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Image Preprocessing for Compression: Attribute Filtering

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Abstract—**This work proposes a preprocessing method for image compression based on attribute filtering. This method is completely shape preserving and computationally cheap. Three filters were investigated, including one derived from the power filter of Evans and Young that removes even more perceptually unimportant information. The results from 22 images that were processed in various ways and compressed using the popular compression algorithms of Jpeg, Jpeg2000 and LZW are presented. Our experiments have shown that all the filters cause an improvement of as much as 11, 10 and 20% for jpeg, jpeg2000 and LZW algorithms respectively.**

Keywords: Attribute filtering, Mathematical morphology, Image compression, Pre-processing for compression, universal quality index

1 Introduction

The amount of compression provided by any process is dependant on the characteristics of the particular image being compressed, the desired image quality and speed of the compression. A reduction in file size will improve systems performance, reduce file processing / transfer time and minimize data storage requirements. All these advantages render data compression a necessary, if not critical part of file processing. Data compression in images takes place through methods like quantization, alternative coding and filtering. In images, ratios as high as 50:1 can be manifested but a tradeoff between size and quality will largely depend on how much compression is desired. Large compression ratios result in poorer quality images as compared to those compressed at smaller ratios. Compression schemes are either lossy or lossless. Lossy schemes like jpeg [1] remove information that the human visual system tends to ignore. These schemes provide higher compression ratios with relatively good quality images. The disadvantage however is that they are irreversible and therefore information once lost can not be recovered. Additionally image quality reduces with increase in compression ratios. Lossless compression schemes like jpeg2000 [2] and the Lempel-Ziv Welch (LZW)[3] re-package information so that less space is utilized. Therefore, although lossless schemes provide better quality and a reversible process, the maximum compression ratios achieved are much lower than those registered by lossy ones. Users desire good quality images even after being highly compressed and preprocessing methods prior to compression are needed to enhance the trade-off between quality and size. Pre-processing methods allow the owners of the images to participate in choosing aspects and sections of the image that can be ignored, over-processed or filtered out. If the right features of an image are chosen and processed at the right levels then irrelevant data can be discarded to reduce the size of the image while improving its quality.

In this paper, we discuss pre-processing methods that can be applied to an image to enhance compression results in terms of size and/or quality. We suggest a pre-processing method for compression that uses either the volume attribute or a modified version that we have called the "vision attribute" to improve compression results in terms of quality and size. The rest of the paper is organized as follows. In Section 2 we briefly survey the current pre-processing methods. Section 3 discusses the theory behind the proposed attribute and method of implementation. Section 4 explores the experimental results obtained prior and after the proposed filtering method, including comparisons with power filtering and results after jpeg, jpeg2000 and LZW algorithms. We provide concluding remarks in Section 5.

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2 Pre-processing for compression

Mathematical morphology is a popular tool for gray scale image analysis. It does not cause blurring even after high level filtering, it allows user flexibility in terms of selection of region of interest and is computationally cheap. Peters [4] proposed the Morphological Image Cleaning (MIC) algorithm that removes noise from an image by use of Alternating Sequential Filters (ASF) that consist of a series of morphological openings and closings with structuring elements of increasing sizes. The MIC algorithm first smoothes the image, then calculates the difference between the smoothed image and the original one. That difference is thresholded at a value greater than the amplitude of the noise, further manipulated and then added to the original image to produce it's noise-less version. The noise removal that the MIC algorithm performs causes an improvement in compression sizes and image quality. However, because it is based on structural morphological openings and closings that are not strictly shape preserving, the final image will have been slightly modified. This is due to the erosion operation that removes the structures that can not contain the structuring element while shrinking the remaining ones. The proceeding dilation may not recover those parts of the remaining components that were lost by the erosion. Connected morphological filtering becomes advantageous because it is shape preserving, idempotent (can not be degraded any further once it has been processed) and can be made to affect desired parts of the image other than the entire image. Young and Evans [5] proposed a connected morphological filtering method based upon attribute filtering using the power attribute in particular. This method is based upon ASF filters consisting of attribute openings and closings and a region can not grow or shrink if its measured power exeeds some defined threshold. Power filtering provides even better compression ratios than the MIC algorithm or filtering by area attribute because this filter removes both the noise and psychovisually redundant information contained in the image.

3 The Proposed Method

We propose an attribute-based preprocessing method to enhance image compression. Attribute filtering views the image as sets of pixels (connected components) rather than single pixels or rigidly defined neighborhoods. For each connected component, an attribute, r, is calculated and compared to a pre-defined threshold T. If $r > T$, the whole connected component is preserved, else, it is removed. Unlike morphological openings and closings which grow/shrink components, attribute filtering totally preserves remaining structures by leaving them untouched and hence resulting in better visually appealing images. In addition to being strictly edge preserving, attribute filtering can be used to create strictly casual scale-spaces, perform both low, intermediary to high level processing tasks and can be given many useful invariance properties like scale and rotation invariance. In this paper, the experiments were performed with binary attribute filters, but the work can be extended further to gray-scale[6].

3.1 Binary Attribute Filtering

Binary attribute filtering has been defined by Breen and Jones [6] as a concept in mathematical morphology that removes connected components from a binary image on the basis of a given criterion of an attribute. Binary attribute filtering is manifested either through binary attribute openings or binary attribute thinnings. Let C, D be connected components of set X and Ψ a binary image operator. Attribute openings remove the bright parts of the image and are characterized by being increasing ($C \subseteq D \Rightarrow \Psi(C) \subseteq \Psi(D)$, idempotent ($\Psi\Psi(C) = \Psi(C)$ and anti-extensive ($\Psi(C) \subseteq C$). Examples include attributes like area, perimeter and moment-of-inertia. On the other hand, attribute thinnings remove the dark parts of an image and are characterised by being idempotent, anti-extensive and non-increasing ($C \subseteq D \nRightarrow \Psi(C) \subseteq \Psi(D)$. Examples include attrributes like perimeter length, elongation, circularity and concavity. Breen and Jones [6] formally defined the binary attribute opening, Γ^T, of a set X, as a trivial opening, Γ_T, of the connected opening, $\Gamma_x(X)$.

$$\Gamma^T(X) = \bigcup_{x \in X} \Gamma_T(\Gamma_x(X)) \tag{1}$$

Where, the connected opening, $\Gamma_x(X)$ at point x is:

$$\Gamma_x(X) = \begin{cases} \text{C that contains } x & \text{if } x \in X, \\ \emptyset & \text{if } x \notin X \end{cases} \tag{2}$$

And the trivial opening, Γ_T of a set C if $C \subseteq E$ and T is an increasing criterion is given by:

$$\Gamma_T(C) = \begin{cases} \text{C} & \text{if } C \text{ satisfies criterion } T, \\ \emptyset & \text{otherwise} \end{cases} \tag{3}$$

On the other hand, it is a trivial thinning, Φ_T, if the T in (3) is a non-increasing criterion. Therefore a binary attribute thinning, Φ^T, of a set X, is a trivial thinning, Φ_T, of the connected opening, $\Gamma_x(X)$.

$$\Phi^T(X) = \bigcup_{x \in X} \Phi_T(T_x(X)) \tag{4}$$

3.2 The Max-Tree Approach

There are three major approaches to implementing attribute filtering. The Pixel queue algorithm [6, 8], the Max-tree approach [9] and the Union-find method [10]. We chose to use the max-tree approach because it implements both attribute openings and thinnings at relatively fast computing time and with more flexibility (variety of filtering rules) [7]. The max-tree approach consists of arranging the subsets of an image into a tree starting from the root node that acts as a parent to all subsequent nodes. Each node represents a flat zone L_h where a set of pixels adopt a single gray-level value of the highest (for max-tree) or lowest (for min-tree) node within that subset. The image is thresholded at level h to obtain the thresholded set consisting of peak components, P_h^k, whose gray-level $\geq h$ (k indicates indices identifying the individual components). C_h^k are the components in P_h^k with gray-level h. Therefore, a max-tree is defined by Meijster and Wilknison [7] as rooted tree in which each of the nodes, C_h^k, at gray-level h corresponds to a peak component, P_h^k. An example is shown in Figure 1 which illustrates the peak components, P_h^k, of a 1-D signal, the

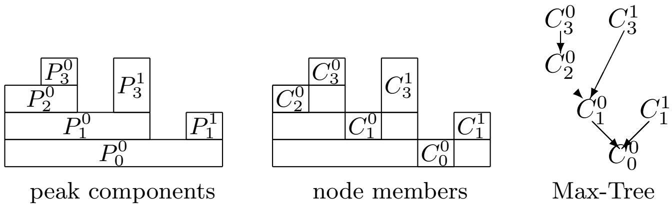

Figure 1: Peak components(P_h^k), corresponding (C_h^k) and the resultant maxtree (right)

corresponding C_h^k at levels $h = 0, 1, 2, 3$ and the resultant max-tree. Filtering is implemented by checking whether a node, C_h^k, satisfies a given criteria of an attribute. If it does not, then the entire node (P_h^k) is removed. If it does satisfy the criteria, P_h^k is preserved.

3.3 The Volume Attribute

The volume attribute [11] in this case behaves in a very similar manner to how the human visual system (HVS) operates. The HVS is not sensitive to small changes in intensity over a large area. Therefore, the volume attribute will be calculated based upon (change in intensity) x area for P_h^k components. The volume attribute is given by:

$$V(X, Y, \alpha) = \sum_{x \in X} (Y(x) - \alpha) \tag{5}$$

where X is the set of pixels in the region, Y is the original image and α is the new intensity value of the region. Our experiments have shown that the volume attribute removes more pychovisually redundant information at a lesser computational time than the power attribute [5] which calculates:

$$P(X, Y, \alpha) = \sum_{x \in X} (Y(x) - \alpha)^2 \tag{6}$$

3.4 The Vision Attribute

We experimented with an attribute which we have called the vision attribute that works in a similar manner with the volume attribute, but calculates (change in intensity) x area for C_h^k components instead of P_h^k and hence removes all C_h^k nodes that do not comply with the conditions.

4 Experimental Results

Twenty two (22) test images obtained from [12] containing 12 natural small grey scale images and 10 natural medium grey scale images were used. They were filtered using the direct criteria which removes nodes if and only if $r < T$[9]. The experiments were implemented in C programming language and matlab 6.5. Quality was measured using the Universal Quality Index [13] metric. The objective of the study was to investigate whether attribute filtering can improve compression of visually lossless images. Comparison of power, volume and vision filtered images versus unprocessed ones at same thresholds, same quality levels and same sizes was conducted.We propose that the preprocessing method goes as follows: Perform an attribute opening and thinning based upon the power, vision or volume attribute of a desired threshold. Determine whether the resultant image is attractive (acceptable) then apply the desired compression algorithm.

4.1 At the same threshold

When processed at a threshold of $T = 100$, six of the images were not affected by either type of filter because the difference in intensities between neighboring connected components is huge and hence 100 was a very low threshold to effect any removal. Our experiments showed that the vision attribute degrades an image very fast, much faster than the volume or power. For example, at T = 3, image *boat* was totally degraded and visually lossy while at T = 100, volume and power filtered ones still looked visually lossless. Vision registered an average quality (for all images at $T = 50$) of 0.5859 in comparison with volume (0.9229) and power (0.8376).
Table 1 shows the overall average compression ratios after processing at thresholds of $T = 50$ and $T = 100$. Comparison of the visually lossless filters (ie volume and power) showed that both filters improve the compression ratios for all compression schemes tested with volume out-performing the power attribute. The percentage improvement exhibited by volume is four times that of power for jpeg and twice for jpeg2000 and LZW. This implies that the volume attribute removes more psychovisually redundant information compared to the power attribute at similar threshold parameters even when the images remain visually lossless. This is because power is a slow filtering attribute that removes relatively smaller particles per unit increase in T.

4.2 At different thresholds

To investigate the behavior of an image over a wide range of threshold values, image *Bridge* was forced to attain size 0 (KB) by processing it at different thresholds of increasing order. It is noted that all the filters reduced file size and behaved in a linear manner, where at thresholds $p, q \in \Re$; $p < q$, $\Rightarrow s(p) > s(q)$, $s(p)$ and $s(q)$ being sizes of the images at p and q respectively. Figure 2 illustrates the findings that show how an increase in bit rate (lower compression) reduces the distortion (1 - quality) in a linear manner for all filters. This reflects how the quality is reduced with an increase in compression. When the three attributes are compared together at similar distortion levels, volume registered the highest compression ratios (lowest bit rates) closely followed by power and then vision (for jpeg/jpeg2000). It is observed that when the images are over filtered upto beyond recog-

Table 1: Comparison of the Compression results (bits per pixel) at same thresholds

	Jpeg			
	None	Power	Volume	Vision
$T = 50$	1.46	1.41	1.27	0.96
$T = 100$	1.46	1.39	1.20	0.85
	Jpeg2000			
	None	Power	Volume	Vision
$T = 50$	4.52	4.28	3.99	3.12
$T = 100$	4.52	4.22	3.85	2.74
	LZW			
	None	Power	Volume	Vision
$T = 50$	6.38	5.83	5.25	3.04
$T = 100$	6.38	5.68	4.99	2.37

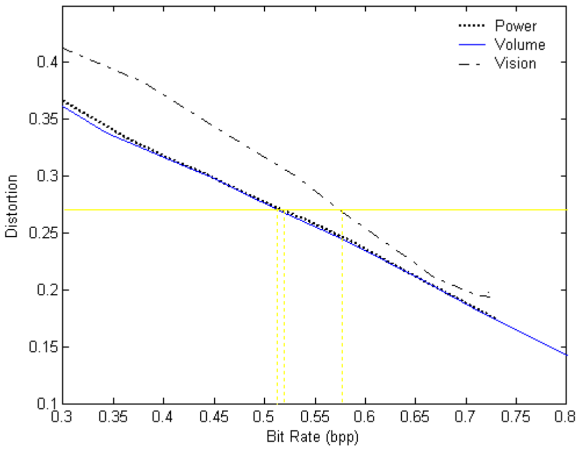

Figure 2: Barbara at selected thresholds after jpeg processing

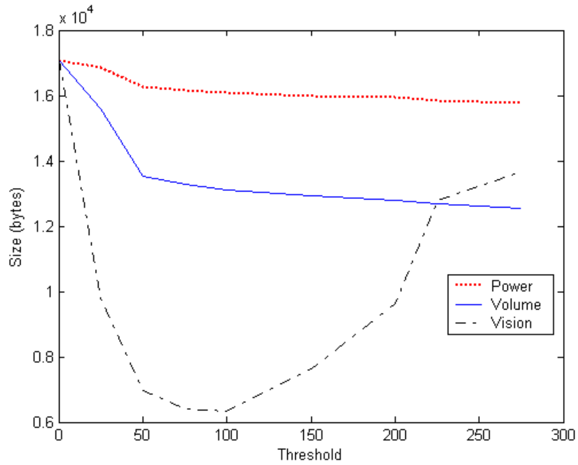

Figure 3: Barbara after huge filtering beyond recognition

nition (98% of nodes deleted), volume and power cause a slow gradual decrease in size as T increases. This linear behaviour ensures that there is a threshold for which $s(p)$ will be 0. On the otherhand, vision decreases size upto a certain point, $s(p)^*$, beyond which increase in T causes $s(p)$ to increase. This is because the vision attribute is edge enhancing. Figure 3 shows the overall behaviour of the *barbara* after vision filters it more than 98%. It shows how vision attains $s(p)^*$ of 6100 at $T = 100$, unlike volume and power that continue reducing $s(p)$ as T increases.

4.3 At the same quality

Fifteen (15) images were filtered at various T values to obtain similar quality of $UQI = 0.90$. At $UQI = 0.90$, the images remain visually lossless as shown in 4. Table 2 shows the various thresholds needed to achieve the target quality for the three attributes. It is observed that the power attribute needs much higher thresholds to attain the given quality in comparison with volume and vision. For example image 6 (*france*) requires a threshold of 250,000 for power as opposed to 2,900 (volume) and 662 (vision). This means that it is quicker to arrive at a desired quality level by using the vision, volume and power attributes respectively. It also emerged that much as a big percentage of the images were being filtered, they remained visually lossless. For example, to achieve $UQI = 0.90$, the power and volume attributes deleted 73,208 and 80,832 nodes respectively. This changed 35% (92,154) and 37 %(96,954) of the pixels respectively. Detailed results are presented in Table 3 which shows that bitrates decreases for all the filters. The highest improvement for jpeg and jpeg 2000 was caused by volume, power and volume respectively. While the highest improvement for LZW was vision followed by power and vision. Furthermore, all filters narrowed the data distribution especially volume with the lowest standard deviation for jpeg / jpeg2000 and vision for LZW.

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Table 2: r needed to attain UQI = 0.90

Image	1	2	3	4	5	6	7	8
Power	295	18	24	1700	20	250,000	340	730
Volume	38	8	9	100	8	2900	21	62
Vision	7	5	4	8	4	662	16	7
Image	9	10	11	12	13	14	15	
Power	900	480	900	13100	144	50	430	
Volume	110	27	64	1240	20	11	85	
Vision	8	14	7	17	11	5	7	

Table 3: Compression results at UQI = 0.90

	Average	None	SD	Power	SD	Vol.	SD	Vis.	SD
Jpeg	bpp	1.54	0.60	1.39	0.55	1.37	0.54	1.44	0.57
	%	-	-	9.96	-	11.21	-	7.00	-
*Jpeg*2000	bpp	4.75	1.29	4.29	1.27	4.28	1.27	4.43	1.29
	%	-	-	9.50	-	9.84	-	6.65	-
LZW	bpp	6.80	2.29	5.70	1.81	5.72	1.83	5.03	1.78
	%	-	-	16.12	-	15.95	-	20.27	-

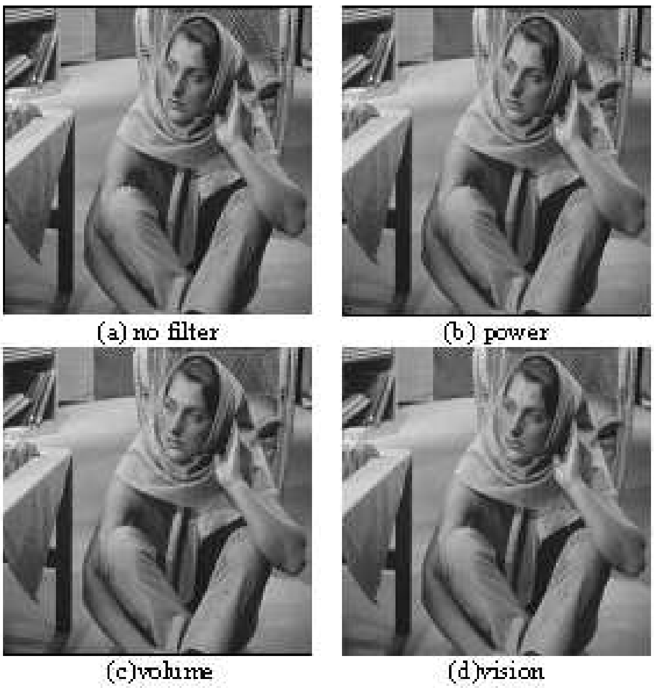

Figure 4: Barbara at UQI = 0.90 after lzw processing

4.4 At the same size

Table 4 shows the quality of 10 randomly selected images forced to attain the same size. For all the images (except *bird*), the volume filtered ones registered the best quality. This generally means that if filtered to the same size, volume exhibits the highest quality, followed by power or vision depending on the image.

5 Conclusion

In this paper, we have discussed an image pre-processing method based on attribute filtering and implemented by the max-tree approach so that visual quality is enhanced through shape preservation. This method also offers more flexibility with attributes and more choice with the different filtering rules. We have applied the power, volume and vision filters on high quality visually lossless images and have found that all consistently increase compression ratios linearly. Even then, each exhibited strengths and weaknesses depending on the environment that was applied. The power attribute needs high parameter values to attain specific sizes / quality. The vision attribute performs best with the LZW scheme and requires relatively low threhold values to achieve a particular size or quality. The volume attribute is best suited for jpeg and jpeg2000 compression. Our experiments have shown that when the three attributes are generally compared, volume consistently produces the best improvements in terms of quality and size after compression. Our prefered choice of filtering rule is the direct rule since the others (like minimum) can cause unpredictable behavior especially with the vision attribute. In conclusion, we

Table 4: UQI indices at selected sizes

Image	Size	Power		Volume		Vision	
		r	UQI	r	UQI	r	UQI
Barbara	41.0	35	0.9285	9	0.9331	4	0.9205
	38.7	360	0.7880	31	0.8024	9	0.7415
	36.1	1,600	0.8011	83	0.8147	14	0.7415
	10.8	14,000	0.6728	580	0.6964	24	0.6232
Bird	5.6	90	0.7496	30	0.7516	7	0.7812
Boat	31.8	450	0.7819	47	0.7980	7	0.7682
Bridge	15.5	250	0.9388	20	0.9424	7	0.8683
Camera	9.8	100	0.7981	17	0.8231	6	0.8070
France	48.2	315,000	0.8372	2,277	0.8639	1500	0.5172
Lena	9.5	3,000	0.8463	150	0.8642	13	0.7803

are convinced that attribute filtering using power, volume and vision attributes is a viable preprocessing method for compression.

6 Future Work

This work can be extended to gray-scale attribute filtering and a super filter that consists of a combination of multiple attributes can be explored.

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