A multiple classifiers-based approach to palmvein identification

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Abstract— **The usual trend for the conventional palmvein recognition techniques is first to extract discriminative hand-crafted feature representations from the raw images, and then feed a classifier with them. Unfortunately, it is not yet clear how the effectiveness of such features may be held in case of a large user population or in environments where the variability among acquisitions of the same person may increase. In order to face with this problem, it may be considered that the use of multiple classifiers may increase the recognition performance with respect to that of the best individual classifier, and also may handle the problem of an effective feature extraction step. In this paper, we explore the ensemble classifier approach based on Random Subspace Method (RSM), where the basic feature space is derived after a preliminary feature reduction step on the source image, and compare results achieved with and without the use of hand-crafted features. Experimental results allow us concluding that this approach leads to better results under different environmental conditions.**

Keywords— **Image processing, palmvein recognition, features, multiple classifiers.**

I. Introduction

Over the two prior decades, biometric security has known a big infatuation in order to increase the security and convenience. Nowadays, biometric systems are used in our everyday life such as airports security, time attendance, law enforcement and buildings access control. A large variety of biometric modalities including face, iris, gait, fingerprint and palmvein, have been investigated providing different rates of robustness, accuracy and user acceptability [13]. Among these modalities, palmvein is one of the newest and emerging biometric techniques which has gained a growing interest thanks to its reliability, stability and high user tolerance [1]. Furthermore, the blood vessels are hidden under the skin and invisible to the human, which make them harder to spoof when compared to other biometric traits.

The usual trend for the conventional palmvein recognition techniques is first to extract discriminative hand-crafted feature representations from the raw images, and then feed a classifier with them. Features are chosen so as to enforce similarities within a class and disparities between classes. The more discriminative the features are, the better the classifier performs to attain valuable recognition accuracies. Unfortunately in the camera-based acquisition, the pixels density, scale, rotation and translation are affected by the distance of the camera from the palm which make the large majority of the predefined hand-crafted features non reliable in practice [11]. Moreover, it is not yet clear which specific contribution is given by hand-crafted features to characterize the person uniqueness, so it is very difficult to explain why palmvein recognition is working and in which scenario it could not be effective.

Aware about the above problems, we explore a data-driven method for palmvein personal identification. The proposed technique was already presented in [12] and directly applied to the image pixels after a preliminary feature reduction step. Here we further investigate the benefits of that method by adding an additional module of hand-crafted features. This may further help in improving the performance when adopting the ensemble classifier approach based on Random Subspace Method (RSM). The RSM builds many individual weak classifiers potentially achieving good accuracy and by aggregating them it can further boost the performances and promote more generalization ability in order to avoid overfitting. In [12], further investigations were pointed out to be necessary. Therefore, experiments reported in this paper pursue that purpose. In addition, we want to confirm how much the well-known ability of multiple classifiers-based systems may help, namely, the increase of robustness and performance independently of the specific working scenario. To this aim, two data sets captured by a contact-based sensor and a contactless-based sensor, with images acquired at different wavelengths, were used.

The paper is organized as follows. Section II summarizes related work. Section III describes the proposed method. Section IV reports the experimental results and discussions. Finally, Section V concludes the paper.

II. Related work

A recent survey on palmvein recognition methods appeared in [24].

In the literature, various palmvein recognition approaches have been proposed. Relying on feature extraction methods they can be organized in four main categories: geometry-based, statistical-based, local-invariant-feature-based and subspace-based [2], [3].

Geometry-based methods, derived from fingerprint and palmprint recognition, extract the local characteristics of the veins as principle lines, wrinkles, minutiae point etc. and are usually based on spatial methods, such as Gaussian filters,

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Gabor filters and points of maximum curvature. However, geometric features suffer from loss of information due to small and/or blurred textures and are sensitive to scaling, rotation and displacement.

Statistical-based methods process palmvein image as a whole and they can be divided into global or local approaches. Global methods work on the whole image and extract physical characteristics such as center of mass, density and moments [7]. Local statistical-based methods divide the image into small regions, according to a predefined scheme, from which it is possible to extract statistical information. Local binary patterns (LBPs) [15], [4], [5], local derivative patterns (LDPs) [5], and their variants [6] are local methods.

Among the statistical-based methods, the textural methods allow to manage changes of scale, rotations and translations, analyzing the image at a global or local level, with the ultimate aim of creating descriptors that represent in a compact way a region of pixels close to each other. Textural methods have a significant discriminative power, independently of the biometrics considered. The LBP [15] is a textural method based on dividing the image into multiple blocks, from which local binary patterns are extracted. A global feature histogram is then constructed that represents both micro-pattern statistics and their spatial locations. Another example of textural methods is the BSIF [14]. The BSIF algorithm calculates a binary code string for the pixels of a given image. The value of each pixel is considered as a local descriptor and may be used to build the histograms that allow to characterize the textural properties within subregions of the image. Each bit in the binary code string is calculated binarizing the response of a linear filter with a threshold at zero. BSIFs were proposed for palmvein recognition in [22], [23].

Methods based on local-invariant features extract stable local invariant features for matching. These methods offer an important advantage, since they are independent of rotation, translation and scaling, they are appropriate for use with contactless sensors. An efficient local-invariant descriptor is the SIFT [8] applied to local key-points. Basically it samples the size and orientation of the image gradients, creating histograms that contain important information about the surroundings of the points considered. Subspace-based methods, also named appearance-based, derive from face recognition. Principal Component Analysis (PCA) [9] and Linear Discriminant Analysis [10] are the main ones in this category. These methods project the palm vein image in a lower space for recognition.

III. THE INVESTIGATED METHOD

In this paper we use an ensemble classifier for palmvein recognition based on Random Subspace Method (RSM), already proposed in [12].

The method proposed in this paper is reported in Fig. 1. Two different approaches were investigated:

1) using a standard hand-crafted features module, basically BSIF and LBP, on which performing the subspace sampling;
2) using raw images (without features extraction).

RSM is a successful ensemble construction method that attempts to reduce the correlation between estimators in an ensemble by dividing the feature space randomly to some subsets and submitting each one to the individual classifiers. In order to build the random subspaces from which the features are randomly extracted, we rely on a two-dimensional PCA (2DPCA) [20] (n subspaces are randomly generated from the eigen-vectors). The resulting subspaces are refined through 2DLDA to ensure classes separability. This step allows to extract discriminative features. Then, for each random subspace, the subject is identified by a classifier C_i (Fig 1). The final classification is obtained using the majority vote (MV) [21] over the outcomes of the n classifiers.

The individual classifier C_i is a Nearest Neighbor, that takes as input the related features from the input data and from each subject templates. The outcome is the most probable class/identity on the basis of the nearest template to the input sample.

Further details on the method are reported in [12].

IV. EXPERIMENTAL RESULTS

A. Data sets and experimental protocol

To compare the performance of the proposed approach, two public datasets containing multispectral palmprint images, PolyU [16] and CASIA [17], are used (Table 1).

The PolyU MS Database (Fig. 2) is composed by multispectral palmprint images collected from 250 volunteers (195 males and 55 females). Samples were collected in two separate sessions, 6 images for each palm per session. The database contains 6000 images from 500 different palms (24 images from 2 palms were collected from each subject). The average time interval between the two sessions was about 9 days. Users have been asked to place their hand on the device, where several pegs serve as control points for the correct positioning of the user's hands. The samples were acquired at different spectral bands. Palmprint characteristics, such as lines for example, are more visible in the " Blue" bands (470 nm) and " Green" (525 nm), compared to the " Red" bands (660 nm) and " NIR" (880 nm), where the characteristics of the palmvein are observed. From each image ROIs were detected and cropped to a 128x128 size.

The CASIA Palmprint Image Database (Fig. 3) is composed of 7200 palmprint images collected from 100 subjects. For each of them, 6 palmprint images were collected from both left and right palms, in two sessions distant more than one month. All images are 8 bit gray-level JPEG files. Since in the acquisition device there are no pegs to restrict postures and positions of palms, subjects were required to put their palms into the device and lay it on a uniform-colored background. The device supplies an evenly distributed illumination and captures palmprint images using a CMOS camera fixed on

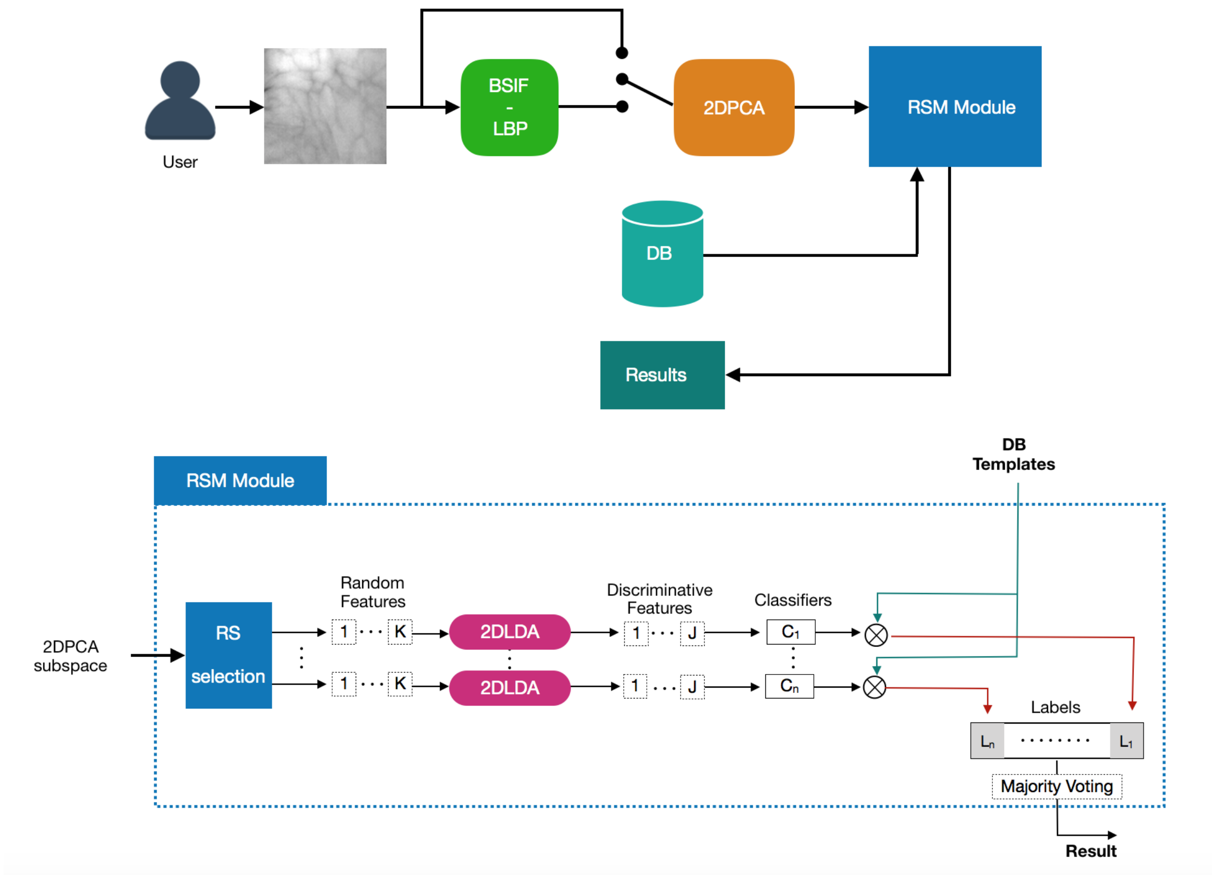


Fig. 1: The proposed approach: the RSM module generates a set of n random subspaces. These are sampled from the reduced feature space provided by the application of 2DPCA-2DLDA. It can be also seen that such step may take as input hand-crafted features such as LBP and BSIF, or the individual gray levels of the ROI extracted from the raw image. The individual classifier C_i is a generic Nearest Neighbor, which takes as input the template of each subject stored in the system's database and generates the most probable class/identity as function of the nearest template to the input sample. The majority voting rule is finally applied for obtaining the final class/identity.

the top of the device. Each sample was captured at 6 different spectral bands: white light, 460 nm, 630 nm, 700 nm, 850 nm and 940 nm. Unlike the PolyU dataset, in the CASIA dataset a preprocessing step is required. As a matter of fact, since there are no pegs to restrict the hands in fixed positions, it is necessary to find reference points in order to compute the relative rotation, scale variation or translation between different samples. Among the various features commonly used, the spaces between the fingers are ideal references thanks to their invariance with the movement of the hand, identified through the use of a contour tracking algorithm. For each image a ROI has been extracted and resized to 236x236.

Histogram equalization was applied to enhance the characteristics of the veins with respect to the background. The ROIs were then divided into 16 blocks of variable size depending on the dataset, 32x32 for PolyU and 64x64 for CASIA. For each of those blocks two textural descriptors, LBP and BSIF, were applied and, for each image, a unique vector that contains the linked features of all the blocks is obtained. This procedure was repeated for each spectral band.

Table 2 summarizes the size of the feature spaces and RS number at each step. For example, by retaining 40 random eigenvectors from the overall set derived by 2DPCA applied to raw images or textural feature vectors (column 2DPCA), we generated a novel 20-sized subspace 2DLDA (column 2DLDA) on which each NN classifier performs the partial classification. Templates are stored as 20-sized feature vectors. This process is repeated 50 times (column # classifiers). The final decision is taken by majority voting.

In Table 2 the details of the experimental protocol are schematized.

Since the RSM uses multiple classifiers, their number must be set. In order to simulate a real-case scenario we tried to limit the execution time, without overly reducing the performance. For these reasons, we decided to set the number of classifiers to 50, considering it is a fair compromise between quality and execution times. In the RSM the N-sized feature vector is reduced to K elements (with $K << N$) by the PCA and then

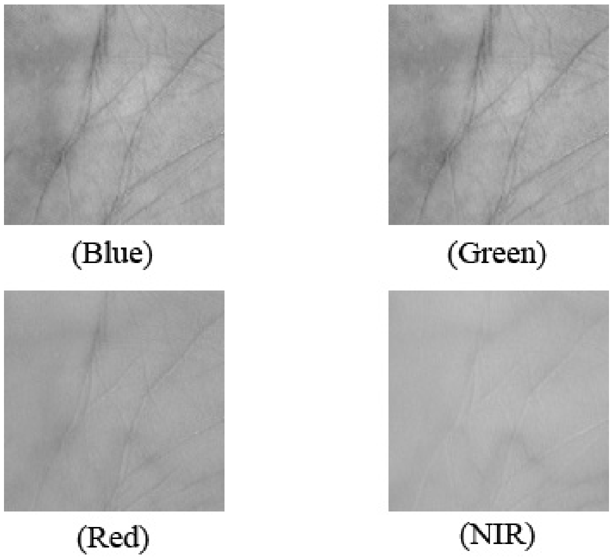


Fig. 2: Typical multispectral ROI images of the PolyU database.

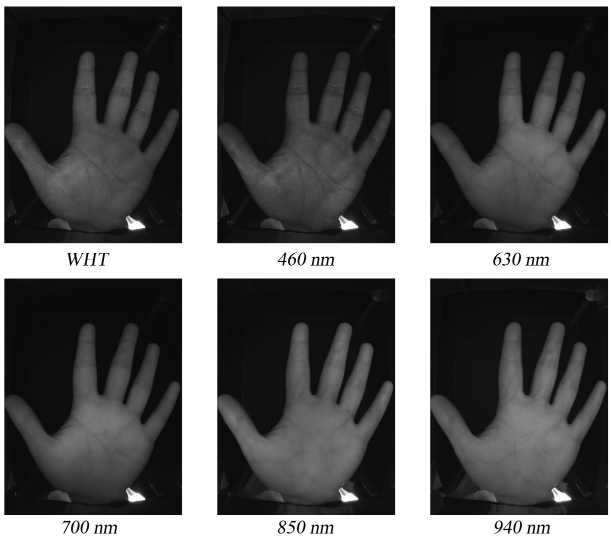


Fig. 3: The six multispectral samples of the CASIA database.

is further reduced to J elements (with $J < K$) by the LDA. In our experiments $K = 10, 20, 30, 40$ and $J = 5, 10, 15, 20$. The datasets have been divided in template and probe sets with two samples per class in the template set and the others in the probe set. The experiments were performed using the LBP and BSIF feature vectors without any RSM, the RSM applied to the LBP and BSIF feature vectors and the RSM applied directly to the raw images.

The performance parameter reported as set of bins in Figs. 4 is the Correct Classification Rate (CCR), also called Accuracy, that is, the ratio between the number of samples correctly classified/identified and the total number of samples submitted to the system during the probing phase.

Table 1: PolyU and CASIA datasets characteristics.

Dataset	**PolyU**	**CASIA**
Sensor	Contact	Contactless
Users (dx & sx)	250	100
Samples per user	12	6
Images per band	6000	1200
Bands per sample	4	6
Wavelength (nm)	470, 525, 660, 880	460, 630, 700, 850, 940, white light

Table 2: Details on the experimental protocol adopted.

# classifiers	**2DPCA subspace**	**2DLDA subspace**	**# templates per user**
50	10, 20, 30, 40	5, 10, 15, 20	2

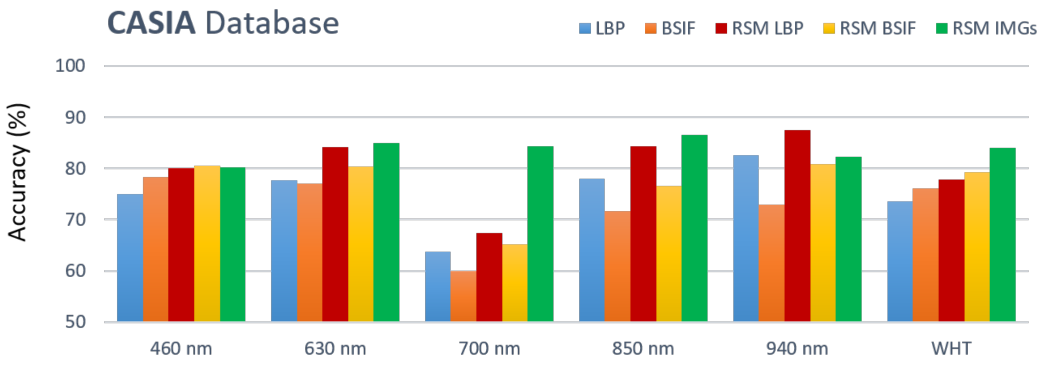
B. Results

Fig.4 summarizes the best outcomes of the experiments carried out.

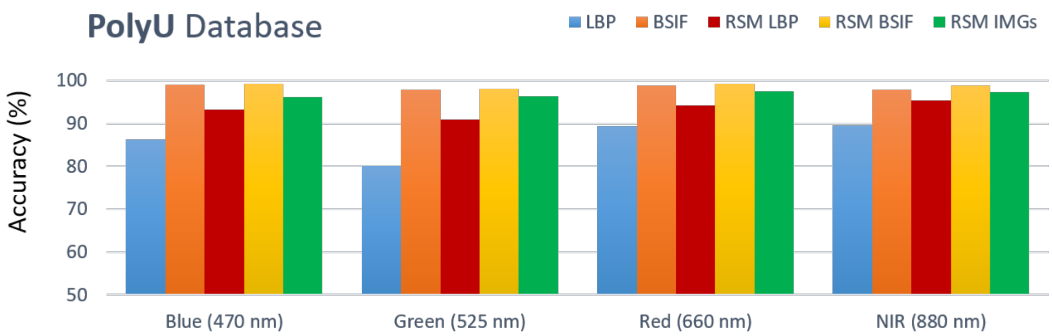
We noticed that experiments on the PolyU data set achieved better results in all cases. We can explain this by the fact that, on overall, this data set has images of high quality. This is basically due to the fact that PolyU was collected using a contact sensor, which allows a better control of the position of the hand with respect to the sensor surface. On the contrary, CASIA data set is made up of images acquired by a contactless sensor, that implies less control on the distance between hand and sensor, an acquisition surface smaller than that of the PolyU sensor and the fact that the user's hand cannot be sufficiently firm during acquisition. This is evident especially when comparing accuracies attained by hand-crafted features (blue and orange bins of Figs. 4).

With regard to LBP and BSIF as individual feature sets, the latter are generally more accurate than the former for both data sets. Zhang et al. [19] showed experimentally how sample's quality is relevant in a biometric system. We confirm their findings, because we voluntarily maintained the same BSIF's parameters for both data sets to test how images' quality has impact on the recognition process. In particular, the best LBP parameters were set as follows: $P = 16$ and $R = 4$ for the PolyU data set and $P = 16$ and $R = 7$ for the CASIA data set; the obtained histogram sized 243 bins. The best BSIF parameters were set as follows: the number of filters is 8, that is the length of BSIF's bit-code, and $W = 7$ for both data sets. The final feature vector size is 243 and 256 for LBP and BSIF, respectively[1] We tested different sizes of the histogram computed by LBP and BSIF in order to show that an appropriate parameterization of the descriptor can partially solve the problems related to low quality images. For example, we optimized LBP parameters in the CASIA data set as done in [5]. This is reflected by Figs. 4, where bands at 850 nm and 940 nm obtained the best recognition rates, in

[1]More information about LBP and BSIF parameters, namely P, K, W and number of filters is given in [15], [14].



(a)



(b)

Fig. 4: Histogram reporting the best Accuracy or Correct Classification Rate (CCR) computed when using individual hand-crafted features with standard template-based recognition approach (blue and orange bins), RSM using hand-crafted features (red and yellow bins) and RSM on raw images (green bins).

agreement with [5]. These bands were the most exposed to a performance decrease due to the images quality. However, by an appropriate and careful optimization step, as done in [5], the recognition rate in those bands is still good. In general, textural descriptors need a careful parameterization and images with sufficiently high quality. It could be interesting to evaluate different parameters of the BSIF algorithm applied to the CASIA database, because it is reasonable to hypothesize that increasing the number of BSIF filters should further improve the performance. If this study was already done in [5] for LBP, to the best of our knowledge this has not yet been done for BSIFs, although they were investigated and cited in [22], [23], [24].

Despite the performance of the basic handcrafted features, the application of RSM brought a further, significant performance improvement in all cases. On the basis of previous works, the performance improvement by RSM when using LBP and BSIF may be expected [22], [23], although not investigated in [12]. On the other hand, obtaining a very high level of accuracy when extracting random subspaces from raw images is surprising: in particular, the CASIA's 700 nm band reached a remarkable level of accuracy, compared to the previous cases. High accuracy was already noticed in [12], but in this paper tests were extended to two data sets (CASIA and PolyU) and we also did the direct comparison with hand-crafted feature alone and coupled with the RSM module. It can be observed that the reported accuracy is comparable with that of RSM using hand-crafted features (green bins against the other ones in Fig. 4); the performance is even better in the case of images captured by a contactless sensor (CASIA data set). An explanation for this is that relevant information, which emphasizes the complementarity among classifiers, is already embedded into the raw images. This makes possible to avoid the textural descriptor, thus speeding up the recognition process, especially in the case of BSIF-based feature extraction.

Finally, we don't know exactly the reason why in some cases the use of raw images did not achieve better results, as well as in the case of textural descriptors. We can assume that during the process of space reduction by PCA and LDA, important information was lost from the features of the textural operators, and thus their expressive power when used individually decreased. This is still an open problem when textural descriptors or statistical feature reduction methods are applied to images and it is not clear the relationship between uniqueness characteristic of the biometric itself and features extracted to look for such uniqueness. Nevertheless, this is a promising starting point for future theoretical and experimental investigations.

V. Conclusions

This paper explored the use of Random Subspace Method (RSM) for palmvein recognition by adding novel evidences to a previously published paper. The architecture includes the extraction of RSs after a preliminary feature reduction step by PCA-LDA. With respect to the early publication, RSM was applied both on raw palmprint/palmvein images and on textural features extracted with two different algorithms, BSIF and LBP. Moreover, the performance was analyzed on two different sets of images, namely, provided by a contact sensor (CASIA data set) and a contactless sensor (PolyU data set).

Our findings suggest that the use of RSM leads to an improvement of the performance especially when applied to raw images, independently of the sensor adopted. This may help in speeding up the recognition process and allow avoiding the non-trivial step of optimizing LBP and/or BSIF parameters. This difficulty is still present because of the lack of explanation of why textural descriptors are so effective in palmprint and palmvein recognition, as reported by many authors and as confirmed by our experiments. Finally, the very good results obtained on images captured by a contactless sensor may be promising for a possible realistic implementation without the need of a strong cooperation from the user, as it is necessary when a contact sensor is adopted.

In the future, we will further extend this investigation to other textural descriptors and also we will show at which extent the proposed architecture can be simplified or improved, by focusing on the feature reduction module or the adoption of hybrid techniques with more than one typology of hand-crafted features.

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