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Super Pixel Image Based Segmentation Using Mean Orientation and Bipartite Graph

R.Srinivas¹, Shyam Sunder Pabboju², Satya Shekar Varma P³, B.Yadaiah.⁴

Assistant Professor, Department of Computer Engineering, MGIT, Hyderabad, India¹

Assistant Professor, Department of Computer Engineering, MGIT, Hyderabad, India²

Assistant Professor, Department of Computer Engineering, MGIT, Hyderabad, India³

Assistant Professor, Department of Computer Engineering, MGIT, Hyderabad, India⁴

ABSTRACT: Image segmentation is significant and difficult task in computer visualization. The super pixels are differentiated as a covariance matrix on a manifold or a vector in a color space, through which graph layers are formed on the common vertex sets. The image segments the super pixels and provides grouping cues to show segmentation, where super-pixels are composed easily by over segmentation of the image utilizing several sensible previous segmentation methods. Super-pixel can capture different and multi scale visual sample of ordinary image with the help of diverse algorithms and different parameters. Successful incorporation of the cues from a large multitude of super-pixels generates a promising yet not fully explored direction. Hence, it may degrades the segmentation accuracy to rectify this problem an efficient super pixel segmentation system is proposed namely Mean Orientation and Bipartite Graph. In this paper Super pixel Aggregation of segmentation technique is proposed for improving the segmentation accuracy over MS COCO 2014 database. The proposed system consists of two major steps such as extracts the relevant features form the sample image using Mean Orientation. In the second step, Bipartite Graph (BG) is used for extracts the particular region from the image. An experimental result demonstrated that the proposed MO+BG performance is compared with the existing work such as Adaptive Shape Prior and Graph Cut (ASP+GC) and Graph cut. The proposed MO+BG method achieves 6% of improvement in super pixel segmentation.

KEYWORDS: Bipartite Graph, Ground Truth, Segmentation, Segmentation by Aggregating Super-pixels, Super-Pixels, Transfer Cut.

I. INTRODUCTION

Development of the web technology has offered us numerous web images, phone cameras and digital cameras, the amount of accessible images are growing at an exponential speed [1], [2]. so as to create the most effective use of those resources, an efficient image searching, browsing, and retrieval tools are required by users from various domains, including remote sensing, medical imaging, criminal investigation, architecture, communications et al. [3]. Hence, automatic image annotation (A-IA) becomes an emerging technique during this field and also attracted the interest of the many researchers within the recent decades [4]. the first annotation approaches depend on professionals or experts for annotation. It suffers from the issues of labor intensity and subjectivity [5]. With the ascent of image archives, both the statistical generative model and also the discriminant methods of machine learning are applied to handle the matter of image annotation. the most idea of A-IA technique may be a task of assigning one or more semantic concepts to a given image and a promising thanks to achieve simpler image retrieval and analysis [6], [7].

The semantic gap between low-level visual features and high-level image semantic, the performances of themany existing image annotation algorithms don't seem to be satisfactory [8]. Segmentation bridges the gap between low-level image features and high-level image semantic. In computer visualization, image annotation continues to be challenging task particularly when substances are highly variable and when image groups are taken fromuge(fine-grained) vocabularies. the everyday visual features, broadly utilized as part of single object detection to capture the rich semantic substance in images. In fact, with basic visual features, images having the identical semantic substance may show solid visual fluctuation while pictures with a high visual similarity, may have diverse semantic analysis. no matter these



difficulties, a generous development has been made in automatic image annotation within the most up-to-date decade [9]. One of the most important concern in segmentation is grouping cue (overlapping of two or more objects), which reduces the performance of image annotation [10]. During this paper, for improving the segmentation accuracy Segmentation by Aggregating Super pixels (SAS) based Mean orientation and BG method is proposed. The proposed segmentation method is decreases the computational complexity and segmentation error. Further, the experimental examination on MS COCO 2014 database proves that the proposed method is superior to the opposite previous. This paper consists as follows. Section II survey several recent papers on image annotation supported segmentation strategies. In section III, an efficient super pixel segmentation method: Mean Orientation and Bipartite Graph based approach. Section IV shows comparative experimental result for proposed and existing segmentation strategies using MS COCO 2014 dataset. The conclusion is formed in section V.

II. LITERATURE SURVEY

A. Bahrololoum, and H. Nezamabadi-pour, [11] evaluated an A-IA multi-expert structure, which was depends on the arrangement of outcomes acquired from concept space and have space. Here, the prototypes were generated in learning phase employing a clustering technique. The input of unlabeled images was allocated to adjacent prototypes in both concept and have spaces, and prime labels were attained from the closest prototypes. Eventually, these labels were fused and final labels for a target image were chosen. Thus, all types of features were uniformly not express the concept label, a couple of prototypes were highly effective to depict an idea and bridge the semantic gap. So, a metaheuristic algorithm was utilized to seek out for the many subset of feature types and best standard of fusion. In training phase, N+ parameter reflects the coverage level of annotation words therefore, concept stream was shows the weaker performance in feature stream line.

C. Jin, and S. W. Jin, [12] proposed an area Set (NS) depends on Image Distance Metric Learning (IDML) algorithm. IDML can directly get the NS of every image, this image distance can sufficiently estimate the space among images for AIA job. The advanced AIA technique can forecast all feasible labels of the image without caption. The investigation results have proved that the NS based IDML can develop the effectiveness of AIA techniques and attained improved performance of annotation than the previous AIA methods. The time complexity was gradually increased due to huge difference between the output and ground truth image.

Z. He, C. Chen, J. Bu, P. Li, and D. Cai, [13] presented an IA algorithm named as multi-view based multi-label Propagation (MMP). MMP deals the various views consistencies by producing the annotation result, and diverse labels correlations are captured by impressive similarity constraints. By using the advantage of dual-heterogeneity from views and labels, MMP was proficient to broadcast the labels superior than state of the art. Moreover, author has introduced an iterative algorithm to crack the optimization problem. Extensive experiments on real image data have shown that the proposed framework has effective IA performance. the large differences were comprehended in label level and consider level of sample images.

C. Jin, and S. W. Jin, [14] have proposed an improved quantum particle swarm optimization (IQPSO) algorithm for visual features selection (VFS) and an ensemble stratagem supported boosting technique to enhance performance of IA approach. to take care of the population diversity, the measure method of population diversity and improvement operation were proposed. the chosen feature sets supported IQPSO improves the efficiency and effectiveness of AIA scheme significantly. Experiment results have confirmed that annotation performance of proposed AIA scheme is additionally satisfactory for an outsized image dataset. But, input images were indicated in various visual features therefore, dimensions of the feature vectors were too high. Hence, image annotation performance was degraded.

Y. Yang, W. Zhang, and Y. Xie, [15] have proposed scheme as Multi-View Stacked Auto-Encoder (MVSAE) among the high level semantic data and low level visual features. This new method has presented the mixing of log-entropy and keyword frequencies, to affect the imbalanced distribution of keywords. so as to utilize the complementarities among diverse visual descriptors they need applied multi-view learning to look for the label-specific features. Subsequently, the image keywords were finally produced by appropriate features. Experimental outcome demonstrated that the proposed framework are able to do effective and favorable performance for image annotation. The sample images were more associated with the bottom truth images. during this level, images annotated with partial correct keywords and a few keywords were missed for his or her abstractive concepts also, similar image texture were difficult to acknowledge .

To overcome the above mentioned drawbacks, an efficient hybrid segmentation method namely SAS+MO is implemented for improving the segmentation accuracy.



III. PROPOSED METHOD

The proposed segmentation framework is capable of combining the multi-layer super-pixels in an ethical and efficient manner. Generally, segmentation framework integrates extra group constraints like those indicating a set of pixels belong to the same group. So, super-pixels are typically predicted to align with object boundaries, but this may not hold strictly in practice due to faint object boundaries and cluttered background. In this paper, Super pixel segmentation technique is proposed for improve the image annotation accuracy. In the first step, two methods are combined for super pixels aggregation such as FH and Mean Shift (MS). Here, FH method is merges the regions greedily and tends to return gross segmentation. The MS method is a mode of a non-parametric probability distribution in a feature space and provides to well respect object details. In the second step, graph based method is applied such as Bipartite graph and transfer cut. The Fig.1 represents the hybrid segmentation processes.

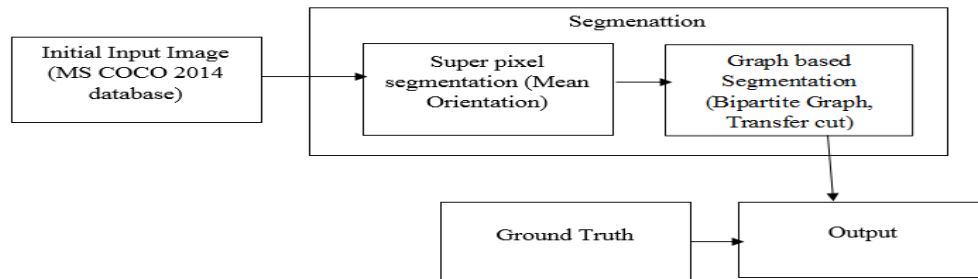


Figure 1 Proposed Architecture of Hybrid segmentation

3.1 Super-pixel aggregation

The graph-based segmentation framework is able to efficiently integrate cues from multi-layer super-pixels simultaneously. Using this framework researcher majorly observed that, pixels inside single super-pixels have placed with one coherent region (super-pixel cues) and adjacent pixels are closed in feature space belongs to the one coherent region (smoothness cues). Both cues can be successfully encoded with the help of one bipartite graph. Further develop a well-organized algorithm for unbalanced bipartite graph partitioning.

3.2 Bipartite graph construction

The pixel and super-pixels are combined in bipartite graph to implement super-pixel cues and attach a pixel to a super-pixel. To implement smoothness cues, attach the adjacent pixels weighted by similarity but this reduce the redundancy because the smoothness regarding neighboring pixels within super-pixels was incorporated when enforcing super-pixel cues. It may also incur complex graph partitioning due to denser connections on the graph.

Formally, denote S as (multi-layer) super-pixels over an image I , and let $G = \{X; Y; B\}$ be a bipartite graph with node set $X \cup Y$, where $X := I \cup S = \{x_i\}_{i=1}^{N_x}$ and $Y := S = \{Y_j\}_{j=1}^{N_y}$ with $N_x = |I| + |S|$ and $N_y = |S|$, the numbers of nodes in X and Y , respectively. The across-affinity matrix $B = (b_{ij})_{N_x \times N_y}$ between X and Y is constructed follows:

$$b_{ij} = \alpha, \text{ if } x_i \in y_j, x_i \in I, y_j \in S; \tag{1}$$

$$b_{ij} = e^{-\beta d_{ij}}, \text{ if } x_i \square y_j, x_i \in S, y_j \in S; \tag{2}$$

$$b_{ij} = 0, \text{ Otherwise,} \tag{3}$$



Where, d_{ij} denotes the distance between the features of super-pixels x_i and y_i , \square denotes a certain neighborhood between super-pixels $\alpha > 0$ and $\beta > 0$ are free parameters controlling the balance between the super-pixel cues and the smoothness cue, respectively. Pixel and super pixels are containing these parameters due to connections between neighborhoods. Particularly, super-pixels are included in both parts of the graph to enforce the smoothness over super-pixels.

3.3 Bipartite graph partitioning

A bipartite graph $G = \{X; Y; B\}$, the task is to partition it into k groups, where k is manually specified. Each group includes a subset of pixels or super-pixels, and the pixels from one group from a segment. Various techniques can be employed for such task. Here spectral clustering is employed as this clustering technique has been successfully used in a variety of applications including image segmentation. Spectral clustering captures essential cluster structure of a graph using the spectrum of graph Laplacian. Mathematically, it solves the generalized eigen-problem:

$$Lf = \gamma Df \quad (4)$$

Where $L := D - W$ is the Laplacian and $D := \text{diag}(W1)$ is the degree matrix with W denoting the affinity matrix of the graph and 1 a vector of one's of appropriate size. For a k -way partition, the bottom k Eigen vectors are computed. Clustering is performed by applying k-means or certain discretization technique. To solve above equation, simply treat the bipartite graph constructed. The normalized affinity matrix, which takes $O(k(N_X + N_Y)^{3/2})$ running time empirically.

3.4 Transfer cut

The above methods of bipartite construction and bipartite partitioning are do not exploit the structure that the bipartite graph can be unbalanced i.e., $N_X \neq N_Y$. Here, $N_X = N_Y + |I|$ and $|I| \square N_Y$ in general. Thus, we have taken $N_X \square N_Y$. This unbalance can be translated into the efficiency of partial SVD that a left singular vector can be derived from its right counterpart, and vice versa. In this paper, we pursue a "sophisticated" path which not only exploits such unbalance but also sheds light on spectral clustering when operated on bipartite graphs. Specifically, we reveal an essential equivalence between the eigen-problem on the original bipartite graph and the one on a much smaller graph over super-pixels only:

$$L_Y v = \lambda D_Y v \quad (5)$$

Where, $L_Y = D_Y - W_Y$, $D_Y = \text{diag}(B^T 1)$, $W_Y = B^T D_X^{-1} B$ and L_Y is exactly the Laplacian of the graph $G_Y = \{Y; W_Y\}$ because $D_Y = \text{diag}(B^T 1) = \text{diag}(W_Y 1)$. It should be noted that our analysis in this section applies to spectral clustering on nay bipartite graph. Our main result states that the bottom k eigenvectors of (4) can be obtained from the bottom k eigenvectors of (5), which can be computed efficiently given the much smaller scale.

Transfer cut Algorithm:

Input: A bipartite graph $G = \{X; Y; B\}$ and a number k .



Output: A k -way partition of G .

1: Form $D_X = \text{diag}(B1)$, $D_Y = \text{diag}(B^T 1)$, $W_Y = B^T D_X^{-1}$, and $L_Y = D_Y - W_Y$.

2: Compute the bottom k Eigen pairs $\{(\lambda_i, v_i)\}_{i=1}^k$ of $L_Y v = \lambda D_Y v$.

3: Obtain γ_i such that $0 \leq \gamma_i < 1$ and $\gamma_i(2 - \gamma_i) = \lambda_i$, $i = 1, \dots, k$.

4: Compute $f_i = (u_i^T, v_i^T)^T$, with $u_i = \frac{1}{1 - \gamma_i} D_X^{-1} B v_i$, $i, i=1, \dots, k$,

5: Derive k groups of $X \cup Y$ from f_1, \dots, f_k .

Super pixels can give powerful alignment cues to conduct segmentation, where superpixels can be collected by over segmenting the image through employing any sensible existing segmentation algorithms. Generated by different algorithms with varying parameters, superpixels can capture diverse and multi scale visual patterns of a natural image. Successful integration of the cues from a large multitude of super-pixels presents a promising yet not fully explored direction. Here, SAS of mean orientation and BG method is improving the accuracy of the segmentation.

3.5 Segmentation by Aggregating Superpixels (SAS)

The main cost of SAS is in collecting superpixels and bipartite graph partitioning. The cost of bipartite graph partitioning is linear in the number of pixels in the image with a small constant, and is negligible to compare that collected superpixels. Potentially, there may be a group consisting of superpixels only. In such cases, the returned number of segments will decrease by 1. However, we never encounter such cases in our experiments probably because of the relatively strong connections between pixels and the superpixels containing them.

Algorithm procedures of SAS:

Input: An image I and the number of segments k .

Output: A k -way segmentation of I .

1: Collect a bag of superpixels S for I .

2: Construct a bipartite graph $G = \{X; Y; B\}$ with $X = I \cup S$, $Y = S$, and B is defined.

3: Apply T-cut in Algorithm 1 to derive k groups of G .

4: Treat pixels from the same group as a segment.

3.6 Mean orientation

The mean orientation method is employed in SAS due to segment exact images in database, which includes mean shift with FH. Mean shift provides more detailed information of object and FH merges the regions greedily and tends to return gross segmentation.



Means shift is clustering technique and a nonparametric density gradient evaluation employing a comprehensive kernel approach. Mean shift described window for every data point and estimates the mean of data point. Then shifts the middle of window to the mean and reiterate the algorithm till it converges. Mean shift is utilized for image segmentation, visual tracking, clustering, mode seeking, space analysis, etc. Kernel density estimation is the most popular density estimation method. Given n data points $i=1, \dots, n$ in the d -dimensional space R^d , the multivariate kernel density estimator with kernel $K(x)$ and a symmetric positive definite d bandwidth matrix H , computed in the point x is given by

$$\hat{f}(x) = \frac{1}{n} \sum_{i=1}^n K_H(x - x_i) \tag{6}$$

Where,

$$K_H(x) = |H|^{-1/2} K(H^{-1/2}x) \tag{7}$$

The multivariate kernel can be generated from a symmetric univariate kernel $K_1(x)$ into two different ways

$$K^P(x) = \prod_{i=1}^d K_1(x_i) \quad K^S(x) = a_{k,d} K_1(\|x\|), \tag{8}$$

Where $K^P(x)$ is obtained from the product of the univariate kernels and $K^S(x)$ from rotating $K_1(x)$ in R^d , i.e. $K^S(x)$ is radially symmetric. The constant $a_{k,d}^{-1} = \int_{R^d} K_1(\|x\|) dx$ assures that $K^S(x)$ integrates to one, though this condition can be relaxed in our context. But, for our purposes the radially symmetric kernels are often more suitable. Special class of radially symmetric kernels satisfying.

$$K(x) = c_{k,d} k(\|x\|^2) \tag{9}$$

Where, $K(x)$ is the kernel profile, only for $X \geq 0$. The normalization constant $c_{k,d}$, which makes $K(x)$ integrates to one, is assume positive. However, it's seen in equation (7) then the validity of a Euclidean metric for the feature space should be confirmed first. One bandwidth parameter is utilized, then the equation (6) becomes,

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right) \tag{10}$$

The superiority of a kernel density estimator is estimated by the mean of the square error between the density and its estimate, incorporated over the domain of definition.

Employing the profile notation, the density estimator (10) can be rewritten as,

$$\hat{f}_{h,K}(x) = \frac{c_{k,d}}{nh^d} \sum_{i=1}^n K\left(\left\|\frac{x - x_i}{h}\right\|^2\right) \tag{11}$$



Initial step in the examination of a feature space with the underlying density $f(x)$ is to find the modes of this density. The modes are located among the zeros of the gradient $\nabla f(x) = 0$ and the mean shift procedure is an establish zeros without calculating the density.

3.7 Gradient estimation

The density gradient estimator is obtained as the gradient of the density estimator by exploiting the linearity of equation (12)

$$\hat{\nabla} f_{h,K}(x) \equiv \nabla \hat{f}_{h,K}(x) = \frac{2c_{k,d}}{nh^{d+2}} \sum_{i=1}^n (x - x_i) k' \left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \quad (12)$$

We define the function,

$$g(x) = -k'(x) \quad (13)$$

Assuming that the derivative of the kernel profile k exists for all $x \in [0, \infty]$, except for a finite set of points. Now using $g(x)$ for profile, the kernel $G(x)$ is defined as,

$$G(x) = c_{g,d} g(\|x\|^2) \quad (14)$$

Where, $c_{g,d}$ is the corresponding normalization constant. The kernel $K(x)$ is called the shadow of $G(x)$ in a slightly different context. The Epanechnikov kernel is the shadow of the uniform kernel, i.e. the d -dimensional unit sphere, while the normal kernel and its shadow have the same expression.

Introducing $g(x)$ into equation (13) yields,

$$\begin{aligned} & \hat{\nabla} f_{h,K}(x) \\ &= \frac{2c_{k,d}}{nh^{d+2}} \sum_{i=1}^n (x - x_i) g \left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \\ &= \frac{2c_{k,d}}{nh^{d+2}} \left[\sum_{i=1}^n g \left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \right] \left[\frac{\sum_{i=1}^n x_i g \left(\left\| \frac{x - x_i}{h} \right\|^2 \right)}{\sum_{i=1}^n g \left(\left\| \frac{x - x_i}{h} \right\|^2 \right)} - x \right] \quad (15) \end{aligned}$$



Where, $\sum_{i=1}^n g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)$ is assumed to be a positive number. This condition is easy to satisfy for all the profiles met in practice. From equation (12), the first term is proportional to the density estimate at x computed with kernel G.

$$\hat{f}_{h,G}(x) = \frac{c_{g,d}}{nh^d} \sum_{i=1}^n g\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \tag{16}$$

The second term is mean shift,

$$m_{h,G}(x) = \frac{\sum_{i=1}^n x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^n g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x \tag{18}$$

The difference between the weighted mean, using the kernel G for weight, and x, the center of the kernel (Window). From equation 16, 17 18 becomes,

$$\hat{\nabla} f_{h,K}(x) = \hat{f}_{h,G}(x) \frac{2c_{k,d}}{h^2 c_{g,d}} m_{h,G}(x) \tag{17}$$

Yielding,

$$m_{h,G}(x) = \frac{1}{2} h^2 c \frac{\hat{\nabla} f_{h,K}(x)}{\hat{f}_{h,G}(x)} \tag{18}$$

The equation (20) shows that, at location x the mean shift vector computed with kernel G is promotional to the normalized density gradient is obtained in kernel K. the normalization is by the density estimation in x computed with kernel G. the mean shift vector always points toward the direction of maximum increase in the density.

3.8 Felzenszwalb and Huttenlocher’s graph-based method (FH) Graph-based segmentation

Let $G=(V, E)$ be an undirected graph with vertices $v \in V$ and edges $(v_i, v_j) \in E$. Edges are between two vertices always. The set that needs to be segmented is the set of vertices V . Each edge has a corresponding weight $w(v_i, v_j)$ which is a non-negative measure of the dissimilarity between neighboring elements v_i and v_j . Dissimilarity between the edges can be measured as the difference in intensity, color, motion, depth, location or any other local attribute. The goal of image segmentation is to find a partition of the set V such that each component of the partition is a connected graph $G'=(V, E')$ where $E' \subseteq E$. Depends on the instruction that the weights estimate the degree of difference among

two vertices. The edges among the similar element vertices have low weights, while the edges among different element vertices have high weights.

3.9 Pairwise region comparison metric

An absolute metric not consider the inconsistencies of the region. This result divides the high inconsistency region into several components. To, overcome this, advanced metric which adjust itself depends on the inconsistency of the region under consideration. The metric depends on estimating the variation among the components along the edges of two element's relation. After that, define internal difference to be the largest edge weight in the minimum spanning tree of the component. That is,

$$Int(C) = \max_{e \in MST(C,E)w(e)} \quad (19)$$

Where, $MST = (C, E)$ is the Minimum Spanning Tree of the sub-graph $G = (C, E)$. A minimum spanning tree is the sub-graph which connects all vertices C and has the least sum total of weights. We define the difference between two components to be the minimum edge weight connecting the two components. That is,

$$Diff(C_i, C_j) = \min_{v_i \in C_i, v_j \in C_j, (v_i, v_j) \in E} w(v_i, v_j) \quad (20)$$

If there is no edge connecting C_i and C_j , we let $Diff(C_i, C_j) = \infty$. While this error metric could be made more robust to outliers by using some statistical measure like median, mean or quantile, it makes the problem NP-hard. The evidence for this state is provided in the paper by Felzenszwalb and HuttenLocher which we omit here. The combination of two elements ensure if the dissimilarity between the two elements are less significant than the inside diversity of each of the elements by a threshold function. In particular we compare $Diff(C_i, C_j)$ and:

$$MInt(C_i, C_j) = \min(Int(C_i) + \tau(C_i), Int(C_j) + \tau(C_j)) \quad (21)$$

Either the components are merged, or the components are not merged and it can be concluded that there is a strong evidence of a boundary between the two components. The threshold function is defined as:

$$\tau(C) = K / |C| \quad (22)$$

The threshold function above implies that for small components, we require a strong evidence for a boundary. A large k prefers larger components and vice versa. Instead of defining the $\tau(C)$ based on some constants and cardinality of the components, it is possible to define $\tau(C)$ based on prior information to favor some desired shape.

IV. EXPERIMENTAL RESULT

In this section, the experimental outcome has been described in detailed. All experiments were implemented on PC with 1.8GHz Pentium IV processor using MATLAB (version 6.5). In our experimental analysis we had used MS COCO 2014 database, which includes lot of natural images of diverse scene categories and provide the ground-truth description for each image. The performance evaluation of proposed image segmentation technique is compared with the result of the



previous work, with the help of pixel accuracy and Jaccard coefficient. These two evaluation metrics are represents the proposed segmentation technique efficiency. Define the TP, TN, FP, FN as the number of pixels being labeled as true, positive, true negative, false positive and false negative respectively. The Jaccard Coefficient is defined in equation (23),

$$Jaccard\ Coefficient = \frac{TP}{(TP + FP + FN)} \times 100 \quad (23)$$

This parameter is the ratio of intersection and union of the segmented region and ground truth region. The pixel accuracy is defined in the equation (24),

$$Pixel\ Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 \quad (24)$$

Probabilistic Random Index: The PRI parameter measures possibility of grouped pair of pixels consistently in two segmentations. The PRI is mathematically shown in the equation (25),

$$PR(S_{test}, \{S_k\}) = \frac{1}{N} \sum_{i,j} [c_{ij} p_{ij} + (1 - c_{ij})(1 - p_{ij})] \quad (25)$$

Whereas, an event represented as c_{ij} and pair of pixels I and j having the same label in the test image S_{test} and Bernoulli distribution with respect to correct segmentations is denoted as p_{ij} . The PRI is a measure of similarity with a score of 1 meaning no similarity (maximum error) and a score 0 is represented as maximum similarity (no error).

Variation of Information: The VoI is a metric that relates to the conditional entropies between the class label distributions. It calculates the sum of information loss and information gain between two regions of images. The VOI is mathematically shown in the equation (26),

$$VI(c, c') = H(c) + H(c') - 2I(c, c') \quad (26)$$

Whereas, $H(c)$ and $H(c')$ are the entropy associated with cluster c and c' . The $I(c, c')$ is denoted as the mutual information between the associated random variables.

Global Consistency Error: GCE estimating the degree to which one segmentation is a refinement of the other. Segmentations which are related are considered to be consistent, since they could represent the same image segmented at different scales. The formula for GCE is represented in equation (27),

$$GCE = \frac{1}{n} \min\{\sum_i E(s1, s2, pi), \sum_i E(s2, s1, pi)\} \quad (27)$$

Whereas, segmentation error measure takes two segmentations S1 and S2 as input and produces a real valued output in the range [0 :: 1] where 0 signifies no error. For a given pixel pi consider the segments S1 and S2 that contain that pixel.

Boundary Displacement Error: BDE computing the average displacement between the boundaries of two segmentations. Particularly, it defines the error of one boundary pixel as the distance between the pixels the closest pixel in the other boundary image. The BDE is shown in equation (28),

$$\mu_{LA}(u, v) = \begin{cases} \frac{u-v}{L-1} & 0 < u - v \end{cases} \quad (28)$$



A lower BDE value means less deviation between the segmentation and ground truth. This parameter is incorporates the both correctly labeled and foreground and background pixels. Compare to the Accuracy and Jaccard Coefficient of our proposed method represents the better results.

Methods	Pixel accuracy (%)	Jaccard Coefficient
ASP+GC [16]	89	76
Graph cut [17]	86.4	31
SAS+MO+BG	92.0	90

Table 1 Performance evaluation of existing and proposed method

The Table 1 represents the performance evaluation of our proposed method. The pixel accuracy of our proposed method depicts 92% and existing work gives 89% of pixel accuracy. The jaccard coefficient of existing work has 0.76 and proposed method consists of 0.90.

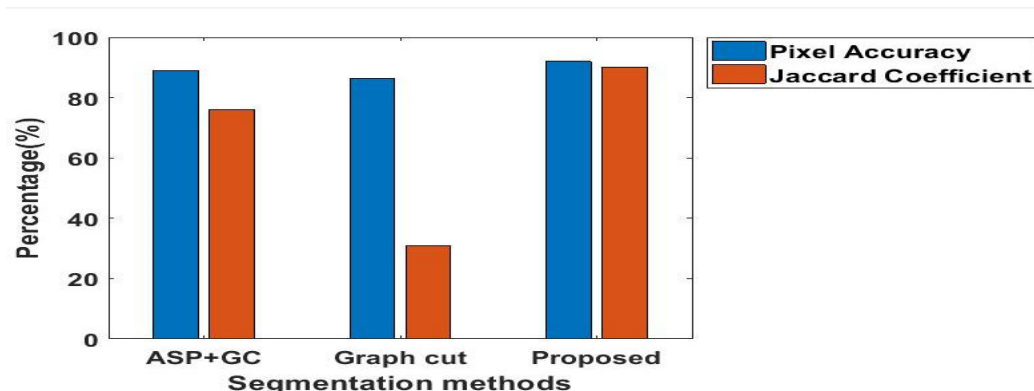


Figure.2 Performance Analysis

The graphical representation of the Accuracy and Jaccard coefficient performance is shown in figure.2. The performance is evaluated with existing methods such as ASP+GC and Graph cut. Compare to the existing proposed shown better results because mean orientation method is applied in the segmentation. The multiple pixels and super pixels are collected and constructed using Bipartite Graph. With the help of transfer cut method the particular portion only extracted. As a result, proposed method decreases the time complexity and improves the segmentation accuracy.



Table 2 Performance evaluation of proposed method

Methods	PRI	VoI	GCE	BDE
Spectral Clustering and Superpixels (SCS) [18]	0.8414	1.6573	0.1795	10.8783
Mean Shift [18]	0.7958	1.9725	0.1888	14.41
FH [18]	0.7139	3.3949	0.1746	16.67
Graph cut and Affinity graph [19]	0.6270	2.0299	0.1050	3.1298
Proposed Method (SAS+MO)	0.8945	1.5144	0.0940	2.359

The results of our experiment are qualified by the four essential parameter such as Probabilistic Rand Index (PRI), Variation of Information (VoI), Boundary Displacement Error (BDE) and Global Consistency of Error (GCE). The Table.2 depicts the four more extra parameter compared and improves the segmentation accuracy.

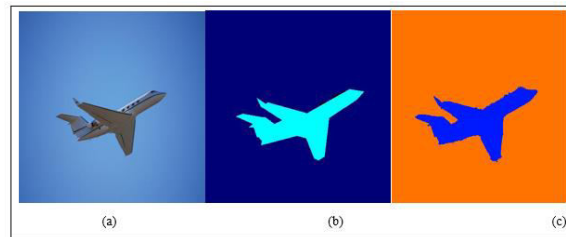


Figure 3 (a) Input Image 3(b) Ground Truth Image and 3(c) Output image

The Fig.3 represents the segmentation accuracy of the proposed method as SAS+Mean Orientation. (a) Represents the input image, (b) shows the Ground Truth Image and (c) depicts the proposed segmentation output. The proposed SAS+Mean orientation method improves the segmentation accuracy and clearly represents the objects like person, ropes, sky and water.

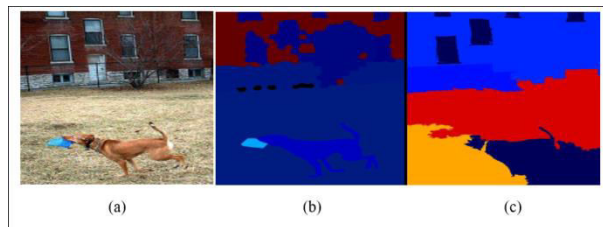


Figure 4 (a) Input Image 4(b) Ground Truth Image and 4(c) Output image

The Fig.4 shows the sample image of the advanced method segmentation accuracy. (a)Shows the input image, (b) Ground Truth Image of the dog and (c) Segmented Output of sample image using SAS+Mean Orientation method.

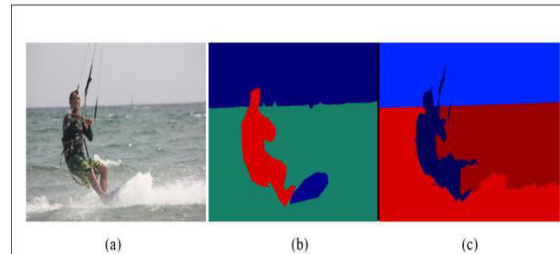


Figure 5 (a) Input Image 5(b) Ground Truth Image and5 (c) Output image

The figure.5 indicates the sample image of super pixel segmentation. The figure.5 (a) is the input image, figure.5 (b) is the ground truth image and figure.5(c) indicates the segmentation image.

V. CONCLUSION

This paper illustrates an effective hybrid segmentation scheme of SAS+Mean Orientation technique that is employed for improving the segmentation accuracy over MS COCO 2014 database. The use of superpixels as grouping cues allows us to effectively encode complex image structures for segmentation. This is done by employing different segmentation algorithms and ranging their parameters in generating superpixels. On the other hand, we have fused diverse super-pixel cues in an effective manner using a principled bipartite graph partitioning framework. The proposed SAS+MO method extends the evaluation parameters such as, PRI, VoI, GCE, BDE, Pixel accuracy and Jaccard Coefficient. The performance evaluation of the advanced method represents the better results compare to existing work such as Graph Cut and ASP+GC. The experimental outcome indicates that the proposed method improves approximately 6% in the image segmentation by means of pixel accuracy than the existing work. In future, proposed work is extended as an efficient feature extraction techniques are used for improve the super pixel segmentation efficiency.

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