

# Unsupervised Texture Classification and Segmentation

V.P.Subramanyam Rallabandi, S.K.Sett

**Abstract**—An unsupervised classification algorithm is derived by modeling observed data as a mixture of several mutually exclusive classes that are each described by linear combinations of independent non-Gaussian densities. The algorithm estimates the data density in each class by using parametric nonlinear functions that fit to the non-Gaussian structure of the data. This improves classification accuracy compared with standard Gaussian mixture models. When applied to textures, the algorithm can learn basis functions for images that capture the statistically significant structure intrinsic in the images. We apply this technique to the problem of unsupervised texture classification and segmentation.

**Keywords**—Gaussian Mixture Model, Independent Component Analysis, Segmentation, Unsupervised Classification.

## I. INTRODUCTION

MODELING the statistical relations in images is an important framework for image processing and synthesis algorithms [1]. In many applications, a fixed representation such as the Fourier transformation is assumed to model a large number of different images. Image processing techniques that use a more flexible model that is adapted to the structure of the underlying data can achieve better results. Adaptive techniques such as Principal Component Analysis (PCA) approximate the intrinsic structure of image data up to the second-order statistics. Independent Component Analysis (ICA) is a technique that exploits higher-order statistical structure in complex image data. This model has recently gained attention due to its applications to signal processing problems such as speech enhancement, telecommunications, medical signal processing and pattern classification. ICA finds a linear non orthogonal coordinate system in multivariate data determined by second and higher-order statistics. The goal of ICA is to linearly transform the data such that the transformed variables are as statistically independent from each other as possible [2]. ICA generalizes PCA and like PCA, has proven a useful tool for finding structure in data.

In this paper, we are interested in finding statistically significant structures in images. Images may be constructed by classes of image types or natural scene itself may have diverse structures or textures. We model the underlying image with a mixture model that can capture the different types of image textures with classes. Each class is learned in an unsupervised fashion and contains the statistical

intrinsic structure of its image texture. In a mixture model, the observed data can be categorized into several mutually exclusive classes [3]. When the data in each class are modeled as multivariate Gaussian, it is called a Gaussian mixture model. We generalize this by assuming that the data in each class are generated by a linear combination of independent, non-Gaussian sources, called as ICA mixture model. The algorithm for learning the parameters of the model uses gradient descent algorithm to maximize log likelihood function. We apply this learning algorithm to the problem of unsupervised classification and segmentation of textures.

A large number of approaches for texture classification and segmentation have been suggested. Commonly, two types of approaches are distinguished, adapted respectively to macro- and microtextures, namely, the structural and statistical approaches. As far as the latter is concerned, we can cite probabilistic methods based on texture modelling, statistical methods which characterize an image in terms of numerical attributes or features and new tools like neural networks, wavelets, multiresolution and multiscale approaches, and fuzzy modelling. A few methods also come from signal processing and seem to be promising: bidimensional autoregressive modelling and, time-frequency and time-scale representations. Claude.I, smolarz. A [17] focus on stochastic approaches and, specifically, on texture modelling by bidimensional autoregressive models (2D-AR models). They describe the AR model and propose a method for choosing an adapted neighbourhood and evaluation. Then, the segmentation algorithm is presented with the classification criterion and the contextual information.

Y-W Wang, Y.-F. Wang, Y.Xue, W.Gao [4] propose a new algorithm for remotely sensed image texture classification and segmentation. They have proposed the regularization technique to suppress the instability of LSE and propose a new stable method, which is based on the total variation, abbreviated TV, for reducing instability in texture analysis, and apply which to remotely sensed image texture classification and segmentation.

Unser .M [5] describes a new approach to the characterization of texture properties at multiple scales using the wavelet transform. A texture is characterized by a set of channel variances estimated at the output of the corresponding filter bank. Finally, the DWF feature extraction technique is incorporated into a simple multicomponent texture segmentation algorithm.

Charalampidis.D, Kasparis.T [6] introduce a rotational invariant feature set for texture segmentation and classification, based on an extension of fractal dimension (FD) features. The FD extracts roughness information from images considering all available scales at once. Scale features are combined with multiple-scale features for a more complete textural representation. Features are extracted in multiple directions using directional wavelets, and the feature vector is finally transformed to a rotational invariant feature vector that retains the texture directional information. An iterative K-means

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scheme is used for segmentation, and a simplified form of a Bayesian classifier is used for classification.

Extended self-similar (ESS) processes were introduced in order to provide a generalization of fractional Brownian motion. Kaplan L.M.[7] evaluate the effectiveness of multiscale Hurst parameters as features for texture classification and segmentation.

Arof. H. [8] introduced a texture descriptor that utilises circular neighbourhoods and 1-D discrete Fourier transforms to obtain rotation-invariant features. For each individual circular neighbourhood centered at every pixel, a number of input sequences are formed by the intensities of pixels on concentric rings of various radii measured from the centre of each neighbourhood. Features extracted from these magnitudes were used in classification and segmentation.

Tan T.N.[9] proposed a model based on a widely adopted human visual model which hypothesizes that the human visual system (HVS) processes input pictorial signals through a set of parallel and quasi-independent mechanisms or channels. This model is referred to as the multichannel spatial filtering model (MSFM). The core of the MSFM presently applied is the recently formulated cortical channel model (CCM), which attempts to model the process of texture feature extraction in each individual channel in the MSFM.

Lueng.M.[10] developed computational image analysis model that resembles the functioning of the brain. The multiple-channel neural network model consists of three stages: multiple-channel representation, neural network classification and spatial context correction.

Mengyang Liao, J.Qin, Y.Tan [11] used simultaneous autoregressive (SAR) model to describe texture. They also propose using the least-squares method to estimate six SAR parameters. Based on the SAR model and the parameter estimation method, they classify and segment images of various natural textures and human B-scan images.

Patel. D, Stonham T.J.[12] propose a new statistical measure, which is not based on a pre-defined formulation. Here, the local information in all directions around a pixel and its neighbourhood is represented in a 'directional RANK-strength' vector. The proposed method leads to texture classification and segmentation methods.

Jiang wen, You zhiseng, Li hui [13] have implemented a texture-based supervised segmentation method to segment a variety of metallographic images which are considered to contain different textured regions. Texture features are computed by using a set of even symmetric Gabor filters which have been successfully used earlier for a variety of texture classification and segmentation tasks.

One of the most useful texture feature sets is based on second-order co-occurrences of gray levels of pixel pairs. An extension of the co-occurrences to higher orders is prevented by the large size of the multidimensional arrays. Oja.E, Valkaelathi.K [14] quantize the higher-order co-occurrences by the self-organizing map, called the co-occurrence map, which allows a flexible two-dimensional representation of co-occurrence histograms of any order.

Gambotto J, Gueguen .C [15] proposed an inverse filtering approach to picture modelling and recognition. A multidimensional vector AR model is fitted to a reference region using a generalized Levinson procedure. The models of other regions are then used as inverse filters on the reference for classification. The approach is

applied to natural pictures for recognition and segmentation using the textural features only.

Texture classification and segmentation in digital images is commonly achieved using spatial grey level dependence matrices (SGLDMs), often referred to as co-occurrence matrices. The approach proposed by Arrowsmith M.J., Varley M.R., Picton P.D, Heys J.D [16] uses a hybrid neural network system, consisting of a self-organising map followed by a backpropagation network, to restrict the number of SGLDMs that need to be computed. The system is trained in two phases on images with known texture content. The trained system is able to provide information, in the form of pixel spacing and orientation, on the texture content of unseen images. This information may be used to select appropriate SGLDMs for further texture classification.

## II. ICA MIXTURE MODEL

Let us assume data  $X = \{x_1, x_2, \dots, x_i, \dots, x_T\}$  are drawn independently and generated by a mixture density model where  $i$  be the total number of data vectors and each data vector  $x_i$  is an N-dimensional data vector where N is the number of sensors. The likelihood of the data is given by the joint density

$$p(X/\Theta) = \prod_{i=1}^T p(X_i/\Theta) \quad (1)$$

The mixture density is

$$p(x_i/\Theta) = \sum_{j=1}^k p(x_i/C_j, \theta_j) p(C_j) \quad (2)$$

where  $\Theta = (\theta_1, \dots, \theta_k)$  are the unknown parameters for each  $p(x_i/C_j, \theta_j)$ , called the component densities.  $C_j$  denotes the class  $j$  and it is assumed that the number of classes, K are known in advance. We can estimate the number of classes with a Bayesian method using split and merge algorithm. Assume that the component densities are non-Gaussian and the data within each class are described by

$$X_i = A_j S_j + b_j \quad (3)$$

where  $A_j$  is a  $N \times M$  scalar matrix and  $b_j$  is the bias vector for class  $j$  and the vector  $S_j$  is called the source vector (i.e. coefficients for each basis function). The equation (3) shows the way of k ways for generating the data vector  $x_i$ . Depending on the values for  $A_j, S_j$  and  $b_j$  there are k ways for viewing  $x_i$ . We assume mutually exclusive classes and maximum likelihood estimation results in one model that best fits the data. For simplicity, we consider the cases where number of sources (M) is equal to number of linear combinations (N). The aim of equality is due to a simpler calculation of the learning rules since an exact inverse exist for  $A_j$ .

Each class was generated from equation (3) using a different  $A_j$  and  $b_j$ . Class 'o' was generated by two uniformly distributed sources and class '+' was generated by two Laplacian distributed sources as shown in the Figure (1).

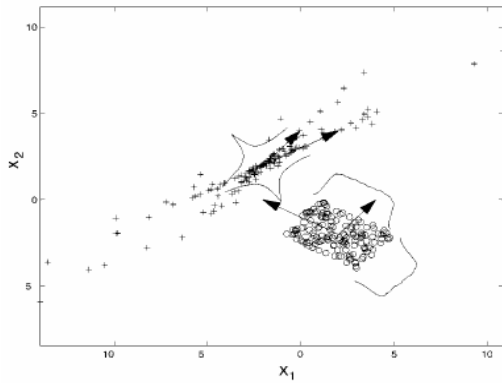


Fig.1 Simple example for classifying an ICA mixture model

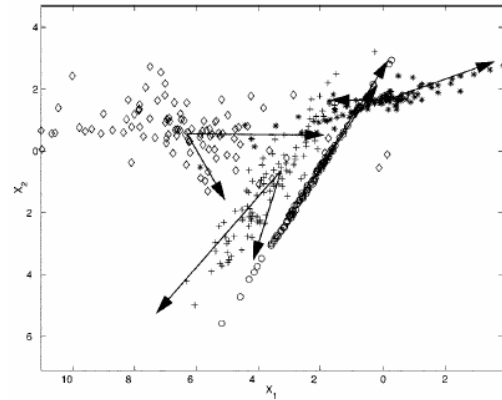


Fig.2 Example of classification of a mixture of non-Gaussian densities as linear combination of independent components

The task is to classify the unlabelled data points and to determine the parameters for each class  $(A_j, b_j)$  and the probability of each class  $p(x_i/C_j, \theta_j)$  for each data point. The iterative learning algorithm which performs the following algorithm in the sequence of steps.

1. Compute the log-likelihood of the data for each class

$$\log p(x_i/C_j, \theta_j) = \log p(S_j) - \log(\det|A_j|) \quad (4)$$

where  $\theta_j = \{A_j, b_j\}$ .

2. Compute the probability for each class given the data vector  $x_i$

$$p(C_j/x_i, \theta) = \frac{p(x_i/\theta_j, C_j)p(C_j)}{\sum_i p(x_i/\theta_j, C_j)p(C_j)} \quad (5)$$

3. Adapt the basis functions

$$A_k = p(C_j/x_i, \theta) \frac{\partial}{\partial A_j} \log p(x_i/C_j, \theta_j) \quad (6)$$

$$\text{and the bias term } b_k = \frac{\sum_i x_i p(x_i/C_j, \theta)}{\sum_i p(x_i/C_j, \theta)} \quad (7)$$

where  $I$  is the data index ranges from 1 to  $T$ . For the log-likelihood function estimation in equation (4) the term  $\log p(S_j)$  can be approximated as follows:

$$\log p(S_j) \propto -\sum_{m=1}^N \left( K_{j,m} \log(\cosh S_{j,m} - \frac{S_{j,m}^2}{2}) \right) \quad (8)$$

#### A. Unsupervised Classification Example

To demonstrate the performance of the learning algorithm, we generated random data drawn from different classes and used the proposed method to learn the parameters and to classify the data. The figure 2 shows an example of four classes in a 2-D data space. Each class was generated using random choices for the class parameters. The parameters for the mixture model were inferred using equations (4)-(7). The implementation of ICA mixture model is given below.

Initialize model parameters  $\theta_1, \dots, \theta_k$ .

Input the data vectors  $x_1, \dots, x_T$

Repeat perform *Main adaptation loop*

Adapt class parameters

Adapt the class probability for each class

Adapt the number of classes

Until the adaptation met convergence

Assign each data vector  $x_i$  to one of the classes

*Main adaptation loop:*

Initialize data index  $i = 1$

Repeat

For each class, calculate  $S_j$ ,  $p(S_j)$  and  $p(x/\theta)$

Calculate  $p(C_j/x_i, \theta)$

Adapt the mixing matrix  $A_j$

Adapt the bias vector  $b_j$

Adapt the probability density function parameters for the sources

End

Until  $i=T$ .

The classification was tested by processing each instance with the learned parameters  $A_j$  and  $b_j$ . For these classes had several overlapping areas, the classification error on whole data set averaged over 20 trials was  $12.5\% \pm 0.8\%$ . using k-means clustering algorithm, the error was observed as 24.3%.

### III. LEARNING BASIS FUNCTIONS FOR TEXTURES

Several methods have been proposed to learn image codes that utilize a set of linear basis functions. The generative texture model assumes a fixed set of basis functions and source coefficients that active the basis functions to generate a small region in the texture. By applying the ICA mixture model, we present the results that show a higher degree of flexibility in encoding the images. We have tested lot of textures including both periodic and random. For learning, the means of the data components were subtracted and the components were scaled to unit variance. This implies that there is no need to estimate the bias vectors in the case of our texture database. Two complete set of basis functions  $A_1, A_2$  were randomly initialized. Then for each gradient in equation (6), a step size was computed as a

function of the amplitude of the basis vectors and the number of iterations. The algorithm is converged after  $T=30,000$  iterations and learned several classes of basis functions. Figure 3 shows the natural texture of a scene. Figure 4 shows the learned basis functions corresponding to the input texture. Note that unlike the case in K-means clustering or clustering with spherical Gaussians, the classes can be spatially overlapping. In the example, the classes had zero mean and the pattern vectors were only distinguished by their relative probabilities under the different classes.

#### IV. UNSUPERVISED TEXTURE CLASSIFICATION & SEGMENTATION

In the earlier section, we applied the ICA mixture model to learn two classes of basis functions. The same approach can be used to identify multiple classes in a single image. The learned classes are mutually exclusive and by dividing the whole texture image into small regions and classifying them we can identify a cluster of texels which encode a certain region or texture of image. Our example illustrates how the algorithm can learn the textures by unsupervised classification and therefore is able to segment the image into different classes. In contrast to the supervised techniques, our method works unsupervised and may be more flexible to a wider range of texture images. The classification result of the ICA mixture model for these classes using image patterns of size  $5 \times 5$  pixel patches. The model classifies foreground as one class and background as another class. Due to high resolution, background within the texture class are automatically segmented. The learned basis functions for these classes reflect the different statistical structures for each class. In some cases, it misclassified the very dark region as background since this region does not contain enough texture information. To evade this problem, the model needs to average out the small individual misclassified patches by taking a maximum-vote over the region or averaging it over the classes.



Fig.3 Sample texture of a natural scene

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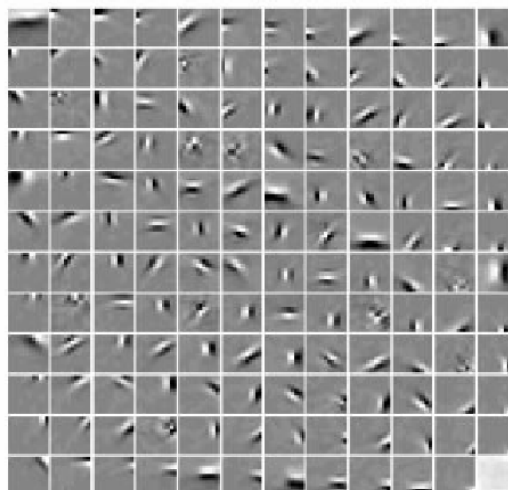


Fig. 4 Learned basis functions for sample texture

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