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ANALYSIS OF TEXTURED AND NON-TEXTURED IMAGES

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ABSTRACT:

In an image, texture is one of the visual characteristics that identify a segment as belonging to a certain class. We recognize many parts of the image by texture. If the texture belongs to a class that has a particular physical interpretation such as grass, hair, water or sand, then it may be regarded as "natural" texture. On the other hand a texture may belong to a class identified by artificial visual characteristics that have a concise mathematical interpretation. A complete definition of texture has been elusive as there does not exist an all-encompassing mathematical model of texture.However from a human perspective we may conjecture that texture is a quality that distinguishes regularity in the visual appearance of local detail. Texture has been an active area for research of computer vision for over Two decades. There are several areas like petrography, metallographic, and lumber processing, which make extensive use of textural features such as grain shapes, size, and distribution for recognizing and analyzing specimens.

***KEYWORDS*: Image, texture, segment, computer vision.**

INTRODUCTION:

Texture is very important in quality control since many inspection decisions are based on the appearance of the texture of the material. There are many different kinds of textures, and these have been classified in the form of taxonomy. Texture is the term used to characterize the surface of a given object or phenomenon and is undoubtedly one of the main features used in image processing, pattern recognition and multispectral scanner images obtained from aircraft or satellite platforms to microscopic images of cell cultures or tissue samples.

Texture also plays an important role in human visual perception, medical image processing, and provides information for recognition and interpretation. That's why research on texture analysis has received considerable attention in recent years. An important approach to region description is to quantify its texture content. Although no formal definition of texture exists, intuitively this descriptor provides measures of properties such as smoothness, coarseness, and regularity.

Julesz's classic approach for determining if two textures were alike was to embed one texture in the other. If the embedded patch of texture visually stood out from the surrounding texture then the two textures were deemed to be dissimilar. The comparisons relied solely on pre-attentive human visual perception, where the subjects were only given a brief time to view the texture.Julesz found that texture with similar first order statistics, but different second-order statistics, were easily discriminated. However Julesz could not find any textures with the same first and second order statistics, but different third order statistics, that could be discriminated.

This led to the Julesz conjecture that "second-order textures are indistinguishable ". This was further substantiated with work on the visual discrimination of stochastic texture fields.However, later caelli, Julesz, and Gilbert did produce second-order textures that could be discriminated with pre-attentive human visual perception .Further work by Julesz revealed that his original conjecture was wrong. Instead; he found that the human visual perception mechanism did not necessarily use third –order statistics for the discrimination of these second order textures, but rather used the second order statistics of textures he called textons. These textons he describes as being the fundamentals of texture. Julesz found three classes of textons: color, elongated blobs, and the terminators (end-points) of these elongated blobs. Julesz revised his original conjecture to state that, "the human pre-attentive human visual system cannot compute statistical parameters higher than second order. "He further conjectured that the human pre-attentive human visual system actually uses only the first order statistics of these textons.

Texture segmentation is first step in natural texture analysis. It plays an important part in image interpretation and understanding. Most natural image textures do not consist of only one type of texture. Texture segmentation is defined as division of the whole image into homogeneous regions characterized by the same texture. In general the number of texture types present in an image is not known as priori. An unsupervised or an automatic segmentation method is therefore preferred. Different types of vegetation induce different textures: forests, rice fields, wheat fields, roads, rivers etc…So the texture of an urban area is finer than the one of its neighboring farming area. The contrast of town center due its dense pattern of streets and its higher buildings is more important than the one of the suburbs. A farming area can be characterized by specific directions due to the existence of furrows and by a more or less important homogeneity according to the no of crop variations. A rice field is usually not homogenous.

TEXTURE AND ATTRIBUTES:

Texture is property inherent in surface; various parameters or attributes describe it and they are listed below:

1. Granularity, which can be, rough or fine.
2. Evenness, which can be, more or less good.
3. Linearity(roads, rivers)

4. Directivity, which is possible occurrence of main directions.
5. Repetitiveness, which indicates the possible occurrence of periodicity.
6. Contrast
7. Order
8. Connectivity, which describes borders.

Other attributes such as the color, the size and the shape must also be considered. The parameters can be quantified as indices of textures and so can be useful for image processing.

These concepts are useful in order to describe the objects as one can see them and are used to discriminate them. Due to our subjectivity, there are important correlations between them. It is rather difficult to mathematize this concepts; however, some topologic (concepts related to neighborhood), geometric, spatial, spectral, and morphology characteristics can be apprehended.

Texture models play an important role in many image analysis systems. Textural features can be crucial for the segmentation of an image and can serve as the basis for classifying image parts. Experienced with analyzing images containing texture regions (especially images of natural scenes) has often led to a qualitative distinction between two classes of textures-micro textures and macro textures. The distinction between micro textures and macro textures is based on the size of the underlying texture elements. For micro textures, the texture elements are assumed to be small (e.g., diameter only several pixels), while macro textures, the texture elements are assumed to be larger. A few features computed from a co-occurrence matrix or a difference histogram could adequately describe most micro textures.

THE USE OF TEXTURE FOR DIGITAL DATA ANALYSIS:

In order to improve the quality of an image, a spatial and radiometric filtering can be processed. Usually this filtering makes use of the radiometric and spatial distribution of the spatial and radiometric characteristics of the considered image. The representation of such a distribution corresponds to the concept of "texture".

THE LEVEL OF OBSERVATION:

It must be stressed that the perception of a texture depends on the observation level (altitude), the surface illumination and the type of sensor (scanner, radar.). For the radar imageries the concepts of regality and texture are well correlated. So, according the type of remote sensed imagery, different levels of texture must be considered. The large-scale aerial photographs allow distinguishing features of some meters in size: the trees can be isolated and their leaves, individually, undiscernibly, contribute to the texture of the crowns and so, allow the identification of some tree species.

On the other hand, the smaller-scale imageries do not permit to discriminate the individual trees; however, the way these are clustered induces a specific texture. The satellite imageries lead to consider only sets of more (NOAA. . .) or less (Land sat TM, SPOT) large landscape units. The observation of texture is sometimes unconsciously performed by the photo-interpreter. He uses imagination and his experience in order to relate what he sees on the image with what does really exist. The analysis of this process must be performed in order to make possible the semi-automatic or fully-automatic photo-interpretation.

THE SYNTHETIC PHOTO-INTERPRETATION:

A space craft or air craft imagery can be considered as random distribution of grey tones. The human eye distinguishes areas with different brightness intensities, shapes. So, a road (linear feature) is geometrically less uniform than a field. This more or less conscious phase of the imagery analysis can be defined as a search for "basic characters ". This notion is subjective but it appears that these intuitive characters (granularity,..) are rather identical for all the photo-interpreters; so, it is possible to define them qualitatively but also quantitatively.

A textural unit can be defined as combination of some of the whole textural characters which are "a-priori" chosen for photo-interpretation. A photo-interpreter will try to observe gatherings (specific distribution) of textural units; they are named "structural elements". Each one can be characterized by specific shape, which means a specific grouping or relation between its textural units. Several structural elements are identical when they have the same type of grouping or structure.

THE VISUAL INTERPRETATION:

The dense forest appears to be granular with a uniform distribution. The size of the granules varies according the type of forest: the denser the forests the larger are the granules.The degraded sparse forest displays anther type of granule. The texture depends on the environment. So, in a mountainous or hilly area the dominant texture is due to the connectivity of the structural elements, which means to the hydrographic network. The savannah and bare soil appear to be homogeneous, with a contrast relative to the neighboring landscapes, and with variable shapes.

The tree-savannah is displayed like grains, with a 3 to 10m size, spread amidst the savannah. The distribution is not homogeneous and there is an important variability of sizes of grains.The parcels of stubble paddy fields look like the savannah and the bare soil. They display precise outlines which are well differentiated in the environment. The parcels of fallow and re-growth have variable sizes and no specific texture; they appear like bare soil, savannah or forest according to the stage of the vegetation re-growth.

An area of these parcels is very heterogeneous. So, according to the landscape and the scale, the textural characteristics are the granularity, the size, the homogeneity, the contrast and the convexity. The present landscape units are characterized by only one or several textural characters, the connexity, which is displayed by the hydrographic network, is due to the strong contrast between the enlightened and the shady areas; it does not really display a texture of the vegetation the granularity is variable and allows to be differentiated. However, this textural character is dependent on the scale; so, with land sat data it cannot be observed. On the other hand, the homogeneity and the contrast do not depend on the size of the object and so can be observed on scale.

THE DIGITAL INTERPRETATION:

The texture present on the satellite imageries is due to a more regional view than on the aerial photographs. On a land sat image the textural characters are due to:

- The large scale relief,
- The main geologic structural orientations,
- The shape of the roads and rivers,
- The spatially large landscape units (vegetation, land-use,..),
- The contrasts between different features.

The enhancement and the analysis of these textural characters are performed with the textural transformation and the co-occurrence matrix of the grey tones.

THE TEXTURAL TRANSFORMATIONS:

They are transformations which modify the brightness value of a pixel according the brightness value of its neighbors. A specific local or textural transformation is needed in order to enhance a specific type of relation between the neighboring pixels. Such a transformations acts like a spatial filter. According to the size of the neighborhood which is considered the filter size is more or less great; which means that the features that are apprehended have a great or similar size.

LATEST LITERATURE SURVEY ON MRF MODEL:

Among the various image models Markov random field model is widely used technique. A variety of distinct models exists within the class of MRFs, depending on the choice of potential function that assigns cost differences between neighboring pixels. Markov random field models are efficient and powerful framework for specifying nonlinear interactions between features of the same nature or of a different one. They help to combine and organize spatial and temporal information by introducing strong generic knowledge about the features to be estimated. When they are associated with the MAP criterion, they lead to the minimization of a global energy function which may exhibit local minima. This minimization is generally performed using deterministic or stochastic relaxation algorithms. Stochastic models are well adapted to cope with ambiguities. Markov models are usually used for sequential data segmentation and recognition.

In the case of images, Markov Random Fields (MRF) is powerful stochastic models of contextual interactions in bidimensional data. MRF framework has been widely studied these last decades on State of art of MRF Modeling TechniquesBased on the nature of potential function, MRF models may be classified into: causal MRF, non-causal MRF, Gaussian MRF, Ising model, pots models and hidden MRFs. Non-causal Markov models are widely used in early vision applications for the representation of images in high-dimensional inverse problem. For most non-causal representations, the graph associated to the Markov model is the rectangular lattice equipped with the nearest (or second nearest) neighborhood system. Non-causal MRFs do not impose unwanted directionality effects.

However implementation of this model is not straightforward. Commonly used Non-causal Markov random fields are not in fact capable of representing the moderate-to-large scale-clustering present in naturally occurring images and can be time consuming to simulate, requiring iterative algorithms which can take hundreds of thousands of sweeps of the image to converge. However the causal MRF such as Pickard random field, the mutually compatible MRFs and Markov chain image model can approximate the non-causal MRFs.Pickard random fields are known to represent only a limited class of spatial statistics and generally yield directional artifacts in the image plane.

On the other hand, accurate causal approximations of non-causal MRFs can be obtained by Markov Chain image model. Gaussian MRFs give rise to linear estimators, but the basic homogeneous Gaussian MRFs are well known to allow noise cancellation only at the expense of over smoothing the object. Generalized Gaussian MRFs preserve edges better while maintaining convex energies. However none of these priors can give rise to maximum a posteriori (MAP) estimators truly accounting for the presence of both homogeneous parts and edges in the objects. Using pairwise interaction piecewise Gaussian MRFs (PG MRFs) with a non-interacting Boolean line process this problem is solved. Compound Gauss-Markov random field (CGMRF) is used to model images by preserving the discontinuity. A hidden Markov process (HMP) is a discrete-time finite state homogeneous Markov chain observed through a discrete time memory less invariant system.

The image is characterized by a finite set of transition densities indexed by the states of the Markov chain. Unlike hidden Markov fields, a hidden Markov chain uses one-dimensional set of pixels by scanning the two-dimensional sets. HMC-based segmentation methods can be competitive in some particular situations, and they are much faster than the HMRF based ones. The partially hidden Markov models (PHMM) combines the power of using the past as context and the power of hidden states in modeling. It differs from conventional hidden Markov models (HMMs) by conditioning the transition probabilities and emission/output probabilities on the previously observed symbols. Ising model attempts to minimize the boundary length between objects, which results in very high estimates for the MRF class transition costs and, thus, a strong favor for smooth boundaries.

A non-stationary Ising model, with different parameters in uniform regions of pure region than at places where objects mix, might be a promising starting point. There are also methods that estimate Gibbs parameters with pre computed derivatives of log-partition functions. These algorithms were used primarily for learning MRF models with pair cliques, such as Ising models and Potts models. It has the advantage of taking the observations directly into account.

Moreover, the study of the case of the homogeneous isotropic Potts model gives reasons dissuading from using the mean field approximation on the marginal field and MRF models have been applied for different tasks in image analysis,

When the MRF theory was first introduced into the field of statistical image analysis in the mid-1980s applied MRFs to image restoration, which can be viewed as a generalization of segmentation. Similar to the work in also added a second MRF (line process) to the original MRF for surface reconstruction. Likewise, in line process (edge MRF) was incorporated into the intensity process (label MRF). In general, adopting two or more MRFs in one task is a way to solve two or more different problems. For example, inintegrated three MRFs, disparity, line process and occlusion, for stereo problems because these three factors are all critical to stereo matching. Similarly insolved two problems, restoration of SAR images and extraction of intensity discontinuities, by using two distinct MRFsused one added MRF, i.e., the bias field, to sweep the obstacle of MRI brain segmentation but they did not couple the two MRFs compactly because the two fields are assumed independent.

CONCLUSION:

The statistical formulation indicates if an image is smooth, rustic, granulated, etc. It is based on a set of features to represent the characteristics of the texture of an image. Those features are contrast, correlation, entropy, etc. They are usually derived from measurement of the gray level of the image; it differentiates from the values of gray or co-occurrence matrix. The characteristics are selected in heuristics form; nevertheless, an image similar to the analyzed one cannot be recreated using some measurement of the set of features. The structural technique, on the other hand, indicates the primitive features that exist in the image, such as regularity of parallel lines. Some textures can be seen as two- dimensional patterns, composed of a set of primitives or sub-patterns, which are organized according to a certain rule of positioning.

Textures like brick walls and mosaics; the primitives used are areas of constant gray level, lines, curves and polygons. The correct identification of those primitives is quite difficult. However, if the textures primitives are identified completely, then it is possible to recreate the texture from the primitives. A work using a structural model is indicated in the stochastic technique is based on the energy properties and it is used mainly to detect global regularity in an image, indicating small peaks of high energy in its spectrum. A texture is assumed to be the realization of a stochastic process, which is governed by some parameters. The analysis is executed, defining a model and considering the parameters.

This way, the stochastic processes can be reproduced from the model and associated to the parameters. The estimation of the parameters can serve to classify and to segment textures. This type of model offers a good possibility to recreate realistic examples of natural textures. The next chapter describes the statistical model based methods and compares the texture features based on Grey Level Run Length matrix (GLRLM), Co-occurrence, Neighboring Grey Level Dependence Matrix (NGLDM), and the new matrix method called The Q-matrix which measures the similarities of grey levels. The problem addressed is to determine which features optimize classification rate. Such features may be used in image segmentation, classification and in evaluation of statistical features. Improvements achieved when using Q-matrix method are highlighted. In addition, their main drawbacks are pointed out.

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