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Salient Region Detection and Analysis Based on the Weighted Band-Pass Features

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ABSTRACT

Researches on visual attention mechanism have revealed that the human visual system (HVS) is sensitive to the higher frequency components where they are distinctive from their surroundings by popping out. These attentive components of the scene can be in any form such as edge to texture differences based on the focus of attention of HVS. There are several visual attention computational models that can yield saliency values of attentive regions on the image. Some of these models take advantage of band-pass filter regions on spatial domain by computing center-surround differences with difference of low pass filters. They use either down-sampling that may cause loss of information or constant scale of the filters that may not contain all the necessary saliency information from the image. Therefore, we proposed an efficient and simple saliency detection model with full resolution and high perceptual quality, which outputs several band-pass regions by utilizing Fourier transform to obtain attentive regions edges to textures from the color image. All these detected important information with different bandwidth, then, were fused in a weighted manner by giving more priority to the texture compared to edge based salient regions. Experimental analysis was made for different color spaces and the model was compared with some relevant state of the art algorithms. As a result, the proposed saliency detection model has promising results based on the area under curve (AUC) performance evaluation metric.

Keywords: Saliency Detection; Low-Level Feature Extraction; Fourier Transform

1. Introduction

The human visual system (HVS) tends to focus its attention on the regions that pop-out significantly compared to their surroundings on the scene [1,2]. There are bottom-up and top-down mechanisms to aid the selective attention process of the visual attention (VA) mechanism on HVS. Bottom-up VA mechanism is a fast process, which is task independent and generally based on low-level features, such as intensity, color, orientation, size, depth, etc. [1,2]. On the other hand, top-down approach is relatively slower and task-dependent mechanism with prior knowledge that may require both low-level and high-level features [2]. These attentive regions can benefit to fast scene analysis, such as detection of proto-objects [3] or segmentation [4], so several computational models have been developed [3-8] since the first proposed model of Itti, Koch, and Niebur [5].

Itti, Koch, and Niebur [5] proposed the first bottom-up computational model by fusing salient information from intensity, color and orientation features. Regarding the intensity and color features, they stated that the salient regions could be obtained by the center-surround differences of Gaussian pyramids as band-pass regions in multi-scale analysis [5]. This biologically plausible model has become inspiration for several studies of the saliency computational models in spatial or transform domains [1-4,6-8], where spatial domain models also take advantage of center-surround differences or contrast for the salient region detection.

One of the most computationally time efficient model was developed by Hou and Zhang's work [7] in which they introduced the notion of spectral residual (SR) approach to find the irregularities in frequency domain. Compared to the study in [5], SR does not have biological plausibility since the saliency computation disregards the use of center-surround differences and attention shifts as in [5]. Instead of using the concept of center-surround differences, SR utilizes intensity and color chromatic channels by removing the redundant content on the spectral data to obtain the saliency map [7].

The studies in [5,7] require down-sampling that can lead loss of information on the image. Also, the resolution of the saliency maps obtained from [5,7] are less than the original image size, and the perceptual quality of the saliency maps are low. Therefore, Achanta, Hemami, Estrada and Susstrunk [4] proposed a saliency computation approach based on the difference of Gaussian to obtain band-pass salient regions. Their algorithm yielded full resolution saliency maps with high perceptual quality. They showed that high perceptual quality could improve the saliency detection performance when integrated with external modules such as mean-shift segmentation [4]. However, they didn't apply any channel normalization or scaling on the input channels or saliency feature maps, also the model did not include all possible salient regions from edge to textures. Hence, we propose a frequency based model to obtain edge to texture salient regions by creating band-pass regions with several bandwidths in Fourier domain. Then, these band-pass salient regions are weighted and fused to obtain saliency maps for each input channel.

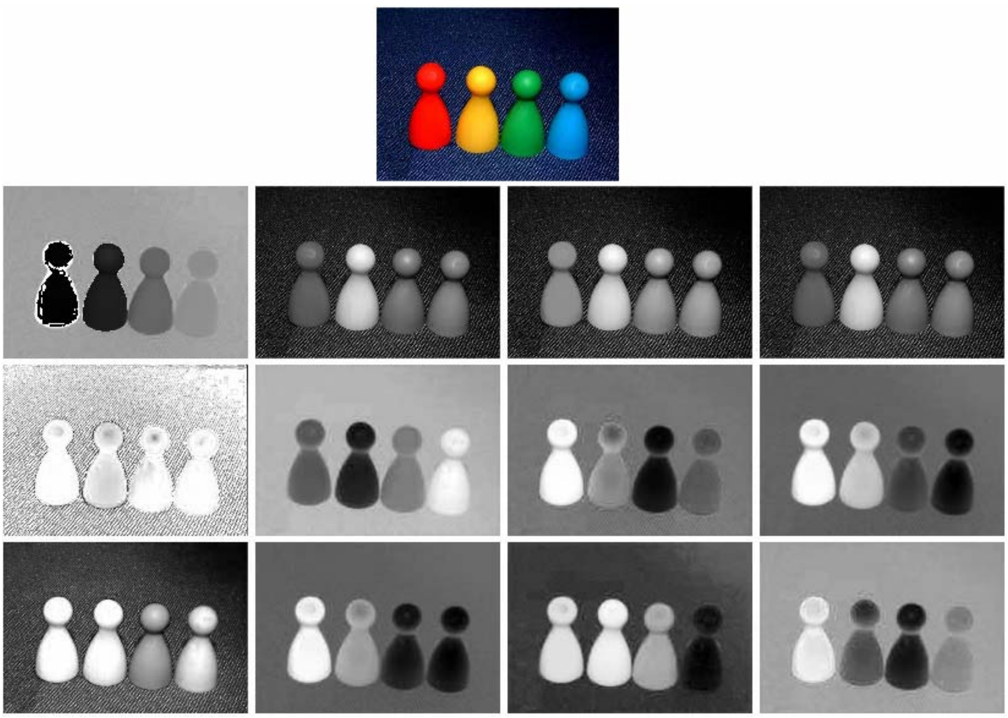
The proposed algorithm demonstrated that use of band-pass regions in frequency domain by providing attentive regions from edges to textures is also efficient without the necessity of downsampling compared to the spectral residual model. Also, the proposed model provides full resolution saliency map as the input image with high perceptual quality. Moreover, the model was tested with various color space inputs. In addition, proposed algorithm was evaluated quantitatively based on commonly used area under curve (AUC) metric [9,10]. Experimental results have promising results by yielding better performance than the compared state of the art algorithms.

2. Methodology of the Proposed Model

A new framework for saliency computation based on spectral domain is proposed in this paper. The algorithm uses the band-pass filtering in Fourier transform (FT) domain with several bandwidths that can represent attentive regions on the image. The higher the bandwidth the more texture level saliency can be found, and with the smaller bandwidths at higher frequency edges or corners can be detected on the image. In this paper, texture representations are given higher weights to create uniformity on the detected salient regions.

2.1. Color Space Transformation

The proposed model, first, converts *RGB* color image to the desired color space since the *RGB* color space does not represent intensity and color information. In this paper, saliency performance of proposed algorithm was tested with four different color spaces that are *HSV*, *YCbCr*, *CIE Lab*, *NTSC* where the details of these color spaces and conversions can be seen in [11,12]. Then, Gaussian filter is applied to converted color space to remove noise, and each channel of the transformed image is scaled to the range {0-255} to prevent suppression of any possible dominant channel. In **Figure 1**, three scaled channels of each color space for a sample image are given.



(a) HSV (b) YCbCr (c) CIE Lb (d) NTSC

Figure 1. (top) sample RGB color image, (a) 1st, 2nd, and 3rd rows are hue, saturation and value, (b) 1st, 2nd, and 3rd rows are intensity and two color chromatic channels, (c) 1st, 2nd, and 3rd rows are luminance and two color chromatic channels, (d) 1st, 2nd, and 3rd rows are intensity and two color chromatic channels respectively.

2.2. Saliency Map Computation

After the color transformation, similar to the SR in [7], Fourier transform is applied to each channel of the input data to obtain amplitude and phase spectrum as in Equation (1) and (2) below [7]:

$$A^c(f) = \log\left(\Re\left(F\left[I^c(x)\right]\right)\right) \quad (1)$$

$$P^c(f) = \Im\left(F\left[I^c(x)\right]\right) \quad (2)$$

where c is the color channels the input color space data, $A^c(f)$ and $P^c(f)$ are the log-amplitude and phase spectra of each channel from image $I^c(x)$ by performing FT operation $F[.]$, $\Re(.)$ is the magnitude calculation of the Fourier transform obtained from $I^c(x)$, $\Im(.)$ yields the phase spectrum from angle between the real and imaginary values of spectral data.

We can use high frequency components by defining low frequency components as zero with different bandwidth since low-pass filter was already applied. By changing the bandwidth of the high-pass filter on high frequency regions and removing more low frequency components, we can obtain several salient feature maps that represent attentive regions on the scene at various scale and perspective such as texture or edges. Then, the salient feature maps representing the attentive regions can be calculated as in Equation (3) with IFT similar to the SR [7]. So, we can have attentive band-pass regions as below:

$$M_r(x) = \frac{\sum_c F^{-1}\left[\exp\left(T_r(f) \times A^c(f) + i \times P^c(f)\right)\right]^2}{\eta^r} \quad (3)$$

where $F^{-1}[.]$ is the inverse FT (IFT), $i = \sqrt{-1}$, $M_r(x)$ is the salient feature map obtained by applying high-pass filter $T_r(f)$ (**Figure 2**) on $A^c(f)$, r is the feature map as {0-N} that also defines the radius of the low frequency components to be assigned zero on $T_r(f)$ as in the range of 2^r, N is the maximum possible number of feature map $M_r(x)$, and $\acute{\eta}^r$ is the weighting parameter for each feature map calculation.

In **Figure 3**, a sample color image and its salient feature maps based on *CIE Lab* color space data and Equation (3) are given respectively. As can be seen, more texture information can be obtained in the saliency feature maps when the frequency content of band-pass region increases. On the other hand, when the bandwidth is getting narrower in higher frequency regions (i.e. white regions on **Figure 2** example), salient regions leads to edges rather than the texture differences.

The saliency feature map examples in **Figure 3** are the results of filtering in frequency domain $T_r(f)$ in Equation (3) where **Figure 2** shows the various $T_r(f)$ with changing r values. As can be seen, the bandwidth of the high-pass region is decreasing with the change of radius r of the low frequency region to be avoided (black regions of the frequency components in **Figure 2**). So, as mentioned, different saliency features can be created which can represent the image from various attention viewpoints regarding the texture and edge based information.

Then, all these weighted feature maps obtained in Equation (3) are fused by addition to result in the final saliency as in Equation (4).

$$S(x) = \sum_r M_r(x) \quad (4)$$

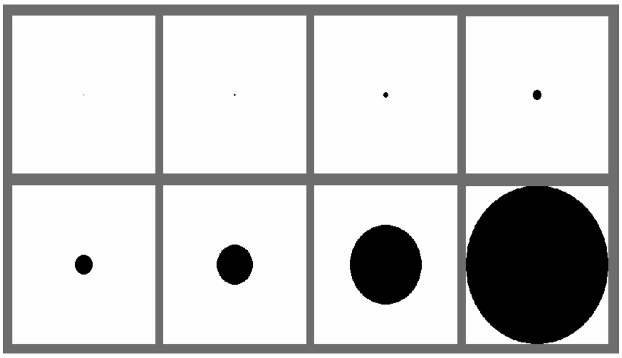


Figure 2. Filter templates $T_r(f)$ of Equation (3) with different bandwidths in frequency domain.

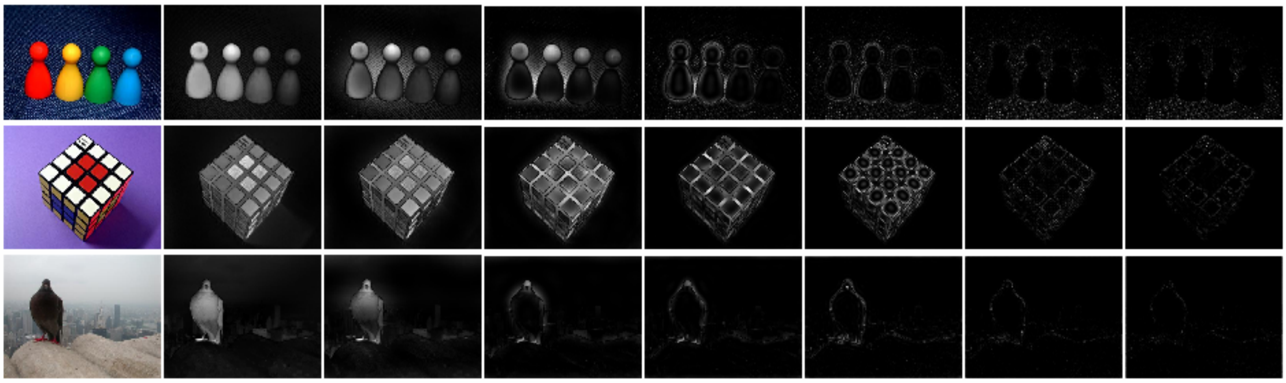


Figure 3. Sample color images and their respective texture to edge based some salient feature maps.

where $S(x)$ is the final saliency that is post-processed by median and Gaussian filter for smoothing in which the effect of textural differences is higher than the edge based band-pass regions.

In **Figure 4**, the final saliency maps were given for the sample color images that were calculated by using *CIE Lab* color space as an example of the resulting saliency of the proposed model. The proposed model provides full resolution saliency maps with high perceptual quality without the necessity of down sampling due to the salient feature maps selection from several band-pass regions of different bandwidths. Evaluation of the model with many color spaces and comparison with existing algorithms can be found in experimental results in the following section.

3. Experimental Results

First, performance of the proposed model was examined with four different color space and three different weighting parameter ($\acute{\eta}^r$) conditions in this paper. Then, the model was compared to existing state of the art algorithms. Evaluation process was done by using a dataset which consists of 1000 images and their ground-truths of segmented object regions [4]. Ground truth data was created by the several human subjects' responses to the images where the subjects were asked to define the boundaries of the object of interest on the image [4]. As for the evaluation metric, widely used area under curve (AUC) was applied to test data in which higher value of the AUC refers to the better performance for the evaluated algorithms [9-10].

Proposed saliency model was tested in four different color spaces in which *HSV*, *YCbCr*, *CIE Lab* and *NTSC* were selected. They have perceptual reliability or usability from the perspective of VA and HVS since all of them includes channels to define intensity/luminance and color/color chromatic values for the input image data. Therefore, using these color space models, we can obtain intensity and color saliency information from separate channels to represent the information on the input image. To be able to have use these color space models, the implementation code was achieved in *Matlab*® that includes built-in functions to convert *RGB* color space to selected color space [11-12].

In addition, each saliency feature map has weight, $\acute{\eta}^r$, as in Equation (3). We have set three different cases for the weighting parameters for each salient feature maps $M_r(x)$ in Equation (3); i) all weights set equal, in another way, they are all assigned as $\acute{\eta}^r = 1$ in the first test case, ii) the second test case assigns weights as $\acute{\eta}^r = 2^r$ to give higher priority to salient feature maps with large bandwidth contents, iii) the third scenario is similar to second case but aiming even higher impact for texture based attentive regions by using $\acute{\eta}^r = e^r$ as the weights for each saliency feature maps. The first condition was selected as equal to demonstrate that suitable weight selections on feature maps as in the other two weighting condition can have performance improvement regarding the AUC evaluation metric. **Table 1** presents AUC results obtained from the experiments on 1000 image dataset for selected color space models and weighting conditions.

The AUC performances of the experiments revealed that weighting the salient feature maps for the propose model was more efficient than using equal weights. Both 2^r and e^r weight assignment on feature map fusion improved the saliency result compared to the addition of feature maps with equal weights.

Among the tested color spaces, *NTSC* color space yielded superior performance compared to other color spaces in all weighting conditions while *CIE Lab* has the second AUC performance over all. In addition, *YCbCr* color space had the least variation on performance while the weighing conditions were changing. *HSV* had the worst performance in all test conditions of the proposed model among the tested color spaces and weighting conditions, and also it had the highest change of performance depending on the weighting parameter selection.

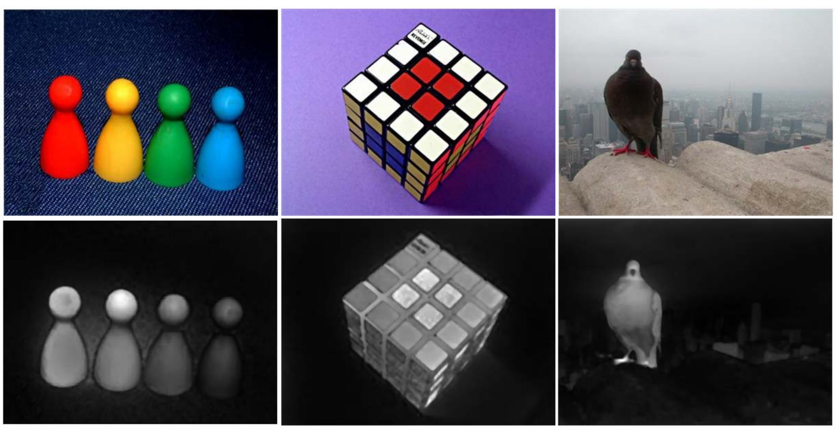


Figure 4. Sample color images and their respective saliency map based on the proposed model.

In addition to the color space and weighting parameter analysis, the proposed model was also compare to several state of the art algorithms to demonstrate the effectiveness of salient regions obtained from frequency domain selected band-pass regions. For the comparison saliency models IT [5], MZ [6], SR [7], and FT [4] models selected. These models were selected due to the fact that they include either center-surround difference, contrast, or frequency domain based approaches which were compatible with the proposed model.

In **Figure 5**, saliency maps are given for the compared models and proposed algorithm with *CIE Lab* color space and weighting case two of **Table 1** since *CIE Lab* color space is a widely used color conversion algorithm to demonstrate the experimental results of the saliency outputs. **Table 2** gives the AUC performance of the state of the art models from 1000 image dataset.

It can be seen that proposed model in all cases outperform the existing algorithms regarding the AUC values. Proposed algorithm has the best saliency performance regarding the AUC values with all color space and weighting conditions with respect to compared state of the art algorithms. Saliency model FT [4] proposed by Achanta, Hemami, Estrada and Susstrunk has the second best AUC performance, which also have high perceptual quality and uses *CIE Lab* color space conversion. On the other hand, AUC performances of IT [5] (i.e. spatial domain model with multi-scale center-surround analysis) and ST [7] (i.e. based on frequency domain analysis to find irregularities) have very close AUC values in average performance. The model MZ in [6] has the lowest saliency performance among the compared models.

4. Conclusions

In this paper, a simple and efficient saliency detection model was introduced which generates salient feature

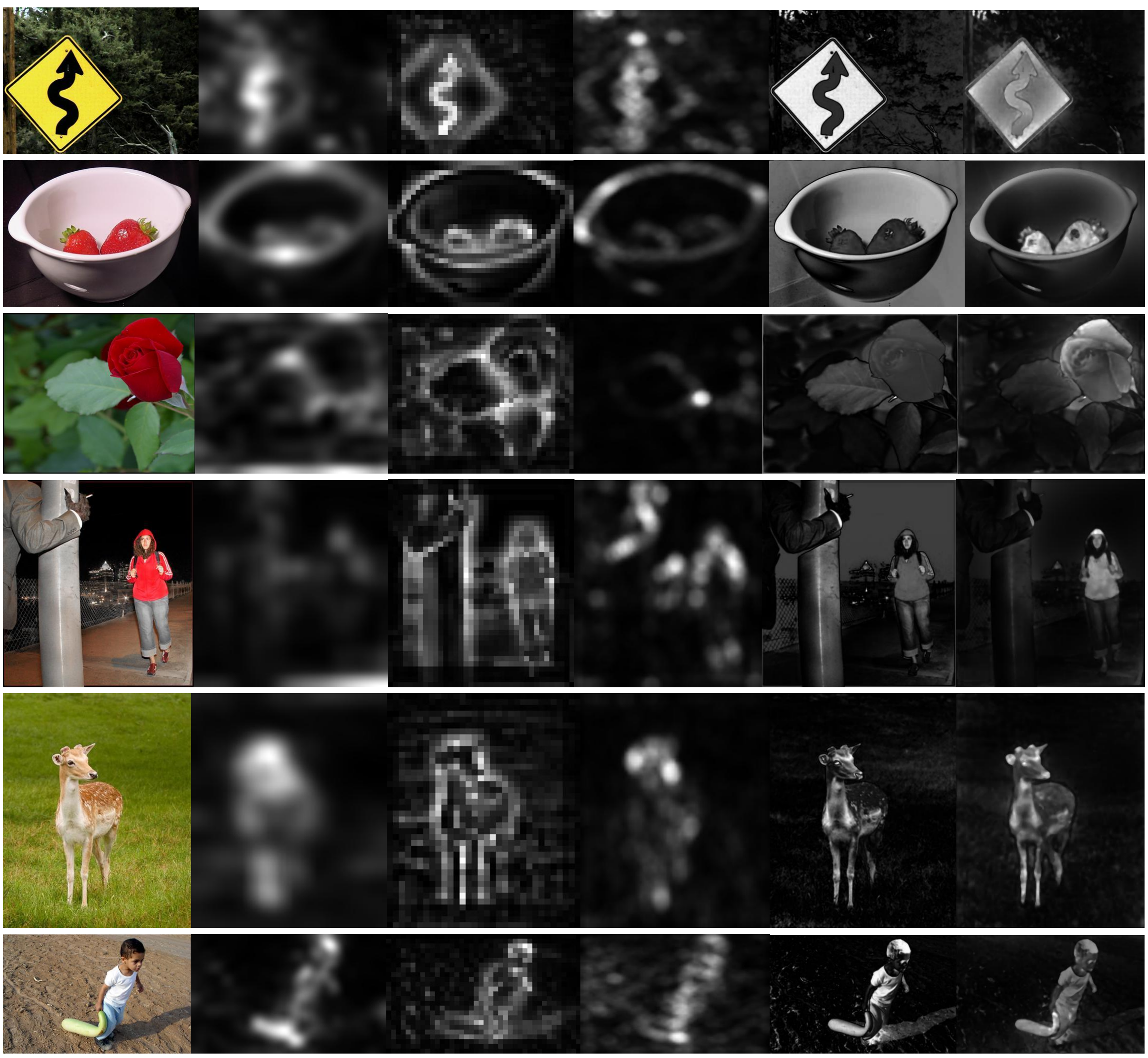


Figure 5. Sample color images, and saliency maps of IT [5], MZ [6], SR [7], FT [4], and proposed model respectively.

Table 1. Color space & weighting parameter performance evaluation of proposed model using AUC.

Color Spaces	AUC for Weighting Parameter Conditions		
	$\eta^r = 1$	$\eta^r = 2^r$	$\eta^r = e^r$
HSV	0.8237	0.8448	0.8527
YCbCr	0.8634	0.8705	0.8699
CIE Lab	0.8656	0.8729	0.8780
NTSC	0.8812	0.8889	0.8884

Table 2. AUC performance of state of the art models.

	Saliency Model			
	IT [5]	MZ [6]	SR [7]	FT [4]
AUC	0.8028	0.7951	0.8025	0.8198

maps from band-pass regions by utilizing Fourier transform. Therefore, the model can obtain attentive regions that represents edge to textural salient regions from the color image by yielding full resolution saliency maps with high perceptual quality. Salient feature maps were combined in a weighted manner where the one with more frequency content, representing the salient texture data, had more effect on the final saliency.

We showed that frequency domain can be used to attain band-pass regions to compute saliency map by outperforming conventional saliency computation models. Also, experimental analysis revealed that the appropriate color space model selection can be beneficial to the result of the saliency computation.

As a future work, weight of the feature maps can be optimized based on the frequency content, and also, bandwidth region and size selection in frequency domain can be improved using image similarity in a top-down manner to increase the overall performance of the proposed model.

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