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On Combining Selective Best Bits of Iris-Codes*

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Abstract. This paper describes a generic fusion technique for iris recognition at bit-level we refer to as Selective Bits Fusion. Instead of storing multiple biometric templates for each algorithm, the proposed approach extracts most discriminative bits from multiple algorithms into a new template being even smaller than templates for individual algorithms. Experiments for three individual iris recognition algorithms on the open CASIA-V3-Interval iris database illustrate the ability of this technique to improve accuracy and processing time simultaneously. In all tested configurations Selective Bits Fusion turned out to be more accurate than fusion using the Sum Rule while being about twice as fast. The design of the new template allows explicit control of processing time requirements and introduces a tradeoff between time and accuracy of biometric fusion, which is highlighted in this work.

1 Introduction

The demand for secure access control has caused a widespread use of biometrics. Iris recognition [1] has emerged as one of the most reliable biometric technologies. Pioneered by the work of Daugman [2] generic iris recognition involves the extraction of binary iris-codes out of unwrapped iris textures. Similarity between iris-codes is estimated by calculating the Hamming distance. Numerous different iris recognition algorithms have been proposed, see [1] for an overview. While a combination of different biometric traits leads to generally higher accuracy (e.g., combining face and iris [16] or iris and fingerprints [6]), solutions typically require additional sensors leading to lower throughput and higher setup cost. Single-sensor biometric fusion, comparing multiple representations of a single biometric, does not significantly raise cost and has been shown to be still capable of improving recognition accuracy [11]. In both scenarios however, generic fusion strategies at score level [7] require the storage of several biometric templates per user according to the number of combined algorithms [13]. Iris recognition has been proven to provide reliable authentication on large-scale databases [3]. Particularly because it is employed in such scenarios, fusion of iris recognition algorithms may cause a drastic increase of both, required amount of storage and comparison time (which itself depends on the number of bits to be compared).

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The human iris has been combined with different biometric modalities, however due to reasons outlined before, we concentrate on single-sensor iris biometric fusion in this work. While the combination of iris and face data is a prospective application, see [18], still the successful extraction of high-quality iris images from surveillance data in less constrained environments is a challenging issue. In case of combining multiple iris algorithms operating on the same input instance, a couple of approaches have been published. Sun *et al.* [14] cascade two feature types employing global features in addition to a Daugman-like approach only if the result of the latter is in a questionable range. Zhang *et al.* [17] apply a similar strategy interchanging the role of global and local features. Vatsa *et al.* [15] compute the Euler number of connected components as global feature, while again using an iris-code as local texture feature. Park and Lee [11] decompose the iris data with a directional filterbank and extract two different feature types from this domain. Combining both results leads to an improvement compared to the single technique. All these techniques have in common, that they aim at gaining recognition performance in biometric fusion scenarios at the cost of larger templates or more time-consuming comparison. In contrast, the following approaches try to improve both, resource requirements (storage and/or time) and fusion recognition accuracy. Konrad *et al.* [9] 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. In previous work [12], we 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 [5]) of a single algorithm. Following a similar idea, Gentile et al. [4] 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 propose a fusion strategy for iris recognition algorithms, which combines the most reliable parts of different iris biometric templates in a common template. While most fusion techniques aiming to provide improvements in comparison time and accuracy operate in identification mode (e.g., [12] or [4]), our technique achieves these benefits in verification mode. In contrast to [12] our approach yields a constant number of bit tests per comparison and may more easily be integrated into existing solutions, since modules for comparison do not have to be changed. However, we adopt the analysis of bit-error occurrences in [12] for a training set of iris-codes. Thereby we can estimate a global ranking of bit positions for each applied algorithm following the observation by Hollingsworth et al. [5], that distinct parts of iris biometric templates (bits in iris-codes) exhibit more discriminative information than others. They found, that regions very close to the pupil and sclera contribute least to discrimination, i.e. the middle bands of the iris contain the most reliable information, and that masking fragile bits at the time of comparison increases accuracy. Based on obtained rankings we rearrange enrollment samples and merge them by discarding least reliable bits of extracted iris-codes. Furthermore, by introducing a ranking of bits, we can avoid keeping track of iris masks, since masked bits in typically distorted regions are most likely to be excluded from comparison by our technique. In experimental studies, we elaborate trade-offs between the accuracy and required storage by combining different iris recognition algorithms. Obtained results illustrate the worthiness of the proposed approach.

The remainder of this work is organized as follows: Section 2 introduces the architecture of the proposed system and presents necessary components for Selective Bits Fusion. Section 3 gives an overview of the experimental setup, outlines results and discusses observations. Finally, Section 4 concludes this paper.

2 Selective Bits Fusion

Selective Bits Fusion is a generic fusion technique and integrates in iris recognition systems as illustrated in Figs. 1 and 2. The following modules are involved:

– **Training Stage and Enrollment**: A training stage estimates a global ranking of bit positions, based on which given templates are rearranged.
– **Template Fusion Process**: The proposed fusion process simply extracts the most reliable parts of iris-codes from different feature extraction algorithms and concatenates relevant information, while discarding the least consistent bits.
– **Verification**: At the time of verification Selective Bits Fusion is performed at several shifting positions prior to comparison.

2.1 Training Stage and Enrollment

Following the idea in [12], we compute a global reliability mask R based on bit reliability [5] in the training stage for each feature extraction method. By assessing inter-class and intra-class comparisons, we calculate the probability of a bit-pair (for a given position) being either 0-0 or 1-1 denoted by $P_{Intra}(i)$ and $P_{Inter}(i)$ for each bit position i. The reliability at each bit position defined as $R(i) = P_{Intra}(i) + (1 - P_{Inter}(i))/2$ now reflects the stability of a bit with respect to genuine and imposter comparisons for a given algorithm. However, in order to account for inaccurate alignment, iris codes are shifted (with a maximum offset of 8) prior to evaluating $P_{Intra}(i)$ and $P_{Inter}(i)$. Reliability measures of all bit positions over all pairings define a global (user-independent) reliability distribution per algorithm, which is used to rearrange given iris-codes. Based on the reliability mask an ideal permutation of bit positions is derived for each feature extraction method and applied to reorder given samples such that the first bits represent the most reliable ones and the last bits represent the least reliable ones, respectively. At the time of enrollment preprocessing and feature extraction methods are applied to a given sample image. Subsequently, permutations derived from the previously calculated reliability masks are used to reorder iris-codes.

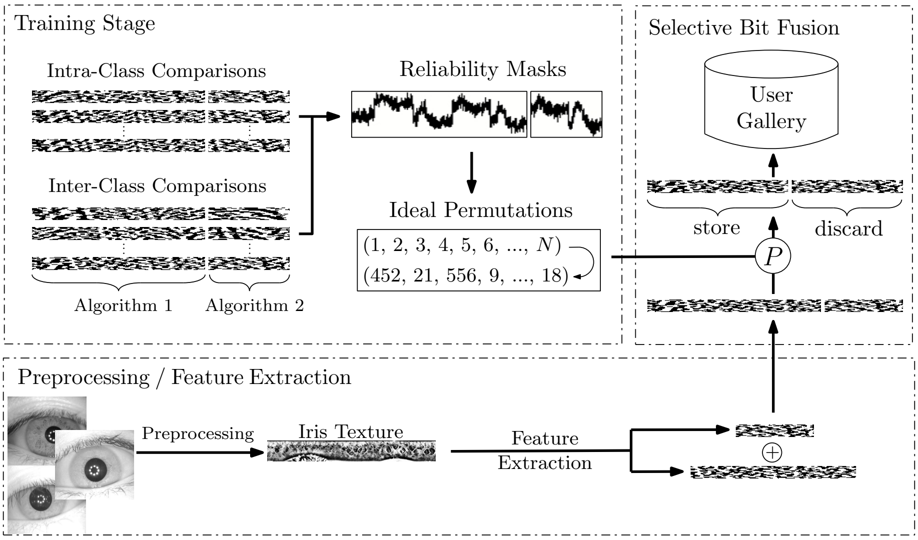

Fig. 1. Training stage and enrollment procedure of the proposed system

2.2 Template Fusion Process

The key idea of Selective Bits Fusion is to concatenate and store the most important bits only. Furthermore, since bits in typically distorted regions (close to eyelids or eyelashes) are moved backwards in the iris-code, this approach makes a storage of noise masks obsolete, i.e. their effect is less pronounced because the least reliable bits are discarded. The result of the fusion process is a new biometric template composed of the most reliable bits produced by diverse feature extraction algorithms. Focusing on recognition performance, a meaningful composition of reliable bits has to be established. In experiments this issue is discussed in more detail. Furthermore, we will show that resulting templates are at most as long as the average code size generated by the applied algorithms while recognition accuracy of traditional biometric fusion techniques is maintained or even increased.

2.3 Verification

In order to recognize subjects who have been registered with the system, in a first step feature extraction is executed for each algorithm in the combined template. Instead of comparing templates of all algorithms individually, Selective Bits Fusion combines iris-codes of different feature extraction techniques based on the global ranking of bit reliability calculated in the training stage. However, since bits are reordered, local neighborhoods of bits are obscured resulting in a loss of the property tolerating angular displacement by simple circular shifts. Instead, in order to achieve template alignment, we suggest to apply feature

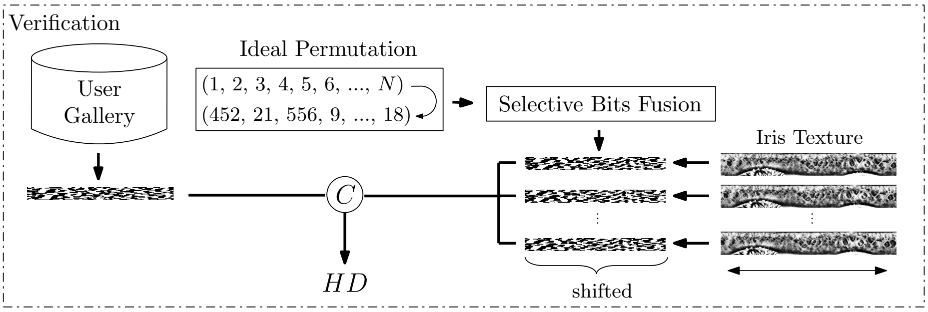

Fig. 2. Verification procedure of the proposed system

extraction methods at different shifting positions of the extracted iris texture. Subsequently, all reordered iris-codes are compared with the stored template. The minimal Hamming distance which corresponds to an optimal alignment of iris textures is returned as final comparison score (note that without loss of generality there is one optimal alignment which exhibits the best comparison scores for all feature extraction algorithms). The verification process is illustrated in Fig. 2.

3 Experimental Studies

For evaluation purposes of the proposed fusion algorithms, we employ the CASIA-V3-Interval[1] iris database. This set comprises 2639 good quality NIR illuminated indoor images of 320×280 pixel resolution from 396 different classes (eyes). Some typical input images and a resulting iris texture are given as part of the system architecture in Fig. 1. For experimental studies we evaluate all left-eye images (1332 instances) only, since the distribution of reliable bits within iris-codes will be highly influenced by natural distortions like eyelids or eyelashes and thus global reliability masks are expected to vary between left and right eyes. For training purposes of reliability masks, images of the first 20 classes are used for parameter estimation purposes.

3.1 Basic System

Selective Bits Fusion may be applied to any iris-code based biometric verification system. The tested basic system comprises the following preprocessing and feature extraction steps: At preprocessing, the pupil and the iris of an acquired image are detected by applying Canny edge detection and Hough circle detection. Once the inner and outer boundaries of the iris have been detected, the area between them is transformed to a normalized rectangular texture of

[1] The Center of Biometrics and Security Research, CASIA Iris Image Database, `http://www.sinobiometrics.com`

512×64 pixel, according to the "rubbersheet" approach by Daugman. Finally, a blockwise brightness estimation is applied to obtain a normalized illumination across the texture.

In the feature extraction stage, we employ custom implementations of three different algorithms, which extract binary iris-codes. The first one resembles Daugman's feature extraction method and follows an implementation by Masek[2] using Log-Gabor filters on rows of the iris texture (as opposed to the 2D filters used by Daugman). Within this approach the texture is divided into stripes to obtain 10 one-dimensional signals, each one averaged from the pixels of 5 adjacent rows (the upper 512×50 are analyzed). Here, a row-wise convolution with a complex Log-Gabor filter is performed on the texture pixels. The phase angle of the resulting complex value for each pixel is discretized into 2 bits. Again, row-averaging is applied to obtain 10 signals of length 512, where 2 bits of phase information are used to generate a binary code, consisting of $512 \times 20 = 10240$ bits.

The second feature to be computed is an iris-code version by Ma *et al.* [10] extracting 10 one-dimensional horizontal signals averaged from pixels of 5 adjacent rows of the upper 50 pixel rows. 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.

The third algorithm has been proposed by Ko *et al.* [8]. Here feature extraction is performed by applying cumulative-sum-based change analysis. It is suggested to discard parts of the iris texture, from the right side [45^o to 315^o] and the left side [135^o to 225^o], since the top and bottom of the iris are often hidden by eyelashes or eyelids. Subsequently, the resulting texture is divided into basic cell regions (these cell regions are of size 8×3 pixels). For each basic cell region an average gray scale value is calculated. Then basic cell regions are grouped horizontally and vertically. It is recommended that one group should consist of five basic cell regions. Finally, cumulative sums over each group are calculated to generate an iris-code. If cumulative sums are on an upward slope or on a downward slope these are encoded with 1s and 2s, respectively, otherwise 0s are assigned to the code. In order to obtain a binary feature vector we rearrange the resulting iris-code such that the first half contains all upward slopes and the second half contains all downward slopes. With respect to the above settings the final iris-code consits of 2400 bits.

It is important to mention that the algorithms by Ma *et al.* and Masek are fundamentally different to the iris-code version by Ko *et al.* as they process texture regions of different size, extract different features and produce iris-codes of different length. Therefore, we paired up each of the two algorithms with the latter one.

[2] L. Masek: Recognition of Human Iris Patterns for Biometric Identification, Master's thesis, University of Western Australia, 2003

3.2 Reliability Concentration in Early Bits

In order to be able to identify reliable bits, we assessed for each algorithm and for each bit position the probability of a bit switch. For this parameter estimation we used the inter- and intra-class comparisons of the training set. Results in form of reliability measures for each bit induced a permutation for each algorithm with the goal of moving reliable bits to the front of the iris-code while more unstable bits should be moved to the end of the iris-code. This approach is more generic than area-based exclusion of typically distorted regions as executed by many feature extraction algorithms including the applied version by Masek (e.g. by ignoring outer iris bands or sectors containing eyelids). The ability to concentrate reliable information in early bits on unseen data has been assessed for each of the applied algorithms and is illustrated in Figs. 3, 4 and 5. We found, that EER performance of Ma and Masek already tendencially increases in the original (unsorted) iris-code. This behaviour is not too surprising, since early iris-code bits correspond to the inner iris texture bands, which typically contain rich and discriminative information. However, it is clearly visible, that the second 1024-Bits block exhibits a better (lower) EER than the first block, which can be explained by segmentation inaccuracies due to varying pupil dilation. EERs for different 480-Bits blocks in the Ko algorithm do not seem to follow a specific pattern (due to the code layout grouping upward and downward slopes). As a first major result of experiments, we could verify the ability of reliability masks to really identify most reliable bits. While for Masek and Ma (see Figs. 3, 4) EERs stay low at approximately 2% for two thirds of the total number of blocks and then increase quickly, Ko's EERs (see Fig. 5) increased almost linearly for the new block order.

3.3 Selection of Bits

We use reliability masks to restrict the size of the combined template. By rejecting unstable bits we can (1) avoid degradation of results (see Figs. 6, 7 and 8) (2) accelerate comparison time and (3) reduce storage requirements. But how many bits should be used for the combination and which mixing proportion should be employed for the combined features? At this point we clearly state, that an exhaustive search for optimal parameters is avoided in order not to run into overfitting problems. Instead, we prefer an evaluation of two reasonable heuristics. Again, with this approach we alleviate a fast and almost parameterless (except for the computation and evaluation of reliability masks) integration into existing iris-code based solutions. Emphasizing the usability of Selective Bits Fusion we will show that even this simple approach will outerform traditional score-based fusion using the sum-rule. We select bits from single algorithms according to the following two strategies:

- **Zero-cost**: this heuristic simply assumes, that all algorithms provide a similar information rate per bit, thus the relative proportion in bit size is retained for the combined template. The maximum feature vector bit size is adopted

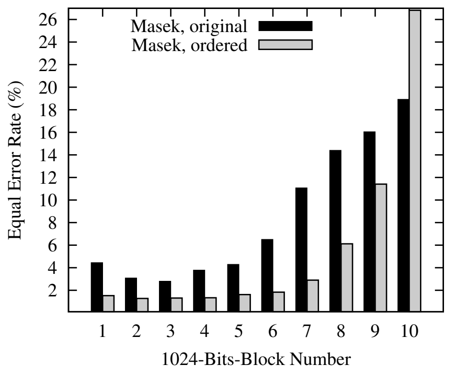

Fig. 3. EERs for Masek on 1024-Bits blocks

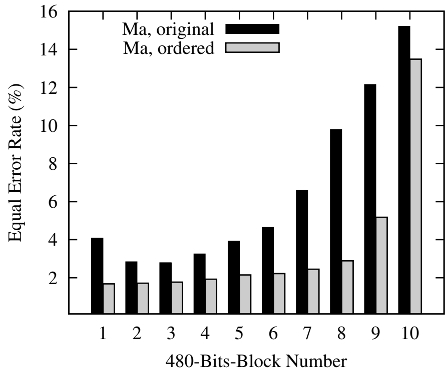

Fig. 4. EER's for Ma's on 1024-Bits blocks

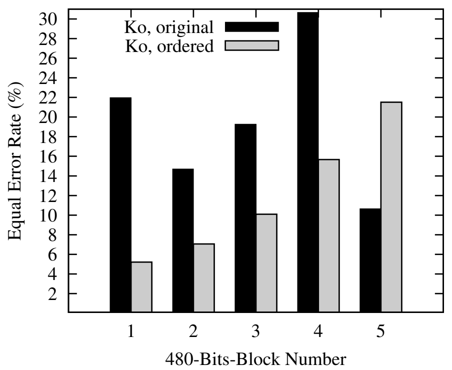

Fig. 5. EERs for Ko on 480-Bits blocks

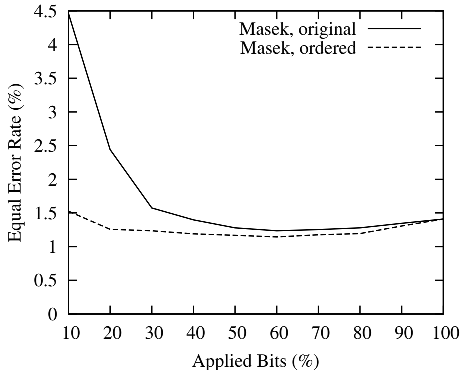

Fig. 6. EER-Bits tradeoff for Masek

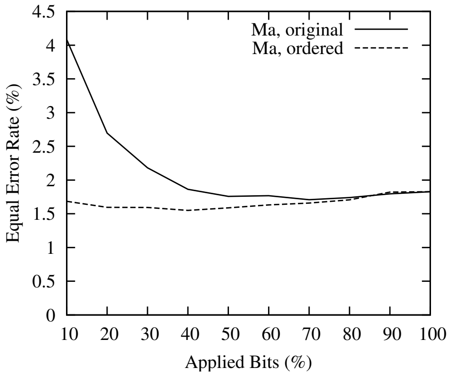

Fig. 7. EER-Bits tradeoff for Ma

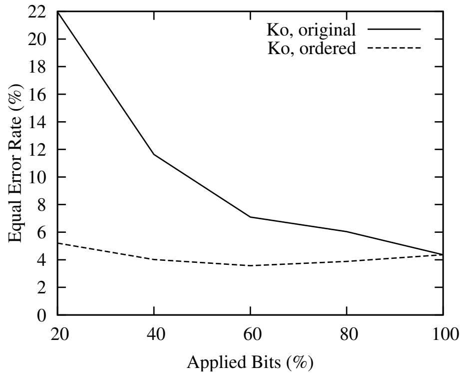

Fig. 8. EER-Bits tradeoff for Ko

Table 1. EERs of presented comparison techniques

	Original			**Sum Rule Fusion**			**Selective Bits Fusion**	
	Masek	Ko	Ma	Masek+Ko	Ko+Ma	Masek+Ma	Masek+Ko	Ko+Ma
Bits	10240	2400	10240	12640	12640	20480	6336	6336
EER	1.41%	4.36%	1.83%	1.38%	1.72%	1.54%	1.15%	1.52%

as the new template size and filled according to the relative size of the algorithm's template compared to the total sum of bits, i.e. for combining the total 10240 Masek bits and 2400 Ko bits, we extract the most reliable 8296 Masek and 1944 Ko bits and build a new template of size 10240 bits.

– **Half-sized**: when assessing the tradeoff between EER and bit count in Figs. 6, 7 and 8 we see, that for the reordered versions already very few bits suffice to obtain low EERs with a global optimum at approximately half of iris-code bits for all tested algorithms. Interestingly, even for the original (unordered) case 50% of bits seems to be a good amount to get almost the same performance like for a full-length iris-code. The new template consists of concatenating the best half-sized iris-codes of each algorithm rounded to the next 32 bits (in order to be able to use fast integer-arithmetics for the computation of the Hamming distance). This yields, e.g., 6336 bits for the combination of Masek and Ko.

3.4 Selective Bits vs. Sum Rule Fusion

Finally, we assessed the accuracy of Selective Bits Fusion in both zero-cost and half-sized configurations and compared their performance with sum rule fusion. The latter technique simply calculates the sum (or average) of individual comparison scores of each classifier C_i for two biometric samples a, b: $S(a,b) = \frac{1}{n}\sum_{i=1}^{n} C_i(a,b)$. Results of tested combinations are outlined briefly in Table 1 (Selective Bits Fusion lists results by the better half-sized variant).

First, we evaluated all single algorithms on the test set. Highest accuracy with respect to EER was provided by Masek's algorithm (1.41%) closely followed by Ma (1.83%). The almost five times shorter iris-code by Ko provided the least accurate EER results (4.36%). In experiments we tested pairwise combinations of these algorithms. It is worth noticing, that improvement in score-level biometric fusion is not self-evident but depends on whether algorithms assess complementary information. Indeed, if we combine the similar algorithms of Ma and Masek, we achieve an EER value (1.54%) right in between values for both single algorithms and at the cost of the iris-code being twice as long as for a single algorithm. For this reason we considered the combinations between the complementary algorithm pairs Masek and Ko as well as Ko and Ma only.

For the combination of Masek and Ko, sum rule yields only slightly superior EER (1.38%) than for the better single algorithm, but still despite the worse single performance of Ko, information could still be exploited and the ROC curve lies above both algorithms over almost the entire range, see Fig. 9. If we employ Selective Bits Fusion, we get a much better improvement than for the traditional combination with EERs as low as 1.15% for the half-sized version (and 1.21% for the zero-cost variant). Indeed it is even better to discard more bits, which is most likely to be caused by the fact that there is a significant amount of unstable bits present in each of the codes degrading the total result. Especially for high-security applications with requested low False Match Rates, Selective Bits Fusion performed reasonably well.

When employing fusion for Ko and Ma results indicate a similar picture. Again sum rule yields slightly better EER results than the best individual classifier (1.72%) which is beaten by Selective Bits Fusion (1.52%), see Fig. 10. Again, the zero-cost Selective Bits Fusion variant was slightly worse (1.59% EER).

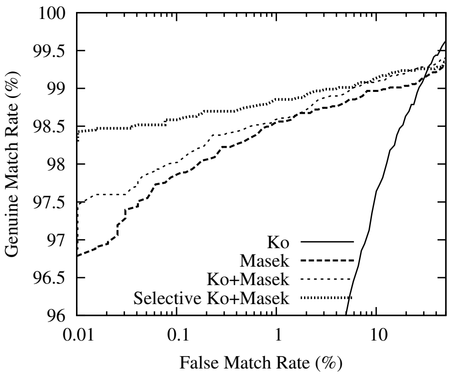

Fig. 9. Ko and Masek fusion scenario

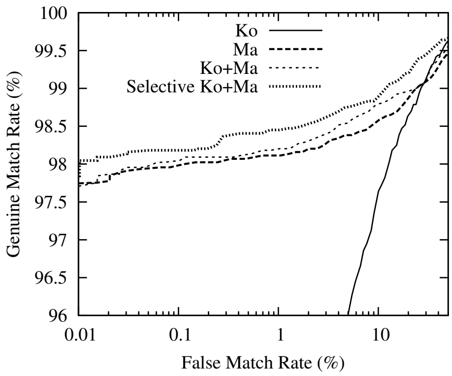

Fig. 10. Ko and Ma fusion scenario

4 Conclusion

Focusing on iris biometric fusion a reasonable combination of diverse feature extraction algorithms tends to improve recognition accuracy. However, a combination of algorithms implies the application of multiple biometric templates. That is, in conventional biometric fusion scenarios improved accuracy comes at the cost of additional template storage as well as comparison time.

In contrast, the proposed system, which is refered to as Selective Bits Fusion, presents a generic approach to iris biometric fusion which does not require the storage of a concatenation of applied biometric templates. By combining the most reliable features only (extracted by different algorithms) storage is saved while the accuracy of the biometric fusion is even improved. Experimental results confirm the worthiness of the proposed technique.

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