



Feature Selection Method for Iris Recognition Authentication System

By Pooja Garg & Anshu Parashar

H.C.T.M Kaithal India

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Feature Selection Method for Iris Recognition Authentication System

Pooja Garg^α & Anshu Parashar^σ

Abstract - Iris-based biometric authentication is gaining importance in recent times. Iris biometric processing however, is a complex process and computationally very expensive. In the overall processing of iris biometric in an iris-based biometric authentication system, feature selection is an important task. In feature selection, we extract iris features, which are ultimately used in matching. Since there is a large number of iris features and computational time increases as the number of features increases, it is therefore a challenge to develop an iris processing system with as few as possible number of features and at the same time without compromising the correctness. In this paper, we address this issue and present an approach to feature Selection Method.

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I. INTRODUCTION

We discuss feature selection method, that operates after the physical installation of the imaging system and through a learning stage where typical images resultant of the imaging setting are processed, selects the higher discriminating features, according to the environment specificities.

The non-cooperative image capturing setting, either under natural light or varying lighting conditions leads to the appearance of images whose typical characteristics are terminated by the used optic device and the environment itself. For instance, it is expectable that some imaging conditions propitiate the existence of reflections (specular or lighting) in specific iris regions,

while others propitiate the iris occlusion by eyelids and eyelashes. Current iris matching proposals (feature extraction and comparison) are independent of the imaging environments and do not take into account this information in the recognition task.

II. FEATURE SELECTION METHOD

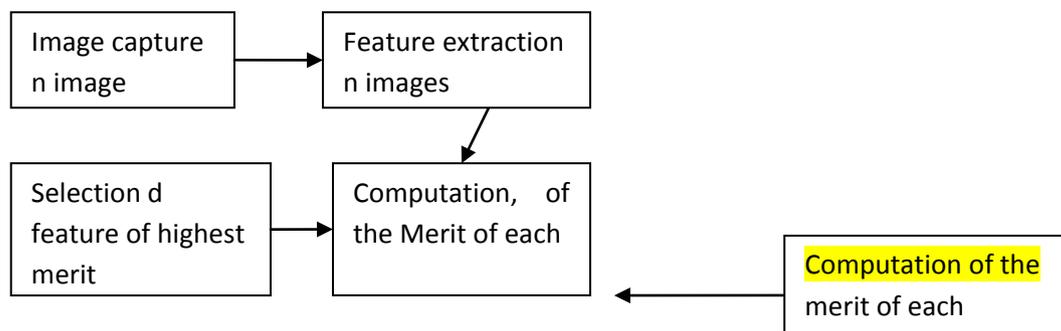
The problem of feature selection is to take a set of candidate features and select a subset that best performs under some classification system [11]. This procedure can reduce the cost associated with classification, by reducing the number of features that must be collected, and in some cases it also provides better results due to the finite sample size effects: as the number of features is reduced, and the number of points is maintained, the feature space becomes more densely populated.

Formally, let T and S be respectively the candidate and selected feature sets, S is subset to T. Also, let $\|\cdot\|$ denote the cardinality of the set, such that $\|T\| = t$ and $\|S\| = s$. The feature selection criterion function for the set X is represented by J(X).

Considering that higher values of J indicate better feature sets, the problem of feature selection is to find a subset S to set T such that

$$|S| = s \text{ and } J(s) = \max_{x \subseteq T, |x|=s} \quad (\text{equ.} \rightarrow 1)$$

Figure 2.1: Block diagram of the feature selection method



According to this definition, the block diagram of the feature selection method is given in above figure. After the physical installation of the image capturing

framework, n images from the irises of k subjects is collected, this should represent the typical characteristics and noise regions of the images captured within the environment. Further, the candidate features are extracted for all these images and their values used in the computation of the features' merit (equ. → 2). Finally, the s features with highest merit are

Author ^α : Department of Computer Engineering M.tech H.C.T.M Kaithal India. (Haryana) E-mail : Erpooja06@gmail.com

Author ^σ : Head of Department Department of Computer Engineering H.C.T.M Kaithal. E-mail : Parashar_anshul@yahoo.com

selected. The motivation behind this proposal is the valorisation of the features which respectively maximize and minimize the signatures dissimilarity in the inter- and intra-class comparisons.

As can be seen in (equ.→ 2), the dissimilarity between two feature values contributes to an increase of the respective merit if they were extracted from different irises and, inversely, contributes to its decrease if the features were extracted from images of the same iris.

In the following discussion we will use F^p_i to denote the i^{th} feature set extracted from the iris p and $f^{p,i,j}$ to denote the j^{th} feature of the i^{th} feature set extracted from the iris p . Thus, $F^p_i = \{f^{p,i,1}, \dots, f^{p,i,t_i}\}$. Let $A = \{F^{p_1}_1, \dots, F^{p_n}_n\}$ be the set of training feature sets extracted from n images of k subjects. The merit value $m(\cdot)$ of each candidate feature i is given by: $m(i) : \{1, \dots, t\} \rightarrow R$

$$m(i) = \sum_{j=1}^{N+1} \sum_{K=j+1}^N \frac{d(f_{j,i}^p, f_{k,i}^r)}{(t_i - t_j) \delta_{p,r} + t_E} (1 - 2 \delta_{p,r})$$

(equ.→ 2)

Where $d(\cdot)$ is the function that gives the features dissimilarity (e.g., Hamming or Euclidean distance), $\delta_{p,r}$ is the Kronecker delta and t_i and t_E are, respectively, the number of intra and inter-class comparisons between elements of A . This definition implies that the highest values occur when the features dissimilarity is respectively smaller in the intra- and higher in the inter-class comparisons, obtaining a value that is directly correspondent to the feature discriminant capacity within the respective imaging environment.

According to (equ.→ 1), the function $J(\cdot)$ that performs the feature selection will give us the feature set S , which contains the s features with highest values of $q(\cdot)$. However, if the features are selected as above described, it is not possible to achieve invariance to iris rotation through signature shifting, and this is a very common technique used in the feature comparison. We compensate this by making the normalization process into the dimensionless polar coordinate system starting from 5 different deviation angles of the segmented iris image (-10°, -5°, 0°, +5°, +10°) and obtaining 5 normalized iris images. The subsequent processing is further made separately for each of these images and the dissimilarity between iris signatures is given by the lowest dissimilarity between the enrolled signature and those extracted from each of these images.

Algorithm contains the pseudo-code of the above described feature selection method. Its computational complexity of $O(n^3)$ is not a concern, as it will be executed before the functioning stage of the recognition system and, due to this fact, without critical time constraints. In this algorithm $f(i, j)$ represents the i^{th} feature extracted from the image j and $id(f)$ the identity of the subject from where the feature f was extracted.

III. ALGORITHM FOR FEATURE SELECTION

```

for i = 1 to n do
merit(i) ← 0
end for
for i = 1 to t - 1 do
for j = i + 1 to t do
for k = 1 to n do
x ← dist(f(k, i), f(k, j))
if id(f(k, i)) = id(f(k, j)) then
merit(k) ← merit(k) - x / ti
else
merit(k) ← merit(k) + x / tE
end if
end for
end for
end for
S=Select_Features_Highest_Merit (n, s, merit)
return(S)
    
```

In the above algorithm

- t → Number of feature sets in the training set
- n → Number of candidate features
- d → Number of features to be selected
- t_i → Number of intra-class comparisons between elements of T
- t_E → Number of inter-class comparisons between elements of T

IV. RESULT

Figure 4.1: 1st Original image of the eye showing the iris



Figure 4.2: Binary image of 1st iris image



Figure 4.3: 2nd Original image of the eye showing the iris

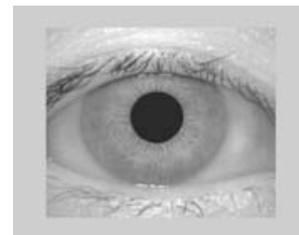
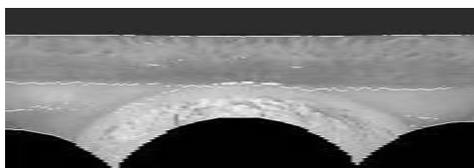
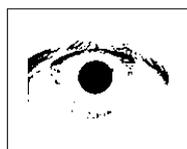
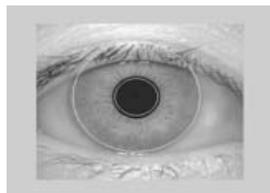
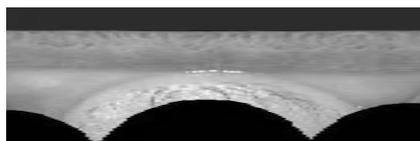


Figure 4.4: Binary image of above iris image*Figure 4.5:* Segmentation results with contours outlining the pupil and the iris*Figure 4.7:* Segmentation results with contours outlining the pupil and the iris

V. CONCLUSION

The typical noise regions and characteristics of the images captured within non-cooperative environments are highly influenced by the used optic device and the specific lighting conditions of each environment. This leads to a significant increment of the error rates, which was the main motivation for this section proposal. We described a method for the feature selection that takes into account the typical characteristics of the images, namely their noise regions determined by the imaging environment. Using a training set composed of images captured after the physical installation of the imaging system, we computed the merit value for each candidate feature and selected those with highest values. Since the training set images are representative of the ones that the recognition system will have to deal with, this process contributes for the adaptability of the recognition system to the specific environment. We stress that this approach is compatible with different imaging environments, since each recognition system will select a proper sub set of features that are further taken into account in the recognition process, through the comparison with the correspondent enrolled features. Experiments led us to conclude about an

improvement in the system's accuracy when the cardinality of the selected feature set is between 30 and 50% of the number of candidate features. In this situation, the error rates significantly decreased (about 50%) in the recognition of noisy iris images, which must be considered an achievement.

VI. FUTURE WORK

We are currently working on the analysis of the requirements for the physical implementation of the non-cooperative prototype system. This has revealed, specially the planning of the optical framework, as a task with higher difficulty than we initially thought. Simultaneously, we are implementing, and in specific situations adapting and improving, algorithms for the real-time human face and eye detection. Our purpose demands algorithms with high performance, which decreased the number of potential alternatives. Regarding the experiments and results contained in this dissertation, we are presently performing the experimental evaluation of the proposed methods with larger data sets, in order to obtain information about the advantages resultant of the methods with higher statistical relevance. Moreover, we are performing the comparison between three common iris recognition proposals (Daugman's [3], Wildes' [14] and Ma et al. [15]) as they are described by the authors and together with the totality of our proposals. This will bring us new information about the improvements in the recognition accuracy, according to different recognition strategies. The evaluated types of noise should be the subject of further work, since this work has not dealt, for instance, with off-angle iris images. This will obviously introduce new challenges to the recognition that must be overcome, and predictably demand the adjustment of some of our methods to these new constraints.

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