Object Boundary Detection and Segmentation using Super Pixel Based Gaussian Mixture Model

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ABSTRACT

Superpixel segmentation segments the image into perceptually coherent segments of comparable size, namely, superpixels.It considerably reduce the number of inputs and gives a meaningful representation for feature extraction, hence it is a pre processing step for many Computer vision tasks. A Proposed pixel-related Gaussian Mixture Model (GMM) to sections pictures into superpixels. GMM could be a weighted sum of Gaussian functions, each one corresponding to a superpixel, to explain the density of every pixel depicted by a random variable. Completely varied from previously proposed GMMs, the weights are constant, and Gaussian functions within the sums are subsets of all the Gaussian functions, resulting in segments of comparable size and an algorithm of linear complexity with respect to the amount of pixels. Additionally to the linear complexity, GMM algorithm is permits quick execution on multi-core systems. Throughout the expectation-maximization iterations of estimating the unknown parameters within the Gaussian functions, Its tends to impose two lower bounds to truncate the eigen values of the covariance matrices, which enables the proposed algorithm to manage the regularity of superpixels.

Keywords

Superpixel , Image Segmentation , Parallel algorithms , Gaussian mixture model , Exceptation - Maximization

1. INTRODUCTION :

A superpixel is usually represented as “a cluster of connected, perceptually unvaried pixels that do not overlap with the other superpixels.” The subsequent properties are commonly desirable to differentiate superpixel segmentation from different image segmentation techniques.

Accuracy: Superpixels ought to adhere well to object boundaries. Superpixels crossing object boundaries indiscriminately may lead to catastrophic results for subsequent algorithms. Accuracy is the most vital demand requirement for any segmentation task.

Efficiency: As a pre processing step, a Superpixel algorithm ought to have occasional machine complexness. This property is crucial for time period applications.

Similar size: Superpixels ought to be similar in size. This property allows succeeding algorithms to handle every superpixel disinterestedly and distinguishes superpixels from alternative over-segmented regions.

Under the constraint of similar size property, the numerous superpixel algorithms have been projected to full fill the requirements of various computer vision applications. As an example, the results of six progressive algorithms square measure planned in Figs. 1a-1f. Color similarity is well handled in SEEDS and ERS to produce extremely correct superpixels. However, their superpixels have significantly irregular shapes even in solid regions (Figs. 1a-1b). Abstraction proximity is well handled in NC and LRW to get regular-shaped superpixels. Nevertheless, many object details (e.g., the rear or the left horn of the kine in Figs. 1c-1d) square measure lost, which ends up in low accuracy. Even worse, NC and LRW run extraordinarily slow thanks to their high process complexities. As shown in Figs. 1e-1f, SLIC and LSC turn out moderately regular-shaped superpixels as a result of color similarity and abstraction proximity measure is well balanced. However, they fail to phase the left horn of the kine from the background.

In this work, every superpixel is related to a Gaussian distribution; every element, diagrammatical by a variable quantity, is described by a weighted total of many mathematician functions, which is that the key plan of (GMM). However, the GMMs proposed antecedent, like the classical GMM and the mixture of GMMS cannot be directly applied to superpixel segmentation. This can be as a result of the previous GMMs do not cipher the desired property of comparable size and have comparatively high procedure complexities. The Gaussian functions within the planned GMM square measure summed with identical weight to satisfy ,Within the expectation-maximization (EM) solutions of the previous GMMs, the high procedure complexities square measure caused by that the parameters of every Gaussian operate would like the information of all the info points. In different words, the points grouped in an exceedingly given cluster will seem all over within the feature space.

To scale back the procedure complexities, we model each element during this study with a pixel-related GMM, in which the Gaussian functions type a set of the all the Gaussian functions and area unit associated with the spatial position of that element. Thus, solely a set of the pixels is employed to estimate the parameters of a given Gaussian operate, that accounts for a low machine quality. With the two modifications, our method will simply exceed the progressive methodologies in terms of accuracy. However, the generated superpixels might have wiggly boundaries, and bound variance matrices might become singular, particularly once a superpixel covers a section of constant color. To beat these problems, have a tendency to impose two parameters on the eigen values of all the variance matrices during the EM iterations. The two parameters will stop variance matrices from being singular, management superpixel form, and reduce the amount of wiggly boundaries. We tend to plot example in Fig. 1g.

List our contributions as follows,

1).Proposed a pixel-related GMM for every individual pixel, that permits the superpixels to unfold domestically over a picture and more end in a rule with a lower process quality than the EM algorithms of GMMs planned antecedently.

2). Within the pixel-related GMM, every normal distribution has identical likelihood of being elite, that is, Gaussian functions area unit summed with identical weight, which ends up in superpixels of comparable size.

3) The planned rule offers the choice to management the regularity of superpixel shapes, Thats feature has not been well explored to the method of GMMs was previously explained.

4) Our rule is inherently parallel and permits quick execution on parallel computers.

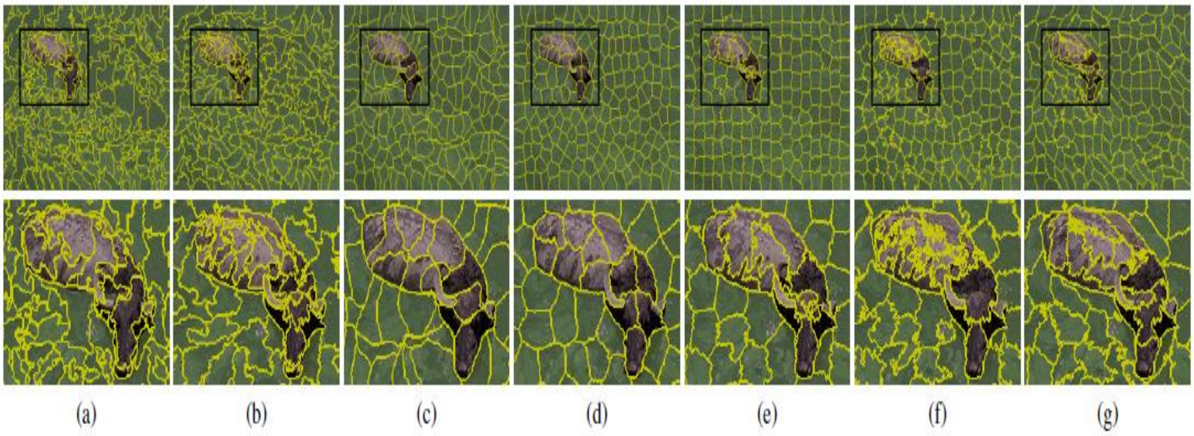


Figure1: Superpixel segmentations by seven algorithms: (a) SEEDS (b) ERS (c) NC (d) LRW (e) SLIC (f) LSC and (g) GMM method.

2. RELATED WORK

NC uses the normalized cuts rule to partition associate affinity matrix fashioned from contour and texture cues, abstraction proximity is implicitly thought of in these cues, which ends in significantly regular superpixels.

However, the process complexness of this technique is relatively high, that is, some O ($N^{3/2}$) wherever N is a range of pixels. Its potency is even worse because of the computation of its dependence, namely, the contour and texture cues. LRW is another rule that can turn out regular and visually pleasing superpixels by considering the compactness constraints in associate energy perform where pixels area unit described by texture options rather than intensities. However, LRW suffers from very slow speed due to its high process complexness, that is, O (nN^2) where n is that the range of iterations.

By victimization level-set-based geometric flow wherever a compactness constraint is encoded, Turbo Pixels provides a quicker solution than American stat and LRW in extracting regular shaped superpixels. However, Turbo Pixels presents comparatively low accuracy and is slow in follow because of the steadiness and potency problems with the underlying level-set technique. In Spatial constraint are incorporated into associate image gradient, on that marker-based watershed rework is performed to come up with superpixels. These two ways run quicker than Turbo Pixels.

However, spatial constraints decrease the accuracy of the watershed rework, which results in comparatively low accuracy. Wherever regularity is encoded within the smooth term of its energy perform. However, this algorithmic program also suffers from poor accuracy. Moreover, on the idea of pre computed line segments or edge maps, superpixels were extracted in Edge-based split-and merge superpixel segmentation and Image partitioning into convex polygons by orientating superpixel boundaries to lines or edges.

Aiming to optimize an energy operate wherever color homogeneity and sleek boundaries square measure inspired, SEEDS, iteratively exchanges superpixel boundaries in an exceedingly ranked structure. However, the data structure makes it difficult to manage the quantity of superpixels. In ERS, Liu et al. planned the objective operate within which color homogeneity and similar size square measure encoded.

To optimize the function, they conferred an algorithmic rule to consecutive add edges to an empty graph edge set till the required variety of superpixels was reached. Though SEEDS and ERS report state of the art accuracy, they manufacture superpixels of significantly irregular form that may be a potential disadvantage for ulterior applications.

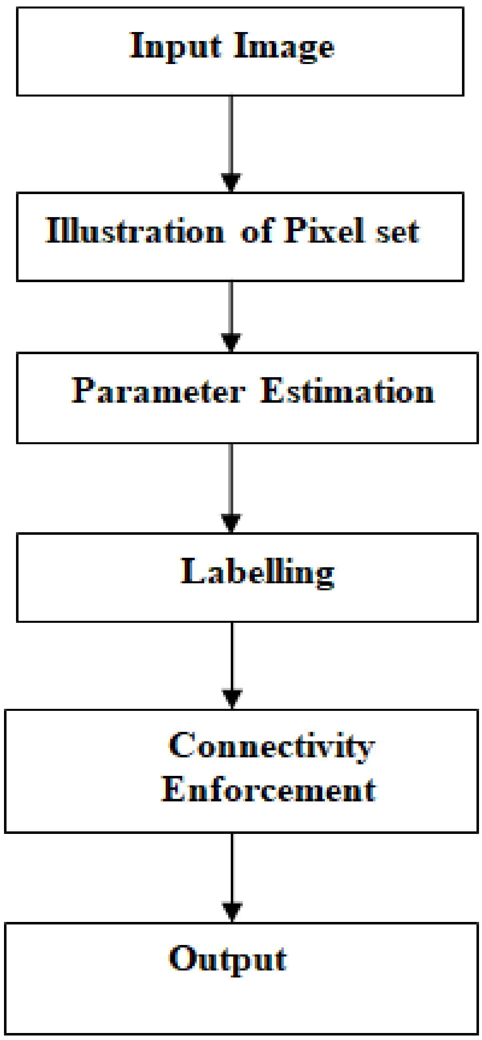
Numerous ways use the target perform of k-means or its variations (e.g., VCells: Simple and efficient superpixels using edge-weighted centroidal voronoi tessellations, Superpixel segmentation using linear spectral clustering, SLIC superpixels compared to state-of-the-art superpixel methods. Among these algorithms, the foremost well-known is SLIC because of its simplicity and potency. SLIC generates superpixels by iteratively applying k-means during a combined 5D coordinate and color space. Several approaches have followed the concept of SLIC to either decrease its run-time. Rather than acting on the 5D vectors similar to SLIC , LSC, applies a weighted k- means to extract superpixels by mapping the 5D vectors to a 10D feature area, that considerably improves the accuracy of SLIC.

A k-means is nice at fitting spherical clusters. However, it's going to fail to section objects with alternative shapes, such as elongated objects. Although FH, mean shift, watersheds, and MC are observed as “superpixel” algorithms in the literature it is not lined during this paper because they manufacture segments of immensely varied size. The variation in sizes is principally as a result of these algorithms don't offer direct management to the scale of the metrics regions.

Structure of content-sensitive superpixels in Manifold slic: A fast method to compute content-sensitive superpixels and Structure-sensitive superpixels via geodesic distance are also not thought-about as superpixels as a result of them are doing not aim to extract regions of comparable size.

A large range of superpixel algorithms are projected. However, few models are given, and with efficiency extracting superpixels with high accuracy still remains a challenge. During this work, we tend to propose another model to address the superpixel downside. Our methodology presents higher accuracy than the progressive superpixel algorithms while not relying on pre computed boundary maps or difficult texture features whereas maintaining similar regularity with LSC. The projected algorithmic rule provides parameters for dominant the regularity of superpixels, creating outperforming LRW possible at little superpixels.

3. PROPOSED METHODOLOGY



3.1MODULES

A. Illustration of Pixel set
B. Parameter Estimation
C. Labelling & Connectivity Enforcement

A. Illustration of Pixel set

Let i denote the picture element index of associate degree input image I of dimension W and height H. Hence, the overall range of pixels N of image I is W .H, and that i € V def = (0, 1…,.N -1) Let (Xi; Yi) denote the position of picture element i on the image plane, wherever Xi € (0, 1….,W – 1) and Yi € (0, 1……,H – 1). Let Ci denote the intensity or color of picture element i. If a color image is employed, then Ci may be a vector; otherwise, Ci may be a scalar. we have a tendency to use vector Zi = (xi; yi; Ci)T to represent picture element i. Most existing superpixel algorithms need the specified range of superpixels K as associate degree input. However, rather than victimisation K directly, we have a tendency to use the specified superpixel dimension Vx and height Vy as essential inputs. If K is such that, then Vx and Vy area unit obtained as follows,

$$v_x = v_y = \left\lfloor \sqrt{\frac{W \cdot H}{K}} \right\rfloor$$

If Vx and Vy square measure most well-liked, then assignment them identical value is inspired. Using the following the specified variety of superpixels K is computed once Vx and Vy square measure directly specified.

$$n_x = \left\lfloor \frac{W}{v_x} \right\rfloor, \;\; n_y = \left\lfloor \frac{H}{v_y} \right\rfloor, K = n_x \cdot n_y$$

Gaussian perform P(. ; .) is outlined in equivalent weight.within which vector ^z and therefore the mathematician parameters in set area unit separated by a punctuation mark. The subsequent text might see
P(. ; .) with completely different symbols for ^z and ѳ^, within which case, the new symbols replace ^z and E^ supported their positions relative to the punctuation mark.

$$p(\hat{\mathbf{z}}; \hat{\boldsymbol{\theta}}) = \frac{1}{(2\pi)^{D/2}\sqrt{\det(\hat{\boldsymbol{\Sigma}})}} \exp\left\{ -\frac{1}{2}(\hat{\mathbf{z}} - \hat{\boldsymbol{\mu}})^T \hat{\boldsymbol{\Sigma}}^{-1} (\hat{\mathbf{z}} - \hat{\boldsymbol{\mu}}) \right\}$$

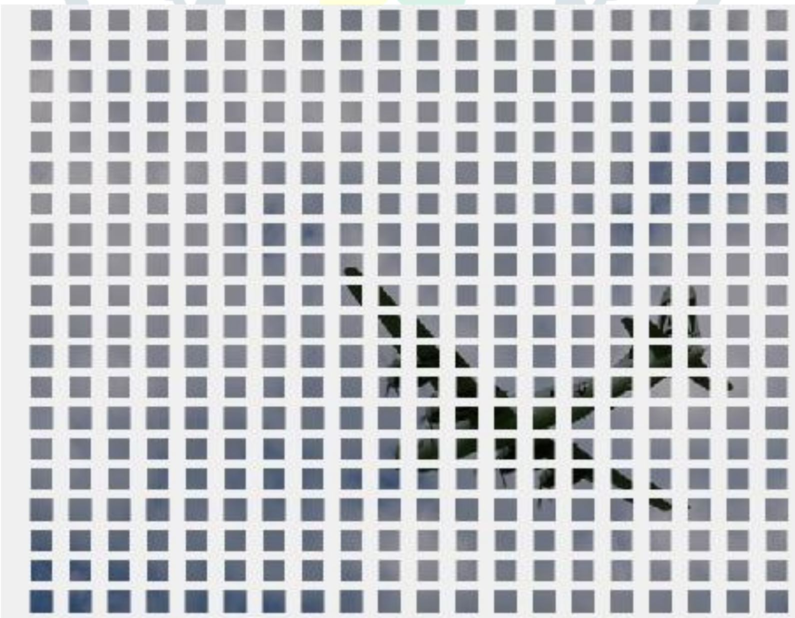


Figure2: Illustration of pixel set

B.PARAMETER ESTIMATION

A Gaussian mixture model is parameterized by two sorts of values, the mixture part weights and therefore the part means that and variances/covariances.

If the quantity of elements is understood, expectation maximization is that the technique most typically will not to estimate the mixture model's parameters. In frequentist applied math, models area unit generally learned by victimisation most probability estimation techniques, It was request to maximise the chance, or probability, of the determined information given the model parameters. Sadly, finding the utmost probability resolution for mixture models by differentiating the log probability and determination for is sometimes analytically not possible.

Expectation maximization (EM) could be a numerical technique for max probability estimation, and is sometimes used once closed kind expressions for change the model parameters will be calculated (which are going to be shown below). Expectation maximization is associate repetitious algorithmic rule and has the convenient property that the utmost probability of the information strictly will increase with every instant iterations, that means it's bound to approach an area most or saddle purpose.

EM for Gaussian Mixture Models

Expectation maximization for mixture models consists of 2 steps.

The first step, called the expectation step or E step, consists of the expectation of the element assignments Ck for every information Xi € Xgiven the model parameters µk,Φk .

The second step is thought because the maximization step or M step,that consists of maximizing the expectations calculated within the E step with reference to the model parameters. This step consists of change the values µk,Φk .

Consequently, superpixels tend to possess identical size Vx,Vy. Note that pixels might have totally different distributions are made that is that the most typical case and a vital distinction between our GMM and therefore the previous GMMs.

$$L_i = \arg_k \max_{k \in K_i} \frac{p(\mathbf{z}_i; \boldsymbol{\theta}_k)}{\sum_{k \in K_i} p(\mathbf{z}_i; \boldsymbol{\theta}_k)}$$

C. LABELLING & CONNECTIVITY ENFORCEMENT

After assignment labels to pixels via equivalent, in which connectivity of every superpixel isn't secured, we add a post processing step to enforce property.

This step is conducted by merging little connected segments with one of their neighbouring segments. If 2 segments should be merged, then their colours ought to be just like succeeding high segmentation accuracy. The merging operation starts from the smallest section to avoid outsized superpixels.

First, we find all the connected segments, during which pixels are connected and have identical label, and type them by size in ascending order. Next, we have a tendency to consecutive valuate the sorted segments.

If the size of the present section is a smaller amount than 1 / 4 of the desired superpixel size, then we have a tendency to mark the present section as supply section. Among all the neighbouring segments of the current supply section, the one with the nearest color is marked as destination section.

The supply section is then integrated with its destination section. At identical time, the size of the supply section is cleared to zero, and the size of the destination section is updated by adding the size of the supply section.

Once merging, every connected segment forms a superpixel. Before the post processing step, superpixel k may be on paper sure to never seem in any regions apart from Ik However, this condition could become untrue as a result of pixels are labelled in the post processing step and every new label cannot mirror the position of the corresponding Superpixel.

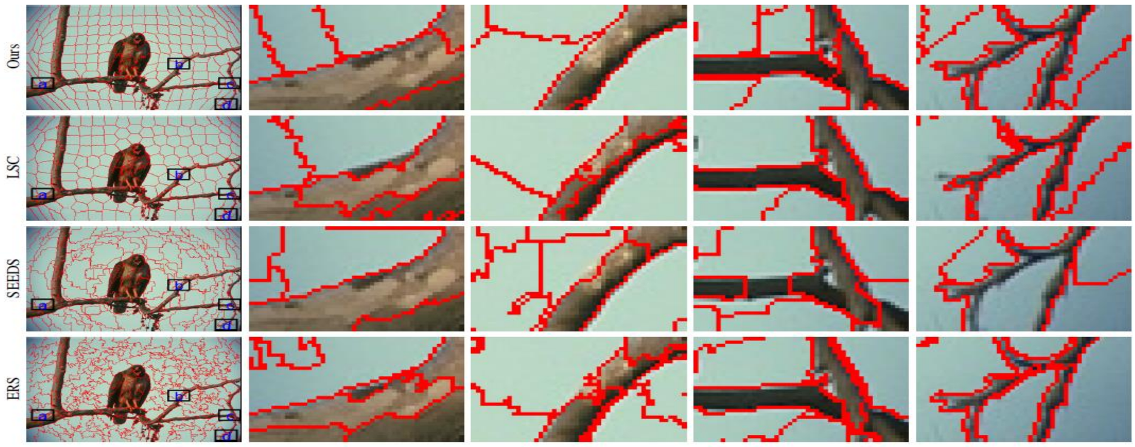


Figure 3: Visual Comparison between GMM, LSC, SEEDS and ERS.

COMPARISON OF CONTENT ADAPTIVE SUPER PIXEL(CAS) SEGMENTATION AND GAUSSIAN MIXTURE MODEL (GMM)SEGMENTATION

Input Image	GMM (ACCURACY)	CAS (ACCURACY)
Plane	0.987	0.975
Building	0.974	0.956
Eagle	0.991	0.947
Church	0.956	0.951
Swan	0.966	0.933

GRAPH REPRESENTATION:

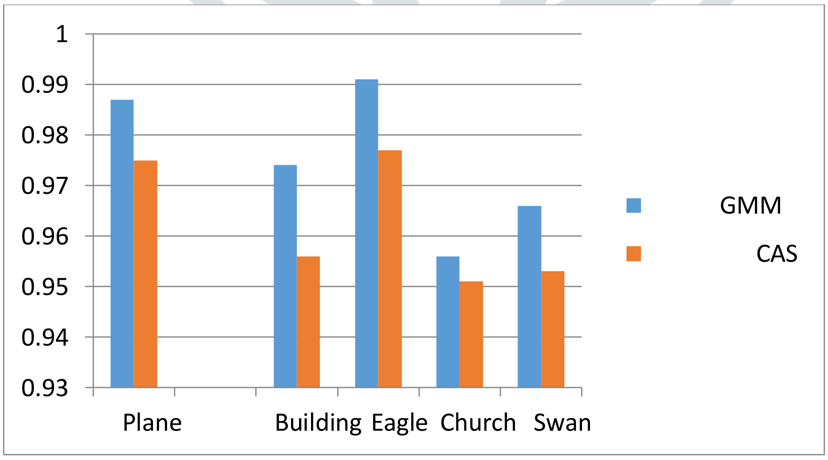


Figure 3: Comparison Graph

4. CONCLUSION

Superpixel segmentation is changing into a elementary technique for numerous computer vision tasks as a result of it will scale back the number of inputs for resultant applications and supply a purposeful image illustration for feature extraction. However, expeditiously extracting superpixels that adhere well to object boundaries remains a challenge. To handle this problem, It tend to planned a pixel-related GMM within which every pixel is sculptural by a weighted add of Gaussian functions, each of that is related to a superpixel.

Totally different from previous GMMs, Gaussian functions within the weighted add are subsets of all the Gaussian functions and have equivalent weights, Its ends up in associate algorithmic rule of linear quality and segments of comparable size. Its tend to obligatory two lower bounds to truncate the eigen values of the variance matrices and management the regularity of superpixels. Experiments on BSDS500 show that proposed algorithmic rule outperforms the progressive strategies in terms of accuracy.

For regularity, It tends to achieved a performance similar with this progressive superpixel algorithmic rule LSC. LRW bestowed the simplest regularity; but, proposed method can outmatch LRW in terms of accuracy and regularity when comparatively large numbers of superpixels are generated. Moreover, get a benefit of data processing as a result of the time consuming elements of the strategy is parallelized in nature

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