Review on: Texture Discrimination Feature Analysis for Visually Similar Texture of Different Fields

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Abstract— In computer vision application texture analysis plays an important role same as Artificial Intelligence plays in classification and decision making. Better texture feature gives better results while classification even the accuracy of classifier is totally depend on the type and values variations of features. Different methods for digital-image texture analysis like Structural, Statistical, Model–Based and Transform based are reviewed based on available literature and research work either carried out or supervised by the authors. Different texture databases available online is also discussed with their characteristics and the best texture feature which can describe the database well. The paper is concluded with texture features which can describe variation in given image.

Key words: Texture Analysis, Support Vector Machine, Invariant Texture, Gabbor Filter, Wavelets

I. Introduction

Texture refers to properties that represent the surface or structure of an object (in reflective or transmissive image, respectively); it is widely used, and perhaps intuitively obvious, but has no precise definition due to its wide variability. One can define texture as a something consisting of mutually related elements; therefore humans are considering a group of pixels (a texture primitive or texture element) and the texture described is highly dependent on the number considered(the texture scale). But the same cannot be true with the visually same textures. The machine vision system will not able define or describe the texture which are same visually but differs in its scale some of this images.

The Study of texture analysis for Grape Plant Species Classification system reveals that the Shape, Color and global texture of all grapes leafs of species remains relatively same that is visually same but the local texture of individual specie varies. So to find texture feature which can well describe texture of visually same but differs in local texture, also the texture feature which are invariant for Scale, Illumination and Rotation are discussed.

Texture consists of texture primitives or texture elements, sometimes called texels. Texture description is scale dependent. The main aim of texture analysis is texture recognition and texture-based shape analysis. People usually describe texture as fine, coarse, grained, and smooth. In this paper we discussing some of the important ways by which this problem can be accomplished and concluding with best texture feature or a combination of feature that can able to discernment the similar textures of different scales using SVM.

Chapter1describes the introduction to study ant literature, chapter 2 continues with the basics theory and model of texture analysis in machine vision. Related literature papers are reviewed in chapter 3. Chapter 4 introduces the concept of invariant texture feature analysis and chapter 5 describes different database available online for texture analysis, finally the study is concluded in chapter 6.

II. Basic Methods of Texture Features Analysis

Approaches to texture analysis are usually categorized into methods.

- Structural,
- Statistical,
- Model-based
- Transform

Structural approaches represent texture by well-defined primitives (microtexture) and a hierarchy of spatial arrangements (macrotexture) of those primitives. To describe the texture, one must define the primitives and the placement rules. The choice of a primitive (from a set of primitives) and the probability of the chosen primitive to be placed at a particular location can be a function of location or the primitives near the location. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks. The abstract descriptions can be ill defined for natural textures because of the variability of both micro- and macrostructure and no clear distinction between them. A powerful tool for structural texture analysis is provided by mathematical morphology. It may prove to be useful for bone image analysis, e.g. for the detection of changes in bone microstructure. In contrast to structural methods, statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture. Instead, they represent the texture in directly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. Methods based on second-order statistics (i.e. statistics given by pairs of pixels) have been shown to achieve higher discrimination rates than the power spectrum (transform-based) and structural methods. Human texture discrimination in terms of texture statistical properties is investigated in Accordingly, the textures in grey-level images are discriminated spontaneously only if they differ in second order moments. Equal second-order moments, but different third-order moments require deliberate cognitive effort.

This may be an indication that also for automatic processing, statistics up to the second order may be most important. The most popular second-order statistical features for texture analysis are derived from the so-called co-occurrence matrix. They were demonstrated to feature a potential for effective texture discrimination in biomedical-images. The approach based on multidimensional co-occurrence matrices was recently shown to outperform wavelet packets (a transform-based technique) when applied to texture classification

Model based texture analysis using fractal and stochastic models, attempts to interpret an image texture by use of, respectively, generative image model and stochastic model. The parameters of the model are estimated and then used for image analysis. In practice, the computational complexity arising in the estimation of stochastic model parameters is the primary problem. The fractal model has been shown to be useful for modeling some natural textures. It can be used also for texture analysis and discrimination however, it lacks orientation selectivity and is not suitable for describing local image structures. Transform methods of texture analysis, such as Fourier Gabor and wavelet transforms represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). Methods based on the Fourier transform perform poorly in practice, due to its lack of spatial localization. Gabor filters provide means for better spatial localization; however, their usefulness is limited in practice because there is usually no single filter resolution at which one can localize a spatial structure in natural textures. Compared with the Gabor transform, the wavelet transforms feature several advantages:

1) Varying the spatial resolution allows it to represent textures at the most suitable scale,
2) There is a wide range of choices for the wavelet function, so one is able to choose wavelets best suited for texture analysis in a specific application.

They make the wavelet transform attractive for texture segmentation. The problem with wavelet transform is that it is not translation-invariant

III. Literature Review

A.H. Kulkarni, et.al. [1] They have proposed a novel framework for recognizing and identifying plants using shape, vein, color, texture features which are combined with pseudo Zernike movements. Pseudo-Zernike moments for feature descriptors is a feasible alternative.

Classifying structurally complex images. They offer exceptional invariance features and reveal enhanced performance than other moment based solutions. Radial basis probabilistic neural network (RBPNN) has been used as a classifier. To train RBPNN they use a dual stage training algorithm which significantly enhances the performance of the classifier. Simulation results on the Flavia leaf dataset indicates that the proposed method for leaf recognition yields an accuracy rate of 95.12%[3].

Abdul Kadir et.al [2] The purposed system involved combination of features derived from shape, vein, color, and texture of leaf. PCA was incorporated to the identification system to convert the features into orthogonal features, Principal Component Analysis (PCA) is a statistical method that the main goal is to reduce dimension of data. With minimal effort PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified structures that often underlie it. PCA has been used for several applications, such as for breast thermal classification and analysis of socioeconomic factors and their association with malaria in children. In those researches, PCA was used to reduce dimension of data. The algorithm of PCA is described as follow and then the results were inputted to the classifier that used Probabilistic Neural Network (PNN). This approach has been tested on two datasets, Foliage and Flavia, that contain various color leaves (foliage plants) and green leaves respectively. The results showed that PCA can increase the accuracy of the leaf identification system on both datasets.

Kyosuke Yamamoto.al. [3] Presented fully automated yield estimation of intact fruits prior to harvesting provides various benefits to farmers. Until then, several studies have been conducted to estimate fruit yield using image-processing technologies. However, most of these techniques require thresholds for features such as color, shape and size. In addition, their performance strongly depends on the thresholds used, although optimal thresholds tend to vary with images. Furthermore, most of these techniques have attempted to detect only mature and immature fruits, although the number of young fruits is more important for the prediction of long-term fluctuations in yield. In this study, they aimed to develop a method to accurately detect individual intact tomato fruits including mature, immature and young fruits on a plant using a conventional RGB digital camera in conjunction with machine learning approaches. The developed method did not require an adjustment of threshold values for fruit detection from each image because image segmentation was conducted based on classification models generated in accordance with the color, shape, texture and size of the images. The results of fruit detection in the test images showed that the developed method achieved a recall of 0.80, while the precision was 0.88. The recall values of mature, immature and young fruits were 1.00, 0.80 and 0.78, respectively .

Ekshinge et.al [4] In this paper, they employed Multilayer Perceptron with image and data processing techniques and neural network to implement a general purpose automated leaf recognition. Sampling leaves and capturing them are low cost and convenient. One can easily transfer the leaf image to a computer and a computer can extract features automatically in image processing techniques. This paper implements a leaf recognition algorithm using easy-to-extract features and high efficient recognition algorithm. Their main improvements are on feature extraction and the classifier .

Vatsal H. Shah et.al.[5] proposed an algorithm for leaf disease detection using image processing and neural network where their work is first image filtering using median filter and convert the RGB image to CIELAB color component, in second step image segmented using the k-means technique, in next step masking green-pixels & Remove of masked green pixels, after in next step calculate the Texture features Statistics, in last this features passed in neural network. The Neural Network classification performs well and could successfully detect and classify the tested disease.

C.Ananthi.et.al. [6] First, they extract certain features from the inputted leaf images, later using different methods like thresholding, segmentation. After preprocessing the image data are applied to Neural Network. And compared with several trained databases. Thus this paper analysis the medicinal leaves with a successfully using image processing. The algorithm they developed capable of recognizes medicinal leaf identification. A novel individual leaf extraction computer program was developed based on grayscale, canny edge detector, morphological and neural network algorithm. With the use of computer, identification of medicinal leaves plant becomes more convenient, and efficient. By using the rapid recognition for different medicinal leaves was realized.

S.Arumugam, et al. [7] the aim of this algorithm is detection of Powdery mildew disease in the betelvine plants using digital image processing techniques. The digital images of the uninfected or normal betelvine leaves and the digital images of the infected in powdery mildew diseased betelvine leaves at different stages are collected from different betelvine plants using a high resolution digital camera and collected betelvine images are stored with JPEG format. The digital image analyses of the leaves are done using the image processing toolbox in MATLAB. The mean values for all sample leaves are computed and calculated mean values are stored in the system. The mean values of test leaves are computed and compared with the stored values. As the result of this comparison, it is identified whether test leaves are affected by powdery mildew disease or not. Finally this analysis helps to recognize the powdery mildew disease can be identified before it spreads to entire crop.

S. Arivazhagan,.al.[8] The proposed system is a software solution for automatic detection and classification of plant leaf diseases. The developed processing scheme consists of four main steps, first a color transformation structure for the input RGB image is created, then the green pixels are masked and removed using specific threshold value followed by segmentation process, the texture statistics are computed for the useful segments, finally the extracted features are passed through the classifier. The proposed algorithm's efficiency can successfully detect and classify the examined diseases with an accuracy of 94%. Experimental results on a database of about 500 plant leaves confirm the robustness of the proposed approach.

Tanakorn Tiay, et.al. [9] Presented the flower recognition system based on image processing. This system uses edge and color characteristics of flower images to classify flowers. Hu's seven moment algorithm is applied to acquire edge characteristics. Red, green, blue, hue, and saturation characteristics are derived from histograms. K-nearest neighbor is used to classify flowers. The accuracy of this system is more than 80%. The first step is the image acquisition. The image data is pre-processed to prepare the image data for analysis. In the image analysis section, Hu's seven-moment algorithm of shapes together with RGB and HS data are used. After that, two data parts will be combined as a vector and classified by the K-nearest neighbor algorithm.

Piyush Chaudhary, et.al [10] presented an algorithm for disease spot segmentation using image processing techniques in plant leaf. This is the first and important phase for automatic detection and classification of plant diseases. Disease spots are different in color but not in intensity, in comparison with plant leaf color. So the color transform of RGB image can be used for better segmentation of disease spots. In their work a comparison of the effect of CIELAB, HSI and YCbCr color space in the process of disease spot detection is done. Median filter is used for image smoothing. Finally threshold can be calculated by applying Otsu method on color component to detect the disease spot. An algorithm which is independent of background noise, plant type and disease spot color was developed and experiments were carried out on different "Monocot" and "Dicot" family plant leaves with both, noise free (white) and noisy background.

Jyotismita Chaki et al[11] propose an automated system for recognizing plant species based on leaf images. Plant leaf images corresponding to three plant types, are analyzed using two different shape modeling techniques, the first based on the Moments-Invariant (M-I) model and the second on the Centroid-Radii (C-R) model. For the M-I model the first four normalized central moments have been considered and studied in various combinations viz. individually, in joint 2-D and 3-D feature spaces for producing optimum results. For the C-R model an edge detector has been used to identify the boundary of the leaf shape and 36 radii at 10 degree angular separation have been used to build the feature vector. To further improve the accuracy, a hybrid set of features involving both the M-I and C-R models has been generated and explored to find whether the combination feature vector can lead to better performance. Neural networks are used as classifiers for discrimination. The data set consists of 180 images divided into three classes with 60 images each. Accuracies ranging from 90%-100% are obtained which are comparable to the best figures reported in extant literature.

From Study of texture analysis its reveals that for Grape Plant Species Classification system reveals the Shape, Color and global texture cannot be used as for all species they remains relatively same that is visually same but the local texture of individual specie varies. So to find texture feature which can well describe texture of visually same but differs in local texture need to study and develop also the invariant texture feature extraction like Scale, Illumination and Rotation are to be discussed therefor section 4deal with the same.

The papers literature reviewed during study are tabulated as in table 1 below where title of paper with year of issued is given in review study the parameters considered are as features used for analysis of a leaf image , Classifier used in classification, classification accuracy and Size of Database.

Research Paper	**Classification Based On**	**Classifiers**	**Accuracy**	**Database Size**
[1]. Plants Images classification Based on Textural Features using Combined Classifier [Aug 2011].	Texture	Combined Classifier (LVQ +RBF)	98.7%	30
[2].Leaf Classification using shape, color, and texture features[Aug 2011].	Shape, vein, color, and Texture.	PNN	93.75%	32 Images
[3]. Edge and texture fusion for plant leaf classification [June 2012].	Edge and Texture.	Radial basis function	85.93%	132 Images

[4]. Shape and texture based Leaf classification [2010].	Shape and Texture. 18 Images	Incremental classification Algorithm.	81.1%	18 Images
[5].Texture Feature Extraction for Identification of Medicinal Plants and Comparison of Different Classifiers [Jan 2013].	GTSDM LBP	SGD, k-NN, SVM	94.7%.	250 Images
[6] Texture Recognition with combined GLCM, Wavelet and Rotated Wavelet Features	Texture by (GLCM) Wavelet (Dabuencheis)	Different distances Techniques is used	85.71%	35 Images

Table 1: Papers Reviewed in Literature

IV. INVARIANT TEXTURE ANALYSIS

Variations in illumination, scale and rotation cause changes in appearance of texture and hence invariant texture analysis is needed. Several research proposals are seen in the literature for invariant texture analysis.

In the computer vision applications used in industrial inspections, image capturing under same lighting conditions may not be possible. In such cases, features that are robust against variation in illumination are required. Chen et al [12] derived features that are invariant with linear gray-scale transforms. Wu et al [13] also assumed that the gray-scale transformation is a linear function and can be corrected with simple normalization. Gray-scale changes caused by illumination variations are often handled with global normalization of the input image. They used histogram equalization to normalize images before feature extraction and a pre-processing step for setting intensity values to have a zero mean and unit standard deviation. Some methods have also been developed for multispectral color images to achieve illumination invariance. Wang et al [14] proposed a method for illumination-invariant color texture classification using Zernike moments. Images captured with different orientation due to viewing angle of the camera or position of the object may result in change in appearance of texture. To achieve same results in texture analysis for various orientations, rotation invariant features have to be used. Some of the earlier rotation invariant texture features were generalized co-occurrence matrices [15], Polarograms and circular autoregressive model [16] several filtering based approaches have been proposed for rotation invariant texture analysis such as wavelet decomposition and hidden Markov models [17], Gabor wavelets, Gabor and Gaussian filters and some other methods are developed to tackle rotation.

Many image processing applications need scale invariant features. Pun and Lee [18] proposed rotation and scale invariant texture features using a log-polar transform and calculated energy signatures in each sub band. Manthalkar et al [19] used wavelet packets for scale and rotation in variations. A combined use of the Radon transform and multiscale analysis with a wavelet transform for rotation and scale invariant texture classification is discussed in [20]. In [21] proposed an invariant texture descriptor algorithm called invariant features of local textures (IFLT).Various invariant texture feature extraction methods are presented in Table 2.

Texture Feature	**RI**	**II**	**SI**
Generalized Co-occurrence Matrices	Y		
Polarograms	Y		
Circular Autoregressive Model	Y		
Gabor and Gaussian Filters	Y		
Wavelet Packet	Y	Y	
Local Binary Pattern	Y	Y	
Log-polar Transform	Y		Y
Wavelet Packets	Y		Y
Autocorrelation Function	Y		
Local Texture Patterns	Y	Y	
Dominant Local Binary Patterns	Y		
Completed Local Binary Patterns	Y		
Radon Transform	Y	Y	Y

Table 2: Invariant Texture Features

Where in table .2.
RI is Rotation Invariant.
SI is Scale Invariant.
II is Rotation Invariant.

V. BENCHMARK TEXTURE DATASETS

Some of the standard texture datasets available for the performance and comparative study of texture analysis tasks are listed in this section.

A. Brodatz Texture Database

The Brodatz texture database is derived from the Brodatz album (Brodatz 1966). The Brodatz texture database has become the standard for evaluating texture algorithms and is used in most of the texture based studies. Images of the Brodatz textures for research purpose are available online at http://www.sipi.usc.edu/database which is provided by USC-SIPI (University of Southern California, Signal and Image Processing Institute).

B. Vistex Texture Database

VisTex (Vision and Modeling Group at the MIT Media Lab) collection is assembled and maintained to aid in the development of robust computer vision algorithms and their comparison on a common set of data. Their lighting conditions used to capture the images are daylight, artificial-florescent and artificial-incandescent. The goal of VisTex is to provide texture images that are representatives of real world conditions. The images are available online at http://www.vismod.media.mit.edu/vismod/imagery/visiontexture/vistex.html

C. Meastex Texture Database

MeasTex (MEASurement of TEXture classification algorithms) is an image database. It is also a framework for the quantitative measurement of texture algorithms targeted on a number of texture testing suites, and an implementation of some major well-known texture classification paradigms. A number of texture sets in MeasTex have been compiled from Brodatz texture database and the VisTex database. The images are available online at http://www.texturesynthesis.com/meastex/meastex.html.

D. Ponce Texture Database

Ponce database features 25 texture classes, 40 samples for each class. All the images are in gray-scale and captured under non-controlled illumination conditions. This database is developed by Lazebnik et al (2005) and is available at http://www-cvr.cli.uiuc.edu/ponce-grp/data/texture-database.

E. Jerry Wu Texture Database

This database contains 30 real textures of 3D surfaces taken by the digital camera with different surface orientations under controlled illumination conditions. The database is developed by Wu (2003) and is available at ftp://ftp.macs.hw.ac.uk/imaging/wu.

F. Outex Texture Database

OUTex (University of Oulu Texture database) is a framework for the empirical evaluation of texture classification and segmentation algorithms. A collection of 319 surface textures are captured by well-defined variations to a given reference in terms of illumination directions, surface rotations and spatial resolutions. Ojala et al (2002b) constructed the image database and is available at http://www.outex.oulu.fi.

VI. Conclusion

Wavelet analysis and color texture analysis has attracted much attention recently in Image analysis. It has been successfully applied in many applications such a as image analysis, classification system and other texture analysis applications. In an image texture analysis and classification system, many parameters affect the accuracy of the classification. These parameters are: dependence or independence from database, Sampling environment, size or resolution of image.

The optimized representation provides important improvements in comparison to the classical features. This suggests that the task of a classifier is simplified when using this optimized representation, due to a better class separation in the features space. Therefore, the proposed strategy provides an alternative feature set for leaf images, which allows improving the classification results in the presence of temporal noise and sampling defects. In order to obtain a representation which allows improving the results in classification, future experiments will include more phonemes in the data-sets used for the optimization.

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyse data and recognize patterns, used for classification and regression analysis.

While studying texture analysis of Grape Plant Species Classification system it has be found that the Shape, Color and global texture of all grape leafs remain relatively same that is Visually same but the local texture varies. So to find texture feature which can well describe texture of visually same but differ in texture, also the texture feature which are invariant for Scale, Illumination and Rotation are discussed.

As describe in table. 1 the combined features and classifiers can improve the accuracy. A color texture analysis plays an important role in describing characteristics of texture as it provides both local and global texture of an image. The size of a database also effect on accuracy of classifier in section 4 the scale, Rotation and illumination invariant texture analysis is discussed which can overcome the quires of local texture analysis like GLCM and Gabor texture filters. Support Vector Machine, as classifier provides overall better accuracy in all cases. SVM also provides different kernel options like Linear, Radial Basis Function, polynomial kernel of various orders and sigmoid kernel while training.

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