

Deep Networks for Saliency Detection via Local Estimation and Global Search

Supplementary Material

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1. Performance Comparison

We evaluate our method (LEGS) on four benchmark data sets (MSRA-5000 [7], SOD [9], ECCSD [10] and PASCAL-S [6]) against ten state-of-the-art models (SVO [1], PCA [8], DRFI [3], GC [2], HS [10], MR [11], UFO [4], wCtr [12], CPMC-GBVS [6] and HDCT [5]). We use either the implementations or the saliency maps provided by the authors for fair comparison. Since the DRFI method is also trained on the MSRA-5000 data set with different training/test images from ours, we do not report its result on this data set. In addition, the CPMC-GBVS method only provides the saliency maps of the PASCAL-S data set. Both quantitative and qualitative results are demonstrated in the following figures.

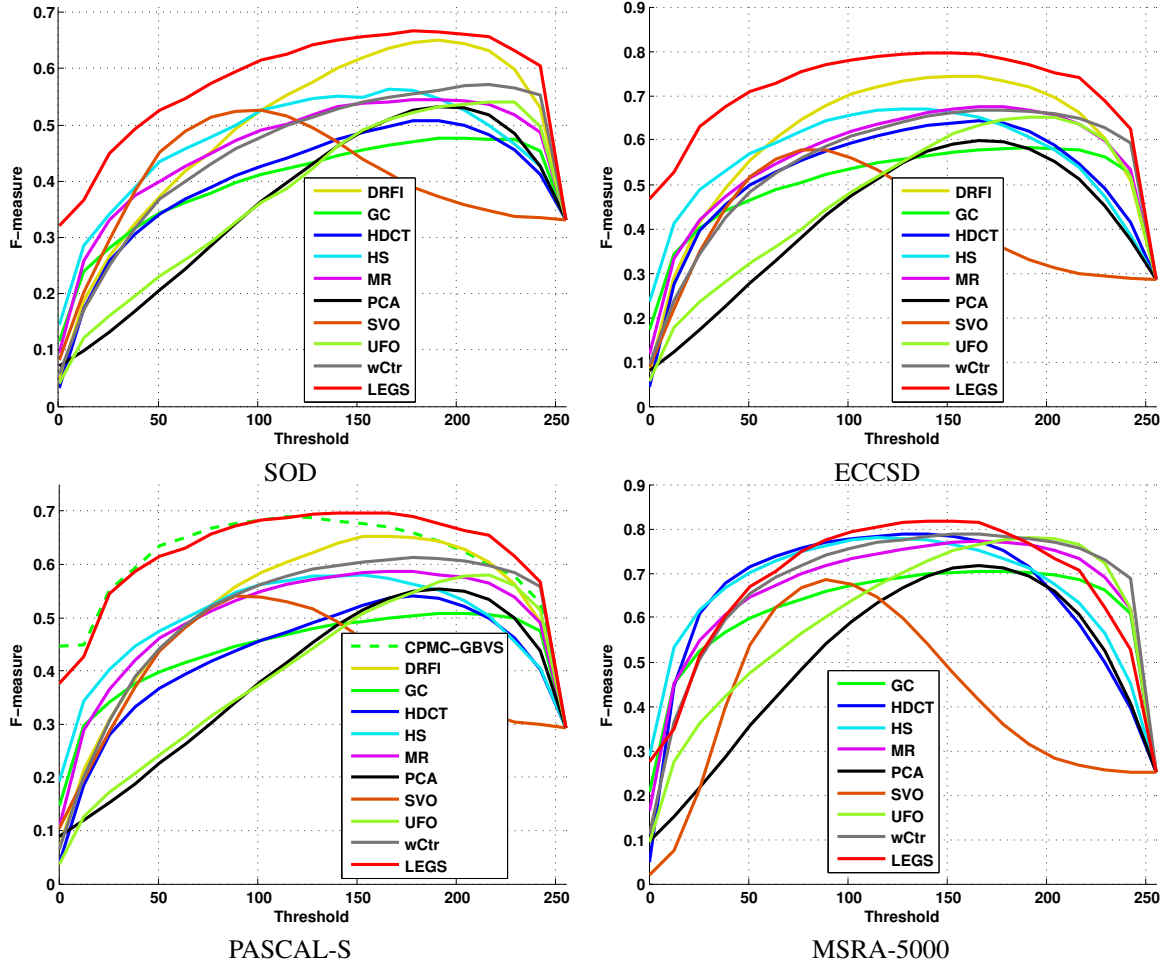


Figure 1. F-measure curves on four benchmark data sets.

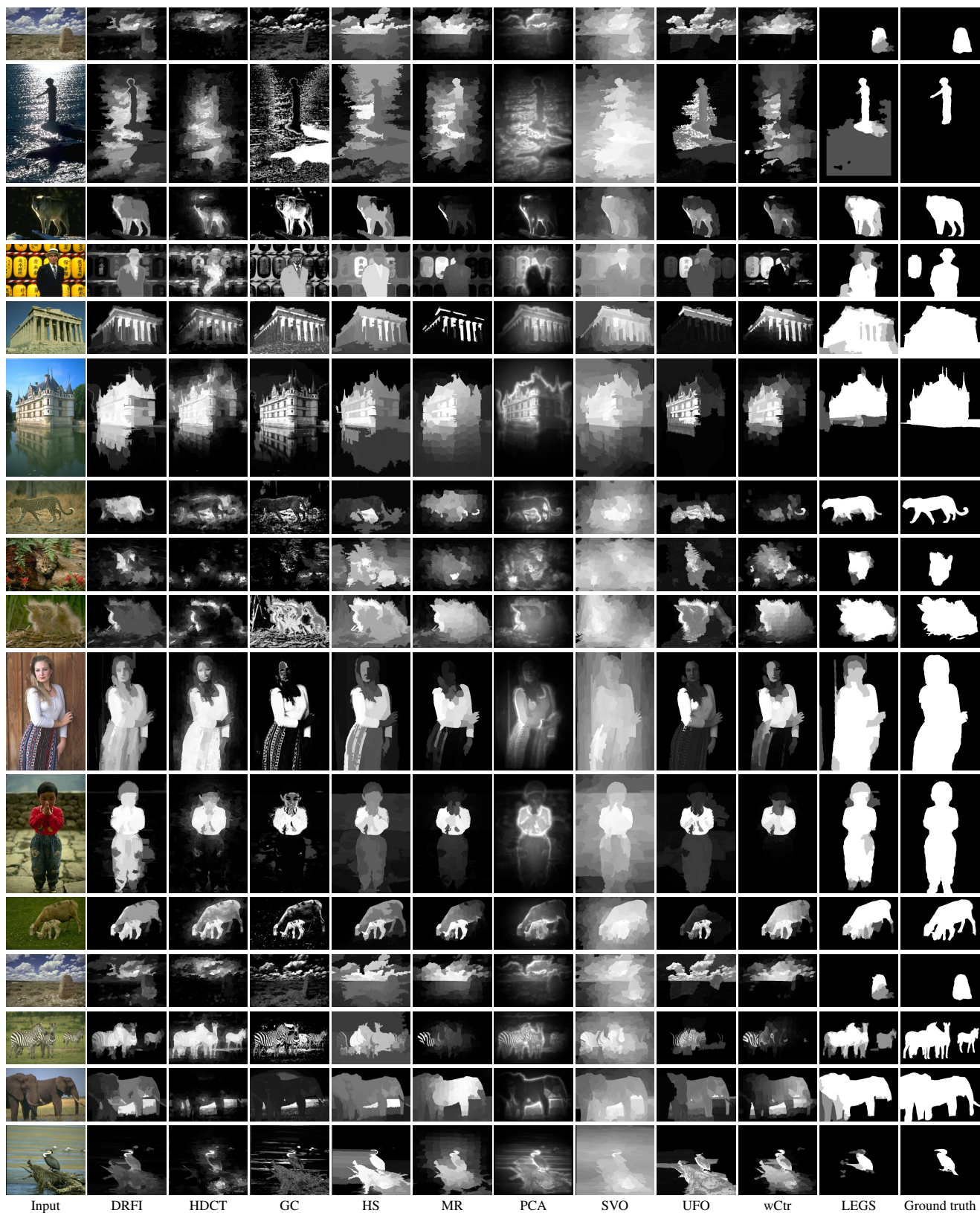


Figure 2. Qualitative comparisons of the state-of-the-art methods on the SOD data set.

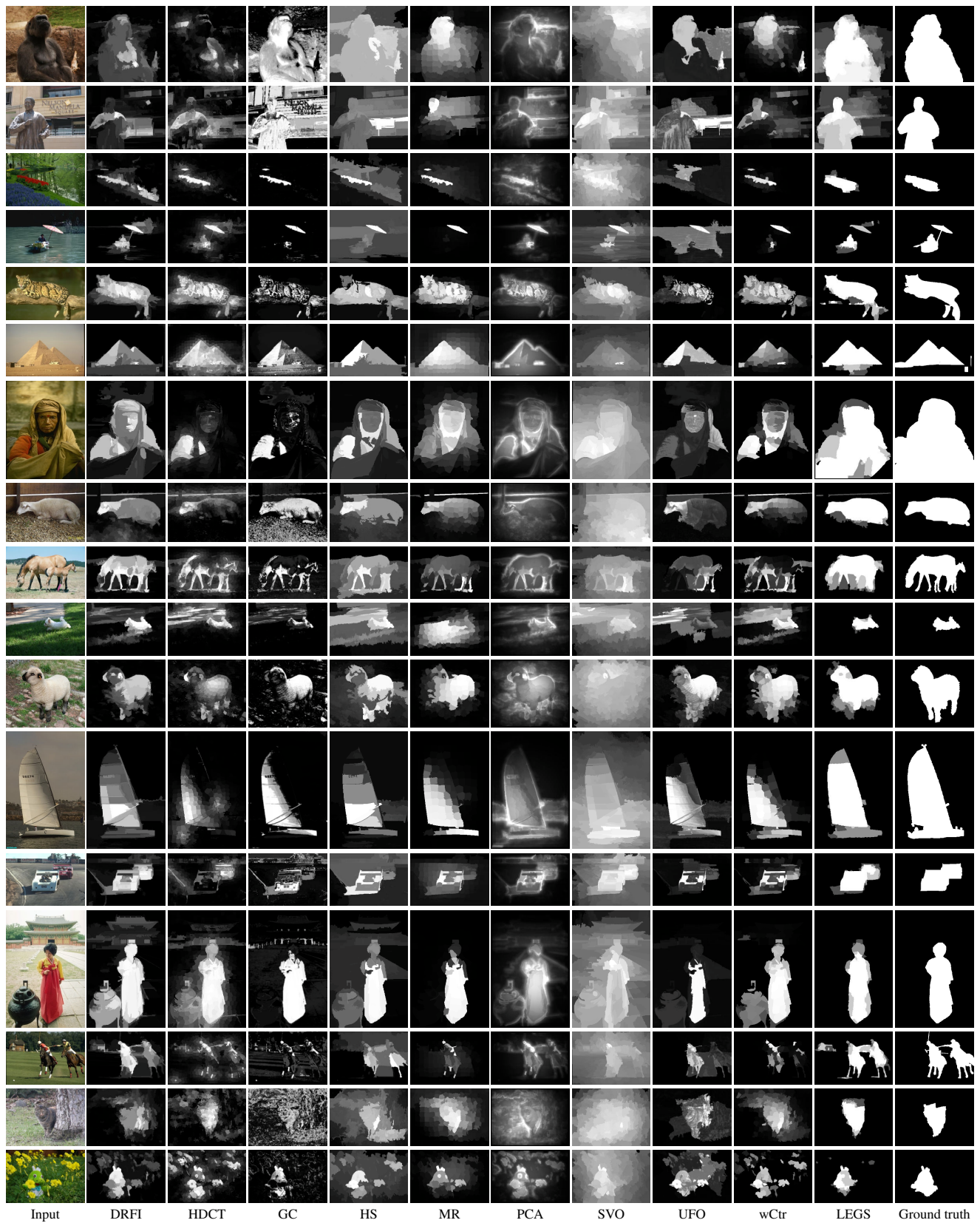


Figure 3. Qualitative comparisons of the state-of-the-art methods on the ECCSD data set.

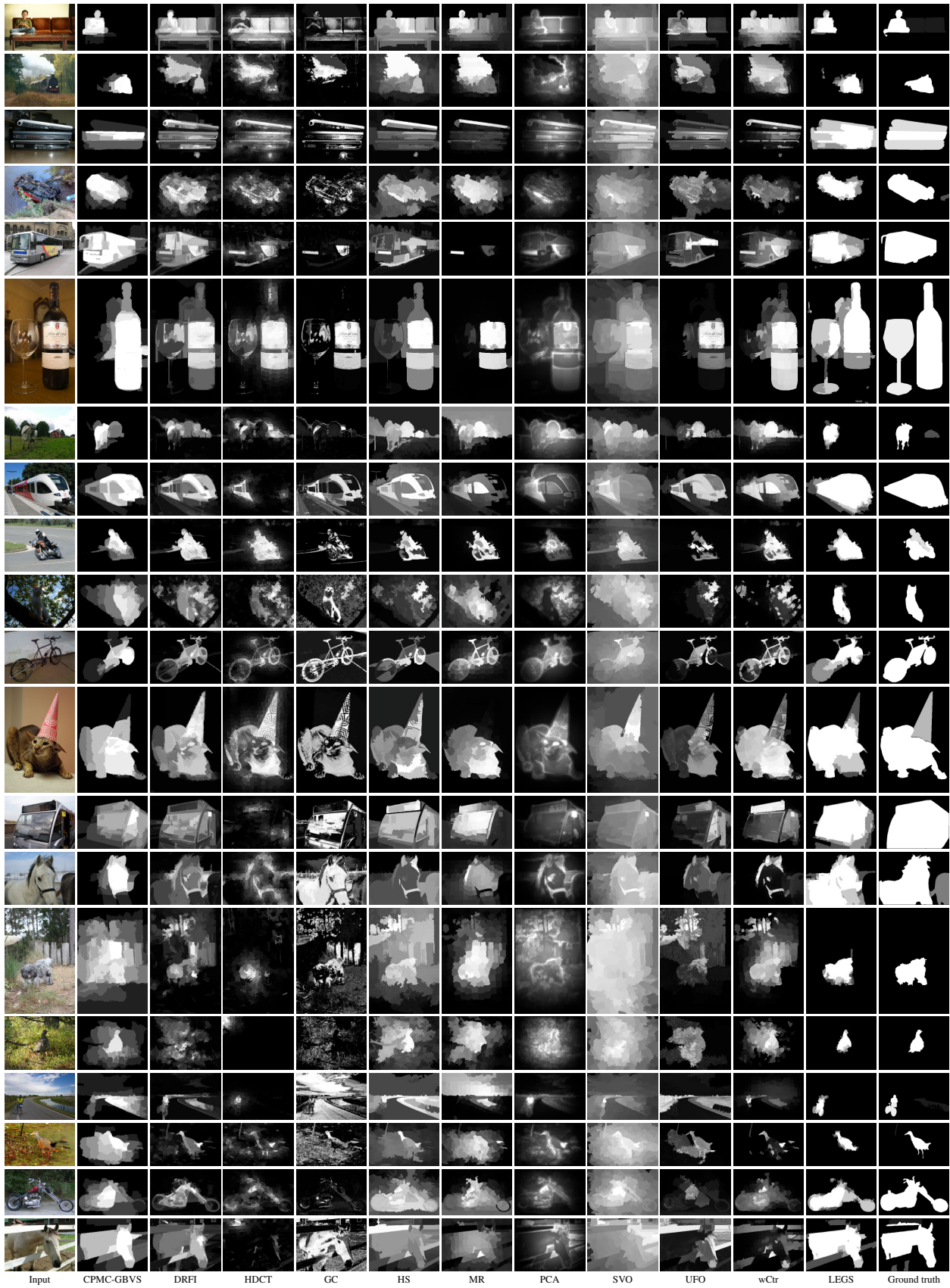


Figure 4. Qualitative comparisons of the state-of-the-art methods on the PASCAL-S data set.

2. Feature Analysis

We present empirical analysis on the discriminative ability of all the global features based on the distribution of both foreground and background regions in different feature spaces. The distribution plots show strong overlaps between foreground and background regions in all three types of feature spaces, which suggests that a heuristic combination of these features can hardly achieve good results for saliency detection. Instead, our method integrates these features through a supervised learning scheme and attains accurate regional saliency scores.

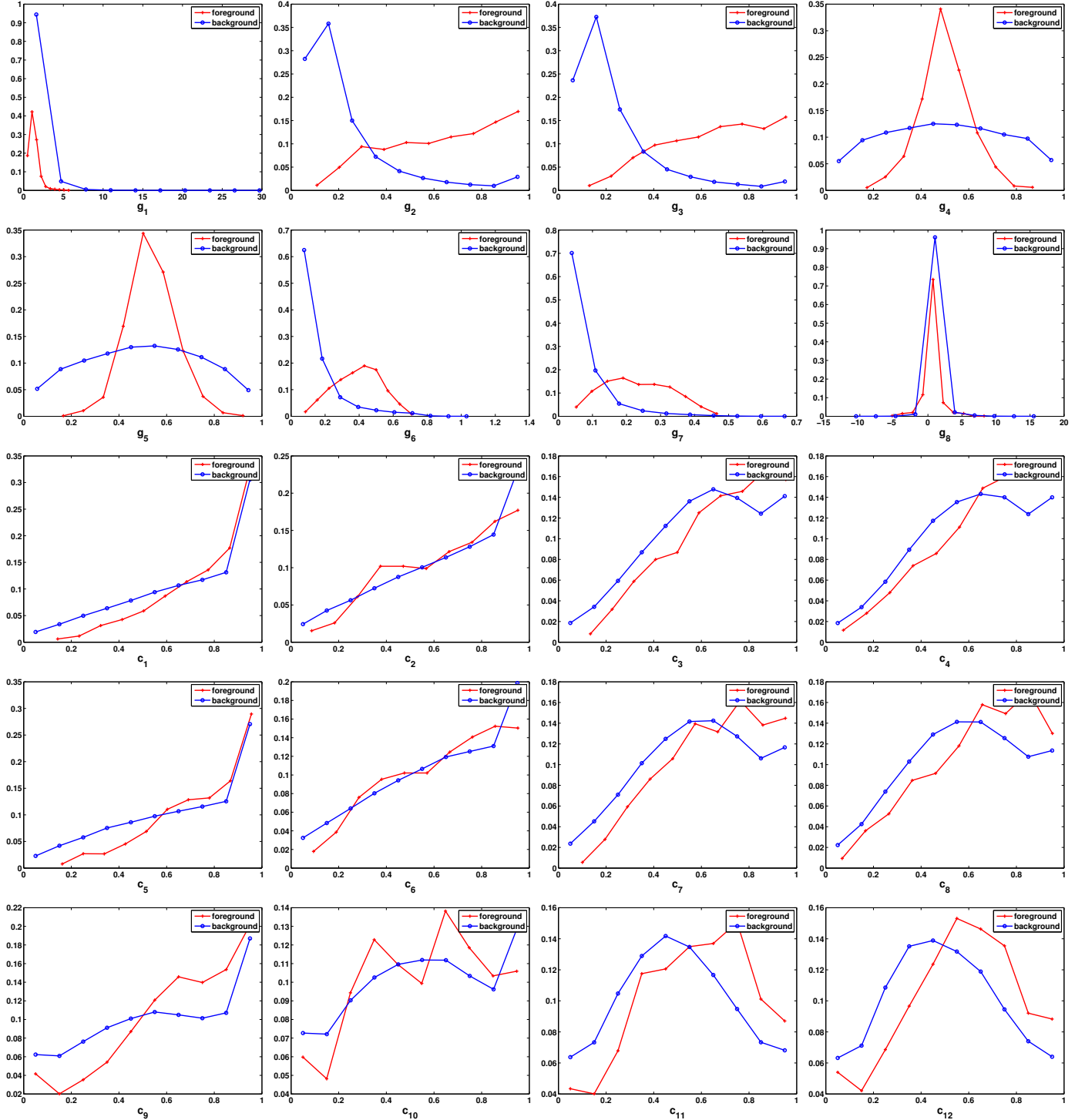


Figure 6. Distribution of foreground and background regions in different feature spaces.

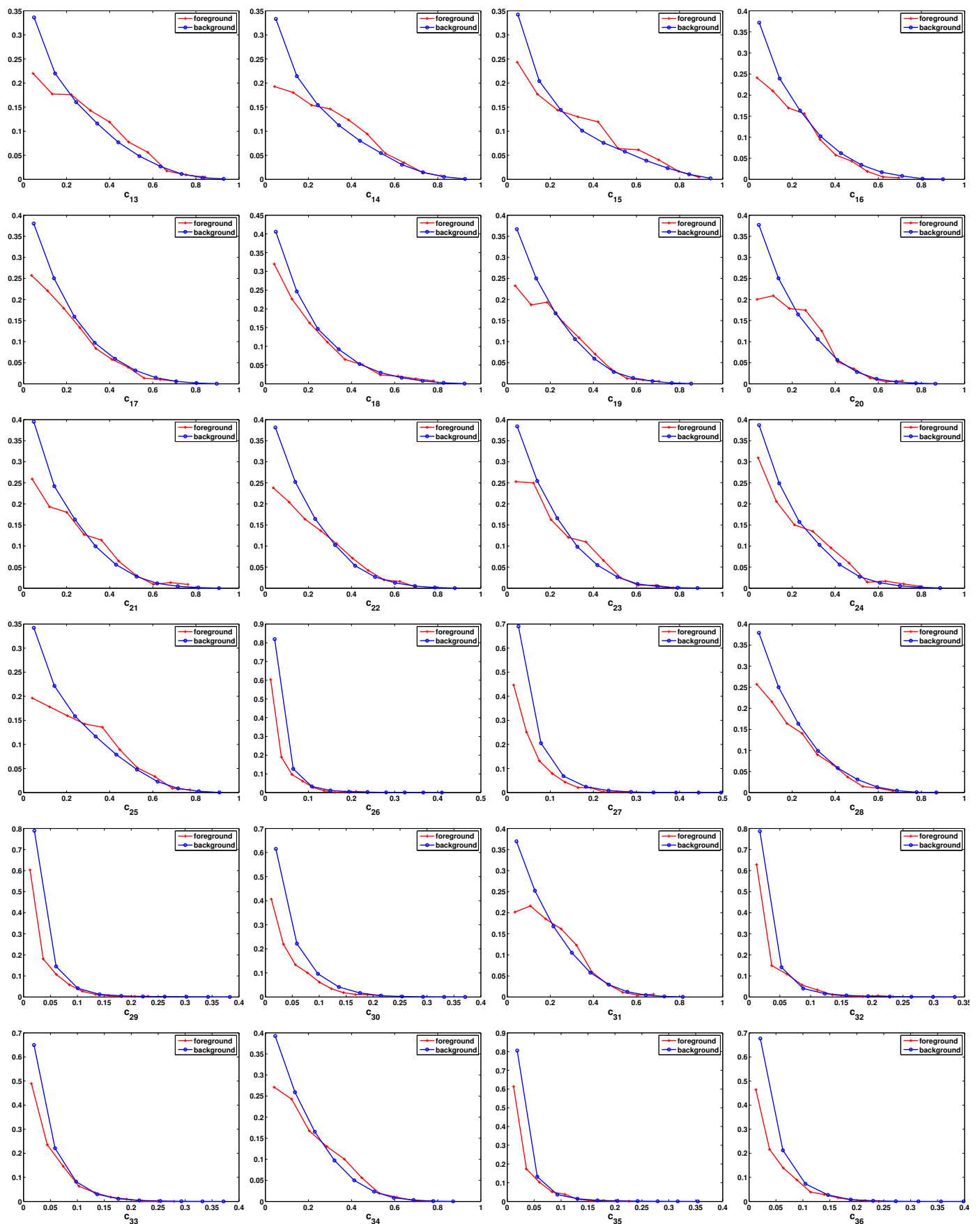


Figure 7. Distribution of foreground and background regions in different feature spaces.

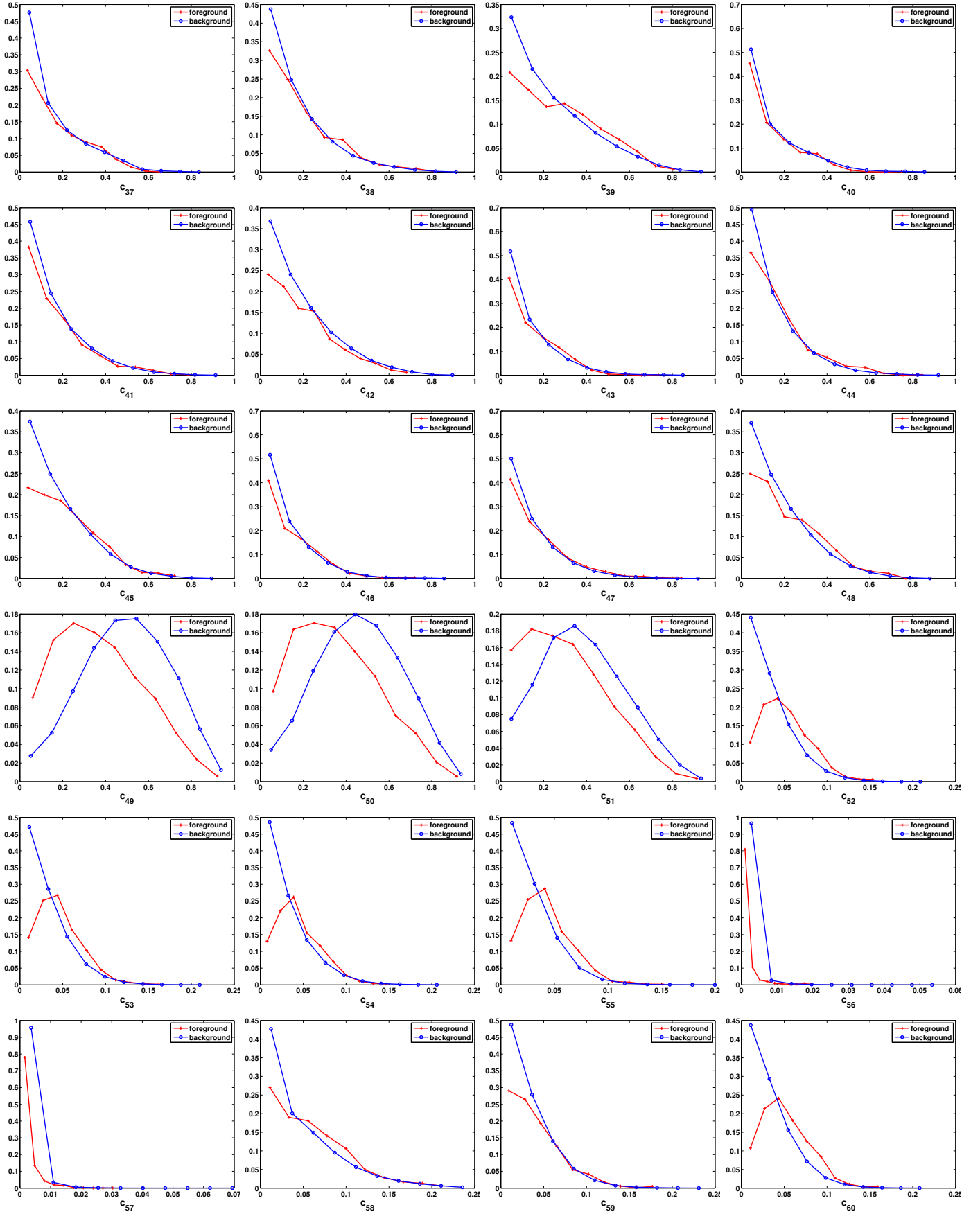


Figure 8. Distribution of foreground and background regions in different feature spaces.

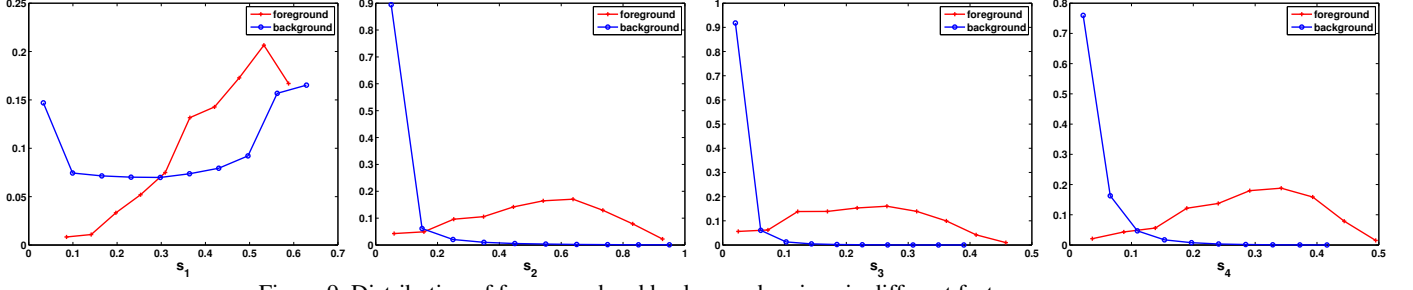


Figure 9. Distribution of foreground and background regions in different feature spaces.

3. Sensitivity Analysis

We present experimental results of the proposed method under different parameter K (See (7) in the manuscript). Since the final saliency map is produced by a weighted sum of salient regions, our method is insensitive to this parameter and achieves good performance when $1 \leq K \leq 30$.

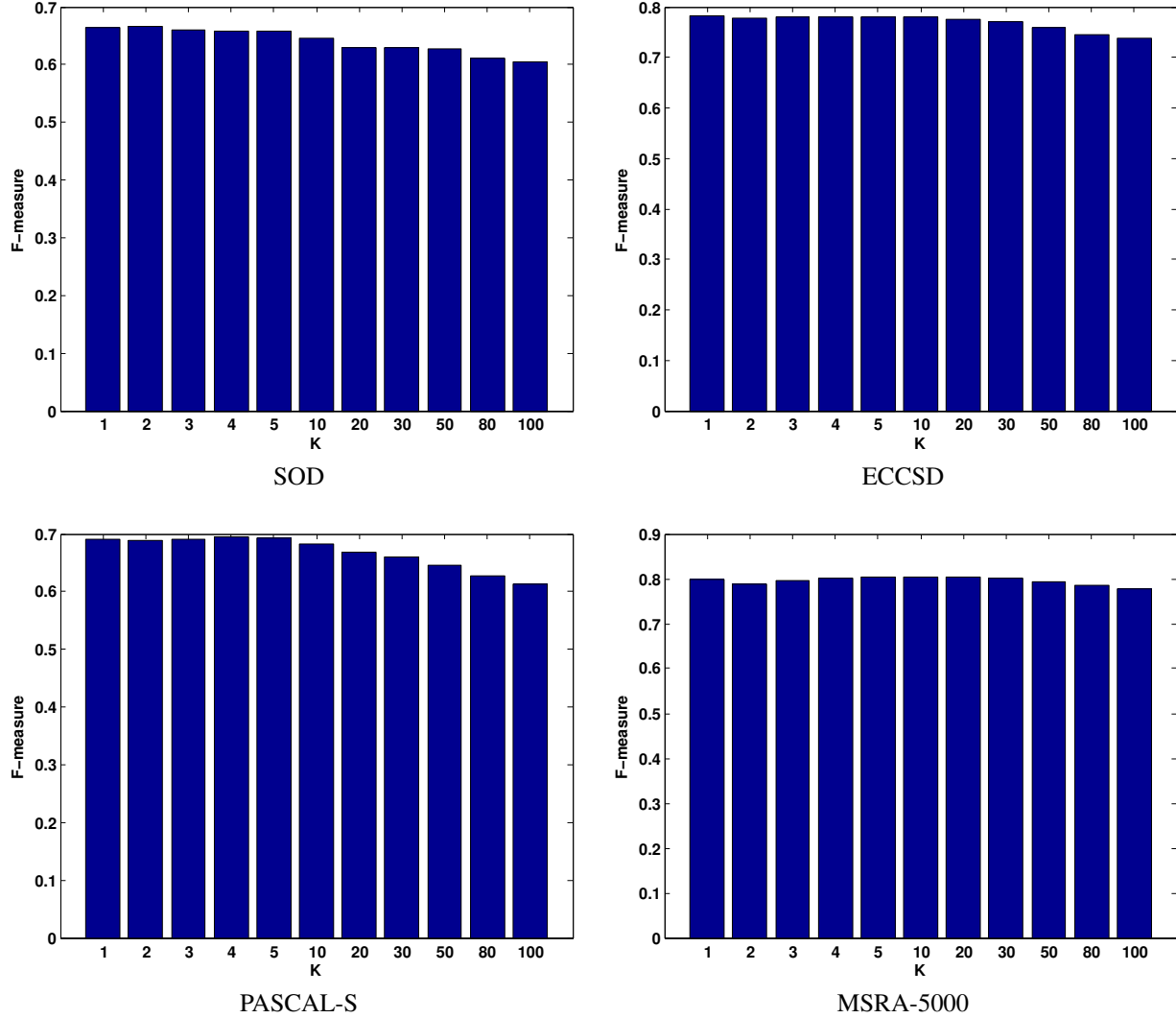


Figure 10. F-measure under different K .

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