LEAP SIGNATURE RECOGNITION USING HOOF AND HOT FEATURES

Ishan Nigam[1], *Mayank Vatsa*[2] *and Richa Singh*[2]

1 - NSIT, Delhi University, India
2 - IIIT Delhi, India

ABSTRACT

With the growing need for secure authentication, there is an increasing interest in establishing newer biometric modalities that are verifiable in a fast manner with as few associated complexities as possible. In this research, we propose a new biometric modality using a Leap Motion device. The *Leap signature* is created by an individual in three-dimensional space in absence of any feedback from objects or surfaces. The proposed framework combines an adaptation of 3D Histogram of Oriented Optical Flow and a new feature descriptor, termed as Histogram of Oriented Trajectories. Experiments are performed on the IIITD Leap Signature Database, which consists of 900 samples from 60 subjects. The results are combined with a four-patch local binary pattern based face verification algorithm. An accuracy of over 91% is achieved on this database, with rate of successful spoofing attempts being approximately 1.4%.

Index Terms— 3D signature, Leap, HOOF, Histogram of Oriented Trajectories

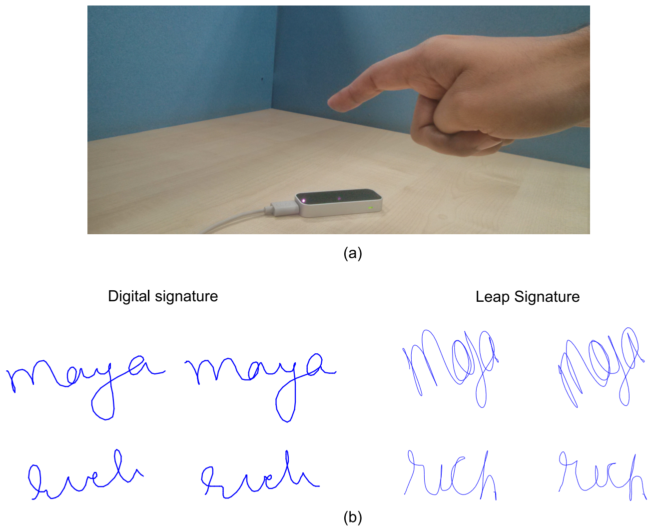

Fig. 1. (a) Environment for capturing Leap signature and (b) digital signature and Leap signature samples for two subjects.

1. INTRODUCTION

Signatures have been a prevalent mode of authenticating an individual. The first recorded use of signatures for automatic recognition was in 1965 by North American Aviation [1]. Since then, multiple methods have been used to capture the signature of a person. For instance, pen and paper method is used for capturing offline signatures [2], whereas digital pads and electronic pens have been used for capturing online signatures [3]. In literature, signatures have been analyzed in two-dimensional space as a behavioral biometric modality [4]. However, recent advances in motion tracking technology provide the possibility of capturing signatures in three-dimensional space.

The Leap Motion device is one such device that allows the hand of a person to be tracked accurately in three-dimensional space using an array of three infrared LED lamps and two infrared sensors. Fig. 1(a) shows an image of the Leap Motion device. It is a compact device that captures the trajectory with an accuracy of approximately 0.01 millimeter. Prior work involving the Leap Motion device includes air-painting on a canvas [5]. Sutton has demonstrated the abilities of the Leap Motion device in accurately capturing small movements of the hand in 3D space. Batelle SignWave Unlock system is proposed to use the device for verification using gestures based authentication [6]. However, the false positive rate is observed to be very high.

In this research, we propose the *Leap Signature* as a new behavioral biometric modality. Leap signature is a pattern rendered by the subject in 3D space, in the absence of any tactile feedback or obstruction. Fig. 1 shows an image of the Leap Motion device and the signatures captured using it. In comparison to an online signature pad, the Leap Motion device is very small, portable, and, at time t, provides the trajectory of movement in terms of $(x, y, z)_t$. To recognize an individual using Leap signature, we have prepared a database of 60 individuals comprising 900 Leap signatures. Since the signature contains trajectory of movement, we propose a new descriptor, Histogram of Oriented Trajectories (HOT) for matching and combine it with Histogram of Oriented Optical Flow (HOOF) [7] feature descriptor to classify the 3D information obtained via the Leap signature. The proposed biometric modality is secure from spoofing attempts even in environments consisting of individuals other than the genuine subjects because there is no visual feedback to the pattern being made by the Leap Motion device.

2. THE IIITD LEAP SIGNATURE DATABASE

To the best of our knowledge, there is no precedence to establish Leap signatures in 3D space as a biometric modality. Hence, the IIITD Leap Signature Database[1] (IIITD LS Database) is collected to benchmark the performance of the proposed algorithm. The IIITD LS Database is prepared in ambient indoor lighting with no occlusion of either the sensor or the subject's hand. The *Leap signature* (that are used to uniquely identify a subject) is the subject's rendering of the first four letters of their name in 3D space using their index finger. The Leap Motion device tracks the subject's finger in 3D space using a publicly available Software Developer Kit[2]. The spatial resolution of the device is approximately 0.01 millimeter. The temporal resolution used in preparing the IIITD LS database is in the range of 45 frames per second to 60 frames per second. Fig. 2 shows sample Leap signatures from the database and the characteristics of the IIITD LS database are summarized in Table 1. Along with genuine samples, we have also collected some forged impostor data where the users are shown other subject's signature and requested to forge it. The last column of Fig. 2 shows forged data. For every subject, there are 12 genuine samples and 3 forged impostor samples.

Along with Leap signatures, 12 face images of each subject are also captured to compare the performance of face recognition with Leap signatures and to combine both of them for improved accuracy. Frontal face images are captured using a Nexus 4 mobile phone camera and sample images are shown in Fig. 3. The size of detected face images is 236×192.

Number of subjects	60
Total number of Leap samples	900
Number of genuine Leap samples per subject	12
Number of impostor Leap samples per subject	3
Number of face image samples per subject	12

Table 1. Characteristics of the IIIT-D LS Database.

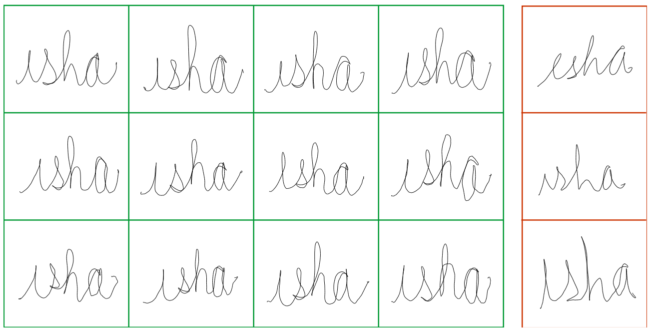

Fig. 2. Sample images from the IIITD Leap Signature Database. The images in the first four columns are genuine whereas the images in the last column are forged samples.

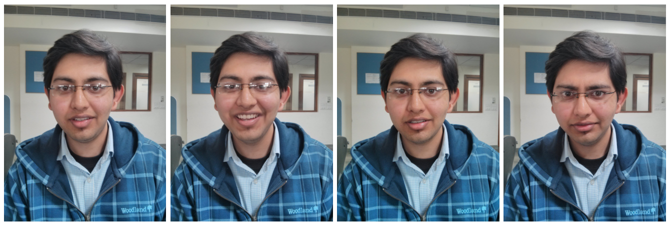

Fig. 3. Sample face images from the database.

3. PROPOSED LEAP SIGNATURE RECOGNITION ALGORITHM

Fig. 4 illustrates the steps involved in the proposed algorithm. The motivation behind the proposed algorithm is the observation that even though a subject's signature can vary across samples, the orientations extracted from the signature in 3D space form a unique pattern for the subject. The proposed algorithm utilizes an adaptation of HOOF descriptor to 3D space, along with the proposed HOT descriptor for feature extraction, followed by Naive Bayes and Support Vector Machine (SVM) for matching, respectively. The decision of these two classifiers is combined for final result.

3.1. Feature Extraction

HOOF and HOT features are extracted from the Leap signature as explained below.

- **Histogram of Oriented 3D Optical Flows**: Chaudhry et al. [7] have proposed the HOOF features to track movement in two-dimensional space. HOOF features are independent of the scale as well as the direction of motion and are particularly suited to encoding the velocity with which an action is performed.

  In this paper, we propose a 3D variant of HOOF for encoding optical flow information. The *Leap signature*, treated as a sequence of image frames, is a single point moving in three-dimensional space. The proposed adaptation of HOOF feature calculates the optical flow of a single point across frames. Since there is no special significance attached to the change in orientation of a point in three-dimensional space, the trajectory of the Leap signature is projected onto the three principal Cartesian planes and is treated as three independent problems in 2D space. The optical flow orientation from every pair of image frames is calculated and

[1]Website: https://research.iiitd.edu.in/groups/iab/lsd.html
[2]Website: https://developer.leapmotion.com/

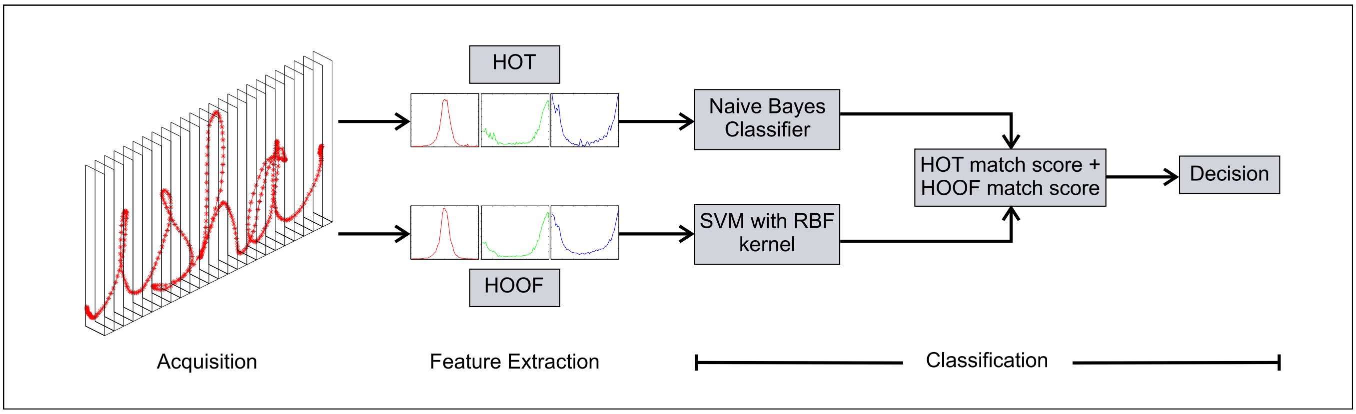

Fig. 4. Block diagram of the proposed algorithm.

binned into a single histogram. An optical flow vector for a pair of adjacent frames, projected into the XY plane having velocity, $vel = vel_x\hat{i} + vel_y\hat{j}$, orientation, $\theta_{HOOF} = tan^{-1}\left(\frac{vel_y}{vel_x}\right)$, and magnitude, $|vel| = \sqrt[2]{vel_x^2 + vel_y^2}$, contributes to the bin b such that,

$$-\pi + \pi\left(\frac{b-1}{B}\right) \leq \theta_{HOOF} < -\pi + \pi\left(\frac{b}{B}\right) \quad (1)$$

where, B represents the total number of orientation bins used for histogram binning.

- **Histogram of Oriented Trajectories**: While HOOF features are suitable for encoding information corresponding to the velocity with which an action is performed, they are not ideal for capturing the structural information of the 3D trajectory of the action. HOOF features do not account for the possibility that a person may perform an action with different speeds at different times. Therefore, we propose a feature descriptor, termed as Histogram of Oriented Trajectories, that encodes the displacement of the action in 3D space. The HOT feature is independent of time taken to perform the action and is more robust towards encoding time-invariant information.

  The trajectory of the Leap signature is projected onto the three principal Cartesian planes and is treated equivalently as three problems in 2D space (i.e. XY, YZ, and XZ planes). The trajectory orientation from every pair of image frames is calculated and binned into a single histogram. A trajectory vector for a pair of adjacent frames, projected into the XY plane having displacement, $dis = dis_x\hat{i} + dis_y\hat{j}$, orientation, $\theta_{HOT} = tan^{-1}(\frac{dis_y}{dis_x})$, and magnitude, $|dis| = \sqrt[2]{dis_x^2 + dis_y^2}$, contributes to the bin b such that,

$$-\pi + \pi\left(\frac{b-1}{B}\right) \leq \theta_{HOT} < -\pi + \pi\left(\frac{b}{B}\right) \quad (2)$$

As discussed earlier, the orientations of the displacement/ velocity across adjacent frames for calculating the HOT/ HOOF feature descriptor of the signature are projected onto the Cartesian planes to reduce the problem into three mutually exclusive problems in 2D space. The orientations of the displacements/ velocities across all the frames comprising of a signature are binned into a single histogram and normalized. Hence, for histogram binning of B bins, a bin b_k in the proposed feature descriptor is transformed as:

$$b_k = \frac{b_k}{\sqrt[2]{b_1^2 + b_2^2 + ... + b_B^2} + 0.01}, \quad \text{for } 1 \leq k \leq B \quad (3)$$

Experimentally, we observe that the proposed algorithm performs optimally for B = 20 bins.

3.2. Matching and Decision Fusion

The HOT and HOOF feature descriptors, while partially correlated, provide complementary information. Hence, combination of HOOF and HOT is used for matching. The HOOF features are used as input to SVM classifier [8] with Radial Basis Function kernel for matching and the HOT features are matched using Naive Bayes classifier [9]. The scores obtained are then combined using sum rule fusion.

4. EXPERIMENTAL RESULTS

Since there is no precedence to studying Leap signatures as a biometric modality, an exclusive set of experiments is performed on the IIITD LS Database. The database is split into subsets of 40% and 60% for training and testing respectively.

Table 2. GAR (%) at 1% (FAR) for individual features and combination of features and classifiers on the IIITD Leap Signature Database.

Features	**GAR-SVM**	**GAR-NN**	**GAR-NB**
HOT	28.58%	51.74%	57.16%
HOOF	62.54%	45.40%	50.17%
Feature Fusion	60.98%	59.38%	60.87%
Score Fusion	65.16%	62.54%	61.92%

The experiments are performed with five times random subsampling cross-validation. The size of HOOF and HOT feature descriptors, individually, is 60 and sum rule is applied with equal weight. The performance of the proposed algorithm is also evaluated with individual HOT and HOOF features. We observe that a combination of Naive Bayes classifier for HOT features and Support Vector Machine for HOOF features outperforms other classifier combinations with an accuracy of 66.84%. The selection of this classifier is validated by comparing with the feature level fusion scores for Support Vector Machine with RBF kernel [8], Neural Network with sigmoid activation function [9], and Naive Bayes classifier [9]. The average performance of the classifiers on the five folds is summarized in Table 2. The Receiver Operating Characteristic (ROC) curve for the proposed Leap signature algorithm is shown in Fig. 5.

To understand the performance of Leap signature in comparison to already established biometric modalities, we have also evaluated the performance of face verification for the same set of individuals. The Four-Patch Local Binary Patterns (FPLBP) algorithm [10] is used for face verification and Fig. 5 shows the ROC curve. The Genuine Accept Rate (GAR) for a False Accept Rate (FAR) of 1% is 78.01%. The ROC curves show that the performance of Leap signature is lower than face verification when the face database does not incorporate any covariates. However, since face and the proposed three-dimensional signatures are uncorrelated biometric modalities, the match scores obtained via face matching are fused with the scores of the proposed algorithm using sum rule. The results show that fusion improves the accuracy and yields the GAR of 91.43% at 1% FAR. Since the IIITD LS Database contains forged Leap signature samples, we compute the verification accuracies pertaining to spoofing attempts. The percentage of successful spoofing attempts for a FAR of 1% is approximately 1.43%.

The results suggest that the *Leap signature* can be used, in conjunction with face recognition for low security applications such as attendance in classroom and work places. It is our assertion that the results obtained from the proposed *Leap signature* will motivate other researchers to further explore this interesting modality.

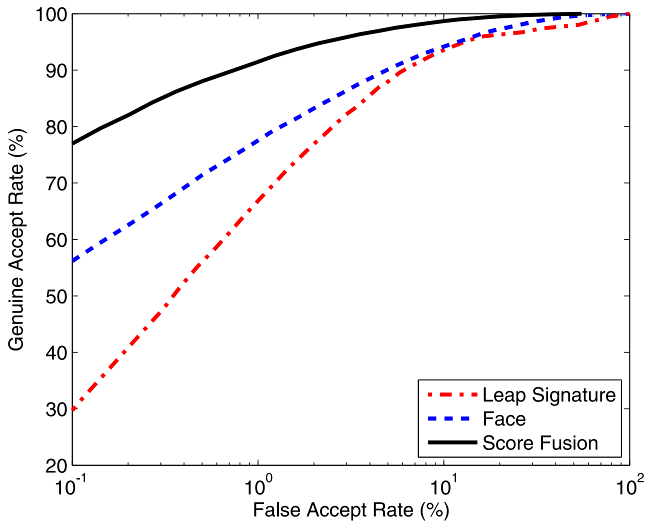

Fig. 5. ROC curves for Leap signature verification, face verification, and score fusion of face and Leap signature.

5. CONCLUSION AND FUTURE WORK

Signature recognition is a well established biometric modality and different applications use online or offline signature for authenticating the identity of an individual. With emergence and availability of new devices, the acquisition method can be enhanced to improve the user experience, convenience, and authenticity. With this motivation, this research presents a new modality, Leap signature, that can be captured using the Leap Motion device to authenticate the identity of an individual. The proposed algorithm comprises of 3D HOOF features and the novel HOT features for matching Leap signatures. A Leap signature database is also prepared to evaluate the results of the proposed algorithm. The experiments performed on this database show promising results and combining face scores with Leap signatures yield the verification accuracy of around 90%. The Leap Motion device has been used as a modality for biometric verification for the first time in this paper. In future, this can also be used as a modality for continuous user authentication.

6. REFERENCES

[1] A. J. Mauceri, “Feasibility study of personnel identification by signature verification,” Tech. Rep. AD0617615, North American Aviation Inc., 1965.

[2] I. Chakravarty, N. Mishra, M. Vatsa, R. Singh, and P. Gupta, “Offline signature recognition,” in *Encyclopedia of Data Warehousing and Mining*, 2005.

[3] I. Chakravarty, N. Mishra, M. Vatsa, R. Singh, and

P. Gupta, "Online signature recognition," in *Encyclopedia of Data Warehousing and Mining*, 2005.

[4] M. Martinez-Diaz, J. Fiérrez, and S. Hangai, "Signature features," in *Encyclopedia of Biometrics*, pp. 1185–1192. 2009.

[5] J. Sutton, "Air painting with corel painter freestyle and the leap motion controller: A revolutionary new way to paint!," in *ACM SIGGRAPH Studio Talks*, 2013, p. 21:1.

[6] "Batelle signwave unlock," http://www.battelle.org/our-work/consumer-industrial/cyber-innovations/battelle-signwave-unlock, [Online; accessed 14-February-2014].

[7] R. Chaudhry, A. Ravichandran, G. Hager, and R. Vidal, "Histograms of oriented optical flow and binet-cauchy kernels on nonlinear dynamical systems for the recognition of human actions," in *IEEE Conference on Computer Vision and Pattern Recognition*, 2009, pp. 1932–1939.

[8] V. Vapnik, *The Nature of Statistical Learning Theory*, Springer, 2000.

[9] R. O Duda, P. E Hart, and D. G Stork, *Pattern Classification*, John Wiley & Sons, 2004.

[10] L. Wolf, T. Hassner, and Y. Taigman, "Descriptor based methods in the wild," in *Workshop on Faces in'Real-Life'Images: Detection, Alignment, and Recognition*, 2008.