

to accurately model the class, high precision (albeit at the expense of recall) can still be achieved by predicting the labels of only those data instances which are “most” similar to the ones with labels. These observations motivate a conservative approach where we restrict the classification process to the immediate spatial and appearance neighbourhood of the labeled data, deeming everything else as unknown.

Segmentation splits an image into a number of mutually exclusive and exhaustive regions (segments) based on the underlying image structure, thus extracting natural intra-image boundaries. These boundaries provide a measure of the extent of underlying image homogeneity and hence the extent to which labels should be propagated (under the assumption that one does not want to propagate labels across inhomogeneous regions). We enforce spatial “closeness” by restricting the classification process to partially labeled segments and their immediate neighbors.

### A. Algorithm Overview

The first step of the algorithm involves segmenting the far field region of an image frame into a collection of segments  $\Omega$ . These are combined with ground/obstacle pixel labels from the robot’s stereo system. We will denote the set of all pixels labeled ground/obstacle by stereo as  $S_g/S_o$ . Segments which have any overlap with  $S_g$  and segments immediately neighboring such segments make up the set *Candidate Ground*  $C_g$  and those which overlap  $S_o$  and segments immediately neighboring them make up *Candidate Obstacle*  $C_o$ . If a segment overlaps (or neighbors) both ground and obstacle labels then it is deemed ambiguous and belongs to the set *Candidate Ambiguous*  $C_{amb}$  (See Fig. 1).

All segments in  $C_g$  which are closer to  $model(S_g)$  than some threshold  $d_g$  and those in  $C_o$  that are closer to  $model(S_o)$  than some threshold  $d_o$  in some feature space  $f$ , according to some similarity measure  $D$ , are labeled as Ground plane and Obstacle respectively. Finally, segments in  $C_g \cap C_o$  which are closer to both the stereo ground plane and the stereo obstacle regions than their respective thresholds, (in other words, segments which can be labeled as either Ground plane or Obstacle) are deemed ambiguous and are classified as unknown. The steps in this process are detailed in Algorithm 1.

### B. Segmentation Algorithms

We compare two segmentation algorithms – the efficient graph based segmentation algorithm and the mean shift based segmentation algorithm. The choice of the algorithms was governed by the need for near real time performance. We briefly explored a contiguity enhanced version of K-means [16] image segmentation. However, K-means can prove to be very slow especially with large values of  $K$  as is often desired in our setting.

1) *Efficient Graph based segmentation*: The first segmentation algorithm we consider here is the Efficient Graph Based segmentation algorithm, introduced in [17]. As the name suggests, this algorithm treats the image as a graph, with the pixels acting as the vertices. Segmentation is

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### Algorithm 1 Far Field classification algorithm

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1: for all image frames do
2:   Extract and Segment the far field region of the image
   frame. Let  $\Omega$  denote the collection of segments thus
   produced.
3:   Use available stereo labels and  $\Omega$  to compute  $C_g$  and
    $C_o$ .
4:   Compute  $C_{amb} = C_g \cap C_o$  and recompute  $C_g = C_g \setminus$ 
    $C_{amb}$ ;  $C_o = C_o \setminus C_{amb}$ .
5:   for all  $\gamma \in \{o, g\}$  do
6:      $\forall c_\gamma \in C_\gamma$  compute distance  $d_{c_\gamma} =$ 
      $D(c_\gamma, model(S_\gamma))$ , where  $D$  is a similarity
     measure in feature space  $f$  and  $model(S_\gamma)$  is a
     model1 representing  $S_\gamma$ .
7:     Compute similarity threshold  $d_\gamma$ .
8:     if ( $d_{c_\gamma} \leq d_\gamma$ ) then
9:       Label  $c_\gamma$  as  $\gamma$ .
10:    else
11:      Label  $c_\gamma$  as unknown.
12:    end if
13:  end for
14:   $\forall c_a \in C_{amb}$  compute  $d_{c_{ga}} = D(c_a, model(S_g))$  and
    $d_{c_{oa}} = D(c_a, model(S_o))$ .
15:  if ( $d_{c_{ga}} \leq d_g$ )  $\wedge$  ( $d_{c_{oa}} \leq d_o$ ) then
16:    Classify  $c_a$  as unknown.
17:  else if ( $d_{c_{ga}} \leq d_g$ ) then
18:    Classify  $c_a$  as ground plane.
19:  else if ( $d_{c_{oa}} \leq d_o$ ) then
20:    Classify  $c_a$  as obstacle.
21:  else
22:    Classify  $c_a$  as unknown.
23:  end if
24: end for

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achieved by splitting the image into a collection of connected components. A minimum spanning tree of the graph is constructed and all edges below an adaptive data dependent threshold are removed from the graph.

2) *Mean shift segmentation*: The mean shift [18] algorithm is a feature space analysis technique popularly used for image segmentation. The algorithm involves first mean shift filtering of the image data in some feature space followed by a hierarchical clustering of the filtered data. In this paper we have used the open source EDISON [19] implementation of the mean shift segmentation. The EDISON system converts the original RGB image into the LUV space. The mean shift filtering is carried out in a 5 dimensional feature space, containing the  $(x, y)$  image coordinates and the LUV values.

### C. Segment proximity measure

Appearance “closeness” is measured in a feature space  $f$ , which captures the appearance of a segment. Here, we use colour histograms (on RGB colour space) to represent segments. Each segment is represented by a 30 bin histogram, with each colour channel occupying 10 bins. Measuring segment appearance “closeness” now reduces to computing histogram similarity. There are several popular distance mea-