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Attribute Based Level Adaptive Thresholding Algorithm (ABLATA) for Image Compression and Transmission

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Abstract

Image processing plays a vital role in the computer vision because most of the scenarios require object extraction & recognition. But there lies a self-concatenated issue with it because such an algorithm is also supposed to simultaneously solves the problem of image restoration and transmission. In order to achieve this objective we furthered the effective ABLATA algorithm for the same Once the image is denoised and features are extracted then it can be resized to the half of the actual image, compressing it in a mathematical equation that shall help it restore with the half of the data and thus can readily be restored with the half of the actual imagery data to reproduce it, while maintaining the high image quality. The advantage of such a process is the low storage cost and image transmission requires less time than that required by the original one.

Keywords: Computer Vision; Object Extraction, Image denoising Image Compression, Transmission.

1. Introduction

With the widespread use of digital imaging and computer vision in automation industry , the efficiency of segmenting algorithm and the quality of objects extracted from digital images has become an important issue today. To achieve the best possible features, it is important for the image under scrutiny should be sharp, clear, and free of noise and artifacts [1-2]. Though, the technologies for acquiring digital images are improving, resulting in images of higher and higher resolution and quality, noise remains as an issue in many images applications whether it be concerned with medical field or of robotics [12]. The presence of noise will degrade the quality of image, and even conceal image details, which consequently influences the subsequent process of image segmentation, object recognition, feature extraction and quantitative analysis [4] [15]. Most of the algorithms require a number of procedures that causes increased computational time or considerable execution time which can be reduced by applying less and simpler algorithms. Thus, several denoising methods that have been proposed such as neighborhood filtering, total variation minimization, Wiener filtering, Gaussian scalar mixture, methods based on partial differential equation [5] Adaptive low pass filtering, adaptive median filtering, Crimmins' geometric filter and others manage to remove substantial amounts of speckle, but also tend to over smooth the features [6]. To avoid this, Gaussian filters have been largely used in some applications. However, they have the disadvantage of blurring the edges due to the averaging of non similar patterns [7]. Image quality is a very essential feature in medical imaging. But, degradation of medical images due to different kinds of noises is highly probable. Removing noise in these digital images remains as one of the major challenges in the study of machine vision & medical imaging [13]. Denoising of these images is particularly challenging due to their peculiar texture [3].

In order to avoid this problem, many edge preserving filters have been proposed. Probably the most well-known is the Anisotropic Diffusion Filter (ADF) and other effective studies had been proposed [8-14]. ADF respects edges by averaging pixels in the orthogonal direction of the local gradient. However, such filtering methodologies is comparatively inefficient to erases small features and transforms image statistics due to its edge enhancement effect resulting in unnatural images [9]. The filters discussed so far are based on the notion of spatial proximity. Local filters instead take into account of grey level values while defining the neighboring pixels. The local adaptive filters, analyze the noisy image in a moving window and in each position of the window its spectrum is computed and modified.

2. Methodology: Image Compression and Transmission Through ABLATA

ABLATA had proved to be an effective approach for feature extraction from the images with the wide application of demising and object extraction [15]. Thus, herein we review its mechanism such that its additive features of image compression and transmission could be discussed fluently at the latter sections. Mathematically, an image is a two dimensional (2 D) function, *f*(x, *y*), where *x* and *y* are the coordinate values in spatial domain or plane; and the magnitude of *f(x, y)* is the intensity value of pixel at (x, y).An example of real time image can be seen in Fig. 1.4 along with the pixel representation of the image. If x, y and the magnitude of *f(x, y)* in an image are discrete quantities then the image is said to be digital image. Image may be represented as two dimensional matrices whose elements are intensities of pixels present in image. Almost all image processing related operations operate on these pixels either in spatial domain or in frequency domain or transform domain. The function *f(x, y)* can be expressed as:

$$f(x,y)=\begin{bmatrix} f(0,0) & \cdots & f(0,N_y-1) \\ \vdots & \ddots & \vdots \\ f(N_x-1,0) & \cdots & f(N_x-1,N_y-1) \end{bmatrix} \qquad (1)$$

Each digital image has certain finite number of elements characterized by some coordinate values and intensity value. The coordinate indicates the position of pixel in an image. In Equation (1) the image elements $f(N_x-1,N_y-1))$ represent the maximum number of resolution starting from *f (0,0).*

Suppose '$\boldsymbol{f}$' is the set of all pixels and 'P' is a uniformity predicate defined over groups of connected pixels. Segmentation is simply a partitioning of the set F into a set of connected subjects or regions (P_1, P_2, ….P_n) such that $\bigcup_{i=1}^{n} P_i = F$ with $P_i \cap P_j = \emptyset \; when \; i \neq j$. The uniformity predicate i = 1 pixels represented as P (P_i) is true for all regions P_i & $P(P_i \cup P_j)$ and is false when P_i is adjacent to P_j. The thresholding algorithm for binary images is applied as: $f_b \coloneqq \sum_{i=0}^{m} r \; (\{g_i \le f_b < g_{i+1}\}$, where r() is the mean value; g_i & $g_{i+1}$are the lower bound and upper bound respectively of the given thresholding pixel boundary condition. Various steps of implementation of algorithm for plate extraction are:

- Determine the set of levels L using: $f_{presegment} \coloneqq (f_{black}, f_{white})$ and $\boldsymbol{L}\colon= \left[\{x \middle| f_{presegment}\;(x)L\middle|\}L \in f_{presegment}\;(IR^3)\right]$; where '$x$' the exclusion of particular set of pixel value and R is the universal set of all the pixels values mapped in binary image; as shown in Fig. 5.6.

- P_i pixel value for dissociation between root mean values of levels L_i & L_j kept at minimal and applies normalization; and extracts all the elements.

The unnatural bias for partitioning is avoided by selecting small sets of points and different measure of dissociation. The problem with cut criterion is that it does not consider association with cluster. In order to circumvent this problem, the cut cost as a function of the total pixel threshold to all those levels formed in the above step is observed and normalized cut is determined. The result of disassociation can be seen in Fig. 2.

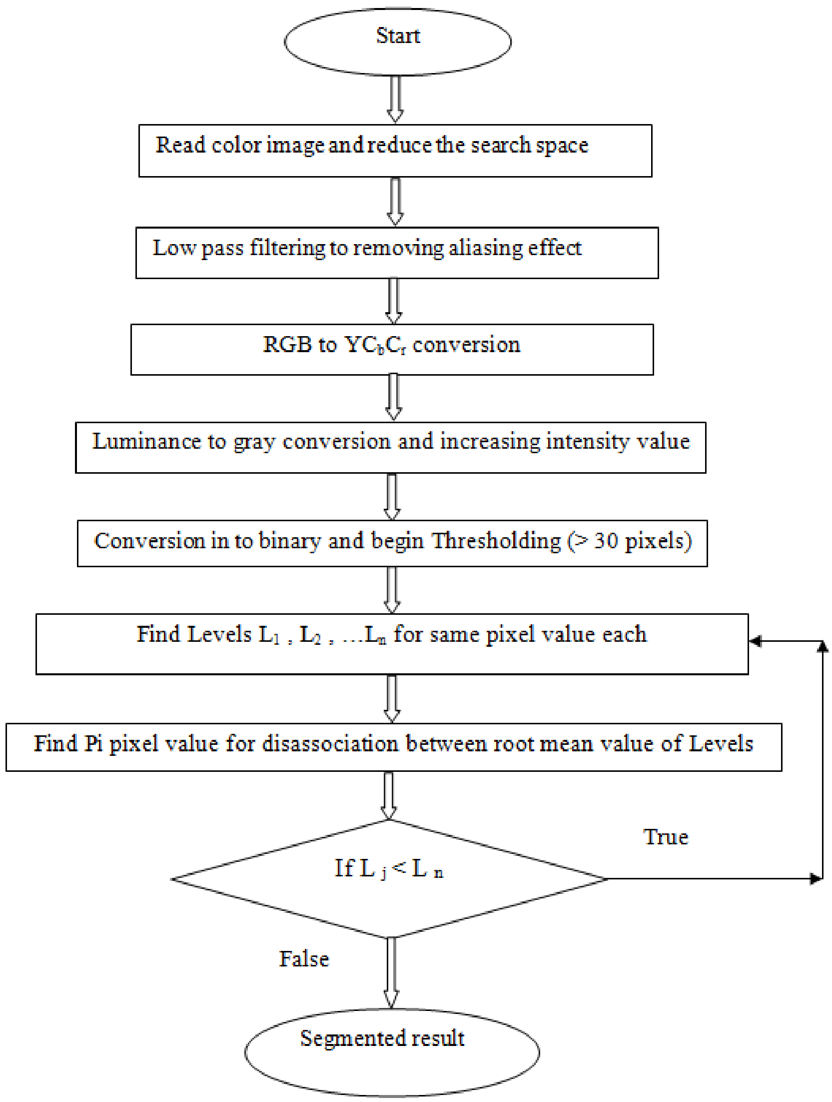

Fig. 1: Algorithm for Object segmentation

Thus, we have the generic equation normalization is defined as:

$$N_{cut}\,(A,B) = \frac{cut\ (A,B)}{assoc\ (A,B)} + \frac{cut\ (A,B)}{assoc\ (B,V)}\,;$$

where, assoc (A,V) = $\sum_{x \in A, v \in V} W(u,v)$ is the total connection from pixels of set A to all set B. By using this definition of the disassociation between the groups, small isolated points are partitioned out and will no longer have distinct N_{cut} values, since the cut value will almost be a large percentage of the total connections from the small set to all other pixels. The mathematical steps of the approach are defined for k=L_i:last level formed upon thresholding: Select level $L_1 \in \boldsymbol{\mathcal{L}}(\text{universal set of all levels})\ \&\ pixel\ P_2 \in \Delta L_1$ with dist (r(L_1), r(P_1)) maximal; find a level $L_2 \in \boldsymbol{\mathcal{L}}$ for which the exchange of P_2 from L_1 to L_2 is allowed & dist (P_1, r(P_2)) is minimal. Finally, while traversing between subsequent levels the pixels taken in account for normalize the cut is based on the formula as:

$$\text{if } \frac{\lambda(L_2)(L_1)}{\lambda(L_2 \cup \{P_1\}(L_1 \cap \{P_i\}))} dist_2\ (r(L_2), r\ (\{P_2\}))^2 < dist_2\ (r(r(\{P_2\}), r(L_1 \cap \{P_2\})^2 \quad set\ L_1 := L_1 \cap \{p\}\ \&\ L_2 := L_2 \cup \{p\}.$$

If no other level changes are found then terminate the operation. The mechanism of segmented image is finally generated after extraction operation and is summed up in Fig. 2.

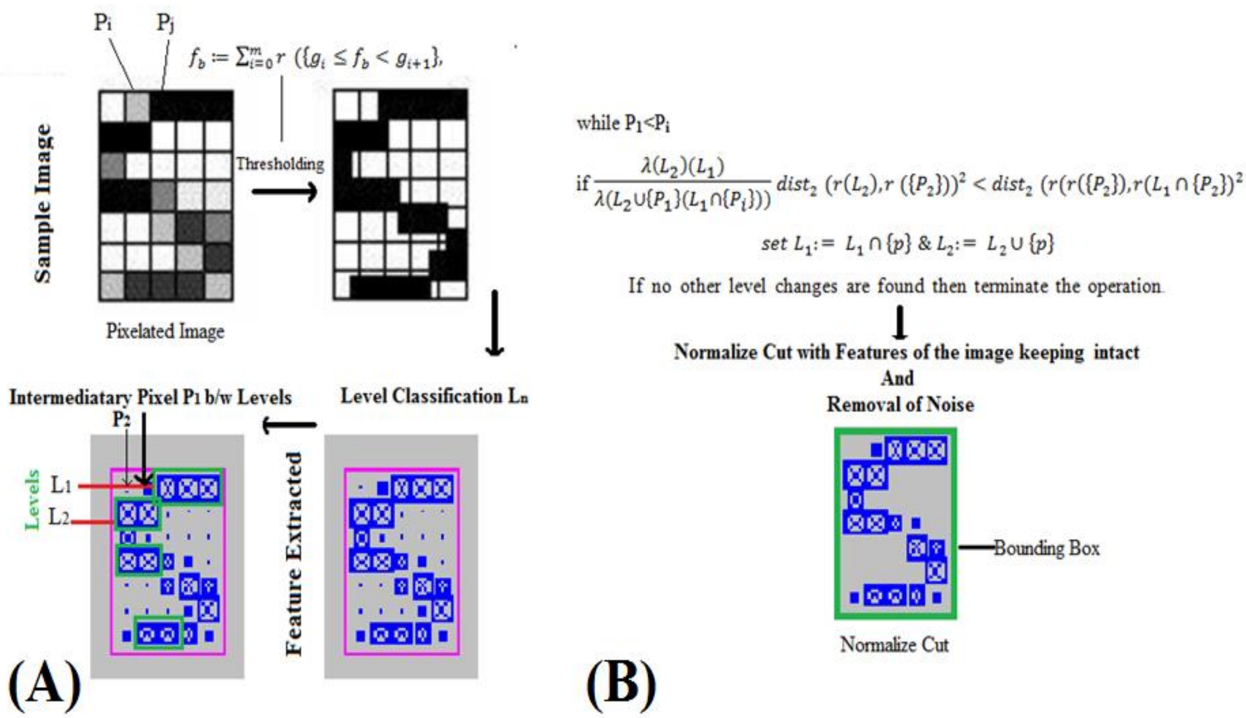

Fig. 2: Mechanism of character segmentation and simultaneously eliminating noise from image characters in the bounding box.

Now, the pseudo code for compression of the extracted features from the image component is compressed by:

While $P_i \leq L_i \cap P_j$ && $L_i \leq L_j$

$$\varphi(L_i, P_i) = \sum_{x=1}^{m}\sum_{y=1}^{n} w(x,y)\, exp^{-2\pi j\left(\frac{xu}{m}+\frac{yu}{n}\right)} //\text{transcripting proximate pixel of } L_i \cap P$$

$$w(x,y) = \frac{1}{m\,n}\sum_{u=1}^{m}\sum_{v=1}^{n} \varphi(L_i, P_i)\, exp^{-2\pi j\left(\frac{xu}{m}+\frac{yu}{n}\right)} //\text{buffered weighted pixel}$$

end

The $\varphi(L_i, P_i)$ function transcripts the selected features from the image with the intersection of the prominent pixel P, whereas $w(x,y)$ is the function to form a weighted pixel for the buffered pixel position in rows and columns arrangement i.e., $m \times n$ respectively. $w(x,y)$ is employed for restoring compressed imagery data. The sample sets of the compressed image and restored image is shown in the figure 3.

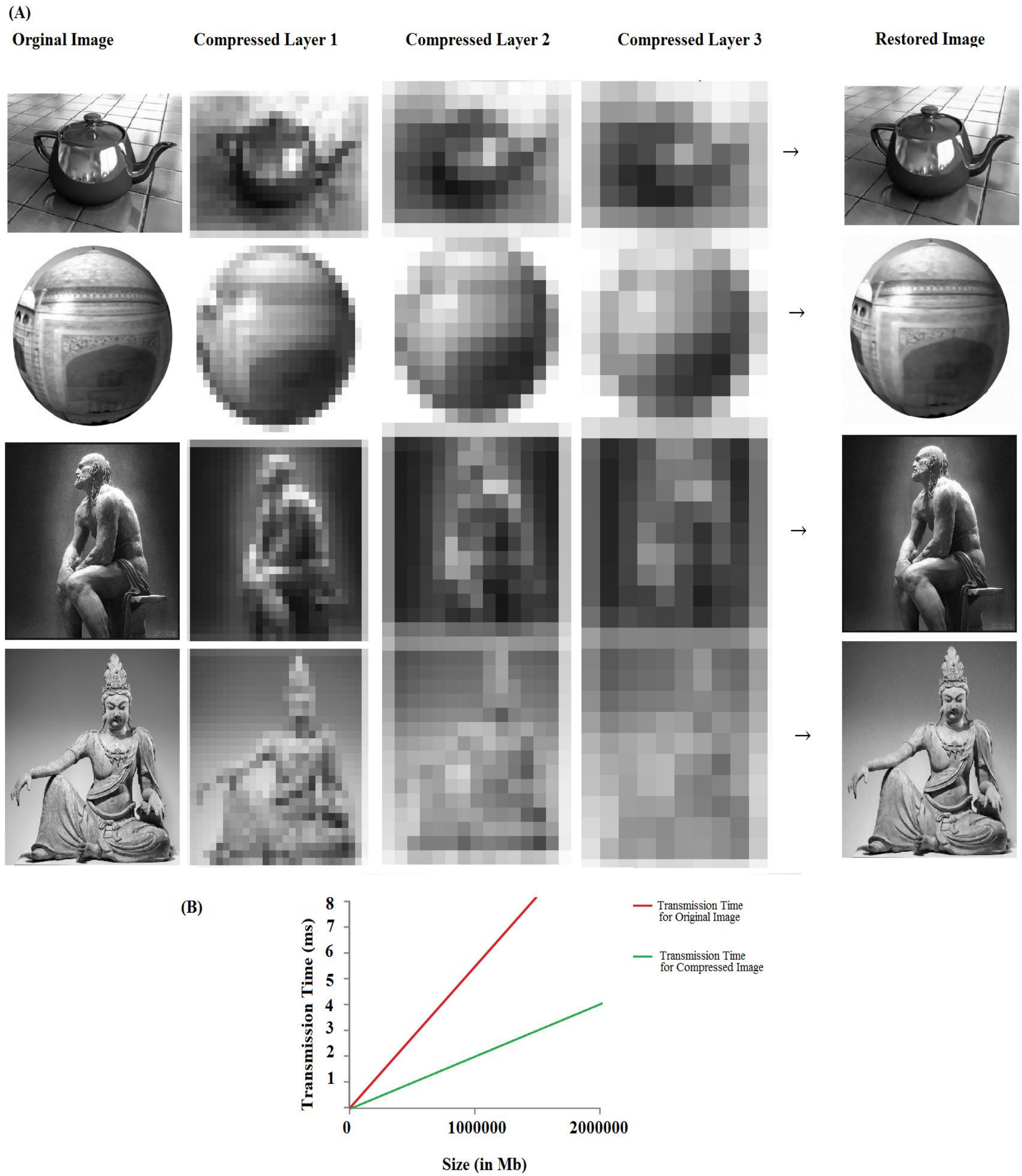

Figure 3: (A) Compression scheme of the imagery data in three pixel weighted compressed layers and the restored image while simultaneously being denoised. (B) Plot of transmission time for the images v/s the size of the image when the original image and the compressed layer 3 image is transmitted over the same network with constant bandwidth & bit rate of 250 Mbps. Clearly, the compressed data shows significantly lower transmission time than that of the original one.

3. Conclusion

As shown in the above fig.3, an effective Object extraction, denoisjng and simultaneously image compression technique is achieved through ABLATA that takes less number of computational steps necessary for the completion of the above mentioned operation. The technique has been evaluated using different levels of harsh lighting environments which had corrupted images. The refining of images and its compression scheme has been performed in less computational steps. Thus, the feature extracted shall be classified with the image type in this compression scheme for which no new method is required to annotate the objects in the images. Since, the restoration is based on the already extracted features with that of other subsidiary background channels this produces a fine quality image and give a good transmission time required over the network delivery.

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