Transform Coefficient Histogram-Based Image Enhancement Algorithms Using Contrast Entropy

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***Abstract*—Many applications of histograms for the purposes of image processing are well known. However, applying this process to the transform domain by way of a transform coefficient histogram has not yet been fully explored. This paper proposes three methods of image enhancement: a) logarithmic transform histogram matching, b) logarithmic transform histogram shifting, and c) logarithmic transform histogram shaping using Gaussian distributions. They are based on the properties of the logarithmic transform domain histogram and histogram equalization. The presented algorithms use the fact that the relationship between stimulus and perception is logarithmic and afford a marriage between enhancement qualities and computational efficiency. A human visual system-based quantitative measurement of image contrast improvement is also defined. This helps choose the best parameters and transform for each enhancement. A number of experimental results are presented to illustrate the performance of the proposed algorithms.**

***Index Terms*—Contrast entropy, contrast measure, discrete cosine transform (DCT), discrete Fourier transform (DFT), human vision system, image enhancement, transform histogram.**

I. Introduction

THE goal of image enhancement techniques is to improve a characteristic or quality of an image, such that the resulting image is better than the original, when compared against a specific criteria [18]. Current research in image enhancement covers such wide topics as algorithms based on the human visual system [21], histograms with hue preservation [33], JPEG-based enhancement for the visually impaired [19], and histogram modification techniques [16]. Two major classifications of image enhancement techniques can be defined: spatial domain enhancement and transform domain enhancement.

Spatial domain enhancement techniques deal with the image's direct intensity values. A common nontransform-based enhancement technique is global 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 [16], [34]. There are other limitations. For example, small-scale details that are often associated with the small bins of the histogram are eliminated [4]. A survey of the spatial domain enhancement techniques can be found in [3], [4], [11], [16], [23], [25], [35], [42], [43].

Transform domain enhancement techniques involve mapping the image intensity data into a given transform domain by using transforms such as the 2-D discrete cosine transform (DCT), Fourier transform, and other fast unitary transforms. A survey of the transform-based image enhancement techniques can be found in [3], [4], [22], [25], [27]–[29], [32]. The basic idea in using this technique is to enhance the image by manipulating the transform coefficients. Recently, many transform-based enhancement techniques have been proposed [3], [18], [22], [28], [29], [32], [35], [36]. One of the more popular and proven enhancement techniques is alpha rooting and its modifications [3], [4], [28], [29], [31], [32], [36]. The basic limitations of the transform-based image enhancement methods are: 1) they introduce certain artifacts which Aghagolzadeh and Ersoy called "objectionable blocking effects" [32]; 2) they cannot simultaneously enhance all parts of the image very well; 3) it is difficult to automate the image enhancement procedure.

Both of these methods have their merits and their shortcomings, given their differing interpretations of image data. It then becomes obvious to ask the question: is it possible to develop a new method, which has the best properties from both transform and spatial domain techniques? For example, is there a way of somehow combining histogram equalization and transform enhancement? The answer: Yes, using transform histograms [9], [10], which have, as of yet, been mostly unexplored.

This paper explores three new methods for which transform histograms can be utilized for contrast enhancement of images: logarithmic transform histogram mapping, logarithmic transform histogram shifting, and logarithmic transform histogram shaping. It also proposes methods for visualizing the transform coefficient histogram and for measuring the overall contrast of the image by using a new contrast measure which uses some of the elements of the human visual system.

The paper is organized in the following manner. Section I lays out the difference between spatial and transform domain enhancement and briefly states the proposed algorithms. Section II is used to define histogram equalization, histogram mapping, discrete orthogonal transforms, alpha rooting, and the logarithmic transform domain. Various measures of enhancement and algorithm performance will also be introduced. Section III

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(a) (b) (c)

Fig. 1. (a) Original image of *Copter*, (b) resulting image after basic histogram equalization of *Copter*, and (c) comparison of (dark blue) original histogram versus (light blue) equalized histogram.

lays out the three proposed enhancement algorithms: logarithmic transform histogram mapping with spatial equalization, logarithmic transform histogram shifting, and logarithmic transform histogram shaping using Gaussian distributions. 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.

II. Background

In this section, we will cover the background topics necessary to understand the proposed methods. An explanation of histogram equalization and of histogram mapping will be given, followed by a definition of various discrete orthogonal transforms. Alpha rooting will be presented next, followed by an explanation of the logarithmic transform domain. Finally, our measure of enhancement will be introduced along with methodology for choosing optimal parameters, transforms, measures, and methods.

A. Histogram Equalization

Histogram equalization maps the input image's intensity values so that the histogram of the resulting image will have an approximately uniform distribution [16], [25]. Given an image $A(x,y)$ and a desired output image $B(x,y)$ there is some transformation function f, which maps A to B. All the intensity values in A in the region of values n_A to $n_A + dn_A$ will have their values mapped to a corresponding region in B in the values range of n_B to $n_B + dn_B$. Each of these images will have a probability density function (PDF) $p_A(n_A)$ and $p_B(n_B)$. Assuming a 1-1 mapping, it is easy to show that

$$p_B(n_B)dn_B = p_A(n_A)dn_A.$$

Using this relationship, it can be shown that the mapping function from A to B is

$$f(n_A) = n\int_0^{n_A} p_A(u)du = nF_A(n_A)$$

where $F_A(n_A)$ is the cumulative probability distribution function of the original image. Therefore, to return a histogram equalized image, an image must be transformed using its cumulative probability function. The primary reason for histogram equalizations success at image enhancement is because it expands the dynamic range of intensity values while flattening the histogram.

On many images, histogram equalization provides satisfactory to good results, but there are a number of images where it fails to properly enhance an image [16], [34]. As an example, Fig. 1(a) shows an image of a helicopter. The resulting image after 256-level histogram equalization was applied is shown in Fig. 1(b). Fig. 1(c) compares the spatial histograms of both images. The main focus of the image has become more of a silhouette than a picture. Other problems with histogram equalization can be artifacts and overall brightness change in the resulting image.

Many alterations of histogram equalization have been proposed to counter the affects of this range expansion [16], [34]. The most basic is local histogram equalization using sub-blocks. These techniques have their own variations such as nonoverlapping and overlapping with temporal filtering to reduce artifacts [40]. Nonoverlapping local histogram equalization normally results in ugly blocking artifacts [40].

B. Histogram Mapping

Histogram mapping, a more generalized version of histogram equalization, allows us to alter the data so that the resulting histogram matches some desired curve. This is also known as histogram matching and histogram specification [26]. In our case, we will use the example of transforming a random exponential PDF to a hyberbolization of our original histogram, effectively mapping the histogram of the data to match our desired PDF. The heart of histogram mapping lies at solving an equation that compares the integrals of the probability density function, basically comparing their cumulative density functions

$$\int_0^{n_B} p_B(y)dy = \int_0^{n_A} p_A(x)dx$$

where $p_B(n_B)$ is our desired hyberbolization of our histogram, and $p_A(n_A)$ is our original histogram, which we will approximate as an exponential

$$p_A(n_A) = A_0 e^{-n_A}, \quad p_B(n_B) = B_0 n_B e^{-n_B^2}.$$

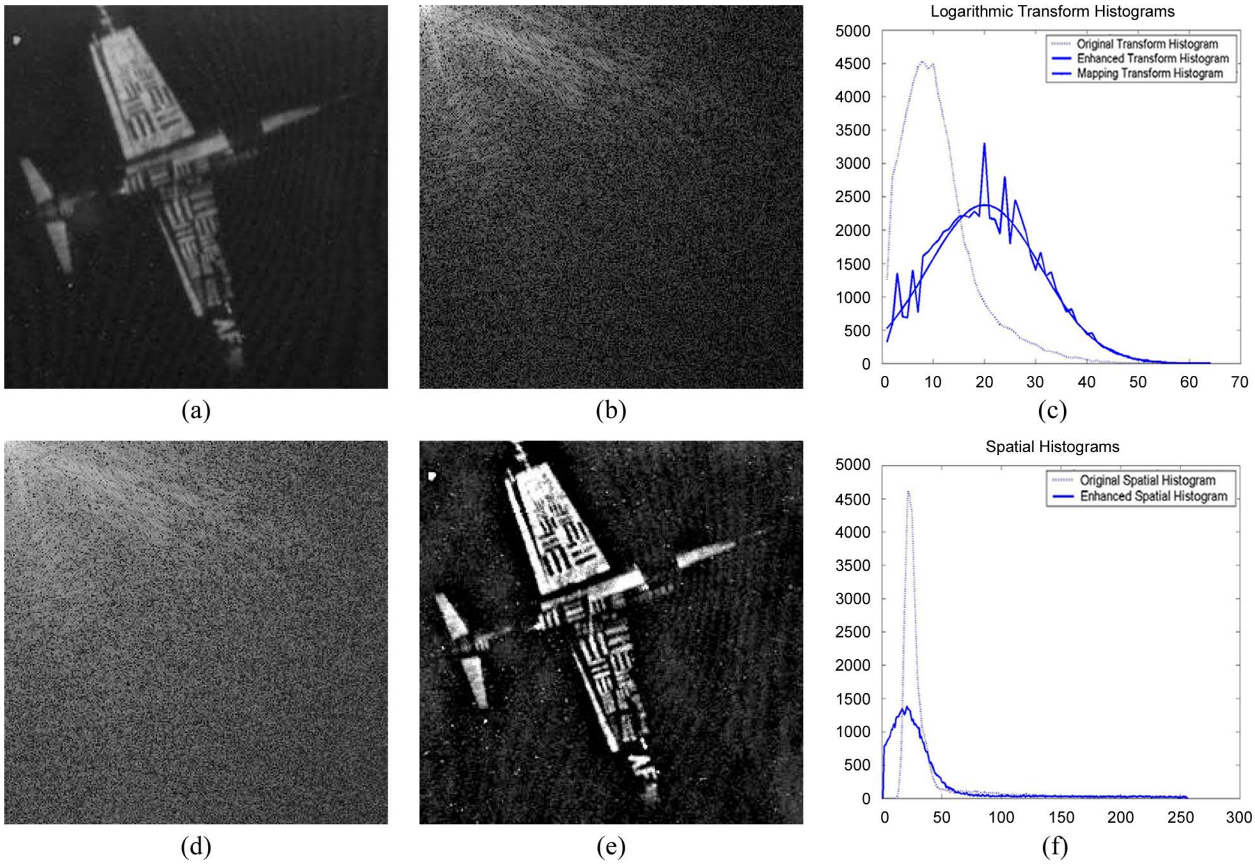


Fig. 2. (a) Original *Plane* image, (b) DCT of original image, (c) plots of the logarithmic transform histograms of the original, desired, and enhanced images, (d) DCT of mapped histogram image, (e) enhanced image, and (f) the resulting spatial histogram.

Plugging into the integral equation and solving, we get

$$B_0 \int_0^{n_B} y e^{-y^2} dy = A_0 \int_0^{n_A} e^{-x} dx$$

$$B_0 \left(\frac{1 - e^{-n_B^2}}{2} \right) = A_0 (1 - e^{-n_A})$$

$$n_B = \sqrt{- \ln \left(1 - \frac{2A_0}{B_0} (1 - e^{-n_A}) \right)}.$$

The resulting equation is the transformation of an exponential distribution to a hyperbolization of that histogram. A common implementation of this general histogram mapping method is done in three steps: 1) equalizing the original image, 2) histogram equalize the desired output image, 3) and apply the inverse of the second transformation to the original equalized image

$$T_1 = F_A(n_A) = \int_0^{n_A} p_A(y) dy$$

$$T_2 = F_B(n_B) = \int_0^{n_B} p_B(x) dx$$

$$T = T_2^{-1} \left(T_1(n_A) \right).$$

Since the data is discrete, it will be almost impossible to generate a perfectly flat or perfectly matched histogram. Therefore, the algorithm we use attempts to minimize a cost function to keep the results as close as possible to a desired result. The cost function is defined as follows:

$$\cos t = |c_1 \left(T(k) \right) - c_0(k)|$$

where c_0 is the cumulative histogram of the original image and c_1 is the cumulative histogram of the desired histogram. An example of this process can be found in Fig. 2, where we map the transform data to a specified distribution.

C. Discrete Orthogonal Transforms

Orthogonal transforms are commonly used in image enhancement, chosen for their various properties [38], [39]. In this section, sinusoidal basis functions will be presented for the Discrete Hartley, Fourier, and Cosine transforms. Each of these transforms has similar properties: DC values in the top-left corner and high frequency content in the lower-left corner.

The forward and inverse N-point 2-D Discrete Cosine transform are defined as

$$y(k,l) = \frac{2}{N} c(k) c(l) \sum_{n=0}^{N-1} \sum_{m=0}^{N-1} x(n,m) \cos \left[\left(n + \frac{1}{2} \right) \frac{k\pi}{N} \right] \times \cos \left[\left(m + \frac{1}{2} \right) \frac{l\pi}{N} \right]$$

$$x(n,m) = \frac{2}{N} \sum_{n=0}^{N-1} \sum_{n=0}^{N-1} c(k) c(l) y(k,l) \cos \left[\left(n + \frac{1}{2} \right) \frac{k\pi}{N} \right] \times \cos \left[\left(m + \frac{1}{2} \right) \frac{l\pi}{N} \right]$$

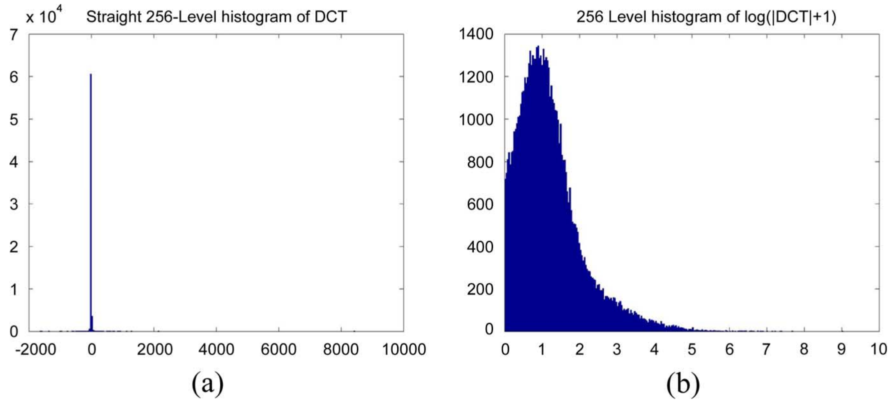


Fig. 3. Comparison of (a) a transform coefficient histogram and (b) logarithmic transform coefficient histogram.

where $\mathrm{n}, \mathrm{m} = 0, 1, \ldots, \mathrm{N}-1; y(k,l)$ is 2-D DCT, and $x(n,m)$ is the original 2-D function.

The standard forward and inverse N-point 2-D Discrete Hartley transform is given as

$$y(u,v) = \frac{1}{N}\sum_{n=0}^{N-1}\sum_{k=0}^{N-1} x(n,k)\mathrm{cas}\left(\frac{2ku\pi}{N}\right)\mathrm{cas}\left(\frac{2nv\pi}{N}\right)$$
$$h(n,k) = \frac{1}{N}\sum_{u=0}^{N-1}\sum_{v=0}^{N-1} x(u,v)\mathrm{cas}\left(\frac{2(nu+kv)\pi}{N}\right)$$

where $\mathrm{cas(x)} = \mathrm{sin(x)} + \mathrm{cos(x)}$

Similar to the Hartley, the 2-D N-point discrete Fourier transform (DFT) has a complex element

$$y(u,v) = \frac{1}{N}\sum_{n=0}^{N-1}\sum_{k=0}^{N-1} x(n,k)e^{-j\left(\frac{2nv\pi}{N}+\frac{2nv\pi}{N}\right)}$$
$$h(n,k) = \frac{1}{N}\sum_{u=0}^{N-1}\sum_{v=0}^{N-1} x(u,v)e^{j\left(\frac{2nv\pi}{N}+\frac{2nv\pi}{N}\right)}.$$

D. Alpha Rooting

Alpha rooting is a simple method originally proposed by Aghagolzadeh and Ersoy [32] and later modified by Agaian [28], [29] that can be used in combination with many different orthogonal transforms such as the Fourier, Hartley, and Haar wavelet and cosine transforms. The mathematical form of this operation can be seen as follows:

$$\widehat{X}(p,s) = X(p,s)\,|X(p,s)|^{\alpha-1} = |X(p,s)|^{\alpha}\,e^{j\theta(p,s)}$$

where $X(p,s)$ is the transform coefficients of the image $x(p,s)$, α is a user defined operating parameter, and $\theta(\mathrm{p,s})$ is the phase of the transform coefficients. The resulting output shows an emphasis on the high frequency content of the image without changing the phase of the image results in an overall contrast enhancement of the entire image. This enhancement is not without its consequences, sometimes resulting in ugly artifacts [17].

E. 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 compact and uninformative, as shown in Fig. 3(a). A work around to this problem is to take the logarithm of the image. This is done in two steps. The first step requires the creation of a matrix to preserve the phase of the transform image. This will be used to restore the phase of the transform coefficients. The next step is to take the logarithm of the modulus of the coefficients as shown by

$$\hat{X}(i,j) = \ln\left(|X(i,j)| + \lambda\right)$$

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

The shifting coefficient is used to keep from running into discontinuities. This results in a much more visible interpretation of the histogram as shown in Fig. 3(b). To return the coefficients to the standard transform domain, the signal is exponentiated and the phase is restored.

This approach can be extended by:

a) using the following operator/function:

$$\hat{X}(i,j) = \gamma\ln\left(\eta\,|X(i,j)| + \lambda\right)$$

where γ, η, and λ are some parameters;

b) a zonal approach or a multiple shift algorithm.

In Fig. 4, examples of the possibilities of using the parameter-based logarithm and the zonal approach to find optimal enhancement values are shown. Of note are the peaks of the EME values, showing obvious optimal values. This method of scanning parameters versus EME values can be extended to include any variable in an enhancement technique including those mentioned in this paper.

F. Measure of Performance

An important step in direct image enhancement approach is to create a suitable image enhancement measure. The improvement found in the resulting images after enhancement is often very difficult to measure. This problem becomes more apparent when the enhancement algorithms are parametric and one needs: a) to choose the best parameters; b) to choose the best transform among class of unitary transforms; c) to automate the image enhancement procedures. The problem becomes especially difficult when an image enhancement procedure is used as a preprocessing step for other image processing purposes such as object detection, classification, and recognition. There is no universal measure which can specify both the objective

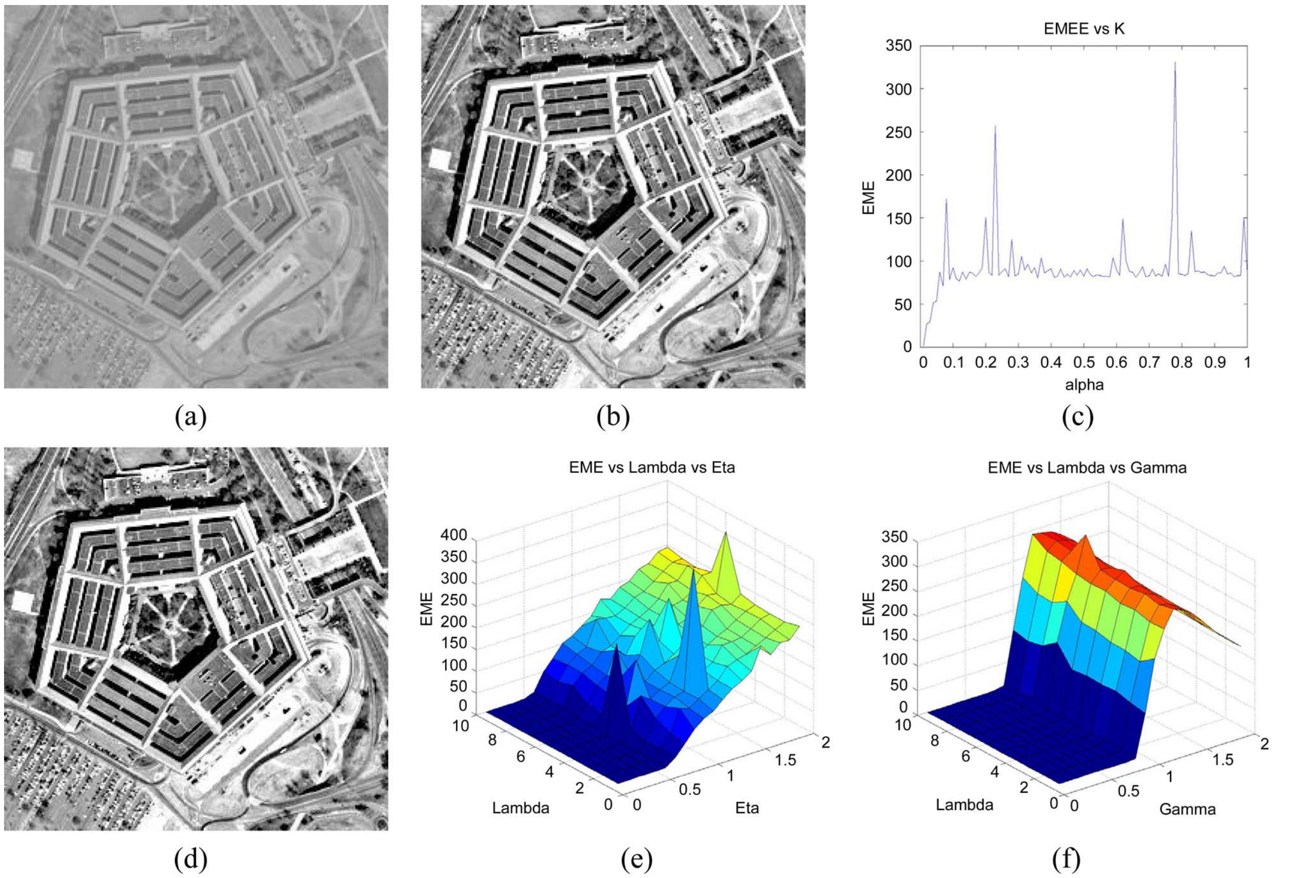


Fig. 4. (a) Original *Pentagon* image, (b) *Pentagon* image enhanced using LTHMHE with alpha rooting, using $\mathrm{k} = 0.78$ (c) EME versus k, where k is a parameter of enhancement. Other examples of using plots of the EME to find optimal parameter values by picking the maximum: (d) *Pentagon* image enhanced using LTHMHE with $\eta = 1.2$ and $\lambda = 3$, (e) EME versus η versus λ, and (f) EME versus γ versus λ (EME is the image enhancement measure explained in Section II-F).

and subjective validity of the enhancement method [20]. In this section, we analyze the commonly used image enhancement measures and present a new quantitative measure.

Many enhancement techniques are based on enhancing the contrast of an image [6], [14], [24], [30]. There have been many differing definitions of an adequate measure of performance based on contrast [2], [20], [43]. Gordon and Rangayan used local contrast defined by the mean gray values in two rectangular windows centered on a current pixel. Begchladi and Negrate defined an improved version of the aforementioned measure by basing their method on local edge information of the image [2]. In the past, attempts at statistical measures of gray-level distribution of local contrast enhancement such as those based on mean, variance, or entropy have not been particularly useful or meaningful. A number of images, which show an obvious contrast improvement, showed no consistency, as a class, when using these statistical measurements. Morrow introduced a measure based on the contrast histogram, which has a much greater consistency than statistical measures [43].

Measures of enhancement based on the human visual system have been proposed before [15]. Algorithms based on the human visual are fundamental in computer vision [13]. Two definitions of contrast measure have traditionally been used for simple patterns [18]: *Michelson* [1], [5] for periodic patterns like sinusoidal gratings, and *Weber* for large uniform luminance backgrounds with small test targets [18]. However, extending these measures is not effective when applied to complex images [7], [18]. The first practical use of Weber's law based on contrast measure was developed by Agaian in [37].

Let an image, I, be split into $k_1 \times k_2$ blocks $B(k,l)$ *with center* (k,l) of size $M_1 \times M_2$

$$\mathrm{AWC} = \underbrace{\max}_{\Phi,\text{parameters}} \left\{ \underbrace{\min}_{k,l} \left\{ \frac{I^{w}_{\max;k,l}(\Phi,\text{parameters})}{I^{w}_{\min;k,l}(\Phi,\text{parameters}) + c} \right\} \right\} \tag{1}$$

where Φ is a given transform from class of fast unitary transforms (including wavelets), where the *parameters* are the processing enhancement algorithm parameters, where $I^{w}_{\max;k,l}$, $I^{w}_{\min;k,l}$ are the maximum and minimum luminance values in a block $B(k,l)$ of the image, and where c is a small constant equal to 0.0001 to avoid dividing by 0.

Weber's contrast values are often used in photography to specify the difference between bright and dark parts of the picture. It should be noted that the small block the ratio

$$\frac{I^{w}_{\max;k,l}(\Phi,\text{parameters})}{I^{w}_{\min;k;l}(\Phi,\text{parameters})}$$

satisfies this application. This definition is not useful for real-world luminance values because of their much higher dynamic range and the logarithmic response characteristics of the human eye [35]

$$\mathrm{C_{simple}} = \mathrm{L_{max}}/\mathrm{L_{min}}.$$

AWC is called the image enhancement *measure*, or *contrast measure*. This measure can be used for finding the best wavelet, which varies across different wavelet sub-bands and different classes of wavelets, from among about 1000 wavelets. A remarkable fact, which can be shown by experimentation, is that the empirically determined best wavelet is also the optimal wavelet found by using this measure. This experiment was done using 100 SAR images and 300 wavelets. The presented *measure* has shown the beneficial effect of detecting the small targets on SAR images [37].

Later, some modifications of this measure were developed by Agaian, and presented in [35]

$$\mathrm{EME}_{\alpha,k_1,k_2}(\Phi) = \frac{1}{k_1k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_2} 20\ln\frac{I^w_{\max;k,l}(\Phi,\mathrm{par})}{I^w_{\min;k,l}(\Phi,\mathrm{par})+c} \tag{2}$$

where the image is broken up into $\mathrm{k_1k_2}$ blocks, Φ is a given transform, α is an enhancement parameter, $I^w_{\max;k,l}$ and $I^w_{\min;k;l}$ are the maximum and minimum in a given block, $B(k,l)$, and c is a small constant equal to 0.0001 to avoid dividing by 0. $\mathrm{EME}_{\alpha,k_1,k_2}(\Phi)$ is called a *measure* of image enhancement or *contrast measure with respect to transform* Φ. Therefore, the optimal transform, Φ, is relative to the measure of enhancement, $\mathrm{EME}(\Phi_0) = \mathrm{EME}$.

This measure of enhancement is used to find the average ratio of maximum to minimum intensities in decibels. Intuitively it makes sense, since it takes the average ratio of maximum to minimum points in each block over the entire image to use the fact that the relationship between stimulus and perception is logarithmic [12]. The Weber–Fechner law attempts to describe the human perception of various physical stimuli. Fechner later offered an elaborate theoretical interpretation of Weber's findings by defining a relationship between brightness and light intensity which is given by the following equation known as the Weber–Fechner law

$$B = k'\ln\left(\frac{f}{f_{\max}}\right) + k'\ln\left(\frac{f_{\max}}{f_{\min}}\right) \tag{3}$$

where $\mathrm{k'}$ is a constant, and fmax and fmin are the "absolute threshold" and "upper threshold" of the human eye [12], [22].

However, the method shown in (2) can be shown to be range dependent, changing itself based on the maximum and minimum range, and may not be ideal for measuring enhancement in all circumstances. This is why a second method of enhancement has been proposed based upon the concept of entropy

$$\mathrm{EME}_{\alpha,k_1,k_2}(\Phi) = \frac{1}{k_1k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_2} \alpha\left(\frac{I^w_{\max;k,l}(\Phi,\mathrm{par})}{I^w_{\min;k,l}(\Phi,\mathrm{par})+c}\right)^{\alpha} \times\ln\frac{I^w_{\max;k,l}(\Phi,\mathrm{par})}{I^w_{\min;k,l}(\Phi,\mathrm{par})+c}. \tag{4}$$

This is known as the *measure of enhancement by entropy*, or EME using entropy [35]. The addition of the alpha coefficient is to better elucidate the optimal parameters, which will be shown later.

We also wish to introduce the Michelson law-based *contrast measure*

$$\begin{aligned}\mathrm{EME} &= \max_{\phi\in\{\phi\}}(\mathrm{EME}(\phi))\\ &= \max_{\phi\in\{\phi\}}\left(\frac{1}{k_1k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1} 20\ln\frac{I^W_{\max;k,l}-I^W_{\min;k,l}}{I^W_{\max;k,l}+I^W_{\min;k,l}+c}\right).\end{aligned} \tag{5}$$

These definitions use the *Michelson Contrast*, or modulation, definition: The relation between the spread and the sum of the two luminances can be represented as

$$\mathrm{Modulation} = (\mathrm{L_{max}} - \mathrm{L_{min}})/(\mathrm{L_{max}} + \mathrm{L_{min}}).$$

The main idea behind this measure is to use the relationship between the spread and the sum of the two luminance values found in a small block. It then takes the average modulation in each block over the entire image. In the context of vision, such a relationship could be caused by scattered light introduced into the view path by a translucent object

$$\begin{aligned}\mathrm{AME} &= \underbrace{\mathrm{Max}}_{\Phi,\alpha}\{\mathrm{AME}_{\alpha,k_1,k_2}(\Phi)\}\\ \mathrm{AME}_{\alpha,k_1,k_2}(\Phi) &= \frac{1}{k_1k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\alpha\left[\frac{I^W_{\max;k,l}-I^W_{\min;k,l}}{I^W_{\max;k,l}+I^W_{\min;k,l}+c}\right]^{\alpha}\\ &\quad\times\ln\frac{I^W_{\max;k,l}-I^W_{\min;k,l}}{I^W_{\max;k,l}+I^W_{\min;k,l}+c}.\end{aligned} \tag{6}$$

An example of the AWC, EME, EME of Entropy, Michelson law EME, and AME plotted versus an enhancement parameter, alpha, can be found in Fig. 5. Fig. 5(c) shows a graph of an image's EME, as defined by (2), against a variable k, showing how there is no obvious optimal point. However, using the EME based upon entropy, as shown in Fig. 5(d), an optimal point is apparent. Our proposed method works best with the measures based upon entropy such as the EME of Entropy and the AME. For this paper, the EME of entropy, (4), will be used to measure results.

G. Choosing an Optimal Measure of Enhancement and Method

In evaluating and choosing an algorithm for enhancement and for measuring this enhancement, it is important to understand how each enhancement measure works with a given enhancement method. By properly matching measures with algorithms one can increase the effectiveness of the overall technique.

We need to establish a basis for what defines a good measure of enhancement. For this paper, we propose the following characteristics of a good enhancement measure; it must 1) measure the desired characteristic in some holistic way, 2) show a proportional relationship between an increase or decrease of that

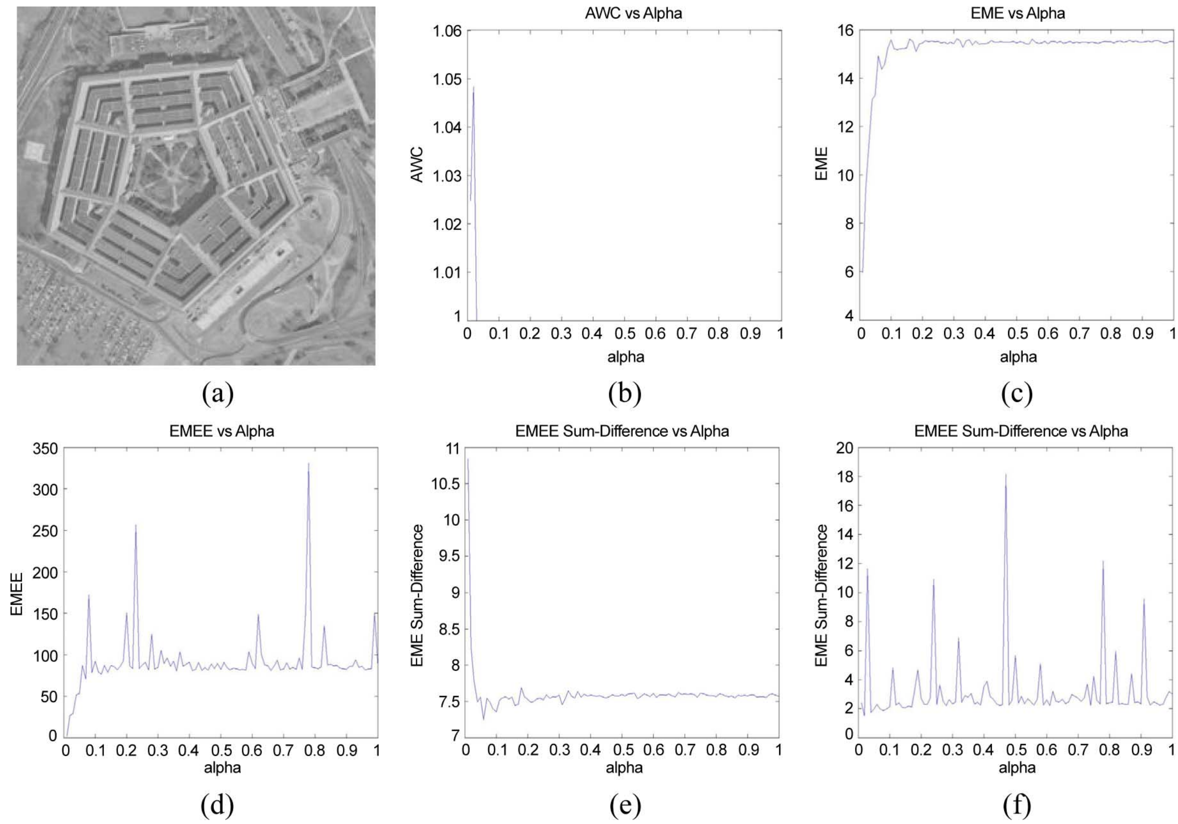


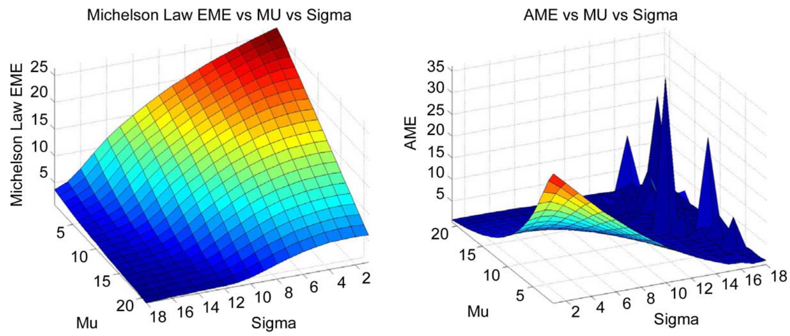
Fig. 5. (a) Original *Pentagon* image; (b)–(f) graphs of alpha versus AWC, EME, EME of Entropy, Michelson Law EME, AME.

Fig. 6. (a) Original 8×8 block with EME, (b) higher contrast 8×8 block with EME, and (c) lower contrast 8×8 block with EME.

characteristic, and 3) have some resulting characteristic to find optimal points. For our recursive methods based on logarithmic transform coefficient histograms, we can meet these requirements by limiting our measures to those that have some inherent peaking nature and show some proportional relationship to increasing contrast.

The first of these characteristics is fairly intuitive; in order for a measure of image enhancement to be successful, it must in some manner measure a characteristic of the image. For instance, the EME by entropy is of the form X log X, which is by definition the entropy formula. Because we replace X with the Weber Contrast, the EME by entropy is actually measuring the entropy, or information, in the contrast of the image. Because this generally measures the image contrast, the measure is consistent with this first characteristic. A measure which is used with an enhancement algorithm before edge enhancement would need to measure some given characteristic in a similar manner. Our emphasis, however, is on low-contrast image enhancement.

The second characteristic is also fairly intuitive. In order to measure distance, a larger number must be returned for longer distances. In order to measure image enhancement, a larger number must be returned for a better enhancement. Fig. 6(a) shows the Lena image, with the corresponding EME shown.



(a) (b)

Fig. 7. Example measures: (a) Michelson-based EME and (b) AME using the transform histogram shaping algorithm.

Fig. 6(b) shows the same image, but with all values above the mean increased by ten and all values below the mean decreased by ten, and the corresponding EME by entropy. As can be seen, this has the effect of increasing the overall contrast in the image by spreading data away from the mean, which further increases the EME of the image. If the opposite were to be done, increase all values beneath the mean and decrease all values above the mean, this would lower the contrast and, hence, the EME value, as shown in Fig. 6(c). This demonstrates the second characteristic.

The third characteristic is necessary for a measure of image enhancement to be useful for real world image enhancement. Although there may be many proportional relationships between image contrast and the input parameters, if there is nothing which indicates optimum parameters then no optimal enhanced image can be selected using the enhancement measure. There are many features, such as zero crossings, discontinuities, or any other definable mark, that can be used to help select parameters. For our work, the local maxima measures are used to select the optimal enhancement parameters. For example, the graphs of Fig. 7 show example measures of enhancement for the transform histogram shaping algorithm. While the graph in Fig. 7(a), the Michelson-based EME, accurately shows a proportional relationship between the parameters and the image contrast, it is difficult to select the best parameters. On the other hand, the AME shown in Fig. 7(b) clearly depicts definable peaks which can be used to quickly and easily select the best operating parameters to obtain a good enhanced image.

Any measure which lacks one of these three characteristics will not be an optimal measure of image enhancement. If the algorithm does not measure a desired quality of the image, for instance, contrast, then the measure is not a meaningful measure of image enhancement. If it does not show some proportional relationship between this quality and the input parameters, then the measure cannot accurately be used to compare images. Finally, if the measure does not have some defining trait which can be used to select optimal operating parameters, then the measure is less useful for real world enhancement.

Fig. 8 compares our various measures of enhancement for our transform histogram shaping algorithm. The graphs were generated by performing the enhancement for the range of parameter values, assessing the output images using a measure, and plotting these results versus the various enhancement variables. By looking at these results, we can see that some obvious candidates for our measure of enhancement were those based on entropy: The EME with entropy and the AME. All of these measures measure the image contrast, and show the same proportional relationship between contrast and the parameters, satisfying the first and second characteristics. While the AWC and EME measures in Fig. 8(a) and (b) shows a distinct ridge from which optimal parameters can be chosen, satisfying the third characteristic, the EME with Entropy and the AME are clearly the best measures for this enhancement method. The distinct peaks in the graphs in Fig. 8(c) and (e) makes selection of parameters quick and easy. The Michelson EME, however, does not satisfy the third characteristic when used with this enhancement method, which indicates that this is not a good measure to use with this enhancement algorithm.

It is important to note that choice of enhancement measure depends on the enhancement algorithm, for example, alpha-rooting pairs well with the standard EME. As shown in Fig. 6, if a measure does not satisfy the third characteristic for a specific enhancement algorithm, then it is not well suited to be used with that algorithm. However, it is also possible for an algorithm to not be matched correctly with the measure. Fig. 9(a) shows the EME graph for alpha rooting, performed on the Pentagon image using the DCT. Fig. 9(b) shows the output image for the parameters corresponding to the highest peak, at $\mathrm{alpha} = 0.78$. Fig. 9(c) shows the output image for the same parameters, however, this time, using the Hadamard transform. As can be seen, the EME value has been decreased and the image is also of less quality.

Keeping the measure of enhancement consistent for the basis of comparison, it is possible to choose the optimal method for enhancement by choosing the method which returns an enhanced image with the best characteristic according to the given measure. In our case, we chose contrast, and our best method would be that method which returns the highest EME based on entropy. Using this approach, a combination of the best measure along with the best method can be combined to return the best image possible.

H. Choosing the Optimal Transform and Parameters

Optimizing any recursive algorithm is based on a proper method for choosing the best parameters and transforms to be

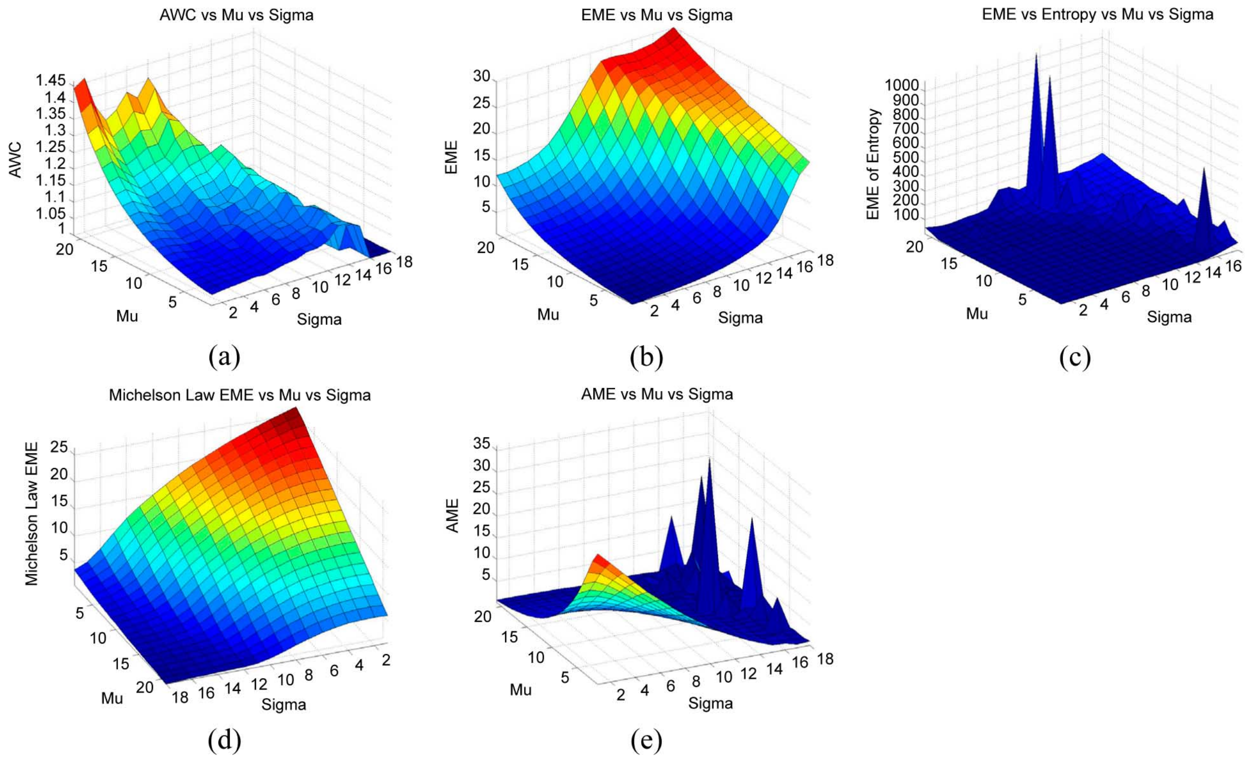


Fig. 8. Example measures of enhancement: (a) AWC, (b) EME, (c) EME using Entropy, (d) Michelson-based EME, and (e) AME.

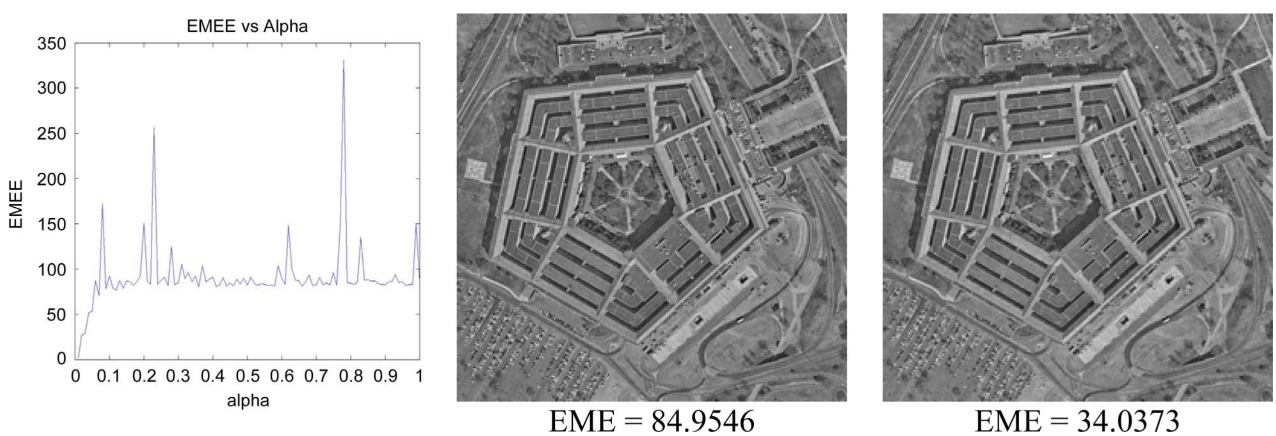


Fig. 9. (a) EME of the Pentagon image using alpha rooting, (b) output image using the DCT with corresponding EME, and (c) output image using the Hadamard Transform with corresponding EME.

used in that algorithm. This criteria will be dependent on the method of enhancement, the measure of enhancement, and the desired results of the enhancement.

Since we have defined our measure of enhancement, it then becomes necessary to define the method of choosing optimal parameters based upon that measure. Utilizing the proposed measure of enhancement based upon entropy affords a simple mathematical basis for determining the optimal parameters of our enhancement. By plotting the EME versus the coefficients of the enhancement on a specific image, we can return a descriptive graph to help choose parameters. Interpreting this graph depends on the properties of the enhancement method.

Our paper discusses two algorithms that require some sort of optimization: transform histogram shifting and transform histogram shaping using Gaussian distributions. The first algorithm, transform histogram shifting, relies on only one specific variable for the shifting distance, k. The second algorithm relies on two the variables that define the desired distribution, in this case, the mean and the standard deviation of a Gaussian distribution. Each of these algorithms is a separate method and requires separate criteria for choosing optimal parameters and transforms.

For the first method, a good shifting distance was found to be usually 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 will over enhance the image, resulting in what appears to be a binary thresholded image. For example, shifting the transform histogram of the helicopter image found in Fig. 1(a), by one half the number of bins, 32, results in the

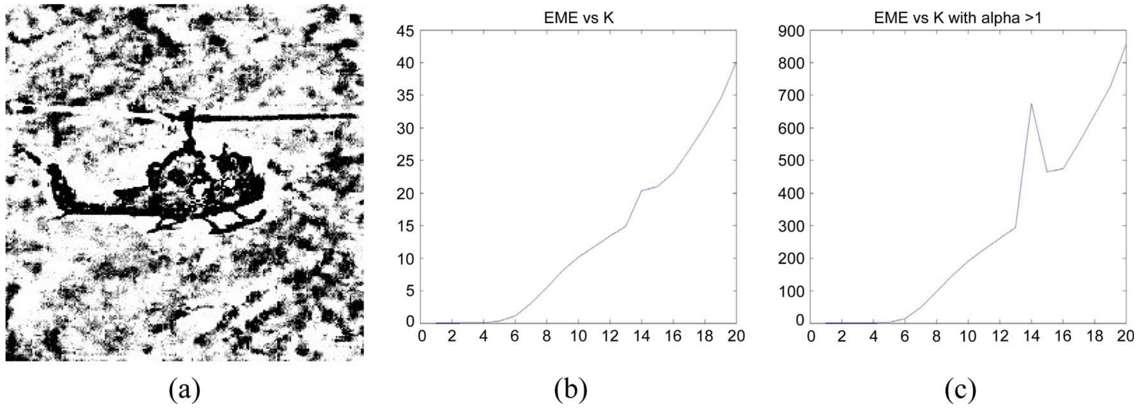


Fig. 10. (a) *Copter* image transform histogram shifted by 32 units out of the 64 histogram bins, (b) *Copter* EME versus K, and (c) EME versus K with $\mathrm{alpha} = 1.5$.

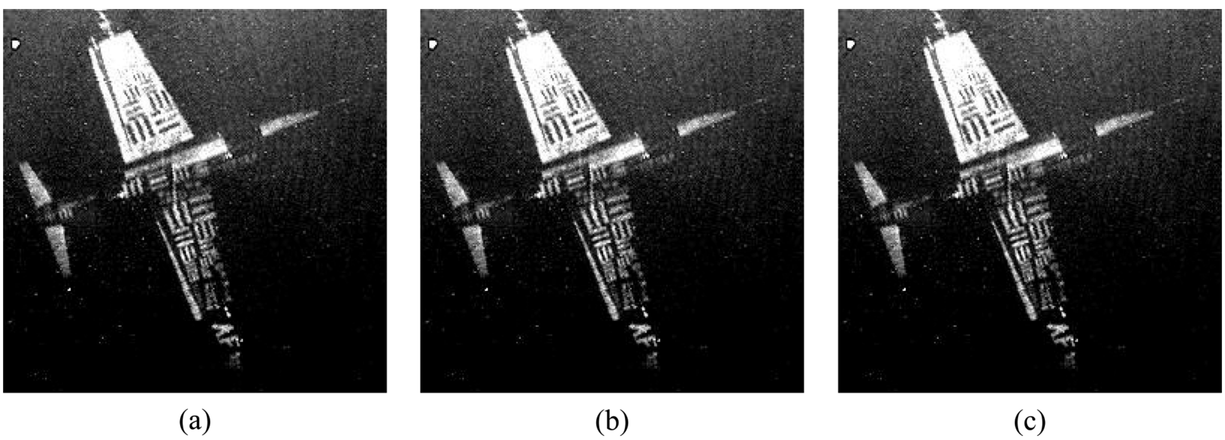


Fig. 11. Comparison of enhanced image using the same method and different transforms: (a) DCT, $\mathrm{EME} = 33.8779$, (b) FFT, $\mathrm{EME} = 78.1154$, and (c) Hartley transform, $\mathrm{EME} = 53.1231$. The FFT returned the highest EME, so, naturally, the FFT would be our optimal transform.

image Fig. 10(a). By plotting the EME based on entropy versus the shifting distance, k, possible optimal distances can be realized. 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.

As is the case with the *Copter* image, there are no local maxima, as shown in Fig. 10(b), but there is a strong area of inflection at a shifting distance of 14. Using this method, the rightmost local maxima or a point of inflection should be used as the optimal shifting distance, as this will usually afford the greatest enhancement. This is because this method returns a larger enhancement the farther the histogram is shifted.

One useful technique that was touched upon in the introduction is to play with the alpha coefficient in the EME equation as a means of finding an optimal point. By increasing alpha, it is possible to help emphasize these optimal areas. Fig. 10(c) shows the same EME versus K graph as Fig. 10(b) except that alpha has been set to 1.5. The point of inflection, that was not a peak, how now become a local maxima better expressing the locations of possible optimum points.

Transform histogram shaping using Gaussian distributions can return optimal points anywhere in the range of values tested. For simplicity, the maximum EME was used to define the best parameters. This can be extended by testing different transforms and picking the optimal point using each transform and then choosing the best combination of transform and parameter values to enhance the image.

In this paper, we simplified this approach by utilizing the DCT as our transform. In place of this, an optimal transform can be found from a class of transforms, such as the Fourier and Hartley transforms. An example for choosing the best transform among a class of transform can be seen in Fig. 11.

III. Logarithmic Transform Domain Coefficient Histograms Algorithms

This section lays out the formulation of three methods of logarithmic transform domain enhancement. Sections III-A–C discuss logarithmic transform histogram matching, logarithmic transform histogram shifting, and logarithmic transform histogram shaping, respectively.

Upon taking the logarithmic transform domain histogram of a low-contrast image, such as the *Artic hare* image, and comparing it with a more balanced image such as the *moon* and the *Pentagon* images' logarithmic transform histogram, it is apparent that there is a fundamental difference in the coefficient distribution in the logarithmic transform domain. This point is illustrated in Fig. 12.

An interesting difference between the graphs is not only the more defined curving shape of the *moon* and the *Pentagon* histogram images, but that the peaks shown by this distribution are farther from the zero line than in the *Artic hare* image.

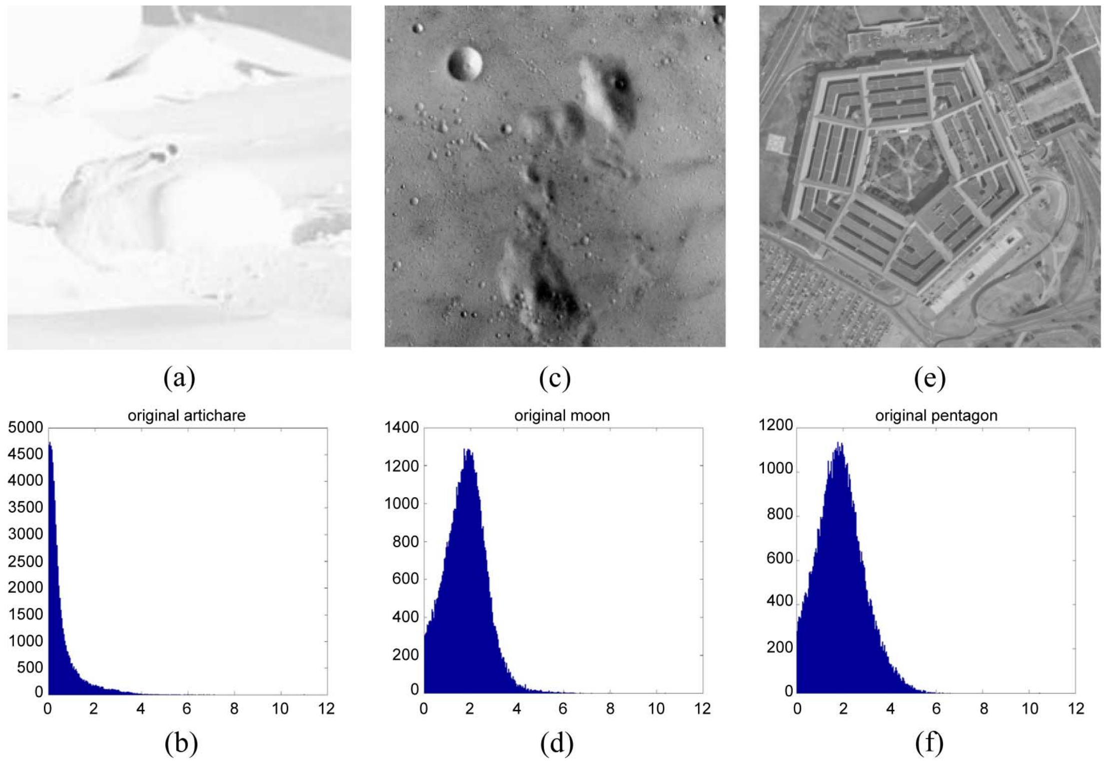


Fig. 12. Comparison of various images and their logarithmic transform coefficient histograms: (a), (b) *Artic hare* image; (c), (d) *moon* image; (e), (f) *Pentagon* image.

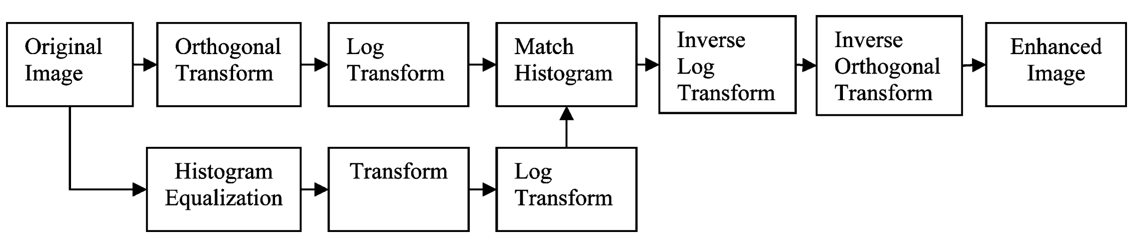


Fig. 13. Block diagram of logarithmic transform histogram matching with spatial equalization.

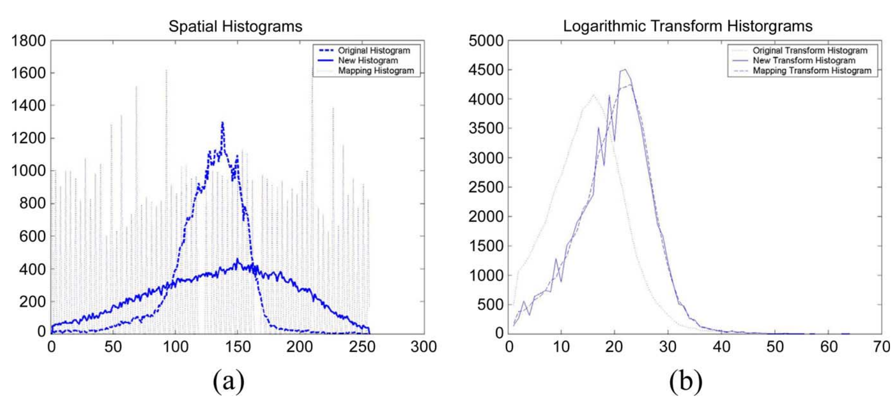


Fig. 14. Transform histogram matching: (a) comparison of spatial histograms; (b) comparison of histogram equalized and histogram matched logarithmic transform histograms. The original spatial histogram, the bell shaped curve in (a) approaches a more uniform distribution after the enhancement.

This warranted inquiry into whether or not we could enhance an image by altering its transform histogram. The first proposed algorithm, which is based on the contrast measure proposed in (4), would attempt to enhance the image using a histogram equalized image as a baseline. Transform histogram matching is detailed in Fig. 13, and by the following steps.

The first step would be to take an image and apply histogram equalization to it. This equalized image would then have its logarithmic transform histogram calculated as previously discussed. The original image would then have its logarithm transform coefficients mapped to create a similar histogram to match the equalized image's transform histogram coefficients as shown in Fig. 14(a) and (b).

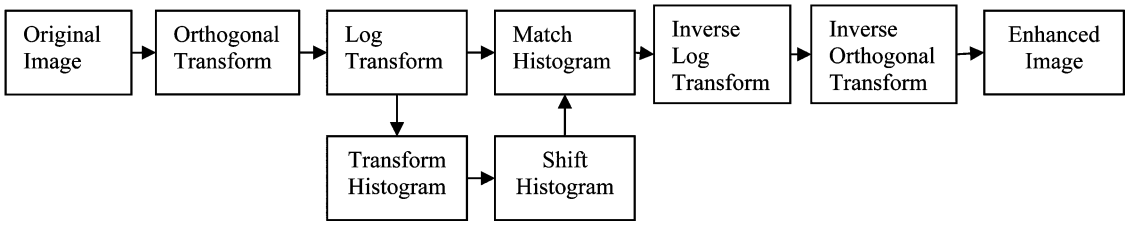


Fig. 15. Block diagram of logarithmic transform histogram shifting.

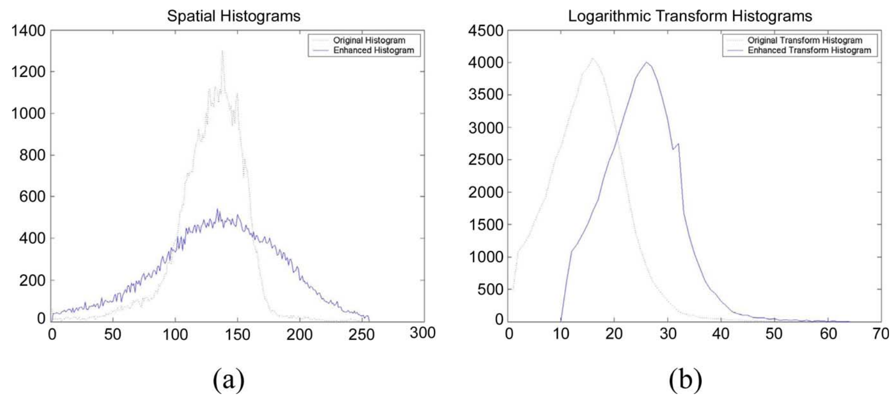


Fig. 16. Transform histogram shifting: (a) Comparison of spatial histograms; (b) comparison of histogram equalized and histogram matched logarithmic transform histograms. (b) As the transform histogram is shifted, (a) the spatial histogram approaches a uniform distribution.

A. *Transform Histogram Shifting*

Using the same concept and properties of transform histogram matching, transform histogram shifting is another effective algorithm for image enhancement. As shown before in Fig. 12, the logarithmic transform coefficient histograms of different qualities of images have different properties. One of these major properties is that more balanced and higher contrasting images have their logarithmic transform coefficient histograms peak farther to the right of zero than lower contrast image. This led to the investigation of transform coefficient histogram shifting as a viable image enhancement technique.

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. This shifting concept is then used as the mapping histogram which is then sent through a histogram matching routine. A block diagram of this process is shown in Fig. 15.

To be more specific the method is executed as follows.

Input: Original image.
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.
Output: Enhanced Image.

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. An example of a shifted histogram and the resulting spatial histogram can be seen in Fig. 16. Of note is the dynamic range expansion shown in the spatial histogram.

One of the interesting properties of this method is that the farther the transform coefficient histogram is shifted, the more the spatial histogram approaches a uniform distribution. However, in practice, this usually means the histogram has been shifted too far, and the image quality has begun to degrade due to information loss.

B. *Transform Histogram Shaping*

Building off the foundation of transform histogram matching and shifting, a more general algorithm can be established. By defining a shape of the desired transform histogram, it is possible to adjust properties of the image based on specific distributions. For example, a Gaussian distribution relies on two variables: the standard deviation, σ, and the mean, μ. By changing these variables and mapping the histogram to some optimal distribution, we can achieve an enhanced image that builds off the strength of the previous algorithms.

Logarithmic transform histogram shaping using Gaussian distributions (LTHSG) achieves two major effects. By changing the mean, μ, we are effectively shifting the transform histogram similar to the LTHS algorithm. By altering the standard deviation, σ, we are changing the spread of that distribution. These are our two variables of enhancement. A block diagram of this method can be found in Fig. 17.

The method is executed as follows.

Input: Original image.
Step 1: Transform image (DCT, Fourier, and others).
Step 2: Take logarithm of magnitude coefficients.
Step 3: Calculate coefficient histogram.
Step 4: Generate Gaussian distribution.

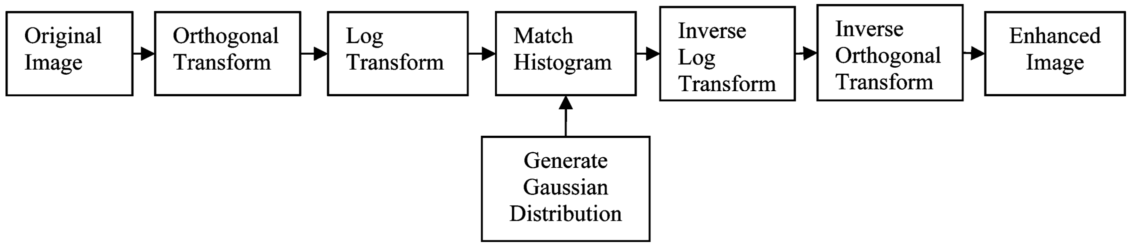


Fig. 17. Block diagram of logarithmic transform histogram shaping using gaussian distributions.

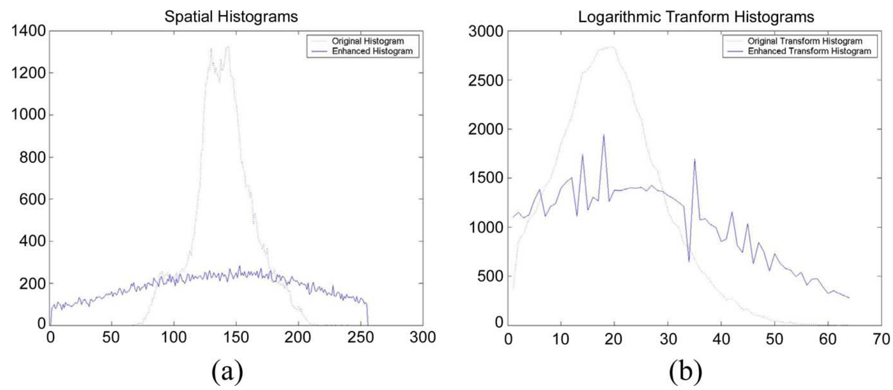


Fig. 18. (a) Comparison of spatial histograms, (b) comparison of histogram equalized and histogram matched logarithmic transform histograms. The Gaussian mapped histogram in (b) results in a more uniform distribution in the spatial histogram (a).

TABLE I
TABLE OF RESULTS, COMPARING THE EMEs OF DIFFERENT ENHANCEMENT METHODS

	Original	**Histogram Equalization**	**Alpha Rooting**		**Transform Histogram Matching**	**Transform Histogram Shifting**		**Transform Histogram Shaping**		
	EME	**EME**	**α**	**EME**	**EME**	**K**	**EME**	**μ**	**σ**	**EME**
Artic Hare	0.012008	2.9321	0.80	0.2856	9.9116	16	7.947	20	15	32.055
Copter	0.0359	1.3027	0.80	2.3506	9.0150	14	20.345	11	13	34.166
Moon	0.8681	6.6359	0.70	156.249	31.8327	13	185.672	25	10	154.2452
Plane	0.3340	23.3756	0.79	55.1932	33.8779	13	237.169	20	11	1072.854
Pentagon	0.2183	41.5252	0.74	110.482	86.8147	18	335.569	19	25	431.543

Step 5: Map transform data to Gaussian histogram.

Step 6: Exponentiate data.

Step 7: Restore phase and inverse transform.

Output: Enhanced image.

Through mapping the data to our desired histogram, we can expand the dynamic range optimally. This leads to an overall contrast enhancement of the image. An example of an image mapped to its optimal Gaussian distribution can be seen in Fig. 18.

IV. EXPERIMENTAL RESULTS

These methods were investigated to show the efficacy of transform domain histogram enhancement when compared to two common enhancement techniques: histogram equalization and alpha rooting. The results from the experimentation can be found in Table I.

The image *Copter* was used because it is a difficult image to enhance due to its very bright outside areas and dark interior [34]. As previously discussed, histogram equalization, Fig. 19(b), destroyed the detail on the helicopter and over emphasized the background. Alpha rooting, Fig. 19(c), returned satisfactory results, enhancing the contrast of the image while darkening the prevailing tone of the image.

After applying the method to the original image and using the histogram equalized version as the mapping image, our enhanced image using transform histogram matching is shown in Fig. 19(d). Compared to the histogram equalized image, the logarithmic histogram matched image has significantly more detail in the helicopter region without sacrificing the detail in the background and on the helicopter. This is reflected in the EME values returned by the enhanced images. Similar and even more desirable results can be found in the *Copter* image after is has

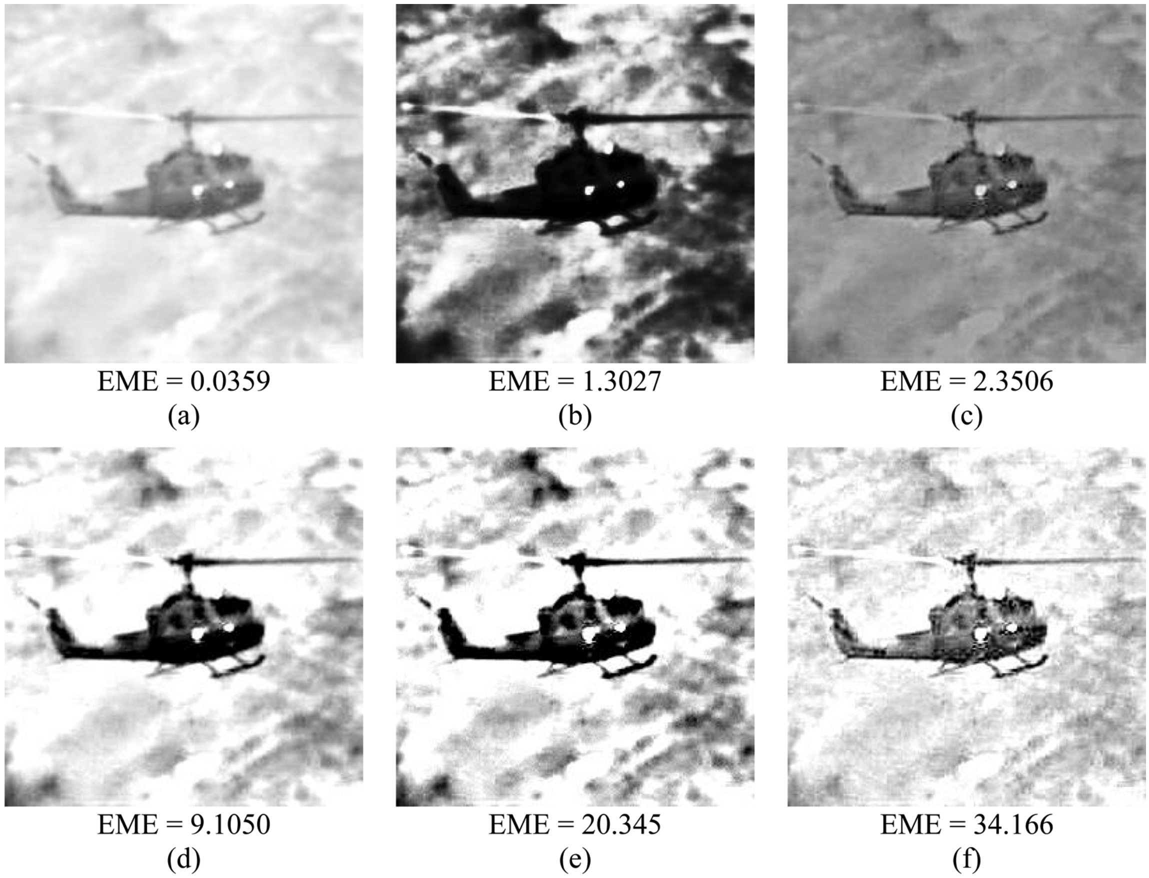


Fig. 19. Original *Copter* image, *Copter* image enhanced using (b) histogram equalization, (c) alpha rooting, (d) logarithmic transform histogram matching, (e) logarithmic transform histogram shifting, and (f) logarithmic transform histogram shaping using Gaussian distributions, all with corresponding values for EME with Entropy.

been enhanced using the transform histogram shifting method, as shown in Fig. 19(e). A shifting distance of 13 was found to be optimal in this case. In this case, the shifting returned even better results, showing more detail in the body of the helicopter. The most dramatic improvement can be seen in Fig. 19(f), when we used the transform histogram shaping routine. The optimal point was found to be at $\mu = 11$ and $\sigma = 13$. Of note is the spectacular detail along the plane and in the background. Both methods caused large increases in the EME values and noticeably outperformed histogram equalization, which had very noticeable artifacts, and alpha rooting, which changed the overall tone of the image, all of which were reflected in the relatively low EME value.

Numerically, the transform histogram shaping method outperformed histogram equalization, alpha rooting, transform histogram matching, and transform histogram shifting. The transform histogram matching and shifting algorithms also outperformed histogram equalization and alpha rooting, implying that all of the proposed techniques are viable as not just alternatives but as improvements to these established techniques when using this type of image.

A second, more dramatic case can be seen using the *Artic hare* image, which suffers from a very high average intensity, and a small dynamic range. This is reflected in the low EME value and makes it notoriously hard to enhance. Fig. 20(a) and (b) shows the *Artic hare* image before and after standard histogram equalization. The image of the rabbit after histogram equalization suffers from the aforementioned large dynamic range expansion [34], artifacts, and overall brightness change. The result is a hardly desirable image; however, the additional contrast artificially inflates the EME value. Alpha rooting [Fig. 20(c)] brought out many characteristics of the image but drastically changed the overall tone of the image, also causing an expected rise in the EME value.

This image is a perfect candidate for our methods, as it is a shining example of the shortcomings of histogram equalization. The *Artic hare* responded very well to the proposed methods, as indicated by the large jumps in the EME values. In the logarithmic transform histogram matching trial, shown in Fig. 20(d), it returned a much clearer image than the original and even the histogram equalized image. As can be seen from the EME values in Fig. 20, this method outperformed alpha rooting not only numerically, but visually, as well. It had nether the artifacts from histogram equalization, nor the tonal change of alpha rooting. The image produced by using the logarithmic transform histogram shifting technique, shown in Fig. 20(e), although not as dark as the previous enhancement, does afford the detail in the sky and the contrast all along the snow that was not brought out by the logarithmic transform histogram matching algorithm. The best enhancement was brought out by our logarithmic transform histogram shaping method, shown in Fig. 20(f) with optimal points at $\mu = 20$ and $\sigma = 15$. The EME value for this

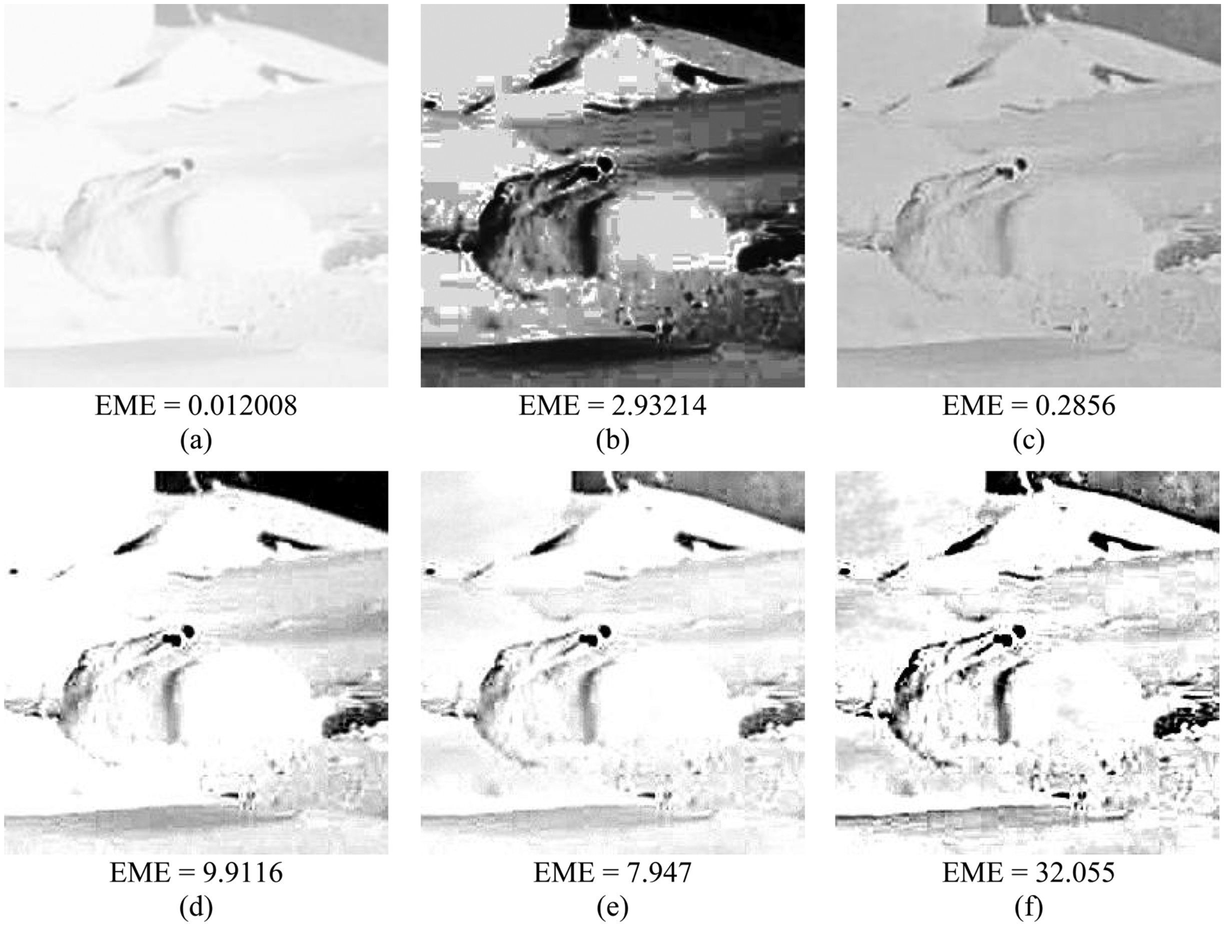


Fig. 20. (a) Original Artic hare image, Artic hare image enhanced using (b) histogram equalization, (c) alpha rooting, (d) logarithmic transform histogram matching, (e) logarithmic transform histogram shifting, and (f) logarithmic transform histogram shaping using Gaussian distributions, all with corresponding values for EME with Entropy.

image shows the largest increase from the original image. Further, this image shows much more textural information than all the previous enhancement attempts, especially along the lighter areas of the snow. All three methods outperformed alpha rooting and histogram equalization, while the best results were found using the histogram shaping algorithm.

A predominantly dark image of a $U2$ plane was used to show the effect of the enhancement techniques on the other end of the intensity spectrum. The $U2$ image and the result of its histogram equalization are shown in Fig. 21(a) and (b), respectively. Despite a fairly large increase in the EME value, histogram equalization works very poorly on the $U2$ image. It destroys the details on the plane, and over emphasizes the faint details in the background. This is when a more moderate approach should be used. Alpha rooting returned a visually improved image over the original, Fig. 21(c). This image also shows a larger increase in the EME value, suggesting that the seemingly large increase seen after histogram equalization may actually be relatively small for this image. However, the image is still dark throughout. This image, which is similar to the *Artic hare* image in its concentrated dynamic range, is a perfect candidate for our enhancement techniques.

Fig. 21(d) shows the effect of using the logarithmic transform histogram matching technique. The details of the plane are enhanced and the contrast has increased; however, it does not suffer from the chronic over compensation found in pure histogram equalization, which is reflected by the better EME value returned by this method compared with histogram equalization. The image is also much clearer than the alpha-rooting image, due to the larger range of intensity values brought out by the range expansion. The second most dramatic enhancement can be found in Fig. 21(e), after the application of the logarithmic transform histogram shifting technique. Numerically, this shows a very large jump when compared to the other methods used. Visually, the details on the wings are clearly shown, while the subtle contours of the background have also become visible. The best enhancement was given by the histogram shaping algorithm, as shown in Fig. 21(f). By using the optimal values $\mu = 21$ and $\sigma = 16$, the image returned more detail in the picture than any other method. Most notably the details on the upper tip of the wing are much more visible than in any of the other methods. This is also reflected in the increase in the EME values, which is even larger than for the shifting method.

Numerically, transform histogram shaping out-classed histogram equalization and outperformed the faster, simpler transform histogram matching, and alpha rooting. Transform histogram matching returned a lower EME than alpha rooting, but visually, all of the proposed algorithms performed admirably,

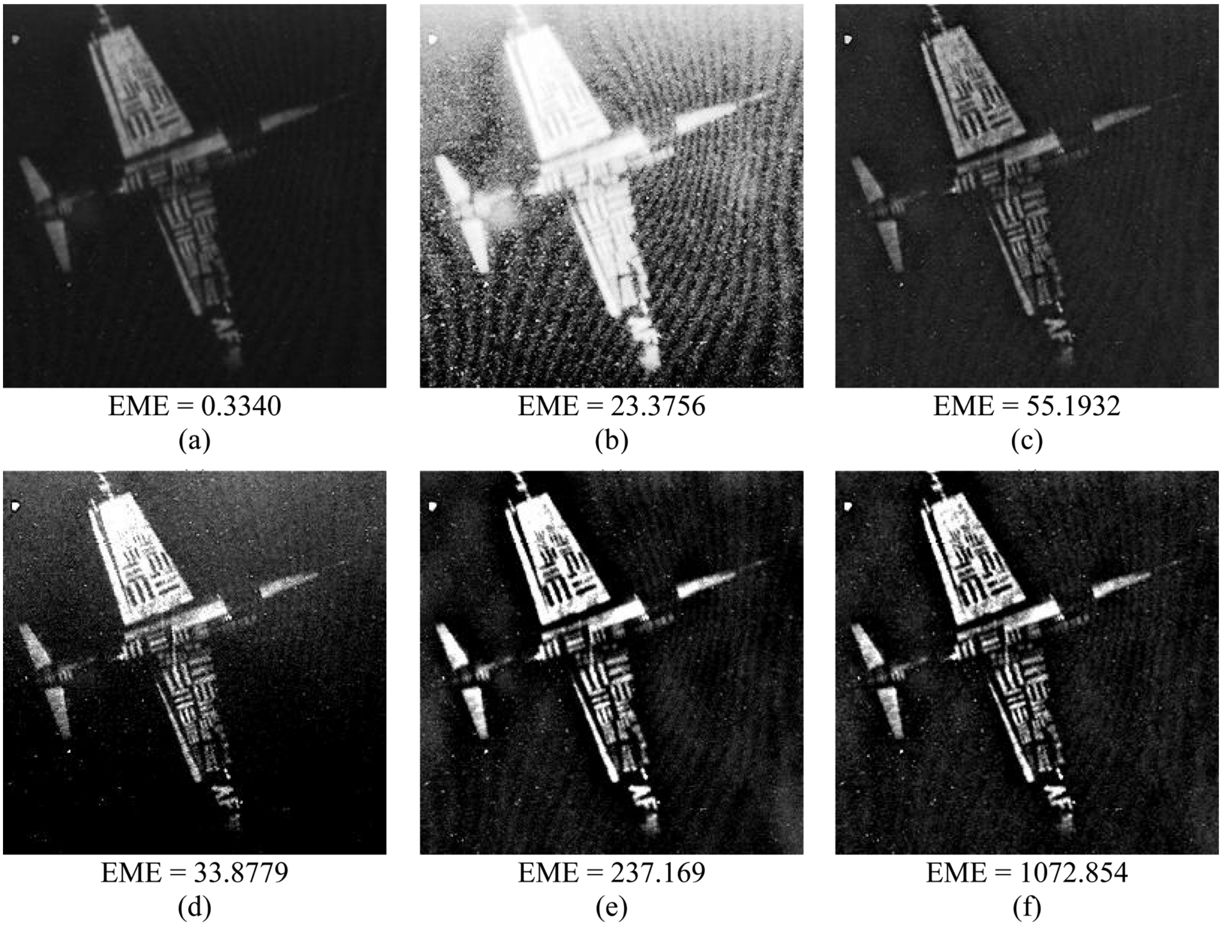


Fig. 21. (a) Original $U2$ image, $U2$ image enhanced using (b) histogram equalization, (c) alpha rooting, (d) logarithmic transform histogram matching, (e) logarithmic transform histogram shifting, and (f) logarithmic transform histogram shaping using Gaussian distributions, all with corresponding values for EME with Entropy.

returning a greatly enhanced version of the $U2$ image than histogram equalization and alpha rooting.

V. Concluding Remarks

The application of histograms to transform coefficients is a relatively new concept. In this work, we have developed and presented three methods of contrast enhancement based upon the properties of the logarithmic transform coefficient histogram using contrast entropy as a measure of performance and optimization. The performance of these algorithms was compared to two popular enhancement techniques: histogram equalization and alpha rooting. This paper also introduced a variety of measures of contrast enhancement.

The first method was the logarithmic transform histogram matching with equalization algorithm. Logarithmic transform histogram matching was demonstrated to show an algorithm that mimics the ability of histogram equalization without suffering from the side effects of an over expansion of the dynamic range [34]. This method has the distinct advantage of being incredibly quick with no built in recursion making it a simple and fast solution for image enhancement based on the transform histogram.

Logarithmic transform histogram shifting has been shown to be a powerful method for enhancing images. It also affords a relatively simple and quick implementation that our results have shown to outperform popular enhancement techniques, such as histogram equalization and alpha rooting, both visually and numerically.

The third method was Logarithmic transform histogram shaping, which was a more general form of histogram shifting. This method allows much more variation in the variables used for enhancement and, in most cases, resulted in a marked improvement in the resulting EMEs and visual images. By changing μ and σ, we were able to adjust the general contrast and spread of image data to match our desired characteristics.

Transform histogram shaping is the best method presented in this paper, but requires the calculation of an optimal point. This means that that although it performs best, it may be slower than other, less computationally complicated techniques that may be preferred. It is because of this complication that logarithmic transform histogram matching was implemented and demonstrated. It affords a marriage between enhancement power and computational efficiency.

Since all three methods produced significant improvement to their respective test images, it warrants further investigation in transform coefficient histogram-based enhancement techniques as viable methods for image enhancement, breaking away from the traditional use of histograms in only the spatial domain.

In choosing our measure of enhancement, we have noted that there is no universal metric for enhancement. When choosing a measure, the desired qualities must be outlined, and a suitable measure must be chosen to match those qualities. Our work shows that an increase in contrast returns a proportional increase in the EME based on entropy. We have also shown that two enhanced images with similar but unequal EME values may be indistinguishable from each other. Our conclusion is that for any noticeable increase in contrast between two comparable versions of a given image can be guaranteed when their EME values differ by a significant magnitude. The exact values may not be perfectly correlated with the resulting quality, but more often than not they are.

A wide range of altered image characteristics can be obtained from a single transform by varying the enhancement parameters, such as shifting distance, magnitude reduction, scaling, or some combination of these. A quantitative measure of signal and image enhancement was presented, which demonstrated the most favorable method to automatically choose the best parameters and transform. The proposed algorithms are simple to apply and design, which makes them practical in everyday image processing.

Acknowledgment

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References

[1] A. A. Michelson, *Studies in Optics*. Chicago, IL: Univ. Chicago Press, 1927.
[2] A. Beghdadi and A. L. Negrate, "Contrast enhancement technique based on local detection of edges," *Comput. Vis. Graph. Image Process.*, vol. 46, pp. 162–274, 1989.
[3] A. Grigoryan and S. Agaian, "Image enhancement," in *Advances in Imaging and Electron Physics*. New York: Academic, May 2004, pp. 165–243.
[4] A. Jain, *Fundamentals of Digital Image Processing*. Englewood Cliffs, NJ: Prentice-Hall, 1989.
[5] A. Khellaf, A. Beghdadi, and H. Dupoiset, "Entropic contrast enhancement," *IEEE Trans. Med. Imag.*, vol. 10, no. 4, pp. 589–592, Dec. 1991.
[6] A. Polesel, G. Ramponi, and V. J. Mathews, "Image enhancement via adaptive unsharp masking," *IEEE Trans. Image Process.*, vol. 9, no. 3, pp. 505–510, Mar. 2000.
[7] A. Rosenfeld and A. C. Kak, *Digital Picture Processing*. New York: Academic, 1982, vol. 1.
[8] A. Toet, "Multiscale contrast enhancement with applications to image fusion," *Opt. Eng.*, vol. 31, no. 5, 1992.
[9] B. Silver, S. S. Agaian, and K. A. Panetta, "Contrast entropy based image enhancement and logarithmic transform coefficient histrogram shifting," presented at the IEEE ICASSP, Mar. 2005.
[10] B. Silver, S. S. Agaian, and K. A. Panetta, "Logarithmic transform coefficient histogram matching with spatial equalization," presented at the SPIE Defense and Security Symp., Mar. 2005.
[11] E. Peli, "Contrast in complex images," *J. Opt. Soc. Amer. A*, vol. 7, pp. 2032–2040, 1990.
[12] G. T. Fechner, *Elements of Psychophysics*. New York: Rinehart & Winston, 1960, vol. 1.
[13] G. X. Ritter and J. N. Wilson, *Handbook of Computer Vision Algorithm in Image Algebra*. Boca Raton, FL: CRC, 1996.
[14] H. D. Cheng and H. Xu, "A novel fuzzy logic approach to contrast enhancement," *Pattern Recognit.*, vol. 33, pp. 809–819, 2000.
[15] J. A. Saghri, P. S. Cheatham, and H. Habibi, "Image quality measure based on a human visual system model," *Opt. Eng.*, vol. 28, no. 7, 1989.
[16] J. Duan and G. Qiu, "Novel histogram processing for colour image enhancement," in *Proc. 3rd Int. Conf. Image and Graphics*, Dec. 2004, pp. 55–58.
[17] J. H. McClellan, "Artifacts in alpha-rooting of images," in *Proc. IEEE Int. Conf. Acoustics, Speech, Signal Processing*, Apr. 1980, pp. 449–452.
[18] J. Tang, E. Peli, and S. Acton, "Image enhancement using a contrast measure in the compressed domain," *IEEE Signal Process. Lett.*, vol. 10, no. 10, pp. 289–292, Oct. 2003.
[19] J. Tang, J. Kim, and E. Peli, "Image enhancement in the JPEG domain for people with vision impairment," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 11, pp. 2013–2023, Nov. 2004.
[20] J. K. Kim, J. M. Park, K. S. Song, and H. W. Park, "Adaptive mammographic image enhancement using first derivative and local statistics," *IEEE Trans. Med. Imag.*, vol. 16, no. 10, pp. 495–502, Oct. 1997.
[21] K. Huang, Q. Wang, and Z. Wu, "Color image enhancement and evaluation algorithm based on human visual system," in *Proc. IEEE ICASSP*, May 2004, vol. 3, pp. iii-721–iii-724.
[22] L. E. Krueger, "Reconciling Fechner and Stevens: toward a unified psychophysical law," *Behav. Brain Sci.*, vol. 12, pp. 251–320, 1989.
[23] N. Netravali and Presada, "Adaptive quantization of picture signals using spatial masking," *Proc. IEEE*, vol. 65, no. 4, pp. 536–548, Apr. 1977.
[24] P. Natendra and Rithch, "Real-time adaptive contrast enhancement," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-3, pp. 655–661, Nov. 1981.
[25] R. Gonzalez and P. Wintz, *Digital Image Processing*. Reading, MA: Addison-Wesley, 1987.
[26] R. Hummel, "Histogram modification techniques," *Comput. Graph. Image Process.*, vol. 4, pp. 209–224, 1975.
[27] R. Kogan, S. Agaian, and K. Panetta, "Visualization using rational morphology," presented at the Europto Conf., 1998.
[28] R. Kogan, S. Agaian, and K. A. Panetta, "Visualization using rational morphology and zonal magnitude reduction," in *Proc. SPIE Symp. Electronic Imaging Science & Technology*, Apr. 1998, vol. 3387, pp. 301–312.
[29] R. Kogan, S. S. Agaian, and K. Panetta, "Visualization using rational morphology and zonal magnitude-reduction," *Proc. SPIE*, vol. 3304, pp. 153–163, 1998.
[30] R. H. Sherrier and G. A. Johnson, "Regionally adaptive histogram equalization of the chest," *IEEE Trans. Med. Imag.*, vol. MI-6, no. 1, pp. 1–7, Mar. 1987.
[31] S. Agaian and F. Arslan, "Two transform based image enhancement methods," presented at the Int. Signal Processing Conf., Dallas, TX, Mar. 31–Apr. 3, 2003.
[32] S. Aghagolzadeh and O. K. Ersoy, "Transform image enhancement," *Opt. Eng.*, vol. 31, no. 3, pp. 614–626, Mar. 1992.
[33] S. K. Naik and C. A. Murthy, "Hue-preserving color image enhancement without Gamut problem," *IEEE Trans. Image Process.*, vol. 12, no. 12, pp. 1591–1598, Dec. 2003.
[34] S.-D. Chen and A. R. Ramli, "Minimum mean brightness error bi-histogram equalization in contrast enhancement," *IEEE Trans. Consum. Electron.*, vol. 49, no. 4, pp. 1310–1319, Nov. 2003.
[35] S. S. Agaian, K. Panetta, and A. M. Grigoryan, "A new measure of image enhancement," presented at the IASTED Int. Conf. Signal Processing Communication, Marbella, Spain, Sep. 19–22, 2000.
[36] S. S. Agaian, K. Panetta, and A. Grigoryan, "Transform based image enhancement with performance measure," *IEEE Trans. Image Proces.*, vol. 10, no. 3, pp. 367–381, Mar. 2001.
[37] S. S. Agaian, "Visual morphology," in *Proceedings of SPIE, Nonlinear Image Processing X*, San Jose, CA, Mar. 1999, vol. 3646, pp. 139–150.
[38] S. S. Agaian, *Advances and Problems of Fast Orthogonal Transform for Signal/Image Processing Applications*. Moscow, Russia: Nauka, 1991, pp. 99–145.
[39] ——, Advances and Problems of Fast Orthogonal Transform for Signal/Image Processing Applications pp. 146–215, 1990.
[40] T. K. Kim, J. K. Paik, and B. S. Kang, "Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering," *IEEE Trans. Consum. Electron.*, vol. 44, no. 1, pp. 82–86, Feb. 1998.
[41] T. L. Ji, M. K. Sundareshan, and H. Roehrig, "Adaptive image contrast enhancement on human visual properties," *IEEE Trans. Med. Imag.*, vol. 13, no. 4, pp. 573–586, Dec. 1994.
[42] T. Zong, H. Lin, and T. Kao, "Adaptive local contrast enhancement method for medical images displayed on a video monitor," *Med. Eng. Phys.*, vol. 22, pp. 79–87, 2000.
[43] W. M. Morrow, R. B. Paranjape, R. M. Rangayyan, and J. E. L. Desautels, "Region-based contrast enhancement of mammograms," *IEEE Trans. Med. Imag.*, vol. 11, no. 3, pp. 392–406, Sep. 1992.

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