Multi-scale Joint Encoding of Local Binary Patterns for Texture and Material Classification

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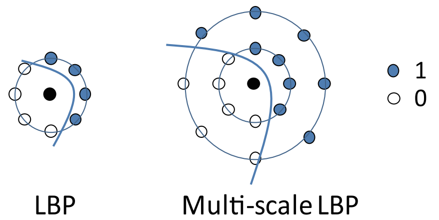

Figure 1: An illustration of LBP and Multi-scale LBP. Compared with LBP, LBPs in multiple scales jointly characterize stronger local structures. The LBP patterns in different scales have high correlation.

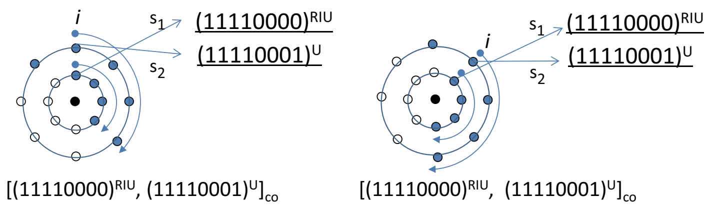

Figure 2: An illustration of the encoding method of MSJ-LBP and its rotation invariance. For the left image, we first compute its LBP^{RIU} pattern in the scale s_1 and determine the start point i which maximizes the binary sequence. According to the start point i, we can compute its LBP^U in the scale s_2. Thus, the joint pattern is $[(11110000)^{RIU}, (11110001)^U]$. Similarly, we can get the same joint pattern for the right joint pattern.

The Local binary pattern (LBP) [4] descriptor has achieved great success on texture and material classification due to its great computational efficiency and texture discrimination. Meanwhile, since its first publication, LBP has been widely applied to a lot of applications, such as face recognition, face detection, image retrieval, lip reading and many more [5]. A lot of LBP variants have been proposed in the past ten years. To achieve great rotation invariance, Ahonen et al. [1] propose an effective LBP histogram fourier (LBP-HF) features. Their method shows great robustness to image rotation. Besides of these two features, there are several powerful LBP variants, such as LTP, CLBP [3], LBPHF_S_M [7], LCP [2] and PRI-CoLBP [6], etc.

To depict texture information in different image resolutions, multi-scale strategy is introduced into texture and material classification. Firstly, single-scale LBP histogram features are extracted in each scale separately. Then, the histograms in each scale are concatenated into a final image representation. Similarly, the same multi-scale strategy are used by LCP, LBP-HF, DLBP and other LBP-based features. Since the multi-scale strategy always achieves much better performance than single scale, it is usually recognized as an indispensable means to achieve the state-of-the-art performance.

However, despite its effectiveness in texture and material classification, the classical multi-scale strategy ignores the correlation information between different scales. As shown on the left panel of Figure 1, each LBP pattern depicts a kind of local image structure. On the right panel, compared to single scale LBP, LBP patterns in multiple scales jointly depicts stronger local structure. In fact, texture patterns in different scales around the same central point usually have a strong correlation. Ignoring such correlation will lead to huge lose of discriminative information.

In this paper, we propose a Multi-Scale Joint encoding LBP (MSJ-LBP) feature to encode the joint distribution of LBP patterns in different scales for texture and material classification. Contrast to the classical multi-scale LBP (MS-LBP) that ignores the correlation between different scales, MSJ-LBP can effectively encode this kind of correlation. Compared to the single scale encoding, the multi-scale joint encoding strategy can depict stronger local structures. Meanwhile, the computational cost of MSJ-LBP is extremely low. In practice, the speed of MSJ-LBP is much faster than MS-LBP due to that MSJ-LBP uses fewer neighbors. In addition, the proposed feature is designed for rotation invariance, and excellent experimental results on the datasets with obvious image rotation demonstrate the robustness of the proposed feature to image rotation.

We have illustrated a detailed encoding strategy of the proposed MSJ-LBP in Figure 2. We can achieve the same co-occurrence encoding for the left and right pairs. In Figure 3, we have shown the experimental result of MSJ-LBP and several other methods on KTH_TIPS2a dataset.

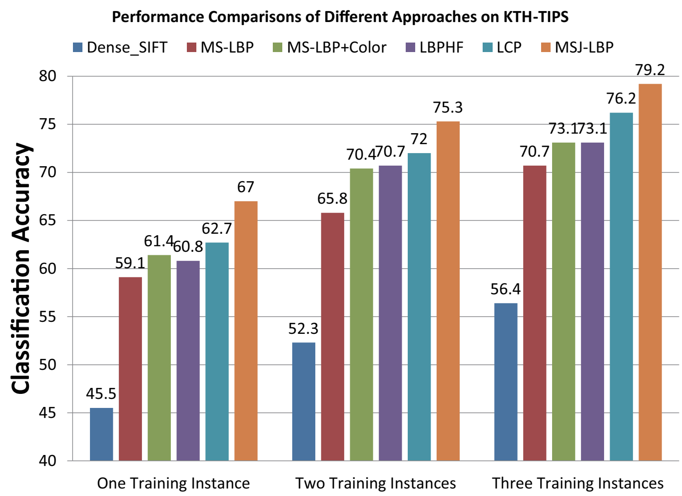

Figure 3: Experimental results of several methods on KTH-TIPS2a.

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