Person Recognition through Eigeneyes Selection based on Fuzzy Distance to Multiple Class Prototypes

JISHU ASHIMINE[1], TEÓFILO E. DE CAMPOS[2], ROBERTO M. CESAR-JR.[1], ISABELLE BLOCH[3],

[1] IME - University of São Paulo, São Paulo, Brazil, email: {jishu,cesar}@ime.usp.br
[2] University of Oxford, Oxford, United Kingdom, email: teo@robots.ox.ac.uk
[3] ENST, Dept TSI, CNRS URA 820, Paris, France, email: Isabelle.Bloch@enst.fr

Abstract. This paper introduces a new criterion function to be used by feature selection algorithms based on fuzzy distances. Experiments using the introduced criterion function applied to the problem of face recognition are described.

Methodology Description. In this work, we investigate the problem of performing person recognition using eye images through PCA and feature selection. In the present approach, the training set is composed by eigeneyes extracted from a public face database. Feature selection is carried out by the the sequential floating search method proposed in [1], which attempts to maximize a given criterion function. We propose here a new criterion function, based on a tolerance-based distance, extending the one proposed in [2] to more than two classes. The basic idea is to fuzzify the training set and to maximize the distance between the fuzzy sets corresponding to each class of the training set. The fuzzification function is inversely proportional to the distance to the prototype of each class, the prototype being defined as the centroid of each crisp class :

$$\nu_\omega(\mathbf{x}) = \begin{cases} \frac{1}{1+d(\mathbf{x},p\omega)}, & \mathbf{x} \in \omega, \\ 0, & \mathbf{x} \notin \omega, \end{cases} \tag{1}$$

where $\mathbf{x}$ is a pattern, $\nu_\omega(\mathbf{x})$ is the membership function of that pattern to the set ω, $p\omega$ represents the prototype of the cluster ω, $d(\cdot)$ is the Euclidean distance. The interpretation behind this function is that it represents typicality: the more typical a pattern, the higher the membership value.

The criterion function $f_p^\tau(\cdot)$ is then defined as:

$$f_p^\tau(\nu_1, \nu_2, \cdots, \nu_c) = [\int_{\mathcal{F}} [f_{\mathbf{x}}^\tau(\nu_1, \nu_2, \cdots, \nu_c)]^p d\mathbf{x}]^{1/p}. \tag{2}$$

where $f_{\mathbf{x}}^\tau(\nu_1, \nu_2, \cdots, \nu_c)$ is a function that evaluates a local measurement of separability between all the patterns from all the classes in the feature space.

Experiments and Results. We performed experiments to evaluate the results with respect to the variation of the parameters of the criterion function and the classifier, obtaining promising results. The experiments have been performed using eye images. We used a subset of the University of Bern face image database, containing images of 29 individuals, 6 gray level images per person with variations in the orientation of the faces. In our experiments, we applied the aforementioned feature selection method to the eigeneyes obtained from the training data. We have selected an increasing number of features to compose the feature vectors, with dimensions varying from 1 to 10 considering a total set of features composed by the first 15 eigeneyes of each face in the database because, according to the literature on face recognition, it is a reasonable number for PCA applications. The obtained results have shown that the single prototype-based approach performed best, and better than the First Eigeneyes in many situations.

Ongoing work aiming at improving our technique includes exploring a new strategy consisting in dividing each class in k parts and representing it by k prototypes (one for each part). This strategy has been carried out by applying a clustering algorithm within each class. The k means found by the clustering algorithm have been used as the set of prototypes of each class, leading to a new fuzzification function $\nu_\omega(\mathbf{x}) = \max_{j=1,2,\ldots,k}\left(\frac{1}{1+d(\mathbf{x},p_j^\omega)}\right)$ We have already obtained encouraging results with this approach and our future advances in this direction will be reported in due time.[1]

References

[1] P. Pudil, J. Novovicová, and J. Kittler. Floating search methods in feature selection. *Pattern Recognition Letters*, 15:1119–1125, November 1994.

[2] T. E. Campos, I. Bloch, and R. M. Cesar Jr. Feature selection based on fuzzy distances between clusters: First results on simulated data. volume 2013 of *Lecture Notes in Computer Science, Springer-Verlag Press*, pages 186–195, March 2001.

[1]The authors are grateful to CAPES, COFECUB, FAPESP, CNPq, P. Somol (U. Cambridge), C. H. Morimoto (U. São Paulo), and to the University of Bern (`http://iamwww.unibe.ch/~fkiwww/staff/achermann.html`)

1530-1834/02 $17.00 © 2002 **IEEE**

IEEE COMPUTER SOCIETY