Saliency Detection Based on Path Price and Fuzzy Reasoning

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Abstract: - Saliency detection is essential for many vision tasks and has become a very active topic in compute vision. Although various computational models have been developed especially these contrast based, there still exist some limitations such as: can't uniformly highlight whole salient regions; usually falsely marking background as salient regions. Aim to solve these, a novel saliency detection method based on path price and fuzzy reasoning rule was proposed in this paper. In detail, we tackle the saliency detection from a different viewpoint: we measure four path prices instead of contrast. Finally, we introduce two fuzzy reasoning rules to capture the properties of these four path prices. Final saliency map is computed by averaging these two fuzzy truth values. Evaluation on two databases validates that the proposed method achieves superior results both on precision recall curve and visual quality.

Key-Words: - Saliency detection, Path price, Fuzzy reasoning, Saliency map, Fuzzy rule, Fuzzy truth value

1 Introduction

Visual saliency is an important and fundamental research problem in neuroscience and psychology and has also become an very active topic in compute vision, due to its various applications to image segmentation [1], object detection [2], object recognition [3], image retargeting [4], image editing techniques [5-6], adaptive compression of images [7], and image retrieval [8]. Visual saliency can be defined as the perceptual quality that makes an object, person, or pixel stand out relative to its neighbors and thus capture our attention [9]. Most of the early works [10-11] in this field are focused on biologically inspired models (where humans look) and evaluated on human eye fixation data [6, 12]. Visual saliency can be classified as two stages: fast, pre-attentive, bottom-up, data driven saliency extraction; and slower, task dependent, top-down, goal driven saliency extraction [10, 16-18]. We focus on bottom-up data driven saliency detection. Visual saliency in this paper is defined as the automatic detection of visually salient regions in images just the same as [9, 13].

Many studies have been published concerning salient object detection over the last decades, there still exist some limitations such as: (1) can't uniformly highlight whole salient regions; (2) usually falsely marking background as salient regions; (3) usually generate low resolution saliency maps; (4) can't compute efficient, which can be seen in Fig 1. This paper is aim to solve these problems.

Most existing visual saliency approaches are contrast-based due to the observation that human cortical cells have high response on contrast stimulus in receptive fields [14]. Although implemented in different ways, their fundamental assumption is that "appearance contrast between object and background is high" [15]. Then the problem becomes how to describe the properties of background or salient object. One simple yet effective solution is to measure the difference between each pixel of an image and its surroundings. In this paper, we tackle this problem in a different way based on the following observations: (1) although backgrounds are always complex in natural scenes, they are connective with each other; (2) the image boundary is mostly background, in other words, the salient objects won't touch the image boundary in general. This is similar with [15] which defined as connectivity prior and boundary prior. Based on these observations, we compute saliency of each pixel by measure its price of coming to the four image boundaries. Background pixel usually

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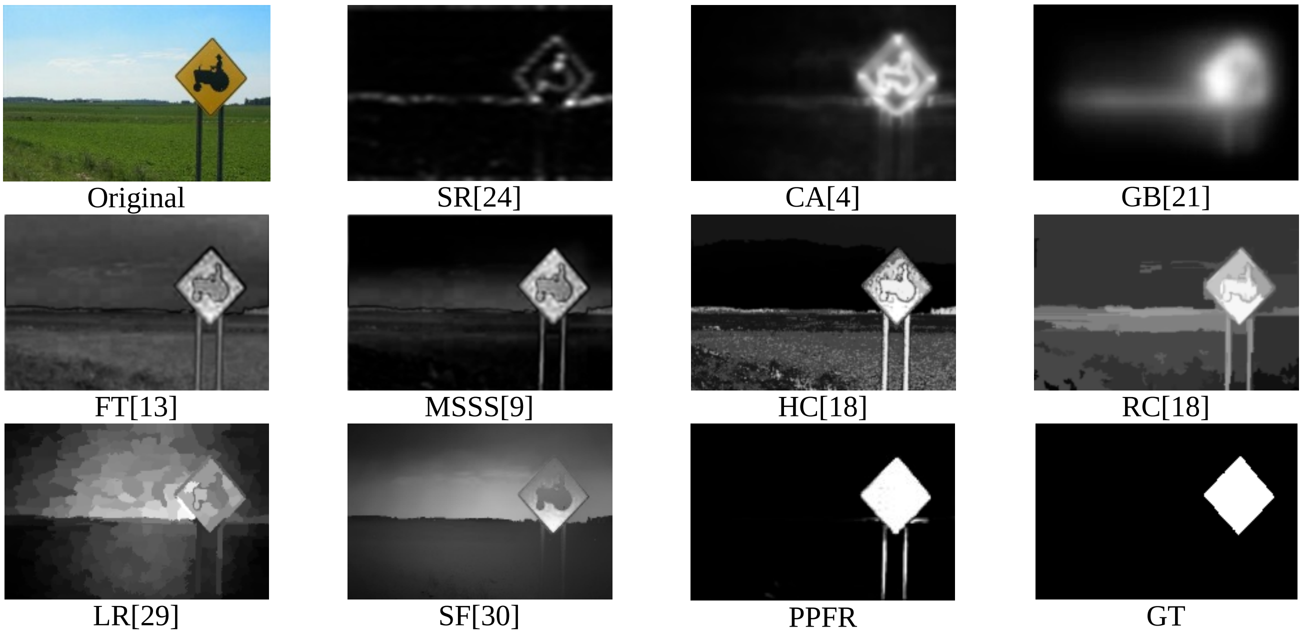


Fig. 1. Saliency maps computed by different state-of-the-art methods with our proposed method (PPFR) and ground truth (GT). Most results highlight edges, falsely mark background as salient regions, or are of low resolution.

have small price coming to image boundary due to its connective to image boundary. For salient pixels, their prices are usually large. However, salient objects may touch one or two image boundaries in some cases. To handle this, we further introduce fuzzy reasoning rules. We have extensively evaluated our approach with state-of-the-art saliency methods on publicly available benchmark dataset, and the experiment results show that our approach achieves not only the best precision and recall rates but also good visual quality. Encouragingly, we also fully highlight the whole salient regions.

The rest of this paper is organized as follows: Section 2 gives a brief overview of the related works. Then, the proposed method is presented in Section 3. The dataset and evaluation metrics are described in Section 4. And the experimental results are carried out in in Section 5. Finally, conclusions are drawn in Section 6.

2 Related Works

We briefly introduce the related works on image saliency detection in this section. Lots of efforts have been devoted to measure visual saliency in images. Saliency estimation methods can broadly be classified as contrast-based, uniqueness with different measurements, or other models. Among them, contrast based methods are mostly concentrated by researchers. These contrast-based methods measure saliency though investigating the rarity of image regions with respect to its surroundings. In [10], Itti et al. proposed a saliency model by computing feature maps for luminance, color and orientation and using center-surrounding operator across multi-scales. Inspired by Itti's model, Ma and Zhang [19] use center-surrounded feature distances to estimate saliency, while Frintrop et al. [20] computed it with square filters and further use integral images to speed up the calculations. By contrasting with both local and global surroundings and combing high-level features, Goferman et al. [21] proposed a context-aware saliency detection method which can highlight salient objects along with their contexts. However, such methods usually produce higher saliency values near edges and can't uniformly highlight the whole salient objects. In [22], Zhai and Shah proposed a pixel-level saliency detection method by comparing each pixel to all others in the image. Achanta et al. [13] thought it is caused by failing to exploit all the spatial frequency content of the original image and then proposed a simple yet efficient frequency tuned method by measuring color differences from the average image color. In [9], Achanta further improved it by varying the bandwidth of the center surround-filtering to handle complex background. Recently, Cheng et al. [18] proposed global contrast-based approaches including a histogram-based contrast (HC) method and a region-based (RC) method. These two methods are further improved by Xin He [23] by combining spatial distribution information.

However, these methods still falsely marking background as salient regions in some cases which can be seen in Fig 1.

There are also some other methods using different uniqueness measurements or models. In [24], Hou and Zhang proposed the spectral residual approach which is processed in the frequency domain. Liu et al. [25] located the salient object by learning a Conditional Random Field to combine multi-sale contrast, center-surround histogram, and color spatial distribution. Z. Liu et al. [26] presented a saliency model based on a set of Gaussian models which are estimated on the basis of segmented regions. N. Bruce [27] use Shannon's self-information to measure the local contrast and site entropy rate is adopted in [28]. Although these methods are novel, their results are not satisfactory. More recently, there are also some novel and encouraging approaches proposed. By representing an image as a low-rank matrix plus sparse noises in a learned feature space, Shen et al. [29] proposed a unified model to incorporate low-level features with higher-level guidance for saliency detection. Perazzi et al. [30] proposed a contrast-based method combining global contrast and spatial relations together to detect salient objects, which can generate full resolution saliency maps and simultaneously be implemented efficiently with linear complexity with the help of permutohedral lattice embedding [31]. In [32], Ali Borji introduced a saliency model by considering local and global image patch rarities as two complementary processes and implemented in both RGB and Lab color spaces. Different from these approaches, we detect salient objects by measuring pixels price and introducing fuzzy reasoning rules.

3 The Proposed Method

As mentioned before, our method is based on two observations. One is background regions are connective with each other and also large and homogeneous. For examples, sky regions are homogeneous by themselves and touch the top image boundary, grass regions are connected with the bottom image boundary. This is also supported by the fact that background regions are usually out of focus during photography [15]. The other observation is that the image boundary is mostly background, in other words, the salient objects won't touch the image boundary in general. This is based on the basic photographic rule that photographers usually capture salient objects in the center of the view frame. We can understand it that salient objects are not connected with image boundaries in most cases. These observations suggest that we can define the saliency of an image pixel as the path price to four image boundaries which is similar with [15]. Fig 2 shows some examples of our observations.

Fig. 2. P_{BG} is background pixel, and P_{FG} is foreground pixel. As we can observe, P_{BG} can be easily connected with image boundaries, but it is hard for P_{FG}.

However, the second observation is not realistic enough because the salient object may partially touch the boundary when it is big or the other reasons. Different from boundary edge weight in [15], we introduce fuzzy reasoning rules. We found that the salient object may touch one even two image boundaries but it must not be connected with the other image boundaries. Detailed discussion will be presented in the following subsections.

3.1 Path Price

For each pixel in an image, we first define four paths to four image boundaries which are clockwise named path 1, 2, 3 and 4 respectively as illustrated in Fig 3.

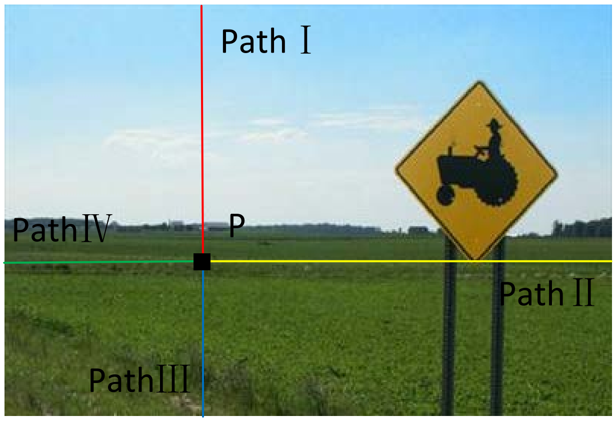
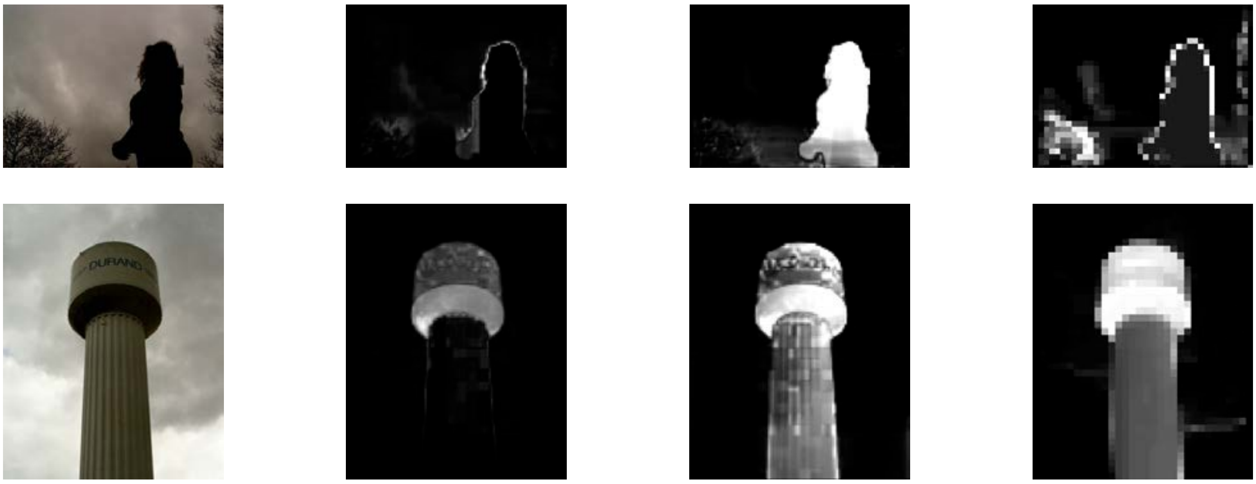


Fig. 3. Illustration of our method.

For each pixel in image at position (i, j), we compute its path price which is defined as:



(a) (b) (c) (d)

Fig. 4. Failure cases: (a) input images; (b) saliency detection results of Eq.2; (c) saliency detection results introducing fuzzy reasoning rules; (d) GSGD[15].

$$\text{Price}_k\left(i,j\right)=\sum_{m=1,\,p_k\in Path_k}^{N_k}\left\{\left|p_k\left(m\right)-p\left(i,j\right)\right|^2\right\} \quad (1)$$

where N_k is the number of pixels in Path k and k=1, 2, 3, 4.

As we can observe that background pixels usually have small price at least in one of the four paths, and object pixels always have large price almost in all of the four paths. Therefore, one simple yet efficient way to compute saliency is just minimize four paths' price:

$$S_P\left(i,j\right)=\min\left\{\text{Price}_k\left(i,j\right)\right\} \quad (2)$$

For efficient computation, each image is separated into 10×10 patches with non-overlap and saliency maps are generated in patch-level, and then a smoothing operation (Gaussian blurring) is needed to reduce the artifacts introduced in the patch-based computation.

Our method summarized in Eq. 2 can work well in most cases except when the object is near to or even touches one or two image boundaries. As illustrated in Fig 4, salient objects are connected with the bottom image boundary, so they are falsely marked as background regions. To solve this situation, we further introduce fuzzy reasoning rules which will be discussed in detail in the next subsection.

3.2 Fuzzy Reasoning Rules

As mentioned above, salient regions usually have large price in four paths in general. When touch one image boundary, they still have large price in the other three paths. In contrast, background regions always have small price in most of the paths. From these failure cases, we also found another observation that these salient objects always touch the bottom image boundary not the other three. Based on this, we only define two fuzzy reasoning rules:

Rule-1: If Price_1 is Big, Price_2 is Big, Price_3 is Big and Price_4 is Big, then p(i, j) is possibly a salient pixel.

Rule-2: If Price_1 is Big, Price_2 is Big, Price_3 is Small and Price_4 is Big, then p(i, j) is possibly a salient pixel connected with the bottom image boundary.

Small and Big are fuzzy membership functions shown in Eq.3 and 4, respectively. Both of them are trapezoid shapes and illustrated in Fig 5.

$$\text{Small}\left(\text{Price}_k\right)=\begin{cases}1, & \text{Price}_k<a\\ \dfrac{\text{Price}_k-b}{a-b}, & a\le\text{Price}_k<b\\ 0, & \text{Price}_k\ge b\end{cases} \quad (3)$$

$$\text{Big}\left(\text{Price}_k\right)=\begin{cases}0, & \text{Price}_k<a\\ \dfrac{\text{Price}_k-a}{b-a}, & a\le\text{Price}_k<b\\ 1, & \text{Price}_k\ge b\end{cases} \quad (4)$$

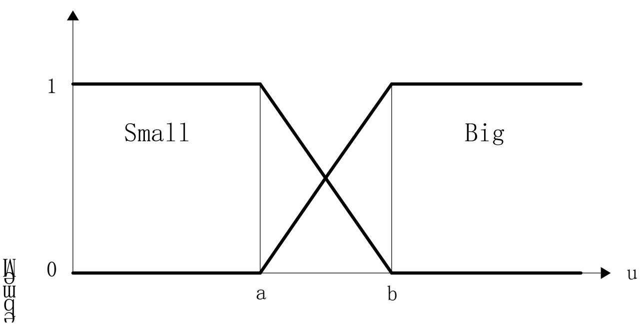
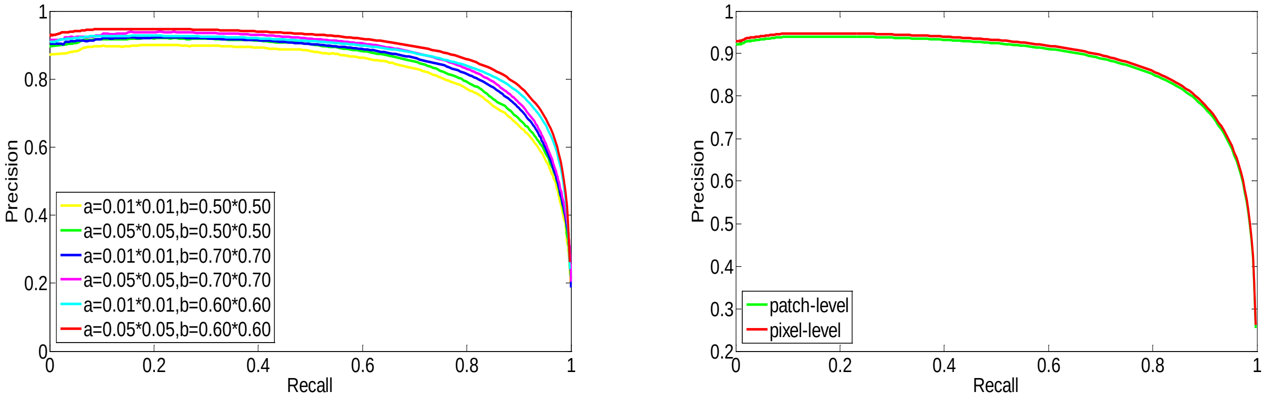


Fig. 5. The fuzzy membership functions Small and Big.



(a) (b)

Fig. 6. Precision-recall curve of our method with different parameters.

The selection of the two parameters will be discussed in Section 5. The original fuzzy rule base has 16 rules due to four inputs, Price_1-Price_4, and two fuzzy membership functions. To simplify the fuzzy rule base and reduce computational cost, only two rules are considered. Experiment results show this two pixel classes can capture most of the salient regions in the image. Then let fuzzy truth value F be defined below:

$$F_1 = \text{Big}(\text{Price}_1)\cdot\text{Big}(\text{Price}_2)\cdot\text{Big}(\text{Price}_3)\cdot\text{Big}(\text{Price}_4)$$
$$F_2 = \text{Big}(\text{Price}_1)\cdot\text{Big}(\text{Price}_2)\cdot\text{Small}(\text{Price}_3)\cdot\text{Big}(\text{Price}_4)$$

Here, we use product inference engine [36] to realize the fuzzy reasoning. After all fuzzy truth values are obtained, the two fuzzy truths are used to compute saliency value. Thus the final saliency value is defined by averaging them:

$$Saliency(i,j) = F_1(i,j) + F_2(i,j) \qquad (5)$$

The final resulting saliency map is normalized to [0, 1]. The effectiveness of introducing fuzzy reasoning rules can be seen from the comparison in Fig 4.

4 Dataset and Evaluation Criterion

We evaluate our approach quantitatively on two public datasets: MSRA-1000 [13] and SOD-300 [34]. MSRA-1000 is a subset of the public MSRA dataset with 5000 images provided by Liu et al [25] and has been widely used in saliency evaluation. SOD-300 dataset is based on the well know Berkeley segmentation dataset [35] and has not been widely used for saliency evaluation yet. Most images in SOD-300 contain multiple foreground objects and have complex background making it more challenging than MSRA-1000. Their corresponding ground truth masks are provided by [13] and [15], respectively. Precision, recall, F-measure and mean absolute error (MAE) are evaluated in our experiments which are defined as

$$\text{precision} = \frac{\sum_{i=1}^{W}\sum_{j=1}^{H} B(i,j)G(i,j)}{\sum_{i=1}^{W}\sum_{j=1}^{H} B(i,j)} \qquad (6)$$

$$\text{recall} = \frac{\sum_{i=1}^{W}\sum_{j=1}^{H} B(i,j)G(i,j)}{\sum_{i=1}^{W}\sum_{j=1}^{H} G(i,j)} \qquad (7)$$

where B is the binary object mask generated by thresholding corresponding saliency map and G is the corresponding ground truth. Fixed thresholding and adaptive thresholding are performed respectively in the process of generating binary object masks. Adaptive threshold is performed to binarize the saliency maps, which is defined as twice the mean saliency values [13]:

$$T_a = \frac{2}{W\times H}\sum_{i=1}^{W}\sum_{j=1}^{H} Saliency(i,j) \qquad (8)$$

where W and H are the width and the height of the saliency map, respectively.

$$F_\beta = \frac{(1+\beta^2)\,\text{Precision}\times\text{Recall}}{\beta^2\times\text{Precision}+\text{Recall}} \qquad (9)$$

where β^2 is set to 0.3 the same as [13, 18, 29, 30].

$$\text{MAE} = \frac{1}{W\times H}\sum_{i=1}^{W}\sum_{j=1}^{H}\left|Saliency(i,j) - G(i,j)\right| \qquad (10)$$

5 Experiments

5.1 Parameter Selection

There are only two parameters in our method: a and b in fuzzy membership functions. In order to study

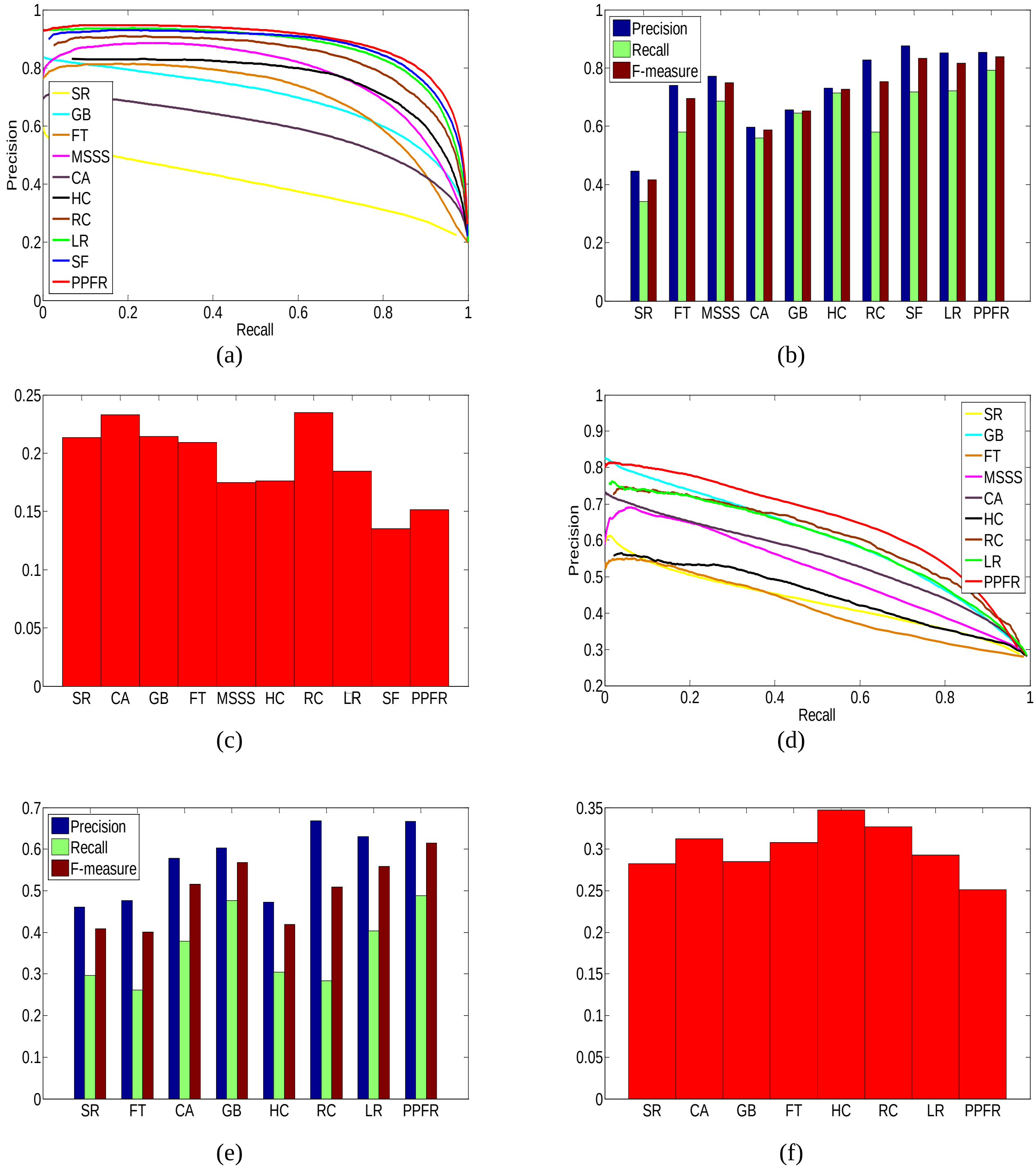
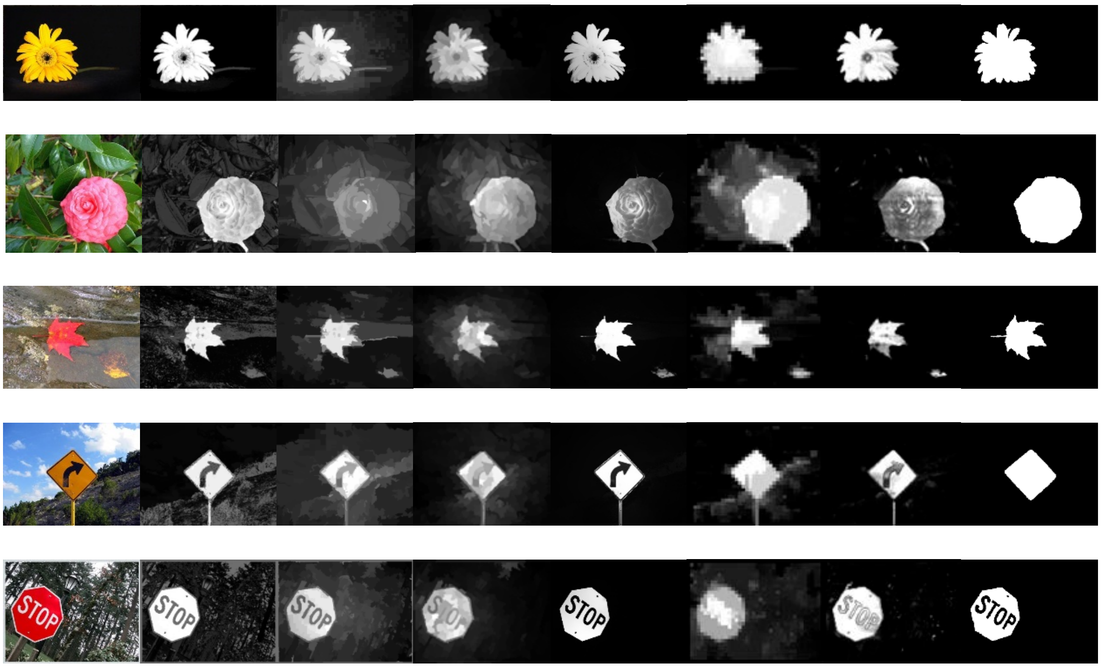


Fig. 7. Performance results on the MSRA-1000 database (a-c) and BSD-300 database (d-f): (a), (d) Precision-recall curve for all algorithms; (b), (e) Average precision, recall and F-measure for adaptive thresholds; (c), (f) Mean absolute error of the different saliency methods to ground truth.

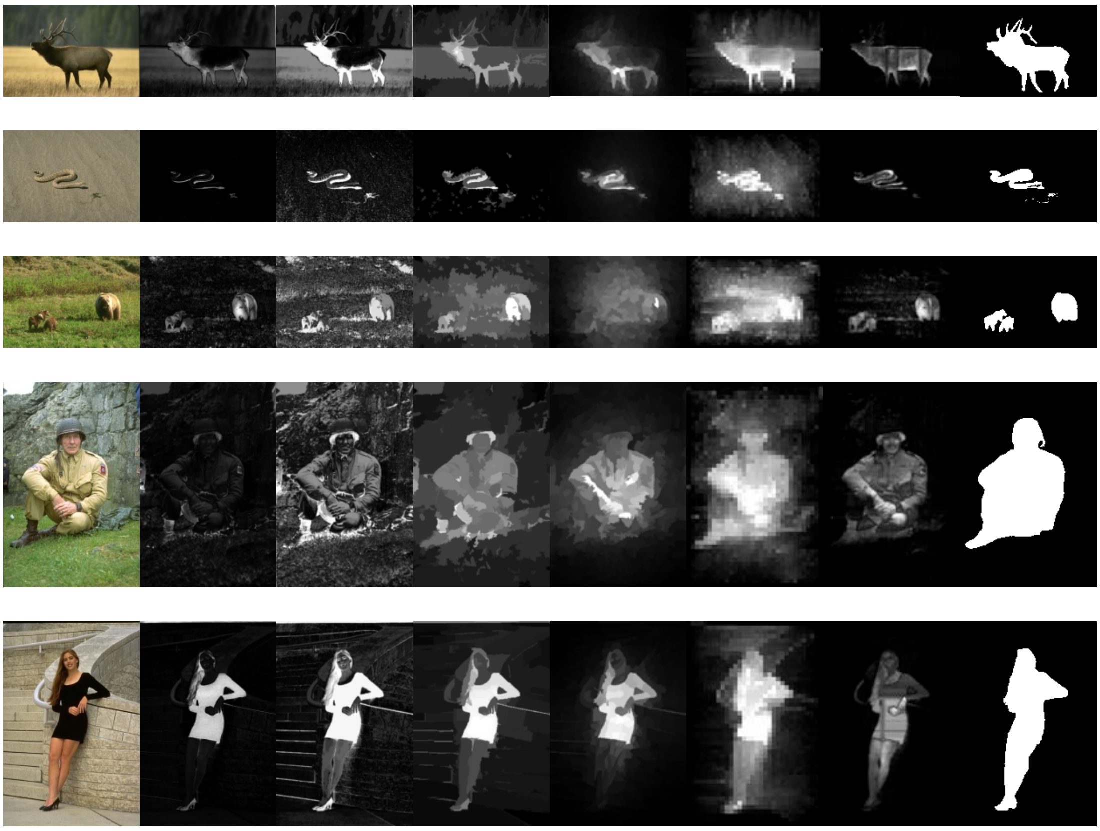
the effect of the parameters on the performance of our method, we performed the following simulation. The performance evaluations varying a (0, 0.05^2 and 0.10^2) and b (0.50^2, 0.60^2 and 0.70^2) on MSRA-1000 are shown in Fig 6(a). It is clear that the settings of {a=0.05^2, b=0.60^2} give best performance. We also compared our methods of two different implementations: path-level (10×10 patches) and pixel-level. The performance results on MSRA-1000 are shown in Fig 6(b).

5.2 Performance Evaluation



(a) Original (b) HC[18] (c) RC[18] (d) LR[29] (e) SF[30] (f) GSGD[15] (g) PPFR (h) GT

Fig. 8. Visual comparison of different methods on the MSRA-1000 database.



(a) Original (b) FT[13] (c) HC[18] (d) RC[18] (e) LR[29] (f) GSGD[15] (g) PPFR (h) GT

Fig. 9. Visual comparison of different methods on the BSD-300 database.

Table. 1. Comparison of averaging running times.

Method	SR	CA	FT	FT	MSSS	HC	RC	PPFR
Time(s)	0.005	55.70	0.028	0.105	1.507	0.020	0.287	0.228
Code	C++	Matlab	C++	Matlab	Matlab	C++	C++	Matlab

We compare our approach with 9 typical state-of-art approaches, including GB [21], SR [24], FT [13], MSSS [9], CA [4], HC [18], RC [18], LR [29] and SF [30]. Such methods are selected for comparison due to their large varieties. Among them, FT, HC and SF output full resolution saliency maps and perform efficient, SR works in the frequency domain, RC is regional contrast based, LR introduces low rank matrix recovery theory and incorporates high-level priors, and LR and SF are proposed recently. Saliency maps of SR, FT, HC, and RC are implemented in C++ provide by [18]. For the other methods, we used the authors' implementations or results.

Results on the MSRA-1000 database are shown in Fig 7. It is clear that our approach not only gets better precision-recall curve but also achieves the best precision, recall and F-measure. For MAE measure, our approach also outperforms the others except SF due to its operation of containing at least 10% saliency pixels in the final step. Some visual comparison results of different methods with ground truth masks are shown in Fig 8. Although the RC and LR methods successfully highlight the salient objects too, they can't generate pixel-level saliency maps. Furthermore, our approach can successfully fully highlight the salient objects while the others can't perform well which also can be clearly seen in Fig 9.

Results on the BSD-300 database are shown in Fig 9. Although the results of all methods are not as well as in MSRA-1000, indicating this database is much more challenging, the conclusions are still similar. From Fig 9(a), we can see that our method still outperform the other methods. Note that the result of our method perform as well as in MSRA-1000, we analyze that it's mainly caused by the complexity and challenging of this database. However our method gets higher precision, recall, and F-measure than the others for adaptive thresholds as can be seen from Fig 9(b). Furthermore, our method fully highlights the salient objects as mentioned before. Some examples of saliency detection are shown in Fig 10.

Running time of different methods are shown in Table 1. Timing tests have been taken on the same hardware devices (Intel Core 2 Duo CPU 2.26GHz with 4GB RAM). Although implemented in Matlab, our approach is still faster than RC and efficient for real-time applications.

6 Conclusions

In this paper, a novel saliency detection method based on path price and fuzzy reasoning rules was proposed to solve the limitations of state-of-art works. It is mainly based on our two observations: image boundaries are mostly background and background regions are connected by themselves. Then we define a new price function to measure each pixel's saliency values in four paths to image boundaries. However, such observations are not realistic enough because sometimes salient objects will touch the bottom image boundary when they are too big or the other reasons. Therefore, we further introducing fuzzy reasoning rules to handle this situation. The final saliency is computed by averaging two fuzzy truth values. Experimental results on public dataset indicate the proposed scheme achieves better results in terms of both precision recall and MAE in comparison with various state-of-art works. Furthermore, our saliency maps not only have low probability of falsely marking background as salient regions but also can fully highlight the salient regions especially inside of the salient objects.

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