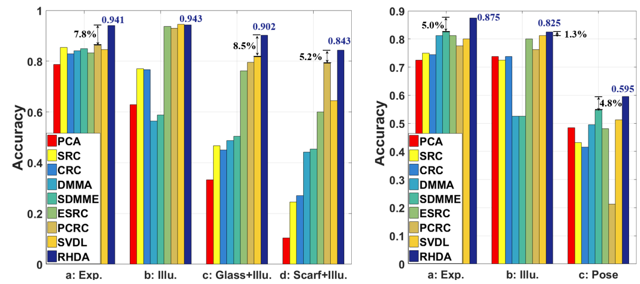
and neutral expressions were used as the gallery images, while the remaining 12 images of each subject were arranged to form 4 probe sets (i.e., expression, illumination, sunglass disguise+illumination and scarf disguise+illumination). Figure 2(a) shows the recognition results of involved methods on AR database. It is clear to see that RHDA achieves promising performance among comparing methods. Compared with the state-of-the-art holistic generic learning method SVDL, our RHDA obtains comparable recognition accuracy in prob set b (i.e., illumination) and boosts the recognition rates by a margin as large as 8.5-20 percent for the variances in expression (prob set a) and disguises (prob set c-d). Moreover, RHDA consistently outperforms the state-of-the-art patch-based methods, i.e., PCRC and SDMME, in all cases.

3.2 Evaluation on FERET Database

In this sub-section, we aim to test the robustness of all the methods to the facial variations of expressions, illuminations and poses on FERET database [9]. To this end, we selected 700 face images of 100 subjects from seven galleries (ba, bj, bk, bd, be, bf and bg) on FERET. Following the strategy on AR database, we also utilized the first 80 subjects for evaluation, while the rest 20 subjects were chosen as the generic set. Figure 2(b) shows the performances of all the methods on FERET database, where RHDA also performs the best in all cases. Furthermore, we found that the performance of PCRC degrades seriously in prob set c (i.e., pose variation). A plausible reason is that the pose variations always result in mismatch of corresponding patches. Simply considering the patch-to-patch distance may lead PCRC to make misjudgment when identifying query patch. By contrast, RHDA exhibits greater robustness against pose variations as well as other facial variations compared with PCRC and other comparing methods owing to two important factors. First, the Fisher-like criterion in RHDA can extract highly discriminant information hidden in partitioned patches, and meanwhile improving the discriminative ability of patch distribution in underlying subspaces. On the other hand, RHDA considers both the patch-to-patch and patch-to-manifold distances for identification, which can greatly increase the error tolerance when handling complex facial variation situations.

4 CONCLUSION

This paper has proposed a new patch-based method, i.e. RHDA, for FR with SSPP. RHDA possesses two major advantages, so that it shows great robustness against different types of facial variations or occlusions. The first advantage attributes to the Fisher-like criterion, which is able to extract hidden discriminant information across heterogeneous feature spaces. The other one is the fusion strategy by leveraging both the patch-to-patch and patch-to-manifold distances, which can generate complementary information and increase the error tolerance for identification. Note that RHDA has been directly applied on the original pixel intensity, therefore its performance can be further improved towards practical FR with SSPP applications. One potential direction is to leverage features learnt via deep learning methods. We will leave it as our future work.



(a) AR (b) FERET

Figure 2: The performances of different methods.

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