Enhanced Figure-Ground Classification with Background Prior Propagation

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Abstract

We present an adaptive figure-ground segmentation algorithm that is capable of extracting foreground objects in a generic environment. Starting from an interactively assigned background mask, an initial background prior is defined and multiple soft-label partitions are generated from different foreground priors by progressive patch merging. These partitions are fused to produce a foreground probability map. The probability map is then binarized via threshold sweeping to create multiple hard-label candidates. A set of segmentation hypotheses is formed using different evaluation scores. From this set, the hypothesis with maximal local stability is propagated as a new background prior, and the segmentation process is repeated until convergence. Similarity voting is used to select a winner set, and the corresponding hypotheses are fused to yield the final segmentation result. Experiments indicate that our method performs at or above the current state-of-the-art on several datasets, with particular success on challenging scenes that contain irregular or multi-connected foregrounds.

1. Introduction

Figure-ground segmentation is a fundamental operation with a great potential in many vision applications [1]. It aims at producing a binary segmentation of the image, separating foreground regions from their background. Modern approaches include solutions based on graphs, statistics, information theory, or variational theory [2, 3, 4, 5]. Automatic segmentation in generic conditions is extremely difficult due to the broad diversity of visual cues in a natural image [6]. As a tradeoff, interactive methods [7, 8, 9] have produced impressive results with a reasonable amount of user guidance. The ideas of multiple hypotheses and classifier fusion have also been applied to segmentation studies [10, 11, 12]. Current state-of-the-art interactive segmentation methods suffer from several limitations, including a restrictive assumption about latent distributions [3], an inability to treat complicated scene topologies [9], or an inefficient similarity measure [13].

In this paper, we propose an iterative adaptive figure-ground classification method, which gives promising solutions in a broadly applicable environment. Foreground extraction is achieved by first generating a large amount of hypotheses through an iterated background prior propagation routine, then fusing most promising hypotheses to obtain the final result. The algorithm yields good result for challenging scenes in both segmentation accuracy and execution efficiency. It is not sensitive to difficult scene topology or loose bounding box, and reliably treats multi-connected, multi-hole foregrounds. Another advantage of our method is that the spatial smoothness term essential in popular conditional random fields (CRF) approaches is removed, and hence no additional learning algorithm is needed for tuning a smoothness parameter.

The rest of the paper is arranged as follows. Section 2 briefly reviews related work. Section 3 presents our figure-ground classification framework. Section 4 presents experimental results and Section 5 concludes the paper.

2. Related work

The four major aspects of figure-ground segmentation, related to our work, are the definition of prior knowledge, similarity measures, parameter tuning, and goodness evaluation. Prior knowledge can provide information about either the foreground or background, or both [3, 14]. It can be assigned by users in several forms, including bounding boxes or seed points [11, 15], to help define hard or soft constraints [2, 16]. Priors can also dynamically change or propagate throughout the segmentation process [7, 13].

Similarity measures are defined over feature spaces, based on appearance cues like color, shape, texture and gradient [5, 17]. As different features often characterize different aspects and are complementary, recent work has focused on mixed feature spaces [14, 17]. In particular, joint color-spatial feature have been successful in many vision applications [18, 19, 20]. Besides traditional Euclidean distance, similarity measures are often based on statistics or information theory [4, 13].

Regarding parameter tuning, a common practice is to learn the parameters via an energy minimization framework using training data and supervised learning [21, 22]. The underlying assumption is that there exists a parameter setting that works for a variety of images represented by the

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In our method we use the idea of similarity voting, which does not require a learning process, to fuse soft-segmentations into a probability map and hard segmentations into a final segmentation.

A preliminary version of our work was introduced in [23]. The new method presented in this paper improves over the original [23] in the following aspects: 1) we use a soft-label scheme based on foreground likelihoods, which leads to significant improvement in the segmentation quality of fine details; 2) we introduce an iterative scheme to propagate the background prior, which increases the accuracy of the segmentation; 3) maximally stable extremal regions (MSER) are used to define a novel score function for goodness evaluation and background prior propagation, which effectively prevent over-propagation of the background and better handles loose bounding boxes; 4) similarity voting is extended for probability map generation and hypothesis set selection, which yields a robust classifier fusion from multiple hypotheses.

3. Enhanced figure-ground classification with background prior propagation

In this section, we propose an enhanced adaptive figure-ground classification framework with background prior propagation. Our framework is based on fusing multiple candidate segmentations, and is guided by two underlying principles: 1) voting or fusion of multiple candidates often has better chance than optimization of a single score function in classification tasks, as long as the candidates are reasonably generated (even by very weak classi-
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3.1. Algorithm overview

Fig. 1 shows the pipeline of our figure-ground segmentation algorithm. Our algorithm consists of two main stages: 1) hypothesis segmentation generation, and 2) similarity voting & fusion. In the first stage, the user box specifies the initial foreground and a large number of candidate segmentations are created, from which a set of best hypothesis segmentations are selected. By using one of the hypotheses to define the new foreground prior, the segmentation process is repeated to form several hypothesis sets. In the second stage, the best hypothesis set is automatically selected by intra-similarity comparison, and the corresponding hypotheses are fused to form the final segmentation.

3.2. Bounding box assignment

Our algorithm is based on a user-specified mask box that helps define the initial foreground prior, as in previous approaches [7, 15]. Either inside or outside of the box can be defined as the background mask, which is assumed to only contain background pixels. The complement of the background mask is the foreground mask, which may contain both foreground and background elements. The mask box can flexibly handle various cases of partially inside or multiply connected foregrounds.

3.3. Image patches by adaptive mean-shift

Defining a segmentation as the grouping of nonoverlapping regions has become popular due to its advantages in information transfer and computational efficiency [28, 29, 30]. In our work, we generate an over-segmented image using an adaptive mean-shift algorithm (Fig. 1a). Mean-shift [28] is a non-parametric clustering method, which is based on finding the modes of the kernel density estimate in the feature space. We choose the mean-shift algorithm because mean-shift patches are better described statistically in comparison to other super-pixel generators [17]. For each pixel we extract a 5D feature vector in a joint color–spatial feature space. We use the Lab space because it is better modeled by a normal distribution in comparison to RGB [31]. We then apply the mean-shift algorithm to cluster the feature vectors, with pixels in each cluster forming an image patch. The result is a partitioning of the original image I into a set of non-overlapping patches $R_i = \{p_1, p_2, ..., p_n\}$, where $p_i$ is an image patch (Fig. 2). Since we use a joint color–spatial feature space, the image patches tend to be visually similar and spatially compact.

![Image](http://dx.doi.org/10.1109/TIP.2015.2389612)

(a) original & mask   (b) initial patches   (c) adaptive patches

Figure 2. Example of over-segmentation by adaptive mean-shift.

In the mean-shift algorithm we use two bandwidth parameters for the kernel, $h_r$ for the spatial features $(x,y)$ and $h_c$ for the color features $(L, a, b)$. The bandwidth controls the smoothness of the estimate, and ultimately determines the mean of mean-shift patches obtained [28]. Different initial settings lead to different image patch sets, only some of which are suitable for the subsequent classification [32]. This is illustrated in Figure 2, where the default setting of $h_r=7$ and $h_c=6$ generates cluttered patches and fails to transfer the background prior reliably into the region of interest. Nevertheless, a bandwidth setting $h_r=10$ and $h_c=8.6$ (determined by our adaptive scheme) generates more consolidated patches.

Based on the relationship between the bandwidth parameters and the covariance matrix of the multivariate normal distribution [33], we propose the following scheme to adaptively set the bandwidths. First, an initial mean-shift segmentation is performed with the default bandwidths $h_r=7$ and $h_c=6$. Next, patches overlapped with the foreground mask region are collected into the set $F_0$, and the 3x3 covariance matrix $\Sigma_0$ of the color features, and the 2x2 covariance matrix $\Sigma_0$ of the spatial features are calculated for each patch $p_i$. Finally, the adaptive bandwidths are estimated by averaging the color/spatial variances over all collected patches in $F_0$.

$$h_r = \frac{1}{\sqrt{|F_0|}} \sum_{p_i \in F_0} \frac{1}{\text{trace}(\Sigma_0)}$$

$$h_c = \frac{1}{\sqrt{|F_0|}} \sum_{p_i \in F_0} \text{max(diag}(\Sigma_0))$$

Whereas $h_r$ is estimated from the variance in both $x$- and $y$-coordinates, $h_c$ is estimated by averaging the Lab components with largest variance, due to the observation that this component often dominates in the Lab space. The mean-shift algorithm is run again with the adapted bandwidths to obtain the final patches.

The bandwidth could be updated iteratively with multiple runs of mean-shift. However, we did not see any improvement using more than one update, and the iterations sometimes did not converge to a fixed value, but instead oscillated within a small range.
from the foreground mask, our approach tunes the band-
width parameters to form better representative patches.

In some cases, when the background contains repetitive
cluttered textures, the adaptive mean-shift may still pro-
duce too many image patches, and cause the background
patches to be mainly distributed along the mask boundary
(as in Fig. 3). This will lead to a poor estimate of the
background prior and a poor segmentation. We suggest
a simple heuristic to identify and circumvent these cases.
If the initial mean-shift creates too many patches (>300)
within the mask region, we double the bandwidths (\(h_i=14,\)
\(h_i=12\)) to group together pixels in a larger neighborhood
to make larger patches. Larger bandwidths merge small
patches into bigger ones and extend background prior
deeper into the mask region.

![Figure 3. Larger bandwidths for cluttered textures: (a) image; mean-shift patches using (b) small and (c) large bandwidths.](image)

3.4. Similarity measure between patches

In the next stage of the segmentation pipeline, patches
are gradually assigned likelihood labels, based on their
similarities to the patches labeled earlier. We will represent
a region as the set of its patches. Hence, we must first de-
fine a suitable dissimilarity measure between two patches,
and between a patch and a region.

To remain consistent with the underlying probabilistic
framework of the mean-shift algorithm, we model each
mean-shift patch \(p_i\) as a multivariate normal distribution
\(N(\mu_i, \Sigma)\) in the 5D feature space defined in (1), where
the mean vector \(\mu_i\) and the covariance matrix \(\Sigma\) are estimated
from the patch. All patches are eroded with a 3x3 structural
element to avoid border effects.

The Kullback-Leibler divergence (KLD) can be used to
measure dissimilarity between two distributions, but is not
symmetric [34]. Here, we use the minimum KLD between
two patches as our dissimilarity measure,

\[
D(p_i, p_j) = \min_{p_k} KL(p_i, p_k) + KL(p_j, p_k),
\]

where patches \(p_i\) and \(p_j\) are represented by two Gaussians,
with distributions \(N(\mu_i, \Sigma_i)\) and \(N(\mu_j, \Sigma_j)\), and the KLD
between two \(d\)-dimensional Gaussians is [34]

\[
KL(p_i, p_j) = \frac{1}{2} [ (\mu_i - \mu_j)' \Sigma_j^{-1} (\mu_i - \mu_j) + \text{Tr}(\Sigma_j^{-1} \Sigma_i) + \log \frac{|\Sigma_j|}{|\Sigma_i|} - d ].
\]

Eq. (3) is a symmetrized version of the KLD in (4), and has
an intuitive interpretation that two patches are similar if
either of them can be well described by the other. With this
dissimilarity the background holes illustrated in Fig. 4 can
be reliably identified as similar to the background.

![Figure 4. An illustration of minimum KL divergence. \(p_1\) and \(p_2\) are two non-adjacent mean-shift patches modeled by multivariate normals. \(p_2\) is a local sample of \(p_1\), \(KL(p_1, p_2)\) is large but \(KL(p_2, p_1)\)
is small. By using the minimum of the 2 values, the two patches
will have low dissimilarity and will likely be grouped together.](image)

A region in an image (e.g., the background) is repre-
sented as a set of patches, \(R = \{p_1, \ldots, p_r\}\), where \(\{r_i\}\) are
the indices of the patches forming the region. Using the dis-
similarity between patches in (3), we define the dissim-
ilarity between a patch \(p\) and region \(R\) as the minimum dissimilarity
between the patch \(p\) and any patch in \(R\),

\[
D(p, R) = \min_{r \in R} D(p, r).
\]

(5)

We define the dissimilarity between two regions \(R_1\) and \(R_2\)
as the minimum dissimilarity between their patches,

\[
D(R_1, R_2) = \min_{p \in R_1} \min_{r \in R_2} D(p, r).
\]

(6)

Note that both background and foreground can be multi-
modal. That is, patches in one region (e.g., background)
may have very different distributions (e.g., sky and grass).
Therefore, for the patch-region dissimilarity, we use the
minimum dissimilarity so as to match the patch to the most
similar part in the region. Likewise, the minimum dissim-
ilarity measure between two regions implies that they are
similar if they have patches in common (e.g., both contain
sky). In our context, using alternatives such as median
dissimilarity or max-min dissimilarity may not work well
due to the regions being multi-modal.

3.5. Soft-label partitions

With the patch distances defined in Section 3.4 we next
describe our foreground extraction algorithm. Under the
assumption that the user-specified box provides sufficient
background statistics, we first initialize the background and
foreground priors (Fig. 1b), and then gradually compute a
soft-label partition (Fig. 1c). Formally, our objective is to
assign each image patch \(p\) a likelihood (soft-label) of be-
longing to the foreground category, denoted by \(L(p)\).

The partitioning process proceeds as follows. First, all
patches \(p\) overlapping with the background mask form the
initial background prior \(B\), and are given zero likelihood,

\[
L(p) = 0, \quad \forall p \in B.
\]

(7)

Next, the initial foreground region \(F_0\) is formed using the
set of patches that are sufficiently far from \(B\),

\[
F_0 = \{ p | D(p, B) > D_t \},
\]

(8)

where \(D_t\) is a foreground threshold whose value will be
discussed at the end of the subsection. The foreground likelihood of these initial foreground patches is set to 1,
\[ L(p_i) = 1, \quad \forall p_i \in F_0 \]  
(9)
The remaining unlabeled patches are progressively labeled with patches furthest from the background considered first, i.e., in descending order based on their distances from the background prior \( B_i \), \( D(p_i, B) \). Let \( \Theta \) be the set of currently labeled patches. For each patch \( p_i \) under consideration, a local conditional probability with respect to any labeled patch \( p_j \in \Theta \) is computed by comparing the distances from \( p_i \) to the background prior \( B \) and \( p_j \) using the softmax (logistic) function,
\[ l(p_i | p_j) = \frac{e^{-D(p_i, p_j)}}{e^{-D(p_i, B)} + e^{-D(p_i, B)}}. \]  
(10)
Because the feature space represents both color and location, (10) will give high likelihood when the two patches are both visually similar and spatially close together, while also being dissimilar to \( B \). The overall likelihood of patch \( p_i \) being foreground is estimated by calculating the maximum likelihood score over all preceding patches,
\[ L(p_i) = \max_{p_j \in \Theta} l(p_i | p_j). \]  
(11)
Eq. (11) considers both the conditional probability of the current patch being foreground given the labeled patch, and the probability of the labeled patch also being foreground. Note that these patches are not explicitly assigned a foreground or background label, but instead assigned a likelihood of being foreground, based on foreground likelihood of preceding labeled patches. After all unlabeled patches are processed with (11), a likelihood \( L \) is defined for every patch, resulting in a soft-labeling of foreground regions in the image. The procedure is summarized in Algorithm 1.

\begin{algorithm}
\caption{Soft-label partitioning}
\textbf{Input:} Image patches \( \mathcal{P} = \{p_1, p_2, \ldots, p_n\} \), background mask \( K \), threshold \( D_{t} \).
\textbf{Output:} Foreground likelihood \( L(p_i) \) for each patch \( p_i \),
Initialize background prior: \( B = \{p_i | p_i \cap K = \emptyset\} \),
Initialize foreground: \( F_0 = \{p_i | D(p_i, B) > D_{t}\} \),
Initial labels: \( L(p_i) = 0, \quad \forall p_i \notin B \); \( L(p_i) = 1, \quad \forall p_i \in F_0 \).
Initialize labeled set: \( \Theta = B \cup F_0 \).
\textbf{Repeat}
1. Find furthest patch: \( p_i = \arg \max_{p_i \neq \emptyset} D(p_i, B) \)
2. Conditional probabilities: \( l(p_i | p_j) = \frac{e^{-D(p_i, p_j)}}{e^{-D(p_i, B)} + e^{-D(p_i, B)}} \), \( p_j \in \Theta \)
3. Foreground likelihood: \( L(p_i) = \max_{p_j \in \Theta} l(p_i | p_j) \)
4. Update labeled set: \( \Theta = \Theta \cup p_i \)
\textbf{Until} no more unlabeled patches.
\end{algorithm}

Overall, the above soft-label method can be interpreted as a likelihood-tree growing procedure, as shown in Fig. 5. The initial foreground \( F_0 \) is the root of the tree. The likelihood of being foreground is propagated from node to node as the tree grows in a top-down manner.

Finally, the hard-label partition, used in our preceding work [23], can be obtained by replacing the softmax function in (10) with a hard binary-valued function,
\[ l_{\text{hard}}(p_i | p_j) = \begin{cases} 1 & \text{if } D(p_i, p_j) \leq D(p_i, B) \\ 0 & \text{if } D(p_i, p_j) > D(p_i, B) \end{cases}. \]  
(12)
Using (12), \( p_i \) will be marked as foreground only if it is more similar to some other foreground patch than the background \( B \). This corresponds to a greedy labeling method, where the foreground set, \( F = \{p_i | L(p_i) = 1\} \), is updated when a new patch is assigned to the foreground.

We now turn our attention to the threshold \( D_{t} \) that determines the initial foreground region \( F_0 \). The choice of threshold is important since it may lead to different tree structures and hence different soft-label partitions (e.g., see Figs. 5d and 5e). Rather than select a single threshold, we instead consider multiple thresholds, i.e., multiple foreground initializations, and produce various candidate soft-label partitions for consideration. In practice, we use all thresholds \( D_{t} \) between the lower and upper bounds, \( D_{t} = 5 \) and \( D_{t}^{\text{max}} = 50 \). This interval allows a large enough set of initial foreground priors but excludes unnecessary initializations\(^3\).

Since there are a finite number of possible \( D(p_i, B) \) values (one for each image patch), we only need to try a finite number of thresholds. In particular, we sort all values of \( D(p_i, B) \) within the interval \([D_{t}, D_{t}^{\text{max}}]\) in ascending order and use the midpoints between two successive values as the set of thresholds. Running the soft-label partitioning method for each threshold, we obtain a large set of soft-label partitions. The size of the set depends on the number of patches in the image. Simple images will have few patches (<5), whereas cluttered images will have more patches (>100), and thus a larger set of soft-label partitions.

3.6. Foreground probability map

We next build a foreground probability map by fusing all soft-label partitions (Fig. 1d). The fusion is based on the idea of similarity voting. That is, partitions sharing more similarities are given higher influence. Denote \( F_i \) as the \( i \)-th soft-label partition from the previous stage, and \( F_i^m \) as the likelihood value of the \( m \)-th pixel in \( F_i \), where pixels take the likelihoods of their corresponding patches. We define the similarity between two soft-label partitions \( F_i \) and \( F_j \) by
\[ d(F_i, F_j) = (\sum_{m=1}^{M} (F_i^m - F_j^m)^2) / (\sum_{m=1}^{M} (F_i^m + F_j^m))^2 \]  
(13)

\(^3\) The K.L divergence values calculated in (4) are typically dominated by the Mahalanobis distance term, which follows a 5-dof \( \chi^2 \) distribution under multivariate Gaussian [35].

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where \( M \) is the total number of pixels, and \( \text{sign}(x) = 0 \) when \( x = 0 \) and \( 1 \) when \( x > 0 \). When \( F_i \) and \( F_j \) are hard-label partitions (i.e., sets of foreground pixels), (13) reduces to the scale invariant measure [36],

\[
d(F_i, F_j) = \| F_i \oplus F_j \| \| F_i \cup F_j \|,
\]

(14)

where \( \oplus \) and \( \cup \) denote symmetric difference and union of two sets, and \( |F| \) denotes the cardinality of a set \( F \). We then construct a symmetric affinity matrix \( A \) with entries

\[
A(i,j) = \exp(-d(F_i, F_j)^2 / 2\sigma_i^2),
\]

(15)

where \( \sigma_i \) is the variance of the pairwise distances between all partitions \( \{F_i\} \) [7, 30]. Finally, a real-valued probability map is calculated as the weighted sum of the soft-label partitions \( \{F_i\} \),

\[
P = \sum w_i F_i.
\]

(16)

The weight vector \( w \) is determined using the following constrained optimization problem,

\[
\max w^T A w, \text{ s.t. } \| w \|^2 = 1.
\]

(17)

Eq. (17) is a standard Rayleigh quotient problem [37], and the optimal \( w \) is given by the top eigenvector of \( A \). Intuitively, the weights found by (17) are higher for partitions sharing more similarities. In short, the probability map is computed as the weighted sum of all soft-label partitions, where larger weights are given to more similar partitions. This corresponds to a similarity voting process leading to a better probability map, compared to [23]. Some example probability maps are given in Figs. 1d and 7a.

### 3.7. Hypothesis segmentation set

Given the foreground segmentation map, a set of candidate segmentations is formed by thresholding the probability map \( P \) (Fig. 1e). Due to the finite number of patches, the probability map \( P \) contains a finite number of values \( \pi_i \) \((i=0,...,n)\). Therefore, it is easy to create multiple hard-label (binary-valued) candidates from \( P \) by brute-force thresholding. In particular, first we sort all values of \( \pi_i \) in ascending order,

\[
0 = \pi_0 < \pi_1 < \pi_2 < \ldots < \pi_n = 1.
\]

(18)

We have \( \pi_0 = 0 \) and \( \pi_n = 1 \) because there must be some definite foreground and background regions in a valid probability map. We then define a threshold set \( T = \{t_i\}_{i=1}^{n} \) as the midpoints between two successive probability values, \( t_i = (\pi_i + \pi_{i+1})/2 \). This threshold set \( T \) is used to binarize the probability map \( P \) into \( n \) hard-label candidates.
From these hard-label candidates we select promising segmentations according to various evaluation scores, denoted as the hypothesis set (Fig. 1f). Taking into account the fact that perceptually meaningful segmentations may correspond to different cost functions, we generate multiple segmentation hypotheses from multiple evaluation scores. In particular, we prefer evaluation scores that encourage different types of segmentations. We consider three score functions from different points of view, which are described below. Other scores could also be used to incorporate any available prior knowledge (like texture or shape).

The average-cut (a-cut) score is defined as the average of the distances $D(f,B)$ from each foreground patch $f$ to the background set, i.e. the selected threshold is given by

$$t_{acut} = \arg\max_{t \in T} \frac{1}{|F|} \sum_{f \in F(t)} D(f,B(t)),$$

(20)

where $F(t)$ and $B(t)$ are respectively the foreground and the background groups in the final segmentation map computed from the threshold $t$. The a-cut score finds a split of foreground and background such that the average distance between the two is large. It is also related to the “average cut” used in spectral partitioning [30], but here we only consider the foreground region when calculating the score.

Inspired by the maximum-margin principles of support vector machines (SVMs), the maximin-cut (m-cut) score maximizes the minimum distance between foreground and background patches,

$$t_{mcut} = \arg\max_{t \in T} \min_{f \in F} \frac{|F(t)|}{|B(t)|}.$$

The m-cut score prefers segmentations where the foreground and background regions have a wide boundary in the feature space, corresponding to the optimization of (6).

The third score is based on the idea of maximally stable extremal regions (MSER) [38], which tries to maximize the local stability of a candidate over the threshold set $T$. Recent evaluations reveal that the MSER detector [38] exhibits good performance on a variety of benchmarks [39]. The original MSER detector finds regions that are locally stable over a wide range of thresholds. In contrast to previous works, we make a modification by using the full foreground map instead of a local connected region to define MSER, and only considering the global maximum over the whole threshold set $T$. In our context, the threshold selected by MSER score is defined by

$$t_{log(MSER)} = \arg\max_{t \in T} \frac{|F(t)|}{|B(t)|},$$

(21)

where $F(t)$ and $B(t)$ are the foreground and background regions at threshold $t$. The log(MSER) curve, and the maxima of the a-cut and m-cut curves. The hypothesis segmentations are selected as the minimum of the log(MSER) curve, and the maxima of the a-cut and m-cut curves.

Different m-cut solutions along the optimal interval tend to have slightly different appearances. Hence, we select two hypotheses from the m-cut score function, corresponding to the left and the right ends of the optimal interval. Thus, in total we have four hypothesis binary segmentations, one by MSER, one by a-cut, and two by m-cut. Figure 7 shows an example of building hypotheses from the probability map.

![Figure 7](image7.png)

Figure 7. Example probability map and hypothesis set for the image of Figure 2. a) probability map (Sec. 3.6); b) multiple binary candidates by thresholding (Sec. 3.7); c) 4 hypothesis candidates by different evaluation scores, corresponding to the 3 optimal points of Figure 6 (Sec. 3.7).

**3.8. Iterated background prior propagation**

The result of Sec. 3.7 is a set of hypothesis segmenta-

$$C_i = \{t \in T_i\}, i = 1, \ldots, n.$$

box is assigned. More importantly, the MSER score is sufficiently robust to allow for the background prior to be updated iteratively, which will be discussed in Sec. 3.8.

Figure 6 plots an example of the three score functions, while varying the threshold $t$. It is worth mentioning that different segmentations may have the same m-cut score. For example, in Figure 6c within the [82, 84] interval the same m-cut score corresponds to 3 different candidates. This means the solutions to m-cut may not be unique. Different m-cut solutions along the optimal interval tend to have slightly different appearances. Hence, we select two hypotheses from the m-cut score function, corresponding to the left and the right ends of the optimal interval. Thus, in total we have four hypothesis binary segmentations, one by MSER, one by a-cut, and two by m-cut. Figure 7 shows an example of building hypotheses from the probability map.

![Figure 6](image6.png)

Figure 6. Three $t_{c}$-score curves for the image of Figure 2. A log-plot is used for the MSER curve to show the minimum clearly. The hypothesis segmentations are selected as the minimum of the log(MSER) curve, and the maxima of the a-cut and m-cut curves. In this example with 87 hard-label candidates, the optimal values are taken at $t_{L}$, $t_{L_{62}}$, and $t_{L_{65}}$ respectively by the three score functions.
tions. The background region of one of these segmentations can be used as the background prior for a new round of segmentation (Algorithm 2), which we call background prior propagation (BPP). We use the background from the MSER segmentation for BPP because of its favorable properties mentioned in Sec. 3.7. The process iteratively continues until the background prior stops changing between iterations. The convergence of BPP is guaranteed because image patches can only be added to the background prior in each round. Hence the background prior region can only grow until it reaches a stable point, or, very rarely in our context, covers the full image. The fact that MSER favors bigger foreground regions contributes to the prevention of over-propagation of the background.

Figure 8 shows the background priors after three iterations of BPP for a few example images with complicated foreground topologies (multiple hole, multiply connected, or irregular contours). These examples demonstrate how the background prior gradually propagates into the region of interest and builds multiple hypotheses.

![Figure 8: Examples of iterative background prior propagation.](image)

### 3.9. Hypotheses selection and fusion

After convergence, BPP generates several sets of hypothesis binary segmentations, with one set from each BPP iteration round. An automatic mechanism is required to build a final result from the hypotheses sets of all iterations (Figs. 1g and 1h). Direct fusing all these hypotheses is not a good choice due to the risk of including over-propagated backgrounds. Instead, based on the principle of similarity voting, we choose the set with highest intra-similarity for the final fusion. The motivation is that under a good initialization, the results selected by different evaluation scores are generally consistent and correct, whereas under a bad initialization, the results selected by different evaluation scores are generally inconsistent and unreliable. We denote the hypothesis set of 4 binary segmentations in the jth iteration of BPP as \( H = \{ H_{\text{MSER}}, H_{\text{acut}}, H_{\text{mcut1}}, H_{\text{mcut2}} \} \). For each hypothesis set \( H \), we calculate the mean pairwise similarity within the set,

\[
s(H') = \frac{1}{12} \sum_{a,b \in \{ \text{MSER, acut, mcut1, mcut2} \}} s(H'_a, H'_b)
\]

where the similarity between two binary segmentations \( H_1 \) and \( H_2 \) is defined as the Jaccard index [16],

\[
s(H_1, H_2) = \frac{|H_1 \cap H_2|}{|H_1 \cup H_2|}.
\]

The set with the largest mean similarity \( s(H) \) is selected as the winner set \( H \). Finally, from the 4 binary-valued hypothesis maps \( H = \{ H_{\text{MSER}}, H_{\text{acut}}, H_{\text{mcut1}}, H_{\text{mcut2}} \} \) of the winner set, we compute the final foreground map \( F \) by a simple pixel-wise majority vote,

\[
F = (H_{\text{MSER}} + H_{\text{acut}} + H_{\text{mcut1}} + H_{\text{mcut2}}) \geq 2.
\]

### Algorithm 2. Enhanced figure-ground classification with background prior propagation (EFG-BPP)

**Input:** A target image \( I \) and a background mask.

**Output:** foreground segmentation \( F \).

**Initialization:** Set initial background prior \( B_0 \) as the set of image patches overlapping the background mask. Set \( j = 0 \). Calculate image patches using adaptive mean shift (Sec. 3.3).

**Repeat**

1. Generate soft-label partitions from \( B_j \) (Alg. 1, Sec. 3.5).
2. Compute a real-valued probability map \( P \) (Sec. 3.6).
3. Generate hard-label candidates from \( P \), and obtain a hypothesis set \( H \) using different score functions (Sec. 3.7).
4. Use the MSER segmentation \( H_{\text{MSER}} \) to define a new background prior \( B_{j+1} \) (Sec. 3.8)

5. \( j = j + 1 \);

**Until** (\( B_j = B_{j-1} \))

Select the winner hypothesis set from \( \{ H_j \} \) based on intra-set similarity (Sec. 3.9): \( H^* \in \{ H_{\text{MSER}}, H_{\text{acut}}, H_{\text{mcut1}}, H_{\text{mcut2}} \} \).

Calculate the final segmentation via majority vote (Sec. 3.9):

\[
F = (H^*_{\text{MSER}} + H^*_{\text{acut}} + H^*_{\text{mcut1}} + H^*_{\text{mcut2}}) \geq 2.
\]

The full framework is summarized in Algorithm 2. Note that most parameters in our system are set automatically based on the image, and our multiple hypotheses framework is based on generating segmentation candidates using all possible thresholds. In addition, because segmentation is based on soft-labeling and multiple hypothesis segmentations are kept, the effects of erroneous outputs in each stage
of the pipeline are minimized.

4. Experiments

In this section, we evaluate our algorithm. Experiments are run on a notebook computer with an Intel core-i7 CPU 2.7Ghz processor and 4GB RAM. Our algorithm is implemented in MATLAB and is available online.

4.1. Evaluation of segmentation results

We make a comprehensive comparison using four image datasets with ground truths; Weizmann 1-obj (100 images), Weizmann 2-obj (100 images), IVRG [41] (1000 images), and grabcut [42] (50 images). We denote our enhanced figure-ground classification using soft-label partitions and background prior propagation as EFG-BPP. We also test the performance using hard-label partitions with (12), which is denoted as EFG-BPP (hard-label). We also compare against grabcut [7] and other methods [4,11,28,43]. The initial mask box is assigned by the user and is fixed for comparisons between box-based methods.

The performance on each image is evaluated using F-measure, \( F = \frac{2PR}{P+R} \), where \( P \) and \( R \) are the precision and recall values [43]. Table 1 reports the 95% confidence intervals of the average F-scores of both hard-label and soft-label EFG-BPP. We also give the output of the first and the last iteration of BPP for both schemes. We note that even in the absence of background prior propagation, the result of the first iteration is sufficiently good. By employing background prior propagation and automatic hypotheses selection the result becomes better. It is worth noting that the performance of the last iteration slightly degrades for the Weizmann and IVRG datasets. This indicates that the best result is not necessarily reached at the time of convergence, but may instead come in some earlier iteration round. Intelligently selecting and leveraging multiple hypotheses improves the F-measure on all the datasets.

Finally, the foreground map closest to the ground truth in all hard-label candidates (last column of Fig. 9) forms an upper bound for the figure-ground classification method. The EFG-BPP result performs close to this upper bound.

Figure 9. Weizmann examples. Rows 1-3 are 1-obj examples. Rows 4-8 are 2-obj examples. The EFG-BPP result is equally good as the user selection for rows 1, 2, 4, 6, & 7; and slightly worse on the remaining rows. The outside of the blue boxes or the inside of the red boxes define the background masks.

Figure 10. IVRG examples. Top: image & mask; middle: grabcut results; bottom: EFG-BPP results.

We first qualitatively examine the major benefits of our segmentation method on some examples. Figure 9 displays some example segmentations from the Weizmann dataset. EFG-BPP successfully labels background holes and multiply connected components, and identifies many details missed in the manual-made truths. Figure 10 shows some example segmentations from the IVRG dataset. In comparison to grabcut [7], EFG-BPP exhibits qualitatively better performance, mainly when segmenting complicated foreground and background shapes.

This validates the principle of similarity voting. That is, we should encourage more candidates to participate in a multiple hypothesis scheme, and similarity comparison plays an important role in smart hypothesis selection. Finally, the foreground map closest to the ground truth in all hard-label candidates (last column of Fig. 9) forms an upper bound for the figure-ground classification method. The EFG-BPP result performs close to this upper bound.

Figure 10. IVRG examples. Top: image & mask; middle: grabcut results; bottom: EFG-BPP results.

http://www.graphics.pku.edu.cn/members/chenyisong/projects/FigureGroundPuzzle/ FGpuzzle.htm
The last row of Table 1 shows the results of several reference algorithms [4,7,11,28,43]. EFG-BPP performs slightly better than the state-of-the-art techniques for single connected foregrounds (Weizmann 1-obj), and outperforms the state-of-the-art on multiple connected foregrounds (Weizmann 2-obj). For the grabcut image set, we also compare the error rate with the result reported in [13]. The error rate is defined as the percentage of mislabeled pixels within the initial box mask. Table 2 shows that EFG-BPP has lower average error rate than grabcut [7] and iterated distribution matching [13]. Figure 11 compares the performance of grabcut and EFG-BPP for the Grabcut and IVRG image sets. The x-axis is the $F$-score threshold, and the y-axis is the number of images with an $F$-score greater than this threshold. The figure shows that EFG-BPP generates fewer poor segmentations.

Table 2. Average error rate comparison on the grabcut dataset

<table>
<thead>
<tr>
<th></th>
<th>Weizmann 1-obj</th>
<th>Weizmann 2-obj</th>
<th>IVRG images</th>
<th>Grabcut images</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFG-BPP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>first iteration</td>
<td>0.93 ± 0.010</td>
<td>0.89 ± 0.019</td>
<td>0.94 ± 0.005</td>
<td>0.93 ± 0.018</td>
</tr>
<tr>
<td>last iteration</td>
<td>0.92 ± 0.014</td>
<td>0.88 ± 0.021</td>
<td>0.93 ± 0.006</td>
<td>0.92 ± 0.021</td>
</tr>
<tr>
<td>EFG-BPP</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>first iteration</td>
<td>0.94 ± 0.010</td>
<td>0.90 ± 0.017</td>
<td>0.95 ± 0.003</td>
<td>0.93 ± 0.017</td>
</tr>
<tr>
<td>last iteration</td>
<td>0.92 ± 0.014</td>
<td>0.89 ± 0.017</td>
<td>0.94 ± 0.003</td>
<td>0.92 ± 0.023</td>
</tr>
<tr>
<td>user-select (upper bound)</td>
<td>0.95 ± 0.009</td>
<td>0.91 ± 0.015</td>
<td>0.96 ± 0.002</td>
<td>0.95 ± 0.013</td>
</tr>
<tr>
<td>Nearest competitors</td>
<td>0.85 ± 0.035 [7] (5.67s)</td>
<td>0.81 ± 0.044 [7] (3.95s)</td>
<td>0.68 ± 0.053 [43]</td>
<td>0.93 ± 0.006 [7] (4.96s)</td>
</tr>
<tr>
<td></td>
<td>0.93 ± 0.009 [11]</td>
<td>0.93 ± 0.004 [7] (3.95s)</td>
<td>0.66 ± 0.066 [28]</td>
<td>0.89 ± 0.035 [7] (12.95s)</td>
</tr>
</tbody>
</table>

The soft-label scheme has better chance of keeping fine details, due to the soft likelihoods that are transferred to the probability map. Some different outputs are given in Figure 14 for comparison.
4.3. Evaluation of background prior propagation

Overall, about 80% of the time, EFG-BPP converges within three iterations of BPP, and most of them select the first round as the winner. This suggests that our method still can perform well without BPP. Nevertheless, we have seen in Table 1 that the output of the first loop is not necessarily the best one. For some cluttered scenes, it may take as long as 10 iteration loops to propagate the background prior deeply into the region of interest. The performance gain of background prior propagation mainly comes from these long iterations. Figure 15 displays some example images that take more than 5 iterations before reaching convergence. Although over-propagation occurs in some trials (row 4 of Fig. 15, and rows 1, 2, & 4 of Fig. 8), similarity voting is able to make a good selection from all iteration rounds and output a satisfactory result.

Table 3 compares the three selection strategies from the BPP results: similarity voting (auto), first iteration, and last iteration. Note that multiple strategies can produce the best segmentation at the same time. The three strategies are consistent to a large extent, with each obtaining good results in at least 70% of the trials.

Table 3. The number of times each selection strategy obtained the best segmentation. The value in ( ) is the total number of images in the images set.

<table>
<thead>
<tr>
<th></th>
<th>Weiz1(100)</th>
<th>Weiz2(100)</th>
<th>IVRG(1000)</th>
<th>Grabcut(50)</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto</td>
<td>81</td>
<td>88</td>
<td>811</td>
<td>41</td>
<td>1021</td>
</tr>
<tr>
<td>First</td>
<td>79</td>
<td>77</td>
<td>725</td>
<td>36</td>
<td>917</td>
</tr>
<tr>
<td>Last</td>
<td>34</td>
<td>82</td>
<td>244</td>
<td>38</td>
<td>936</td>
</tr>
</tbody>
</table>

An interesting observation is that the last iteration outputs better results more times than the first iteration whereas the F-score is inferior as shown in Table 1. This is due to the higher risk of over-propagation in the last-iteration. Even though over-propagation occurs only in a small number of trials it can cause significant drop of the F-score. The auto-choice (EFG-BPP) consistently outperforms the two competitors in both F-scores and number of best segmentations. This provides strong evidence for the power of similarity voting as a winner selection criterion. Some examples of the three schemes are given in Fig. 16.

4.4. Evaluation of initial mask box

The background prior propagation mechanism makes EFG-BPP tolerant to loose initial mask boxes around the foreground subject, since for each iteration the background region can move further into the initial box. We test 500 IVRG images that allow looser bounding boxes while keeping parts of the background prior. For each image, we manually assign the maximally allowed range of the 4 edges of the mask box such that some common parts of the
background remain, and test various box sizes within the range. Table 4 shows that EFG-BPP is stable and insensitive to looser boxes, and outperforms both the first and last iterations of BPP. Fig. 17 shows example segmentation results by various mask box sizes. Fig. 18 shows that different mask boxes can be used to successfully extract different foreground elements.

Table 4. Results of EFG-BPP for various mask box sizes on 500 IVRG images. Each column shows the average F-measure when randomly expanding the box edges within a range of allowed values (as a percentage of the maximum allowed value).

<table>
<thead>
<tr>
<th></th>
<th>0% (Tight)</th>
<th>33%</th>
<th>67%</th>
<th>100% (Loosest)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFG-BPP</td>
<td>0.94 ± 0.004</td>
<td>0.94 ± 0.005</td>
<td>0.94 ± 0.005</td>
<td>0.94 ± 0.005</td>
</tr>
<tr>
<td>First iter.</td>
<td>0.94 ± 0.004</td>
<td>0.93 ± 0.005</td>
<td>0.93 ± 0.006</td>
<td>0.93 ± 0.006</td>
</tr>
<tr>
<td>Last iter.</td>
<td>0.93 ± 0.008</td>
<td>0.92 ± 0.008</td>
<td>0.93 ± 0.008</td>
<td>0.93 ± 0.007</td>
</tr>
</tbody>
</table>

4.5. Failure cases

Figure 19 shows two failure cases of EFG-BPP. In general, the method fails if the background prior does not match true background well. This can be caused by similar foreground and background appearances (Fig. 19a), or too cluttered background which prevents successful background prior propagation (Fig. 19b). These can be improved by employing a more flexible initial mask.

5. Conclusion

We have proposed an enhanced figure-ground classification algorithm. Our framework is based on the principles of generating multiple candidate segmentations, selecting the most promising using several scoring functions, and then fusing them with similarity voting. Specifically, an adaptive mean-shift algorithm is used to generate image patches, and soft-segmentations are produced using tree-structured likelihood propagation. We put forward the idea of similarity voting to guide the generation of multiple foreground map hypotheses, and use several score functions to select the most promising ones. To improve robustness we iteratively propagate the background prior and generate multiple hypothesis sets. The most promising hypothesis set is automatically determined by similarity voting, and the corresponding hypotheses are fused to yield the final foreground map. Our method produces state-of-the-art results on challenging datasets, and is able to segment the fine details in the segmentation, as well as background holes and multiply-connected foreground components.

Future work includes more intelligent schemes with multiple background prior hypotheses, as well as extensions to box-based segmentation in video. Finally, our segmentation algorithm could be applied to other computer vision tasks like tracking, recognition and retrieval.

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