Combined Classifier versus Combined Feature Space in Scale Space Texture Classification

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Extended Abstract

Multiresolution techniques become more and more important in texture classification due to the intrinsic multi-scale nature of textures. Hence, scale space theory is a natural framework to construct multi-scale textures by deploying multi-scale derivatives up to certain order. The main issue in multiresolution techniques is the large feature space generated (multi-scale, multi-resolution, multi-derivative order). The common trend in the literature, which is the fusion of the features generated from different scales to come up with one feature space to be fed to the classifier, makes the problem even more serious. The large feature space generated is hampered by the 'curse of dimensionality'. To tackle this problem typically severe feature reduction is applied in multiresolution techniques, e.g. by calculating moments of the histogram [1] or calculating the energy [2]. However, the performance of the classifiers trained using this reduced feature space depends on how good these features can represent the data in the particular application.

Recently, an alternative solution was proposed by the authors using combined classifiers [3]. Using combined classifiers alleviates the problem of generating a large feature space, as the features generated from each scale/derivative are directly fed to a base classifier. In this approach, instead of concatenating features generated from each scale/derivative, the decision made by the base classifiers are combined in a two-stage combined classifier.

In this paper, the performance of the proposed classification system is first compared against the combined feature space for only the zeroth order Gaussian derivative at multiple scales (Fig. 1). The results clearly show that the proposed system using combined classifiers outperforms the classical approach of the combined feature space. The significance of the parameters, especially the fraction of variance maintained after applying PCA (principal component analysis) is also discussed (Fig. 1-right graph).

Next, the performance of our proposed texture classification system using combined classifiers is compared against multiresolution histograms [1]. In multiresolution histograms, after construction of multi-scale textures using scale space theory, the moments of the histograms are calculated for each scale/derivative. These moments are then concatenated to construct a combined feature space. The performance of this system for four textures of the well-known Brodatz Album, i.e. D4, D9, D19, and D57 (Fig. 2, the same textures as used in [2]) is shown in Fig. 3 (right graph) using learning curves.

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The performance of the proposed technique is also shown in Fig. 3 (left graph) using the same textures for comparison. The results suggest that our proposed technique can significantly improve the performance for both small and large training set sizes.

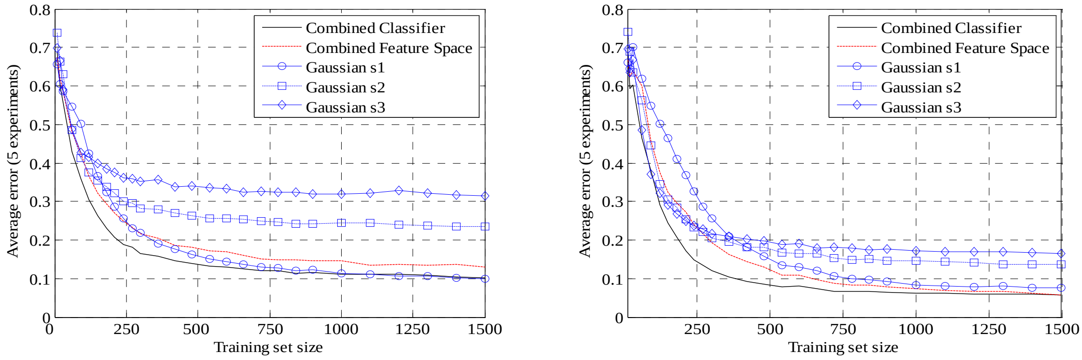

Fig. 1- Learning curves obtained using the combined classifier and the combined feature space methods for the zeroth order derivative with regularization of classifier in scale 1 and for the combined feature space with fraction of variance retained for PCA equivalent to 95% (*left graph*) and 99% (*right graph*).

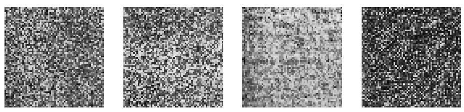

Fig. 2- Textures D4, D9, D19, and D57 from Brodatz Album used in the experiments

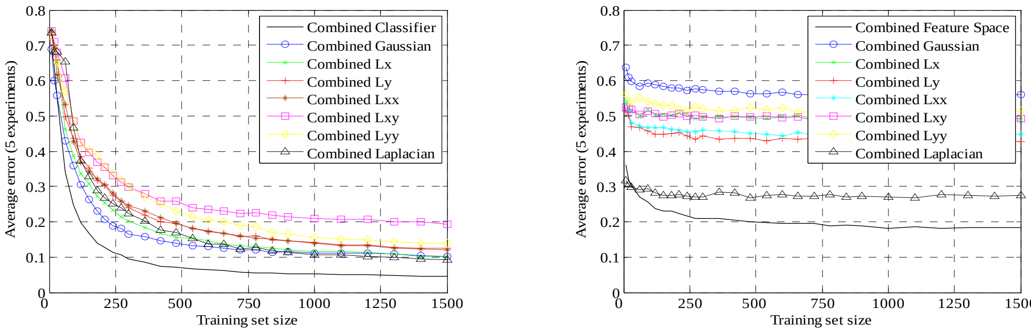

Fig. 3- Learning curves for the classification of 4 textures from the Brodatz album at multiple scales of single and multiple derivative orders using combined classifiers (*left graph*) and using multiresolution histograms (*right graph*).

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