CONTRAST ENTROPY BASED IMAGE ENHANCEMENT AND LOGARITHMIC TRANSFORM COEFFICIENT HISTOGRAM SHIFTING[†]

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ABSTRACT

This paper will present an enhancement technique based upon a new application of histograms on transform domain coefficients called logarithmic transform coefficient histogram shifting (LTHS). A measure of enhancement based on contrast entropy will be used as a tool for evaluating the performance of the proposed enhancement technique and for finding optimal values for variables contained in the enhancement. The algorithm's performance will be compared quantitatively to classical histogram equalization using the aforementioned measure of enhancement. Experimental results will be presented to show the performance of the proposed algorithm alongside classical histogram equalization.

1. INTRODUCTION

All image enhancement techniques have one major goal: to improve some characteristic of an image. Image enhancement techniques can be broken up into two major classifications: spatial domain enhancement and transform domain enhancement.

Spatial domain enhancement techniques deal with the image's intensity values by modifying them based upon various methods. A common example of a spatial technique is histogram equalization, which attempts to alter the spatial histogram of an image to closely match a uniform distribution. Histogram equalization suffers from the problem of being poorly suited for retaining local detail due to its global treatment of the image. It is also common that the equalization will over enhance the image, resulting in an undesired loss of visual data, of quality, and of intensity scale [1].

Transform domain enhancement techniques involve transforming the image intensity data into a specific domain by using such methods as the DCT, Fourier, and Hartley transforms [2-5,7]. These methods utilize these transforms to alter the frequency content of an image to improve desired traits. Many enhancement techniques have been proposed that attempt to enhance the image based upon other transform domains and their characteristics [2-5,7].

This paper will explore a new method for which transform histograms can be utilized to enhance images. The proposed algorithm will address visualizing and altering the transform coefficient histograms through shifting and mapping using the Discrete Cosine Transform (DCT). This paper will also demonstrate a quantitative measurement based upon contrast entropy to determine the efficacy and the optimization of the method.

The paper is organized as follows: Section I lays out the difference between spatial and transform domain enhancement and briefly states the proposed algorithm. Section II is defines the measure of algorithm performance and the logarithmic transform domain. Section III is an explanation of the logarithmic transform domain histogram shifting algorithm (LTHS), and section IV is an analysis of the experimental results using this method. Section V is a discussion of the results and some concluding comments are made.

2. BACKGROUND

In this section, background topics necessary to understand the new methods proposed are discussed. The measure of performance will be explored first followed by a definition of the logarithmic transform domain.

2.1. Measure of performance

A key step in retrieving the image enhancement method's optimal parameters is to create a suitable image contrast measure. A number of contrast measures have been proposed for complex images [2-6]. For example: A local contrast measure [6] is calculated using the mean

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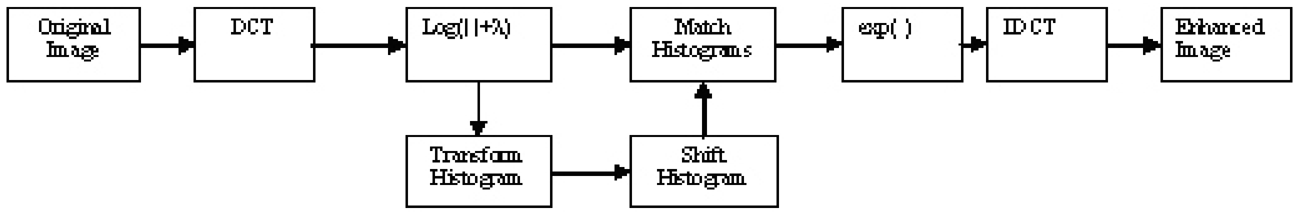


Figure 1: Block Diagram of Logarithmic Transform Histogram Shifting

gray values in two rectangular windows centered on a given pixel. Another contrast measure, defined in [7], is based on a local analysis of edges derived from the definition in [6]. However, there is no universal metric to help identify the "best" enhancement for complex images.

It is natural to modify the Michelson and Weber contrasts in such way that they can be used as a suitable measure of the contrast in complex images. Some modifications of the Weber contrast were proposed in [2,3,5]. Note that Fechner's law gives a relationship between brightness and light intensity which is given by the following equation.

$$B = k' \ln\left(\frac{f}{f_{\max}}\right) + k' \ln\left(\frac{f_{\max}}{f_{\min}}\right) \qquad (1)$$

Where k' is a constant, and fmax and fmin are the maximum and minimum luminance values in a block of the image. Fechner's law provides the basis for the contrast measure based on contrast entropy which was proposed in [3].

$$EME_{\alpha,k_1,k_2}(\Phi) = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} \alpha \left(\frac{I^w_{\max;k,l}(\Phi)}{I^w_{\min;k;l}(\Phi)}\right)^{\alpha} \log \frac{I^w_{\max;k,l}(\Phi)}{I^w_{\min;k;l}(\Phi)} \qquad (2)$$

Where the image is broken up into k_1k_2 blocks, Φ is a given transform, α is an enhancement parameter, and $I^w_{\max}$ and $I^w_{\min}$ are the maximum and minimum in a given block *w*.

This is known as the *measure of enhancement by entrop*y, or EME [3]. The addition of the alpha coefficient is to better elucidate the optimal parameters by emphasizing points of inflection. This creates a powerful visual tool for identifying proper values, but for comparative numerical values alpha is generally set to one.

2.2. Logarithmic transform domain:

The transform domain affords us the ability to view the frequency content of an image. However, the histogram of this data is usually less useful and may require another type of transformation. This is because a plot of the histogram of a typical image is compact and uninformative.

By taking the logarithm of the modulus of the coefficients, the histogram becomes much clearer. This is defined by equation 3.

$$\hat{X}(i,j) = \log(|X(i,j)| + \lambda) \qquad (3)$$

Where λ is some shifting coefficient, usually set to 1.

To return the coefficients to the standard transform domain the process is reversed, through exponentiating the data and restoring the phase. This ensures that the image does not lose its underlying information content in the logarithmic process.

3. ALGORITHM

The algorithm of logarithmic transform coefficient histogram shifting is simple and its implementation can be explained by two major categories: the procedure and choosing optimal parameters for the method.

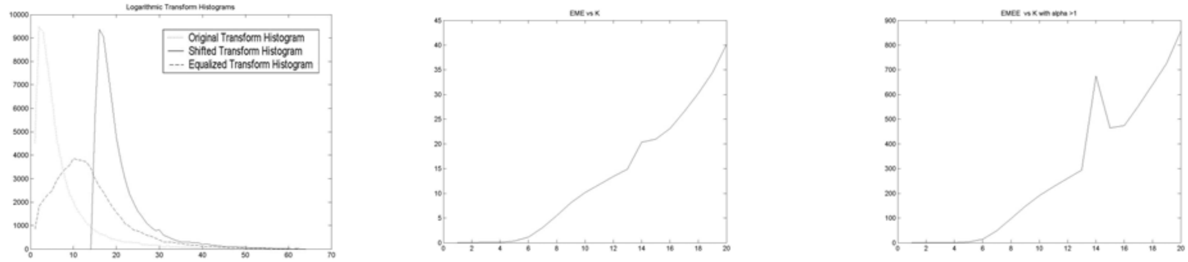
3.1. Transform coefficient histogram shifting

Transform coefficient histogram shifting is a simple, yet effective, procedure. While investigating different qualities of images and their respective transform coefficient histograms, it had become apparent that the visually better images returned distinctly different transform histograms from their worse counterparts. The proposed method stemmed from observation that images enhanced using other enhancement techniques resulted in a positive shift in the logarithmic transform coefficient histogram of the image, as shown in Figure 2a. This shifting concept is then used as the mapping histogram which is then sent through a histogram matching routine as shown in Figure 1.

The algorithm is executed as follows:

Step 1: Transform Image (DCT, Fourier, and others)
Step 2: Take logarithm of magnitude coefficients
Step 3: Calculate coefficient histogram
Step 4: Shift histogram by k bins
Step 5: Map transform data to shifted histogram
Step 6: Exponentiate data
Step 7: Restore phase and Inverse Transform

By mapping the image to the shifted histogram and returning the data to the spatial domain, the dynamic range of the image has been expanded, improving contrast and enhancing details throughout.



(a) (b) (c)

Figure 2: (a) Comparison of LTH of an original image, histogram equalized image, and a LTHS enhanced image, (b) Example of an EME vs K where there is no definitive peak, (c) shows the effect of changing alpha to 1.5

3.2. Choosing optimal parameters

In exploring the LTHS algorithm, it becomes apparent that some defined measure should be used to determine the optimal shifting distance. Utilizing the proposed measure of enhancement based upon entropy affords a simple mathematical basis for determining the best shifting distance. The best shifting distance can be found by

$$EME_{\alpha,k_1,k_2}(\Phi) = \underbrace{local\max}_{shift}\left[\frac{1}{k_1 k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\alpha\left(\frac{I^w_{\max;k,l}(\Phi)}{I^w_{\min;k,l}(\Phi)}\right)^{\alpha}\log\frac{I^w_{\max;k,l}(\Phi)}{I^w_{\min;k,l}(\Phi)}\right] \quad (4)$$

This can also find the best transform for the process, such as the DCT, Fourier, or Hartley transforms.

Through experimentation, a good shifting distance was found to be less than 1/3 the number of histogram bins. For example, a 64 bin histogram will have 64 data points. A shift of more than about 20 data bins, in this case, will over-enhance the image, creating artifacts and other undesirable results.

By plotting the EME based on entropy versus the shifting distance, k, possible optimal shifting distances can be seen. Staying within the bounds of the maximum shifting distance, an easy way to determine optimal shifting distance would be to look for local maxima, and if none exist, areas of strong inflection. A rule of thumb is to take rightmost local maxima or a point of inflection as the optimal shifting distance, as this will usually afford the largest enhancement without heavily distorting the image. Even with images with multiple local maxima's or points of inflection, the best option is usually the point that is on the rightmost part of the EME versus K graph.

One useful technique that was touched upon in the introduction is to play with the alpha coefficient as a means of finding an optimal point. By increasing alpha, it is possible to help emphasize these optimal areas. Figure 2b and 2c shows a comparison of a standard EME vs K graph when alpha is set to one and of the same data with alpha set to 1.5. The point of inflection, that was not a local peak, has now become a local maxima, better expressing the location of a possible optimal point.

4. EXPERIMENTAL RESULTS

This method proved a power and fast method for image enhancement. For the purposes of this paper, two images are shown. A table of results can be found in table 1, and example images can be found in figure 3.

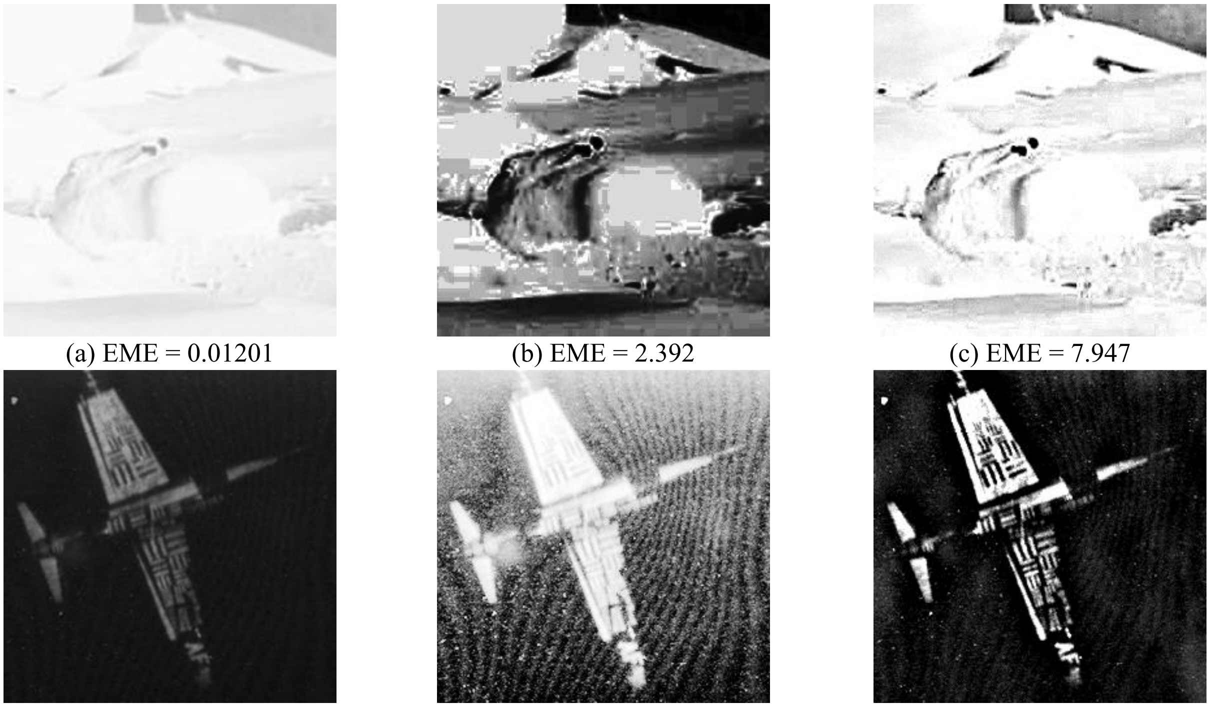
The first was an image of an *artic hare*, chosen because of its strong concentration of data points around the intensity level of 255. This type of image, when enhanced, can have its dynamic range expanded to the point of changing the overall tone of the picture, along with creating ugly artifacts as shown in [1].

The second image chosen was the *U2* image. This image is the direct opposite of the *artic hare* image, because it has data points concentrated around the lower end of the intensity spectrum.

The first image overall tone is almost perfectly white, with very little variation, making it a hard image to enhance without altering the image drastically. The original EME had an extremely low value of 0.01201. After applying our algorithm to the image using a 64 bin histogram, we found the optimum shifting distance to be 16 bins. After the enhancement, the EME had risen to 7.947, which is a drastic improvement from the low EME value of the original image. Compared to straight histogram equalization, which caused artifacts and tonal change to the image and an EME of 2.392, LTHS enhanced the image better and avoided the undesirable side effects.

The second image, the *U2*, is characteristically dark and dull. Our enhancement technique brought out the subtle details on the wings of the plane and in the background without overemphasizing any specific part of the image. The original image had an EME of 0.3340. After our process, the enhanced image returned an EME of 237.169, a staggering improvement.

Standard spatial histogram equalization had some nasty side effects. The *U2* image was lost in a grain and noise, as the process over emphasized the subtle background ripples and film grain. The histogram equalization method returned an EME of 23.376.



(a) EME = 0.01201 (b) EME = 2.392 (c) EME = 7.947

(d) EME = 0.3340 (e) EME = 23.376 (f) EME = 237.169

Figure 3: (a-c) *Artic Hare:* Original image, enhanced by histogram equalization, and enhanced by LTHS, respectively, (d-f) *U2:* Original image, enhanced by histogram equalization, and enhanced by LTHS, respectively.

Image	**Original**	**Histogram Equalization**	**LTHS**	
Artic Hare	0.01201	2.392	K=16	7.947
Copter	0.0359	1.303	K=14	20.345
Moon	0.8681	6.636	K=13	185.672
Plane	0.3340	23.376	K=13	237.169
Pentagon	0.2183	41.525	K=18	335.569

Table 1: EME of original images, histogram equalized images, and LTHS enhanced images.

5. CONCLUDING REMARKS

This paper proposed a new method of image enhancement based upon the logarithmic transform coefficient histogram using contrast entropy as a measure of performance and of optimization. The performance of this algorithm was compared to a popular enhancement technique, histogram equalization.

LTHS has been shown to be a powerful method for enhancing images. It affords a simple and quick implementation that our results have shown to outperform popular enhancement techniques, such as histogram equalization, both visually and numerically, and although the results focused on the DCT transform, it is possible to find an optimal transform by using the EME.

This leads into the possibility of further investigation and research into the properties and the flexibility of the logarithmic transform coefficient histogram as a viable method for image enhancement, whereas histograms have been usually been traditionally restricted to the spatial domain.

6. REFERENCES

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