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A Survey on Texture Classification

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Abstract :- Texture classification is a fundamental problem in computer vision with a wide variety of applications. It is a trendy and catchy technology in the field of texture analysis. Texture classification is important in many applications ranging from remote sensing to medical image analysis like image database retrieval, industrial, agricultural and bio-medical applications. The accuracy of texture image classification depends on quality of texture features and classification algorithm used. Texture classification is based on four different approaches; they are structural, statistical, model based and transform. This paper aims to compile the recent trends on the usage of feature extraction, classification methods and texture datasets used in the research of texture classification. The study shows that the transform methods, such as Gabor filters and wavelets are gaining popularity but old methods such as GLCM are still used with new calculations or combined with other methods. For the classifiers, nearest neighbor algorithms are popular despite being simple and SVM has become a major classifier used in texture classification. For the datasets, Brodatz texture dataset is the most popularly used dataset while other datasets are less used.

Keywords: - Texture, Texture Feature Extraction, Texture Classification, Computer Vision, Pattern Recognition, Machine Learning.

I. INTRODUCTION

Texture classification plays an important role in the engineering fields and scientific researches. It has some of the real world applications that involve textured objects of surfaces include rock classification [1], wood species recognition [2], face detection [3], fabric classification [4], geographical landscape segmentation [5] and etc. All these applications allowed the target subjects to be viewed as a specific type of texture and hence they can be solved using texture classification techniques.

Training phase and Testing phase/Recognition phase are the two different process involved in texture image classification. In the training phase a set of known texture images are trained by feature extraction method and stored in the library or database. In the recognition phase the unknown sample image is tested by using same feature extraction method and compares the values with the already stored features in the database. Based on the classification algorithm the unknown sample can be classified as correctly or sometimes misclassified.

The main objective of this paper is to compile the recent trends in texture classification in terms of feature extraction and classification methods used as well as the texture datasets used in the training and testing process.

Section 2 presents the feature extraction methods used in the recent years. Classification methods used in the recent years are represented in section 3. The popularly used texture datasets are described in section 4. Section 5, concludes the paper.

II. FEATURE EXTRACTIOM

The quality of texture image classification depends on the quality of texture features and classification algorithms. Most important is to select texture features with highly discriminative to inter-class textures. The process of texture analysis usually produces some kind of numeric descriptions of the texture, called texture features. The process of computing the texture features is known as feature extraction. Features are used as inputs to classifiers that assign them the class that they represent. The purpose of feature extraction is to reduce the original data by measuring certain properties, or features, that distinguish one input pattern from another pattern.

The different methods for feature extraction are divided into four main categories namely: structural, statistical, model-based and transform domain.

2.1 Structural Method

Structural approaches represent texture by well-defined primitives (microtexture) and a hierarchy of spatial arrangements (macrotexture) of those primitives [6, 7, 8]. The macrotexture approach is based on the view that the texture is the comparison of textural primitives. However, there are few successful techniques for this approach as it faces at least two complex problems, one of which is the need to identify the textural primitives while the other is the description of the spatial relationship between these primitives. In contrast, the microtexture approach measures textures without identifying textural primitives. The features, for example, statistical or structural features, are extracted from the texture images or regions rather than predefined texture elements. The microtexture approach has been extensively developed over the last three decades and appears to be much more promising than the macrotexture approach. There are an enormous number of texture analysis methods under this category although none predominates.

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. This method is not suitable for natural textures because of the variability both of micro-texture and macro-texture and there is no clear distinction between them [9]. The examples of structural method are Edgeness [10, 11, 12], Run – Length [13 -17], etc.

2.2 Statistical Method

Statistical methods represent the texture indirectly according to the non-deterministic properties that manage the distributions and relationships between the gray levels of an image. This technique is one of the first methods in machine vision [9]. By computing local features at each point in the image and deriving a set of statistics from the distributions of the local features, statistical methods can be used to analyze the spatial distribution of gray values. Based on the number of pixels defining the local feature, statistical methods can be classified into first-order (one pixel), second-order (pair of pixels) and higher-order (three or more pixels) statistics [6]. The difference between these classes is that the first-order statistics estimate properties (e.g. Average and variance) of individual pixel values by waiving the spatial interaction between image pixels, but in the second-order and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. The most popular second-order statistical features for texture analysis are derived from the co-occurrence matrix [18]. An example of statistical method is Co – occurrence method [19, 20].

2.3 Model Based Method

Model based texture analysis, such as Fractal model and Markov are based on the construction of an image that can be used for describing texture and synthesizing it [9]. These methods describe an image as a probabilistic model or as a linear combination of a set of basic functions. The Fractal model is useful for modeling certain natural textures that have a statistical quality of roughness at different scales [9] and also for texture analysis and discrimination. This method has a weakness in orientation selectivity and is not useful for describing local image structures. Pixel-based models view an image as a collection of pixels, whereas region-based models view an image as a set of sub patterns. There are different types of models based on the different neighborhood systems and noise sources. These types are one- dimensional time-series models, Auto Regressive (AR), Moving Average (MA) and Auto Regressive Moving Average (ARMA). Random field models analyze spatial variations in two dimensions, global random and local random. Global random field models treat the entire image as a realization of a random field, and local random field models assume relationships of intensities in small neighborhoods. A widely used class of local random field models is Markov models, where the conditional probability of the intensity of a given pixel depends only on the intensities of the pixels in its neighborhood (the so called Markov neighbors) [9]. The examples of the model based method are Fractal Model [21 – 26] and Markov Random Field Models [27 – 30] etc.

2.4 Transform Method

Transform methods, such as Fourier, Gabor and wavelet transforms represent an image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size). They analyze the frequency content of the image. Methods based on Fourier transforms have a weakness in a spatial localization so they do not perform well. Gabor filters provide a means for better spatial localization, but their usefulness is limited in practice because there is usually no single filter resolution where one can localize a spatial structure in natural textures [9]. These methods involve transforming original images by using filters and calculating the energy of the transformed image. They are based on the process of the whole image that is not good for some applications which are based on one part of the input image. The examples of transform method are Fourier transform [31 – 33], Gabor filters [34 -40] and wavelet transform [41 – 43] etc.

III. CLASSIFICATION

Classification is one of the decision making task of human activity. A classification problem occurs when an object needs to be assigned in a predefined group or class based on a number of observed attributes related to that object. It concerns constructing a decision procedure based on a sequence of cases. The process of learning a classifier is usually supervised learning. Classification can be approached without machine learning.

3.1. k- Nearest Neighbors based Classifier

The nearest neighbor algorithm is one of the simplest classifier. It selects the training samples with the closest distance to the query sample. It computes the distance from the query sample to every training sample and selects the best neighbor or neighbors with the shortest distance. K numbers of best neighbors are selected and the winning class will be decided based on the best number of votes among the k neighbors [13]. It does not require a training process. The k NN algorithm is based on a distance function and a voting function in k - nearest neighbors, the metric employed is the Euclidean distance. The k nearest neighbor classier is a conventional nonparametric supervised classier. It consists of a training phase and a testing phase. In the training phase, data points are given in n-dimensional space. These training data points have labels associated with them that designate their class. In the testing phase, unlabeled data are given and the algorithm generates the list of the k nearest (already classified) data points to the unlabeled point. The algorithm then returns the class of the majority of that list [14]. It is useful when database is small and not effectively trained using other machine learning methods.

3. 2 Support Vector Machine

SVM is the new machine learning algorithm used in pattern recognition problems including texture classification. It is a binary classification method which is used to minimize structural risk. SVM is an attractive and systematic method for two class classification problems. It is designed to maximize the marginal distance between classes with decision boundaries drawn using different kernels [15, 16]. This is done by maximizing the margin from the hyper plane to the two classes. The samples closest to the margin that were selected to determine the hyper plane is known as support vectors. Various two class SVMs are used to build multiclass SVM. Multiclass classification can be obtained by using one vs.-all or one-vs.-one. The winning class is then determined by the highest output function or the maximum votes respectively. SVM has a strong mathematical base and strong, realistic ability. It takes intelligence from its training set to classify unknown data in testing phase. SVM is an excellent method for small training dataset and high dimensional feature space. It needs two preparation stages; training and testing stage. It trains itself by features given as an input to its learning algorithm. SVM chooses suitable margins between two classes during training resulting in effective classification.

3.3 Artificial Neural Network

An ANN is a mathematical or computational model consisting of a number of highly interconnected processing elements called neurons. These neurons are organized in layers. The neurons are connected with each other through links (connections). Each link is assigned a weight. A neuron also has an associated bias. The output of a neuron is the output of the activation function, the argument of this function is the sum of incoming signals multiplied with respective weights, plus the bias. Activation function is usually sigmoid. The geometry and functionality of neural network resemble the human brain. The basic form of ANN is the Multilayer Perceptron (MLP) which is a neural network that updates the weights through back-propagation during the training. The most frequently used training algorithm in classification problems is the back-propagation algorithm with the Levenberg–Marquardt learning rule. The neural network has been trained to adjust the connection weights and biases in order to produce the desired mapping. At the training stage, the feature vectors are applied as an input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship between the input patterns and outputs.

3.4 Classification Using Fuzzy Relational Calculus

This deals with the multidimensional fuzzy implication (MFI) the notion of a fuzzy pattern vector to represent a population of training patterns in the pattern space and to denote the antecedent part of the said particular interpretation of the MFI. A new method for computation of the derivative of the fuzzy max-function and min - function using the concept of a generalized function. During the construction of the classifier based on FRC, we use fuzzy linguistic statements (or fuzzy membership function) to represent the linguistic statement to represent the values of the features (e.g., feature 1 is small and 2 is big) for a population of patterns [44, 45]. Fuzzy relational calculus (FRC) is used to design pattern classifier, measurement of similarities and the multidimensional fuzzy implication (MFI). Fuzzy Pattern Vector is used to interpret MFI. The construction of the fuzzy classifier essentially depends on the estimate of a fuzzy relation between the input (fuzzy set) and output (fuzzy set) of the classifier. Once the classifier is constructed, the non fuzzy features of a pattern can be classified. At the time of classification of the non fuzzy features of the test patterns, it uses the concept of fuzzy masking to fuzzy the non fuzzy feature values of the test patterns. The performance of the proposed scheme is tested on synthetic data [46].

3.5 Genetic Algorithms

The genetic programming system is based on a linear chromosome which manipulates image processing programs [47]. It takes the raw pixel data planes and transforms them into a set of feature planes. This set of feature plans is in effect just a multi-spectral image of the same width and height as the input image, but perhaps having a different number of planes, and derived from the original image via a certain sequence of image processing operations. The system then applies a conventional supervised classification algorithm to the feature planes to produce a final output image plane, which specifies for each pixel in the image, whether that feature is there or not.

Different genes have different numbers of parameters, and each parameter is associated with a fixed set of attributes that determine such things as what range it is randomly initialized within when that gene is first created, what range of values it can possibly take, and how it is affected by the mutation. There are three kinds of parameters: 1) Float parameters are initialized to a random floating point number in the initialization range, and are mutated by a floating point offset that is Gaussian distributed with a standard deviation given by that parameter's delta attribute; 2) Integer parameters are initialized to a random integer in the initialization range, and are mutated by an integer offset that is uniformly distributed in a range given by plus or minus the delta attribute; 3) Symbolic parameters are like integers, but when mutated are simply re-initialized randomly. In general, genes produce output that is roughly on the order of the same scale as their input. Thus, by using GA a robust classifier is developed.

IV. TEXTURE DATABASE

There are a number of texture datasets that were used in experiments on texture classification. They are Brodatz, Vistex and Meastex.

Brodatz textures originate from a book called "Textures: A Photographic Album for Artists and Designers" published in 1966 [48]. The pictures in this book were taken by Phil Brodatz, a highly skilled professional photographer, whose original intention was not to produce a book for scientists. However, this album is very widely used in the texture analysis community and is widely used by researchers as their texture database. It is now a kind of de facto standard database in texture related research [49]. The textures in the Brodatz album are very diverse. They include beach sand, grass, canvas, cork, cloud and many other natural textures. Such diversity supports Brodatz textures as an important benchmark for evaluating texture analysis methods. There are 112 textures in the album, which were labeled by Phil Brodatz from D1 to D112. These textures all have names associated with them to describe their origins such as D1 as "Woven aluminum wire", D3 as "Reptile skin" and D108 as "Japanese rice paper".

Vistex was published by the Media Laboratory of Massachusetts Institute of Technology (MIT) in 1995, mainly for research and application development of image processing and computer vision [50]. This collection aims to "provide texture images that are representative of real world conditions". It contains 167 texture images with two formats 128 x 128 and 512 x 512, which have been semantically organized into several groups such as bark, buildings and paintings. Compared to Bordatz textures, Vistex images are less suitable for texture classification. Unlike Brodatz textures, "the images in Vistex do not conform to rigid frontal plane perspectives and studio lighting conditions", which brings in a large variety of scale, rotation, contrast and perspective? Moreover the semantic annotation in Vistex makes the classification task more difficult. For example, there are 13 paintings with different styles and different content which are treated as one class, if the classes are determined by the annotation. Such difficulties have been shown in the study of Guy [51], in which Brodatz textures generally had a higher classification accuracy of several methods than Vistex images. In short the images in Vistex might complicate the investigation of new method, especially when the main goal of the investigation is to develop the new method. Furthermore, the Brodatz album provides a much richer variety of textures while Vistex only has 19 texture categories.

Meastex is also well known, but less popular [52]. This database combines Brodatz textures and Vistex images, in addition to collecting some additional natural textures and artificial textures. For the same regions as Vistex, Meastex is less suitable in classification. So, the study only uses Brodatz textures.

V. CONCLUSION

In this paper, the trend of usage in the feature extraction methods, classification methods and texture datasets in the last few years is discovered. For the feature extraction methods, wavelet transforms and other signal processing methods are among the most popularly used feature extraction due to their promising accuracy. Surprisingly, old methods such as GLCM are still used but their implementations are improved or combined with other methods. In terms of the classification method, SVM has took over ANN as the most commonly used classifier which has also proven to be able to outperform the ANN in terms of accuracy. For the experimental datasets, variants of the Brodatz texture datasets remained to be the most popular benchmark dataset in the research of texture classification.

REFERENCES

[1] L. Lepisto, L. Kunttu, J. Autio, and A. Visa, "Rock Image Classification Using Non-Homogenous Textures and Spectral Imaging," WSCG, 2003.
[2] J.Y. Tou, Y.H. Tay, and P.Y. Lau, "A Comparative Study for Texture Classification Techniques on Wood Species Recognition Problem," ICNC, vol. 5, pp. 8-12, 2009.
[3] W.H. Yap, M. Khalid, and R. Yusof, "Face Verification with Gabor Representation and Support Vector Machines," AMS, pp. 451-459, 2007.

[4] Y.B. Salem, and S. Nasri, "Texture Classification of Woven Fabric Based on a GLCM Method and using Multiclass Support Vector Machine," SSD, 2009.

[5] J.A.R. Recio, L.A.R. Fernandez, and A. Fernandez-Sarria, "Use of Gabor Filters for Texture Classification of Digital Images," Física de la Tierra, no. 17, pp. 47-56, 2005.

[6] Haralick, R.M., "Statistical and Structural Approaches to Texture," Proceedings of the IEEE, 67, pp. 786-804, 1979.

[7] M. A. Fischler. Intelligence: the Eye, the Brain, AND the Computer. Addison – Wesley, 1987.

[8] A. R Rao. A taxonomy for Texture Description and Identification. Springer – Verlag, New York, 1990.

[9] Taun Anh Pham, "Optimization of texture feature extraction algorithm "master thesis, Delft University of Technology, 2010.

[10] L. Davis and A. Mitiche. Edge detection in textures. Computer Graphics and Image Processing, 12 (1): 25 – 39, January 1980.

[11] L. Ganesan and P. Bhattacharyya. Edge detection in untextured and textured images – a common computational framework. IEEE Transactions on Systems, Man and Cybernetics, 27(5): 823 – 834, October 1997.

[12] T. H. Hong, C. R. Dyer, and A. Rosenfeld. Texture primitive extraction using an edge based approach. IEEE transactions on Systems, Mn and Cybernetics, 10:659 – 675, 1980.

[13] M. Galloway. Texture analysis using gray level run lengths. Computer Graphics and Image Processing, 4: 172 – 179, 1975.

[14] A. Chu, C. M. Sehagal and J. F. Greenleaf. Use of gray value distribution of run lengths for texture analysis. Pattern Recognition Letters, 11:415 – 420, June 1990.

[25] B. R. Dasarathy and E. B.Holder. Image characterizations based on joint gray –level run – length distributions. Pattern Recognition Letters, 12:497 – 502, 1991.

[16] F. Albregtsen, B. Nielsen and H. Danielsen. Adaptive gray level run length features from class distance matrices. In Pattern Recognition, 2000. Proceedings. 15th International Conference on, volume 3, pages 738 – 741, 2000.

[17] X. Tang. Texture information in run – length matrices. Image Processing, IEEE Transactions on, 7(11) : 1602 – 1609, November 1998.

[18] Hong-ChoonOng, Hee-KooiKhoo,"Improved Image Texture Classification Using Grey Level Co-occurrence Probabilities with Support Vector Machines Post-Processing", European Journal of Scientific Research ISSN 1450-216X Vol.36 No.1 (2009), pp.56-64.

[19] R. M. Haralick, K. Shanmugan and I. Dinstein. Texture features for image classification. IEEE Transaction On Systems, Man and Cybernetics, SMC – 3(6): 610 – 621, November 1973.

[20] A. Baraldi and F. Parmiggiani. An investigation of the texture characteristics associated with gray level co - occurrence matrix statistical parameters. IEEE Transactions on Geoscience and Remote Sensing, 33(2): 293 – 304, March 1995.

[21] B. B. Mandelbrot. The Fractal Geometry of Nature. W. H. Freeman, New York, 1983.

[22] Q. Hang, J. Lorch and R. Dubes. Can the fractal dimention of images be measured? Pattern Recognition, 27(3): 339 – 349, March1994.

[23] A. P. Pentland. Fractal based description of natural scenes. IEEE Transactions on Pattern Analysis and Machine Intelligence, 6 (6): 661 – 674, 1984.

[24] H. Kaneko. A generalized fractal dimension and its application to texture analysis – fractal matrix model. In 1989 International Conference on Acoustic, Speech and Signal Processing, volume 3, pages 1711 – 1714, 1989.

[25] A. Ait – Kheddache and S. A. Rajala. Texture classification based on higher order fractals. In 1988 International Conference on Acoustic, Speech and Signal Processing, volume 2, pages 1112 – 1115, 1988.

[26] T. Kasparis, N. S. Tzannes, M. Bassiouni and Q. Chen. Texture description using fractal and energy features. Computers and Electrical Engineering, 21 (1): 21 – 32, January 1995.

[27] G. R. Cross and A. K. Jain. Markov random field texture methods. IEEE Transaction on Pattern Anlysis and Machine Intelligence, PAMI – 2(3): 201 – 221, May1983.

[28] M. Hassner and J. Sklansky. The use of markov randon fields as modles of texture.Computer Graphics and Image Processing, 12:357 – 370, 1980.

[29] S. Z. Li. Markov Random Field Modeling in Image Analysis. Springer, 2001.

[30] R. Chellapa and S. Chattergee. Classification of textures using Gaussisn markov random fields. IEEE Transactions on Acoustics, Speech and Signal Processing, 33(4):959 – 963, August 1985.

[31] J. O. Eklundh. On the use of Fourier features for texture discrimination. Computer Graphics and Image Processing, 9: 199 – 201, 1979.

[32] D. Gibson and P.A. Gaydecki. Definition and application of a Fourier domain texture measure: application to histological image segmentation. Computers in Biology and Medicine, 25(6): 551 -557, November1995.

[33] D. D. Day and D. Rogers. Fourier based texture measures with application to the analysis of the cell structure of backed products. Digital Signal Processing, 6 (3): 138 – 144, July 1996.

[34] M. R. Turner. Texture discrimination by gabor functions. Biological Cybernetics, 55(2-3):71 – 82, November 1986.

[35] C.C. Chen and D.C. Chen. Multi resolution Gabor filter in texture analysis. Pattern Recognition Letters, 17(10):1069 – 1076, September 1996.

[36] S. Grigorescu, N. Petkov and P. Kruizinga. Comparison of texture features based on gabor filters. Image Processing, IEEE Transactions on, 11(10):1160 – 1167, October 2002.

[37] A. Jain and F. Farrokhnia. Unsupervised texture segmentation using gabor filters. In Systems, Man and Cybernetics, 1990. Conference Proceedings, IEEE International Conference on, pages 14 – 19, 1990.

[38] D. K. L.C. Mittal, N.:Mital. Features for texture segmentation using Gabor filters. In Image Processing and its Applications, 1999. Seventh International Conference on, volume 1, pages 353 – 357, 1999.

[39] C. Setchell and N. Campbell. Using colour gabor texture features for scene understanding. In image processing and Its applications, 1999. Seventh International Conference on , volume 1, pages 372 – 376, 1999.

[40] M. Lyons, J. Budynek, A. Plante and S. Akamastu. Classifying facial attributes using a 2- D Gabor wavelet representation and discriminate analysis. In Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on, pages 202 – 207, 2000.

[41] S. G. Mallat, "A Theory of Multiresolution Signal Decomposition: The Wavelet Representation," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, 1980, pp. 674-693.

[42] R. C. Gonzalez and R. E. Woods, "Wavelet and Multiresolution Processing," In: Digital Image Processing, 2nd Edition, Pearson Education, Upper Saddle River, 2004, pp. 349-408.

[43] S. Chaplot, L. M. Patnaik and N. R. Jagannathan, "Classification of Magnetic Resonance Brain Images Using Wavelets as Input to Support Vector Machine and Neural Network," Biomedical Signal Processing and Control, Vol. 1, No. 1, 2006, pp. 86-92.

[44] Kumar S. Ray and Tapan K. Dinda, "Pattern Classification Using Fuzzy Relational Calculus," IEEE Transactions On System, Man and Cybernetics, Vol. 33 No.1 Feb 2003 pp.

[45] Yixin chen, James Ze Wang and Robert Krovetz, "CLUE: Cluster based Retrieval of Images by Unsupervised Learning," IEEE transaction on Image Processing, vol. 14, No 8, pp. 1187-1190, Aug 2005.

[46] Kumar S. Ray and Tapan K. Dinda, "Pattern Classification Using Fuzzy Relational Calculus," IEEE Transactions On System, Man and Cybernetics, Vol. 33 No.1 Feb 2003 pp.

[47] W. Banzhaf, P. Nordin, R. E. Keller, and F. D. Francone, Genetic Programming: An Introduction, Morgan Kaufmann, San Francisco, CA, 1998.

[48] P. Brodatz. Textures: A Photographic Album for Artists and Designers. Dover, NY, 1996.

[49] R. Picard, T. Kabir and F. Liu. Real time recognition with the entire Brodtaz texture database. In Computer Vision and Pattern Recognition, 1993. Proceedings CVPR '93, 1993 ieee Computer Society Conference on, pages 638 – 639, 1993.

[50] Vistex texture dataase, 1995. Maintained by the Vision and Modeling group at the MIT Media Laboratory.
http://www–white.mit.edu/vismod/imagery/Vision.Texture/vistex.html.

[51] G. Smith and I. Burns. Measuring texture classification algorithms. Pattern Recognition Letters, 18 (14): 1495 – 1501, December 1997.

[52] Meastex texture database, 1997. Center for Sensor Signal and Information Processing (CSSIP) at The University of Queensland.
http://www.cssip.uq.edu.au/staff/meastex/www/for_images.html.