International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:268
Vol.1, No.5, September 2012 DOI:10.15693/ijaist/2012.v1i5.24-28

Image Segmentation Using Fusion Bayesian Model

C.Yasotha
Assistant professor, Department of ECE,
Anna University of Technology, Coimbatore, India.

***Abstract*–A new simple and efficient segmentation approach based on a fusion procedure is implemented in this paper. The method aims at combining several segmentation maps associated to simpler partition models in order to finally get a more reliable and accurate segmentation result. The proposed fusion model is derived from the recently introduced probabilistic Rand measure for comparing one segmentation result to one or more manual segmentations of the same image. This non parametric measure allows us to derive an appealing fusion model of label fields, easily expressed as a Gibbs distribution .Gibbs energy model encodes the set of binary constraints, in terms of pairs of pixel labels provided by each segmentation results to be fused. Results show that proposed method provides better performance in terms of PRI than many other fusion model variants for segmentation.**

***Keywords: - Bayesian model, Berkeley image database, label field fusion, Markovian (MRF) model, probabilistic Rand index*.**

I. INTRODUCTION

Image segmentation is a frequent preprocessing step which consists of achieving a compact region based description of the image scene by decomposing it into spatially coherent regions with similar attributes. This low-level vision task is often the preliminary and also crucial step for many image understanding algorithms and computer vision applications.

In this method, the fusion model is derived from the recently introduced probabilistic rand index (PRI) which measures the agreement of one segmentation result to multiple (manually generated) ground-truth segmentations. This measure efficiently takes into account the inherent variation existing across hand-labeled possible segmentations.

This non-parametric measure allows us to derive an appealing fusion model of label fields, easily expressed as a Gibbs distribution, or as a nonstationary MRF model defined on a complete graph. Finally, this fusion model emerges as a classical optimization problem in which the Gibbs energy function related to this model has to be minimized. The application is the robust multiresolution coarse-to-fine minimization strategy.

Our segmentation strategy based on the fusion of quickly estimated segmentation map. In the fusion strategy can be viewed as a two-step hierarchical segmentation procedure in which the first step remains identical and a set of initial input texton segmentation maps (in each color space) is estimated. Second, a final clustering, taking into account this mixture of texton (expressed in the set of different color space) is then used as a discriminant feature descriptor for a final -mean clustering whose output is the final fused segmentation map.

II. RELATED WORK

Mignotte.M [1] proposed an efficient segmentation approach based on a fusion procedure which aims at combining several segmentation maps associated to simpler partition models in order to finally get a more reliable and accurate segmentation result. This fusion approach is simple to implement, fast and applied to various computer vision applications.

Unnikrishnan.R [2] proposed the use of a nonparametric regularization energy term for devising an example-based rendering and segmentation technique. This nonparametric energy minimization is an efficient coarse-to-fine recursive optimization method to minimize the cost function related to this hierarchical model. This measure is exploited to define an efficient shape descriptor for the contour-based shape recognition and indexing problem.

Kato .Z [3] proposed the fusion process which alters the pixel value of the original images. These processes analyze the effects of different image fusion algorithms on the classification of fused images and to relate the quality of the fused image to the classification results.

Pantofaru. C [4] proposed a new image segmentation algorithm based on a tree-structured binary MRF model. The image is recursively segmented in smaller and smaller regions. To improve segmentation accuracy, a split-and-merge procedure is also developed and a spatially adaptive MRF model is used. Numerical experiments on multispectral images show that the proposed algorithm is much faster than a similar reference algorithm based on flat MRF models, and its performance, in terms of segmentation accuracy and map smoothness.

Martin [5] proposed the use of Gibbs distributions for modeling and segmentation of noisy and textured images. This presents dynamic programming based segmentation algorithms for noisy and textured images, considering a statistical maximum a posterior criterion. Since model parameters are needed for the segmentation algorithms, a new parameter

International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:268
Vol.1, No.5, September 2012 DOI:10.15693/ijaist/2012.v1i5.24-28

estimation technique is developed for estimating the parameters in a GD.

Unni. D [6] proposed a database containing ground truth segmentations produced by humans for images of a wide variety of natural scenes. This denotes an error measure which quantifies the consistency between segmentations of differing granularities and fined that different human segmentations of the same image are highly consistent. Use of this data set is demonstrated in two applications: Evaluating the performance of segmentation algorithms. Measuring probability distributions .Grouping factors as well as statistics of image region properties.

Song.G.Q [7] proposed an unsupervised segmentation of color-texture regions in images and video is presented. This method refers to as JSEG which consists of two independent steps: color quantization and spatial segmentation. In the first step, colors in the image are quantized to several representative classes that can be used to differentiate regions in the image. The image pixels are then replaced by their corresponding color class labels, thus forming a class-map of the image.

III. OBJECTIVE OF THE PROPOSED MODEL

A. Rand Index

The Rand index is a clustering quality metric that measures the agreement of the clustering result with a given ground truth. This non-parametric statistical measure was recently used in image segmentation as a quantitative and perceptually interesting measure to compare automatic segmentation of an image to ground truth segmentation and to evaluate the efficiency of several unsupervised segmentation methods.

Let n_s be the number of pixels assigned to the same region in both the segmentation to be evaluated s^{test} and the ground truth segmentation s^{gt} and n_d is the number of pairs of pixels assigned to different regions. The Rand index is defined as the ratio of $(n_s+ n_d)$ to the total number of pixel pairs, N (N-1)/2, for an image of size N pixels. More formally if$\{l_i^{stest}\}$ and$\{l_i^{sgt}\}$designate the set of region labels respectively associated to the segmentation maps s^{test} and s^{gt} at pixel location X_i and χ is an indicator function, the Rand index is given by the following relation:

$$\mathrm{Rand}(S^{test}, S^{gt}) = \frac{1}{\frac{N(N-1)}{2}} \times \sum_{i,j\ i<j} \Big[\overbrace{\mathcal{I}\left(l_i^{S^{test}} = l_j^{S^{test}} \text{ and } l_i^{gt} = l_j^{gt}\right)}^{n_s} + \overbrace{\mathcal{I}\left(l_i^{S^{test}} \neq l_j^{S^{test}} \text{ and } l_i^{S^{gt}} \neq l_j^{S^{gt}}\right)}^{n_d} \Big] \quad (1)$$

Which simply computes the proportion (value ranging from 0 to 1) of pairs of pixels with compatible region label relationships between the two segmentations to be compared. A value of 1 indicates that the two segmentations are identical and a value of 0 indicates that the two segmentations do not agree on any pair of points. When the number of labels in s^{test} and s^{gt} are much smaller than the number of data points N.

B. Probabilistic Rand Index (PRI*)*

The PRI was recently introduced as it is the Inherent variability of possible interpretations between human observers of an image, the multiple acceptable ground truth segmentations associated with each natural image. This variability between observers, recently highlighted by the Berkeley segmentation dataset, is due to the fact that each human chooses to segment an image at different levels.

In the absence of a unique ground-truth segmentation, the clustering quality measure has to quantify the agreement of an automatic segmentation with the variation in a set of available manual segmentations representing, in fact, a very small sample of the set of all possible perceptually consistent interpretations of an image More formally, let us consider a set of L manually segmented (ground truth) images $\{S_1^{gt},S_2^{gt},......S_l^{gt}\}$ corresponding to an image of size N . Let be the segmentation to be compared with the manually labeled set and $\{l_i^{skgt}\}$ designates the set of region labels associated with the segmentation maps S at pixel location, the probabilistic RI is defined by

$$\mathrm{PRand}\left(S^{test},\{S_k^{gt}\}\right) = \frac{1}{\frac{N(N-1)}{2}} \sum_{i,j\ i<j} \times \left[p_{ij}\,\mathcal{I}\left(l_i^{S^{test}} = l_j^{S^{test}}\right) + (1-p_{ij})\mathcal{I}\left(l_i^{S^{test}} \neq l_j^{S^{test}}\right)\right] \quad (2)$$

Where a good choice for the estimator of P_{ij} (the probability of the pixel and having the same label across $\{S_k^{gt}\}$ is simply given by the empirical proportion

$$p_{ij} = \frac{1}{L}\sum_{k=0}^{k=L}\delta(l_i^{S_k^{gt}}, l_j^{S_k^{gt}}) \quad (3)$$

Where is the delta Kronecker function.

C. Label Field Fusion Model for Image Segmentation

The fusion model of L segmentations $\{S_1, S2_{........}S_L\}$ associated to an image of size to be fused (i.e., to efficiently combine) in order to obtain a final reliable and accurate segmentation result. The generative Gibbs distribution model of correct segmentations gives us an interesting fusion model of segmentation maps, in the maximum PRI sense, or equivalently in the maximum likelihood (ML) sense for the underlying Gibbs model expressed as

$\hat{S}_{ML fusion}$ = arg max P $(\{p_{ij}\} |S$

$$= \arg\min \Big\{ \qquad \Big\} \quad (4)$$

$$= \arg\min U_L (\{p_{ij}\}, S = \{l_i\})$$

Where U_L is the likelihood energy term of our generative fusion model which has to be minimized in order to find $\hat{S}_{MLfusion}$. U_L encodes the set of constraints, in terms of pairs of pixel labels, provided by each of the segmentations L to be fused. The minimization of U_L finds the resulting segmentation which also optimizes the PRI criterion.

D. Bayesian Fusion Model for Image Segmentation

This is an ill-posed problem exhibiting multiple solutions for different possible values of the number of classes which is not a priori known. To render this problem well-posed with a unique solution, some constraints on the segmentation process are necessary, favoring over segmentation or, on the contrary, merging regions. From the probabilistic viewpoint, these regularization constraints can be expressed by a prior distribution of the unknown segmentation $S=\{l_i\}$treated as a realization of a random field, for example, within a MRF framework or analytically, encoded via a local or global prior energy term added to the likelihood term.

In these models, we consider an energy function that sets a particular global constraint on the fusion process. This term Restricts the number of regions (and indirectly, also penalizes Small regions) in the resulting segmentation map. So we consider the energy function

$$U_P(S) = |R(S)|.H(R(S)-) \quad (5)$$

Where |R(S) |designates the number of regions (set of connected pixels belonging to the same class) in the segmented image S, H (.) is the Heaviside (or unit step) function, and an internal parameter of our fusion model which physically represents the number of classes above which this prior constraint, limiting the number of regions, is taken into account. From the probabilistic viewpoint, this regularization constraint corresponds to a simple shifted (from) exponential distribution decreasing with the number of regions displayed by the final segmentation.

IV.EXPERIMENTAL RESULTS

A. Set Up

In all the experiments, we have considered our fusion methods on initial segmentations obtained with the following parameters: the size of the squared window, used to compute the local histogram for the initial segmentations or the fusion procedure is set to $N_{W=}$ 7*7. The number of bins for each local re-quantized histogram is set to $N_{b\ =}$ 5*5*5.We use Ns = 6 segmentations provided by the following color spaces RGB, HSV, YIQ, XYZ, LAB, and LUV. Several quantitative performance measures will be given for several values (comprised between 6 and 13) of K_1 and K_2 respectively, the number of classes of the segmentation to be fused and the resulting number of classes of the final fused segmentation map. The optimal value of K seems to be comprised between 0.10 and 0.15.

B. Comparison with State-of-the-Art Methods

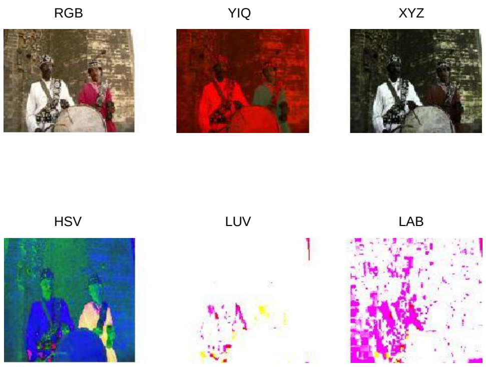
We have replicated the scenario used in the evaluation of State-of-the-art segmentation methods. In these experiments, we have to test our segmentation algorithm on the Berkeley segmentation database consisting of 300 color images of size 481* 321. For each color image, a set of benchmark segmentation results, provided by human observers is available and will be used to quantify the reliability of the proposed segmentation algorithm.

The comparison is based on the following performance measures, namely the PRI measure (higher probability is better and a score equal to means that on average 80% of pairs of pixel labels are correctly classified in the segmentation results) which seems to be highly correlated with human hand-segmentations along with the F-measure . This F-measure deduced from the Precision/Recall values and characterizing the agreement between region boundaries of two segmentations, is now widely used in the computer vision and edge detection community. Qualitatively, the precision measure (P) is defined as the fraction of detections that are true boundaries; this measure is low when there is significant over-segmentation, or when a large number of boundary pixels have poor localization. The Recall (R) measure gives the fraction of true boundaries detected; a low recall value is typically the result of under-segmentation and indicates failure to capture salient image structure.

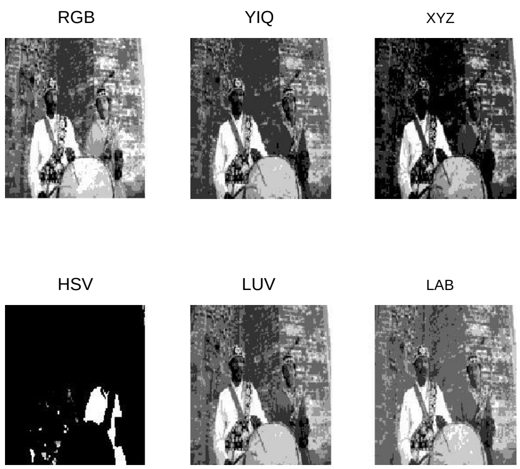
C. Results

In terms of PRI measure, we observe that the discussed fusion strategy gives competitive results (a score equals to means that on average 80% of pairs of pixel labels are correctly classified in the segmentation results) with a relative low variance over the set of images of the Berkeley image database.

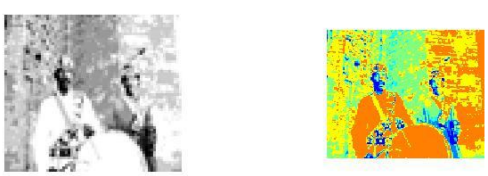
DIFFERENT COLOR SPACES



K-MEAN CLUSTERING RESULT



FUSION RESULT



D. Discussion

PRI performance measure is better when (number of segmentation to be fused) is high. The same observation can be made for the F-measure. This experiment shows the validity of our fusion procedure which is perfectible. For further improvement, we could add, to the set of segmentations to be fused, the segmentation maps obtained with $Nb_{=}3^{3}$ or the clustering results obtained by using (in the K-mean algorithm) different feature descriptors or different similarity measures between the histogram descriptors. The resulting fusion map exhibits an average number of regions, comparatively to the set of ground-truths, and can be compared to the input manually generated segmentations with the same number of regions. Let us add that the Gibbs energy of our fusion model can also be used in a second step in order to compute the fidelity of each ground-truth segmentation to the set of input ground-truths; the negative Gibbs energy being proportional to the PRand metric of each input segmentation to the resulting fusion map.

PERFORMANCE MEASURES

Humans	PRI	VOI	GCE
RGB	0.28726	1.4129	1.3766
HSV	0.31197	1.2879	1.2451
YIQ	0.31403	1.2481	1.2971
XYZ	0.25956	1.9825	0.5169
LAB	0.30813	1.2337	1.2174
LUV	0.31922	1.8947	1.3344
FUSION	0.31403	1.2337	0.5169

MEAN NUMBER OF REGIONS IN THE K MEANS SEGMENTATIONS TO BE FUSED AND IN THE FINAL SEGMENTATIONS FOR THE FUSION MODEL

ALGORITHMS	MEAN NUMBER OF REGIONS	
	K-MEANS	FINAL
PRIF	28.62	12.95
PRIF	28.54	12.87
PRIF	25.65	12.34
PRIF	23.83	18.95
PRIF	29.56	22.56

V. Conclusion

In this paper, a new and efficient segmentation strategy based on a Markovian Bayesian fusion procedure. The goal is to combine several quickly estimated segmentation maps in order to achieve a more reliable and accurate segmentation result. This fusion is achieved in the penalized maximum PRI sense which has a perceptual meaning. This fusion framework remains simple to implement, perfectible, by increasing the number of segmentation to be fused, and general enough to be applied to various digital image and computer vision applications.

REFERENCES

[1] Destrempes.F and Mignotte.M(2006) ,"Fusion of hidden markov random field models and its bayesian

estimation",IEEETrans.Imge process.,vol.15,No.10,pp.2920-2935.

[2] Kato.Z and Song.G.Q(2003),"Unsupervised segmentation of color textured images using a multi-layer mrf model",IEEETrans.Image process.,Vol .10,No.10,pp.961-964.

[3] Martin.D and Malik.J(2007),"A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics",IEEETrans.Bio inf.,Vol.2,No.8,pp.416-423.

[4] Mignotte.M(2004), "Nonparametric multiscale energy based model and its application in some imagery problems",IEEETrans.Signal process.,Vol.26,No.2,pp.184-197.

[5] Mignotte.M(2008)," Segmentation by fusion of histogram basedKmeans clusters in different color spaces",IEEETrans. Image process.,Vol. 17,No. 5, pp.780-787

[6] Mignotte.M(2004),"Effects of image fusion algorithms",IEEE Trans.image process.,vol.25,No.5,pp.424-428.

[7] Pappas.T (1998),"An adaptive clustering algorithm for image segmentation",IEEETrans.Signal Process.,Vol.40,No.4,pp.901-914.

[8] Saber. E and Tekalp.A(1999), "Fusion of color and edge information for improved segmentation and edge linking",IEEE Trans.Imaging.,Vol.15,No.10,pp.769-780.

[9] Schmid.p(1999),"Segmentationofdigitized dermatoscopicimages by twodimensional color clustering",IEEETrans.medical maging.,Vol.18,No.2,pp.164-171.

[10] Unnikrishnan. R and Hebert.M(2007),"Toward objective evaluationofimagesegmentationalgorithms",IEEE Trans.,Vol.29,No.6,pp.929-944.