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A SURVEY OF TEXTURE CLASSIFICATION USING RECENT TECHNOLOGY

Keerthana.A.V[#1], Ashwin M[*2]

[#1]PG Scholar ME-Computer science and Engineering Final year,
Adhiyamaan College of Engineering
Krishnagiri, Tamil Nadu, India
[1] keerthana.be12@gmail.com
[*2]Associate Professor
Adhiyamaan College of Engineering
Krishnagiri, Tamil Nadu, India

ABSTRACT: This paper attempts in exploring the survey of various methodology for Texture classification. Now-a-days due to high availability of computing facilities, large amount of data in electronic form is generated. The data generated is to be analyzed so as to maximize the benefits, for intelligent decision making. If the data generated is in the structured form then large amount of work in analyzing such structured data is available. The survey has taken for statistical approach for learning joint distribution of filter responses for image distribution mapping, texton distribution and comparing the distribution by learnt models in classification. Then Feature extraction stage for set of small random feature are extracted from local image patches, here bag of words are used to perform texture classification. It is focused on binary images texture pattern and investigate a class of texture descriptor that characterize the probability of occurrence of the patterns associated to the neighbourhood of given size and shape. HEP(Histogram of equivalent patterns) combine the CLBP(Completed Local Binary Patterns) and ILTP(Improved Local Ternary Patterns).When texture analysis history has algorithm range from random field models to multi-resolution representation based on Gabor filters. Next survey says Noise Resistant LBP(NR-LBP) and Extended Noise Resistant LBP(ENRLBP)is used to reduce the noise. Finally the survey says BRINT texture classification is better than all other classification. So BRINT Texture Classification can be used for Snake Texture classification and for future work it can be at Face Recognition.

Keywords: Completed Local Binary Patterns, Extended Noise Resistant Local Binary Patterns, Histogram of equivalent patterns, Noise Resistant Local Binary Patterns, and Improved Local Ternary Patterns.

1. INTRODUCTION

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. In a (8-bit) grayscale image each picture element has an assigned intensity that ranges from 0 to 255. A gray scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey. A normal grayscale image has 8 bit colour depth = 256 grayscales. A "true colour" image has 24 bit colour depth = 8 x 8 x 8 bits = 256 x 256 x 256 colours = ~16 million colours.Some grayscale images have more greyscales, for instance 16 bit = 65536 greyscales. In principle three greyscale images can be combined to form an image with 281,474,976,710,656 greyscales.

There are two general groups of 'images': vector graphics (or line art) and bitmaps (pixel-based or 'images').Some of the most common file formats are: 1.)GIF — an 8-bit (256 colour), non-destructively compressed bitmap format. Mostly used for web. Has several sub-standards one of which is the animated GIF. 2.)JPEG — a very efficient (i.e. much information per byte) destructively compressed 24 bit (16 million colours) bitmap format. Widely used, especially for web and Internet (bandwidth-limited). 3.)TIFF — the standard 24 bit publication bitmap format. Compresses non-destructively with, for instance, Lempel-Ziv-Welch (LZW) compression. 4.)PS — Postscript, a standard vector format. Has numerous sub-standards and can be difficult to transport across platforms and operating systems. 5.)PSD – a dedicated Photoshop format that keeps all the information in an image including all the layers.

Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter relationships between objects. They portray spatial information that we can recognize as objects. Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form. An image is digitized to convert it to a form which can be stored in a computer's memory or on some form of storage media such as a hard disk or CD-ROM. This digitization procedure can be done by a scanner, or by a video camera connected to a frame grabber board in a computer. Once the image has been digitized, it can be operated upon by various image processing operations.

1.1 IMAGE PROCESSING

Image processing operations can be roughly divided into three major categories, Image Compression, Image Enhancement and Restoration, and Measurement Extraction. It involves reducing the amount of memory needed to store a digital image. Image defects which could be caused by the digitization process or by faults in the imaging set-up (for example, bad lighting) can be corrected using Image Enhancement techniques. Once the image is in good condition, the Measurement Extraction operations can be used to obtain useful information from the image. Some examples of Image Enhancement and Measurement Extraction are given below. The examples shown all operate on 256 grey-scale images. This means that each pixel in the image is stored as a number between 0 to 255, where 0 represents a black pixel, 255 represents a white pixel and values in-between represent shades of grey. These operations can be extended to operate on colour images. The examples below represent only a few of the many techniques available for operating on images. Details about the inner workings of the operations have not been given, but some references to books containing this information are given at the end for the interested reader.

1.2 PIXEL

In order for any digital computer processing to be carried out on an image, it must first be stored within the computer in a suitable form that can be manipulated by a computer program. The most practical way of doing this is to divide the image up into a collection of discrete (and usually small) cells, which are known as *pixels*. Most commonly, the image is divided up into a rectangular grid of pixels, so that each pixel is itself a small rectangle. Once this has been done, each pixel is given a pixel value that represents the color of that pixel. It is assumed that the whole pixel is the same color, and so any color variation that did exist within the area of the pixel before the image was discretized is lost. However, if the area of each pixel is very small, then the discrete nature of the image is often not visible to the human eye.

Other pixel shapes and formations can be used, most notably the hexagonal grid, in which each pixel is a small hexagon. This has some advantages in image processing, including the fact that pixel connectivity is less ambiguously defined than with a square grid, but hexagonal grids are not widely used. Part of the reason is that many image capture systems (*e.g.* most CCD cameras and scanners) intrinsically discretize the captured image into a rectangular grid in the first instance.

1.3 CLASSIFICATION

Classification refers to as assigning a physical object or incident into one of a set of predefined categories. In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes. Texture classification is one of the four problem domains in the field of texture analysis. The other three are texture segmentation (partitioning of an image into regions which have homogeneous properties with respect to texture; supervised texture segmentation with a priori knowledge of textures to be separated simplifies to texture classification),[18] texture synthesis (the goal is to build a model of image texture, which can then be used for generating the texture) and shape from texture (a 2D image is considered to be a projection of a 3D scene and apparent texture distortions in the 2D image are used to estimate surface orientations in the 3D scene).

1.4 TEXTURE ANALYSIS

Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. A successful classification or segmentation requires an efficient description of image texture. Important applications include industrial and biomedical surface inspection[1], for example for defects and disease, ground classification and segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases. However, despite many potential areas of application for texture analysis in industry there is only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high.

1.5 TEXTURE CLASSIFICATION

Texture classification process involves two phases: the learning phase and the recognition phase. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image.

These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images,[1] such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match. Optionally, if the best match is not sufficiently good according to some predefined criteria, the unknown sample can be rejected instead.

2. LITERATURE SURVEY

Manic et al [1] proposed the investigation for texture classification from single images obtained under unknown viewpoint and illumination. Texture classification use joint probability distribution to modelled the texture for filter responses. Hence superior performance is achieved by filter and methods using malik[11] through comparison of classification performance. The Utercht texture database present the classification by primarily function for texture image to be followed by texture surface, its albedo, the illumination ,camera and its viewing position. If the parameters kept at fixed position may be minor changes is made and solve through classification algorithm. The statistical approach for learning joint distribution of filter responses for image distribution mapping, texton distribution and comparing the distribution by learnt models in classification. It can classify by the two ways 1.) In low dimensional , rotation invariant and texture clustering is done, 2.) small set off models has been represented by each class texture. To reduce the number of models in classification we are using many machine learning technique nearest neighbour classifier then it remove each models neighbour belongs to the same class. Advantages: Maximize the classifier accuracy and reduce the number of models. Drawback: No significant scale changes.

Li Liu et al [2] says a novel and simple approach for texture classification based on compressed sensing, suitable for large texture database application. Feature extraction stage, set of small random feature are extracted from local image patches, here bag of words performed for texture classification. Issues in computer vision and image processing, which has a major role in medical image analysis, remote sensing, object recognition and content based image retrieval. Texture classification design has been performed by feature extraction and classification. Survey of texture feature extraction through the methods[1],gray level co-occurence histogram[1],markov random fields[1],gray level Aura histogram[1] ,LBP[1], gabor filter banks, wavelet and fractal models. Its choose the low dimensionality of the source of image patch. Extracting features from local patch focus on local texture information characterized by gray level pattern of pixels in surroundings. Here Bag of words model is used to encodes the local texture information by using features from local patches to form textons and global texture appearance, then statistically computing an orderless histogram to represent the frequency of the textons repetition. There are two ways to construct textons: 1.) Detecting a sparse set of points in a given image. 2.)Densely extracting local features pixel by pixel over the input image. Disadvantages: Irrelevant and noisy features and High dimensions on data may be very sparse. Advantages: Reduced storage requirements and Reduced computational complexity through low dimensional feature.

Manic et al [3] classification materials from their appearance in single images taken under unknown view point and illumination condition, here the task is made more challenging because it has no prior knowledge about the imaging conditions is available. Texture classification is focused on binary images texture pattern , then evolved to classification of 2D variations by grayscale images at third classification problems of classifying real-world textures with 3D variations by the camera-position. VZ algorithm gives the best 3D texture classification result on Columbia ultrecht database(CUReT). Its has level of difficulty for single image classification. The database has 61 materials to classify and each of the material in the database has been imagedunder 205 different viewing and illumination conditions, then it achieve the classifier performance.

B.S.Manju et al [4] concentrate on browsing and retrival of picturial data. In some cases face or texture features are ambiguous, so we are taking texture image feature for pattern retrieval. Consider a mosaic different texture regions and image for search and retrieval. Texture analysis history has algorithm range from random field models to multi-resolution representation based on Gabor filters[12][13].Gabor filter is used in extracting image features in various factor like optimal the sense of minimizing the joint 2D uncertainity in space and frequency[10].Main contributions of this paper is 1.) A simple texture feature representation based on Gabor fiter features to reduce the redundancy,2.)An adaptive filer selection algorithm is proposed for fast image browsing. 3.)The performance can be compared through other Multi-scale texture feature for feature computation and retrieval accuracy and 4.)for browse a air photos.

Anto et al [5] texture analysis plays a important role in many applications like computer-assisted diagnosis, remote sensing, surface grading, defect detection and food inspection. The challenging tasks for many textures. This paper investigate a class of texture descriptor that characterize the probability of occurrence of the patterns associated to the neighbourhood of given size and shape.HEP(Histogram of equivalent patterns) combine the CLBP(completed local binary patterns) and ILTP(Improved Local Ternary patterns).HEP renown methods for texture spectrum,Local binary pattern and Co-occurence matrices and variations of the same underlying idea a texture analysis between unlearnt and learnt feature system. Texture images has single type of textud through the probability distribution [14] can be characterize of gray scale possible instance of neighbourhood. some elements use bag-of-words to prove highly descriptive class[15] of texture. Here probability could be estimated by the frequency of occurrence measured through a histogram by the gray-scale patterns. This approach is straight forward application for impractical for small neighbourhoods. Advantages: Higher effectiveness, higher accuracy, Increasing performance withincreasing dimensionality and better performance for point-to- average and point-to-point thresolding.

Marko et al [6] proposed a Center Symmetric Local binary pattern (CS-LBP) by SIFT and LBP. CS-LBP is a local feature for SIFT algorithm, it detect the interest region for class of transformation co-variant and built a invariant Descriptor then it compare the interest region with image. It uses different image properties for detection of region descriptor like pixel intensite, color, texture and edges. for interest region descriptor many use distributed based histogram for various characteristics like size and shape. For 2D-histogram distance, dimensions from center point and intensity value. SIFT is used for 3D histogram of gradiant locations and its uses gradient and Magnitude for originate the bin weight.SIFT Descriptor reduce the sizeand large dimensional for reliable descriptor[16].CS-LBP has combine both SIFT and LBP good features and properties to robustness. Advantages: Tolerant to illumination changes ,Perspective Distortions for image blur and image zoom and very robust. Drawbacks: Long histogram is produced and not too robust for flat image.

Jianf et al [7] proposed a Local Binary Pattern(LBP) to transform an image into an array. This pattern formed by pixel and its immediate neighbour. LBP encodes the sign of the pixel by difference between pixel and its neighbouring pixels to a binary code. LBP is sensitivity to noise so uniform LBP is used to reduce the noise. The LBP code are defined by uniform pattern otherwise non-uniform patterns. Uniform patterns are mapped on one separate histogram bin and all other non-uniform patterns are mapped in single bin, moreover uniform patterns are used for reliable pattern. Non-uniform patterns are used when Random Subspace approach to reduce noise. Here LTP is used to reduce dimensionality by spilt the LBP into positive and negative approach. But it only solve partially, So Noise Resistant LBP(NR-LBP) and Extended Noise Resistant LBP(ENRLBP)is used to reduce the noise. Advantages: 1.)The exact intensities are discarded and only the relative intensities with respect to center are presented then LBP is less sensitive to illumination variations. 2.) Extracting the histogram of micropatterns in a patch, the exact location information is discarded and only the patch-wise location information is presented.3.)LBP features can be extracted efficiently ,which enables real-time image analysis.

Barb et al [8] proposed the challenging tasks to get materials recognition through the visual texture. It can be used in robotic tasks, so robust recognition algorithm can be used to recognize the materials from a variety of poses and with different illumination conditions by

Curet database. This classification performance can be determine through robust feature descriptors. Issue: 1.) Robustness to scale changes: Different variations and illumination changes in visual appearance of material distance. 2.) Generalization across material samples: Different sample of same material will give single piece of material, but it needs many materials samples for practical application. The objective is to bring material recognization algorithm at closer 1.) Robustness to scale variation by State-of-art algorithms are very sensitive to scaling effects and classification accuracy degrades. Then pure-learning approach based on Support Vector Machine algorithm Features are used in the absence of local minima by the kernel for sparseness of the solution and capacity control to optimizing margin. The SVM for real-world application can be obtained by CUReT database several kernel types and comparing with Varma-Zisser algorithm. The variation in scaling during training samples at different illumination and pose. To sufficient scaling comparing the nearest neighbour through classification scheme.

Loris et al [9] proposed the image technology needs by large database of digital images for new classification problems. This is particular in medical images and face classification. To prove the experts untraveling causes and progress of many disease that are currently poor understanding. They have demonstracted the machine system to detect some disease through the facial expression and structure of face recognition system applied to medical diagnosis to do in research. many methods can be used to search image database and classify faces by texture-based descriptor by LBP to take State-of-art among descriptor.Some property of LBP: It has proven to be powerful discriminator is low in computational complexity and less sensitive to changes in illumination. LBP is very resistant to lighting changes,some research using LBP in novel search and retrival method for finding relevant slices in brain MR volumes. LBP will extract the image and SVM will classify the textural features . Here LBP uses a misro pattern to derive by binary gradiant directins. Histogram of micropattern uses both uniform and non uniform patterns. Mostly unifrom patterns are used to extract features but in this paper we use non uniform patterns it has high dimensionality and introduce new noise. To improve the performance we combine both uniform and non uniform patterns. non uniform pattern use Random subspace classifier to handling noise , correlation and the dimensionality.

Li Liu et al [17] proposed Binary Rotation Invariant and Noise Tolerant(BRINT) Texture descriptor its easy to implement, yet computationally efficient, noise robust, multi-resolution descriptor BRINT to gray scale and rotation invariant texture classification based on Local Binary Pattern(LBP). Methodology used here is BRINT_C, BRINT_S and BRINT_M based on approach. Advantages: Fast to build, robust to noise, increasing the feature distinctiveness, invariant to illumination and rotation changes. Drawbacks: Rapid increase of feature dimensionality.

3. CONCLUSION

The more recent descriptors have been proved in some measures of image texture [17] However, they have also been shown to have serious limitations including the instability of the uniform patterns, the lack of noise robustness, the inability to encode a large number of different local neighborhoods, an incapability to cope with large local neighborhoods, and high dimensionality (CLBP). In order to avoid these problems, we have presented BRINT, a theoretically and computationally simple, noise tolerant yet highly effective multi-resolution descriptor for rotation invariant texture classification. The BRINT descriptor is shown to exhibit very good performance on popular benchmark texture databases under both normal conditions and noise conditions.

The main contributions is in the development of a novel and simple strategy — circular averaging before binarization — to compute a local binary descriptor based on the conventional LBP approach. The BRINT approach firmly puts rotation invariant binary patterns back on the map, after they were shown to be very ineffective in [17]. Since the key advantage of the traditional LBP approach has been its computational simplicity, in our opinion a complicated or computationally expensive LBP variant violates the whole premise of the LBP idea. So BRINT is firmly consistent with the goal of simplicity and efficiency.

The BRINT descriptor is noise robust, in contrast to the noise sensitivity of the traditional LBP and its many variants. Furthermore the idea can be generalized and integrated with existing LBP variants, such as conventional LBP, rotation invariant patterns, rotation invariant uniform patterns, CLBP, Local Ternary Patterns (LTP) and to derive new image features for texture classification. This noise robustness characteristic is evaluated quantitatively with different artificially generated types and levels of noise (including Gaussian, salt and pepper and multiplicative noise) in natural texture images. The BRINT approach is to produce consistently good classification results on all of the datasets, most significantly outperforming the state-of-the-art methods in high noise conditions. The current work has focused on texture classification. Future work can be focused on different texture classification (snake) face recognition and object recognition.

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A.V Keerthana B.E Degree (first class with honour) in Computer Science and Engineering, Paavai Engineering College, Nammakkal, Tamilnadu in 2012,where she is pursuing the M.E Degree . she is currently visiting student at Adhiyamaan College of Engineering , Krishnagiri, Tamil nadu. She has a membership in Computer Society of India. Her current interest in Texture classification and Image processing.

M. Ashwin B.E Degree in Computer Science and Engineering, Adiyamaan College of Engineering ,Krishnagiri, Tamilnadu at 2004 , M.E Degree at Jayam College of Technology , Dharmapuri, Tamil nadu at 2007. He is working as Associate professor from 2008 at Adiyamaan College of Engineering ,Krishnagiri, Tamilnadu. He is currently pursuing the Ph.D in Adhoc Networks at Anna University Chennai. His current interest is in Adhoc networks.