Non-uniform Image Compression using Biologically Motivated Saliency Map Model

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Abstract

We propose a new non-uniform image compression using biologically motivated selective attention model for effective storage and transmission of natural images. One of important issues in the non-uniform image compression is to decide a meaningful region according to a purpose. The proposed saliency map model can generate a scan path that contains plausible interesting objects in natural scene. The proposed non-uniform image compression method uses the saliency map results, which differently compress the selected interesting areas and the uninteresting areas by lossless coding algorithm and lossy compression, respectively. Experimental results show that the proposed non-uniform compression method gives better peak signal to noise ratio (PSNR) but slightly decrease the compression ratio.

1. INTRODUCTION

As many digital devices and use of internet keep growing, the amount of date to be handled dramatically increases. The data compression is highlighted to develop an efficient information processing terminal.

In general, there exist two standard image compression methods [1]. The first is to compress an image by lossless coding algorithm. The lossless compression method does not suffer from the missing problem of information, which means no decoding error. However, the compression ration is not so high. Thus, the lossless compression method is just used in specific application problems such as medical image and microscope images of barley leafs [2, 3]. General lossless algorithms are LZW(Lumpel-Ziv-Welch), RLC(Run length Coding) and Huffman Coding and etc [4]. On the other hand, the lossy coding is popularly used for real time transmission of an image through the internet. Its compression ratio is very high, but the loss of information inevitably occurs due to the compression. The representative methods for lossy compression are JPEG, Wavelet, JPEG2000 and etc [5, 6, 7]. Even though the lossy compression method is efficient, important information may loose because the uniform compression algorithms processes all contents equally. If we can consider the non-uniform image compression that differently compress the contents in an image according to the relative importance, we are able to realize more efficient image compressing coding scheme.

The non-uniform image compression has been applied in many engineering application domains. According to Udo's research, they said that non–uniform image compression is suitable algorithm in biomedical engineering fields. Because the properties of biomedical screen image such as microscope images have a huge amount of data and contain very similar information obtained thousands, millions or even more equal investigations, similar information except important information contained special feature and shape against homogeneity background need to pass lossy compression [2]. He suggested the non-uniform image compression method by classifying input image divided into fixed size image block with complexity measure and symmetry regarded as a compression relevant complexity [8]. However, it is difficult to define and compute the complexity measure in real application. Also, Tony proposed a compound image compression algorithm for real-time applications of computer screen image transmission [9]. This method extracts a primitive shape from image compounded text and graphics for real-time transmission and successfully works for segmentation between the texts and background images simply using the number of color. But, it can be applied to only the specific application and the algorithm may give an error when the background consists of simple contexts.

The main issue of the non-uniform image compression is to discriminate between the regions to be compressed by lossless coding algorithm and those to be compressed by lossy coding method. The possible way to decide the lossless compression region in natural image is to consider the human's selective attention function. The human eye can focus on an attentive location in an input scene and select interesting visual information to process in the brain. These mechanisms are very effective in processing high-dimensional data with great complexity. If we apply the human-like selective attention function to the image compression problem, an efficient and intelligent image compression method can be developed.

Considering the human-like selective attention function, top-down or task-dependent processing can affect how to determine the saliency map as well as bottom-up or task-independent processing. The top-down processing is so subjective that it is very difficult to model. Thus, we consider only the bottom-up processing to find a salient area according to various stimuli in a static input image.

In this paper, we propose a new non-uniform image compression method that uses the result of bottom-up saliency map model. The regions selected by the bottom-up saliency map model are coded by lossless method, and another region is compressed by lossy coding algorithm.

In Section 2, we briefly review the bottom-up saliency map model together with the biological background. In Section 3, we explain the proposed non-uniform image compression method using bottom-up saliency map model. In Section 4, computer simulation and experimental results are shown with compression performance. Conclusion and further work will be made in the end.

2. BOTTOM-UP SALIENCY MAP MODEL

A. Biological background for selective attention

Fig. 1 shows the biological visual pathway from the retina to the visual cortex through the LGN for the bottom-up processing.

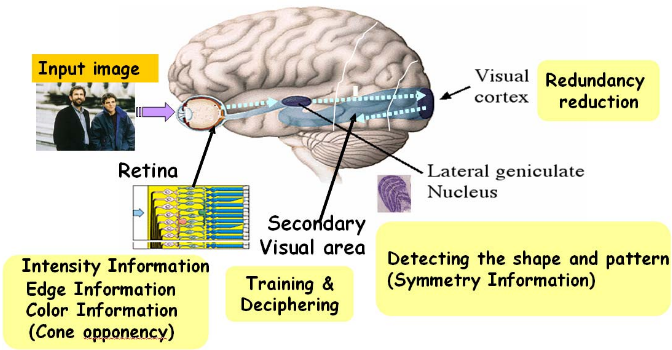


Fig. 1: Biological visual pathway of bottom-up processing.

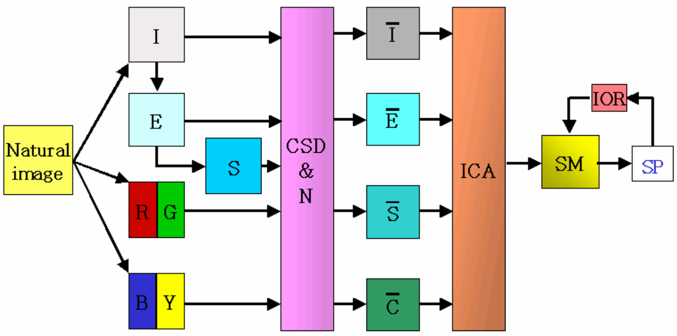
In the vertebrate retina, three types of cells are important processing elements for performing the edge extraction. Those are photoreceptors, horizontal and bipolar cells, respectively [10, 11]. According to these well-known facts, the edge information is obtained by the role of cells in visual receptor, and it would be delivered to the visual cortex through the LGN and the ganglion cells. The horizontal cell spatially smoothes the transformed optical signal, while the bipolar cell yields the differential signal, which is the difference between optical signal and the smoothed signal. By the output signal of the bipolar cell, the edge signal is detected.

On the other hand, a neural circuit in the retina creates opponent cells from the signals generated by the three types of cone receptors [12]. R+G− cell receives inhibitory input from the M cone and excitatory input from the L cone. The opponent response of the R+G− cell occurs because of the opposing inputs from the M and L cones. The B+Y- cell receives inhibitory input by adding the inputs from the M and L cones and excitatory input from the S cone. Those preprocessed signal transmitted to the LGN through the ganglion cell, and the on-set and off-surround mechanism of the LGN and the visual cortex intensifies the phenomena of opponency [12]. Moreover, the LGN plays a role of detecting a shape and pattern of an object [12]. In general, the shape or pattern of an object has symmetrical information, and resultantly the symmetrical information is one of important features for constructing a saliency map. Even though the role of visual cortex for finding a salient region is important, it is very difficult to model the detail function of the visual cortex. Owing to the Barlow's hypothesis, we simply consider the roles of the visual cortex as redundancy reduction.

B. Bottom-up saliency map processing

Previously, Itti and Koch introduced brain-like model to generate the saliency map [13]. However, the weight values of the feature maps for constructing the saliency map are artificially determined. Li proposed a saliency map model based on a nonlinear differential equation that successfully explains simple psychological effects in humans, but her model is difficult to implement in engineering applications because of solving nonlinear differential equation in each sampling instant. On the other hand, Barlow suggested that our visual cortical feature detectors might be the end result of a redundancy reduction process [14]. We supposed that the saliency map is one of the results of redundancy reduction in our brain. The scan path that is a sequence of salient points may be one of the results of our brain's attempt at information maximization.

Fig. 2 shows the previously proposed bottom-up SM model based on Fig. 1 [15]. Since the retina cells can extract the edge information and color opponency, we use the edge and color opponent coding as the basis features of SM model [16]. Also, the intensity information is also used as a basis to reflect the Treisman's result [17]. In order to consider the LGN function as a way of detecting the shape of an object, we consider symmetry information as an additional basis.



I : intensity image, E : edge image, S: symmetry image, RG : red-green opponent coding image, BY : blue-yellow opponent coding image, CSD & N : center-surround difference and normalization, $\overline{I}$: intensity feature map, $\overline{E}$: edge feature map, $\overline{S}$: symmetry feature map, $\overline{C}$: color feature map, ICA : independent component analysis, SM : saliency map, SP : saliency point, IOR : inhibition of return

Fig. 2: Block diagram of the bottom-up saliency map model.

In a course of preprocessing, SM used a Gaussian pyramid with different scales from 0 to n level, in which each level is made by subsampling of 2^n, thus constructing five feature maps [15]. Consequently, five feature maps are obtained by the following equations.

$$I(c, s) = |I(c) - I(s)| \quad (1)$$

$$E(c,s) = |E(c) - E(s)| \quad (2)$$

$$Sym(c,s)=|Sym(c) - Sym(s)| \quad (3)$$

$$RG(c,s)=|R(c) - G(c)| - |G(s)-R(s)| \quad (4)$$

$$BY(c,s)=|B(c)-Y(c)| - |Y(s)-B(s)| \quad (5)$$

where “$\ominus$” represents interpolation to the finer scale and point-by-point subtraction. Totally, 30 feature maps are computed because the five feature maps individually have 6 different scales [13]. Feature maps are combined into four “conspicuity maps,” as shown in Eq. (5) where $\overline{I}$, $\overline{E}$, $\overline{S}$ and $\overline{C}$ stand for intensity, edge, symmetry, and color opponency, respectively. These are obtained through across-scale addition “$\oplus$” [13].

$$\overline{I} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} N(I(c,s)),$$
$$\overline{E} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} N(E(c,s)),$$
$$\overline{Sym} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} N(S(c,s)),$$
$$\overline{C} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} N(RG(c,s)+BY(c,s)) \quad (6)$$

Finally, the function of the visual cortex is also considered as a redundancy reduction based on Barlow’s hypothesis [9, 13]. We used independent component analysis (ICA) algorithm to model the roles of the visual cortex because the ICA is the best way to reduce the redundancy [15]. After the convolution between the channel of the feature maps and the filters obtained by the ICA learning, the saliency map is computed by summation of the feature maps for every location [15]. . Fig. 3 shows the procedure of realizing the saliency map from four feature maps, $\overline{I}$, $\overline{E}$, $\overline{Sym}$ and $\overline{C}$.

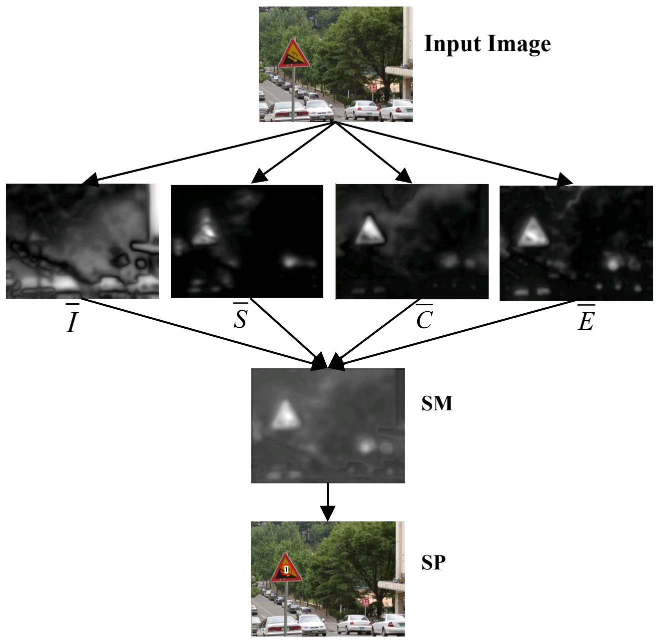


Fig. 3: Bottom-up saliency map processing

3. Non - uniform image compression using bottom up saliency map model

Fig. 4 shows a block diagram of the proposed non-uniform image compression using the bottom-up saliency map model. The bottom-up processing is to model a function of primitive selective attention in the human vision system since humans selectively attend to a salient area according to various stimuli in an input scene [13]. The most salient point is used as the beginning point to decide the region for segmenting a context from the background images, and followed by an adaptive segmentation processing to determine the region for lossless compression. Another region that does not be selected by the bottom-up saliency map model is compressed by lossy coding algorithm.

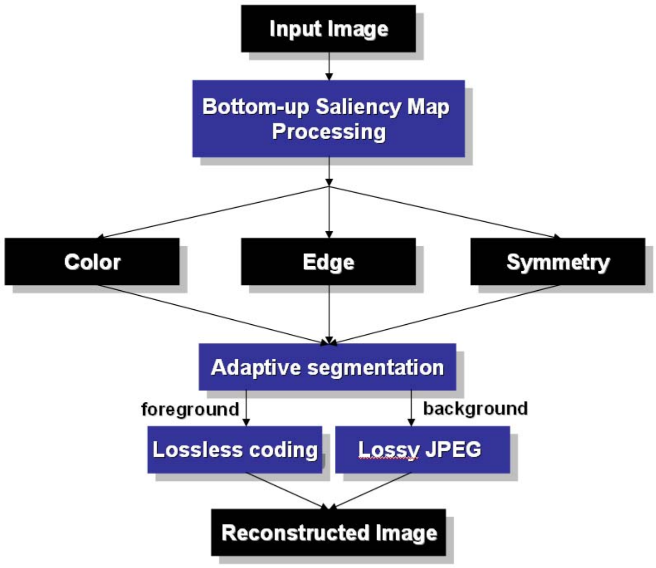


Fig. 4: Block diagram of the Non-uniform Image Compression

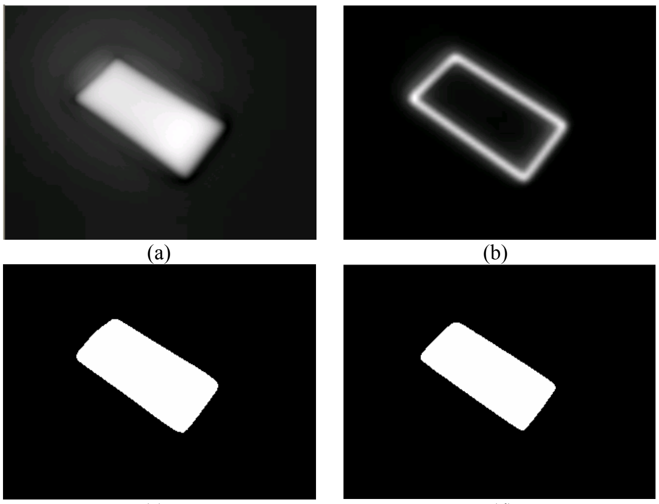
A. *Adaptive Segmentation*

The bottom-up saliency map model indicates a salient area that would be compressed without loss. If we can segment a context in an input image selected by the bottom-up saliency map model and compress the segmented region for the context by lossless coding algorithm together with lossy compressing for another region, more effective non-uniform compression can be developed.

Instead of segmenting the context in an image with fixed size mask, we propose an adaptive segmentation method that can decide precise boundary according to shape and size of the contexts. Using the adaptive segmentation method, it is possible to remove worthless area in a fixed size mask.

In general, the segmentation is very difficult problem. In this paper, we use the feature map information such as color, edge and symmetry for segmenting a context. If an input scene contains an object with symmetry information, the symmetry feature map shows a conspicuous information in the symmetry feature map. Also, if the context has homogeneous color information that is different from background color information, the context is remarkable in the color feature map. Together with the symmetry and color information, the edge feature map is considered to segment a context in around the most salient point that is determined by the bottom-up saliency map model.

Region based segmentation methods are used to decide region information of a context in each feature map. Traditionally, such a method has been grouped under image segmentation technique and there exists a large body of literature [18]. The edge-based and histogram-based methods are too simple to give meaningful region, while region based methods are suitable algorithm for merging a same level region. The region based segmentation method is simply realized so as to quickly search its shape boundary. It keeps growing a spatial area to left, right, up and down direction from a starting pointer until threshold. If a region grows over the threshold, region growing is stopped and the integrated regions become groups for segmentation. There are two approaches according to its direction. Fig. 5 shows that a simple figure segmented by region growing in upper bound color feature map and lower bound symmetry feature map.



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

(a) color feature map (b) edge feature map (c) segmented area from color feature map (d) segmented area from edge feature map

Fig. 5: Region based segmentation in simple rectangular

In case that the starting pointer is a upper bound than threshold such as Fig. 5 (a), the starting pointer with merging other area keeps growing until threshold is equal to upper bound. As shown Fig. 5 (b), in case that the starting pointer is a lower than threshold such as edge feature information almost all of the edge information exist at the corner of the feature. Fig 5 (c) and (d) are the results of the region based segmentation using color and edge information, respectively. However, the threshold used to find a context region for segmentation is obtained by a heuristic method until now. It is a critical problem to get a nice segmentation. We determined the threshold value by an average of each feature map using a lot of experiment. Using the threshold, we transform the color, symmetry and edge feature map with gray level to those with binary.

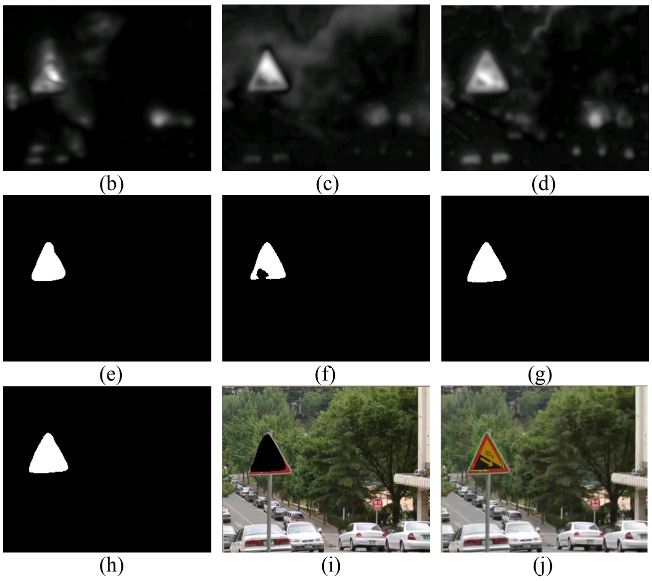
B. Lossless/Lossy coding

Adaptive segmentation process separates a context area and a background in input scene. The context area extracted by region based segmentation is coded by lossless method. The LZW, RLC and Huffman coding can be used for the lossless compression. Lossless compression algorithms process repetitive context or novel context with saving the temporary tables. Compression ratio of the lossless coding is at most 50%. Also, compression data is often greater rather than original image. Thus, it is important to select a suitable algorithm for the purpose. In this paper, we want to compress meaningful information in natural image without loss. Therefore, the segmented area is saved by raw file data format. In order to compress the background, we can use one of popular lossy compression ways such as JPEG and wavelet compression, etc. We use the DCT based JPEG compression algorithm to compress the background image except the context selected by the bottom-up saliency map model. In lossy compression progress, the context area segmented for lossless coding is filled by zero values because there is no information. We also use the Q-factor to adjust an image quality. When the image is restoring, the compressed areas by lossless coding and loss coding are merged to one image file.

4. COMPUTER SIMULATION AND RESULTS

We present experimental results of proposed non-uniform image compression using bottom–up saliency map model. We use an input image at 320 × 240 resolution and 24-bit true color information in experiments. Fig. 6 shows the simulation results of proposed non-uniform image compression in a complex natural image. As shown in Fig. 6 (a), the bottom-up saliency map model successfully indicates the road mark sign as the most salient area. Fig. 6 (b), (c) and (d) represent the symmetry, color and edge feature map. As shown in Fig 6 (e), (f) and (g), the context information obtained by region growing segmentation method in each feature map is converted to binary images. The context information is finally obtained by sum of converted feature map binary images as in Fig. 6 (h). Fig. 6 (i) shows the background images after segmenting the context information shown in Fig. 6 (h), Fig. 6 (j) shows the reconstructed image by the proposed non-uniform image compression. The inside of green line in Fig. 6 (j) indicates the context information without loosing information during the compression.

(a)



(a) original image remarked by bottom-up saliency map processing (b) symmetry feature map (c) color feature map (d)edge feature map (e) segmented region from symmetry feature map (f) segmented region from color feature map (g)segmented region from edge feature map (h) summation of each feature map (i) original image except meaningful information (j) reconstructed image

Fig.6: Simulation results of non-uniform image compression using bottom-up saliency map model

The evaluation of the proposed compression is measured by a compression ratio and peak signal to noise ratio (PSNR). The PSNR is defined by following equation.

$$PNSR(dB) = 10\log_{10}(\frac{255^2}{MSE^2}) \quad (7)$$

where 255 means the intensity level from 0 to 255. MSE is the mean square error computed by difference of pixel by pixel between reconstructed image and original image.

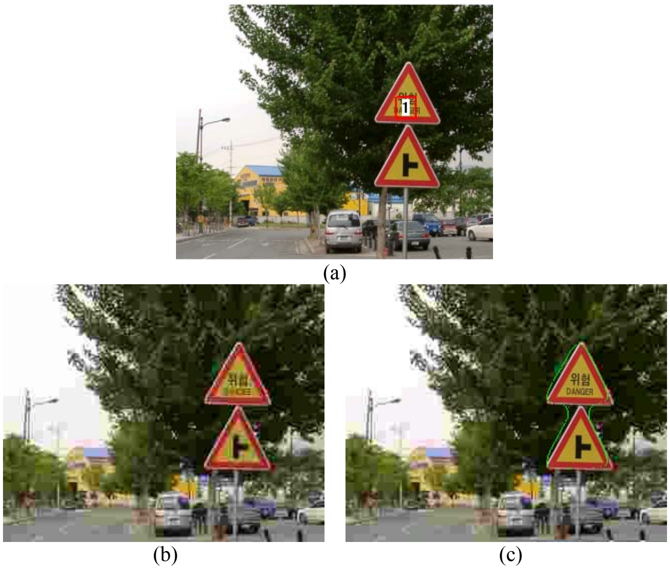
Table 1 shows the comparison between the uniform JPEG compression method and the proposed non-uniform image compression method of Fig. 6 (a). As shown in table 1, the proposed non-uniform image compression is better than the uniform JPEG algorithm. Of course, the compression ratio of the non-uniform image compression method is worse than that of uniform JPEG algorithm.

TABLE 1: COMPARISON WITH JPEG ALGORITHM AND PROPOSED NON-UNFORM COMPRESSION(NIC) IN PERFORMANCE

Performance	JPEG	NIC
Compression ratio (%)	95.2%	92.7%
PSNR	R : 28.445403 G : 28.748563 B : 28.611434	R : 28.611434 G : 28.891476 B : 28.643406

(Original image size : 230.454kb)

Fig. 7 shows that the proposed non-uniform image compression method represents exact information for road mark sign board, but the conventional uniform JPEG may loose the important context information. Fig. 7 (a) shows a road mark sign board remarked by the bottom-up saliency map model. Fig.7 (b) is a result of uniform JPEG compression. As shown in this figure, the road mark sign board is corrupted by compression and reconstruction process. Fig. 7 (c) is a result of proposed non-uniform image compression. Although the background information looses by the lossy JPEG compression, we can obtain the vivid road mark sign board.



(a) original image (b) the uniform JPEG compression (c) the proposed non-uniform Compression

Fig. 7: Comparison with uniform image compression and non-uniform image compression in an image

Fig. 8 shows that the proposed method is successfully applied to multiple salient contexts.

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(a) original image with multiple salient contexts (b) reconstructed image with multiple salient contexts

Fig. 8: Simulation results of multiple salient contexts

5. CONCLUSION

We proposed non-uniform image compression using bottom-up saliency map model in natural image. The bottom–up saliency map model can indicate meaningful area in natural image. The most salient point is used as a beginning pointer to determine the segmentation region for a context. The proposed adaptive segmentation method using the feature map and region growing method successfully segments the context region. The segmented area is compressed by lossless coding algorithm, and background area is compressed by lossy coding algorithm. Using the proposed method, the PSNR is enhanced with slightly decrease of the compression ratio. As a further work, we are considering a new method to determine the threshold for binarization of the feature maps in segmentation process. Also, we are under investigation to replace the bottom-up saliency map model by the trainable selective attention model to indicate a desired context in complex natural image.

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