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MODELING TEXT RECOGNITION IN IMAGES

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Abstract
Computer Vision and its applications are the core of industry digitization which is known as industry . For automating a process, texts embedded in images are considered as good source of information about that object. Reading text from natural images is still a challenging problem because of complicated background, size and space variations, irregular arrangements of texts. Detection and Recognition are the main stages of reading texts in the wild. In last few years, many researchers have provided many methods for recognizing texts in images. These methods have fine results on horizontal texts only but not on irregular arrangements of texts.

Keywords: Reading, information, horizontal, model, perspective detection, text recognition in imagine, Texture classification, Feature extraction.

Introduction

Tactile texture refers to the tangible feel of a surface and visual texture refers to see the shape or contents of the image. In the image processing, the texture can be defined as a function of spatial variation of the brightness intensity of the pixels. Texture is the main term used to define objects or concepts of a given image. Texture analysis plays an important role in computer vision cases such as object recognition, surface defect detection, pattern recognition, medical image analysis, etc. Since now many approaches have been proposed to describe texture images accurately. Texture analysis methods usually are classified into four categories: statistical methods, structural, model-based and transform- based methods. This paper discusses the various methods used for texture or analysis in details. New researches shows the power of combinational methods for texture analysis, which can't be in specific category. This paper provides a review on well known combinational methods in a specific section with details. This paper counts advantages and disadvantages of well-known texture image descriptors in the result part. Main focus in all of the survived methods is on discrimination performance, computational complexity and resistance to challenges such as noise, rotation, etc. A brief review is also made on the common classifiers used for texture image classification. Also, a survey on texture image benchmark datasets is included. In information processing and control systems based on computer vision technologies, it is necessary to provide an effective indicative representation of images for their subsequent analysis. One of the widely used approaches is based on the construction of texture models. In this paper, the description of the texture using energy features is considered. The proposed model is a set of weights of image pixels reflecting their significance from the point of view of image perception. The significance of the pixel is estimated using the energy of the coefficients of the orthogonal discrete multiresolution wavelet transform. The paper presents expressions for calculating pixel weights and shows that the resulting texture models can be used to classify images. As it is indicted in the Fig 2, texture classification, texture segmentation, texture synthesis, and texture shape are among the main issues that texture analysis deals with . In the “Texture Shape Extraction”, the objective is to extract 3D images which are covered in a picture with a specific texture. This field studies the structure and shape of the elements in the image by analyzing their textual properties and the spatial relationship each with each other. The purpose of “Texture Synthesis” is to produce images that have the same texture as the input texture. Applications of this field are creation of graphic images and computer games. Eliminate of a part of the image and stow it with the background texture, creation of a scene with lighting and a different viewing angle, creation of artistic effects on images like embossed textures are other applications of this field. The purpose of the “Texture Segmentation” is to divide an image into distinct areas, each of which is different in terms of texture. The boundaries of different textures are determined in the texture segmentation. In other words, in texture segmentation, the features of the boundaries and areas are compared and if their texture characteristics are sufficiently different, the boundary range has been found. Texture classification is one of the important areas in the context of texture analysis whose main purpose is to provide descriptors for categorizing textural images. Texture classification means assigning an unknown sample image to one of the predefined texture classes. In real condition, there are two major challenges in the analysis and classification of images which has many destructive effects. These two important phenomena are rotation and noise image. If the methods used to classify against these common phenomena are not sustainable, in practice, the accuracy of the results can be severely reduced; therefore, in actual circumstances, the methods used to analyze and categorize the

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images should be as robust and stable as possible to these two phenomena and neutralize their devastating effects. In addition to the above ismay differ from one another in terms of scale, viewpoint or intensity of light. This is one of the leading challenges in the texture classification system. For this reason, various methods have been proposed, each of which tries to cover these aspects.

The purpose of the work №1

As mentioned above, the texture classification means assignment of a sample image to a previously defined texture group. This classification usually involves a two-step process. A) The first stage, the feature extraction phase: In this section, textural properties are extracted. The goal is to create a model for each one of the textures that exist in the training platform. B) The second stage, the classification phase: In this phase, the test sample image texture is first analyzed using the same technique used in the previous step and then, using a classification algorithm, the extraction features of the test image are compared with the train imagery and its class is determined. The general flowchart of methods for the texture images classification is indicated in Fig 3, based on the two preceding The first stage in extracting texture features is to create a model for each one of the textures found in educational imagery. Extractive features at this stage can be numerical, discrete histograms, empirical distributions, texture features such as contrast, spatial structure, direction, etc. These features are used for teaching classification. So far, many ways to categorize texture have been proposed which the efficiency of these methods depends to a great extent on the type of features extracted. Among the most common ones, they can be divided into four main groups of "statistical methods", "structural methods", "model-based methods", "transform methods" Each of these methods extracts the various features of the texture [3, 4] It is worth noting that today it is difficult to put some methods in a particular group due to the complexity of the methods and the use of the combined properties because most of them fall into several groups. Types of widely used and popular methods of features extraction texture will be described in detail in the next section. In the second stage, the texture classification is based on the use of machine learning algorithms with monitoring or classification algorithms; so that the appropriate class for each image is selected from the comparison of the vector of the extracted features in the educational phase with the vector of the selection test phase characteristics and its class is determined. This step is repeated for each image that is in the test phase. At the end, the estimated classes for testing with their actual class are adapted and the recognition rate is calculated which indicates the efficiency of the implemented method which the recognition rate of each algorithm is used to compare the efficiency of its algorithm with other available methods. The image texture gives us a lot of useful information about the content of the image, the objects inside it, the background context, background, and so on. Texture analysis in most areas of image processing, especially in the process of learning and extracting the feature is being discussed when we want to compare the images such as: This article has been compiled in 7 sections. In the second section, we review the four categories of texture classification and some of the many methods and features used to describe the texture. After reviewing the fundamental methods in this area, the combined methods of texture analysis are discussed in the third section. The fourth section of the well-known texture data set is introduced. In the following, we describe several efficient classifier algorithms including K-nearest neighbor, artificial neural networks, support vector machines, and so on. In Section six, a general overview of the data used in the textures and the summary of the methods are gathered with their advantages, The methods of statistical processing of texture that make up many of the methods presented in the machine vision field, spot localization of pixel values. These batches of methods for analyzing the texture of images perform a series of statistical calculations on the lightness intensity distribution functions of pixels. In general, the methods used to derive feature vector from statistical computations fall into this group. The first, second and higher level statistical characteristics are among these methods. The difference between these type of three features is that the first- level single-pixel specification is calculated without taking into account the interaction between pixels of the image. While in a second-level and higher- level statistical characteristic, the specification is calculated taking into account the dependence of two or more pixels. The Co-Occurrence Matrix that is known as the second-level histogram is one of the methods to be included in this group. II.A.1 Histogram Features and Specifications: First-order statistical indicators are calculated directly from the gray levels of the pixels of the original image, regardless of the spatial relationship between them. Typically, the first- level statistical indexes are derived from the calculation of the statistical moments of the histogram of the image. The image histogram is a two-dimensional representation of how the gray levels are dispersed in the image. Simply, histogram is a graphical representation. It shows us the optical content of the image. The meaning of optical content is the amount of light and darkness of the image. One of the easiest methods to describe a texture is the use of statistical torques related to the histogram of the intensity of an image or region, and many features can be extracted from it which is used to calculate the nth torque around the mean as follows: One of the oldest operators for extracting texture features is the co-occurrence matrix introduced by Haralick [26]. The cooccurrence matrix of an image is created based on

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the correlations between image pixels. For a k-bit image with $L = 2k$ brightness levels, an $L \times L$ matrix is created whose elements are the number of occurrences of a pair of pixels with brightness of a.b separated by d pixels in a certain direction. After calculating the matrix, the textual characteristics of the second statistic . Local binary pattern is one of the textural image descriptors that can define the local spatial structure and the local contrast of the image or part of that. LBP has become a widely used texture descriptor due to its simple implementation and extraction of proper features with high classification accuracy, and this is why many researchers have considered it. An important feature of this method, i.e., its sustainability in the uniform changes of the gray scale and computational efficiency, has made it one of the most suitable image analysis methods. Ojala et al first introduced the LBP operator.[27] This descriptor is independent of the rotation. In this method, a neighborhood is considered first for each point of the image. Then the intensity of the central pixel is compared with the intensity of the neighboring pixels. If the intensity of the neighboring pixel illumination is larger than the central pixel, then the value for that neighbor in extracted binary pattern considered as is one, and otherwise it is zero. Finally, with a binary weighted sum of the values in the binary extraction pattern we obtain values at the base of ten, which is called the LBP value. The calculation of the final LBP is shown in the equation below. In this set of methods, the texture is introduced based on the initial units and their spatial layout. Initial units can be simply as a pixel, a region, or a line like shape. Their spatial layout rules are arranged together by calculating geometric relationships or examining their statistical properties. In other words, structural methods consider texture as a combination of initial patterns, once the primary texture is detected, and then the statistical properties of the primary texture are calculated, and used as a feature. These methods are suitable for textures with a regular structure but for images with irregular texture, is not optimal method. II.B.1 Edge Features: The edge of the border is between an object and its background, in other words, it is the edges of the two gray levels or the values of the two-pixel brightness adjacent which occurs in a specific place of the image. The purpose of the edge detection is to identify the points of an image in which the intensity of light shifts sharply. The edges may be subject to vision. That is, they can change by changing the point of view, and, typically, the geometry of the scene, the objects that intercept each other and so on, or may be affiliated with the perspective - Which usually represents the features of the objects seen, such as markings and surface shape. This action can be done by various operators like Sobel[30], Pewit[31], Robert and etc. II.B.2 Scale Invariant Feature Transform (SIFT): SIFT operator today is one of the best and most powerful tools for extracting and describing features. This method was introduced by David Loo in 1999[32]. The advantage of this operator is that it has local features therefore, it has good accuracy in occlusion it is differentiable. In the following Fig, the process of extracting features is indicated by the SIFT operator. In the first step, the key points of the image are identified. The key points of the image are the points of the image that Difference of Gaussian (DoG) is maximized or minimized in those points[33]. The process of finding these points begins by constructing a pyramid of images and convolution of the original image with the Gaussian filters G x, y, σ therefore the scale space is displayed as follows, Model-based methods on the basis of model design can describe texture images. The model-based method is used for texture modeling, and the most popular ones are Autoregressive (AR) method, Markov Square theory, Gibbs RMF, Hidden Markov Model(HMM), and fractal model. In this way, a model of the image is created and then this model is used to describe the image synthesis. Model parameters extract the basic qualitative properties of the texture. A fractal geometric model is a model used to analyze many natural and physical phenomena. II.C.1 Fractal: In 1970 Mendelbert introduced a new field of mathematics called fractal to the world[34]. He introduced a new class of collections called fractal. This collection contains many complicated objects which were produced by repeating simple rules. The fractals can be used to model the coarseness and harshness and self-similarity in a texture image. This feature is in the category of model-based methods. If a collection A of repetition of N is a separate copy of itself, the collection A is called self-similar. Each of these copies is shifted to r from the original image. The fractal dimension in Fig. The Fourier spectrum is suitable for describing the alternate patterns or nearly alternating two-dimensional patterns in an image. These general texture patterns can be well-identified as concentrations above the energy in the spectrum. Three features of the Fourier spectrum that are useful in describing texture are as follows [39] • Peak arrives in the main direction pattern of the texture pattern • Peak on the main alternate frequency plate of the pattern location • Elimination of any proportional components by filtering non-alternate image components The spectrum around the source is symmetric, so only half of the frequency plate is considered. Therefore, for the analysis of each alternate pattern, only one peak is related to the spectrum. It is usually performed by displaying the spectrum of polar coordinates as a function $s(r, \theta)$where s is the function of the spectrum and r is the variables of this coordinate system. For each, θ and $s(r, \theta)$ can be considered as one dimension of$s\theta$ (r). Similarly, for each frequency r, sr $(\theta)$is a one-dimensional function. The analysis of $s\theta$ (r) for a constant value of θ shows the behavior of the spectrum (the presence of peaks in the spectrum) along the radial direction of the origin while a more general description is obtained by integration of this function, it is easier to distinguish and interpret spectral properties by expressing the spectrum in polar coordinates. S is the spectral function; r and θ are variables in polar coordinates. R0 is the radius of the circle corresponding to the origin; S (r) is constant toward the rotati

The purpose of the work №2

One of the considerable methods in the texture analysis is transform method. The Gabor transform is similar to the wavelet transform, in which functions have the Gaussian nature base and as a result, this transformation is optimal in the frequency domain arrangement Gabor wavelet is an optimal transform to minimize the two dimensional uncertainty associated with the location and frequency domains. This wavelet can be used as directional and comparable scale detectors for revealing lines and edges in images [41]. Also, the statistical properties of this transformation can be used to determine the structure and visual content othe f images. The features of Gabor's transformation are used in several applications of image analysis, including categorization and texture segmentation, image recognition, alphabet recognition, image recording, and routing and movement. Two-dimensional Gabor filters are defined in the spatial and frequency domains. A two-dimensional Gabor consists of a Gaussian modulus function with a mixed sinusoidal function. This function can be expressed in terms of σy and σx and the standard deviation ψ of the sinusoidal function of the Gaussian function is as follows. Different applications of the computer vision, such as texture analysis and edge detection, Gabor filter has been used extensively. The Gabor filter is a linear and local filter. The convolutional nucleus of the Gabor filter is the product of a complex exponential and Gaussian function and Gabor filters, if tailored and accurately adjusted, have a very good function in distinguishing the features of the texture and the edges of it. The other feature of Gabor's filters is the high degree of separation above them; this means that their response is completely local and adjustable in the area of the place as well as in the frequency domain. In order that the extracted property of the Gabor filter to be constant over time, and to change the scale and the intensity changes, the Fourier transform is used in addition to using the Gabor filter bank. It is worth noting that the Fourier transform is non-sensitive. Using a Gabor filter is one of the most common filter-based methods for texture extraction. This filter operates in both spatial and frequency domains. In the spatial domain, the core of the filter is obtained from the product of a Gaussian function with a directed sinusoidal function. As a result, the filter produces outstanding responses at points of the image that locally have a certain orientation and frequency. When using the Gabor filter, it can be used to get

directions that can be Fernando Roberti and et al. [42] presented a new strategic approach to expand the gray scale level co- occurrence matrix with two different approaches. The first approach is to pyramid the image. That is, the image is considered in five layers and the cooccurrence matrix is obtained on these five images in four directions (0, 45, 90 and 135). In order to extract the features of the image from the five co-occurrence matrix combinations in each direction, 12 characteristics (contrast, correlation, total power, instantaneous inverse difference, total average, total variance, total irregularity, variance difference, difference of irregularity, maximum correlation coefficient) has been extracted. In the end, the combination of the obtained vectors is in each direction, in other words, the resulting response is 48 for this approach. In the second approach, instead of pyramiding the image, we will blur the image into five layers with a Gaussian filter. And then, as in the first turn, 48 statistical attributes are obtained from the combination of the co-occurrence matrix in 4 directions. The two approaches are indicated in the following Fig which a, As the binary string is obtained, the rotational shift is given until it reaches its maximum value. Then each of these bits is multiplied by their respective weight and get together that produces a number. This number is called BGP. For each texture, this value is calculated and then the histogram of the image is obtained. This method uses the closest neighboring algorithm for classifier. The following Fig illustrates an example of applying this method to a different image with different rotation angles. In the process of creating a classification system for texture images, after the selection stages of the training set and extraction of features from the images, the model of this categorizer should be created. In order to train this model, machine learning algorithms are used with supervision. For each image, in addition to the feature vector extracted from the image, its class information is also available in the educational set.
A. K- Nearest Neighbor: The K-nearest neighbor (KNN) algorithm is a sample based and supervised learning method. Just as people try to solve new problems, and use similar solutions that have already been solved; thmethod in order to classify new data uses the class of previously categorized data. In this method, for each new sample, a separate approximation of the objective function is created; this approximation applies only to the range in the neighborhood of that sample. The KNN algorithm's performance is assumed initially that all examples of $x\ i$ which is having N-dimensional vector, have some vector points in the N-dimensional feature space and k is a positive and determined constant number. In the educational phase, all, that is done is to hold the feature vectors and label each educational sample in this N-dimensional space. In the classification phase, the feature vector of the samples whose class is unknown is received as input. Based on the similarity function, k is

determined from the educational sample that maps their features closer to the feature vector. Then the k label of the nearest neighbor of the new sample is being voted and the label that was present in more quantities in this neighborhood would be assigned as new sample. Determining the best value k depends on the problem data. If k is large, it reduces the effect of noise, but in the case of classes with few samples, it isn"t being considered and the probability of error increases. The following is a sample of KNN in Fig 27. Experimental samples are (red circles), educational samples are (green circles and blue circles). In order to specify the experimental sample class to one of the classes (green and red), you must specify k value then assign the educational sample to one of the categories. As you can see in the Fig, if the value of k is 3, then the new sample belongs to the green class, since there are two green circles from the green class and a sample of the blue class and if k is 7, then it will be, bayesian theory is one of the statistical methods for classification. Bayesian theory allows a cost function to be introduced for a situation where it is possible that an input vector that is a member of Class A is mistakenly attributed to Class B. In this way, different classes, each in the form of a probability hypothesis, are considered. Each new educational sample increases or decreases the likelihood of previous hypotheses and finally, the assumptions with the highest probability are considered as a class and they will be attacked by them. Bayesian decision theory is a statistical approach to the pattern recognition problem. The Decision tree method creates a tree-based classification model. The decision tree is the tree in which the samples are categorized in some way that they grow from the root to the bottom and eventually reaches the nodes of the leaf. This method is considered as part of the classification method with the supervisor and using the educational samples, can draw a tree called the decision tree based on the characteristics of each of the data or label samples in the test phase and recognize the type of class or label. Via using this tree, rules can be drawn for the inference system and using those label data or samples that do not specify the class or labels. The CLS algorithm was developed by Ross Quilan in 1986 more fully called Inducing Decision trees . Subsequently, a more complete alternative algorithm entitled .

Conclusion

In this study we try to consider almost all articles which are proposed methods for texture analysis in field of texture classification. As four main categories are defined for texture classification methods, some of primary methods are under unique. However, through expand methods and in novation of combined methods, new extended method of the texture analysis are allocated to more than one category (see

Table1). In statistical category co-occurrence matrix and Local Binary Patten Methods are more popular, and for Model based category the Fractal models is more famous, Gabor and Wavelet are more applicable through Transform based category. Majority of methods are categorized under statistical and transform based methods or a combination of these method. A main reason of method diversity is change is in way of texture image analyzing (e.g. noise, rotation, scale, illumination, view point). As a result, each new method looking for overcomes some of challenges. Almost all methods are rotation invariant; however, a majority of methods are noise sensitive. For example, DRLBP and LBP variance methods are extend LBP and get better results but those are continuously noise sensitive. Most of methods could applied for gray scale texture images and Fekri-Ershad , Haon and Siqueira have used their own for color texture.

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