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Wood Image Annotation Using Gabor Texture Feature

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Abstract

Nowadays due to quick development in digital images devices and using different imaging tools such as mobile, camera and so on, a huge numbers of images are available. Therefore, efficient management of these images especially by computers is one of challenges in this field. In recent years, automatic image annotation is a problem that is still open widely because of semantic gap between low level features and content of image. Image annotation techniques are automatically assigning a few relevant text keywords to test images, which reflect their visual image contents. This paper doesn't a wood classification and the aim of this work has an automatic image annotation for wood texture images. In this paper, Wood Image Annotation for the first time is presented. We used the Gabor filters for wood texture features extraction. After this, we compare the similarity of features vector extracted from the training images and the test images. Experimental results show that the proposed method applying Gabor filter has significant impact on system performance.

Keywords: Automatic Images Annotation, Gabor Feature Extraction, Wood Images Annotation, Wood Texture Features.

1. Introduction

Nowadays due to quick development in digital images and using different imaging tools such as mobile, camera and so on, huge numbers of images are available. Therefore, images efficient management especially by computers is one of challenge in this field.

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Automatic image annotation is an important problem in many areas, such as image understanding and content based image retrieval (CBIR) [1]. Content Based Image Retrieval is the branch of image retrieval that focuses on the contents of image for searching purpose. In CBIR, low level content features are used for example color and texture features. Search results depend on the best possible matching of feature vector extracted from query image. The only problem with techniques under this category is that users are not concerned about such low level features as they can't interpret images based on such features. They are more comfortable with natural languages [2]. In image classification and retrieval, images are represented using low level features, because an image is an unstructured array of pixels, the first step in semantic understanding is to extract efficient and effective visual features from these pixels. Appropriate feature representation significantly improves the performance of the semantic learning techniques [1]. The aim of image annotation techniques is to automatically assign a few relevant text keywords to test images, which reflect their visual contents [3]. Clearly the majority of the data gleaned from scanned books will be text, but there will also be tens of millions of pages of images. Many of these images will defy automation annotation for the foreseeable future, however a considerable fraction of the images may be amiable to automatic annotation by algorithms that can link the historical image with a modern contemporary, with its attendant Meta tags [4]. The main idea of automatic image annotation (AIA) techniques is to automatically learn semantic concept models from large number of image samples, and use the concept models to label new images. Once images are annotated with semantic labels, images can be retrieved by keywords, which is similar to text document retrieval. The key characteristic of automatic image annotation is that it offers keyword searching based on image content. Automatic image annotation employs the advantages of both the text based annotation and CBIR [1]. Each image is a concept that the concept of putting together the image feature be obtained. For example, these features can include

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points, colors, edges, shapes, objects, textures or curves in the image are. Color is one of the most important features of images. Color features are defined subject to a particular color space or model. A number of color spaces have been used in literature such as, RGB, LUV, HSV, HMMD [1, 5]. Texture is another important image feature. While color is usually a pixel property, texture can only be measured from a group of pixels. Due to its strong discriminative capability, texture feature is widely used in image retrieval and semantic learning techniques. Texture has been well studied in image processing discussion [6]. A number of techniques have been proposed to extract texture features based on the domain from which the texture feature is extracted. They can be broadly classified into spatial texture feature extraction methods and spectral texture feature extraction methods [1]. In spatial approach, texture features are extracted by computing the pixel statistics or finding the local pixel structures in original image domain. The spatial texture feature extraction techniques can be further classified as structural, statistical and model based [1]. But in spectral texture feature extraction techniques, an image is transformed into frequency domain and then feature is calculated from the transformed image. The common spectral techniques include Fourier transform (FT), discrete cosine transform (DCT), wavelet and Gabor filters. FT and DCT are very fast to compute but are not scale and rotation invariant [11, 17]. Wavelet is both efficient and robust, but it only captures horizontal and vertical features. Among them, Gabor features are most robust because it captures image features in multi-orientations and multi-scales [12]. For images or regions with sufficient size, spectral texture features are a desirable choice. However, for small images or regions, especially when the regions are irregular, spatial features should be considered [1].

In this work, for first time we presented a system for automatic wood image annotation. We used from Gabor filter for features extraction from wood surface images. Our Experiment shown the Gabor filter bank with five scales, eight orientations and 39×39 size

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is best setting for this work. To provide this paper due to the lack a standard dataset for the evaluation and testing results, we have attempted to create a dataset of images of wood. For create an appropriate dataset, first nine different models choose from a variety of woods and then search for images on Google and Yahoo search engines is done. Finally, a collection has been created that includes 360 images that 300 random image as a training dataset and the remaining images for test suite has been selected. To annotate these images 45 keywords selected of them features. Then a matrix contains a number of images in the row and in the column number of keywords as the manual annotation is created. We used from 2-D Gabor filter bank and obtained the feature vector from each wood surface gray image with fixed size by the same filter bank and invariant size of Gabor filters. After features extraction from images, we compare feature vector of each image in the test set with training set images by using cosine similarity method. Feature vector with maximum similarity selected and keywords of the image is returned.

The rest of this paper is organized as follows: background of image annotation approaches and in Section 2. Proposed method explained in section 3. Experimental result of proposed method based on Gabor texture filter is in Section 4 and conclusion of paper presented in Section 5.

2. Related Work

The surveys for image retrieval systems are done and some of the examples are given as follows. The techniques are grouped into the following: Annotation, Searching and Retrieval techniques. Zhang et al. have provided a comprehensive study on automatic image annotation techniques [1]. This is a vast survey on AIA methods where they have classified AIA techniques into categories such as SVM, ANN, DT, non-parametric and parametric approach and annotation incorporating metadata. Cusano et al. gave an image annotation tool [13] that classifies image

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region in one of seven classes. This tool has been provided to maintain huge image and video databases. The seven classes that are deemed are sky, skin, vegetation, snow, water, ground and buildings. The tool proposed uses as input tiles of an image by computing subdivisions in form of square which is the size of fixed fraction of total area of an image. A multiclass SVM is used for classification using "one per class" approach. Lei et al. have given an automatic image annotation technique [14] which incorporates both Hidden Markov Model (HMM) and Support vector Machines. Using two kinds of HMM and keyword correlation this approach gives a better result. This approach uses a two-staged mapping model. At the first, two hidden markov models are used for classifying color and texture features separately. Then SVM is used to classify results and give the final annotations of the image. Sumana et al. proposed Content based image retrieval using curvelet transform [12], Recently, researches on multi-resolution analysis have shown that curvelet features have significant advantages over wavelet features, because curvelet features are more effective in capturing curvilinear properties, like lines and edges. Shi et al. proposed adaptive content representation scheme. This encompassed two main parts: (i) adaptive visual representation of image contents; and (ii) adaptive two-level segmentation method. To sufficiently represent the contents of image they used texture of image as features centred on matching pursuit algorithm coupled with color histograms. To segment an image into meaningful regions, at diverse levels segmentation is done. At global level segmentation is done using color, texture and position i.e. global features of an image. At local level, segmentation is done using adaptive matching point features of an image. Also at global level, Gaussian Mixture Model is used while at local level, K-means algorithm is used for segmentation [15]. Goh et al. use one-class, two-class and multiclass SVMs [8]. They have proposed a confidence-based dynamic ensemble (CDE) so that it can be concluded when

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retraining of classifier is needed and whether new low-level features or training data can be included. A three level classification scheme is proposed. At the base level, SVMs are used for computing the prediction of one semantic label. A confidence factor is given for each prediction by employing algorithm for one-class SVMs which also uses a density distribution of training data. At multiclass level, the confidence factors of all multiple classifiers are cumulated to give only one prediction. Again a multi class level confidence factor is computed for this prediction. At the bag level, CDE cumulates the predictions from multiple bags to give an aggregated prediction. An overall confidence factor is given at this level. If this is high, a semantic is assigned. This approach overcome the disadvantages of traditional static classifiers as it makes adjustments to include semantics leading to discovery of low level features and thus improving accuracy. Qi et al. have used multiple SVMs for automatic image annotation. The system gives the concept of combining multiple instances learning (MIL) based and global feature based SVMs. In this system, each image is divided into blocks so that MIL method could be used to extract features based upon color and texture of the block. The efficiency is boosted by utilizing an enhanced diversity density method and a fast searching algorithm to accurately extract features. These features called bag features are then given as input to a set of SVMs to annotate. Another set of SVMs are trained using global color and edge histogram based features. This second set allows for removal of any inaccuracy issues related to the first set. From any test image, features both bag as well as global can be constructed so that they can be fed to their respective set of SVMs .The output received from these two harmonizing SVMs is then integrated by an automatic weight estimation method to give final results of annotation [9]. In [16] Ying Liu and friends proposed a block-wise automatic texture segmentation algorithm based on texture feature in wavelet domain. In [7] Gang Yu et al. proposed a new cluster-based approach that

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used for extracting features from the coefficients of a two-dimensional discrete wavelet transform. Their work based on the applications for texture classification and wood surface defect detection have shown that the proposed method is able to effectively extract important intrinsic information content from the test images, and increase the overall classify accuracy as compared with conventional feature extraction methods.

3. Proposed Method

Texture analysis is a fundamental problem in image processing and pattern recognition with a wide variety of applications such as remote sensing, medical image analysis, and quality inspection. In this paper, we want to integration the classification of wood types based on wood image texture features and automatic image annotation, proposed a system for automatic wood images annotation based on texture feature extraction for all types of wood.

3.1. Gabor Filters

In this work, we used a bank of Gabor filters to extract wood image texture features. This filters bank consists of four components: the scales, orientations and other components to specify the size of the filters. Typically, an input image I(x, y) is convolved with a 2-D Gabor function G(x, y). In the spatial domain, a two-dimensional Gabor filter is a Gaussian kernel function modulated by a complex sinusoidal plane wave, defined as:

$$G(x,y) = \frac{f^2}{\pi\gamma\eta} exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) exp\,(j2\pi f x' + \phi) \qquad (1)$$

$$x' = x\cos\theta + y\sin\theta \qquad (2)$$

$$y' = -x\sin\theta + y\cos\theta \qquad (3)$$

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Where f is the frequency of the sinusoidal factor, θ represents the orientation, ϕ is the phase offset, σ is the standard deviation and γ is the spatial aspect ratio. Gabor filter employed on whole image to extract the features from the wood surface images. One dimensional feature vector is obtained from this feature extracted images and used for further processing. Gabor features demonstrate two desirable characteristic: spatial locality or scale and orientation selectivity as in Figure 1. We used one Gabor filter bank that comprises 40 Gabor filters that are the result of using five different preferred scales, and eight different equidistant preferred orientations. This type of sampling of the spatial frequency domain takes into account the bandwidth properties of the Gabor filters used. The application of such a filter bank to an input image results in a 40-dimensional feature vector for each point of that image. In last step of feature extraction we apply down sampling along rows and columns that this step most be a factor of columns and rows in input images.

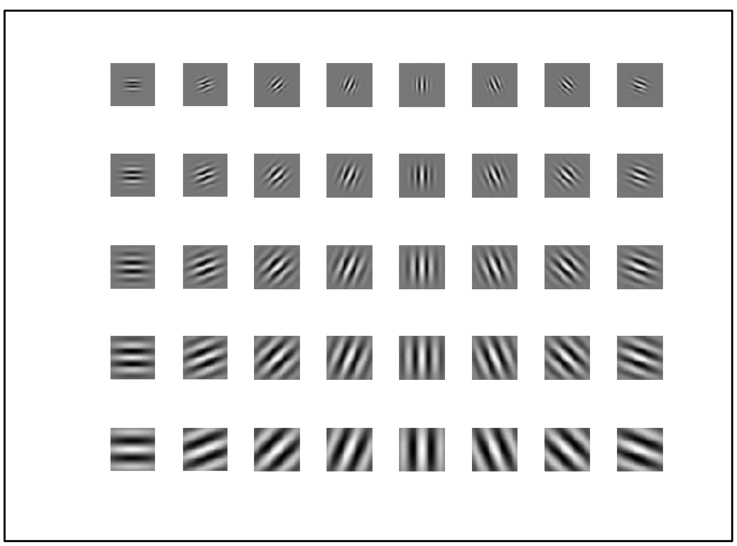

Figure 1: Real part of Gabor function for five different scales and eight different orientations.

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3.2. Cosine similarity

Cosine similarity is a measure of similarity between two vectors of an inner product space that measures the cosine of the angle between them. This metric is frequently used when trying to determine similarity between two vectors. In this similarity metric, the attributes (or feature vectors, in the case) is used as a vector to find the normalized dot product of the two vectors. The cosine of 0° is 1, and it is less than 1 for any other angle. It is thus a judgment of orientation and not magnitude: two vectors with the same orientation have a Cosine similarity of 1, two vectors at 90° have a similarity of 0, and two vectors diametrically opposed have a similarity of -1, independent of their magnitude. Cosine similarity is particularly used in positive space, where the outcome is neatly bounded in 0 and 1.

$$a \cdot b = \|a\| \, \|b\| \cos\theta \tag{4}$$

$$Similarity\ (A,B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} \tag{5}$$

$$Sim\ (A,B) = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}} \tag{6}$$

Note that these bounds apply for any number of dimensions, and Cosine similarity is most commonly used in high-dimensional positive spaces. For example, in Information Retrieval and text mining, each term is notionally assigned a different dimension and a document is characterized by a vector where the value of each dimension corresponds to the number of times that term appears in the document [10]. Cosine similarity then gives a useful measure of how similar two documents are likely to be in terms of their subject matter.

After we extracted texture feature of wood surface training set images based on bank of Gabor filters, apply this work for each images of test set and then compared each test image with all training image and used cosine similarity for feature vectors. In this step we used

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Nearest Neighbor Classification for find the best feature vector. The vector with maximum similarity selected for return automatic image annotation. For obtained best keywords we send suggested image feature vector to feature and keyword dataset and then return keywords. In the next step compared the manual images annotation keywords and automatic images annotation keywords. The flow diagram of the system is shown in Figure 2.

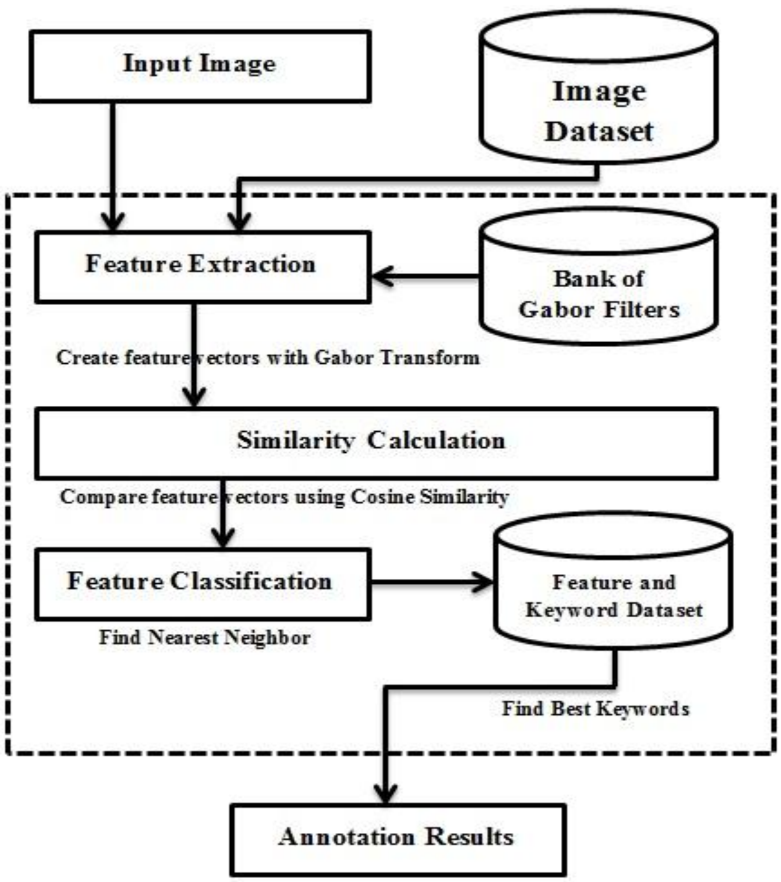

Figure 2: Flow diagram of the system.

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4. Exprimental Result

In this section, the details of dataset and keywords are represented and then evaluating the results of the experiments will be described.

4.1. Dataset

Normally for image annotation we would be training a model for every annotation keyword, and would annotate a query image with the keywords whose models evaluate the query image most favorably. To evaluate the performance of the proposed approach, experiments have been performed on a set of 360 images of size 200×200. In these experiment 300 images as training and 60 randomly images as testing and evaluating the performance of the system has been used. For this work we haven't standard dataset of wood texture images and other texture dataset like VisTex haven't enough sample and not appropriate for this work, so we must create a dataset of wood texture images. Due to the lack of appropriate dataset for this approach, the images from different types of wood texture after search in Google and Yahoo search engines is achieved. Also for annotating wood images a collection with 45 keywords is considered. Each image is manually tagged with few descriptive keywords (typically 3 to 5). We provide some manual and automatic annotation examples in Figure 3.

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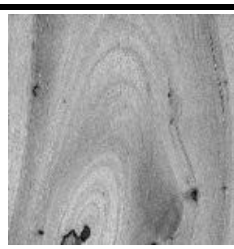
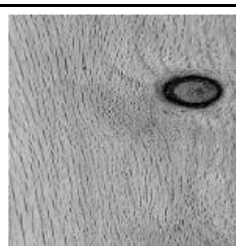
Images	Manual Annotation	Automatic Annotation
	Ripple Texture Fine Grain Brown Lines Leaf Knot Edge Knot	Tiny Texture Ripple Texture Leaf Knot
	Stripes Flake Ring Porous Coarse Texture Sound Knot	Flake Coarse Texture Encased Knot Ring Porous Stripes
	Edge Knot Encased Knot Distinctive Grain	Distinctive Grain Sound Knot Bird's eye Pattern Encased Knot

Figure.3 Test images with manual annotation and automatic annotion.

4.2. Performance Metrics

In this step to measure the effectiveness of our proposed method, three measures, namely precision, recall and F1 are used.

$$Precision = \frac{TP}{FP} \tag{7}$$

$$Recall = \frac{TP}{FN} \tag{8}$$

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$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (9)$$

Where TP means the number of images correctly annotated, FP is the number of images that are automatically annotated and FN is the total number of images that are manually annotated. The Precision, Recall and F1 measures shown in the above are obtained by averaging the results over all the keywords.

Experimental results show that the Gabor filter window size to extract image features vector is one of the most important and impressive parameters. Because the texture features of image a feature of a group of pixels is not the only feature of a pixel, if our filter window size is too small compared to the size of the image Gabor filters do not provide us with proper feature vector. Also if the selected window size is large, the extracted feature vector cannot be found the curves and contours and texture in the image and extracted them. The Table 1 and plot in Figure 4 shown the values of the evaluation measures in this paper with different sizes for the Gabor filter window. This may well reflect the values of the window size have huge impact on the obtained system performance.

Table 1: Measures for different Gabor filters window sizes

Filter Size	*Precision*	*Recall*	*F1*
4×4	17.13 %	14.33 %	15.61 %
8×8	**46.61 %**	**37.66 %**	**41.66 %**
10×10	15.52 %	13.33 %	14.34 %
20×20	17.52 %	14.66 %	15.97 %

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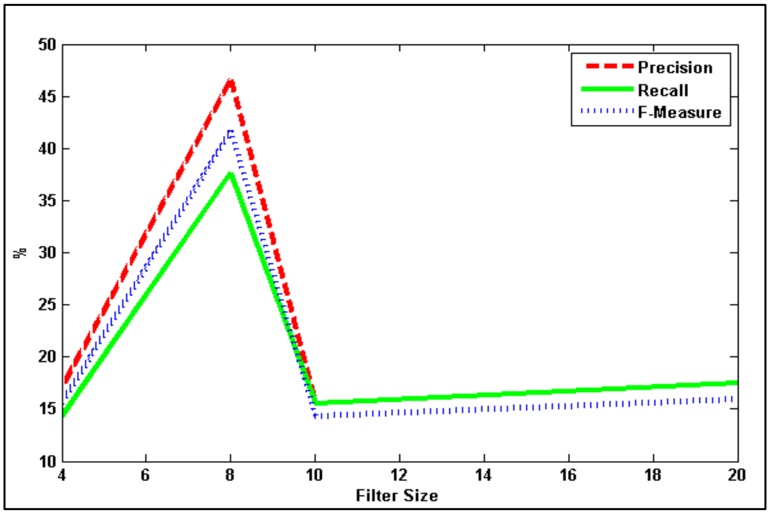

Figure 4: Percent of Precision, Recall and F-Measure for each filter size.

Conclusion

In this paper, an efficient and effective automatic image annotation system is presented. This work can be easily integrated with image retrieval systems. The Proposed method shows that results of automatic wood images annotation based on feature extraction with Gabor filters. As we have shown, the accuracy of this approach is efficient. Also this work can be used for each group of images that have different texture's features. We attempted to provide new applications of automatic images annotation with a special emphasis on texture feature extraction. Future work is logically quantify these experiments and to validate it on other datasets.

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