Supplementary Document for Amulet

1. Performance on the SED dataset

The **SED** [1] dataset contains two subsets: **SED1** and **SED2**. The **SED1** has 100 images each containing only one salient object, while the **SED2** has 100 images each containing two salient objects.

Tab. 1 provides the results of F-measure and MAE on the **SED** dataset. Fig. 1(a) and Fig. 1(b) show the PR curves on the **SED1** and **SED2** subset, respectively.

Both the F-measure in Tab. 1 and the PR curves in Fig. 1 show that our **Amulet** consistently outperforms other methods with a considerable margin. In addition, our **Amulet** performs much better on the complex SED2 subset, which has two salient objects.

2. PR curves on the DUT-OMRON and SOD datasets

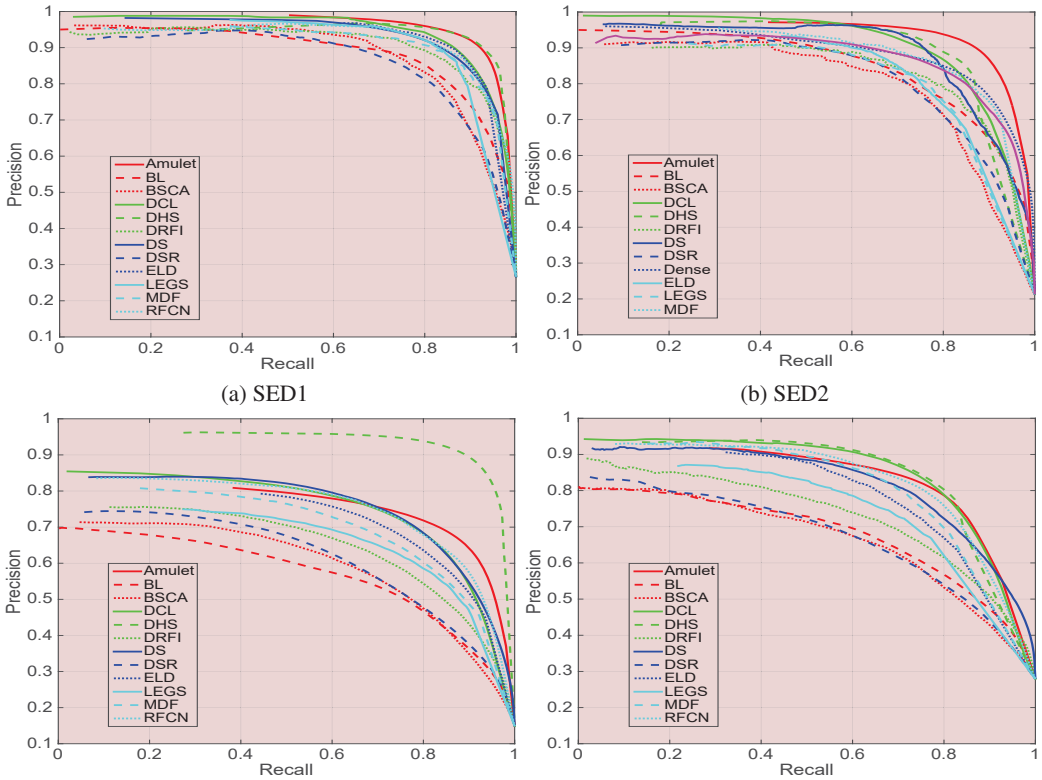
The **DUT-OMRON** [13] dataset has 5,168 high quality images. This dataset is difficult and challenging, and provides more space of improvement for related research in saliency detection.

The **SOD** [12] dataset has 300 images, and it was originally designed for image segmentation. This dataset is challenging since many images contain multiple objects either with low contrast or touching the image boundary.

Fig. 1(c) and Fig. 1(d) show the PR curves on the **DUT-OMRON** [13] and **SOD** [12] dataset, respectively. In Fig. 1(c), DHS ranks the first over other methods with a large margin. The key reason is that DHS selected 3,500 images from **DUT-OMRON** dataset as the training set and we use DHS test the overall dataset.

	SED1		SED2	
Methods	F_β	MAE	F_β	MAE
Amulet	0.8917	0.06019	0.8298	0.06204
Amulet-1/1	0.8918	0.06087	0.8333	0.06104
Amulet-1/2	0.8914	0.06095	0.8327	0.06112
Amulet-1/4	0.8904	0.06124	0.8312	0.06142
Amulet-1/8	0.8871	0.06212	0.8243	0.06265
Amulet-1/16	0.8805	0.06424	0.8109	0.06695
Amulet$_{BPR-}$	0.8725	0.06610	0.8143	0.08651
DCL [4]	0.8546	0.15131	0.7946	0.15652
DHS [7]	0.8773	0.05404	0.8239	0.07886
DS [6]	0.8445	0.09306	0.7541	0.12330
ELD [3]	0.8715	0.06704	0.7591	0.10282
LEGS [10]	0.8542	0.10340	0.7358	0.12356
MDF [14]	0.8419	0.09893	0.8003	0.10136
RFCN [11]	0.8502	0.11662	0.7667	0.11306
BL [9]	0.7675	0.18489	0.7047	0.18564
BSCA [8]	0.8048	0.15347	0.7062	0.15784
DRFI [2]	0.8068	0.14799	0.7341	0.13336
DSR [5]	0.7909	0.15794	0.7116	0.14063

Table 1. The F-measure and MAE of different saliency detection methods on the SED dataset. The best three results are shown in red, green and blue. The proposed methods rank first or second on this dataset.



(a) SED1 (b) SED2

(c) DUT-OMRON (d) SOD

Figure 1. PR curves of the proposed algorithm and other state-of-the-art methods on the DUT-OMRON, SED and SOD datasets .

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