The above ratio can be also considered as a probabilistic measure of similarity between x_1 and x_2 for the face verification problem. In [1], two conditional probabilities in Eqn. (1) are modeled as Gaussians and eigen analysis is used for model learning and efficient computation.

Because of the simplicity and competitive performance [2] of Bayesian face, further progresses have been made along this research lines. For example, Wang and Tang [3] propose a unified framework for subspace face recognition which decomposes the face difference into three subspaces: intrinsic difference, transformation difference and noise. By excluding the transform difference and noise and retaining the intrinsic difference, better performance is obtained. In [4], a random subspace is introduced to handle the multi-model and high dimension problem. The appearance difference can be also computed in any feature space such as Gabor feature [5]. Instead of using a native Bayesian classifier, a SVM is trained in [6] to classify the the difference face which is projected and whitened in an intra-person subspace.

However, all above Bayesian face methods are generally based on the difference of a given face pair. As illustrated by a 2D example in Fig. 1, modeling the difference is equivalent to first projecting all 2D points on a 1D line (X-Y) and then performing classification in 1D. While such projection can capture the major discriminative information, it may reduce the separability. Therefore, the power of Bayesian face framework may be limited by discarding the discriminative information when we view two classes jointly in the original feature space.

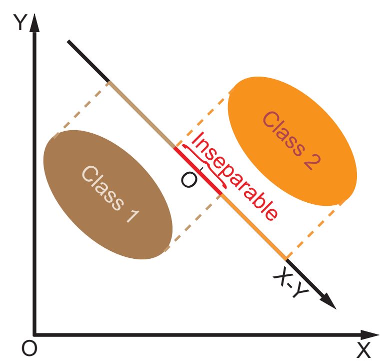

Fig. 1. The 2-D data is projected to 1-D by $x-y$. The two classes which are separable in joint representation are inseparable after the projecting. "Class1" and "Class2" could be considered as an intra-personal and an extra-personal hypothesis in face recognition.

In this paper, we propose to directly model the joint distribution of $\{x_1, x_2\}$ for the face verification problem in the same Bayesian framework. We introduce an appropriate prior on face representation: each face is the summation of two independent Gaussian latent variables, i.e., intrinsic variable for identity, and intra-personal variable for within-person variation. Based on this prior, we can effectively learn the parametric models of two latent variables by an EM-like algorithm. Given the learned models, we can obtain joint distributions of $\{x_1, x_2\}$