Frontal Face Recognition [3]

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The goal of face identification (Figure 1) is to assign a label w $\in \{1...M\}$ indicating which of M possible identities the face belongs to based on a data vector x. The model is learned from labeled training data $\{x_i, w_i\}_{i=1}^{I}$ where the identity is known. In a simple system, the data vector might consist of the concatenated grayscale values from the face image, which should be reasonably large (say 50 X 50 pixels) to ensure that the identity is well represented.

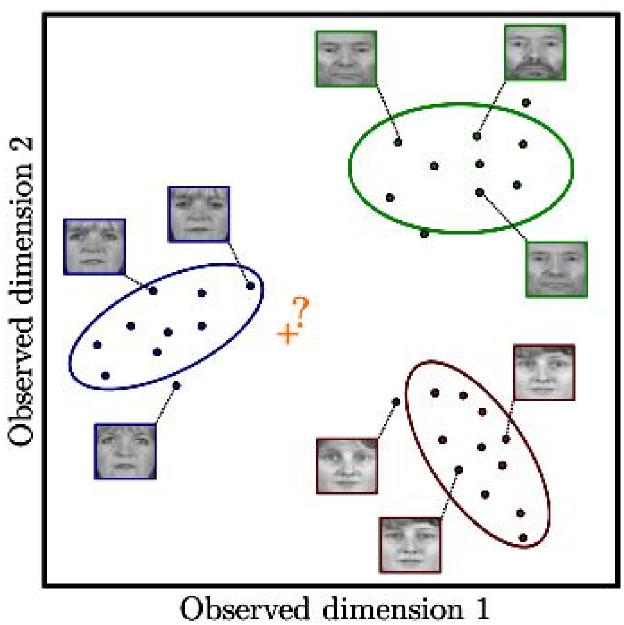

Figure 1. Face recognition. Our goal is to take the RGB values of a facial image x and assign a label w $\in \{1...K\}$ corresponding to the identity. Since the data are high-dimensional , we model the class conditional density function Pr(x|w = k) for each individual in the database as a factor analyzer. To classify a new face, we apply Bayes rule [4] with suitable priors Pr(w) to compute the posterior distribution [1] Pr(w|x). We choose the label $\hat{w}$ =argmax_w [Pr(w = k|x)] that maximizes the posterior. This approach assumes that there are sufficient training examples to learn a factor analyzer for each class.

Since the data are high dimensional, a reasonable approach is to model each class conditional density function with a factor analyzer in Equation 1.

$$Pr(x_i|w_i = k) = Norm_{x_i}[\mu_k, \Phi_k\Phi_k^T + \Sigma_k] \quad (1)$$

where the parameters for the k^{th} identity $\theta_k = \mu_k$, Φ_k, Σ_k can be learned from the subset of data that belongs to that identity using the EM algorithm [2]. It also assign priors P(w = k) according to the prevalence of each identity in the database.

To perform recognition, it computes the posterior distribution Pr(w*|x*) for the new data example x* using Bayes rule. And it assign the identity that maximizes this posterior distribution. This approach works well if there are sufficient examples of each gallery individual to learn a factor analyzer, and if the poses of all of the faces are similar. In the next example, it develops a method to change the pose of faces, so that we can cope with the case where the poses differ.

References

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