Human Identification using Low Resolution Outer Ear Images: A Multiple Connectionist Framework

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Extended abstract.

In this paper, we propose the use of outer ear images to identify a person by means of different classification techniques. Two main approaches have been mainly used for this problem: one is based in the detection and analysis of facial features (i.e. eye distance, chin's angle,…); the other approach avoids feature extraction and processes faces as general images using appropriate tools (i.e. neural networks, principal component analysis, histogram analysis,…). In this work, this dichotomy has been considered. Two classifiers corresponding to the first approach have been implemented. Another classifier, corresponding to the second approach using a compression network [2], is also developed. Finally, the predictions of the three constituent classifiers are combined by defining multiple classification techniques [1].

A set composed of 174 left-side face images (6 photos for each one of 29 different individuals) was acquired. Images were taken in several different sessions, and individuals were invited to change his/her expression and face orientation. Ears were manually extracted and slightly normalized. The complete set of images is organized in three subsets: a training set (three images per individual), a validation set (one image), and the test set (two images).

Fig. I.a shows the location of considered feature points defining the *biometric vector*. These points are automatically extracted from the profile of an ear image (obtained by Sobel filters) using heuristic procedures. This vector, normalized to be invariant with respect to translations and scales, is the input to a perceptron. We use a 9-9-29 (9 input, 9 hidden and 29 output units) MLP network, with QuickProp learning algorithm for the adjustment of weights, and a learning rate parameter μ=0.05. This method achieves identification rates of 43%.

The construction of *morphology vector* is as follows [1]. A profile ear image is obtained as in the previous technique. Then a number of h horizontal cuts, v vertical cuts, and $2(h+v)$ diagonal cuts are performed over the profile for an $h \times v$ size image, as showed in Fig.I.b. The

intersections among the ear profile and the different defined cuts determine a vector that is normalized to obtain the morphology vector for each ear image. As classifier, we use a 40-35-29 MLP network, with QuickProp learning algorithm for the adjustment of weights, and a learning parameter μ=0.1. This method achieves identification rates of 83%.

The third technique uses neural networks in two stages. A first network, called compression network [2] (Fig. I.c), is trained autoassociatively on the original ear images to extract its statistically salient properties of the image data or macrofeatures. QuickProp learning algorithm was used with μ=0.001, and initial weight set had small values (0.001 in magnitude) to avoid overflow errors. This vector which is an intermediate codified representation of the original image, is the input to a single perceptron (15-29) that performs the identification task itself. This method achieves identification rates of 93%.

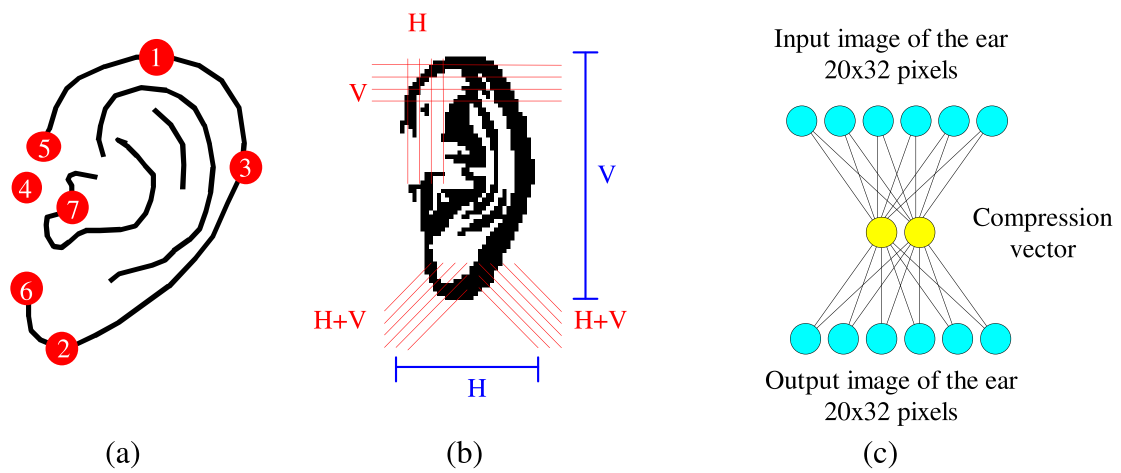

Figure I. Sketch of the automatic extraction of feature vectors in each particular identification technique: **(a)** biometric, **(b)** morphology, and **(c)** compression vectors.

The objective of multiple classifiers is to benefit from the results provided by each individual classifier in the hope that a combination can be found which will yield a final recognition/identification rate superior to those of each constituent. Many combination techniques have been proposed recently [1]. Most of them are based on ideas like voting, Bayesian combination, linear weighting, or neural network techniques. The combination of predictions produced the best results using the Weighting Bayesian method.

References.

[1] G. Dimauro, S. Impedovo. "Automatic bankcheck processing: A new engineered system". Intl Journal on Pattern Recognition and Artificial Intelligence (1997), vol. 11, pp. 467-504.

[2] D. Valentin et al.“Connectionist models of face processing”. Pattern Recognition(1994), v.27, pp.1209-1230.