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Unsupervised Segmentation of Natural Images Based on Contour

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Abstract: We propose an algorithm for the robust segmentation of natural images based on their texture and other features apart from the prevailing contours. As the natural images has homogeneous textures, an optimal segmentation is possible if the clusters are properly formed based on edges (contours) as well as textures. But most of the methods are sensitive to noise and other artifacts, segmentation and formation of cluster based on the textures may not be possible as easy. Hence we propose to model the homogeneous pattern of the natural image as a Gaussian distribution to achieve optimal segmentation. To validate the segmentation algorithm, the Berkeley Segmentation Dataset is being used and the simulations are carries out in MATLAB 2012a. From the output segmented image, it is clear that the algorithm performs segmentation on natural images and its robustness is clear both subjectively and objectively.

Key words: Segmentation · Cluster · Texture · Contour

INTRODUCTION

The segmentation of natural images is important for the algorithms which implement object detection, tracking on the real time natural images. Object recognition in various scenarios would not be possible by segmentation of the desired region of interest. The segmentation algorithm works efficiently when it is preprocessed for noise elimination and contrast enhancement. This steps makes the resulting image suitable to segment the region of interest. Figure 1 shows the hierarchical steps to segment the image efficiently. It starts with noise estimation and noise removal and further enhancing the contrast of the image eases the segmentation process.

There are several approaches and methods available in the literature to implement and to improve the segmentation performance. A novel textural similarity measure which utilizes texture and color information is introduced and convex multi label optimization methods are used for interactive segmentation [1]. As the unsupervised segmentation methods are hard to accomplish, it is better to choose supervised segmentation methods. The color and the texture plays a major role in segmenting natural images and this can be computed by a mean value of a small window [2] or based on 1D or 2D histograms [3, 4] and Gaussians [5, 6] or considering spatial information [7, 8]. Also there are few papers available in the literature utilizing active contour models for mainly motion tracking and segmentation. These models are based on the contours and edges of various shapes and motion vectors. The two types of contour models used in image segmentation are parametric [9-11] and non- parametric [12-14] methods. There are few parametric active contour models like Gradient vector Flow (GVF) [15], Vector field convolution (VFC) [16] and decoupled active contour (DAC) [17] proposed in the literature. These parametric models are either sensitive to noises or they lack convergence and sometime needs initial contour to start the segmentation, whereas the non-parametric models can converge easily even for high curvature boundaries [11-14]. Figure 2 shows the parametric and non-parametric contour active models available in the literature.

Finding the edges in image is primary in a contour based segmentation technique and then linking suitable edges by considering the colour and texture information yields robust segmentation of natural images. By appropriately varying the threshold, edge detection can be carried out based on the homogeneity of the image. But if the image has various textures, the edge detection may not work properly even after choosing suitable threshold value.

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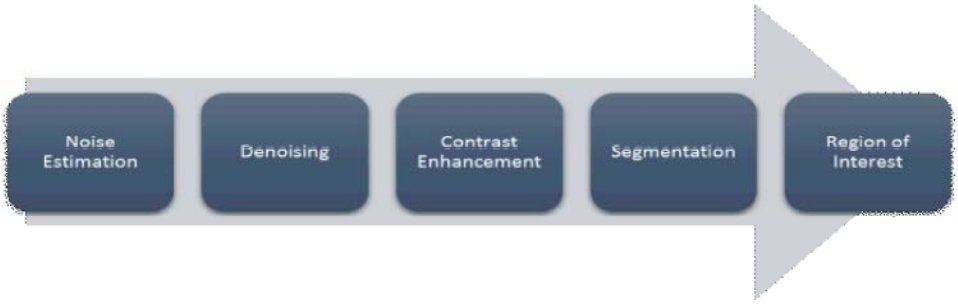

Fig. 1: Segmentation with pre-processing stages

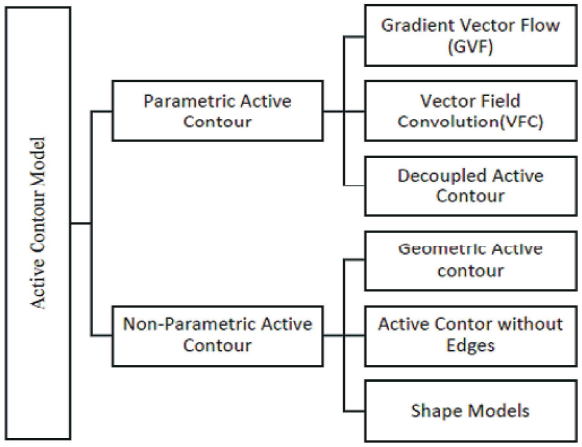

Fig. 2: Taxonomy of active contour approach

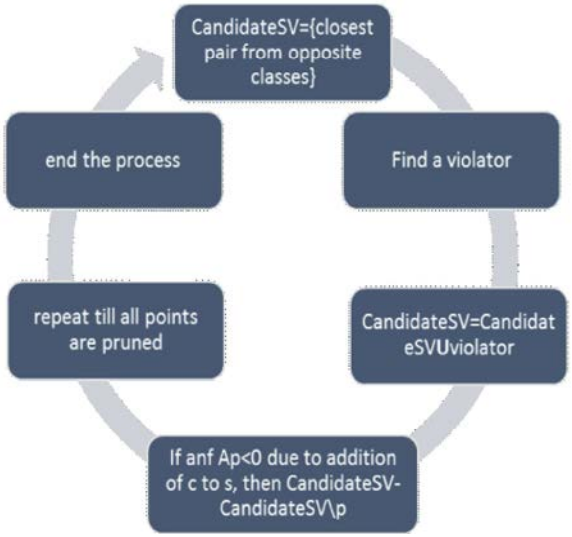

Fig. 3: simple SVM Algorithm

Another interesting method is the simple and fast SVM algorithm proposed by Vishwanathan *et al.* [18]. In this simple SVM the initialization followed in the direct SVL is used to speed up the convergence of the solution. The algorithm shown in Figure 5 stores all the candidate support vector set and it initializes with the points from opposite classes similar to the Direct SVM. While iterating the algorithm all the violating points are added to its candidate set. The quadratic penalty formulation is used for better linear separation of the data points in the considered kernel space.

Proposed Method: Identification of the region of interest is based on the texture and colour information and hence we propose to model the texture and colour information for segmenting objects. The filter value of a location x is;

$$f_c(x) = \max(s_c(x)) - \min(s_c(x))$$

where $s_c(x)$ is the structural variation value, $f_c(x)$ is the filter value with respect to the neighbourhood and $r_c(x)$ is its local randomness;

The $r_c(x)$ in the nXn patch for p neighbours is;

$$r_c(x) = \sum_p s_c(x).\log s_c(x)$$

For each colour channel, the local textural representation *lc(x)* of a pixel is calculated as;

$$l_c(x) = \left[s_c(x) f_c(x) r_c(x) \right] \quad (1)$$

This *lc(x)* which is the local textural representation can be taken as initial information to implement higher level segmentation algorithms.

Coding Length Minimization for Segmenting: The non-overlapping segments of a segmented image I is a set R given by;

$$R = \{R_1, R_2, ..., R_k\}, \bigcup_{i=1}^{k} R_i = 1$$

And its corresponding coding length is given by;

$$L^S_{\omega,\varepsilon}(R) = \sum_{i=1}^{k} L_{\omega,\varepsilon}(R_i) + \frac{1}{2} B(R_i) \quad (2)$$

By minimizing the equation 2, an optimal segmentation can be achieved. To start the optimization process, a superpixel which is a subimage void of strong edges is chosen with the help of colour and texture information derived from the equation 1. Thus superpixel initialization itself is a complex task to start with and it is discussed in the existing literature like [19], [20], [21].

At each iteration of the algorithm the pair of over-segmented regions *Ri* and *Rj* will decrease the equation (2) if both are merged together. Thus, the iterations are repeated till the coding length L_s cannot be reduced further. Using the iterative algorithm, various natural images are segmented and the optimum results are shown in the Figure 4. A segment map is created showing the individual segments.

Experiments and Results: An exhaustive simulation were performed by adapting the above discussed method and the qualitative outputs like the segmented image map is shown in Figure 4. The quantitative outputs like MCR, RMSE, PRI and BDE is given in the following tables. The sample images are taken from Berkeley Segmentation Dataset (BSD) [22, 23].

Evaluation of Segmentation Techniques: The following measures namely misclassification rate (MCR), root mean squared error (RMSE), Under segmentation (*UnS*), Over segmentation (*OvS*), Incorrect segmentation (InC) evaluates the segmentation results quantitatively, which is used to analyze the performance of the segmentation algorithm.

MCR is the ratio between the number of misclassified pixels and the total number of pixels available in the object of interest ignoring the background pixels in the slice [24].

$$MCR = \frac{number\ of\ misclassified\ pixels}{total\ number\ of\ all\ pixels}$$

RMSE is widely used to quantify the difference between the true partial volumes and the algorithm estimations. The RMSE of the proposed estimator $RMSE(\hat{\theta})$ is the difference between the original parameter (θ) value and its estimation $(\hat{\theta})$ [24].

$$RMSE(\hat{\theta}) = \sqrt{MSE(\hat{\theta})} = \sqrt{E\left[(\hat{\theta} - \theta)^2 \right]}$$

N_{fp} - The number of pixels that do not belong to a cluster and are segmented into the cluster.
N_{fn} - The number of pixels that belong to a cluster and are not segmented into the cluster.
N_p - The number of all pixels that belong to a cluster.
N_n - The total number of pixels that do not belong to a cluster

Three parameters in this evaluation system may now be defined as follows [25].

- Under segmentation (*UnS*): $UnS = \frac{N_{fp}}{N_n}$ representing the percentage of negative false segmentation.
- Over segmentation (*OvS*): $OnS = \frac{N_{fn}}{N_p}$ representing the percentage of positive false segmentation.
- Incorrect segmentation (InC): $InC = \frac{N_{fp} + N_{fn}}{N}$, representing the total percentage of false segmentation.

Fig. 4: Segmentation results

Table 1: Evaluation of segmentation performance

Evaluation Criterion	Humans	CTM	Mean-Shift	PCM	FCM	Proposed
UnS (%)	2.12	5.82	8.79	25.2	9.56	3.28
OvS (%)	5.89	9.52	13.08	22.8	23.79	2.52
InC(%)	3.95	12.55	18.33	43.75	14.24	2.46

Table 2: MCR

Method	MCR % for zero noise
Humans	4.81
CTM [26]	4.22
Mean-Shift [27]	3.89
PCM [28]	2.72
FCM [29]	2.28
Proposed Method	1.18

Table 3: RMSE

Method	RMSE
Humans	18.96
CTM	18.22
Mean-Shift	12.86
PCM	10.02
FCM	8.66
Proposed	6.98

Table 4: PRI and BDE

Method	PRI	BDE
Humans	0.8754	4.994
CTM	0.7617	9.8962
Mean-Shift	0.755	9.7001
PCM	0.7317	9.6162
FCM	0.7759	9.8632
Proposed Method	0.8019	9.9983

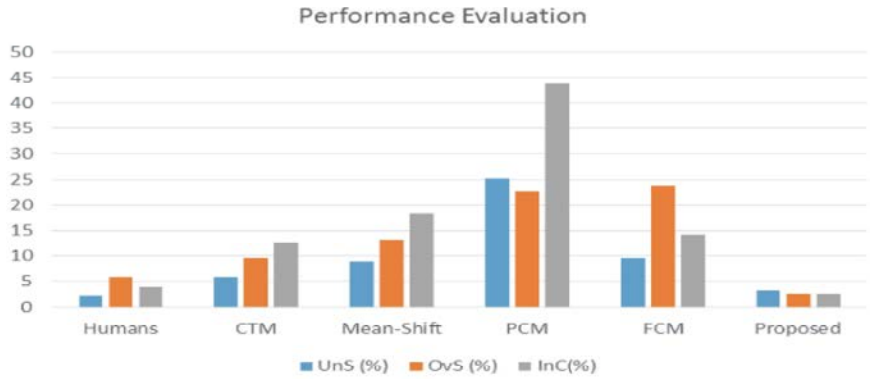

Fig. 5: Performance Evaluation

The Table 1 compares the evaluation performance of several known segmentation techniques for the sample images taken from the Berkley segmentation image database. Evaluating the UnS, OvS and InC values the proposed method works well for natural images. The corresponding graphical representation of the Table 1 is shown in Figure 5. From the values of Table 1, it is clear that the PCM based segmentation technique under segments the natural images and FCM technique over segment the images. Though the human crafted segmentation is comparable with the proposed contour based segmentations, it leads to incorrect segmentation for few cases. Figure 5 shows a peak InC and peak UnS for the PCM and low UnS for the human segmentation. The minimum of OvS and InC is clear for the proposed technique from the chart.

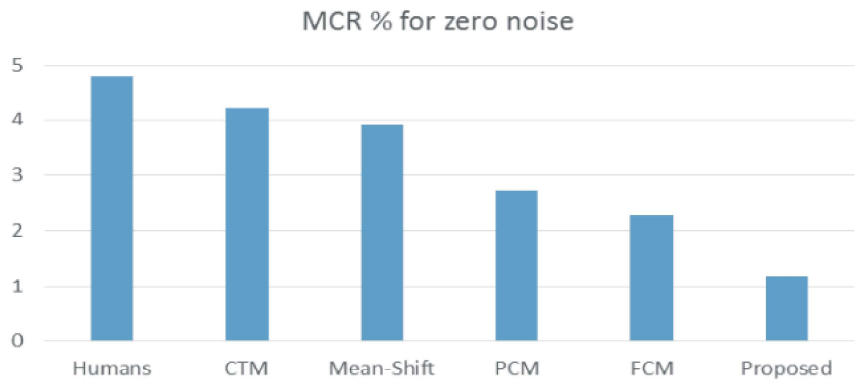

Fig. 6: Misclassification Rate

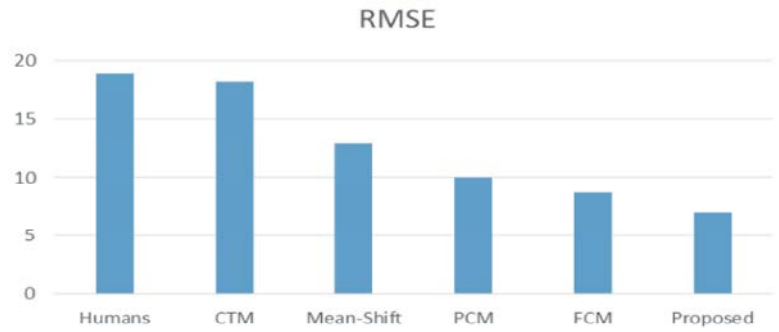

Fig. 7: Comparison of RMSE

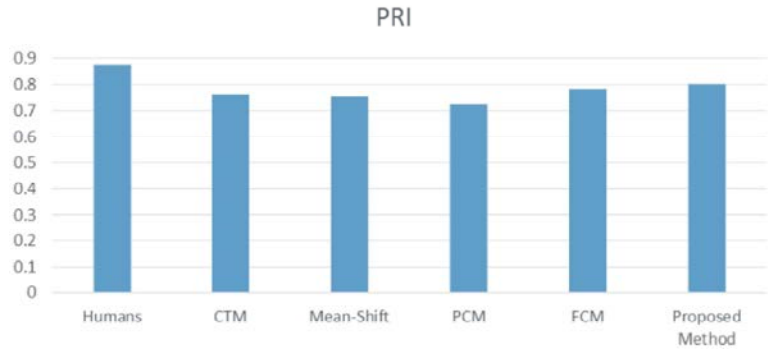

Fig. 8: Probabilistic Rand Index

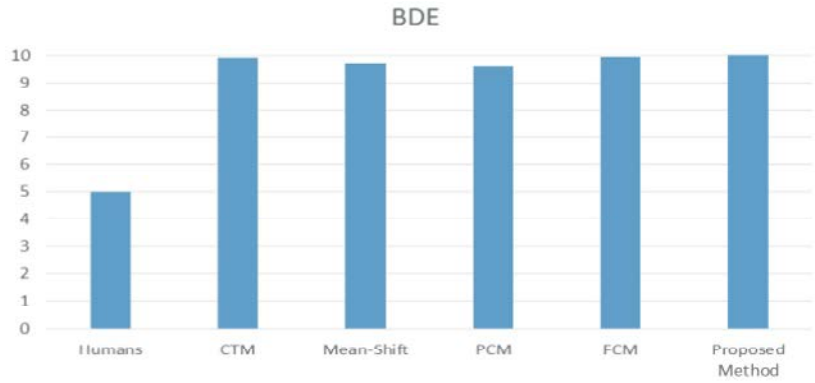

Fig. 9: Boundary Displacement Error

Table 2 gives the MCR values of various segmentation techniques, table 3 provides the RMSE value and Table 4 gives the PRI ad BDE values for comparing with other suitable algorithms.

Figure 6 plots the MCR for the values given in Table 2. The MCR value is more for human made segmentation and least for the proposed technique. Figure 7 plots the RMSE values and Figure 8 and 9 plots the PRI and BDE values. The RMSE is high for manual segmentation and it is also close to the CTM technique and the proposed segmentation method has a least RMSE.

The probabilistic Rand index (PRI) [30] indicates the similarity between two partitions and its value lies in the range of [0, 1] when the similarity increases the PRI also increases to a maximum value of 1 when both the partitions matches exactly. Another metric is boundary displacement error (BDE) [31] which measures the average displacement error of the boundary pixels between two segments. The distance between two pixels one lies in the boundary and the closest other pixel lies in the nearest segment in the BDE. The BDE and PRI index values are used to evaluate the quality of segmentation.

CONCLUSION

The proposed segmentation algorithm is evaluated using various performance criteria like PRI, BDE, MCR and RMSE. It is compared with the other region based segmentation algorithm or contour based segmentation algorithm for its performances and the numerical values in tables 1 to 4 shows its effectiveness. The proposed algorithm is verified with few sample test images taken from the Berkeley Segmentation Dataset. Thus the optimal segmentation estimates the segments by minimizing the coding length. By minimizing the coding length, the MCR is reduced and the optimal segmentation is carried out.

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