MULTISPECTRAL IMAGE INDEXING BASED ON VECTOR LIFTING SCHEMES

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1. MOTIVATION

In the last years, the continuous improvement of imaging systems has led to the proliferation of multispectral remote sensing image databases of huge size. In practice, the user needs to browse and interact with these databases. In fact, he often wants to retrieve from a given database the most similar images to a query one. On one hand, such requirement has led to the development of Content Based Image Retrieval Systems (CBIR) [1]. On the other hand, the images are usually stored in a compressed form in order to reduce the storage resources, the transmission delays. Consequently, it seems interesting to design CBIR systems which directly operate in the compressed domain. Indeed, as the matching step between the database images and the query one only involves information from the compressed version, unnecessary decompression is avoided. To this respect, the Wavelet Transform (WT) domain chosen has been found as an appealing compression tool since it provides multiscale compact representations of the image allowing a progressive telebrowsing of the stored images [2, 3]. In the case of multispectral images, very often, the WT built according to lifting schemes is separately applied to each component of a multispectral image and features reflecting the image content are extracted from the resulting wavelet coefficients. This latter task could be performed in two different ways. In the first approach, the spectral components are considered as mutually independent and their salient features are separately extracted from their related WT coefficients. In contrast, in the second approach, the cross-component correlations are exploited. For instance, a parametric multivariate distribution could be employed to model the joint statistical distribution of the WT coefficients of all the spectral components at a given spatial location [4, 5, 6]. In all these reported works, exploiting the spectral redundancies has led to substantial gains in terms of precision-recall performances.

In this work, we aim at taking into account the spectral correlation in a complementary way. More precisely, in addition of considering the joint distribution of the WT coefficients, we propose to replace the conventional 2D lifting scheme usually applied separately to each component by a more sophisticated one called the Vector Lifting Scheme (VLS) [7]. The VLS captures *simultaneously* the spatial and the spectral correlations of the spectral components. It is a very performant multiresolution decomposition in terms of image coding of [8, 9]. However, to the best of our knowledge, it has not been considered in the context of multichannel image retrieval. In the remainder of this summary, we will start by a brief presentation of the VLS. Then, we will present the proposed method for features extractions from the resulting coefficients.

2. A BRIEF REVIEW OF THE VLS

As the VLS could be applied in a separable way (on the rows then on the columns), for the sake of clarity, it is enough to describe it in the case of a 1D B-component signal $\mathbf{s}_0(n) = (s_0^{(1)}(n), \ldots, s_0^{(B)}(n))^T$ where n denotes the spatial location and $B \in \mathbb{N}^*$. The VLS over $J \in \mathbb{N}^*$ resolution levels outputs J sequences of B-variate detail coefficients $\mathbf{d}_j(n) = (d_j^{(1)}(n), \ldots, d_j^{(B)}(n))^T$ computed at the resolution levels $j = 1, \ldots, J$ and a B-variate coarse approximation signal $\mathbf{s}_J(n)$. This multiresolution representation is obtained through a recursive decomposition according to the scale j. More precisely, let $(b_1, \ldots, b_B)$ denote some permutation of the B components. Firstly, the band b_1 is coded in an intraband mode through a conventional WT and, thus, it is considered as a reference band. Then, at each scale j, for each component b_i ($1 < i \leq B$), the current component $s_j^{(b_i)}$ (for $i = 2, \ldots, B$) is predicted both from the component b_i (spatial mode) *and* from the samples of the previous bands b_k

(for $k < i$). The resulting prediction error corresponds to the wavelet coefficient $d_{j+1}^{(b_i)}(n)$ at the next coarser resolution $j+1$:

$$d_{j+1}^{(b_i)}(n) = s_j^{(b_i)}(2n+1) - \lfloor \sum_{k=1}^{i-1} \sum_{l \in \mathcal{P}_{j,b_i}^{b_k}} p_{j,b_i,l}^{(b_k)} s_j^{(b_k)}(2n-l) \rfloor \tag{1}$$

where $\lfloor \cdot \rfloor$ is a rounding opertor, $\mathcal{P}_{j,b_i}^{b_k}$ is the mask of the predictor and $p_{j,b_i,l}^{(b_k)}$ are its related weights. In the same way, the approximation coefficient $s_{j+1}^{(b_i)}(n)$ at resolution $j+1$ is updated as follows:

$$s_{j+1}^{(b_i)}(n) = s_j^{(b_i)}(2n) - \lfloor \sum_{k=1}^{i-1} \sum_{l \in \mathcal{U}_{j,b_i}^{(b_k)}} u_{j,b_i,l}^{(b_k)} d_{j+1}^{(b_k)}(2n-l) \rfloor \tag{2}$$

where $\mathcal{U}_{j,b_i}^{b_k}$ is the support of the update operator of the component b_i from component b_k at scale j and $u_{j,b_0,l}^{b}$ are their weights. It clearly appears that both the spatial and the spectral correlations are captured since $s_{j+1}^{(b_i)}(n)$ and $d_{j+1}^{(b_i)}(n)$ involves information from the previous components. It is also worth noting that provided that the prediction and update operators fullfill some (nin restricting) conditions, it has been shown that the VLS ensures a perfect reconstuction. As it maps integers to integers, it is also suitable for multispectral lossless coding.

3. PROPOSED FEATURES EXTRACTION

Once the wavelet coefficients are computed, the problem amounts in extracting their salient features. In this work, we focus on a statistical characterization of the resulting coefficients. More precisely, we model the joint distribution of the vector of the wavelet coefficients $\mathbf{d}_j(n)$ in order to reflect the parsimony of the multiscale representation. The following alternatives were envisaged.

- The B components of $\mathbf{d}_j(n)$ are assumed to be mutually independent and their joint distribution is modeled as the product of marginal Univariate Generalized Gaussian Distribution (UGGD).
- The joint distribution is the product of the marginal UGDD *and also* a copula function which reflect the remaining correlation between the components of $\mathbf{d}_j(n)$ [10, 6].

Finally, retrieval performances and the evaluation of the complexity load are evaluated on multispectral remote sensing image database.

4. REFERENCES

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