Local Texton Dissimilarity with Applications on Biomass Classification

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Abstract: Texture classification, texture synthesis, or similar tasks are an active topic in computer vision and pattern recognition. This paper aims to present a novel texture dissimilarity measure based on textons, namely the Local Texton Dissimilarity (LTD), inspired from (Dinu et al., 2012). Textons are represented as a set of features extracted from image patches. The proposed dissimilarity measure shows its application on biomass type identification. A new data set of biomass texture images is provided by this work, which is available at http://biomass.herokuapp.com. Images are separated into three classes, each one representing a type of biomass. The biomass type identification and quality assessment is of great importance when one in the biomass industry needs to produce another energy product, such as biofuel, for example. Two more experiments are conducted on popular texture classification data sets, namely Brodatz and UIUCTex. The proposed method benefits from a faster computational time compared to (Dinu et al., 2012) and a better accuracy when used for texture classification. The performance level of the machine learning methods based on LTD is comparable to the state of the art methods.

1 INTRODUCTION

Computer vision researchers have developed sophisticated methods for image related tasks, such as image retrieval, image categorization, image segmentation or image synthesis. Indeed, many of the most powerful of these methods are patch-based (Barnes et al., 2011). Such methods divide the image into many small patches and then manipulate or analyze the image based on its patches. Some of these methods have been designed or adapted to work on textures, where vector quantized image patches are also referred to as textons (Leung and Malik, 2001), (Xie et al., 2010).

Texture classification, texture synthesis, or similar tasks are an active topic in computer vision and pattern recognition, having many practical applications. This paper aims to present a novel texture dissimilarity measure based on textons, namely the Local Texton Dissimilarity (LTD), inspired from (Dinu et al., 2012). Textons are represented as a set of features extracted from image patches. Similar textons will be represented through similar features. Thus, images patches are implicitly quantized into textons. Textons provide a lighter representation of patches, allowing for a faster computational time and broader application to practical problems. LTD sums the spatial offsets of similar textons to measure the similarity between two texture images.

Several experiments are conducted on three texture data sets. LTD shows its first application on biomass type identification, a direct application of texture classification. A new data set of biomass texture images is provided by this work. Images are separated into three classes, each one representing a type biomass. A method to determine the biomass type has practical motivations for the biomass industry. Such methods are of great importance when one in the biomass industry needs to produce another energy product, such as biofuel or bioenergy, for example. Is the type of biomass appropriate to efficiently obtain the bioproduct? Is the biomass conversion method the right one for this type of biomass? Answering such questions can help reduce the operating costs of biomass power plants. But, such questions can be answered with the help of a simple biomass type identification method, such as the one presented in this work. The other experiments are conducted on two

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popular texture classification data sets, namely Brodatz and UIUCTex. The proposed method benefits from a faster computational time compared to (Dinu et al., 2012) and a better accuracy when used for texture classification. The performance level of the machine learning methods based on LTD is comparable to the state of the art methods.

The paper is organized as follows. Related work about texton-based and patch-based techniques, and biomass classification is discussed in Section 2. LTD is described in Section 3. Experiments with machine learning methods based on LTD are presented in Section 4. Finally, the conclusions are drawn in Section 5.

2 RELATED WORK

2.1 Patches and Textons

For numerous computer vision applications, the image can be analyzed at the patch (or texton) level rather than at the individual pixel level or global level. Patches and textons contain contextual information and have advantages in terms of computation and generalization. For example, patch-based methods produce better results and are much faster than pixel-based methods for texture synthesis (Efros and Freeman, 2001). However, patch-based techniques are still heavy to compute with current machines (Barnes et al., 2011).

The authors of (Lazebnik et al., 2005b) develop a texture representation that is invariant to geometric transformations based on descriptors defined on affine invariant regions. A probabilistic part-based approach for texture and object recognition is presented in (Lazebnik et al., 2005a). Textures are represented using a part dictionary obtained by quantizing the appearance of salient image regions.

In (Leung and Malik, 2001) texture images are classified by using 3D textons, which are cluster centers of filter response vectors corresponding to different lighting and viewing directions of images. The authors of (Varma and Zisserman, 2005) model textures by the joint distribution of filter responses. This distribution is represented by the frequency histogram of textons. For most texton based techniques, the textons are usually learned by k-means clustering. In (Xie et al., 2010) the authors propose a novel texture classification method via patch-based sparse texton learning. The dictionary of textons is learned by applying sparse representation to image patches in the training data set. In (Barnes et al., 2011) the authors present a new randomized algorithm for quickly finding approximate nearest neighbor matches between image patches.

2.2 Biomass Classification

In a general sense, *biomass* refers to the biological material from living, or recently living organisms. In this work, the term *biomass* refers to a renewable energy source, that can be directly converted into another type of energy product. The Biomass Texture data set provided by this work is a collection of close-up photos of different samples of three types of biomass: municipal solid waste, corn, and wheat. The goal is to build a classifier that is able to distinguish between these three types of biomass. This is a totally different approach and understanding of the biomass classification problem, compared to other researches. Usually, biomass classification refers to land cover type or forest biomass classification. Land cover classification (Dash et al., 2007) and forest biomass estimation (Wulder et al., 2008) are active research topics in the area of remote sensing. The authors of (Hoekman and Quinnones, 2000) show that remotely sensed image classification systems may be designed to accurately monitor processes of deforestation, land and forest degradation and secondary forest regrowth.

3 LOCAL TEXTON DISSIMILARITY

To compute LTD between two gray-scale texture images, the idea is to sum up all the offsets of similar textons between the two images. The LTD algorithm is briefly described next. For every texton in one image, the algorithm searches for a similar texton in the other image. First, it looks for similar textons in the same position in both textures. If those textons are similar, it sums up 0 since there is no spatial offset between textons. If the textons are not similar, the algorithm starts exploring the vicinity of the initial texton position in the second image to find a texton similar to the one in the first image. If a similar texton is found during this process, it sums up the offset between the two textons. The spatial search goes on until a similar texton is found or until a maximum offset is reached. The maximum texton offset must be set a priori. The computation of LTD is similar the algorithm presented in (Dinu et al., 2012). In practice, this computation is too heavy for a large set of images. To speed up the algorithm, textons are extracted and compared using a dense grid over the image.

Notice that the algorithm proposed in (Dinu et al., 2012) compares image patches by using the mean euclidean distance. LTD differs in the way it compares these patches. First, texture specific features are extracted from each patch. A patch can then be represented by a feature vector. Similar patches will be represented through similar features. Thus, images patches are implicitly quantized into textons. Textons are compared using the Bhattacharyya coefficient between their feature vectors. Section 3.1 describes the features extracted from image patches. The algorithm is presented in Section 3.2.

3.1 Texture Features

Before computing LTD between texture images, a set of several image features is extracted from each patch to obtain the texton representation. There are 9 features extracted from patches, that are described next. An interesting remark is that the more features are added to the texton representation, the better the accuracy of the LTD method gets. However, a lighter representation, such as the one based on 9 features, results in a faster and more efficient algorithm. One may choose to add or remove features in order to obtain the desired trade-off between accuracy and speed. The texton representation based on the 9 features that are about to be presented next gives state of the art accuracy levels in several experiments presented in Section 4.

The first two statistical features extracted are the mean and the standard deviation. These two basic features can be computed indirectly, in terms of the image histogram. The shape of an image histogram provides many clues to characterize the image, but the features obtained from an image histogram are not always adequate to discriminate textures, since they are unable to indicate local intensity differences.

One of the most powerful statistical methods for textured image analysis is based on features extracted from the Gray-Level Co-Occurrence Matrix (GLCM), proposed in (Haralick et al., 1973). The GLCM is a second order statistical measure of image variation and it gives the joint probability of occurrence of gray levels of two pixels, separated spatially by a fixed vector distance. Smooth texture gives co-occurrence matrix with high values along diagonals for small distances. The range of gray level values within a given image determines the dimensions of a co-occurrence matrix. Thus, 4 bits gray level images give 16×16 co-occurrence matrices. Relevant statistical features for texture classification can be computed from a GLCM. The features proposed by (Haralick et al., 1973), which show a good discriminatory power, are the contrast, the energy, the entropy, the homogeneity, the variance and the correlation. Among these features that show a good discriminatory power, LTD uses only four of them, namely the contrast, the energy, the homogeneity, and the correlation.

Another feature that is relevant for texture analysis is the fractal dimension. It provides a statistical index of complexity comparing how detail in a fractal pattern changes with the scale at which it is measured. The fractal dimension is usually approximated. The most popular method of approximation is box counting (Falconer, 2003). The idea behind the box counting dimension is to consider grids at different scale factors over the fractal image, and count how many boxes are filled over each grid. The box counting dimension is computed by estimating how this number changes as the grid gets finer by applying a box counting algorithm. An efficient box counting algorithm for estimating the fractal dimension was proposed in (Popescu et al., 2013). The idea of the algorithm is to skip the computation for coarse grids, and count how many boxes are filled only for finer grids. LTD includes this efficient variant of box counting in the texton representation.

The work of (Daugman, 1985) found that cells in the visual cortex of mammalian brains can be modeled by Gabor functions. Thus, image analysis by the Gabor functions is similar to perception in the human visual system. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. The local isotropic phase symmetry measure (LIPSyM) presented in (Kuse et al., 2011) takes the discrete time Fourier transform of the input image, and filters this frequency information through a bank of Gabor filters. The work of (Kuse et al., 2011) also notes that local responses of each Gabor filter can be represented in terms of energy and amplitude. Thus, Gabor features, such as the mean-squared energy and the mean amplitude, can be computed through the phase symmetry measure for a bank of Gabor filters with various scales and rotations. These features are relevant because Gabor filters have been found to be particularly appropriate for texture representation and discrimination.

Finally, textons are represented by the mean and the standard deviation of the patch, the contrast, the energy, the homogeneity, and the correlation extracted from the GLCM, the (efficient) box counting dimension, and the mean-squared energy and the mean amplitude extracted by using Gabor filters. These texton features can be extracted from all images before comparing them with LTD. Thus, the LTD computation can be divided in two main steps, one for texton feature extraction, and one for dissimilarity computation. After the feature extraction step, features should be normalized. In practice, the described features work best on squared image patches of a power of two size.

3.2 Local Texton Dissimilarity Algorithm

Algorithm 1 computes the LTD between gray-scale texture images img_1 and img_2, using the underlying Bhattacharyya coefficient to compute the similarity between texton feature vectors.

Algorithm 1. *Local Texton Dissimilarity*
Input:
img_1 – a gray-scale texture image of $h_1 \times w_1$ pixels;
img_2 – another gray-scale texture image of $h_2 \times w_2$ pixels;
n – the number of features that represent a texton;
gridStep – the skip step that generates a dense grid over the image;
offsetStep – the skip step used for comparing patches at different offsets;
w – a vector of feature weights (some features can be more important than others);
th – the texton similarity threshold.
Initialization:
$dist = 0$
$h = \min\{h_1, h_2\} - p + 1$
$w = \min\{w_1, w_2\} - p + 1$
Computation:
for $x = 1$:gridStep:h
for $y = 1$:gridStep:w
get $texton^l$ at position (x,y) in img_1
$d = 0$
while NO texton at offset d similar to $texton^l$
get $texton^r$ at offset d from (x,y) in img_2
$$s_1 = \frac{1}{n}\sum_{i=1}^{n}\left(w_i \cdot \sqrt{texton_i^l} - w_i \cdot \sqrt{texton_i^r}\right)^2$$
if $s_1 < th$
$dist = dist + d$
break
endif
if all textons at offset d were tested
$d = d +$ *offsetStep*
endif
endwhile
get $texton^r$ at position (x,y) in img_2
$d = 0$
while NO texton at offset d similar to $texton^r$
get $texton^l$ at offset d from (x,y) in img_1
$$s_2 = \frac{1}{n}\sum_{i=1}^{n}\left(w_i \cdot \sqrt{texton_i^r} - w_i \cdot \sqrt{texton_i^l}\right)^2$$
if $s_2 < th$
$dist = dist + d$
break
endif
if all textons at offset d were tested
$d = d +$ *offsetStep*
endif
endwhile
endfor
endfor
Output: *$dist$ – the dissimilarity between textures img_1 and img_2.*

Algorithm 1 needs a few input parameters besides the two images. The number of features gives the size of the feature vector. In this work, the 9 features described in Section 3.1 were used. In the algorithm, $texton_i$ represents the i-th feature of the texton representation, and w_i represents the weight associated to the i-th feature.

The results of the LTD algorithm can further be improved by adding more features or probably by using completely different features. The parameter that generates a dense grid over the image, and the skip step used for comparing patches at different offsets are used to speed up the LTD algorithm without loosing too much accuracy. These parameters induce a sparse representation of the images. Using a sparse representation is indeed necessary, since patch-based algorithms are heavy to compute with current computers because they usually manipulate millions of patches (Barnes et al., 2011). The texton similarity threshold is a value in the $[0,1]$ interval, that determines when two textons are considered to be similar. All these parameters need to be adjusted with regard to the data set size and to the image dimensions, in order to obtain a good trade-off between accuracy and speed.

4 EXPERIMENTS

In the experiments, LTD is evaluated with different kernel methods to show that good performance levels are due to the use of LTD. Two data sets of texture images are used to assess the performance of several kernel methods based on LTD, namely the Brodatz data set and the UIUCTex data set. Another experiment is performed to show the application of LTD on biomass type identification. All the experiments presented in this work aim at showing that LTD has general applications for texture classification, and that LTD is indeed a robust dissimilarity measure.

4.1 Data Sets

The first data set used for testing the dissimilarity presented in this paper is the Brodatz data set (Brodatz, 1966). This data set is probably the best known benchmark used for texture classification, but also one of the most difficult, since it contains 111 classes with only 9 samples per class. Samples of 213×213 pixels are cut using a 3 by 3 grid from larger images of 640×640 pixels. Figure 1 presents three sample images per class of three classes randomly selected from the Brodatz data set.

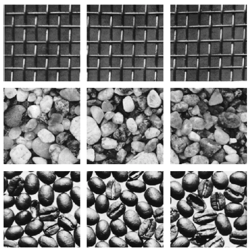

Figure 1: Sample images from three classes of the Brodatz data set.

The second experiment is conducted on the UIUCTex data set of (Lazebnik et al., 2005b). It contains 1000 texture images of 640×480 pixels representing different types of textures such as bark, wood, floor, water, and more. There are 25 classes of 40 texture images per class. Textures are viewed under significant scale, viewpoint and illumination changes. Images also include non-rigid deformations. This data set is available for download at http://www-cvr.ai.uiuc.edu/ponce_grp.

The third experiment is conducted on a new data set of biomass texture images provided by this work. It contains 270 images of 512×512 pixels representing close up photos of three types of biomass resulted after the processing of wheat, municipal waste and corn, respectively. Photos where taken at different zoom levels under various lighting conditions. Figure 2 show a few random samples of biomass images. There are 90 images per class. The goal is to build a classifier that is able to identify the three types of biomass: wheat, waste, and corn, respectively. The Biomass Texture data set is available for use at http://biomass.herokuapp.com.

4.2 Learning Methods

To use LTD for texture classification, it should be plugged into a similarity-based learning method. Several similarity-based classifiers are proposed. The first one is the Nearest Neighbors model (k-NN). It was chosen because it directly reflects the discriminatory power of the dissimilarity measure. Several state of the art kernel methods are also used, namely the Kernel Ridge Regression (KRR), the Support Vector Machines (SVM), the Kernel Discriminant Analysis

Figure 2: Sample images from the Biomass Texture data set.

(KDA), and the Kernel Partial Least Squares (KPLS). Kernel methods are based on similarity. LTD can be transformed into a similarity measure by using the Gaussian-like kernel (also known as the RBF kernel):

$$k(img_1, img_2) = \exp\left(-\frac{LTD(img_1, img_2)}{2\sigma}\right),$$

where img_1 and img_2 are two gray-scale texture images. The parameter σ is usually chosen to match the number of features so that values of $k(img_1, img_2)$ are well scaled.

For a particular classification problem, some kernel methods may be more suitable than others. The accuracy level depends on many aspects such as class distribution, the number of classes, data noise, size of the training data, and so on. For example, the KRR classifier can be used with success for problems with well-balanced classes. But, in some particular cases, when the number of classes is greater than 2, there is a serious problem with the regression methods. More precisely, some classes can be masked by others. The KDA classifier is able to improve accuracy by avoiding the masking problem (Hastie and Tibshirani, 2003).

4.3 Brodatz Experiment

The baseline method proposed for this experiment is a 1-NN model that is based on the Bhattacharyya coefficient computed on the 9 texture features described in Section 3.1. The features are extracted from entire images. The second proposed model is a 1-NN classifier based on LTD. The baseline is useful to assess the performance gained by the use of LTD. The other proposed classifiers are the KRR, the KPLS, the SVM and the KDA, all based on LTD. The KDA method is particularly suitable for problems with many classes, such as Brodatz.

In (Lazebnik et al., 2005b), the accuracy rate reported on the Brodatz data set using 3 training samples per class is 88.15%. Table 1 compares accuracy rates of the proposed classifiers with the accuracy rate of the state of the art method described in (Lazebnik et al., 2005b), using the same setup with 3 random samples per class for training. The accuracy rates presented in Table 1 are actually averages of accuracy rates obtained over 20 runs for each method. The 1-NN based on LTD model has a far better accuracy than the baseline, proving that LTD helps the learning method to achieve better results. All the kernel methods based on LTD are above the state of the art classifier. The best classifier among them is KDA, which has an accuracy of 90.87%. It is 5.46% better than the 1-NN based on LTD, and 2.72% better that the state of the art method. It seems that LTD is a good dissimilarity measure for texture classification. Combined with suitable learning methods, LTD gives results comparable to state of the art method. Despite better texture classification methods exist (Zhang et al., 2007), the classifiers based on LTD can also be improved by adding more features to the texton representation.

Table 1: Accuracy rates on the entire Brodatz data set using 3 random samples per class for training. Learning methods based on LTD are compared with the state of the art method.

Method	Accuracy
baseline 1-NN	77.68%
Best of (Lazebnik et al., 2005b)	88.15%
1-NN + LTD	85.41%
KRR + LTD	89.43%
SVM + LTD	89.48%
KPLS + LTD	89.57%
KDA + LTD	**90.87**%

In this experiment, LTD was computed on patches of 32×32 pixels, using a similarity threshold of 0.02 and a maximum offset of 80 pixels. Patches were extracted on a dense grid with a gap of 32 pixels. Feature weighting can improve accuracy by almost 1%. Thus, adjusting feature weights is not very important, but it helps the classifier. However, the feature weights were manually adjusted to increase the importance of Gabor features and fractal dimension by a factor of two, and to decrease the importance of the mean and the standard deviation by a factor of two. The weights were tuned on the baseline 1-NN model, which also uses feature weighting in the reported results. The parameter σ of the LTD kernel was chosen to be 10^{-3}. All the parameters were chosen by cross validation on a subset of the Brodatz data set. An interesting remark is that these parameters do not change by too much on the other data sets.

Using these parameters, it takes less than 1 second to compute LTD between two images on a computer with Intel Core Duo 2.26 GHz processor and 4 GB of RAM memory using a single Core. Reported accuracy rates can be improved by a few percents using a more dense grid and a greater maximum offset, but the LTD computation will also take more time. However, with the current parameters, LTD is much faster than Local Patch Dissimilarity, which takes about 5 minutes to compare two images from the Brodatz data set with similar parameters, without skipping overlapping patches.

4.4 UIUCTex Experiment

In this experiment, the same classifiers evaluated on the Brodatz data set are also evaluated on the UIUCTex data set. More precisely, the evaluated classifiers are the baseline 1-NN model based on the Bhattacharyya coefficient, the 1-NN classifier based on LTD, and the kernel classifiers based on LTD, namely the KRR, the KPLS, the SVM, and the KDA. These classifiers are compared with the state of the art classifier of (Lazebnik et al., 2005b). The best accuracy level of the state of the art classifier on the UIUCTex data set, reported in (Lazebnik et al., 2005b) using 20 training samples per class, is 97.41%.

Table 2 compares accuracy rates of the classifiers based on LTD with the accuracy rate of the state of the art classifier of (Lazebnik et al., 2005b), using the same setup with 20 random samples per class for training. The accuracy rates are averaged over 20 runs for each method. The accuracy of the 1-NN model based on LTD is 9.32% better than accuracy of the baseline 1-NN, proving again that LTD is able to achieve much better results. However, the accuracy of the 1-NN based on LTD is far behind the state of the art classifier. Even the kernel methods have accuracy rates that are roughly 4% lower than the state of the art classifier. The best classifier based on LTD is the KPLS, with an accuracy of 93.79%, which is 3.62% lower than the state of the art method. The accuracy of these kernel methods depend on LTD, which depends in turn on the features extracted from images to obtain textons. Better features will result in a dissimilarity measure capable of making finer distinctions, and, consequently, in a better kernel classifier. But even with the 9 features proposed in Section 3.1, LTD seems to give results that are comparable to the state of the art method.

In this experiment, LTD was computed on patches of 64×64 pixels, using a similarity threshold of 0.02 and a maximum offset of 240 pixels. Patches were extracted on a dense grid with a gap of 64 pixels. The same feature weights as in the Brodatz experiment

Table 2: Accuracy rates on the UIUCTex data set using 20 random samples per class for training. Learning methods based on LTD are compared with state of the art method.

Method	Accuracy
baseline 1-NN	79.34%
Best of (Lazebnik et al., 2005b)	**97.41%**
1-NN + LTD	88.66%
KRR + LTD	93.51%
SVM + LTD	93.62%
KPLS + LTD	93.79%
KDA + LTD	93.38%

were used. The parameter σ of the LTD kernel was chosen to be 10^{-3}. All the parameters were chosen by cross validation on a subset of the UIUCTex data set.

4.5 Biomass Experiment

The classifiers evaluated in this experiment are the baseline 1-NN model based on the Bhattacharyya coefficient, the 1-NN classifier based on LTD, and the kernel classifiers based on LTD, namely the KRR, the KPLS, the SVM, and the KDA. These classifiers must identify the three classes of biomass from the Biomass Texture data set.

Table 3 presents accuracy rates of the proposed classifiers using three different setup procedures. The first setup is to use 20 random samples per class for training and the rest of 70 samples for testing. The second setup is to use 30 random samples per class for training and 60 samples for testing. The last setup is to use 40 random samples per class for training and 50 samples for testing. The accuracy rates are averaged over 50 runs for each method. As expected, the accuracy of each method improves when more training samples are used. For example, the accuracy of the baseline method grows by 6.83% from 20 training samples to 40 training samples. However, the classifiers based on LTD are more stable, since the accuracy of each classifier grows only by roughly $3-4\%$ from 20 training samples to 40 samples. The learning methods based on LTD show a significant improvement in accuracy over the baseline. The best classifier based on LTD is KPLS. In all the test cases, the KPLS based on LTD has an accuracy of at least 10% better than the accuracy of the baseline 1-NN. Overall, the kernel classifiers achieve roughly similar accuracy levels. The empirical results show again that LTD is a powerful dissimilarity measure for texture classification.

In this experiment, LTD was computed on patches of 64×64 pixels, using a similarity threshold of 0.02 and a maximum offset of 256 pixels. Patches were extracted on a dense grid with a gap of 64 pixels. Again,

Table 3: Accuracy rates on Biomass Texture data set using 20, 30 and 40 random samples per class for training and 70, 60 and 50 for testing, respectively.

Method	20/70	30/60	40/50 Acc.
baseline 1-NN	80.35%	84.72%	87.18%
1-NN + LTD	88.09%	90.20%	91.28%
KRR + LTD	93.72%	96.40%	97.64%
SVM + LTD	93.98%	96.58%	97.72%
KPLS + LTD	**94.48%**	**96.90%**	**97.97%**
KDA + LTD	94.08%	96.40%	97.67%

feature weights were adjusted to increase the importance of Gabor features and fractal dimension by a factor of two, and to decrease the importance of the mean and the standard deviation by a factor of two. The parameter σ of the LTD kernel was chosen to be 10^{-3}. All the parameters were chosen by cross validation on a subset of the Biomass Texture data set.

5 CONCLUSIONS AND FURTHER WORK

This work presented a texture dissimilarity measure based on textons, called Local Texton Dissimilarity. It is based on the idea of comparing textons that are represented as a set of features extracted from image patches. Experiments showed that LTD can be used to obtain accuracy levels comparable to state of the art methods. The proposed dissimilarity measure showed its application on biomass type identification. To assess the performance level of LTD on biomass classification, a new data set of biomass texture images was provided by this work. On this data set, the accuracy level of a classifier based on LTD can be as high as 97.97%, which is more than enough for a practical application.

In future work, LTD can be improved by adding more features to the texton feature set, or by changing the features completely. For example, textons can be obtained by vector quantizing local image descriptors, such as the SIFT descriptor (Lowe, 1999). Finally, a system for biomass type identification will be designed to analyze photos taken on mobile devices. A classifier based on LTD will be integrated in this system.

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The contribution of the authors to this paper is equal.

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