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Classification of Image at different Resolution using Rotation Invariant Model

Divyanshu Rao*
EC,SRIT
divyanshu3@gmail.com

Prof Sumit Sharma
EC,SRIT
sharma.sumit3@gmail.com

Prof Ravi Mohan
EC,SRIT
ravimohan7677@yahoo.co.in

***Abstract*— In this paper a multi resolution-rotation invariant simultaneous autoregressive (MR-RISAR) model for texture classification along with a multivariate rotation-invariant SAR (RISAR) model which is based on the circular autoregressive (CAR) model have been used. RISAR model is used to obtain rotation invariant features. Experiments show that the multivariate RISAR model outperforms the CAR model in texture classification. Integrating the information extracted from multi resolution SAR models gives much better performance than single resolution methods in texture classification. Result of both models gives significant information and advantages over simultaneous autoregressive model (SAR).**

***Keywords*— MR-RISAR, SAR, RISAR, CAR**

INTRODUCTION

Texture features play a very important role in computer vision and pattern recognition, especially in describing the content of images. It also plays an important role in human visual perception and provides information for recognition and interpretation 'Texture' is a widely used and implicitly understandable term Texture is characterized not only by the grey value at a given pixel, but also by the grey value `pattern' in a neighbourhood surrounding the pixel. The unit of texture is texels, and the repetitiveness of the texels determines the type of texture and decides the texture analysis approach." Texture is one of the important characteristics that exist in many natural images. As a result, research on texture analysis has received considerable attention in recent years. A large number of approaches for texture classification and segmentation have been suggested.

However, there is no precise definition of texture. Hence, it can be observed that the definition of texture is an open issue.

The simultaneous autoregressive (SAR) model has been successfully used in texture classification. But there are two major difficulties associated with the utilization of the SAR model. One is choosing an appropriate neighborhood size in which pixels are regarded to be dependent. The other is to select an appropriate window size over which local textural characteristics are extracted. Most approaches in the literature use fixed-size neighborhoods and windows, which are usually determined empirically.

Several texture analysis approaches have adopted the multi resolution paradigm, a fixed-size neighborhood and window is used to derive features at varying scales corresponding to input image at different resolutions. However, these multi resolution approaches seldom integrate the information extracted from different image resolutions. Some approaches use the coarse level information only as an initial segmentation for the higher resolution images in order to speed up the segmentation process and to avoid getting trapped in a local minimum.

The basic SAR model is rotation-variant, which means that when the textured image rotates, the model parameters also changes. This requires that the training samples and test samples from a texture class have the same orientation. Although sometimes such an orientation dependency is desired, e.g. discriminating between similar textures, which are oriented differently, in general, it reduces the flexibility of the model.

There have been many attempts to derive rotation-invariant features for texture analysis Researchers have suggested a rotation-invariant model named as circular autoregressive (CAR) model. RISAR is an improved version of CAR model.

SIMULTANEOUS AUTOREGRESSIVE MODEL (SAR)

Texture is a neighborhood property; therefore, it is logical to utilize the spatial interactions among neighboring pixels to characterize it. There are two classes of commonly used models for specifying the underlying interaction among the given observations: the simultaneous models, such as SAR models, and the conditional Markov (CM) models.

The basic SAR, we can describe as, let g(s) be the gray level value of a pixel at site s = (sl, s2) in an M x M textured image, sl, s2 = 1,2 . . . . . M. The SAR model can be expressed as

$$g(s) = \mu + \sum_{r \epsilon D} \theta(r) * g(s+r) + \varepsilon(s)$$

Where D is the set of neighbors of pixel at site s. In Equation (1), ε(s) is an independent Gaussian random variable with zero mean and variance σ^2; θ(r), r ε D are the model parameters characterizing the dependence of a pixel to its neighbors, and μ is the bias which is dependent on the mean gray value of the image. All model parameters, μ, σ and θ(r), r ε D, can be estimated from a given window (sub image) by using the least squares error (LSE) technique or the maximum likelihood Estimation (MLE) method. These model parameters, excluding μ, are often used as features for texture classification and segmentation. The basic SAR model is rotation-variant, which means that when the textured image rotates, the model parameters also change. This requires that the training samples and test samples from a texture class have the same orientation. Although sometimes such an orientation dependency is desired, e.g. discriminating between similar textures which are Oriented differently, in general, it reduces the flexibility of the model

PROBLEM IN SAR

The basic SAR model is rotation variant model. This means when image is rotated, model parameters will also change. The other major difficulty associated with SAR model is choosing a proper neighborhood size in which pixels are regarded as being dependent. The third difficulty in SAR model is to select an appropriate window size in which the texture is regarded as being homogeneous.

Hence to overcome these problems following models have been described in this report.

1. Rotation Invariant Simultaneous Model (RISAR)
2. Multi resolution Simultaneous Autoregressive Model (MR-RISAR)

ROTATION INVARIANT AUTOREGRESSIVE MODEL (RISAR)

To obtain rotation invariant features for texture classification multi variant rotation invariant autoregressive model is defined.

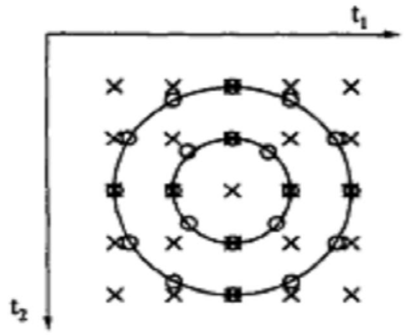

Fig. 1. Formation of rotation-invariant variables, where "x" denotes a pixel (grid point) And "O" denotes a resample point

$$xi(t) = 1/ni \sum_{k=0}^{ni-1} g(t + j\, exp(j * \frac{k\pi}{\frac{ni}{2}}) \qquad \text{.................(1)}$$

i = 1 , 2 . . . . . p, Where p is the order of the model (the number of variables in the model).
ni = 8i and g (.) denotes the gray level. In this equation, in this model site notation s has been changed from variable s to a complex variable, t = tl +j*t2, where tl, t2 = 1,. . , M, in order to represent the equation more concisely. When the textured image rotates around pixel t, the values of *xi (t)* remain approximately the same. A small error occurs due to the digitization of the image and the resampling interval. Therefore, *xi (t)* can be used as rotation invariant variables in the SAR model, resulting in rotation-invariant SAR (RISAR) model. From Fig. 1, it can be seen that most of the resampled points on circles do not correspond to pixels (grid points). Therefore, the gray values at these points must be interpolated. I use the bilinear interpolation technique in which the gray value at a point is estimated by taking the weighted average of its four nearest neighbor pixels. The weight assigned to a pixel is proportional to its distance from the point under consideration. Substituting the interpolated values into Results shows that the multivariate RISAR models achieve higher classification accuracies than the CAR model on the given textures. Results show that classification accuracy does not necessarily increase with an increase in the number of variants in the model. This is because the extent of dependence between neighboring pixels in a textured image generally decreases as the distance between them increases. Substituting the interpolated values into Equation (1) and changing the site notation back to the original one used in Section 2.1; Equation (2) can be rewritten as

$$xi(s) = \frac{1}{8i} \sum_{r \in Ni} wi(r) * g(s + r) \qquad \text{................................ (2)}$$

where N_i is the neighbor set containing the pixels which are used for interpolating the points on the ith circle and the pixels which happen to be on the ith circle; $w_i(r)$, $r \varepsilon N_i$ are the corresponding weights which indicate the contribution of the pixel r. Note that the intersection of two successive neighbor sets is not empty.

$W_i(r)$ is symmetric with respect to the origin, that is,

$$w_i(r) = w_i(-r).$$

versus-one classifiers are marginally more accurate than one-versus-all classifiers [6], [7]. Nevertheless, for computational efficiency, we chose to use one-versus-all classifiers in all Support Vector Classification.

TEXTURE CLASSIFICATION USING RISAR MODEL

Thus, the RISAR model can be established as follows:

$$g(s) = \mu + \sum_{i=1}^{p} \theta i \, xi(s) + \varepsilon(s)$$

Where p is the number of variables in the RISAR model. When p = 1, the RISAR model reduces to the CAR model. The parameters, θ1, θ2 . . . . . θp, which will be estimating using the LSE technique, can be used as rotation-invariant features for texture classification. To perform rotation invariant classification using RISAR model, 5 different types of texture has been used. These textures are mainly wave-like sand, scale-like sand; branch-like sand, grass and bricks. These different types of textures are referred as known classes from Brodatz album. Each image of size 512 x 512. These images are further rotated by 30, 45 & 60 deg. These images are used as training samples. Each image is divided in several 128 x 128 subimages resulting 32 training samples per class. For every subimage, parameter θ_i referred as feature set using LSE method, has been calculated. For classification phase, a test image from original 5 textures and their rotated version by 30, 45, 60, 90,120 & 135 deg, have been generated. From these 8 textured images, we have to select a subimage of size 128 x 128. This subimage will be the test image. For the classification both classifier, the euclidian & mahalanobis classifier have been used. From the results, we can conclude that the classification efficiency of mahalanobis classifier is better than the euclidian classifier.

MULTIRE SOLUTION-ROTATION INVARIANT SIMULTANEOUS AUTOREGRESSIVE MODEL (MRSAR)

There are two major difficulties associated with the utilization of the SAR model. One is choosing a proper neighborhood size in which pixels are regarded as being dependent. The other is to select an appropriate window size in which the texture is regarded as being homogeneous and the parameters of the SAR model are estimated. Most approaches in the literature use a fixed-size neighborhood and a fixed-size window, which are usually empirically determined. The major problem of the fixed-size neighborhood and window is that it is "nonadaptive". For some images with fine texture, a small neighborhood and a small window are adequate, but for others, both small and large neighborhoods and windows may be necessary in order to extract information at different scales or resolutions.

Although it is true that a model with a large neighborhood will fit the texture better than a model with a small neighborhood if the window is chosen sufficiently large to estimate the model parameters reliably, it does not provide more discriminatory information. In fact, the severe averaging effect caused by a large number of parameters in the model often degrades the performance of those parameters that have strong discriminatory power. It seems, therefore, that it is unnecessary to use a large neighborhood in fitting SAR models. But this does not mean that pixels that are far apart are necessarily independent. If an image with a coarse texture is sub sampled, a SAR model with a small neighborhood will fit the sub sampled image well. In the sub sampled image, two neighboring pixels are several pixels apart in the original image. Therefore, establishing SAR models at different resolutions of the input image can provide useful discriminatory information for many texture types. The most commonly used multi resolution image representation is the Gaussian pyramid image model. One constructs a low-pass filtered and subsampled image sequence, G_l, $l = O, 1, \ldots, L - 1$, in which the successive image sizes decrease as texture changes from fine to coarse. Note that Go denotes the input image and as l increases, the image resolution goes from high to low. If a small fixed size window is used for $\{G_l\}$, then in high resolution images (small /), this window is more likely to emphasize the information regarding the texture "primitives", while in low resolution images (large /), the same window will cover many texture "primitives", so that the placement rule information can be obtained. The fixed neighborhood in different Resolution images also covers different region sizes in the original image. Therefore, we expect that image classification and segmentation results will improve if multi resolution images are used. The multi resolution SAR model is drawn schematically in fig. 2. At each image resolution, a SAR model or a RISAR model is fitted to the image, forming the MR-SAR model or MR-RISAR model, respectively. The collection of all the model parameters can be used as features for both texture classification and texture segmentation. This is the simplest way to integrate the multi resolution information.

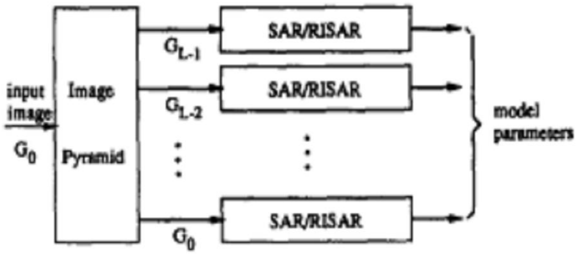

Fig. 2. Multiresolution SAR/RISAR model

The classification accuracies using the single resolution images are not encouraging, while the multi resolution rotation invariant SAR model provides very high classification accuracies. By using the 4-resolution (L = 4) and 2 variants (p = 2) MR-RISAR model for the given textured images, a classification accuracy of 100% can be achieved.

IMPLEMENTATION & RESULTS

IMAGE CLASSIFICATION USING RISAR MODEL

$$xi(t) = 1/ni \sum_{k=0}^{ni-1} g\left(t + j\, exp\left(j * \frac{\frac{k\pi}{ni}}{2}\right)\right) \ldots\ldots(1)$$

In this equation site notation has been changed from variable s to a complex variable t. where t = t1 + jt2 t1, t2= 1,2 ,3…M. In this equation g(.) denotes the gray level and Ni = 8*i where i=1,2……..p and p is the order of the model. When the textured image rotates around pixel t, the values of *Xi(t)* remain approximately the same. For different values of i, when we draw a plot between t1 & t2, we get various resampled points. But most of the resampled points don't correspond to grid point. Hence for those points, which are not on the grid we can not get gray value directly. To find out gray value on these pixels, I used bilinear interpolation technique in which the gray value at a point is estimated by taking the weighted average of its four nearest neighbor pixels. The weight assigned to a pixel is proportional to its distance from the point under consideration.

Substituting the interpolated values into Equation (1) and changing the site notation back to the variable s; Equation (2) can be rewritten as

$$xi(s) = \frac{1}{8i} \sum_{r \in Ni} wi(r) * g(s + r) \ldots\ldots(2)$$

where N_i is the neighbor set containing the pixels which are used for interpolating the points on the ith circle and the pixels which happen to be on the ith circle; $w_i(r)$, r ε N_i are the corresponding weights which indicate the contribution of the pixel r. $w_i(r)$ is symmetric with respect to the origin, that is,

$w_i(r) = w_i(-r)$.

For i= 1 & 2, and following values of r and w, I found out results of equation (1) and equation (2). I got almost equal results from both equations. All the coding has been done using MATLAB.

FOR i= 1

Here in this table it can be verified that the values of Xi (t) & Xi(s) are almost equal. Hence if we rotate an image around pixel location around Xi (t), model parameter won't be changed. Hence we can use the value of Xi (t) instead of Xi(s) for classification.

$$y(s) = \mu + \sum_{i=1}^{p} \theta i\, xi(s) + \varepsilon(s)$$

The euclidian classifier was used for classification gives when we increase the value of p, the classification efficiency also gets increase. As we can easily conclude from the above table that as we increase the value of p the classification efficiency also gets increase. We also notice that the classification efficiency does not necessarily increase with an increase in the number of variants in the model.

CONCLUSION

In this paper, proposed scheme is Multi resolution rotation invariant auto regressive model. Image was classified using rotation invariant simultaneous auto regressive model. The euclidian classifier was used for classification. Even though by now some progress has been achieved, there are still remaining challenges and directions for further research, such as, image classification using mahalanobis classifier has to be performed and integration of classifiers to reduce the classification

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