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Volumetric texture modeling using dominant and discriminative binary patterns

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ABSTRACT

Volumetric texture analysis is an import task in medical imaging domain and is widely used for characterizing tissues and tumors in medical volumes. Local binary pattern (LBP) based texture descriptors are quite successful for characterizing texture information in 2D images. Unfortunately, the number of binary patterns grows exponentially with number of bits in LBP. Hence its straightforward extension to 3D domain results in extremely large number of bit patterns that may not be relevant for subsequent tasks like classification. In this work we present an efficient extension of LBP for 3D data using decision tree. The leaves of this tree represent texture words whose binary patterns are encoded using the path being followed from the root to reach the leaf. Once trained, this tree is used to create histogram in bag-of-words fashion that can be used as texture descriptor for whole volumetric image. For training, each voxel is converted into a 3D LBP pattern and is assigned the label of it's corresponding volumetric image. These patterns are used in supervised fashion to construct decision tree. The leaves of the corresponding tree are used as texture descriptor for downstream learning tasks. The proposed texture descriptor achieved state of the art classification results on RFAI database 1. We further showed its efficacy on MR knee protocol classification task where we obtained near perfect results. The proposed algorithm is extremely efficient, computing texture descriptor of typical MRI image in less than 100 milliseconds.

Keywords: Local Binary Patterns, 3D texture, medical volumes, decision trees

1. INTRODUCTION

Texture operators have been widely used for characterizing tissue and tumors in medical volumes. While 2D texture has been extensively studied, there has been little work done in the use of 3D volumetric texture operators. The exploitation of multi-slice volumetric features may offer additional information that can improve the accuracy of task at hand. For instance, in 2, intensity, gradient and anisotropy 3D textural features have been used for separating between brain MR images of controls and patients suffering from white-matter encephalopathy and/or Alzheimer's disease. Another study 3 has found that 3D volumetric features were more sensitive and more specific than corresponding 2D features in assessing patterns of emphysema ranging from mild to severe and in distinguishing normal nonsmokers from normal smokers. In yet another study 4, it has been shown that 3D features achieved higher classification accuracy when applied to lung pathology compared to 2D features. Although exploitation of full 3D information to compute image texture descriptor provide clear advantage over accumulation of 2D descriptors, it can be challenging to meet both the overall system run-time performance and accuracy constraints. In this work, our goal is to develop a generic 3d volumetric texture descriptor that is efficient both in terms of speed and memory while simultaneously being highly discriminative enabling accurate learning tasks. The main highlights of our works are as follows:

- Our work provides an easy extension of local binary patterns to 3D domain which is challenging on account of an exponential rise in number of binary patterns with number of bits. Furthermore, the dimensionality of final descriptor can be systematically controlled.

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- The proposed descriptor is extremely efficient in terms of speed and memory footprint that are important factors in medical imaging domain, part of the benefit coming from the usage of binary trees which can be efficiently implemented.
- By Virtue of it's construction we further argue that our features are robust to small perturbations in image texture due to random noise patterns.

2. RELATED WORK

The problem of 3D texture analysis using statistical methods has been addressed by researchers in different ways. The most basic approach is to extend the GLCM approach 5. In an MRI volume of interest (VOI), adjacency and consecutiveness occur in each of 13 directions (compared to 4 directions in a 2D image) and, thus, 13 gray-level co-occurrence and run-length matrices can be generated. For example 6 proposes a semi-automated approach where in the physician marks a VOI. The approach uses two types of volumetric co-occurrence and run-length features, the average and range of feature values over all 13 directions. Additionally, this set was enriched with features derived from the VOI's histogram (mean value, standard deviation, skewness and kurtosis). An SVM classifier was used to perform texture classification. The time complexity of computing such features in a completely automated setting can be significantly high. In order to alleviate these problems, 7 proposes a texture classification strategy by a sub-band filtering technique similar to a Gabor decomposition followed by a generalized sequential feature discriminative selection method based on a measure of feature relevance that reduces the number of features required for classification. Their approach has some similarities with 7, where the authors compute statistical, gradient and Gabor filter features at multiple scales and orientations in 3D to capture the entire range of shape, size and orientation of the tumor. For an input scene, a classifier module generates likelihood scenes for each of the 3D texture features independently. These are then combined using a weighted feature combination scheme. Again the complexity of computing 3D Gabor features can be rather high. This will lead to higher memory and speed usage at run time. Furthermore both these approaches rely on sequential feature selection ignoring possible feature correlations that can be exploited. In the following section, we provide description of our 3D texture descriptor based on local binary patters that alleviates the aforementioned limitations.

3. METHODS

In this work, we propose an extension of Local binary patterns (LBPs) approach to analyze 3D volumetric texture. The idea behind LBPs based texture analysis in images is to convert each pixel in a given image or region of interest into decimal number based on neighboring pixels called local binary pattern as shown in Fig. 1. These values are then used to build histogram that represent feature vector for whole image or region of

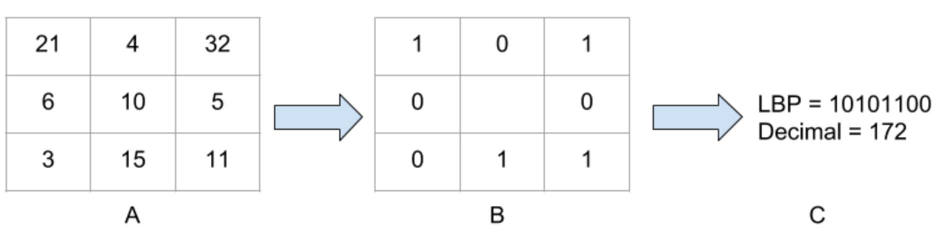
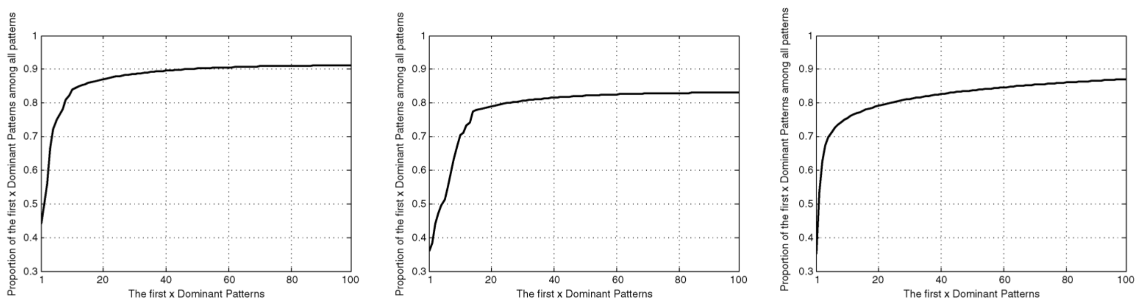


Figure 1. A) Sample 8 neighborhood image patch B) Result after thresholding neighbors w.r.t central pixel C) Corresponding LBP pattern and decimal representation by taking bits in clock-wise direction starting from top-left.

interest. This representation can then be used to perform various learning based tasks like texture classification or detection. This is analogous to bag-of-words model[8] where all the image pixels represent key-points (exhaustive sampling strategy) and the possible combinations of bit patterns represent words. In 2D there are usually 8 bit binary patterns (Fig. 1) and hence every pixel can be assigned value between 0 and 255 based on its bit pattern. Although LBP 9 based texture descriptor has been extremely successful for 2D texture analysis and classification problems, there is no straightforward way to extend it for 3D cases as the number of possible combinations of binary patterns grows exponentially with number of bits in the pattern. This results in many non-informative patterns that may deteriorate the performance of downstream learning tasks. One simple way to deal with exponential rise in the number of patters is to only keep the most commonly occurred patterns and discard the remaining ones. This is the main idea behind dominant local binary patterns proposed by 10. In following sub-section, we briefly describe the work of 10 as it forms the basis of our proposed approach.

3.1 Dominant local binary patterns

The motivation behind 10 is that not all the possible local binary patterns are prominently present in texture data at hand. Only few binary patterns are in majority and rest of them represents very small percentage of overall pixels in given image dataset. This fact is well established in literature 9,10 as well as corroborated by our own experiments. In 10, authors have done simple experiment that measures the proportions of total pixels represented by the most dominant binary patterns. Fig. 2(a)(c) 10 shows the pattern proportions occupied by different numbers of most frequently occurred patterns in the texture images obtained from the Brodatz, Meastex,and CUReT databases, respectively. The dominant patterns can be found easily by calculating the



(a) (b) (c)

Figure 2. Proportions of the first x patterns among all patterns appeared in the texture images of the (a) Brodatz database, (b) Meastex database, and (c) CUReT database.

occurrence count for each pattern in given set of samples. The main challenge in extending this approach to 3D is the sheer size of the possible number of patterns making the counting of bin populations into an intractable problem. For instance, there are 2^{26} possible patterns in case of 3D considering LBP with radius 1. In the following section we propose a simple and elegant solution which has linear space and time complexity in the number of bits. We further argue that our proposed method not only identifies the most dominant patterns but the found patterns are discriminative and hence are suitable for classification task.

3.2 Proposed Method

Our goal in this work is not only to identify combinations of bits that are dominant but are also simultaneously discriminative. Instead of the histogram based approach to identify dominant patterns 10, we propose a method that is motivated from the work of 11 on extremely randomized clustering forests where authors have used decision trees to build codebooks. Similar to their work, we use a decision tree to identify relevant combinations of bits in binary patterns. We call these bit patters as texture words analogous to visual words in bag-of-words model 8. By virtue of it's construction, these texture words are both discriminative and dominant. This leads to a stable and meaningful representation for classification tasks.

Given a set of volumetric images with known class, we sample voxels from given image. The considered voxels can be picked up randomly from a given VOI or relevant voxels can be picked exhaustively, for instance, from segmented volume of interest. We then calculate 3D LBP for each voxel resulting is a 26 dimensional binary string representation of each voxel. All of these patterns are assigned the class of the original volumetric image. These patterns are then used to construct decision tree in supervised fashion. The construction process of decision tree is demonstrated in following figure using 4 bit binary pattern: During tree construction, we select the bit at particular node which provides maximum information gain after splitting. We stop splitting until one of the following criteria is met:

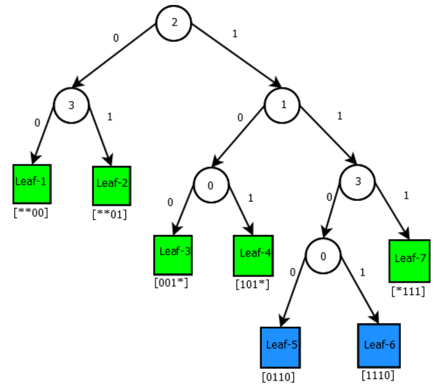


Figure 3. Constructing Binary Tree for 4-bit binary codes with 100 samples.

- We exhaustively used all the bits (blue leaves in Fig. 3).
- The number of samples reaching particular node are below certain percentage of total samples (green leaves in Fig. 3).
- The information gain associated with splitting the node is below certain threshold.

As shown in toy example in Fig. 3, we have 7 leaves instead of 16 if we would have exhaustively use all possible binary patterns for 4 bits. Given training data from multiple classes, the same procedure is followed to build a tree that encodes the texture vocabulary. We use leaves of the resulting tree as our new features as shown in Fig. 4. These features are then used to build the histogram similar to bag-of-words model. We pass all the samples (pixels/voxels) represented by 3D LBP codes from a given image or region of interest through the constructed decision tree. The final count of the number of samples falling in various leaves represent our final texture descriptor for given volumetric image. Note that most of the tree leaves (green leaves in Fig. 3) represent

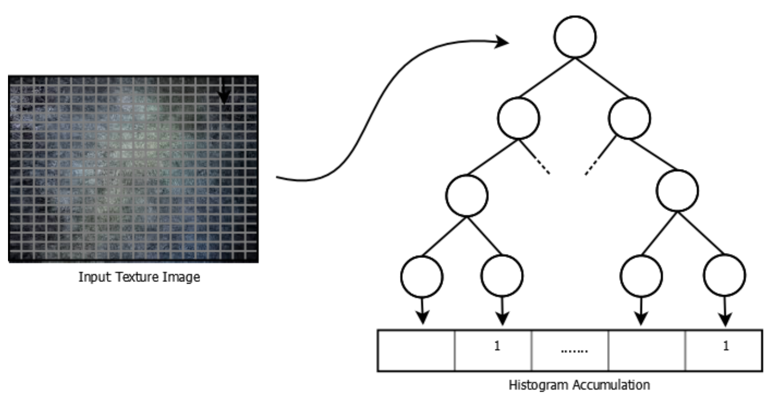


Figure 4. Feature generation process

incomplete or partial binary pattern. This is yet another useful property of our proposed texture descriptor which is a by-product of 2^{nd} stopping criteria. This property is useful in a sense that leaves of constructed tree are invariant to the value of bits that are not considered in the path to reach them from the root. Hence even if some of the bits in 3D LBP code are corrupted for given voxel let say due to noise, that voxel still have good chance to end up in its corresponding leaf. This gives more robustness to the final feature descriptor.

4. RESULTS

We tested our proposed texture descriptor on two datasets as follows.
Dataset 1: RFAI database of 3D synthetic texture images is publicly available 3D texture database 1. Their

Table 1. Accuracy obtained for 16 different test cases in RFAI 3D texture database using our approach

	Noise	Normal	Smooth	Sub-Sampling
Fourier	98.40%	98.13%	97.87%	97.87%
Geometric	99.44%	99.76%	99.68%	100.00%
Interpolate	91.21%	94.36%	89.40%	97.79%
Mix Texture	99.44%	99.36%	98.72%	100.00%

Table 2. Accuracy obtained for 16 different test cases in RFAI 3D texture database using DLBP[10]

	Noise	Normal	Smooth	Sub-Sampling
Fourier	87.47%	90.53%	97.33%	96.00%
Geometric	96.80%	99.84%	97.92%	100.00%
Interpolate	87.45%	93.83%	85.17%	96.17%
Mix Texture	96.96%	97.52%	95.60%	99.92%

database contains three-dimensional texture images with a size of $64 \times 64 \times 64$. Each test case contains between 25-30 classes with 10 samples in each class. We randomly split data into 50% training and 50% test Images. Table 1 shows our test results on 16 different test cases that are averaged over 10 independent trials. On an average, we got around 250 leaves for the constructed trees and hence the average dimension length of feature vectors is around 250. We further perform same experiment using DLBP 10 as features. The number of dominant patterns is fixed to the maximum number of leaves we obtained during construction of decision tree among all independent trials for corresponding texture type. Table 2 shows corresponding test results. Our proposed method consistently outperformed DLBP 10 based feature descriptors. Further notice the significant performance improvement for Noise data, which provide additional evidence that our proposed features are robust in the presence of noise. The authors of the above database 1 published accuracy in range of 83-88% for normal case and 75-79% for noisy case whereas our algorithm consistently gives near perfect results except for interpolation. Local frequency descriptors 12 obtained the accuracy of 98.51% on Fourier dataset. The authors 12 further compared their results with other state of the art 3D texture analysis methods, all of reported performance numbers are considerably lower than our algorithm.

Dataset 2: Another problem we have considered is the automatic classification of MR protocols based on image texture. We have tested our method for classification and novelty detection of six different MR protocols for knee data. Fig. 5 shows sample coronal images from these protocols. For brevity, we refer these protocols as

Table 3. Confusion Matrix for MR Knee protocol dataset

	P1	P2	P3	P4	P5	P6	others
P1	9471	1	1	0	0	0	10
P2	0	4913	0	0	2	0	1
P3	2	0	9456	0	0	0	5
P4	1	0	2	9483	0	0	1
P5	0	0	0	0	4731	0	33
P6	0	0	0	0	0	3780	8
Others	1	0	3	1	3	25	13387

P1 through P6. All the samples not belonging to these 6 known protocols are named as others. Our data-set consists of 42,901 series in total for six protocols and 13420 series for other MR protocols. We used SVM for classification and Kernel-PCA 13 for novelty detection tasks. We constructed our descriptor tree and trained classifier using 1000 randomly selected volumes from six known protocols. The number of leaves in descriptor tree and hence the dimensionality of feature vectors is 128. During testing, we first pass the volume through novelty detector. If novelty test fails, i.e. the volume is not classified as others, we pass it through trained classifier for protocol classification. Table 3 provides the confusion matrix showing near perfect classification and novelty detection performance.

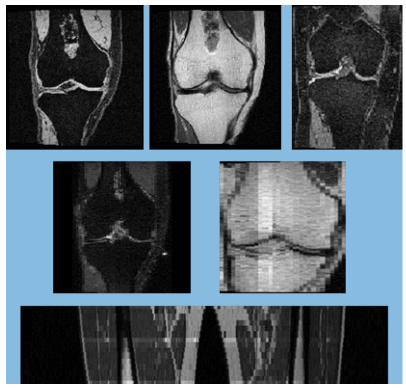


Figure 5. Coronal snapshots from 6 different MR protocols for knee data

5. CONCLUSION

In this work, we proposed an efficient approach to extend LBP to 3D domain using decision tree. Our algorithm ensures that the learned binary patterns are simultaneously discriminative and dominant resulting in robust texture descriptor. The proposed algorithm is extremely efficient during run-time consuming memory only in order of kilobytes and calculating texture descriptor on the order of few 10s of milliseconds for typical imaging volume. This makes it quite attractive to apply in medical imaging domain where both time and memory are quite crucial factors. We have demonstrated the efficacy of proposed algorithm by achieving state-of-the-art results on RFAI database and by successfully applying the texture descriptor for MR knee protocol classification task. In future, we would like to explore the possibilities to make our descriptor rotation invariant as also consider a wider context beyond the immediate neighborhood.

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