Hand-Geometry Recognition Using Entropy-Based Discretization

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Abstract—**The hand-geometry-based recognition systems proposed in the literature have not yet exploited user-specific dependencies in the feature-level representation. We investigate the possibilities to improve the performance of the existing hand-geometry systems using the discretization of extracted features. This paper proposes employing discretization of hand-geometry features, using entropy-based heuristics, to achieve the performance improvement. The performance improvement due to the unsupervised and supervised discretization schemes is compared on a variety of classifiers: k-NN, naïve Bayes, SVM, and FFN. Our experimental results on the database of 100 users achieve significant improvement in the recognition accuracy and confirm the usefulness of discretization in hand-geometry-based systems.**

Index Terms—**Biometrics, feature discretization, feature representation, hand geometry, personal recognition.**

I. Introduction

THE ever-increasing demand for better security technology for public- and private-access control has highlighted the need to improve user acceptance and recognition accuracy of current biometric systems. The face is the most highly accepted and user-friendly biometric but the reliability of personal identification system based on face images is quite low. This can be attributed to the problems resulting from variations due to pose, expression, or lighting. The user acceptance of hand geometry is second only to the face [1]. However, the recognition accuracy of hand-geometry-based identifications is limited and, therefore, efforts are still required to achieve acceptable performance.

The commercial usage of biometric technology began more than 25 years ago when the hand-geometry-based attendance system was installed at Shearson Hamil on Wall Street. The U.S. patent office later issued several patents [2]–[5] for personal identification devices that measure hand-geometry features. Jang *et al.* [6] describe a device and system for personal authentication using a bootstrap technique which effectively utilizes hand-geometry features. A recent European patent [7] discloses a similar system using hand-geometry features. Sanchez-Reillo *et al.* [8] extracted 25 hand-geometry features and employed a Gaussian mixture model for user identification. However, the results in [8] and [9] may be biased by the small size of the database. The usability of the approach detailed in [10] and [23] is limited due to the usage of the digital scanner and large number of features (30 and 40, respectively). Jain *et al.* [11] employed 17 geometric features from the images acquired from digital-camera-based low-resolution imaging. These authors have used fixation pegs to restrict the hand movement but have shown promising results. Kumar *et al.* [12] have also demonstrated the performance from hand-geometry features using peg-free imaging. However, their work is more focused on palm features since, unlike [8] or [11], they use high-resolution imaging to extract palm features.

A. Motivation

The feature representation in biometrics has received very little attention and prior work has been quite limited to the use of normalization schemes[1] for performance improvement. A survey on available biometrics literature [22] suggests that there has not been any effort to exploit user-specific dependencies in the feature-level representation. The usefulness of discretization schemes is yet to be investigated in biometric-based user identification. This paper therefore suggests and investigates the possibility of performance improvement using both supervised and unsupervised discretization schemes. The performance improvement due to the discretization schemes is investigated on the real biometric data acquired from the hand-geometry trait. The way features should be discretizaed is highly dependent on the classifiers. Therefore, the improvement in the recognition accuracy, using different discretization approaches, is ascertained on a variety of classifiers.

II. Feature Discretization

The discretization of hand-geometry features offers several advantages. The discrete features are closer to knowledge-level representation than the continuous (nominal) values which may be unstable due to noise or inaccuracies in the feature extraction or image normalization algorithms. The problems due to such perturbations are likely to be smaller than those for hand-geometry systems [8], [11] that use user pegs to constrain the rotation and translation of the hand than those systems [9], [12] employing unconstrained peg-free imaging, which highly relies on

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[1]The score normalization schemes suggested in [13] for multimodal score normalization can also be employed for feature normalization.

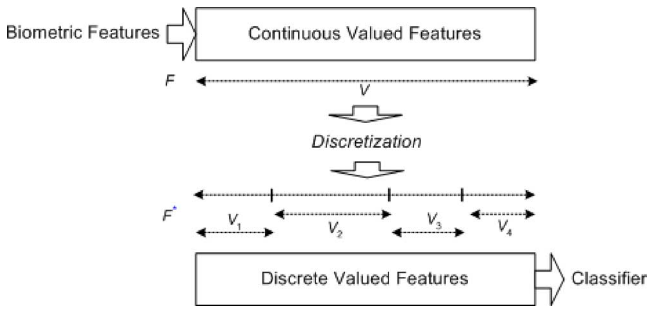


Fig. 1. Discretization of biometric features to exploit class-specific dependencies.

the efficiencies of the algorithm to achieve illumination, translation, and rotation-invariant features.

The idea of discretization is to project continuous feature values into discrete ones such that the projection preserves important distinction among different users. Fig. 1 illustrates the transformation of continuous feature F into discrete feature $F*$ with values $\{V_1, V_2, V_3, \ldots, V_n\}$ for $n = 4$. Each value V_i of the new feature $F*$ represents a certain range of numeric values in the original feature F. Discretization methods in the machine learning literature have been categorized into supervised and unsupervised categories. The unsupervised discretization in its simplest form, also known as equal-interval width, divides an observed feature value range into k equal-size bins where the parameter k is provided by the user. Another unsupervised approach for the discretization is to use equal-frequency intervals. This approach sorts the available values of a feature and then assigns them to $1/k$ of the values in each bin. The supervised approaches also examine the distribution of class labels (users) and are more likely to give higher accuracies. The supervised discretization allows interclass feature dependencies to be captured in the feature discretization and, thus, indirectly promoting accuracy.

A. Entropy-Based Discretization

The potential problems with the unsupervised discretization methods is the loss of classification information because of the resulting discretized feature values that are strongly associated with different classes in the same interval [18]. The supervised discretization uses sorted feature values to locate the potential interval boundaries (i.e., cutpoint T) such that the resulting interval has the strong majority of one particular class. The cutpoint for discretization is selected by evaluating the favorite disparity measure (i.e., class entropies) of candidate partitions. The multiple intervals of a feature are computed by recursively applying this algorithm on two intervals of those previous split until some stopping criteria are satisfied.

The set S of instances (i.e., training samples) of a sorted feature array is first partitioned into subset S_1 and S_2. The class entropy of subset S is defined as

$$\mathrm{Ent}(S) = -\sum_{i=1}^{Z} p(C_i, S) \log_2(p(C_i, S)) \tag{1}$$

where $p(C_i, S)$ is the proportion of samples/instances lying in a class C_i and Z is the total number of classes. The resulting class entropy, due to the partition of S into S_1 and S_2, is estimated by weighted average of resulting individual entropies. The class information entropy of the partition induced by a cutpoint T, for a feature F, is computed as follows:

$$E(F, T; S) = \frac{|S_1|}{S}\mathrm{Ent}(S_1) + \frac{|S_2|}{S}\mathrm{Ent}(S_2). \tag{2}$$

The cutpoint for which $E(F, T; S)$ is minimum among all the candidate cutpoints is taken as best cutpoint T_F and determines the binary discretization of feature F [16], [21]. The splitting procedure is recursively applied unless a stopping criterion is reached. The stopping criteria prescribe to accept a partition induced by cutpoint T only if there is any gain after splitting. Thus, a partition due to cutpoint T is accepted only if

$$\mathrm{Gain}(F, T; S) > \frac{\log_2(M-1)}{M} + \frac{\Delta(F, T; S)}{M} \tag{3}$$

where

$$\begin{aligned}\mathrm{Gain}(F, T; S) &= \mathrm{Ent}(S) - E(F, T; S), \text{ and}\\ \Delta(F, T; S) &= \log_2(3^Z - 2)\\ &\quad -[z\mathrm{Ent}(S) - z_1\mathrm{Ent}(S_1) - z_2\mathrm{Ent}(S_2)]. \end{aligned} \tag{4}$$

The number of samples in set S is denoted as M, and the number of classes present in S_1 and S_2 are z_1 and z_2, respectively.

Another supervised approach for evaluating the worth of the features is to measure the average compression (per sample) of the class afforded by an attribute. Kononenko [15] has shown that this criterion is the most promising on multivalued features among a number of other simple impurity-based measures. This measure, commonly referred to as minimum description length (MDL), is defined as

$$\begin{aligned}\mathrm{MDL}(F_i) = \frac{1}{n}\Bigg(&\log_2\binom{n}{n_1, \ldots, n_Z} + \log_2\binom{n+Z-1}{Z-1}\\ &-\sum_j \log_2\binom{n_{.j}}{n_{1j}, \ldots, n_{Zj}} - \sum_j \log_2\binom{n_{.j}+Z-1}{Z-1}\Bigg)\end{aligned} \tag{5}$$

where n is the number of training samples, Z is the total number of classes, n_i is the number of training samples from class z_i, $n_{.j}$ is the number of training instances with the jth value of a given feature, and n_{ij} is the number of training samples of class z_i having the jth value of the feature. The first two terms in (5) represent the description length of the class labels prior to partitioning on the values of a feature, while the remaining two terms represent the description length after partitioning. The model for MDL is simply the difference in probability distribution over a class label (number of training samples in each class), before and after the partition is induced by a given feature using (2).

III. Experiments

The right-hand images of users using a digital camera were acquired from the 100 users within an interval of three months. Each user contributed about five images in one session and only ten images from every user were employed in our experiments. The hand images were acquired using a simple peg-free imaging setup as detailed in [12]. The acquired images were binarized and employed for feature extraction. The thresholding limit was automatically computed, once for each acquisition setup using Otsu's approach, and used in subsequent images. We extracted 23 hand-geometry features and used in our experiments: 4-finger length ($h_1 - h_4$), 8-finger width ($h_5 - h_{12}$), palm width (h_{13}), palm length (h_{14}), hand area (h_{15}), hand length (h_{16}), perimeter (h_{17}), solidity(h_{18}), extent (h_{19}), convex area (h_{20}), eccentricity (h_{21}) and x–y position of centroid relative to shape boundary ($h_{22} - h_{23}$). The details of these features and preprocessing steps can be found in [12] and [17]. The 5-hand images from each user were used for the training and the remainder were employed for the testing.

The training samples from the 100 users were subjected to discretization as discussed in Section III. The performance for unsupervised discretization using equal interval width and equal frequency interval was investigated on four classifiers: neighbor (k-NN), 2) Naïve Bayes, 3) support vector machine (SVM), and 4) feedforward neural network (FFN). The k-nearest neighbors were obtained from the minimum Euclidean distance between the query feature vector and those from training samples. The parameters of SVM and FFN employed in the experiments were empirically selected. The SVM using the second-order polynomial kernel achieved much better results than those from the radial basis function. Therefore, to conserve the space, only the results from the polynomial kernel are reported. The SVM training was achieved with C-SVM, a commonly used SVM classification algorithm [14]. The training parameter γ and ε were empirically fixed at 1 and 0.001, respectively. Similarly, the number of input nodes in FFN were also empirically selected for the best performance; 80. The FFN neuron weights were updated using the resilient backpropagation algorithm and the training was aborted if the maximum number of training steps reached 1000. The confusion matrix resulting from the experiments on 500 test samples is quite large to be reproduced in this paper. Therefore, we selected the following few performance indices, that is, Kappa Statistic [19], accuracy, and precision [20] to ascertain the performance improvement

$$\text{Kappa} = \frac{P(A) - P(E)}{1 - P(E)},$$
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},$$
$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

where $P(A)$ is the observed proportion of true positive (TP) and true negative (TN), $P(E)$ is the expected proportion of TP and TN, and FN and FP, respectively, represent the false-negative and false-positive matches from the test data.

IV. Results

The k-NN classifier is a simple nonparametric classifier that does not involve the training phase and, hence, it provides an easier way to include a new user in the biometric system. Therefore, it has been commonly preferred in biometric recognition applications. Fig. 2 illustrates its gain in recognition accuracy with an increase in the number of bins used to discretize the

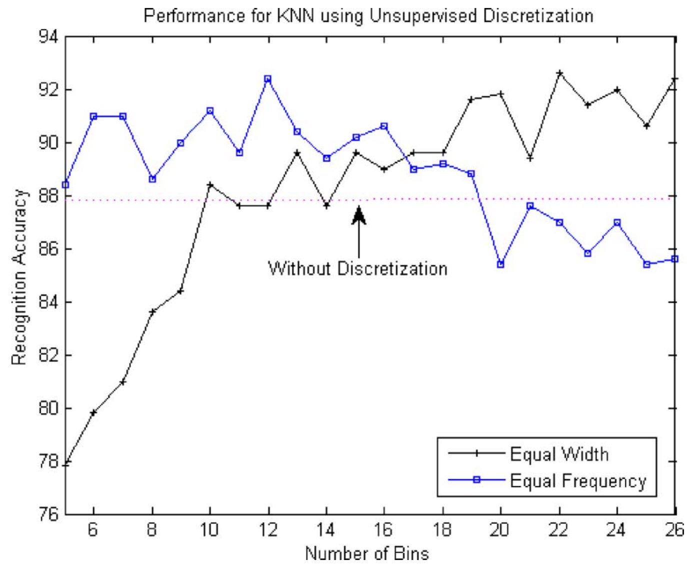


Fig. 2. Performance improvement for k-NN classifier due to unsupervised discretization.

TABLE I
Comparative Performance for k-NN With and Without Feature Discretization

	KNN		
	Accuracy	*Kappa*	*Precision*
Supervised - Entropy	**93.8**	**0.9374**	**93.94**
Supervised - MDL	89.2	0.8909	89.07
Unsupervised - *Equal Frequency*	92.4	0.9232	92.90
Unsupervised – *Equal Width*	92.6	0.9232	92.92
Without Discretization	87.6	0.8747	79.57

features in an unsupervised approach. We can observe the initial increase in performance and its stabilization in subsequent stages/increase. The equal frequency approach achieves better performance for a smaller number of bins while the equal width approach outperforms a higher number (crossover of about 16) of bins. Table I illustrates the comparative performance for k-NN classifier using unsupervised and supervised discretization schemes with k empirically selected as unity. The average precision result in this table closely follows the recognition accuracy, except those in the last row which suggest the presence of large false positive matches in absence of any feature discretization. The overall performance indicator kappa closely follows the results from recognition accuracy, suggesting a significant increase in performance with the feature discretization. The results in Table I suggest that the feature discretization using entropy-based heuristics outperforms those based using the MDL representation of hand-geometry features.

The supervised discretization of features using entropy gain discretized 23 hand-geometry features into 181 discrete levels. The discretization of some of these features from the training samples is illustrated in Fig. 3. The first feature (h_1, the left finger length) required only seven discrete levels which can be observed from Fig. 3. This figure also illustrates the distribution of these seven discrete levels among 500 training samples. Similar partitioning of continuous feature values into discrete ones for the feature h_2, h_3, and h_4 is illustrated in Figs. 4–6,

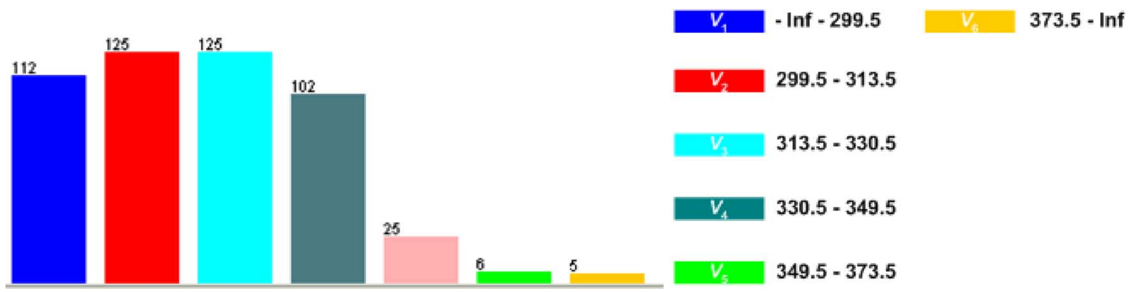


Fig. 3. Supervised discretization of feature h_1 from the training samples.

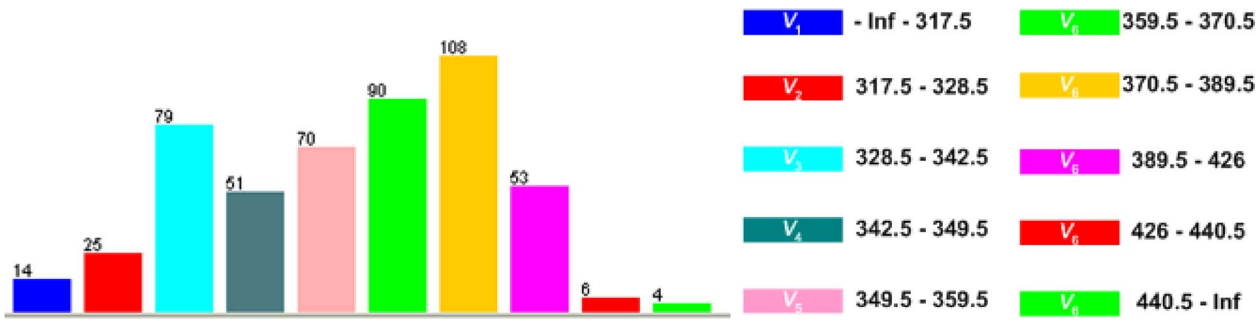


Fig. 4. Supervised discretization of feature h_2 from the training samples.

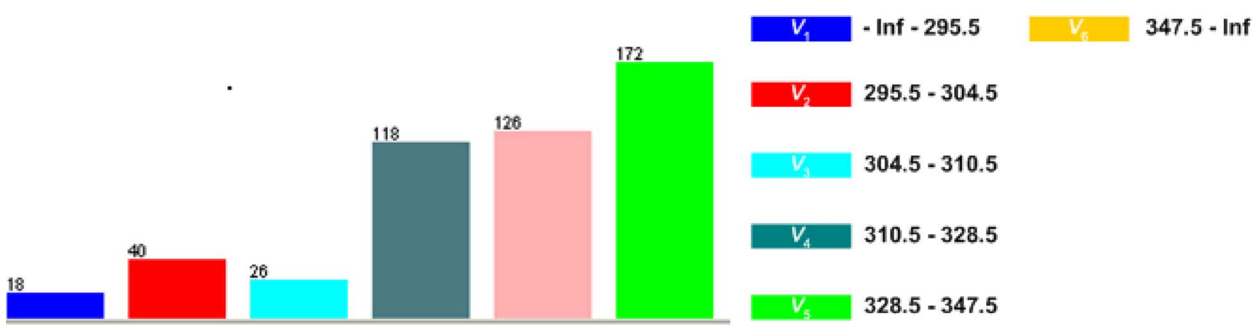


Fig. 5. Supervised discretization of feature h_3 from the training samples.

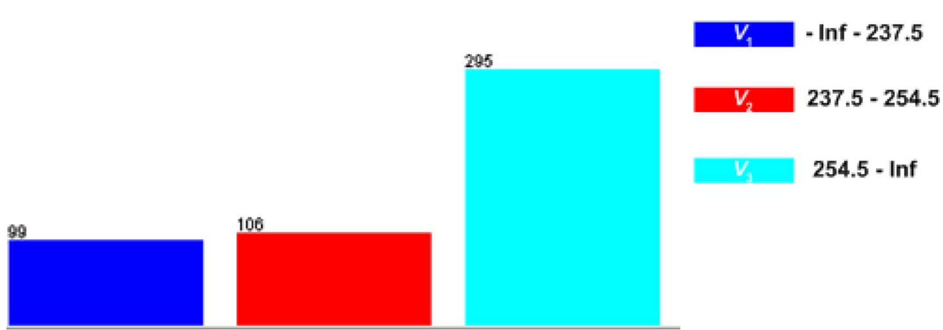
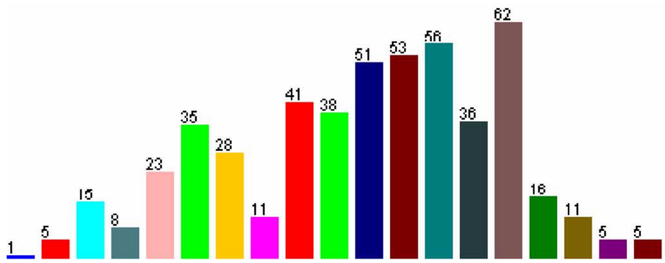
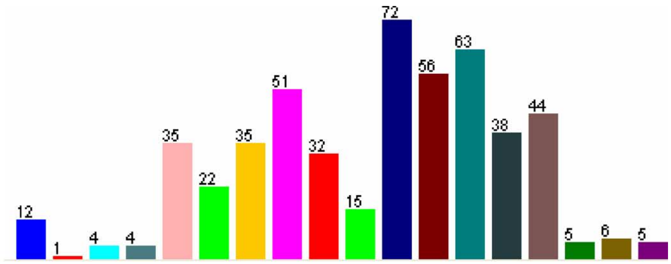


Fig. 6. Supervised discretization of feature h_4 from the training samples.

respectively. The feature representation for h_{16} and h_{17}, representing the hand-length and perimeter, respectively, required the highest number of discrete levels (i.e., 19 and 18 levels, respectively) (Fig. 7). The discretization scheme using an entropy-based heuristic, on average, required 7.87 discrete levels per feature. However, the supervised discretization using the equal interval width does not offer any gain in recognition accuracy if less than 12 bins are employed for discretization. Even with the increase in the number of bins, the maximum recognition accuracy that can be achieved from an equal interval width is 92.6% (22 bins) while those from the equal frequency interval are 92.4% (12 bins) (i.e., smaller than that can be achieved from the supervised entropy-based approach, requiring only 7.87 bins on average). The feature discretization requirements using MDL were huge (i.e., requiring an average of 23 discrete levels per feature), while achieving a maximum accuracy of only 89.2%.



(a)



(b)

Fig. 7. Supervised discretization of (a) feature h_{16} representing the hand length and (b) feature h_{17} representing the perimeter into 19 and 18 bins, respectively, resulting from the training samples.

TABLE II
COMPARATIVE PERFORMANCE FOR NAÏVE BAYES WITH AND WITHOUT FEATURE DISCRETIZATION

	Naïve Bayes		
	Accuracy	*Kappa*	*Precision*
Supervised - Entropy	**94.6**	0.9455	94.83
Supervised - MDL	91.2	0.9111	90.68
Unsupervised - *Equal Frequency*	93.4	0.9333	93.11
Unsupervised – *Equal Width*	94.6	0.9455	94.86
Without Discretization	89.4	0.8929	95.20

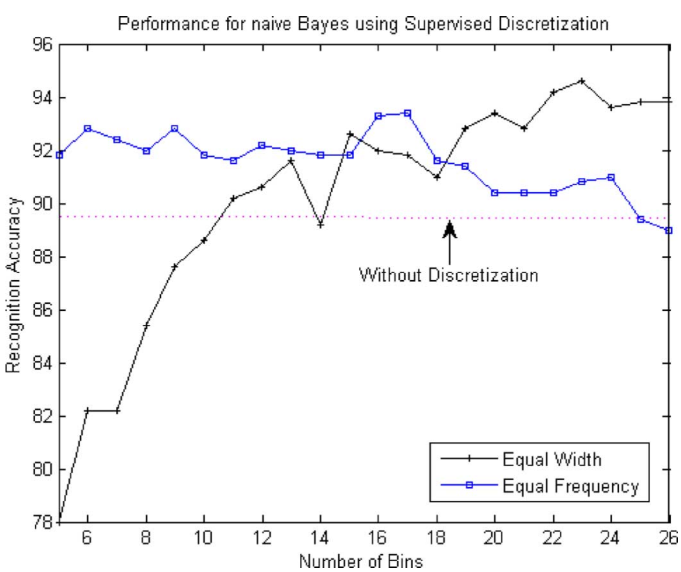


Fig. 8. Performance improvement for the naïve Bayes classifier using unsupervised discretization.

Table II illustrates the summary of comparative performance achieved from the Naïve Bayes classifier. The usage of unsupervised discretization can deliver 5.2% improvement in recognition accuracy for an equal interval width and 3.4% for equal frequency interval discretization. The entropy-based discretization achieves the best performance (i.e., recognition accuracy of 94.6%), while employing a minimum average number (7.87) of bins for feature representation. Figs. 8–10 illustrate gain in recognition accuracy with the increase in the number of bins for naive Bayes, SVM, and FFN classifiers, respectively. The performance indices from the naïve Bayes are slightly better than those from k–NN but this comes with the additional cost of increased classifier complexity. Table III similarly presents comparative results from SVM while Table IV summarizes results from FFN classifiers. The comparison of Tables I–IV suggests that the discretization of features achieves a significant increase in performance for these four classifiers while SVM performs the best of all with a recognition accuracy of 95%. Although our experiments have been focused on the performance improvement for recognition, we also performed few experiments to illustrate the performance improvement for biometric verification. The receiver operating characteristics using the SVM classifier for verification experiments are illustrated in Fig. 11. The results in this figure illustrate an equal error rate (EER) improvement of 1.1% due to the entropy-based discretization of hand-geometry features.

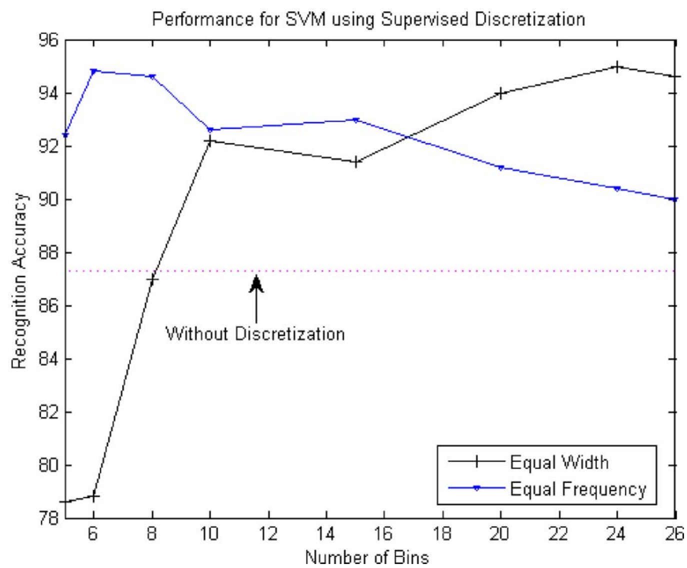


Fig. 9. Performance improvement for SVM classifier using unsupervised discretization.

V. CONCLUSION

Our experimental results illustrated in the previous section suggest that 1) the discretization of hand-geometry features achieves significant improvement in the performance (6.1% for k-NN, 5.2% for naïve Bayes, 7% for SVM, 4% for FFN) and 2) a gradual increase (decrease) in performance for equal frequency (width) unsupervised discretization with an increase

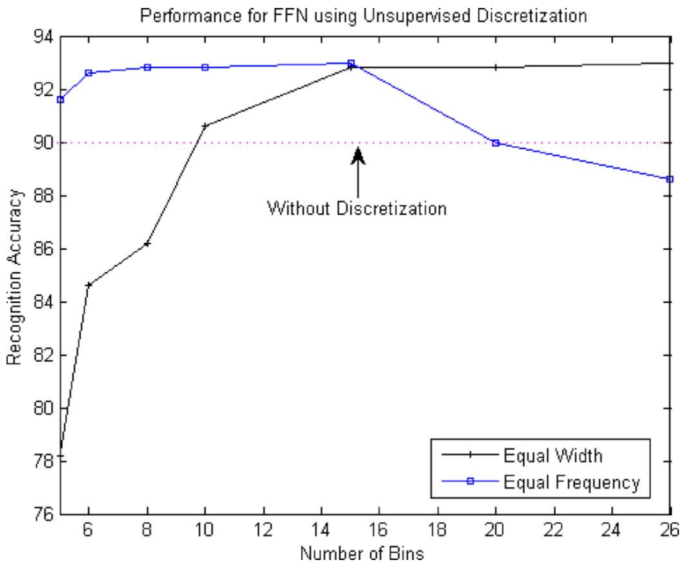


Fig. 10. Performance improvement for the FFN classifier using unsupervised discretization.

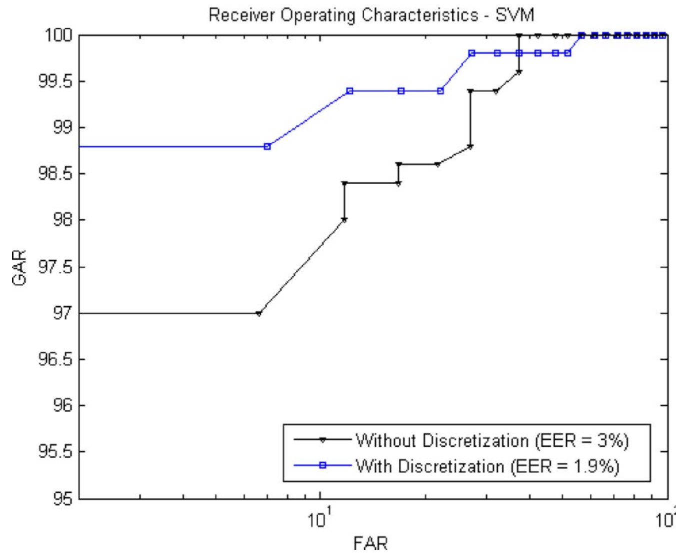


Fig. 11. Performance improvement for the verification using the SVM classifier.

TABLE III
COMPARATIVE PERFORMANCE FOR SVM WITH AND WITHOUT FEATURE DISCRETIZATION

	SVM		
	Accuracy	*Kappa*	*Precision*
Supervised - Entropy	**95**	0.9495	95.83
Supervised - MDL	92.2	0.9212	94.81
Unsupervised - *Equal Frequency*	94.8	0.9475	95.82
Unsupervised – *Equal Width*	95	0.9495	95.83
Without Discretization	87.2	0.8707	77.65

TABLE IV
COMPARATIVE PERFORMANCE FOR FFN WITH AND WITHOUT FEATURE NORMALIZATION

	FFN		
	Accuracy	*Kappa*	*Precision*
Supervised - Entropy	**94**	0.9394	94.29
Supervised - MDL	91.2	0.9111	90.99
Unsupervised - *Equal Frequency*	92.8	0.9273	92.95
Unsupervised – *Equal Width*	93	0.9293	94.21
Without Discretization	90	0.8990	91.45

in the number of bins and the crossover is between 14–17 bins, 3) the performance of the equal frequency interval is much better for a smaller number of bins which is computationally attractive for online biometric devices, and 4) the supervised discretization scheme using entropy-based heuristics achieves the best overall performance (i.e., highest recognition accuracy with the smallest average number of bins, and is highly recommended for its usage).

The discretization of hand-geometry features significantly reduces the number of possible values of the continuous features and can be useful for several reasons—the classifier operating on discretized data investigates the narrow space of possible hypotheses and, thus, reduces the likelihood of overfitting (i.e., chances of finding complex hypotheses that fits well for the training samples just by chance). Second, the discretization accelerates learning [21], [24] because discrete features processed faster than continuous ones, assuming that the time required for the discretization of continuous features is negligible. Thus, in addition to higher recognition accuracy, the discretization significantly reduces the complexity of classifiers than those directly operating on normalized biometric data.

The supervised discretization requires recomputation of discrete intervals (levels) every time a new user is added to the biometric system and, therefore, is highly suitable for those biometric systems in which a number of users is fixed (e.g., access in buildings and offices). In situations where the number of users varies dynamically, unsupervised discretization can be a better alternative to avoid the recomputation of discretization intervals with each new user addition. This work has illustrated the benefits of discretization for the hand-geometry system and its exploitation for other biometric traits (i.e., ear, palmprint, face, etc.) is suggested for performance improvement. The cost-effective discretization of continuous biometric features, based on some performance indices (EER, FAR, or FRR), can be highly useful in dynamically controlling the performance of biometric systems and is suggested for future work.

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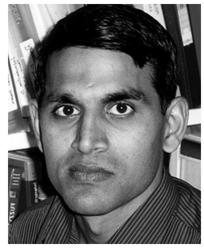

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