Shifting Score Fusion: On Exploiting Shifting Variation in Iris Recognition

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ABSTRACT

Iris recognition applies pattern matching techniques to compare two iris images and retrieve a comparison score that reflects their degree of (dis-)similarity. While numerous approaches to generating iris-codes have been proposed for the relatively young discipline of automated iris recognition, there are only few, usually simple, comparison techniques, e.g. fractional Hamming distance. However, in case of having access to specific iris-codes only or black-boxed feature extraction, there may be situations where improved comparison (even at potentially higher processing cost) is desirable. In this paper we present a new strategy for comparing iris-codes, which utilizes variations within comparison scores at different shift positions. We demonstrate that by taking advantage of this information, which even comes at negligible cost, recognition performance is significantly improved. The soundness of the approach is confirmed by experiments using two different iris-code based feature extraction algorithms.

Categories and Subject Descriptors

B.m [**Miscellaneous**]: Biometrics; I.4 [**Image Processing and Computer Vision**]: Applications

General Terms

Algorithms, Performance, Verification, Security

Keywords

Iris Recognition, Template Comparison, Template Alignment, Score Fusion, Hamming Distance

1. INTRODUCTION

The human iris has a unique pattern, from eye to eye and person to person. In the past years iris recognition [1] has emerged as a reliable means of recognizing individuals. Applications include identity cards and passports, border control or controlling access to restricted areas, to mention just a few [9]. Daugman's standard approach [2], unwrapping the "iris ring" of a data subject in order to analyze a rectangular iris texture has proven worth. Throughout the years several different feature extraction methods have been proposed where the vast majority of approaches extract binary iris-codes out of these textures (see [1]) such that similarity between iris-codes is defined applying the fractional Hamming distance (HD) as metric (small HDs indicate high similarity). That is, fast comparison, which is essential in case of large scale databases, is provided while template alignment is performed within a single dimension, applying a circular shift of iris-codes, in order to compensate against head tilts of a certain degree. In Fig. 1 the procedure of aligning two iris-codes during comparison is illustrated. That is, the similarity between two iris-codes is estimated at numerous shift positions and the comparison score at an optimal alignment is returned. Common iris recognition systems (we do not consider feature extraction methods which generate real-valued feature vectors) are based on this operation mode [1] providing a fast and simple method to authenticate individuals.

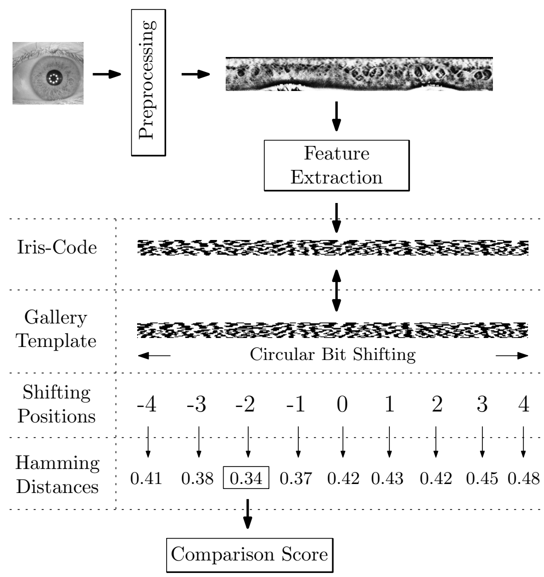

Figure 1: Template alignment in iris recognition: circular bit shifting is applied to align iris-codes and the minimum HD is returned as comparison score.

While most publications regarding iris recognition aim at

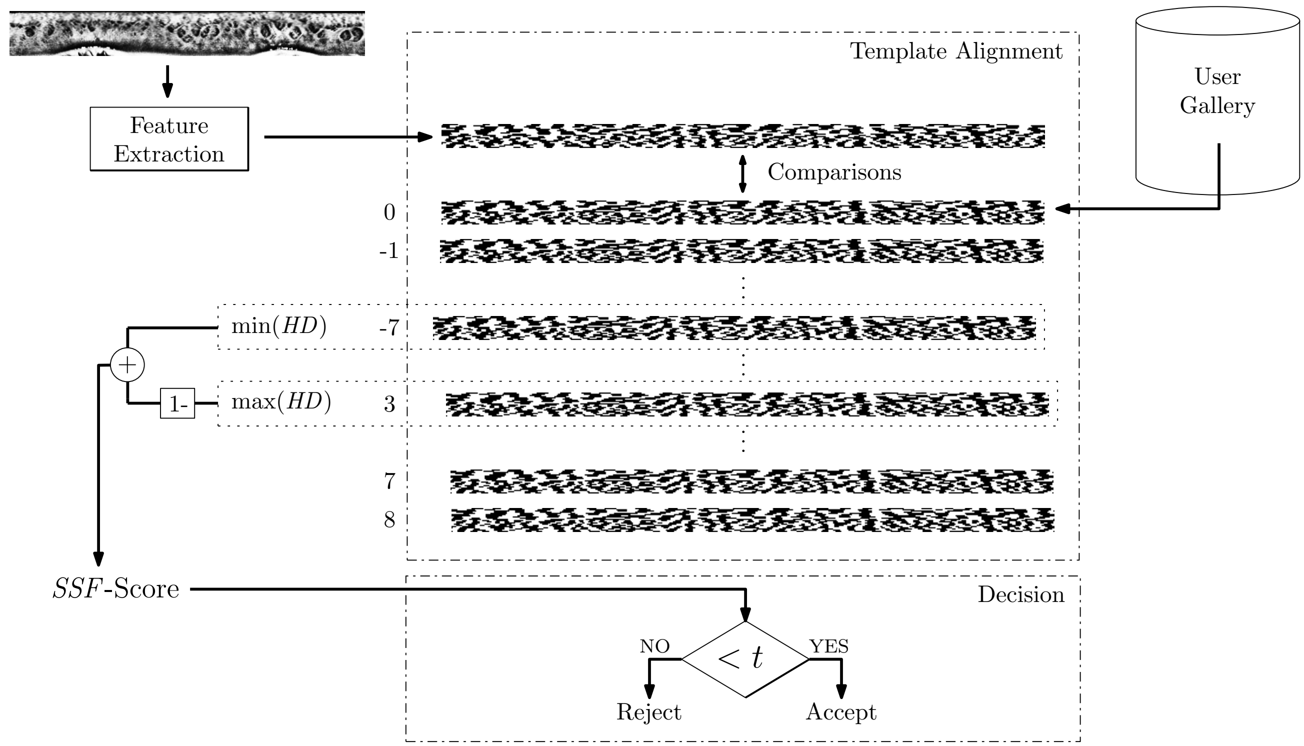

Figure 2: Proposed Comparison: the basic operation mode of the proposed comparison strategy.

extracting discriminative iris-codes during feature extraction comparison techniques have received only little consideration. Besides conventional bit-masking techniques, which are designed to detect occlusions originating from eye lids or eye lashes, Hollingsworth *et al.* [5] have proposed a method to detect iris-code bits which underlie high variations. By masking out these "fragile bits" during matching recognition performance is increased. Recently, Rathgeb and Uhl [8] have demonstrated that a context-based comparison of binary iris-codes increases recognition rates as well. Within this approach iris-codes are arranged in a two-dimensional manner in order to detect clusters of matching as well as non-matching bits. Based on the idea that large connected matching parts of iris-codes indicate genuine samples and non-genuine samples tend to cause more randomized distortions according context-based match scores are extracted. However, more complex approaches to template comparison generally require additional effort and are not suitable for biometric identification systems. To obtain representative user-specific iris templates during enrollment Davida *et al.* [3] and Ziauddin and Dailey [10] analyze several iris-codes. While Davida *et al.* propose a majority decoding where the majority of bits is assigned to according bit positions, Ziauddin and Dailey suggest to assign weights to each bit position which are afterwards applied during comparison. Obviously applying more than one enrollment sample yields better recognition performance [4], however, commercial applications usually require single sample enrollment.

The contribution of this work is the proposal of an iris-code comparison technique which exploits variations of comparison scores of iris-codes at different shift positions. Based on the idea that comparison scores (HDs) of genuine data subjects exhibit higher variations with respect to different shift positions than those of non-genuine data subjects, the information of shifting variation is leveraged. That is, for genuine pairs of iris-codes a distinct shifting position reveals an optimal comparison score while iris-codes of different data subjects tend to exhibit equally low similarity scores across different alignments. This claim is justified through the fact that unaligned iris-codes of a single data subject appear almost random to each other while iris-codes of different data subjects should appear random to each other per se, regardless of shifting positions. In experiments we demonstrate that the proposed comparison, which except from tracking the worst HD comparison and computing a final score sum of best and worst HD does not require additional computational cost, improves the recognition performance of different iris recognition algorithms.

This paper is organized as follows: Sect. 2 introduces the proposed comparison strategy and establishes a connection to score sum fusion techniques. In Sect. 3 experimental setup is summarized. Evaluations are presented in Sect. 4 and Sect. 5 concludes this work.

2. SHIFTING VARIATION IN IRIS VERIFICATION

As outlined in Fig. 2 the main focus of our approach is put on a modification of the comparison stage. In traditional iris comparison [1], in order to obtain a comparison score indicating the (dis-)similarity between two iris-codes, the minimum fractional HD over different bit shifts is calculated. The main reason for shifting one of the two paired iris-codes is to obtain a perfect alignment, i.e. to tolerate a certain amount of relative rotation between the two iris textures. Since iris-codes are composed of localized features, bit shifts in an iris-code correspond to angular shifts of the underlying iris texture. It is a very natural approach to preserve the best match only, i.e. the minimum HD value over different shifts, because this value most likely corresponds to the best alignment of two codes. The impact of bit shifts on inter-class comparisons has been shown to just skew the distribution to the left and reduce its mean [2]. However, there is no evidence, that the other computed HD scores of less perfect alignments can not contribute to an even better recognition result. While other traditional combination rules, such as maximum, product or sum of HD scores at different bit positions did not improve overall recognition accuracy in our experiments, it is interesting to look at the shifting variation, i.e. difference between maximum and minimum obtained HD scores. Let $s(a, i)$ denote an iris-code a shifted by $i \in I_n = \{z \in \mathbb{Z} : |z| \leq n\}$ bits and $HD(a, b)$ be the Hamming distance of two iris-codes, then we define the shifting variation (SV) score for two iris-codes a, b as:

$$SV(a,b) = \max_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big) - \min_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big). \tag{1}$$

Since multiplication and addition with constant values does not alter the ROC behavior of SV scores (denoted here with an equivalence relation $\approx$), we perform the following modifications to illustrate an interesting connection between SV and sum rule fusion:

$$\begin{aligned} SV(a,b) &\approx \min_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big) - \max_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big) \\ &\approx 1 - \max_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big) + \min_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big) \\ &\approx \frac{1}{2}\bigg(\Big(1 - \max_{i \in I_n}\big(HD(a, s(b,i))\big)\Big) + \min_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big)\bigg). \end{aligned} \tag{2}$$

That is, shifting variation corresponds to a score level fusion of the minimum (i.e. best) Hamming distance and one minus the maximum (i.e. worst) Hamming distance using the sum rule [6]. By combining "best" and "worst" observed HD scores we also track the variation between these scores, which we will show to be a good indicator for genuine and imposter classes (SV scores tend to be higher for intra-class comparisons than for inter-class comparisons). In order to obtain distance scores comparable to minimum HD we use the latter reformulated term using sum rule fusion:

$$SSF(a,b) = \frac{1}{2}\bigg(\Big(1 - \max_{i \in I_n}\big(HD(a, s(b,i))\big)\Big) + \min_{i \in I_n}\Big(HD\big(a, s(b,i)\big)\Big)\bigg). \tag{3}$$

From this point of view, the proposed approach is a new shifting score fusion (SSF) technique for iris recognition.

In Sect. 4, we will illustrate that SSF is superior to traditional approaches assessing the minimum Hamming distance only. Furthermore the improvement comes at almost no additional cost, since a calculation of the minimum Hamming distance already involves a calculation of all Hamming distances in a specified range I_n. The only required additional operation is a tracking of the maximum observed HD (besides the minimum HD) and an application of the fusion rule outlined before.

3. EXPERIMENTAL SETUP

For experiments we employ the CASIA-V3-Interval[1] iris database consisting of good quality NIR illuminated indoor images with 320×280 pixel resolution. An example of input and processed textures is illustrated as part of Fig. 1. For experiments, we considered left-eye images only yielding a total of 1307 out of 2655 instances.

In the preprocessing step, the pupil and iris of a given sample are detected by applying Canny edge detection and Hough circle detection. After localizing the pupil and iris circles, the area between them is transformed to a normalized rectangular texture of 512×64 pixel, according to the "rubbersheet" approach by Daugman. As a final step, illumination across the texture is normalized using blockwise brightness estimation.

In the feature extraction stage, we employ custom implementations of two different algorithms extracting binary iris-codes. The first one was proposed by Ma *et al.* [7]. 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). A dyadic wavelet transform is then performed on each of the resulting 10 signals, and two fixed subbands are selected from each transform resulting in a total number of 20 subbands. In each subband all local minima and maxima above an adequate threshold are located, and a bitcode alternating between 0 and 1 at each extreme point is extracted. Using 512 bits per signal, the final code is then $512 \times 20 = 10240$ bit. The second feature extraction method follows an implementation by Masek[2] in which filters obtained from a Log-Gabor function are applied. 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 $512 \times 20 = 10240$ bit. The algorithm is somewhat similar to Daugman's use of Log-Gabor filters, but it works only on rows as opposed to the 2-dimensional filters used by Daugman.

With respect to different comparison techniques the recognition performance of the previously described algorithms, is carried out in terms of equal error rates (EERs) and zero false match rates (ZeroFMRs). For both feature extraction methods we evaluate three different similarity metrices: (1) *MinHD*: the minimum Hamming distance, (2) *1-MaxHD*: one minus the maximum Hamming distance, and (3) *SSF*: the proposed shifting score fusion, where we perform circular shifts of up to seven bits in both directions. All experiments were executed in verification mode with 4028 genuine comparisons (intra-class cross-comparison) and 15576 imposter comparisons (comparing only the first template of each data subject against each other).

4. EXPERIMENTAL RESULTS

The EERs and ZeroFMRs obtained by applying the according comparison techniques for the algorithms of Ma and

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

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

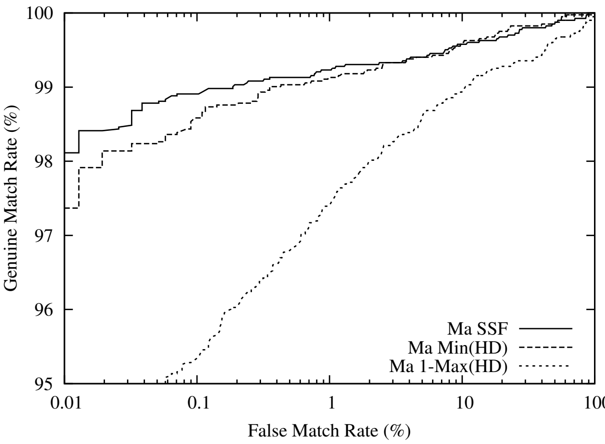

Figure 3: ROC curves for presented comparison techniques on Ma's feature vector.

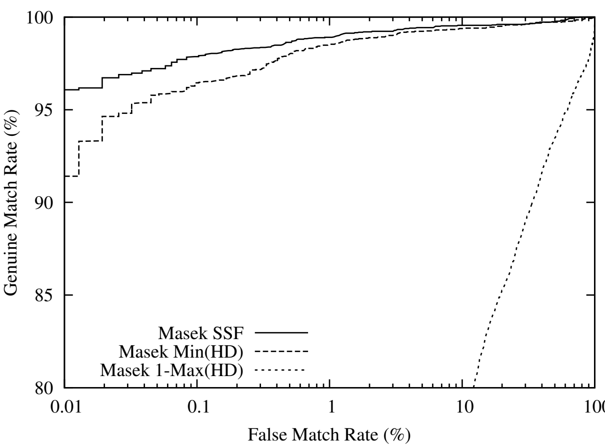

Figure 4: ROC curves for presented comparison techniques on Masek's feature vector.

Masek are summarized in Table 1 and Table 2, respectively. The resulting receiver operation characteristics (ROCs) are plotted in Fig. 3 and Fig. 4. As can be seen, for both feature extraction methods, *SSF* reveals a slightly better performance over *MinHD* when evaluating EERs while *1-MaxHD* shows rather unpractical rates (e.g. 16.4% for the algorithm of Masek). It is interesting to see, that despite this weak performance of *1-MaxHD*, still the measured scores can well be combined with *MinHD* to even improve the total combined score. Even more surprisingly, *MaxHD* has an inverse similarity comparison property, i.e. if the maximum HD between two samples is very high, they are likely to be a genuine comparison pair - as opposed to *MinHD* where exactly the opposite is true. This suggests, that for iris-codes originating from the same data subject, there are misalignments inducing some kind of systematic error - unseen for HD comparisons with iris-codes from different data subjects.

Table 1: EER rates (in percent) of presented comparison techniques

EER	MinHD	1-MaxHD	SSF
Ma	0.89	2.00	0.80
Masek	1.29	16.40	1.07

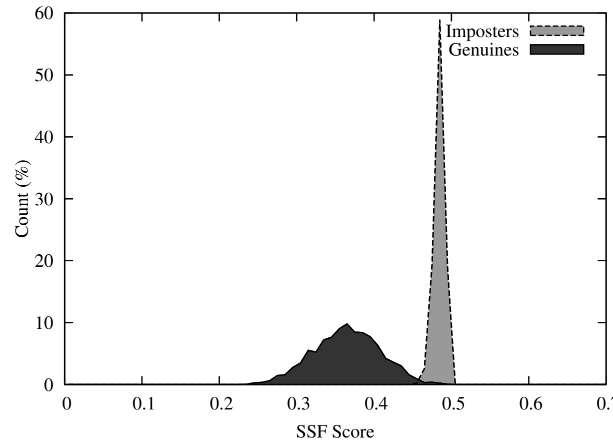

Figure 5: Genuine and imposter score distribution for SSF using Ma's feature vector.

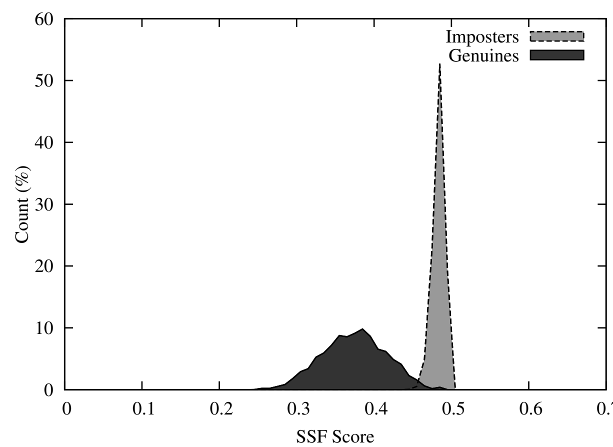

Figure 6: Genuine and imposter score distribution for SSF using Masek's feature vector.

With respect to ZeroFMR, performance gains become even more clearly visible (see Table 2). For the algorithms of Ma and Masek the ZeroFMR is decreased from 4.87% to 1.94% and from 10.87% to 3.97%, respectively. The according intra-class and inter-class distributions for *SSF* are plotted in Fig. 5 and Fig. 6. That is, the *SSF* comparison technique is capable of reducing the ZeroFMRs to a level twice as low compared to *MinHD* which underlines the worthiness of the approach since low ZeroFMRs are generally demanded, in particular, for high security applications. Together with the property of easy integration in existing comparators (only 4 lines of code needed to be changed in our implementation to switch from *MinHD* to *SSF*) and almost no additional time requirements (time differences were too small to be measured in our experiments) the proposed technique would be an ideal enhancement of current *MinHD*-based implementations.

Table 2: ZeroFMR rates (in percent) of presented comparison techniques

ZeroFMR	MinHD	1-MaxHD	SSF
Ma	4.87	7.52	1.94
Masek	10.87	91.48	3.97

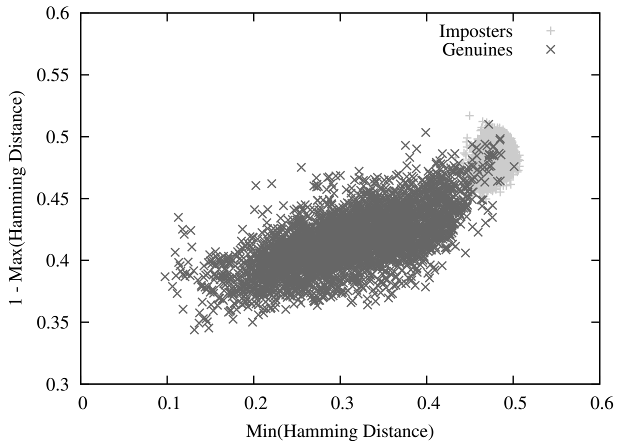

Figure 7: 1-Max(HD) scores vs. Min(HD) scores for 7 shifts using Ma's feature vector.

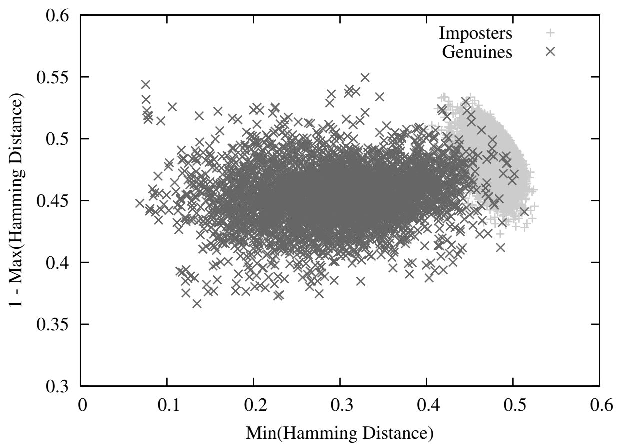

Figure 8: 1-Max(HD) scores vs. Min(HD) scores for 7 shifts using Masek's feature vector.

In Fig. 7 and Fig. 8 for both algorithms the inter-relation between *MinHD* and *1-MaxHD* is shown. It is interesting to see, that for both Ma and Masek the intra-class variance is rather low, i.e. there is not much difference between minimum and (one minus) maximum Hamming distance. Furthermore, we can identify a much better separability of genuine and imposter score points by lines parallel to $y = -x$ than lines parallel to x-axis or y-axis. Finally, there is no strong correlation between both scores, indicating a promising fusion.

5. CONCLUSION AND FUTURE WORK

The rich texture of an iris offers a strong biometric cue for recognizing individuals [9]. While most approaches to iris recognition systems put their main focus on the feature extraction stage, improving comparison strategies has received only little consideration. Applying the fractional Hamming distance to estimate the similarity between two binary iris-codes has proven worth with respect to accuracy and speed, while template alignment is implemented through circular bit shifts.

In this work we investigated the variation of comparison scores between iris-codes at different shifting positions to propose a new comparison technique. We demonstated that by taking into account the variation of comparison scores at several shifting positions (which comes at negligible cost) recognition rates of different iris recognition algorithms can be significantly increased. Since pairs of iris-codes from the same data subject exhibit an optimal comparison score at a distinct alignment, mis-alignments reveal rather low comparison scores causing high variation. In contrast, pairs of non-genuine data subjects tend to yield low comparison scores regardless of shifting positions. These observations motivate a sensible fusion of comparision scores and shifting variation. While the simplicity of the proposed scheme preserves resources, the resulting increased recognition rates confirm the soundness of the proposed technique.

Future work will comprise performance evaluations of the proposed comparison procedure in iris biometric fusion scenarios.

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