Survey On Image Texture Classification Techniques

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Abstract

Recent advances in digital imaging technology, computational speed, storage capacity and networking have made it possible to capture, manipulate, store, and transmit images at interactive speeds with equipment available at every home or business. As a result, images have become a dominant part of information exchange. They are used for entertainment, education, commerce, medicine, science, and other applications. The rapid accumulation of large collections of digital images has created the need for efficient and intelligent schemes for image classification. Texture is an important feature of objects in an image .Nowadays there has been a great interest in the development of texture based Image Classification methods in many different areas. Most of the image texture classification systems use the gray-level co-occurrence matrices (GLCM) and self-organizing map (SOM) methods. The GLCM is a matrix of how often different combinations of pixel brightness values (grey levels) occur in an image. The GLCM matrices extracted from an image database are processed to create the training data set for a SOM neural network. The SOM model organizes and extracts prototypes from processed GLCM matrices.

Keywords: *Grey Level Co-occurrence matrices (GLCM), Self Organizing map(SOM).*

1. Introduction

Texture classification is a fundamental problem in computer vision with a wide variety of applications. Two fundamental issues in texture classification are how to characterize textures using derived features and how to define a robust distance/similarity measure between textures, which remain elusive despite considerable efforts in the literature. Because images of the same underlying texture can vary significantly, textural features must be invariant to (large) image variations and at the same time sensitive to intrinsic spatial structures that define textures.

Texture is an important feature of objects in an image. The perception of texture is believed to play an important role in the human visual system for recognition and interpretation. There has been a great interest in the development of texture based pattern recognition methods in many different areas, especially in the areas of industrial automation, remote sensing and medical diagnosis. Texture classification passes through the difficult step of texture representation or description. What is seen as a relatively easy task to the human observer becomes a difficult challenge when the analysis is made by a computational algorithm. How can we copy the human brain in its capability to analyze, classify and recognize textures? Putting aside these questions about human brain workings, and focusing mainly on the necessity of how to describe a texture from its content, different approaches and models have been proposed [1].

1.1 Artificial Neural Network in Texture Classification

ANN is a parallel distributed processor that has a natural tendency for storing experiential knowledge. They can provide suitable solutions for problems, which are generally characterized by non-linear ties, high dimensionality noisy, complex, imprecise, and imperfect or error prone sensor data, and lack of a clearly stated mathematical solution or algorithm. A key benefit of neural networks is that a model of the system can be built from the available data. Image classification using neural networks is done by texture feature extraction and then applying the back propagation algorithm.

Texture is characterized by the spatial distribution of gray levels in a neighbourhood. In texture classification the aim is to assign an unknown sample image to one of set of known texture classes. Textural features are scalar numbers, discrete histograms or empirical distributions. In the design four textural features namely the angular second moment, contrast, correlation and variance are considered. Texture and tone have an inexpressible relationship to one another. They are always present in an image, although on occasion one property can overlook the other. In order to capture the spatial dependence of gray-level values, which contribute to the perception of texture, a two dimensional dependence, and texture analysis matrix is considered. Since, texture shows its characteristics by both pixel and pixel values, there are many approaches used for texture classification [2].

2. Literature Survey

There are a lot of researches in the way of visual features extraction: for example texture has been considered as one of the most important features that refer to natural relationship between objects and theirs environment in an image [3]. Several authors have worked in finding descriptors and features for texture identification. Existing features and techniques for modelling textures include Bidirectional Texture Function(BTF), a sampled 6D data structure parameterized by position (x,y) as well as light (wi) and view (wo) direction: b(x,y;wi,wo). Essentially, BTFs are textures that vary with view and light direction and are acquired by taking photographs of a material under many view/light configurations. Kautz et al. introduced a set of editing operators that enable the manipulation of view and light-dependent BTF effects. For effective editing, these operators can be restricted to work on subsets of the BTF, e.g., shadow areas, using selections. A current major limitation of BTFs is that the user is limited to the measured data and cannot easily modify the material appearance[4].

Zhao and Pietikainen have proposed a novel, theoretically and computationally simple approach in which dynamic textures are modeled using Local binary patterns(LBP) in three orthonormal planes within a volume. The texture features extracted in a small local neighborhood from three planes not only reflect the spatial-temporal features, but also are robust with respect to illumination changes.The key problem of dynamic texture recognition is how to combine motion features with appearance features. To address this, a recently proposed method is the volume LBP method (VLBP). But with the increase in the number of neighboring points, the number of patterns for basic VLBP will become very large. Due to this fast increase it is difficult to extend VLBP to have a large number of neighboring points, which limits its applicability [5].

Varma and Zisserman investigated the classification from single images obtained under unknown view point and illumination [6]. Some invariant feature descriptors such as Zernike moments among these, Haralick features are the most widely used [7]. In his work, Haralick et. al suggested the use of Gray-tone Spatial-dependence matrices also called Gray-level co-occurrence matrices(GLCM) to extract texture features from an image. Since then, GLCMs became widely used for image texture features extraction in many types of applications [8]. The benchmark data set called Brodatz database is considered [9].

Arnold et al. have proposed texture representation that includes Wavelet transform, Markovian analysis, Geometrical method, Statistical method, and methods derived from them [10] [11]. Gabor wavelet proves to be very useful texture analysis and is widely adopted to extract texture features from the images for image retrieval and has been shown to be very efficient. Manjunath and Ma have shown that image retrieval using Gabor features outperforms that using pyramid-structured wavelet transform (PWT) features, Tree-structured wavelet transform(TWT) features and multiresolution simultaneous autoregressive model (MR-SAR) features [12].

Zhang et al. proposed energy distribution, mean, and standard deviation extracted from Gabor filtered image as texture features. Than the texture vector shifted circularly to be normalized so that the element by Dominate Direction1 to be the first element. In result all images that have a same texture by deferent orientation have a same feature vector; this method is more useful for images that main part of them has a regular surface [13]. William et al. proposed texture representation has been done by employing some steerable filters to achieve scale and rotation invariant texture representation [14]. Oriented filters are used in many vision and image processing tasks, such as texture analysis, edge detection, image data compression, motion analysis and image enhancement. Guang-Hai Liu et al. used the spatial correlation of Textons to characterize the relationships between neighbouring pixels and extraction texture features energy, contrast, entropy and homogeneity. This procedure is powerful to detect texture features. Color is another important visual feature that is an agent for differences between images. It is true to say that color toward other visual features such as shape and texture, carryout more visual data [15] [16].

Yong et al. proposed the approaches that used to measure color feature, and L1- metric and L2-relative metric are the similarity measures for the color histogram [17]. The methods proposed by Yang et al. extract the RGB color space and divide it into eight sub-regions. Each sub-region is represented by a color percentage, and if a color percentage of the sub- region is less than a threshold then it is merged by nearest region with same color agents. In this approach, color similarity between two images have two phase: first , comparing each color of the input image by all color of the other images to detect the nearest color, then comparing theirs percentages. According to the quantity of each color component, the RGB color space is uniformly divided into 8 coarse partitions[18].

3. Methodology

In the proposed system for texture classification we will use Grey level co-occurrence matrices(GLCM) to extract the texture features from the image and then Self organizing maps are used for the classification of image textures[1].

3.1 Statistical Methods of Texture Analysis

Since texture is a spatial property, a simple one-dimensional histogram is not useful in characterizing texture (for example, an image in which pixels alternate from black to white in a checkerboard fashion will have the same histogram as an image in which the top half is black and the bottom half is white). In order to capture the spatial dependence of gray-level values which contribute to the perception of texture, a two-dimensional dependence matrix known as a gray-level co-occurrence matrix is extensively used in texture analysis.

3.2 The Grey Level Co-occurrence Matrix

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

Gray level co occurrence matrix (GLCM) is the basis for the Haralick texture features. This matrix is square with dimension *Ng*, where *Ng* is the number of gray levels in the image. Element [*i*,*j*] of the matrix is generated by counting the number of times a pixel with value *i* is adjacent to a pixel with value *j* and then dividing the entire matrix by the total number of such comparisons made. Each entry is therefore considered to be the probability that a pixel with value *i* will be found adjacent to a pixel of value *j*.

$$G = \begin{matrix} p(1,1) & p(1,2) & .... & p(1,N_g) \\ p(2,1) & p(2,2) & ... & p(2,N_g) \\ . & . & ... & . \\ . & . & ... & . \\ p(N_g,1) & p(N_g,2) & ... & p(N_g,N_g) \end{matrix} \quad ------ \quad (1)$$

GLCM (also called the Grey Tone Spatial Dependency Matrix) is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. Grey-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since they were proposed by Haralick in the 1970s.The GLCM described here is used for a series of "second order" texture calculations. First order texture measures are statistics calculated from the original image values, like variance, and do not consider pixel neighbor relationships. Second order measures consider the relationship between groups of two (usually neighboring) pixels in the original image. Third and higher order textures (considering the relationships among three or more pixels) are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. There has been some recent development of a more efficient way to calculate third-order textures.

GLCM texture considers the relation between two pixels at a time, called the reference and the neighbour pixel. The texture calculations require a symmetrical matrix. The next step is therefore to get the GLCM into this form. A symmetrical matrix means that the same values occur in cells on opposite sides of the diagonal.

3.3 Kohonen Self Organising Feature Maps (SOM)

Kohonen Self Organising Feature Maps (SOM) were invented by a man named Teuvo Kohonen, a professor of the Academy of Finland, and they provide a way of representing multidimensional data in much lower dimensional spaces - usually one or two dimensions. This process, of reducing the dimensionality of vectors, is essentially a data compression technique known as *vector quantisation*. In addition, the Kohonen technique creates a network that stores information in such a way that any topological relationships within the training set are maintained.

The principal goal of an SOM is to transform an incoming signal pattern of arbitrary dimension into a one or two dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion. Therefore SOM can be set up by placing neurons at the nodes of a one or two dimensional lattice. Higher dimensional maps are also possible, but not so common. The neurons become selectively tuned to various input patterns (stimuli) or classes of input patterns during the course of the competitive learning. The locations of the neurons so tuned (i.e. the winning neurons) become ordered and a meaningful coordinate system for the input features is created on the lattice. The SOM thus forms the required topographic map of the input patterns. The self-organization process involves four major components:

Initialization: All the connection weights are initialized with small random values.

Competition: For each input pattern, the neurons compute their respective values of a discriminant function which provides the basis for competition. The particular neuron with the smallest value of the discriminant function is declared the winner.

Cooperation: The winning neuron determines the spatial location of a topological neighbourhood of excited neurons, thereby providing the basis for cooperation among neighbouring neurons.

Adaptation: The excited neurons decrease their individual values of the discriminant function in relation to the input pattern through suitable adjustment of the associated connection weights, such that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced.

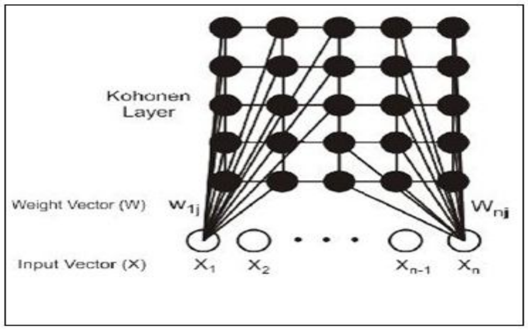

Figure 1: SOM Neural Network Architecture

3.4 Learning Algorithm Overview

A SOM does not need a target output to be specified unlike many other types of network. Instead, where the node weights match the input vector, that area of the lattice is selectively optimized to more closely resemble the data for the class the input vector is a member of. From an initial distribution of random weights, and over many iterations, the SOM eventually settles into a map of stable zones. Each zone is effectively a feature classifier, so you can think of the graphical output as a type of feature map of the input space. If you take another look at the trained network shown in figure 1, the blocks of similar colour represent the individual zones. Any new, previously unseen input vectors presented to the network will stimulate nodes in the zone with similar weight vectors[19].

Training occurs in several steps and over many iterations:

1. Each node's weights are initialized.
2. A vector is chosen at random from the set of training data and presented to the lattice.
3. Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).
4. The radius of the neighbourhood of the BMU is now calculated. This is a value that starts large, typically set to the 'radius' of the lattice, but diminishes each time-step. Any nodes found within this radius are deemed to be inside the BMU's neighbourhood.
5. Each neighbouring node's (the nodes found in step 4) weights are adjusted to make them more like the input vector. The closer a node is to the BMU, the more its weights get altered.
6. Repeat step 2 for N iterations.

4. Conclusion

The research shows that the GLCM method and Self organizing maps can be effectively used in image texture classification system .The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. The GLCM can be used for gathering vector information. The SOM model can be used to group similar image texture and to extract prototypes for each group. A novel strategy to classification by searching through prototypes is used in the proposed system.

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