Object Localization Enhancement by Multiple Segmentations Fusion

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Abstract

Despite being a complex task, image segmentation is a crucial prerequisite for many computer vision applications, including object tracking, object recognition and object localization. Image segmentation is known to be unstable because it is highly affected by image perturbations such as shadows, shading and highlights. In our work, we effeciently combine different cues from multiple segmentations of an image to obtain a better segmentation and, hence, better localization. We propose a novel framework for object class segmentation that (i) combines different complementary cues from multiple segmentations in a bottom-up fashion and (ii) augments the power of the bottom-up segmentation by fusing multiple segmentations in a top-down approach. To combine multiple segmentations in a bottom up fashion we propose an efficient evaluation criteria for assessing the quality of the generated segments. We refer to it "segments goodness measure". On the other hand, for fusing multiple segmentations in a top-down fashion we introduce a novel "voting" technique that assigns each segment to its corresponding category. Finally, we discuss some possible extensions for our method that could potentially boost the performance. Our results exceed state-of-the-art results on PASCAL VOC 2007 object segmentation dataset.

1. Introduction

Image segmentation is a computer vision process focusing on partitioning an image into a set of non-overlapping regions. This is an extremely challenging task for real images. The shape variations of the objects provoke several effects related with the illumination such as shadows, shadings and highlights. These effects are one of the main problems that should be solved in order to obtain an efficient segmentation.

Image segmentation algorithms can be divided in several ways, however, all of the existing approaches can first be divided into two main hierarchies: bottom-up approaches and top-down approaches.

Bottom-up segmentation approaches mainly examine the image and try to figure out how to divide it into coherent and meaningful segments. Comprehensive surveys as presented in [33, 3] drew the basis for the current classification of bottom-up segmentation techniques. From all of these existing methods, segmentation methods can be divided into four main categories: feature-based, image-based, physics based and hybrid approaches.

Feature based approaches mainly focus on the photometric information of an image represented by its histogram as in the work by [1, 32]. Image-based approaches exploit the spatial coherence of color in an image. An example is given from the work of [11]. Physics-based methods use physics and psychophysics information to perform the segmentation. Finally, hybrid techniques combine methods of the previous categories.

Top-down approaches, on the other hand, are guided primarily by high-level information and the use of class-specific criteria. The motivation for using these class-specific criteria, as shown by [2], has two parts. The first is that although recent image segmentation algorithms provide impressive results, they still often fail to capture meaningful and at times crucial parts of the objects in the image. The second is that these methods are analogous to human vision in the sense of indicating high-level, class-based criteria to segment the images in a meaningful manner. Examples of using top-down approaches to perform segmentation are shown in the work of [2, 15, 31].

Image segmentation has been applied to solve a variety of computer vision problems. A robust and efficient segmentation is an important preprocessing step for several computer vision tasks. However, extensive experiments by [25] show that when using a single region generated by an image segmentation algorithm, the segmentation quality is highly variant and dependent on image data, the segmentation algorithms and the parameters used to create this segmentation. This was a motivation for the emerging new trend in object recognition that uses the segments generated from multiple segmentation algorithms and tries to merge them efficiently to recognize objects in the scene [22, 20, 16].

This trend of using multiple segmentations was also the motivation for our work. In our work we focus on two parts. The first one is building a robust and efficient segmentation method. This method uses the information provided by several other segmentation algorithms to build a more reliable image segmentation in a bottom-up fashion. The second is using this new segmentation along with the other segmentation methods to recognize and localize objects in the image. We perform object class segmentation using each segmentation method separately. Afterwards, we combine the results in a top-down approach.

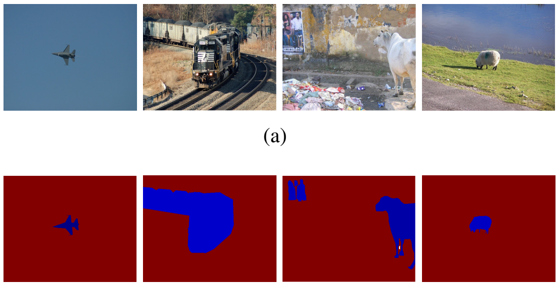


Figure 1. (a) Original images (b) Object class segmentation

The goal of object class image segmentation is to produce a pixel-level classification of the input image. In other words, it is required to indicate which class does each pixel lie into. In figure 1 we show an example of object class image segmentation. This is a highly constrained problem where most state-of-the-art approaches focus on exploiting contextual information available around each pixel. Afterwards, they measure feature statistics from this information (in this case histograms of visual words) and use the bag-of-words technique in order to determine the class that each pixel belongs to.

Instead of working on pixels, Fulkerson et al. in [12] present a method to perform object class segmentation by aggregating the histograms in the neighborhood of the small regions obtained from a conservative over-segmentation, or "superpixels" [21, 19]. They don't use the information obtained by superpixels alone. They also use information from neighboring superpixels to provide more contextual information. However, in our work we show that even when adding neighborhood information, superpixels are still not the best choice for describing an object.

In our work, instead of using pixels or superpixels, we use regions emerging from several segmentation techniques. Our results show that superpixels do not capture enough information about the objects being recognized and localized that can be better captured by using larger segments. We learn a model from each segmentation method to classify the regions of this segmentation method. Afterwards, we combine all of the results coming from each model separately into a new model using our proposed technique that we call, the "voting technique". Our results show that combining results from outputs of several segmentations that use complementary information give a significant improvement over using each segmentation method solely. The results are even better than those obtained using superpixels with aggregating neighborhood information for classification. Figure 2 shows our proposed framework for approaching the object class segmentation problem.

This paper is organized as follows. In section 2, we describe our different generated segmentation techniques. In section 3, we explain how we combine different segmentation techniques in a bottom-up fashion to obtain a new segmentation technique. In section 5, we show how we augment the performance of the bottom-up segmentation by combining information from multiple segmentations in a top-down fashion. Our framework relies on VLBlocks [12] framework. We briefly show the steps for extracting our descriptors in section 4 and for refining our final results with Conditional Random Field (CRF) in section 6. In section 7, we'll show our experiments and results. Finally, we'll give our conclusions and future work in section 8

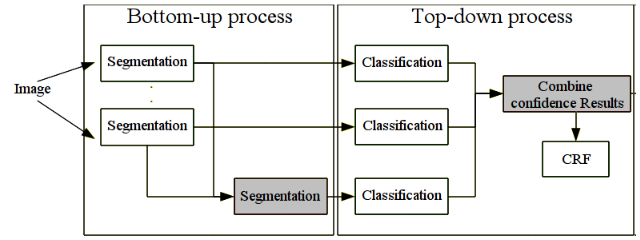


Figure 2. Our object class segmentation model. Our contributions are highlighted in grey.

2. Generating Multiple Segmentations

Our proposed framework makes use of the complementary cues provided by different segmentation approaches, in order to build a more reliable segmentation. We generate a segmentation based on mean-shift [6]. In this segmentation we guarantee that the segments mainly vary in the color distribution. In addition, we use the graph-based method [10] to guarantee a variation along the edges. Finally, we benefit from the existence of large segments by using the normalized cut technique [24].

Using these different and complementary segmentations, we maintain the desired qualities from each aspect yielding a more robust segmentation model.

To this end, our goal is to: (i) combine these segmentations in a bottom-up fashion in order to obtain a new more reliable segmentation. (ii) Fuse these complementary segmentations along with our newly proposed ones in a top-down fashion for a better final object class segmentation.

3. Building a More Reliable Segmentation (Bottom-up Fusion)

In this section we propose a novel approach for combining multiple segmentations in a bottom-up fashion. We introduce a segments evaluation method. We refer to it as "segment goodness evaluation". This method allows us to effectively combine the different segments that emerge from each of the considered segmentation approaches .

Our technique is inspired by the work of Fulkerson et al. [12]. Instead of applying the neighborhood operator on superpixels, we applied it on segments. We get these segments from the several segmentation techniques that we previously described (Section 2). We investigated the effect of increasing the neighborhood size for the concerned segmentation techniques on the final average accuracy (Figure 3).

Figure 3 illustrates two important conclusions. First, large segments produce good results. This conclusion is based on the observation of increasing the overall average accuracy in

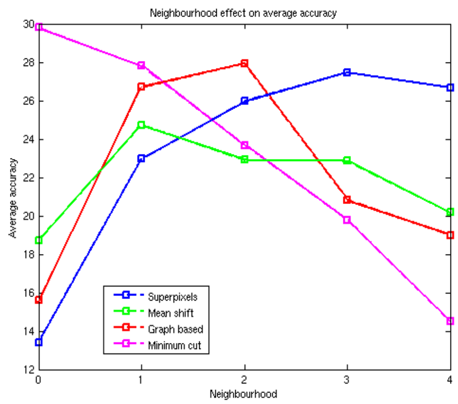


Figure 3. Effect of increasing the neighborhood on the average accuracies

case of (i) the large segments generated by the normalized cut technique, and (ii) the generated segments using the superpixels or mean-shift methods when taking larger neighborhood size into account.

The second conclusion is that up to a certain limit, increasing the size of the segments or the neighborhood, decrease the final average accuracy. We attribute this to the loss of semantic information due to the combination of segments that are no longer related to each others. Consequently, our target is to find a criteria to decide whether combining smaller segments or splitting larger ones is more useful.

Assume we have N segmentations S_i, where $i = 1, ..., N$ and each of the segmentations correspond to $S_i = \bigcup_{j=1}^{M_i} T_{ij}$, where T_ij is a segment in the segmentation S_i and M_i is the number of segments obtained from the segmentation S_i. Our objective is to obtain a better segmentation $S^* = \bigcup_{k=1}^{M^*} T_k^*$, where T_k^* is a segment in our final set of optimized segments and M^* is the total number of optimized segments. Segmentation S^* should satisfy the following criteria:

1. The segments of the final segmentation should be as large as possible. In other words, we need to minimize M^*.
2. The segments should be "good" segments. In our context, we defined a "good segment" as the largest set of connected pixels that lie in the same class.

Consequently, our motivation for combining segmentations is to start looking for the large segments and then check if this segment is a "good" segment. We applied a greedy algorithm that favors large segments and check if they pass a certain criteria of "goodness". Our proposed approach is described as follows: We examine the largest segment obtained from all segmentations methods and check whether this segment is a "good" segment. If the segment is "good", we include it in our final segmentation (Add to S^*). Otherwise, we try to segment it recursively using the least number of segments from the other segmentations. Similarly, we segment the remaining part of the image.

To this end, we need to determine whether the generated segments are "good" or not. To do this, we investigate several

(a) (b) (c)

Figure 4. (a) Original images (b) Current largest segments (c) Histograms from every channel. As we can see the first image can be approximated into a normal distribution or a unimodal distribution while the second one fails in that test.

"goodness" evaluation criteria. First, we studied the possibility of assuming that the color of each region should follow a normal distribution. However, this "goodness" criteria didn't hold on real images as shown in figure 4(c). Second, we examined the unimodality test to check whether the distribution of the histogram of each RGB channel follow a unimodal function. We use Dip test [14] for unimodality. Although the resulting segments were slightly better than those obtained using the normality test, it also fails to handle real images' segments as in figure 4(c). In addition, we also investigated the outliers detection and the Ridge based Distribution Analysis (RAD) methods. We'll describe each of these three techniques in more details in the next sections.

3.1. Good Segments Evaluation Using Outliers Finding

As defined by [13], "An outlying observation, or outlier, is one that appears to deviate markedly from other members of the sample in which it occurs." In our work, we consider a segment to be "good" if the number of outliers inside this segment is below a certain threshold. We use the Z-Test to find the outliers of a certain segment. The Z-Test indicates that the point is considered an outlier if it satisfies the following formula:

$$\frac{|X - \mu|}{\sigma} > 3, \quad (1)$$

where X is a label for each point of a segment in the image, μ is the mean of the color values of the considered segment and σ is the standard deviation of these colors.

We performed a series of experiments to empirically determine the best value for the tolerance of outliers inside the segment. We finally decided that a segment is considered "good" if the number of outliers lying inside is less than 2% of the number of pixels in the segment.

Although outliers detection worked well in detecting the segments shown in Figure 4(b), they didn't work on detecting the segments that contain variations in shadows and highlights. Consequently, we examined other evaluation methods that work well in the presence of shadows and illuminations. For this purpose, we use the RAD evaluation method due to its robustness to shadows and highlights.

3.2. Good Segments Evaluation Using RAD

We use the RAD method presented in [26] for obtaining image segmentations in the presence of shadows and highlights. This method is based on the insight that the distributions formed by a single-colored object have a physically determined shape (i.e. follow the same ridge) in the color histogram space [23]. To capture these ridges Vazquez et al. [26] proposed a new Ridge based Distribution Analysis (RAD) to find the set of ridges representative of the dominant color.

We model the region "segment" by its set of dominant colors (DC). This DC is described by a distribution in histogram-space. We assume that if this segment contains only 1 DC then this segment is a "good" segment as this segment contains only 1 semantic object. Based on this technique, the evaluation method becomes very robust to shadows and highlights and becomes closely related to the physical features of each segment than the previously investigated methods.

To perform this evaluation we use the first step proposed by [26] which extracts ridges as a representative of a dominant structure (DS). Afterwards, we check whether we have only one single ridge in the considered segment. Accordingly, we consider this segment as a "good" segment.

3.3. Segmentations Evaluation on the Berkeley Dataset and Benchmark

In this section, we perform a series of experiments on the standard Berkeley Segmentation Dataset and Benchmark [17]. We evaluate the performance of the three considered segmentation methods with our newly proposed segmentation method. Our method combines the complementary information obtained by all the considered segmentation methods using the RAD criteria for segments "goodness" evaluation.

We evaluate four different error measurements for evaluating the quality of the segments generated by our approach. These four error measures are: First, the Probabilistic Rand Index (PRI) [25], which counts the fraction of pairs of pixels whose labellings are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. The second error measure is the Variation of Information (VoI) [18]. It defines the distance between two segmentations as the average conditional entropy of one segmentation given the other, and thus roughly measures the amount of randomness in one segmentation which cannot be explained by the other. The third is the Global Consistency Error (GCE) [17] that measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations which are related in this manner are considered to be consistent, since they could represent the same natural image segmented at different scales. The fourth measure is the Boundary Displacement Error (BDE) by [11]. It measures the average displacement error of boundary pixels between two segmented images. Particularly, it defines the error of one boundary pixel as the distance between the pixel and the closest pixel in the other boundary image.

	PRI	VoI	GCE	BDE
Mean-Shift	0.7424	4.5293	**0.0842**	**14.2716**
Graph-Based	0.7082	5.1148	0.1150	17.2428
Normalized-cut	0.7079	4.1370	0.1153	14.7337
Mix+RAD	**0.7483**	**3.5364**	0.1433	14.8047

Table 1. Segmentation benchmarks results for the Berkeley Segmentation Dataset and Benchmark. 4 error measures were considered for 4 different segmentations.

Table 1 demonstrates that our proposed segmentation method improves both of the PRI and the VoI error measures. We attribute this to the fact that PRI and VoI are clearly concerned about comparing segments entirely with the ground truth segments. This justifies our motivation behind our proposed segmentation method which is based on improving the size and the quality of the segment. In contrary, GCE and BDE measures don't perform well on our approach. These measures are mainly concerned about the boundaries of the segments which our approach doesn't take into concern.

4. Describing and Classifying Regions From Each Segmentation

Relying on the same framework by Fulkerson et al. [12], a bag of features classifier is constructed. It operates on the regions defined by the segments obtained from each segmentation method. SIFT descriptors are extracted for each pixel in the image at a fixed scale and orientation.

The extracted descriptor are then quantized using a K-means dictionary and aggregated into one l^1 normalized histogram. For training the classifier, the most frequent class label contained by each segment is assigned to it. Afterwards, a one-vs-rest support vector machine (SVM) with an RBF-χ^2 kernel is trained on the labeled histograms for each of the object categories.

The χ^2 distance between histograms h_1 and h_2 is calculated using the following formula:

$$d^2_{\chi^2}(h_1, h_2) = \sum_{m=1}^{M} \frac{(h_1(m) - h_2(m))^2}{h_1(m) + h_2(m)}. \quad (2)$$

From the previous equation it can be concluded that the larger the segment is, the more discriminative this distance will become. This is because the larger the segment will be the more the information it will carry from the dictionary and the more the variance will be in the final value of the distance which will lead to better classification.

5. Combining Region Classifications (Top-down fusion)

In this section, we first briefly revisit the approach proposed by Pantofaru et al. [20] to combine multiple segmentations. Firstly, pixels that are grouped together by every segmentation should be classified consistently. These groups of segmentations are called Intersection of Regions (IofRs). Secondly, these IofRs are consistently classified based on the information obtained from their original segments emerging from each of the segmentation techniques.

In our approach, we classify each IofR by combining the information from all of the individual segmentations. Each classifier results in a confidence map which is then combined together with all individual segmentation results (confidence maps) to obtain a final confidence for each IofR. Instead of averaging all the confidence maps as in [20], we adapt a voting methodology that assigns different weights to each instance (category) in a confidence map. In this way, we construct a weighted confidence map per segmentation. Consequently, these weighted confidence maps are combined to obtain a final confidence map. It is noteworthy to mention that instead of simple averaging all the confidence maps, in our approach, each confidence map is weighted by rearranging the confidence values per category.

We now introduce some mathematical notations to formulate our approach: Let I be a given Image, k be a certain class label in the set of class labels $\mathcal{C}$, S_s be a specific segmentation in the set of segmentations $\mathcal{S}$, r be a certain IofR, $CF_{r,s}$ be the confidence map for the IofR r that indicates for each class k, the $P(c_r = k|S_s)$, where c_r is the class label of r. For each IofR, our aim is to construct a set of weights $W^k_{r,s}$ that weighs each class k for each IofR r based on its position $O^k_{r,s}$ in the ordered $CF_{r,s}$. Thus, the index of a class k in $CF_{r,s}$ can be obtained as:

$$O^k_{r,s} = \#\{P(c_r = t|S_s) > P(c_r = k|S_s)\}_{t \neq k} \qquad (3)$$

Where t is a class label in $\mathcal{C}$. The probabilities are obtained from our confidence map $CF_{r,s}$. Our weights are then assigned depending on the value of $O^k_{r,s}$:

$$W^k_{r,s} = H(O^k_{r,s}) \qquad (4)$$

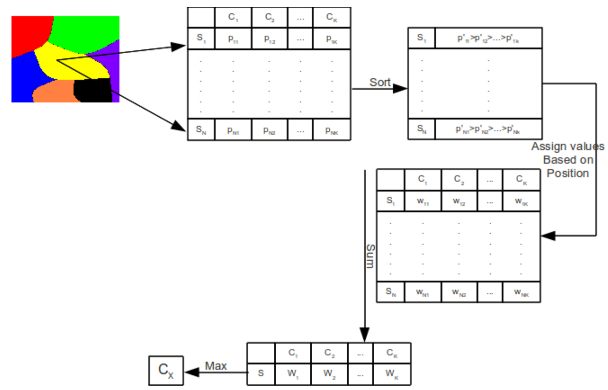
Where $H(O^k_{r,s})$ is the weighting function that determines the appropriate weight based on the position $O^k_{r,s}$. Finally, the class label c_r for each r can be intuited from the following formula:

$$P(c_r = k|I) \propto \sum_{S_s \in \mathcal{S}} W^k_{r,s} \qquad (5)$$

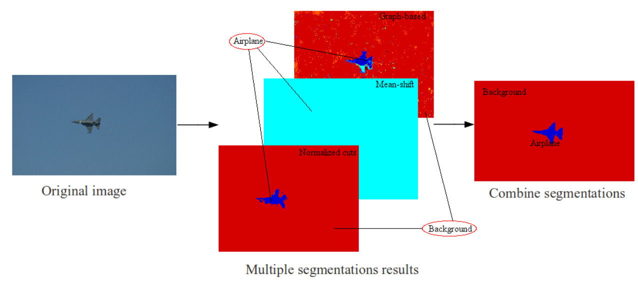
From eq. 5 the final class assigned to r, C_r is expressed as:

$$C_r = \arg\max_k \sum_{S_s \in \mathcal{S}} W^k_{r,s} \qquad (6)$$

Note that the confidence for each IofR is altered based on the probability of it belonging to a certain category. To calculate $H(O^k_{r,s})$, a fixed set of weights are then assigned depending on the position $O^k_{r,s}$. In this work, we keep the weights fixed to $H(p) = \frac{1}{p+1}$, but this can easily be learned on the validation set through cross-validation. This way, an improved object class segmentation is obtained as depicted in the figure 5(b). A final confidence map is then obtained by averaging all weighted confidence maps. In figure 5 we also show a graphical explanation of this procedure.



(a) The voting algorithm.



(b) Combining Mean-Shift, Graph-Based and Normalized-cut segmentations resulted in a better segmentation.

Figure 5. Voting scheme illustrated

6. Refining Results With a CRF

This is the final step of our framework. In order to recover more precise boundaries and reduce the effects of misclassifications inside the image, we finally refined our results with a conditional random field.

In our framework, we used the same technique explained in [12]. However, instead of working on segments emerging from superpixels, we worked on Intersection of Regions (IofRs) as our basic units. Our formulas are similar to [12]. They are included again for the sake of clarity. However, instead of applying the CRF on superpixels, we apply them on IofRs.

Assume the final segmentation $G(I, E)$ where I is an Intersection of Regions in an adjacency graph. $P(c|G; w)$ is the conditional probability of the set of class label assignments c where w is a weight.

$$\begin{aligned} -\,log(P(c|G;w)) \;&=\; \sum_{I_i \in S} \psi(c_i|I_i) \\ &+\; \omega \sum_{(I_i,I_j)\in E} \phi(c_i, c_j|I_i, I_j). \end{aligned} \qquad (7)$$

The unary potentials ψ are obtained from probability outputs provided by our SVM for each segment:

$$\psi(c_i, I_i) = -log(P(c_i|I_i)), \qquad (8)$$

and the pairwise edge potentials ϕ are obtained using the following formula:

$$\phi(c_i, c_j|I_i, I_j) = (\frac{L(I_i, I_j)}{1+ \parallel I_i - I_j \parallel})[c_i \neq c_j], \tag{9}$$

where $\parallel I_i - I_j \parallel$ is the norm of the color difference between the two neighboring IofRs in the LUV colorspace. $L(I_i, I_j)$ is the shared boundary length between IofRs I_i and I_j and acts as a regularizing term discouraging small regions.

7. Experiments

We evaluated our method on the standard PASCAL VOC 2007 [9] segmentation competition data set. This dataset contains multiple object classes with extreme variation in deformation, scale, illumination, pose and occlusion. While the challenge specifies that the detection challenge training data may also be used, we use only the 422 fully segmented images to train our core approach. The performance measure for this dataset is the average pixel accuracy: for each category the number of correctly classified pixels is divided by the ground truth pixels plus the number of incorrectly classified pixels. We also show the total percentage of pixels correctly classified.

Our results are divided into three main parts. In the first one we show the obtained results for combining the considered segmentation techniques in a bottom up fashion using different evaluation criteria, namely: Outliers and RAD. Follwing this, we show the effect of combining the considered segmentation results in a top-down fashion. We don't include our newly created segmentation method that aims to look for larger segments. Finally, we include our new segmentation method and show its effect on the overall average accuracy.

7.1. Parameters Setup

In our experiments, we use VLBlocks [12]. Furthermore, we added our extra modules for combining segmentations in various ways. In this section, we'll explain in more details the different parameters chosen in our experiments.

7.1.1 Framework Parameters

We used the same framework proposed by Fulkerson et al. [12]. We extract SIFT descriptors at each pixel using the quick SIFT technique in the VLFeat framework [27]. The patch size for the SIFT descriptors is 12 pixels. Descriptors are quantized into a K-means dictionary learned using the training data. $K = 400$ was chosen for all of the performed experiments.

For training, labels are assigned to training segments coming from each segmentation by the majority of class votes that we get from our training ground truth. We randomly select an equal number of training histograms from each category as the training data for our SVM. We learn a one-versus-rest SVM model for each class with an RBF-χ^2. We used the libSVM tool [5]. Finally, we refined our final labeled results with a CRF model as described in section 6.

7.1.2 Multiple Segmentations Parameters

In this section we explain the parameters used for the different segmentations that we take in concern. We evaluated three types of segmentations, Mean-shift segmentation [6], Graph-based segmentation [10] and normalized cut segmentation [24].

For the mean-shift segmentation we use the EDISON wrapper [4]. This code requires the following parameters: hs, indicating the spatial bandwidth for mean shift analysis, hr, indicating the range bandwidth for mean shift analysis and M which is the minimum size of final output regions. For our experiments we use $hs = 11$, $hr = 8$ and $M = 40$.

For the efficient Graph-Based (GB) image segmentation we use the code in [10]. The following parameters are required: $threshold$, the larger this value is, the larger the segmented area becomes. $minsize$, indicates the minimum size of segmentation component. $nRadius$, the radius of neighborhood of a pixel. We use the following values. $threshold = 0.5$, $minsize = 50$, and $nRadius = 2$.

For the minimum cut we use the version explained by the work of [7]. The framework requires the number of requested segments as its parameter. We chose the value of 100 to be the number of requested segments each time.

We generate an over-segmentation to obtain superpixels using quickshift [28] These superpixels are controlled with the following three parameters: λ, the trade-off between color importance and spatial importance, σ, the scale at which the density is estimated and τ the maximum distance in the feature space between members of the same region. In our experiments we use the following parameters, $\lambda = 0.5$, $\sigma = 2$ and, $\tau = 8$.

In all our segmentations we chose our values after we applied several tries on the validation set and manually tuned the parameters in order to find the best description for the segments and their boundaries.

7.2. Results

First, we evaluated the different methods proposed for combining segments in a bottom-up fashion. We clearly show that the RAD criteria for "segments goodness" evaluation outperforms the other method that searches for outliers inside the segments.

Following this, we we evaluated our voting technique by combining the mean-shift, graph-based and normalized-cut segmentations. We compared it against the method described in [20]. We extracted the same features under the same conditions and we show that our "voting technique" outperforms the results obtained from combining the segments using the method in [20].

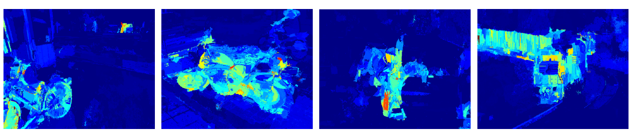
Finally, we incorporate the voting method with our newly created segmentation method's results and we compare it with the state-of-the-art results. Our results show a significant improvement over state of the art approaches on a number of classes. It also shows an improvement for the overall average accuracy.

Table 2 demonstrates our results. It's clearly seen that ap-

	Background	Airplane	Bicycle	Bird	Boat	Bottle	Bus	Car	Cat	Chair	Cow	Dinningtable	Dog	Horse	Motorbike	Person	Pottedplant	Sheep	Sofa	Train	TVmonitor	Avg Accuracy
Outliers	22	9	15	8	25	14	18	11	43	11	13	16	31	22	27	6	31	15	35	27	18	20
RAD	26	12	11	26	17	16	28	17	53	14	14	40	28	21	50	20	50	38	30	50	32	28
Voting (MS+NC+GB)	48	20	21	16	10	30	32	42	56	23	19	35	51	18	63	52	28	20	29	40	34	33
[20] (MS+NC+GB)	38	30	21	11	14	9	25	24	61	36	21	14	53	24	65	52	27	15	31	42	42	31
Voting + RAD	49	21	20	10	15	9	32	48	56	28	13	37	56	19	61	48	33	32	45	44	38	**34**
[29]	23	19	21	5	16	3	1	78	1	3	1	23	69	44	42	0	65	40	35	89	71	30
[12]	56	26	29	19	16	3	42	44	56	23	6	11	62	16	68	46	16	10	21	52	40	32
[20]	59	27	1	8	2	1	32	14	14	4	8	32	9	24	15	81	11	26	1	28	17	20

Table 2. MS = Mean-Shift, GB = Graph-Based, NC = Normalized-Cut. Comparison on the average accuracy for different segmentation algorithms, segmentations created using other segmentations, combining already existing segmentations and combining all segmentations with newly created segmentations.

(a) Ground truth



(b) Confidence of corresponding class

Figure 6. Qualitative results. The higher the intensity of the color the more confident is the classifier about its classification. Best viewed in colors.

plying the voting technique by itself (in the middle portion of the table) outperforms the state of the art results. Making use of the bottom up segmentation combination into the voting technique yields in boosting the overall performance.

Finally, in figure 6 we show some qualitative results for our method. We show the original images along with the confidence for the class it should be assigned to.

8. Conclusions and Future Work

We have demonstrated the effect of using multiple segmentations on improving the segments and hence improving the applications that use image segmentations as a prerequisite. We presented a novel framework for recognizing and segmenting objects. Our approach relies on multiple bottom-up image segmentations to build another intuitive more accurate image segmentation. These bottom-up segmentations then support top-down object recognition and localization. We have shown how these techniques improve the average accuracy of a challenging dataset. The PASCAL VOC 2007 object segmentation challenge.

We also showed that superpixels are usually not the best level of representation for objects. They provide very basic information about each segment that don't usually vary between different object classes. Hence, we showed the effect of using larger segments on the final object segmentation which was in all cases better than using superpixels.

We also believe there are still some of the possible extensions that can be added to our method to help in boosting the results even higher. We show these extensions with a simple analysis on how they can be done and how it'll affect the results.

One possible extension will be learning weights that are assigned to each segmentation method per category per position. Currently, our weighting function just assigns fixed constant weights to each position. This can be improved by learning those weights and assigning the optimal weights for each segmentation method.

Another possible extension is to incorporate image level priors. For example, if the classification results show that a certain class exist in the image with a certain probability, we can boost the weights assigned to this class specifically in our voting scheme. Also we can demote other categories where their concurrent existence with our existing class is unlikely.

One other possible extension is the use of object detection to guide segmentation. In this case our framework will promote our existing class within the detection bounding box. In other words, within the bounding box we can recognize only two categories, the detected object and its background.

Finally, we can find other ways for segments "goodness" evaluation. For instance, for the JSEG segmentation [8], the criterion chosen for good segmentations evaluation is the spatial relation existing between the pixels in the image space. Another way is to use the color boosting algorithm introduced in [30] and consider a segment "good" if the number of salientpoints is below a certain threshold.

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