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Segmentation of Noisy Images Using Hidden Markov Gauss Mixture Models

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Abstract - Image segmentation is an important tool in image processing and can serve as an efficient front end to sophisticated algorithms and thereby simplify subsequent processing. A common problem in segmentation of a monochrome image occurs when an image has a background of varying gray level such as gradually changing shades, regions or classes assume some broad range of gray scales. This problem is inherent since intensity is the only available information from monochrome images. This paper design an extended Hidden Markov Gauss mixture models (HMGMMs) for multi-class noisy image segmentation. The system evaluates noise removal for context based image blocks using convolution filters. The deploy implementing procedure sequence for segmenting the noisy image using convolution filter based HMGMMs. The fundamental idea is to use the convolution of Gaussian functions and image-histogram to generate a scale space image and then find the proper interval bounded by the local extrema of the derivatives.

Keywords— Gauss Mixture Models (GMMs), Gauss Mixture Vector Quantizer (GMVQ), image classification, image segmentation, Convolution filters, Minimum Discrimination Information (MDI)

I. INTRODUCTION

In computer vision, segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). 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 (lines, curves, etc.) in images. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic. Image segmentation is used in multimedia services for extracting explicit information about content so that human observers can interpret images clearly by highlighting specific regions of interest. For example, if segmentation of important regions from the background areas can be automated, the subsequent quantizer can be optimized to allocate more resources in areas of interest. The main purpose of this paper is to devise an automatic context dependent segmentation algorithm yielding a reasonable classification error or Bayes risk between the original and the automatically segmented image. Compression and classification are intimately related to each other. Classification can be considered as a form of compression since segmenting an image into disjoint regions with class labels can be considered as a mapping from inputs into labels using an encoder. On the other hand, compression can be viewed as classification since a codeword label is assigned to each input pixel group.

II. LITERATURE REVIEW

For classification of different regions of interest (ROI), Gauss mixture models (GMM) was used. GMM have been a popular tool for fitting smooth densities to data in statistics and statistical signal processing. GMM has the following advantages. First, the Gaussian pdf maximizes the differential entropy and has the largest Shannon distortion-rate function and the worst high-rate distortion rate tradeoff given the mean and the covariance.GMM inherits the nice properties of Gaussian pdf mentioned above, with better modeling of multimodal source densities. Second, GMM lead to a robust quantizer minimizing the quantizer mismatch. A Gauss Mixture Vector Quantizer (GMVQ) is a vector quantizer where the codewords correspond to Gaussian models. For image distortion measure for VQ, the MDI distortion was used, since MDI has been shown to be competitive with other distortion measures for image classification and segmentation. The overall VQ structure is a classified VQ, which can be viewed as a mixture of GMMs. To design a GMM, a clustering approach using the Lloyd algorithm was employed instead of the popular EM algorithm to design a Gauss mixture. Advantages of the Lloyd algorithm over the EM algorithm include more rapid convergence, and roughly half of the computational complexity of EM algorithm. Accurate classification of GMM does not necessarily coincide with clear segmentation since the latter requires smooth boundaries between classes and better clustering for the same classes. Thus, additional spatial modeling is required for image segmentation.

Among many context dependent image segmentation algorithms, one popular method is based on 2-D Hidden Markov Models. A 2-DHMM assumes that the hidden states (true segmentations) are from a Markovian model, and the given states of blocks, the feature vectors are drawn from conditionally independent distributions, usually assumed to be Gaussian whose parameters vary with the states. Since GMVQ is block-based, the proposed algorithm is based on a block-based segmentation paradigm. Here, interblock modeling is necessary for the spatial correlation between the blocks. For block-based causal modeling, assume that both training and testing images share same underlying Markovian model up to transition probabilities. Causal HMMs and MHMMs are used and estimate transition probabilities with path-constrained 2-D Viterbi algorithms in training step. Also, note that both and impose one dimensional causal dependency, which is not natural for 1-D noncausal image data.

To overcome this drawback, the Hidden Markov Random Field (MRF) was used. MRF model-based techniques can show generality for modeling images and fit naturally into the Bayesian formulation. MRF techniques were applied to image restoration, mine segmentation, and texture segmentation.

III. METHODOLOGY

A. *Block Classification*

Bandwidth is a very important limiting factor in application of image segmentation. Several segmentation schemes require morphological analysis of the different regions, and multiple passes over the image being segmented. However, each pass normally requires loading memory data from slow to fast memory (L1 cache, etc.), which is a slow process. Segmentation solutions based on multiple passes are much slower (or costly) than what can be expected by, for instance, counting the number of operations. Thus, an ideal solution would use a single pass to decide on the type of image region. Such solution would be very difficult with arbitrary shapes of segmentation regions, but it is feasible if to consider only a pre-defined shape.

Some factors mitigate the sub-optimal performance of a block-based scheme around region boundaries. First, compound images now have fairly high resolutions. If the block size is small enough, image type changing for every block should not be expected. Therefore, boundary blocks consist of a small fraction of the image. Those boundary blocks can be identified doing a simple analysis on a block level. Such analysis would not require as much bandwidth, because the number of blocks is much smaller than the number of pixels, and it is required only when some transition is found. Using those techniques a segmentation that is good enough for image compression can be obtained, allowing high text quality, and with a complexity that is practically the same as required by a one-pass segmentation.

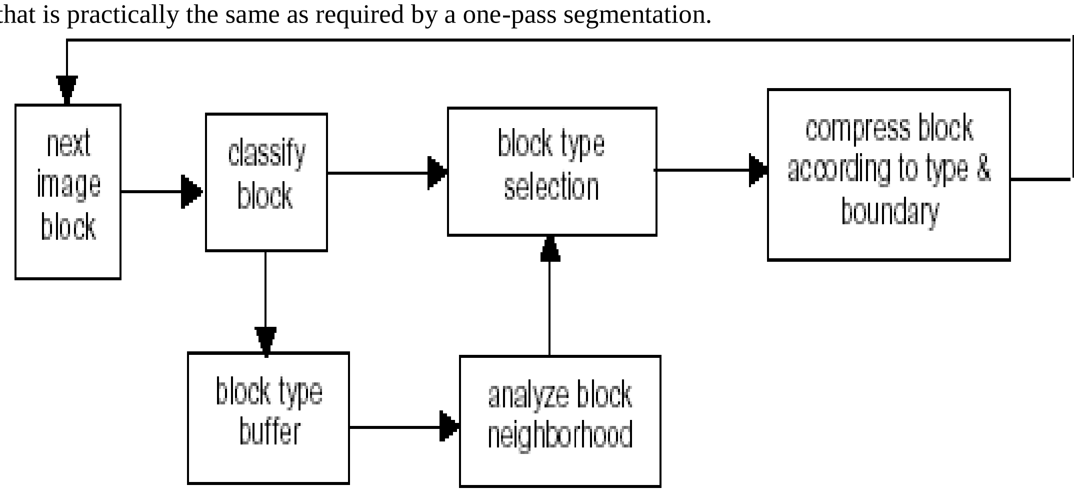

Fig. 1: One pass block classification using neighborhood analysis

Furthermore, the resulting segmentation has very attractive features. For instance, many image compression methods are efficient on rectangular regions, but do not work well on arbitrary regions. Figure.1 shows how the block classification is applied to an individual block. First, the block is classified according to the distribution of its pixels. Next, the class of the neighboring blocks is analyzed. At this stage if a block is in the boundary between two regions can be identified, or change the classification if its confidence is low. To avoid adding the burden of analysis to the decoder, the final classification is added to the compressed stream. Finally, the block is compressed according to the identified type.

The identification of boundaries is important because compression parameters for those blocks can be changed. For instance, a different quantization when moving from a lossy to lossless region can be set. By introducing extra buffering, it is possible to use the block neighborhood analysis for merging blocks that are classified in the same manner. This can be useful for some compression methods that work better in large blocks (e.g., it allows longer runlength, overlapping transforms, etc.).

B. MDI Distortion Measure

The minimum discrimination information (MDI) distortion assigns a distortion resulting from modeling an input vector as a pdf as follows: If we had an estimate of the density that produced, then the relative entropy provides a measure of how dissimilar it is. In general, it cannot produce an accurate estimate of the joint pdf from a single vector, but we can estimate the moments of the underlying distribution from sample averages

C. Gaussian Mixture Model

Image is a matrix which each element is a pixel. The value of the pixel is a number that shows intensity or color of the image. Let X is a random variable that takes these values. For a probability model determination, we can suppose to have mixture of Gaussian distribution as the following form

$$f(x) = \sum_{i=1}^{k} p_i N(x|\mu_i, \sigma_i^2) \qquad (1)$$

Where k is the number of regions and pi > 0 are weights such that $\sum_{i=1}^{k} p_i = 1$

$$N(\mu_i, \sigma_i^2) = \frac{1}{\sigma\sqrt{2pi}} exp \frac{-(x-\mu_i)^2}{2\sigma_i^2} \qquad (2)$$

Where μ_i, σ_i are mean, standard deviation of class i. For a given image X, the lattice data are the values of pixels and GMM is our pixel base model. However, the parameters are $\theta = (p_1, \dots, p_k, \mu_1, \dots, \mu_k, \sigma_1^2, \dots, \sigma_k^2)$ and it can guess the number of regions in GMM by histogram of lattice data.

IV. SYSTEM MODEL

The following techniques were used to remove noise from the image.

A. Image Block Processing

An image to be classified is divided into blocks and is modeled separately for intra-block and inter-block information. Block processing is used for capturing global information and reducing the computation. Intra-block information plays a role in classifying blocks according to their own states (GMM). Inter-block information works as a regularizing factor in segmentation (HMM).

B. Block Noise Removal

The sequences followed in block noise removal process are

i) Producing a map of features in the digital image
ii) Storing an original value of the pixel of interest from the map of features
iii) Using values of features from the map to determine a variable shape neighborhood region of cleaning pixels with respect to the original value of the pixel of interest
iv) Using the neighborhood region of cleaning pixels and the value of the pixel of interest to change the original value of the pixel of interest in the digital image so that it has been noise cleaned
v) repeating steps i)-iv) for other pixels of interest.

C. Convolution Filter

Blocks create a map of features, or edge map, from the luminance / chrominance data. To create the map, four edge detector filters are convolved with each channel and the results summed to create the edge map. The four filters are "h" for horizontal, "v" for vertical, "s" for slash and "b" for backslash. If the channel image is f(x) and the resulting edge map channel is g(x), then

g(x)=|h**f(x)|+|v**f(x)|+|s**f(x)|+|b**f(x)|

where "x" is either the luminance channel, L*, or one of the chrominance channels, a* or b*, "**" is the two-dimensional convolution operation, and absolute values of the components are added together. The four edge detector kernels are 5×5 truncated pyramid filters that were chosen to provide some robustness when used with noisy data.

D. Gaussian Mixture Vector Quantization (GMVQ) with MDI distortion measure

In Gauss mixture modeling, estimation of the means and covariances of the Gaussian components are difficult. To estimate the parameters of the Gauss mixture, use the Lloyd clustering method. In GMVQ design by the Lloyd algorithm, an input vector is mapped to the closest codeword (covariance and mean), i.e., the one minimizing the MDI distortion.

After applying this minimum distortion mapping to the entire training set, the codeword is replaced by the centroid of data assigned to the same class. These two steps are iterated until convergence. The resulting GMVQ is the collection of the probabilities of occurrence, means, and variances, which describes a single image, the underlying prior, is given by the relative frequency.

E. Segmentation with HMGMM

The proposed HMGMM is defined as two stages. First, given the hidden states, the observed images are conditionally independent Gauss mixture distributions estimated by GMVQ. Second, model the inter-block dependency between the hidden states using the BP model or its extension to MBP model with single tuning parameter.

The only parameter in the multi-state bond percolation (MBP) model is unknown and estimates it jointly with the true segmentation. The system use a maximum a posteriori (MAP) estimate for the true segmentation and compute the approximate maximum likelihood estimator (hyper parameter for Gibbs prior).

V. EXPERIMENTAL EVALUATION

HMGMM classifier was applied to aerial images in order to classify them according to whether they are images of manmade or natural areas, and to composite textures in order to segment the particular texture of interest. The implementation has used BP for the segmentation of two classes, and has used MBP for the segmentation of more than two classes.

During training, divided the images into 8 * 8 blocks. Each block was processed independently by sliding a 2 * 2 AR window in a traditional scanning pattern. This first-order AR operation reduced the feature dimension of inputs from 64 dimensions to 4 dimensions. Estimates of the 4 * 1 mean vector and the 4 * 4 covariance matrix were used as features of the 8 * 8 block X.The number of clusters was chosen to minimize the classification error based on six-fold cross-validation for all input images by varying the number of clusters in GMM from 1 to 10. With this fixed cluster number L, the Lloyd algorithm with an MDI distortion was run to convergence to produce a GMM.

After training, the test image was divided into 8 * 8 blocks and an initial classification using MDI clustering was performed independently for each block. After this initial classification result, the test image was divided again into 2 * 2 blocks for the fine classification. Invoked a BP model for spatial homogeneity using the interblock dependence between 2 * 2 blocks. Stochastic EM was employed to find the MAP hidden states.

In EM-MAP algorithm, there are some difficulties. The following parameters are chosen: the number of classes, the weights, the means and the variances. A practical way that we can guess the prior of parameters is drawing the histogram of the observed image. Not only image histogram gives us four above parameters for using initial values in the EM algorithm, but also this extracted information usually has maximum entropy. This claim has shown in experiments. Besides, the final posterior probability will get stable entropy.

VI. CONCLUSION

The paper developed enhanced HGMM algorithm for image segmentation and noise reduction. A sequence of prior and posterior in reference analysis are used. The initial values by histogram of image have suggested which is caused to convergence of EM-MAP method. After convergence of our algorithm, it had stability in entropy.

The problem was formulated on the basis of Bayesian statistics. The block-wise context information using a 2-D hidden Markov model was incorporated to cluster the homogeneous classes. In order to improve segmentation by context, we devised an algorithm that models images by combining GMVQ and the MBP model to produce a 2-D noncausal HMGMM. A Bayesian prior was assumed to follow the MBP model. The stochastic EM algorithm was applied to optimize the MAP hidden states of the HMGMM of the image.

The resulting MAP states were more accurate and smoother than those produced by the other well-known algorithms, including the causal HMM, the multiresolution HMM, the CART, and the LVQ in terms of Bayes risk and spatial homogeneity of the segmented objects, with a computational load similar to that of the causal HMM.

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