A Summary of Deep Segmentation Techniques for Textured Images

K. Meenakshi Sundaram[1]
[1]Associate Professor / IT
Dhanalakshmi Srinivasan College of Engineering,
Coimbatore

C.S.Ravichandran[2] , Ph.D
[2]Professor & Dean / EEE
Sri Ramakrishna Engineering College,
Coimbatore.

ABSTRACT

In this paper, it is intended to summarize and discuss the methods of Segmentation for textured images in various applications of image processing. In particular, the problem of real time approaches for textured images is analyzed and their performances are studied and discussed. The main aim of segmentation is to locate objects of interest based on the available criteria and is sometimes a computer vision problem. But many important segmentation algorithms are too simple to solve this problem accurately. They compensate for this limitation with their predictability, generality, and efficiency.

Keywords : Image Segmentation, Textured images.

1. INTRODUCTION

DIGITAL image processing is enhancement by improving image quality by filtering etc.; and restoration by compressing data to save storage and channel capacity during transmission. It is a rapidly evolving field with growing applications in science and engineering. It holds the possibility of developing the ultimate machines that could perform the visual functions of all. Image analysis technique, the same input gives out somewhat detail description of the scene whose image is being considered. Most of the image analysis algorithms perform segmentation as a first step towards producing the description. The segmentation of textured images is a long standing problem in Computer Vision, which has been addressed from various perspectives, with variational models, and MRFs, [1] being the most common approaches. Although texture is a fundamental characteristic of a region, the complexity involved in its quantification has prevented its effective incorporation into the segmentation process. Segmentation divides the special domain, on which the image is defined, into meaningful parts or regions. The level to which this subdivision is carried depends on the problem solved i.e. segmentation should stop when the objects of interest in an application have been isolated. Generally segmentation is one of the most difficult tasks in image processing. There exists no general segmentation algorithm which can work reasonably well for all images. The suitable segmentation algorithm for the particular problem must be chosen or developed as they are ad hoc in nature. The algorithms may be incorporated explicitly or implicitly, or even in the form of various parameters. These algorithms are based on satisfying homogeneity property or detecting abrupt changes in image features or both approaches. This step in the process of analysis determines the eventual success or failure. Generally these techniques can be classified based on three different aspects: First the model used for segmenting (explicitly stated), secondly, the optimized criterion (implicitly stated) and finally, the algorithm which is employed to compute the segmentation. A large variety of segmentation methods can be found in the literature. Of more interest to us are the segmentation methods which try to retrieve regions using different models [2]. The idea of using a combination of different segmentations to obtain the best segmentation of an image has been suggested by Cho and Meer [3]. However, they make use of small differences resulting from random processes in the construction of a Region Adjacency Graph (RAG) pyramid to generate their segmentations.

Algorithms for subsequent image processing stages like motion analysis and tracking, stereo vision, object recognition and scene interpretation often rely on high quality image segmentation [4]. For textured images one of the main conceptual difficulties is the definition of a homogeneity measure in mathematical terms [5]. A number of distinct approaches have been suggested for textures images falling into two major classes [6]. We have four traditional methods for image segmentation, namely, Fuzzy C-Means clustering based segmentation, Region split and merge segmentation, Region growing segmentation and Histogram thresholding based segmentation. Some other methods are Pixel based Segmentation; Model based Segmentation, Multi-scale Segmentation, Semi-automatic Segmentation etc.

The objective of this paper is to review the methodologies of segmentation of real time approaches for textured images. The aim of segmentation is to locate objects of interest based on the available criteria and it is sometimes considered as a computer vision problem.

The rest of the paper is described as follows. Section 2 discusses the segmentation process. The review of previous work is discussed in Section 3. Section 4 discusses the summary of the methods and Section 5 discusses the review evaluation. Conclusions are drawn in the final Section.

2. SEGMENTATION PROCESS

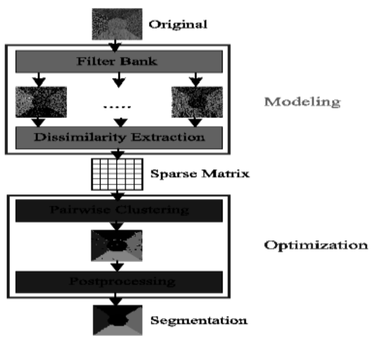

Fig. 1: Segmentation

Segmentation is based on four cascaded design decisions, concerning the image representation, texture homogeneity, objective functions and optimization procedures. The fig 1 gives the process involved in segmentation. The original image forms the input, and modeling is performed by two steps such as reducing the noise, and dissimilarity extraction based on texture homogeneity. The image is represented as sparse matrix. Based on the objective function and optimization procedures, pair wise clustering is performed and after post processing steps, the segmented image would be available for analysis.

3. RELATED WORKS

Texture segmentation is an important task in many computer vision applications. Texture can be described in a variety of ways. It can be generated by primitives organized by placement rules, or as the result of some random process. It can be found in a continuous spectrum, from purely deterministic to purely stochastic. Texture is an important surface characteristic and based on it shape and motion can be estimated. Taxonomy of problems encountered within the context of texture analysis could be that of classification/discrimination, description, and segmentation. These problems are listed in order of increasing difficulty, and it is clear that the major problem is that of texture segmentation. Generic segmentation is the partitioning of an image into regions that are "homogeneous" with respect to one or more characteristics [7]. The process of segmentation is rigorously defined by Pavlidis and its corresponding computational complexity is discussed by Gurari and Wechsler. A basic issue to be considered is that of the cell unit size, i.e., the resolutions of the area over which measurements are taken in order to test for homogeneity.

The segmentation is achieved in two phases: the first one consists of evaluating, from disjoint blocks which are classified as homogeneous, the model parameters for each texture present in the image. This unsupervised learning phase uses a fuzzy clustering procedure, applied to the features extracted from every pixel block, to determine the number of textures in the image and to roughly locate the corresponding regions. The second phase consists of the fine segmentation of the image, using Bayesian local decisions based on the previously obtained model parameters.

The problem considered in Unsupervised Segmentation of textured images by Edge Detection in Multidimensional feature operating in unsupervised mode. A set of m features are used to represent such characteristics. Consequently, the problem is transformed into edge detection problem in the multidimensional feature space.

In addressing the problem, it requires resolution of two major issues, namely, 1) selection of m features to represent texture, and 2) selection of an appropriate local size for texture measurement. The segmentation algorithm which is presented here can employ any set of m features provided that they possess the following three properties: 1) strong within-class invariance, 2) strong between - class separation, and 3) low sensitivity to small sample size, meaning that satisfying requirements 1) and 2) should not be contingent upon availability of large size texture fields. The selected features are the estimated parameters of a class of spatial interaction non causal random field models called the "Simultaneous Auto Regressive (SAR)" Model which is fitted to the local region under consideration. A second and very important problem is how to select an appropriate window size over which local textural characteristics are observed and measured. The window should be large enough to contain several texture elements for the enclosed region to exhibit similar textural characteristics as that of the underlying region that it masks. At the same time, it should be as small as possible to enable accurate detection of the edges. Operating in an unsupervised mode prevents a priori selection of a good window size. In fact, a major shortcoming of the previously developed edge-based algorithms for texture segmentation is the arbitrary pre selection of this parameter. A systematic method is used in SAR model which enables the algorithm to automatically select an appropriate window size. Other approaches besides edge-based ones include studies relying on estimation theory, clustering in the feature space and the split-and-merge technique.

Segmentation is approached as a statistical approach problem [8]. These methods of segmentation use MRF to model the discrete field containing the individual pixel classification. The result is quite difficult to maximize globally. For global optimum Stochastic relaxation algorithms have been applied. Though a reasonable method between performance and computation, greedy minimization algorithm known as estimation by Iterated Conditional Modes (ICM) is efficient. The Multiple Resolution Segmentation (MRS) is less likely to be trapped in local minima than ICM and also requires less computation. The above mentioned methods are good than Multi grid methods. For individual texture GAR model is used for segmentation as well as parameter estimation and for multiple resolution techniques extract texture features for each pixel average it to yield an aggregate statistic for the region and is well adapted to use with it.

Todd and Harry addressed the generic issue of clustering/grouping. Recent research, both in computer and human vision, suggests the use of joint spatial/spatial-frequency (s/sf) representations. The spectrogram, the difference of Gaussians representation, the Gabor representation, and the Wigner distribution are discussed and compared. It is noted that the Wigner distribution gives superior joint resolution proving the feasibility of using s/sf representations for low-level (early, pre-attentive) vision.

Iasonas [9] incorporates recent results from AM-FM models for texture analysis into the variational model of image segmentation and examines the potential benefits of using the combination of these two approaches for texture segmentation. Using the Dominant Components Analysis (DCA) technique they obtained a low-dimensional, yet rich texture feature vector that proves to be useful for texture segmentation. By using an unsupervised scheme for texture segmentation, where only the number of regions is known apriori, synthetic and challenging real-world images results demonstrate the potential of the proposed combination.

The algorithm for segmentation of textured images using a Multiresolution Bayesian approach uses a Multiresolution Gaussian Autoregressive (MGAR) model for the pyramid representation of the observed image, and assumes a multiscale Markov random field model for the class label pyramid. In unsupervised segmentation strategy for textured images, based on a hierarchical model in terms of discrete Markov Random Fields, the textures are modeled as Gaussian Gibbs Fields, while the image partition is modeled as a Markov Mesh Random Field[10].

In the study of segmentation both complex and real filters were used[11]. Complex prolate spheroidal sequences were used as channel filters, and channel envelopes were extracted to form a feature vector. In another study complex Gabor filters were applied, and envelope and phase information were extracted from two quadratic components of distinct output channels. Use of real Gabor filters was reported, where feature extraction included a nonlinear transformation, r > (f) = tanh(at), and a statistical measurement of average absolute derivation was performed on overlapping windows. However, even this sophisticated approach of feature extraction had limitations.

Although Gabor filters possess desirable properties for this application, recent developments in wavelet theory provide an alternative approach with several advantages as listed below.

- Wavelet filters cover *exactly* the frequency domain (provide a mathematically complete representation).
- Correlations between features extracted from distinct filter banks can be greatly reduced by selecting appropriate filters.
- Adaptive pruning of a decomposition tree makes possible the reduction of computational complexity and the length of feature vectors.
- Fast algorithms are readily available to facilitate implementation.

Gabor filters adopts real wavelet packet frames (tree structured filter banks) for channel filters, and introduces two envelope detection algorithms for feature extraction.

By using color image in textured analysis [12] is to incorporate the chromatic information into texture analysis, assuming that the RGB color space is used, the following choices exist.

- Each color band (i.e., R; G;B) is processed separately.
- Information across different bands (e.g., cross-correlations RG, RB, GB) is extracted.
- Both individual color band and cross-band information is used.
- A composite measure to describe the chromatic information is used.

The fourth alternative is explored using the xyY color space. The main goal of the system is to separate a given image into two parts, namely, a Region of Interest (ROI), and the rest of the image (i.e., the background. The system performs analysis on luminance and chrominance in parallel, and, at the final stage, results are combined to detect changes (i.e., loss/gain) in a specific area of the image (ROI).

Processing starts by transforming a given image from RGB to xyY. This produces the luminance component (Y) directly, whereas the two chromaticity values (x; y) are combined to provide for a single-valued chrominance. Textural information, such as sizes and orientations of basic image features (e.g., edges, blobs), is contained in the luminance component. Thus, a set of filters tuned to different sizes and orientations is applied on luminance and produces a corresponding set of filtered images. Smoothing of the filtered images follows, thus, eliminating spurious/negligible regions. The smoothed images are combined into a single image, based on a neighborhood pixel similarity measure, and boundaries of potential .ROI's are extracted using a perceptron-type processing mechanism. The result of luminance processing is, thus, a Boundary Image. Chrominance processing proceeds in two stages. First, the chrominance histogram is computed and multiple thresholds are identified.

Secondly, these thresholds are used to segment the chrominance image into a corresponding number of regions (i.e., potential ROI's). Thus, the result of chrominance processing is a Region Image. Using a region expansion algorithm, the Boundary and Region Images are combined to locate the desired Region of Interest. The result is a ROI Image showing the identified ROI.

The final stage involves the comparison of two or more ROI images to locate possible scene changes. Typically, two or more images of the same real-world scene are taken at different times. Each of these images will result in a corresponding ROI image, after going through the various segmentation stages (i.e., luminance and chrominance processing). Change detection and measurement is performed by comparing two such ROI Images using logical pixel operators.

The end result is threefold:

- Incorporation of texture and color attributes for scene analysis;
- Development of computationally efficient and easily implementable algorithms for the analysis of color textures;
- Development of appropriate neural network architectures for image segmentation and classification.

This methodology provides the analysis component of an autonomous system. It incorporates color and texture visual attributes into a unified framework and utilizes them to detect and measure loss/gain.

Recently, the multichannel / multiresolution approach has drawn a lot of attention. There is evidence that images are decomposed into a collection of band pass subimages by the simple visual cortical cells to form features for the segmentation task. Gabor filters are suitable for such decomposition because their impulse responses and the joint space/spatial-frequency resolution is optimal. Though successful results using a large set of Gabor filters that cover a half frequency plane with the orientation and frequency selectivity requirements have been reported, the computational effort and storage requirement cause major problems, furthermore if the filters' parameters do not match the spectral characteristics, the segmentation results are usually unsatisfactory. To eliminate these shortcomings, it is desirable to reduce the number of Gabor filters, which may not cover a half frequency plane in full yet still capture significant spectral information by tuning the parameters adaptively. Many tuning algorithms have been proposed [13] through a global Fourier analysis or a spectral feature contrast analysis. More recently, wavelet theory has been developed enabling a new space/spatial-frequency analysis. Mallat applied the wavelet transform with an efficient pyramid structured algorithm to texture analysis in a multiresolution framework. Unser proposed an over complete wavelet transform by incorporating redundant information.

4. REVIEW EVALUATION

Here, the gray level co occurrence matrix (GLCM) type of features is considered rather than SAR features. It has been very popular in texture analysis. Six such features, namely, energy, contrast, entropy, correlation, homogeneity, and cluster shade are utilized. The performance of the GLCM algorithm is quite satisfactory. However, it should be pointed out that since a window-based technique is utilized, one cannot expect the algorithm to locate edges with pixel level accuracy. Errors on the order of several pixels should be tolerated. It takes around 25 min to segment an image on a VAX 111750. However, the extensive computation time is not really a drawback since the algorithm is very easily implementable on a parallel processor.

The MRS algorithm is better than ICM as it requires less computation though the algorithm performs comparably to Simulated Annealing. MRS yields improvement when the information in pixel is low, else it must be combined over larger regions to correctly segment the images.

Usually, the MRF contains the discrete class of each pixel in the image. The objective then becomes to estimate the unknown MRF from the available data. In practice, the MRF model typically encourages the formation of large uniformly classified regions. Generally, this smoothing of the segmentation increases segmentation accuracy, but it can also smear important details of segmentation and distort segmentation boundaries. Approaches based on MRFs also tend to suffer from high computational complexity. The non causal dependence structure of MRFs usually results in iterative segmentation algorithms, and can make parameter estimation difficult. Moreover, since the true segmentation is not available, parameter estimation must be done using an incomplete data method such as the EM algorithm.

A tradeoff exists between over segmentation, partition into too many regions, and under segmentation, in which case larger regions are obtained at the expense of possible erroneous fusions. A complete segmentation system is the complex and makes use of many heuristics. To reduce over segmentation, in the absence of context dependent information, probabilistic models are required to guide the fusion process. The difficulty of segmentation is an aspect of the local/ global duality problem. A region is declared homogeneous by analyzing small local neighborhoods. The larger these neighborhoods, the more reliable are the extracted spatial statistics given that the data in the neighborhood is indeed homogeneous. On the other hand, using a larger neighborhood increases the chances of analyzing non homogeneous data under the assumption of homogeneity.

While providing a framework for predicting visual grouping effects, the Gestalt laws are not yet grounded in any specific theory of vision. Wigner distribution performs the superior joint resolution. The s/sf representations, in particular the WD, seem to be appropriate for performing such tasks. An experimental system based on the pseudo-Wigner distribution was implemented, and experiments in texture segmentation and Gestalt grouping were performed. Evidence was given linking energy content of the primary frequency plane in the PWD with the ability of human subjects to spontaneously discriminate between texture fields. Groupings of elements consistent with the psychophysical predictions of Gestalt laws were achieved. A correlation between the perceived grouping of elements and the energy of associated PWD frequency planes was also demonstrated. This correlation indicates a direction for future research on the relationships between perceptual parameters, such as distance, and perceived groupings.

Andrew Laine and Jian Fan tested their representation using an ISODATA clustering algorithm. The number of distinct classes in each textured image was a required parameter for the program. Their test images included samples of two distinct families of textures as Natural textures and Synthetic textures. For the difficult test image, the algorithm achieved outstanding performance. The performance is consistent with the difficulty of segmentation perceived by human observers. It is observed that boundary errors were dependent on shape, i.e., complex boundaries yielded more variance.

George Paschos and Kimon P. Valavanis presented a visual monitoring system that incorporates color and texture processing principles for image analysis. Here the gray-scale information has been given major consideration than chromatic information. Emphasis has been given to its segmentation capabilities which are directly applicable to environments where detection and measurement of change in the sensed scenes is of primary importance. The approach is part of a complete color texture analysis system that includes the described segmentation subsystem as well as additional classification algorithms that form the corresponding color texture classification subsystem. The system can be applied in areas as 1) automated underwater surveillance in which the visual monitoring system becomes part of a sensor based control architecture of an AUV (Autonomous Underwater Vehicle); 2) wetlands monitoring; and 3) GIS (Geographical Information Systems).

The wavelet transform has many properties such as multiresolution analysis, fast algorithms, perfect reconstruction etc. that are beneficial for the image applications. However, the diagonal high pass filter involved in the 2-D wavelet transform gives a strong response to textures with orientations at or close to both + or – 45 degree, which causes ambiguity in textures with symmetric orientations. Motivated by the AM-FM representation, the orientation information can be taken into account while decomposing the amplitude function into wavelets (wavelet packets). The results in the modulated wavelet (packet) transform, not only generalizes the wavelet (packet) transform but also preserves the desirable properties. The modulated wavelet transform zooms in the frequency region centered at the modulating frequencies for further decompositions, so texture segmentation can be improved by adapting the modulating frequencies to the spectral energy contrast of a given image. The image segmentation techniques are difficult to maximize globally the performance and computation tapped in local minima, computation and good than Multi grid methods Parameter estimation and multiple resolution techniques. The erroneous fusions, use of many heuristics, over segmentation or under segmentation, duality problem, homogeneity problem. The techniques have wide range of application and also applicable to medical area.

Table 1: Comparison Chart of Assorted Segmentation Techniques

S.No.	Segmentation Analysis	Features	Description
1.	Multiscale Bayesian Segmentation using a Trainable Context Model	Distort segmentation boundaries, high computational complexity, difficult in parameter estimation	EM algorithm
2.	Image segmentation from consensus information	Erroneous fusions, use of many heuristics, over segmentation or under segmentation, duality problem, homogeneity problem.	Bootstrap
3.	Segmentation of Textured Images and Gestalt Organization Using Spatial / Spatial-Frequency Representations	The Gestalt laws are not yet grounded in any specific theory of vision.	Wigner distribution
4.	Modulation-feature based textured image segmentation using curve Evolution	Image intensity is a poor cue, spurious Edges.	Combines the best of the DCA and curve evolution methods
5.	Unsupervised Segmentation of textured images by Edge Detection Multidimensional feature	Selection of m features(energy, contrast, entropy, correlation, homogeneity, and cluster shade) to represent texture, and selection of an appropriate local size for texture measurement	SAR model & GLCM algorithm
6.	Multiple Resolution Segmentation of textured images	Difficult to maximize globally Performance and computation Tapped in local minima, computation and Good than Multi grid methods Parameter estimation and Multiple resolution techniques	Stochastic relaxation algorithms Greedy minimization algorithm - Iterated Conditional Modes (ICM) MRS GAR model
7.	Segmentation of Textured Images using a Multiresolution Gaussian Autoregressive Model	Pyramid representation Class label pyramid Hierarchical model in terms of discrete Markov Random Fields Image partition	MGAR Multiscale Markov random field model Gaussian Gibbs Fields, Markov Mesh Random Field
8.	Frame Representations for Texture Segmentation	Natural textures and Synthetic textures difficult test image	ISODATA clustering algorithm
9.	A Color Texture Based Visual Monitoring System For Automated Surveillance	Analysis component of an autonomous system	Incorporates color and texture visual attributes into a unified framework and utilizes them to detect and measure loss/gain
10.	Texture Segmentation using Modulated Wavelet Transform	Multichannel / multiresolution approach fast algorithms, perfect reconstruction	Gabor filters Wavelet packets

5. CONCLUSION

In this paper, the survey of various segmentation techniques was discussed for textured images. In computer vision, segmentation is the process of partitioning a digital image into multiple segments .The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze Image segmentation is typically used to locate objects and boundaries in images. Future research work is on how to handle the limitations in the algorithm and improve the results.

6. REFERENCES

[1] Hui Cheng and Charles A. Bouman, Multiscale Bayesian Segmentation Using a Trainable Context Model, IEEE Transactions on Image Processing, vol. 10, no. 4, April 2001, pp. 511 – 525.

[2] Allan Hanbury, Jocelyn Marchadier and Walter G. Kropatsch, The Redundancy Pyramid and its Application to Image Segmentation, Pattern Recognition and Image Processing Group, Vienna University of Technology, Favoritenstra_e 9/1832, A-1040 Vienna, Austria.

[3] K. Cho and P. Meer. Image segmentation from consensus information. Computer Vision and Image Understanding, 68(1):72{89, 1997.

[4] Kyujin Cho and Peter Meer, Image Segmentation from Consensus Information, Computer Vision and Image Understanding Vol. 68, No. 1, October,1997, article no. IV970546, pp. 72–89.

[5] Yongyue Zhang*, Michael Brady, and Stephen Smith, Segmentation of Brain MR Images Through a Hidden Markov Random Field Model and the Expectation-Maximization Algorithm, IEEE Transactions on Medical Imaging, vol. 20, no 1, January 2001, pp. 45 – 57.

[6] Davide Corso, Roberto Fioravanti and Stefan0 Fioravanti, Morphological Analysis of Textured Images for Identification of Thin structures, DIBE - University of Genova, Italy Via Opera Pia 11/A, Genova 1-16145, ITALY.

[7] Todd R.Reed and Harry Wechsler, "Segmentation of Textual Images and Gestalt Organization using Spacial / Spacial-Frequency Representatives", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12 ,No.1, Jan1990.

[8] Charles Bouman and Bede Liu, "Multiple Resolution Segmentation of textured images" , IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 13,No.2, Jan1991, pp 99 -113.

[9] Iasonas Kokkinos, Evangelopoulos and Petros Maragos, "Modulation – Feature based Textured Image Segmentation using curve evolution", Proceedings of International Conference Image Processing (ICP-2004) Singapore, 24-27 Oct-2004, pp. 1201-1204.

[10] Mary L.Comer and Edward J.Delp, Segmentation of Textured Images using a Multiresolution Gaussian Autoregressive Model", Computer Vision and Image Processing Laboratory, School of Electrical Engineering, Purdue University, West Lafayette, Indiana.

[11] Andrew Laine and Jian Fan, Frame Representations for Texture Segmentation, IEEE Transactions on Image Processing, vol. 5, no. 5, May 1996, pp 771 – 780.

[12] George Paschos and Kimon P. Valavanis, "A Color Texture Based Visual Monitoring System For Automated Surveillance" , IEEE Transactions on Systems, Man, and Cybernetics—part c: applications and reviews, vol. 29, no. 1, february 1999 , pp 298-307.

[13] Hsi-Chin Hsin, Texture Segmentation Using Modulated Wavelet Transform, IEEE Transactions on Image Processing, vol. 9, no. 7, July 2000, pp 1299 – 1302.

K.Meenakshi Sundaram Karuppaswamy Meenakshi Sundaram obtained his Bachelor's degree in Electrical and Electronics Engineering from Madurai Kamaraj University. Then he obtained his Master's degree in Computer and Information Technology from Manonmaniam Sundaranar University, Tirunelveli. Currently, he is a **Research Scholar at the Faculty of Information and Communication Engineering, Anna University, Chennai**. He is working as Associate Professor in Information Technology Department at Dhanalakshmi Srinivasan College of Engineering, Coimbatore. His specializations include Digital Image Processing, Software Engineering, Software Testing and Bluetooth Networks, His current area of research interests are Medical Imaging Techniques, Computer Vision and Information Security.

Dr.C.S.Ravichandran Subramanian Ravichandran received his **B.E in Electrical & Electronics Engineering from Bharathidasan University and M.E in Power Systems from National Institute of Technology, Tiruchirapalli and Ph.D from PSG College of Technology, Coimbatore**. He is currently working as a Professor and Dean in Electrical & Electronics Department at Sri Ramakrishna Engineering College, Coimbatore. His research interests include Discrete Time Control System, Power System Applications and Signal Processing. He is guiding assorted research scholars in Control System, Signal Processing and Power Optimization.