Review of Rotation Invariant Classification Methods for Color Texture Analysis

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Abstract: The paper aims at analyzing the algorithms which provide rotation invariant to the images. Double Dyadic Dual Tree Complex Wavelet Transform method for providing rotation invariance is compared with Cluster Coordinated Representation method. The Result of analysis shows that Coordinated Representation is easier to implement and provide better method of classification than wavelet based transformation for rotation invariance whereas it lacks scale invariance. The multi-resolution wavelet based method is invariant to scale and shifts the texture with shift in scale in the direction of change of scale and while rotation the texture shifts in the direction of rotation. The coordinated cluster-based representation provides rotation invariance by using same index to the rotation invariant textures

Keywords: Double Dyadic Dual Tree Complex Wavelet Transform, Scale invariance, Rotation invariance, Rotation invariant Coordinated Cluster Representation, Multilayer Coordinated Cluster Representation

1. Introduction

Image segmentation, i.e., identification of homogeneous regions in the image[1], has been the subject of considerable research activity over the last three decades. Image segmentation still remains a difficult problem because it is related to human perception. Color and texture are essential features for image segmentation since these features are commonly observed in most images, especially in color textured images of natural scenes as illustrated in Fig. 1, where natural objects, such as the flowers in Fig. 1(a) or the wild animals in Fig. 1(b), have their own color and texture. Most segmentation methods use color or texture as key features for image segmentation. Color and texture have been combined to enhance the basic performance of color or texture segmentation by using color texture based segmentation.

2. Color and Texture

2.1 **Color** :

That aspect of things that is caused by differing qualities of the light reflected or emitted by them, definable in terms of the observer or of the light, as:

1) The appearance of objects or light sources described in terms of the individual's perception of them, involving hue, lightness, and saturation for objects and hue, brightness, and saturation for light sources.

2) The characteristics of light by which the individual is made aware of objects or light sources through the receptors of the eye, described in terms of dominant wavelength, luminance, and purity.

"Only after years of preparation young artist should touch color – not descriptively but as means of personal expression" [1]

Color is thus a powerful descriptor.

2.2 **Texture**:

It is measure of the variation of the intensity of a surface. It specifies quantifying properties such as smoothness, coarseness and regularity. It's often used as a {region descriptor} in {image analysis} and {computer vision}.[1]

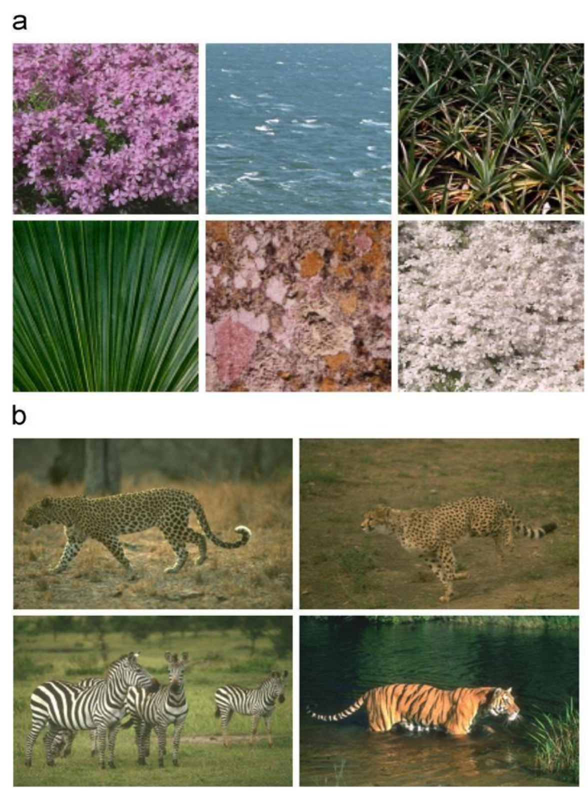


Fig. 1. Example color textured images from:(a)the MITV is texture database [2] and (b)the Berkeley image segmentation database

3. Color Image Segmentation

Color image segmentation is a process of extracting from the image domain one or more connected regions satisfying uniformity (homogeneity) criterion which is based on feature(s) derived from spectral components [2]. These components are defined in a chosen color space model. The segmentation process could be augmented by some additional knowledge about the objects in the scene such as geometric and optical properties. Brief history of color based segmentation is as follows

3.1 **Pixel based segmentation**:

In this section we discuss segmentation techniques which operate in color space. Available papers can be broadly divided into three groups:

3.1.1 **Histogram based techniques:** One or more peaks are identified; surrounding intervals are next utilized in pixel classification process.

3.1.2 **Segmentation by clustering data in color space**: pixel values are collected into groups with one or more representatives which next are used in pixel classification process;

3.1.3 **Segmentation by fuzzy clustering**: Fuzzy membership functions is evaluated for all pixels and for all fuzzy clusters defined; hard clusters of pixels are obtained by de fuzzification process and next subdivided into maximal connected regions.[2]

3.3 Area based segmentation

In this section segmentation algorithms use uniformity criteria calculated in regions of image domain. We divide available techniques into two groups:

3.3.1 **Region growing**: In this class of algorithms a number of basic uniform regions (seeds) are given and different strategies are applied to join surrounding neighborhoods; to distinguish this group from the next one it is important that seeds here are not resulting from splitting or subdivision processes of non uniform regions.

3.3.2 **Split and merge**: Here algorithms start from non uniform regions, subdivide them until uniform ones are obtained, and then apply some merging heuristics to them to maximal possible uniform area.[3]

3.4 Edge based segmentation

3.4.1 **Local techniques**: The local technique to determine an edge point needs only information in the neighborhood of that point.

3.4.2 **Global technique**: on the contrary, makes a sort of global optimization, and therefore the given edge point could be identified after many optimization steps involving changes in large areas.[4]

3.4 Physics based segmentation

The goal of these methods is to segment images according to the real contour of objects avoiding being misled by shades and highlights in the image. This is a pretty difficult goal since measures coming from a single surface may vary in a great extent due to interactions, shadows, shades, sensor noise, non uniform illumination or texture surface.

3.4.1 **Approaches designed exclusively for inhomogeneous dielectrics**:

Images are segmented into regions representing the same material by employing the dichromatic reaction model;

3.4.2 General approaches:

That are not limited to inhomogeneous dielectrics: Regions correspond to different materials which are, for example, metal, plastic, etc.[5]

4. Texture Based Segmentation

There is no specific definition of texture. It is measure that provides measure of properties such as smoothness, coarseness and regularity. [1]Brief overview of texture based techniques is as follows

4.1. **Structural approaches**: (Haralick 1979, Levine 1985)[6] represent texture by well defined primitives (micro texture) and a hierarchy of spatial arrangements (macro texture) of those primitives. [7]

4.2. **Statistical**: approaches do not attempt to understand explicitly the hierarchical structure of the texture. Instead, they represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image.

4.3 **Model based**: texture analysis using fractal and stochastic models, attempt to interpret an image texture by use of, respectively, generative image model and stochastic model [8]. The parameters of the model are estimated and then used for image analysis. In practice, the computational complexity arising in the estimation of stochastic model parameters is the primary problem. The fractal model has been shown to be useful for modeling some natural textures. It can be used also for texture analysis and 3 - discrimination however, it lacks orientation selectivity and is not suitable for describing local image structures.

4.4 **Transform methods**:

Transform methods of texture analysis, such as Fourier (Rosenfeld 1980), Gabor (Daugman 1985, Bovik 1990) and wavelet transforms

(Mallat 1989, Laine 1993, Lu 1997) represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size)[8]. Methods Based on the Fourier transform perform poorly in practice, due to its lack of spatial localization.

4.4.1 Gabor filters:

Provide means for better spatial localization; however, their usefulness is limited in practice because there is usually no single filter resolution at which one can localize a spatial structure in natural textures.

4.4.2 Wavelet transforms:

Wavelet function vary the spatial resolution and allows it to represent textures at the most suitable scale, there is a wide range of choices for the wavelet function, so one is able to choose wavelets best suited for texture analysis in a specific application. They make the wavelet transform attractive for texture segmentation. The problem with wavelet transform is that it is not translation-invariant (Brady 1996, Li 1997).

5. Disadvantages of existing techniques

1) Color based segmentations do not provide best results.

2) Texture based segmentation methods are usually to complex.

3) The automatic segmentation using color only or texture only provides poor results.

4) Currently available method of color and texture combination have not been able to provide generalized automatic method for segmentation

5) Extraction of information using only color neglects the spatial correlations

6) Texture based methods however because of their complexity are difficult to understand and individually does not provide visually tempting segmentations (even though analytically strong).

6. COLOR AND TEXTURE BASED SEGMENTATION

Color and texture based segmentation implements the combination of color based segmentation techniques and texture based segmentation techniques to provide the best of both techniques. The approaches to deal with colour texture can be classified into three groups: parallel, sequential and integrative (Palm, 2004)[9].

6.1 **Parallel approaches**: They consider texture and color as separate phenomena. Color analysis usually relies on the distribution of colors in an image, regardless of the spatial relationship between pixel intensity; texture analysis is based on the relative variation of the intensity of neighboring pixels, regardless of their colour.

6.2 **Sequential approaches**: It consists in applying a color indexing method to the original color images. As a result we obtain indexed images that can be processed as grayscale textures.

6.3 **Integrative models**: These are based on the spatial relationship of pixels. These approaches can be further subdivided into single-band if data are considered separately from each channel or multiple-band if two or more channels are considered jointly. Rotation invariant texture features are important concepts in image segmentation.

7. Double Dyadic Dual Tree Complex Wavelet Transform

A complex wavelet transform is a Discrete Wavelet Transform (DWT) that produces complex valued coefficients. A useful property of the complex wavelet transform is that the magnitude of the transformed data is approximately shift invariant. This property makes the complex wavelet transform useful for certain signal analysis applications.

7.1 Scale and rotation invariant feature, DFT method

A texture feature invariant to scaling and rotation was using the DFT [10,11]. Earlier, Hill, Bull and Canagarajah described a process for generating a single rotation invariant texture descriptor from the DT-CWT from a texture image. To naively apply their technique directly for segmentation would require dividing up an image into tiles and generating a rotation invariant texture feature for each tile. However, segmenting this way would not produce a suitable result because the output would appear to be pixilated. Extension to this earlier work produced localized texture features from the D3T-CWT and was specifically designed for image segmentation. An important property of this new feature is its approximate invariance to scaling and rotation changes. Segmenting images with this new feature enabled scaled and rotated textures to be combined while offering good discriminating ability to different textures. This approach is referred to herein as generating scale and rotation invariant texture features using the DFT approach [12,13].

Following Fig. 2, the step-by-step details of the algorithm using the D3T-CWT are as follows:

1) Decompose an image to Ψ by considering the D3T-CWT as a scale and orientation selective filter.

2) Scale each resulting sub-band to the size of the original image using nearest-neighbor interpolation.

3) Produce jΨj2 by taking the square of each value in the scaled sub-bands.

4) Smooth each sub-band using a Gaussian low pass filter

5) For each level l at some pixel location, consider the coefficients pd (where d=1,...,6) from each sub-band in smoothed jΨj2.

6) Generate Pm (for m=1,...,6) by applying the DFT to pd and form the rotation invariant vector FRI=fjP1 j;...; jP6.

7) Vectors from each level and location can be combined to form FRI, a 4-D matrix containing localized rotation invariant texture features.

8) For each pixel location, consider the 2-D matrix of coefficients from FRI. Apply the 1-D DFT to this matrix in scale dimension and take the magnitude of values. Remove redundant coefficients corresponding to complex conjugates.

9) Aggregate the resultant localised scale and rotation invariant texture features into the 4-D matrix FSIRI.

10) Perform the logarithm over the values in FSIRI and output the texture feature.

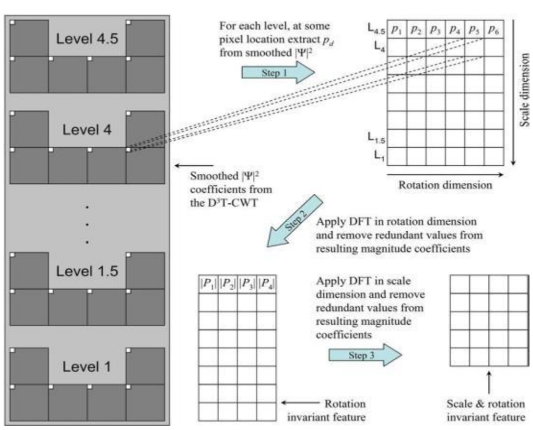


Fig. 2. Generating scale and rotation invariant texture features from smoothed magnitude features from the D3T-CWT using DFT operations.

7.2 Scale and rotation invariant feature, non- DFT method

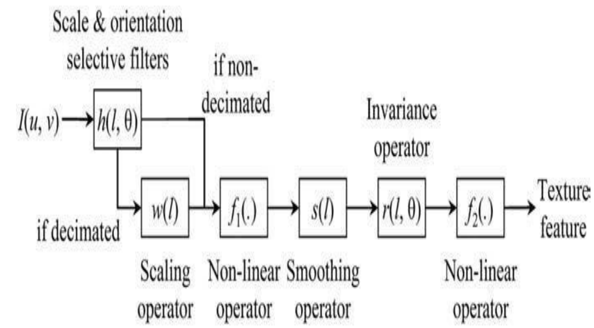


Fig 3 Feature extraction model for rotation or scale and rotation invariant texture features generated from the magnitude of the DFT over wavelet coefficients.

An identifying feature characteristic is extracted at each pixel location and used as a scale and rotation invariant texture feature. After applying the smoothing operator in Fig. 3, each pixel location will produce a 2L×6 energy feature, for smoothed Ψj2 extracted from each sub-band, covering the 2L dyadic and midway scales, and six orientations in the D3T-CWT. The first step in developing our desired feature involves scaling this matrix in the orientation dimension by interpolating with the DFT method [14]. Performing this operation produces a new texture feature f covering 12 orientations. A study by Zhang showed how texture features from the Gabor wavelets with overlapping half-peak support respond to changes in scale and orientation. He demonstrated that a change in scale caused the texture feature to shift in scale dimension while a change in orientation caused the texture feature to shift in rotation dimension. Apart from those dimensional shifts, the identifying feature characteristic being tracked appeared to remain largely unchanged.

8. The Rotation – invariant – version of CCR

A. Rotation-invariant CCR [15]features can be obtained following an approach similar to the one proposed for the LBP3_3 operator [16], a related model in which the value of the central pixel of the 3*3 window is used for thresholding, resulting in 28 possible patterns. The first step consists in replacing the squared neighborhood of the CCR3_3 by a circular one. The gray-level values of the pixels that are not placed exactly on pixels positions are estimated through bilinear interpolation. We refer to this arrangement as the CCR 8:1. The rotation-invariant CCR operator, denoted by CCRri 8;1, is obtained by clustering all the patterns that are rotated version of the same pattern. This operation reduces the number of possible texels, and thus the dimension of the feature space from 512 to 72. Rotationally equivalent patterns are assigned the same index.

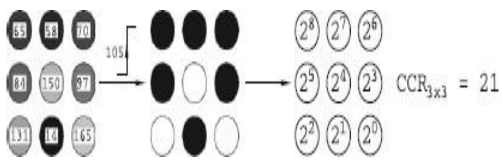


Fig 4. Basic version of the CCR (CCR 3*3). From left to right: original grayscale window, binary pattern after thresholding, weighting mask and CCR3*3 code.

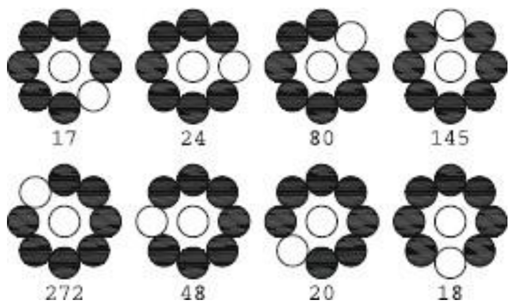
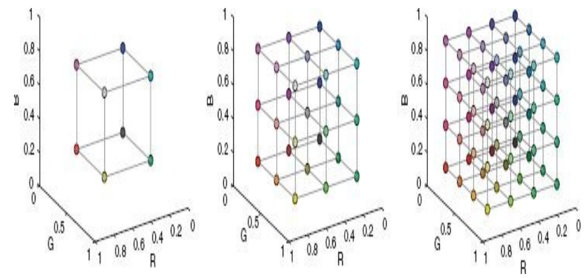


Fig 5. Sample of rotationally equivalent patterns.

B. Multilayer Version for Color Textures

The basic idea behind the multilayer CCR[17] is that, given a set of representative colors (palette), a color pattern (such as, for instance, a 3 _ 3 window) can be represented through a stack of binary patterns, one for each representative color. Color texture description through a stack of binary images obtained by color indexing has been previously reported in (Song et al., 1996; Boukouvalas et al., 1998). In these works texture is modeled by extracting morphological features from the binary layers. Herein we also perform a color indexing pre processing stage to build a stack of binary images, but we characterize each binary layer by the frequency of occurrence of rotation-invariant elementary texture patterns. In order to ensure meaningful comparison among different color texture images, the set of representative colors have to be image-independent. To this end we adopted uniform quantization of the colour space: n samples are taken on each axis of the colour space, resulting in a palette of N ¼ n3 colours. Provided that the original colour images are given in the RGB space, we considered a good practice to do uniform quantization in this space. Fig. 6 shows the resulting palettes with 8, 27 and 64 levels.



Once the palette has been computed, each pixel of a 3 * 3 color neighborhood is assigned the index of the nearest color of the palette (herein we used the Euclidean distance to determine the nearest color). Afterwards the neighborhood is split into a set of N binary layers, each layer corresponding to one of the N colors of the palette, with the convention that a pixel in the layer $l \in \{1, 2, \ldots, N\}$ takes value 1 if its color index is l, and 0 otherwise. This results in a set of binary patterns (of the type of Fig. 3), one for each layer. Now each binary pattern can be characterized through a proper binary texture descriptor, such as the CCR. Sequential scanning of the original image gives rise to N pattern distributions (histograms), one for each layer. The feature vector is formed by concatenating the histogram of each layer. The process is described as (1) establishment of an image- independent color palette;(2) replacement of each square neighborhood by a circular one;(3) color indexing; (4) subdivision in binary layers;

(5) calculation of the CCR code of the resulting binary patterns in each layer; (6)calculation of the CCR histogram of each layer; (7) concatenation of the resulting CCR histograms.

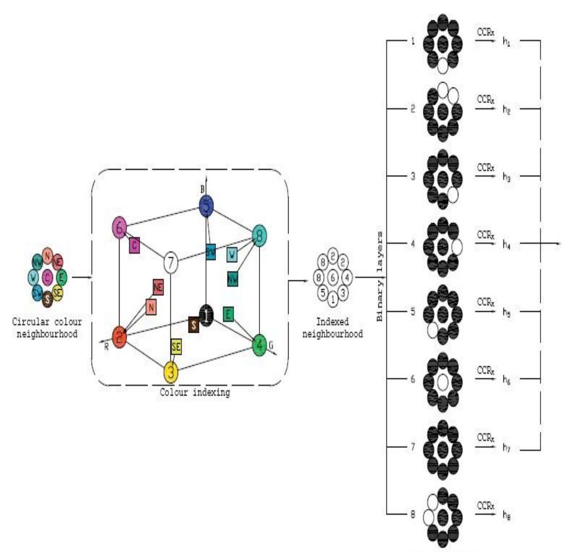


Fig. 6. Procedure to compute the multilayer CCR.

Each colour pixel of the circular neighbourhood is assigned an index of a predefined palette composed of N colours (in this case N ¼ 8). Cardinal points are used in the figure to indicate the position of the colours of each pixel of the circular neighbourhood in the colour space (RGB in this case).

9. Conclusion

The paper presents two methods one using wavelet that extensively use texture for providing rotation invariance features and the other one use color model for extracting rotation invariant features. The wavelet based use Dual dyadic tree that provides higher analysis capabilities and is more tolerable to texture variations and responses for characterization are highly positive. Similarly, The Coordinated Cluster based method provides higher the layers of color samples selected higher is the efficiency of classification. The wavelet based method is not only invariant to rotation but also invariant to scale as well in multi-scale analysis. Coordinated cluster based analysis provide information about spatial information which can efficiently be used in segmentation and the analysis can provide benchmark for absolutely new ways of segmentation in future. The result can be summarized as we should prefer the wavelet based method for scale invariance and for rotation invariance coordinated cluster based technique provide better results.

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