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An Efficient Implementation of Context-aware Saliency Using a Stochastic Approach

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Abstract

The computation of saliency from an image and a video is an interesting challenge in image processing and computer vision. Context-aware saliency, which addresses the saliency based on the geometric structure of an image, is known as one of the most powerful schemes for computing saliency. An obstacle of the context-aware scheme is the heavy computation load. We reduce computational loads in a great scale by applying the dart throwing algorithm.

Keywords: *saliency; context-aware; stochastic; dart throwing*

1. Introduction

Saliency is one of the most challenging properties of visual contents. Many schemes proposed for detecting saliency can be classified into three categories: those schemes using local properties [5, 6, 8, 10, 3, 4], those using global properties [2, 16, 11] and those using both properties [9, 15, 14, 17]. Among them, context-aware scheme [14] is recognized to present most outstanding result in detecting saliency. This scheme, however, suffers from heavy computational loads that prohibits from real-time saliency detection.

To address this problem, we apply a blue noise generation scheme for reducing the computational load. We sample *k* important pixels from *n* x *n* pixels of an image and estimate the saliency at the sampled points. For the sampling, we build a strategy that evaluates the importance of the pixels and assigns the order of sampling. Our strategy is constructed based on the dart throwing algorithm [1]. Using this strategy, the noise of higher gradient has smaller radius than those of lower gradient. This property allows the blue noise distribution of the positions where the saliency is estimated. In our experiment, the computation time required for the saliency detection is reduced in 10~20% of the time required for the original context-aware saliency detection [14] while our scheme produces almost similar results.

The overview of our algorithm is illustrated in Figure 1. In the first step, we sample *k* locations where the saliency detection is estimated using the dart throwing algorithm. In the second, we estimate the saliency at the sampled locations. Finally, we propagate the estimated saliencies to the neighboring positions and build a saliency map.

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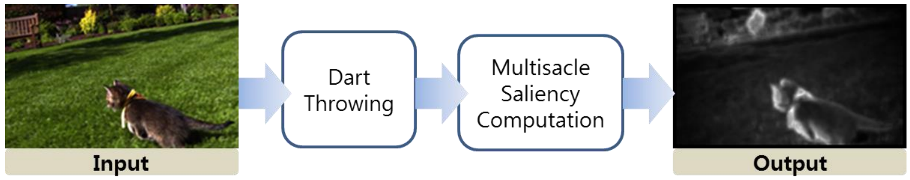

Figure 1. The overview of the algorithm

2. Related work

Most of the local schemes estimate saliency using low-level features and a bottom-up model. Itti *et al.*, [5] have presented a saliency estimation scheme based on neuronal architecture of the visual system. Later, Itti and Koch [6] extended their previous work by analyzing five important trends in computing focal visual attention. Bruce and Tsotsos [8] proposed bottom-up overt attention method based on Shannon's self-information measure using a neural circuit. Meur *et al.*, [10] developed a coherent model for bottom-up visual attention using the current understanding of human visual system behavior including contrast sensitivity functions, perceptual decomposition, visual masking and center-surround interactions. Walther and Koch [3] proposed a biologically plausible model of forming and attending to proto-objects, which is defined as volatile units of visual information accessed by selective attention and subsequently validated as actual objects. Harel *et al.*, [4] presented a graph-based visual saliency model, which is a novel bottom-up visual saliency model. Their model forms activation maps on certain feature channels and normalize them by highlighting conspicuity and by admitting combination with other maps.

Some schemes exploit global feature analysis algorithms such as Fourier transform to detect saliency. Hou and Zhang [16] presented a saliency detection model, which is independent of features, categories or other forms of prior knowledge of the objects. Guo *et al.*, [2] proposed the phase spectrum of the Fourier transform saliency detection method to obtain the location of salient areas. Achanta *et al.*, [11] introduced a method for salient region detection with full resolution saliency map and well-defined boundaries of salient objects. Their model exploits features of color and luminance.

Some schemes combine both local and global approaches. Boiman and Irani [9] proposed a scheme that detects irregularities in visual data by composing a new observed image region or a new video segment using chunks of data extracted from previous visual examples. Liu *et al.*, [15] presented a scheme that detects a salient object in an input image as an image segmentation problem by separating the salient object from the image background. Seo and Milanfar [17] developed a bottom-up unified framework for static and space-time saliency detection. Visual saliency is computed using self-resemblance measure. The resulting saliency map indicates that its pixel values represent the statistical likelihood of saliency of a feature matrix. Goferman *et al.*, [14] presented a context-aware scheme for detecting saliency by considering a multi-scale approach. The saliency map is utilized in resizing and compressing a photograph while preserving its contents [7, 12] or composing a collage image [13].

3. Sampling

We sample *k* pixels among *n* x *n* pixels on the image. Our strategy to sample the pixels is to control the sampling possibility according to the magnitude of gradient at the pixel. The outline of our strategy is summarized in Figure 2 and the result of the noise is in Figure 3. The keypoint is to sample a position from the image and test whether the sampled position is acceptable or not. We accept the sampled position if it lies outside the radii of the generated points. After the accepting the position, we assign a radius for the sampled position according to the gradient estimated at the position by $r_i = 1/(g_i + 0.1)$, where r_i is the radius and g_i is the gradient. According to the dart throwing algorithm, we reduce the radii of the sampled positions as the sampling proceeds.

```
void Sample ( int k )
{
    int cnt = 0;
    Point set ← Φ;
    while ( cnt < k ) {
        p ← generate point ( );
        for ( pti in Point set )
            if ( | p - pti | < ri )
                discard p;
                continue;
        r ← estimate r according to the gradient of p;
        add (p, r) to Point set;
        reduce ri in Point set;
        cnt++;
    }
}
```

Figure 2. The outline of the sampling algorithm

4. Saliency Detection

The context-aware saliency detection scheme proposed by Goferman *et al.*, [14] estimates the saliency at each pixel using a multi-scale approach. At each scale, we compute the difference of color and position between the sampled *k* pixels and all the pixels in the image.

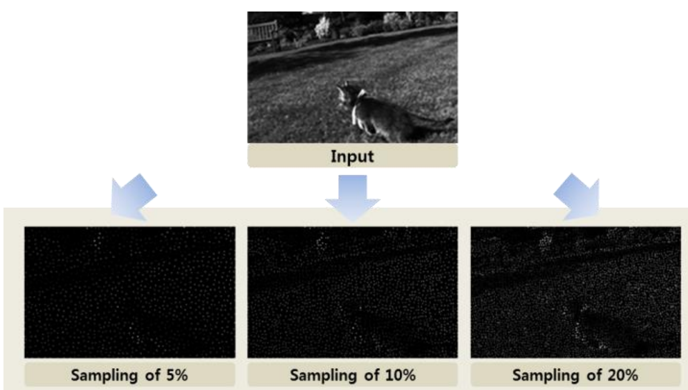

Figure 3. Sampling results of 5%, 10% and 20%.

At a pixel, we assign m, the size of a patch and build a vector of m x m neighbor pixels of the sampled pixel. d_c (p_i, p_j), the Euclidean distance of the color of the patches of the pixels p_i and $_{pj}$ is estimated as follows:

$$d_c(p_i, p_j) = \sum_{l=1}^{m\times m} \left| C^i{}_l - C^j{}_l \right|$$

Note that $C^i{}_l$ and $C^j{}_l$ are the color of l-th pixels of the patch from p_i and p_j. $d_p(p_i, p_j)$ denotes the distance between the pixels p_i and p_j. The final difference between pixels p_i and p_j is estimated as follows:

$$d(p_i, p_j) = \frac{d_c(p_i, p_j)}{1 + c \cdot d_p(p_i, p_j)}$$

$S_i{}^m$, the saliency of a pixel p_i with scale m is estimated as follows:

$$S_i{}^m = 1 - \exp\left(\frac{-1}{K} \sum_{k=1}^{K} d(p_i, p_j)\right)$$

Note that the p_k are the pixels whose d(p_i, p_j) value is highest among all the pixels. The final saliency S_i is estimated by averaging the saliencies of various scales as follows:

$$S_i = \frac{1}{M} \sum_{a=1}^{m} S_i{}^a$$

The process of saliency detection is illustrated in Figure 4.

5. Implementation and Results

We have implemented our algorithm in a personal computer with Pentium i7 CPU and 4 GB main memory. In our implementation we have sampled 10% of pixels from the input image and computed saliency. We reduce the comparison by 10% and improve the computational loads in a great scale. For three input images in Figure 5, we compare the computation time of our algorithm with [14] in Figure 6. We show that our scheme reduces the computation time of [14] to 10% scale.

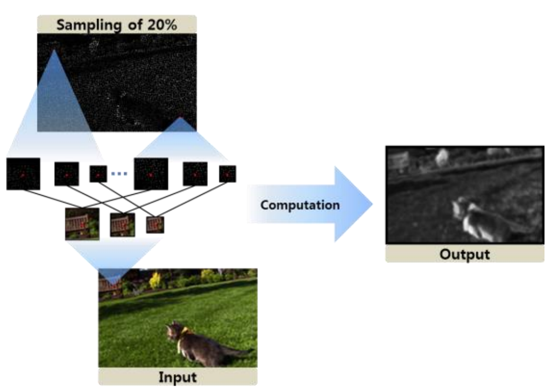

Figure 4. The process of saliency detection

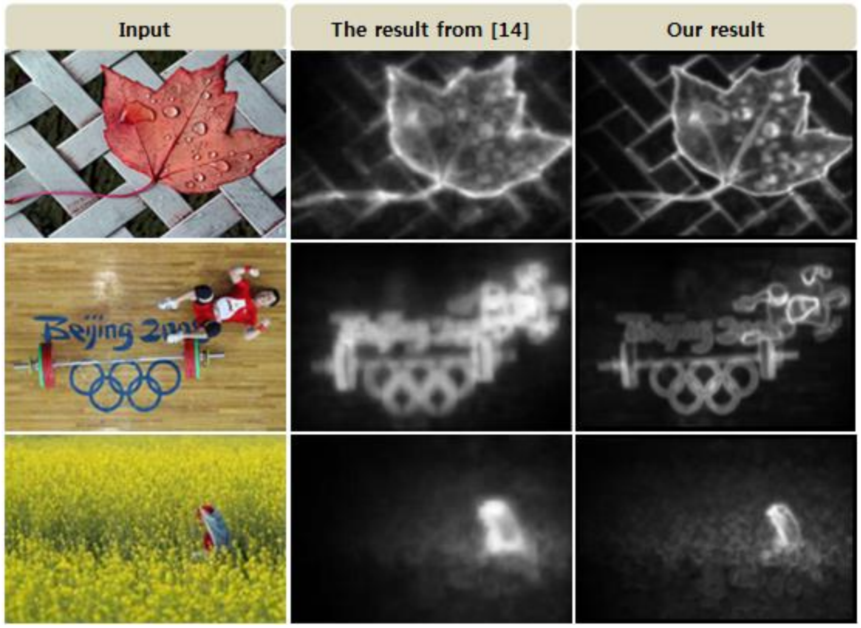

Figure 5. The result of our work and comparison with those from [14]

Figure 6. Tracking of objects using saliency

6. Conclusion and Future Work

In this paper, we have presented an improved saliency detection algorithm with a stochastic approach. We used a dart throwing algorithm to sample the important pixels from an image and reduced the computation time in 10% with similar saliency detection results. We further improve our algorithm to develop a real-time saliency-based object tracking in a video.

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