic coder similar to the IBM Q-coder. In this section we will only focus on this hierarchical progressive coding mode since we employ the associated techniques for constructing iris codes of smaller size. A binary multiresultion hierarchy is being constructed as shown in Fig. 1.

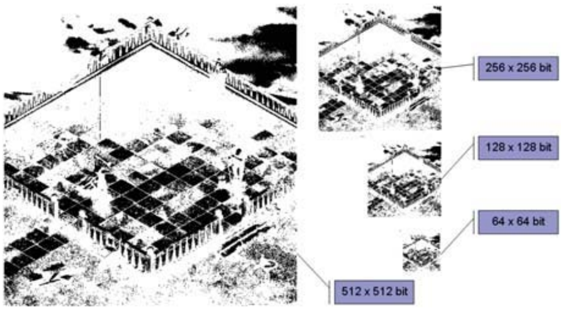

Fig. 1. JBIG hierarchical representation

In order to see the connection to gray-scale images, Fig. 2 shows all bitplanes of a 8bpp scan of an artwork by M.C. Escher. The MSB bitplane is then hierarchically represented in Fig. 1.

For constructing the binary multiresultion hierarchy simple downsampling is not suited in the context of encoding since it violates the Nyquist sampling theorem and leads to severe artifacts especially for typed documents and halftoned images. Therefore, a linear recursive IIR filter employing a 3×3 window in the higher resolution level and 3 neighbouring samples from the already filtered low resolution image is used to recursively create the low-pass filtered versions of the binary image. Replacing the Escher MSB by an iris code in Fig. 1, it gets clear how smaller versions of the iris code are being generated. Due to better quality as compared to sub-sampling, we might expect better behaviour in the context of iris recognition as compared to simple subsampling.

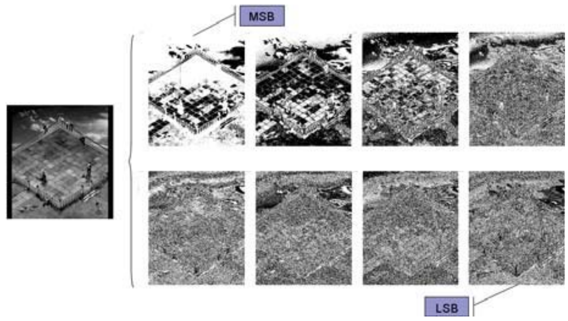

Fig. 2. Bitplane representation

C. Pre-Selection Identification using Reduced-Size Templates

A different approach, only applicable in an identification scenario, to possibly increase the speed of identification is to use pre-selection. The idea of pre-selection is that we divide the matching process into two phases. In the first phase we use low resolution templates to build up a rank based list consisting of n possible candidates. These n candidates are then re-processed in the second phase using high resolution templates to determine the actual outcome of the matching process. Of course, this approach is only able to reduce the computational effort, but not storage requirements as potentially, all iris codes need to be present in full resolution for the second phase.

III. Experiments

A. Experimental Settings

We set up an iris recognition experiment using data from the CASIA V3 Interval database (NIR illuminated indoor images of 320×280 pixel resolution). For these experiments an Intel Core i7-2600 4x3400MHz PC with 4GB DDR3 RAM is used and data of 30 individuals are selected.

For feature extraction and matching, software from the University of Salzburg USIT Toolkit is used (available from www.wavelab.at/sources/Rathgeb12e/ [9]). For iris locating and segementation (see Fig. 3), a context adaptive Hough Transform (CAHT) is used.

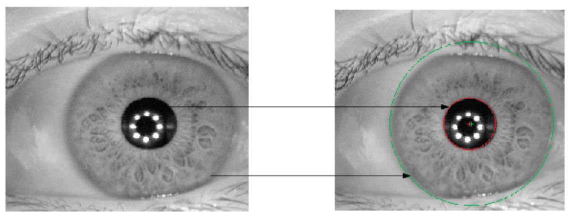

Fig. 3. Locating pupil and iris.

Once the inner and outer boundaries of the iris have been detected, the area between them is transformed to a normalized rectangular texture of 512×64 pixel, according to the "rubbersheet" approach by Daugman (see Fig. 4). Finally, a blockwise brightness estimation is applied to obtain a normalized illumination across the texture.

For feature extraction, an iris-code version by Ma *et al.* [5] extracting 10 one-dimensional horizontal signals averaged

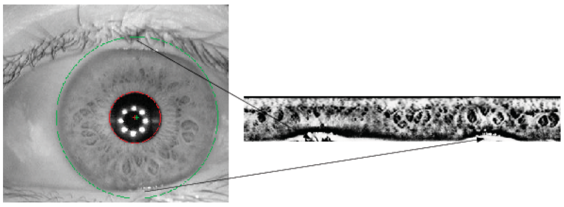

Fig. 4. Iris unwrapping

from pixels of 5 adjacent rows of the upper 50 pixel rows is used. Each of the 10 signals is analyzed using dyadic wavelet transform, and from a total of 20 subbands (2 fixed bands per signal), local minima and maxima above a threshold define alternation points where the bitcode changes between successions of 0 and 1 bits. Finally, all 1024 bits per signal are concatenated yielding a total number of $1024 \times 10 = 10240$ bits (see Fig. 5).

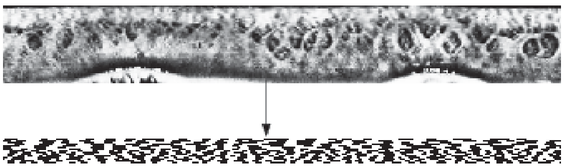

Fig. 5. Computing iris code.

In the matching procedure, the Hamming distances for aligning probe and gallery iris codes with 17 different cyclic shifts are computed and the minimum is taken as the matching result. The decision threshold in the identification system is set such that the FAR = 0, thus all "wrong" matches only are false negatives (i.e. genuine matches that have been rejected incorrectly). Thus, the rate (given in % in the subsequent tables) is a genuine acceptance rate in the absence of false positives (i.e. impostor matches that have been accepted incorrectly). Note also that the Tresholds given in the Tables refer to the decision threshold employed to achieve FAR = 0 and minimal FRR.

B. Experimental Results

As we can see in Table I, a reasonable matching rate of 98.49% is obtained using 17 cyclic shifts (8 left-rotations, 8 right-rotations and the original template). On the other hand, if the cyclic rotations are omitted, this leads to a fundamental result degradation of the matching rate to 80.00%.

TABLE I
MATCHING RATES

Template Bits	Shifts	Records	Threshold	Rate (%)
10240	17	510	4550	98.49
10240	1	30	4550	80.00

Table II displays the matching results for the different kinds of sub-sampling. As we can see, matching rates for "Front" and "Back" are not as stable as desired whereas "Sub-n" is able to maintain the original accuracy up to $n = 4$. The difference between "Front" and "Back" is to be expected since it is widely known that certain parts of the iris texture are more reliable (i.e. the "Front" part corresponds to the more stable parts close to the pupil, while the "Back" part contains many unstable bits due to noise generated by (eye-lash) occlusions). It is of particular interest that "Sub-4", which results in a 2560-bit template, is even better than JBIG hierarchical feature extraction with a level of 1 (same tamplate size, see Table III) and even yields identical accuracy to matching without any sub-sampling applied.

TABLE II
MATCHING RATES: SUB-SAMPLING

Type	Template Bits	Resulting Bits	Threshold	Rate (%)
None	10240	10240	4550	98.49
Front	10240	5120	2180	98.11
Back	10240	5120	2116	91.70
Sub-2	10240	5120	2257	98.87
Front	10240	2560	1056	97.35
Back	10240	2560	1006	78.87
Sub-4	10240	2560	1121	98.49
Front	10240	1280	471	86.41
Sub-8	10240	1280	544	89.43

For JBIG hierarchical feature extraction each level reduces the original template bit size by 4 e.g. level 1 results in $\frac{10240}{4} = 2560$ bits. As we can see in Table III, although we only use 3 levels of depth the matching rates decrease very fast. It is interesting to observe, that for a template size of 2560 (level 1 for hierarchical feature extraction, "Sub-4") both "Sub-4" and "Front" are clearly superior to the JBIG based iris code size reduction. Only the "Back" strategy is clearly worse.

Iris bits are generated from coarse quantisation and in the specific iris code used in the experiments, they represent sign changes in the wavelet maxima representation, which correspond to significant luminance changes in the original signal. The JBIG hierarchical resolution reduction scheme employs a low-pass filter, thus smoothing data in a specific manner, while the sharp transitions are maintained in subsampling. We conjecture that this is the reason for the decrease in matching accuracy when using the JBIG-based iris code size reduction approach.

In any case it is very interesting to observe that "Sub-n" is always better as compared to simply cutting off the first or second parts of the iris codes, respectively. This result contradicts the findings with respect to stability and reliability of iris bits which would suggest "Front" to be alway superior.

TABLE III
MATCHING RATES: HIERARCHICAL FEATURE EXTRACTION

Level	Template Bits	Resulting Bits	Threshold	Rate (%)
0	10240	10240	4550	98.49
1	10240	2560	1119	96.98
2	10240	640	240	75.09
3	10240	192	51	49.81

For the last experiment, we focus on pre-selection in identification. We combine JBIG hierarchical feature extraction and sub-sampling, as described in Section II.*C*. As we can see from Table IV, reasonable matching rates can be established e.g. with a 640 bit feature vector which results from a 10240 bit template by applying "Level-2 Hierarchical Feature Extraction". Hence the best compromise between Rank-10 matching rates and input data size is gained without any sub-sampling. The same is true for 2560 bit iris codes, where "Level-1 Hierarchical Feature Extraction" is superior to pure subsampling only.

TABLE IV
MATCHING RATES: PRE-SELECTION

Level	Template Bits	Result Bits	Rank3 (%)	Rank5 (%)	Rank10 (%)
0	10240	10240	98.49	98.87	98.87
0	5120	5120	98.49	98.49	98.87
0	2560	2560	98.49	98.49	98.49
0	640	640	92.07	93.96	95.85
1	10240	2560	98.49	98.49	98.87
1	5120	1280	98.49	98.49	98.49
1	2560	768	98.11	98.49	98.49
2	10240	640	96.23	97.73	98.11
2	5120	384	94.34	94.72	96.60
3	10240	192	65.66	70.94	83.39

Thus, in the context of a pre-selection scenario, JBIG-based iris code size reduction can be beneficial.

IV. CONCLUSION

Several techniques for reducing the size of iris code templates have been compared and it turns out that the most sophisticated approach, based on the binary resolution reduction scheme of JBIG, cannot compete with simple sub-sampling based schemes (which seems to be due to the smoothing in the corresponding FIR low-pass filtering which destroys sharp transitions in the data). As expected, keeping only the front part of iris codes (corresponding to inner iris texture regions adjacent to the pupil) is superior to keeping the back part. When comparing and combining the schemes in a pre-selection identification scenario, both techniques can be combined to achieve promising results.

Interestingly, we have observed that actual subsampling turns out to be superior to cutting off parts of the iris codes, which somehow contradicts earlier findings with respect to stability and reliability of iris bits. We will investigate this issue using more data, several iris code variants, and larger subsampling factors.

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