A New Measure of Image Enhancement

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Abstract— **A novel quantitative measure of image enhancement is considered. This measure is related with concepts of the Weber's law of the human visual system. This article also offers a new class of the frequency domain based parametric image enhancement algorithms for the object detection and visualization. A number of experimental results is illustrated the performance of these algorithms. Particularly the quantitative measure has helped to select (automatically) optimal processing parameters: the best parameters and transform. The comparative analysis of transforms based image enhancement algorithms is described.**

Keywords: Frequency domain enhancement, magnitude-reduction, visualization.

I. Introduction

It is well known that the image enhancement is a problem-oriented procedure and the goal of the image enhancement is to improve the visual appearance of the image, or to provide "better" transform representation for future automated image processing. Many methods proposed to enhance image are based on gray-level histogram modification [1], [2], while other methods are based on local contrast transformation and edge analysis [3], [6], or the "global" entropy transformation [7]. That is due to the absence of general standard for image quality which could be used as a design criteria for image enhancement algorithms [8].

It is fact that there is no general unifying theory of image enhancement. Methods of image enhancement techniques can be generally classified into two categories: spatial domain methods, which operate directly on pixels and frequency (transform) domain methods. The analysis of the existing transform based image enhancement techniques [9], [10] shows that it is difficult to select optimal processing parameters, and there is no efficient measure that can be served as a building criterion for image enhancement. The solution of the last task is very important especially when the image enhancement procedure is used as a preprocessing step for other image processing techniques such as the detection, recognition, and visualization.

This paper describes new quantitative measures of image enhancement and novel frequency domain based image enhancement methods for the object detection and visualization.

II. Measure of image enhancement

When analyzing the signals and systems, it is useful to map data from the time domain into another domain (the frequency domain). The basic characteristics of a complex wave are the amplitude and phase spectra. Specifying amplitude spectrum is an important concept for complex waves. For example, an amplitude spectrum contains information about the energy content of a signal and the distribution of the energy among the different frequencies, which is often used in many applications.

The improvement in images after enhancement is often very difficult to measure. A processed image can be said to have been enhanced over the original image if it allows the observer to better perceive the desirable information in the imaging. In images, the improved perception is difficult to qualify. There is no universal measure which can specify both the objective and subjective validity of the enhancement method [11]. In practice, many definitions of the contract measure are used [2]. For example, the local contrast proposed by Gordon and Rangayyan [12] was defined by the mean gray values in two rectangular windows centered on a current pixel. Baghdan and Negrate [13] proposed another definition of the local contrast based on the local edge information of the image, in order to improve the first mentioned definition. Use of statistical measures of gray level distribution measures of local contrast enhancement (for example, mean, variance or entropy) have not been particularly meaningful for mammogram images [14]. A number of images, which clearly illustrated an improved contrast, showed no consistency, as a class, when using these statistical measurements. A measure proposed in [2], which has greater consistency than the statistical measures, is based on the contrast histogram.

Intuitively, it seems reasonable to expert that a image enhancement measure values at given pixels should depend strongly on the values at pixels that are close by weekly on those that are further away and also this measure has to related with human visual system. In our definition, we will use a modification of Weber's and Fisher's laws. In image enhancement measure definition we will also use the well known entropy concept. In [15], Weber established a visual law, argued that the human visual detection depends on the ratio, rather than difference of light intensities. The Weber definition of contrast was used to measure the local contrast of a single object. Fechner's law [16] proposed the following relationship between the light intensity $f(x, y)$ and brightness:

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

where k' is a constant, $f_{\max}$ and $f_{\min}$ respectively are the maximum and minimum luminance values (within a small window).

Let an image $x(n, m)$ be split into $k_1 k_2$ blocks $w_{k,l}(i, j)$ of sizes $l_1 \times l_2$, and let and $\{\Phi\}$ be a given class of orthogonal transforms used for image enhancement with enhancement parameters (or, vector parameter) α, β, and λ to be found. We define the value

$$\begin{aligned} EME &= \max_{\Phi \in \{\Phi\}} \chi(EME(\Phi)) \\ &= \max_{\Phi \in \{\Phi\}} \chi\left(\frac{1}{k_1 k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1} 20 \log \frac{I^w_{\max;k,l}(\Phi)}{I^w_{\min;k,l}(\Phi)}\right) \end{aligned} \qquad (2)$$

where $I^w_{\min;k,l}(\Phi)$ and $I^w_{\max;k,l}(\Phi)$ respectively are the minimum and maximum of the image $X(n, m)$ inside the block $w_{k,l}$, after processing the block by Φ transform based enhancement algorithm. The function χ is the sign function, $\chi(x) = x$, or $\chi(x) = -x$, depending on the method of enhancement under the consideration. The decision of adding this function has been done after the study various examples of enhancement by transform methods using the different coefficients $C_i(p, s)$, $i = 1, 2, 3$. This will be described in the following section.

Definition 1: EME is called a *measure of enhancement*, or *measure of improvement*.

To define another image enhancement measure, we will use the well known entropy concept. Given an image enhancement transform Φ, we define a measure element as

$$EME(\Phi) = \frac{1}{k_1 k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1} \frac{I^w_{\max;k,l}}{I^w_{\min;k,l}} \log \frac{I^w_{\max;k,l}}{I^w_{\min;k,l}}. \qquad (3)$$

Definition 2: The quantity

$$EMEE = \max_{\Phi \in \{\Phi\}} \chi(EME(\Phi)) \qquad (4)$$

is called a *measure of enhancement by entropy*.

Definition 3: The best (optimal) transform relative to the measure of enhancement, EME, is called a transform Φ_0 such that $EME(\Phi_0) = EME$. The image enhancement algorithm based on this transform is called an *optimal image improvement transform-based* enhancement algorithm.
Similarly, relative to the measure of enhancement by entropy, we define *the best (optimal) transform* Φ_0, such that $EMEE(\Phi_0) = EMEE$, and an *optimal image improvement transform-based* enhancement by entropy algorithm. These two definitions result in different optimal transforms. At present, both definitions of transform Φ_0 for the best transform-based enhancement of image will be considered equally optimal.

A. Enhancement in the frequency domain

Image enhancement in the frequency domain is straightforward. One simply perform the transform of an image to be enhanced, then manipulated with the transform coefficients, and perform the inverse orthogonal transform. Image transforms give the spectral information about the image, by decomposition of the image into spectral coefficients that can be modified (linearly or non-linearly), for the purposes of enhancement and visualization.

Let $X(p, s)$ be transform coefficients, for example the coefficients of the two-dimensional discrete Fourier transform (2-D DFT),

$$\begin{gathered} F(p, s) = \sum_{n=0}^{N-1}\sum_{k=0}^{N-1} x_{n,k} e^{-j2\pi(np+ks)/N} \\ p, s = 0 : (N-1), \quad j = \sqrt{-1}. \end{gathered} \qquad (5)$$

The particular case of this transform is the 2-D discrete cosine (non-separable) transform (DCT), coefficients of which are defined as follows:

$$X_{p,s} = \sum_{n=0}^{N-1}\sum_{k=0}^{N-1} x_{n,k} \cos\Big(\frac{\pi}{N}[(n+\frac{1}{2})p + (k+\frac{1}{2})s]\Big). \qquad (6)$$

We also consider the 2-D discrete Hadamard transform (DHT), which is defined as follows:

$$X_{p,s} = \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} x_{n,k} a(p,n) a(s,k), \quad (7)$$

where the kernel of the one-dimensional DHT is of the form:

$$a(p,n) = (-1)^{n_0 p_0 + n_1 p_1 + \cdots + n_{r-1} p_{r-1}} \quad (8)$$

and p_i, n_i respectively are the ith bits in the binary representation of numbers p and n. Methods of fast algorithms for computing the above 2-D transforms can be found in [18], [19].

Analyzing the existing transform-based enhancement algorithm (α-rooting and magnitude reduction methods [4], [5], [10]), we find a common algorithm, which encompasses all of these techniques. The actual procedure of the signal/image enhancement via an invertible transform consists of the following steps:

Step 1) perform the orthogonal transform;

Step 2) multiply the transform coefficients $X_{p,s}$ by some factors, $O_{p,s}$;

Step 3) perform the inverse orthogonal transform.

The frequency ordered system-based method can bee represented as

$$x \to X \to \mathbf{O} \cdot X \to \mathbf{T}^{-1}[\mathbf{O}(X)] = \widehat{x}, \quad (9)$$

where $\mathbf{O}$ is an operator applied on the coefficients $X(p,s)$. Let the enhancement operator $\mathbf{O}$ be of the form $X(p,s) \cdot C(p,s)$, where the latter is a real function of the magnitude of the coefficients, i.e. $C(p,s) = f(|X|)(p,s)$. $C(p,s)$ must be real because we only wish to alter the magnitude information, not the phase information. In the framework of this constrain, we have several possibilities for $C(p,s)$, which can offer much far greater flexibility:

1) $C(p,s)^\gamma = constant$ (when $\gamma = 0$ the enhancement preserves all constant information);

2) $C_1(p,s) = C(p,s)^\gamma |X(p,s)|^{\alpha-1}$, $0 \le \alpha < 1$ (which is the so-called *modified α-rooting* [10]);

3) $C_2(p,s) = \log^\beta \left[|X(p,s)|^\lambda + 1 \right]$, $0 \le \beta$, $0 < \lambda$ [4];

4) $C_3(p,s) = C_1(p,s) \cdot C_2(p,s)$.

Denoting by $\theta(p,s) \ge 0$ the phase of the transform coefficient $X(p,s)$, we can write

$$X(p,s) = |X(p,s)| \exp[j\theta(p,s)] \quad (10)$$

where $|X(p,s)|$ is the *magnitude* of the coefficients. Rather than apply the enhancement operator $\mathbf{O}$ directly on the transform coefficients $X(p,s)$, we will investigate the operator which is applied on the *modules* of the transform coefficients,

$$\mathbf{O}(X)(p,s) = \mathbf{O}(|X|)(p,s) \exp[j\theta(p,s)]. \quad (11)$$

We assume the enhancement operator $\mathbf{O}(|X|)$ takes one of the forms $C_i(p,s)|X(p,s)|$, $i = 1,2,3$, at every point (p,s).

In practice, the coefficient $0 \le \alpha < 0.99$ is used in $C_1(p,s)$ for image enhancement. The optimal value of α is image dependent and should be adjusted interactively by the user [10]. One can ask: What are the optimal values of α, β, and λ? Can one choose α, β, and λ automatically? What is the best enhancement frequency ordered system? What is the optimal size of the transform, N?

Selection of parameters. Suppose the transform based enhancement algorithm depends on the parameters α, β, and γ, or vector (α, β, γ), i.e. $\Phi = \Phi_{\alpha,\beta,\gamma}$.

Definition 4: Let Φ be the best (optimal) transform. The best (optimal) Φ-transform-based enhancement image vector parameter (α, β, γ) is called a parameter $(\alpha_0, \beta_0, \gamma_0)$ such that $EME(\Phi_{\alpha_0,\beta_0,\gamma_0}) = EME$.

If the measure of mage improvement is defined by entropy according to Eqs. 3 and 4, then we use the condition $EMEE(\Phi_{\alpha_0,\beta_0,\gamma_0}) = EMEE$ in Definition 4. It should be noted that the window size can be also included in the vector α as a parameter of optimal enhancement. We should note in addition, that although all above definitions are based on the concept of enhancement of an image, each image is considered as a realization of a random process. Therefore, the measure of image enhancement could be considered over all random images, which leads to the difficult problem of finding a global best (optimal) transform Φ (or vector parameter) for the given random process.

The following problems have been investigated: How to design the best improvement transform-based image enhancement algorithm, and how to design the best Φ-transform-based enhancement image vector parameter (α, β, γ)?

III. Experimental results

We performed a number of experiments in order to evaluate the enhancement algorithm for 1-D and 2-D signals. For more clarity/visibility, we demonstrate the experimental results for 2-D signals such as "moon" plus "clock" image. We use three classes of algorithms, namely, the transform based enhancement algorithms via operators $C_k(p,s)$, $k = 1,2,3$ respectively. The first class shows how to choice the best operator parameter (or, the best enhancement algorithm) for the given transform. The second class shows how to choice the best image enhancement transform for the given image.

In order to enhance our images before passing them through a visualization algorithm, we reduce the magnitude information of the image while leaving the phase information intact. Since the phase information is much more significant than the magnitude information in the determination of edges, reducing the magnitude produces better edge detection capabilities. This method also tends to reduce more the low-frequency components than the high-frequency components (both the low-frequency components, which are associated with sharp edge, and high-frequency components, which are associated with the edge elements).

The "clock" image was taken as the original, $x(n,m)$, and the "moon" image was superimposed. This results in an illegible image, as shown in Figure 1. The result, $\widehat{X}(p,s)$, is an enhanced image, which can now be passed through a visualization algorithm. To choose the best image enhancement transform for the given image, we used different transforms and varying parameters λ and β respectively in the intervals $[0,2]$ and $[0,1]$, and analyzed the 3-D surface of the measure for the Fourier method. The differences between the measures has been also observed, when the Fourier, Hadamard, and cosine transforms are used for enhancement. The results of the Fourier transform based image enhancement for the boundary parameters show that big values of β bring to the eliminating of the higher frequencies on the image spectrum, and the operator $\mathbf{O}$ works as the filter of low frequencies. Opposite, the small values of β increase the image enhancement.

The enhancement measure of the original image shown in Fig. 1 is 4.5, or $EME_I(X) = 4.5$, where I is the identical transform. Figure 2 shows three curves described the measure of the enhancement, when applying the Fourier, Hadamard, and cosine transforms. The curves have two maximums, at points $\alpha_1 = 0.92$ and $\alpha_2 = 0.6$, where the maximum measure is provided by the Fourier transform. The experimental results show that the parameter α_1 corresponds to the best visual estimation of enhancement. The enhancement by the transforms are very closed between these two extreme points. Figure 3 illustrates the enhancement of the original image via α-rooting based on the transforms when $\alpha = 0.92$.

To choose the best operator parameter, the enhanced images have been analyzed by varying parameter α, when using the Fourier transform, Hadamard transform, and cosine transform. The log-magnitude reduction using $C_2(p,s)$ served to enhance the edges around regions in the image.

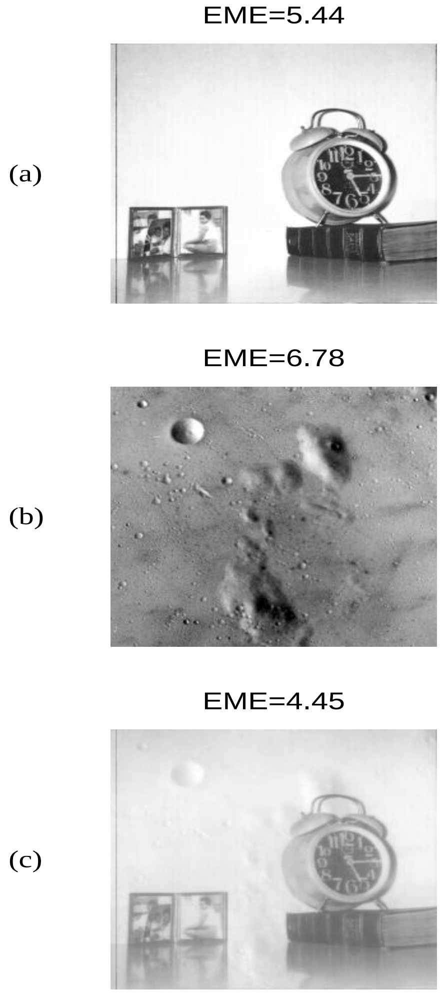

Fig. 1. Linear combination of the clock (a) and moon (b) images, which results in an illegible image (c).

IV. Conclusion

A new class of "frequency domain" based signal/image enhancement algorithms (magnitude reduction, log-magnitude reduction, iterative magnitude, and log-reduction zonal magnitude technique, etc.) have been studied and applied for detection and visualization objects within the image. Two quantitative measures of signal/image enhancement were presented. These measures are related with concepts of the Weber's law of the human visual system. It helps to choose (automatically) the best (optimal) parameters and transform for image enhancement.

We have improved upon the current magnitude re-

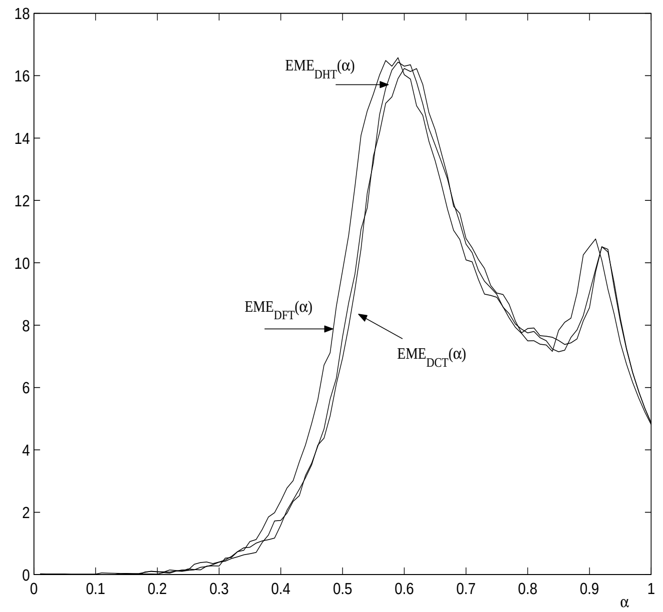

Fig. 2. α-rooting by the 2-D Fourier, cosine, and Hadamard transforms.

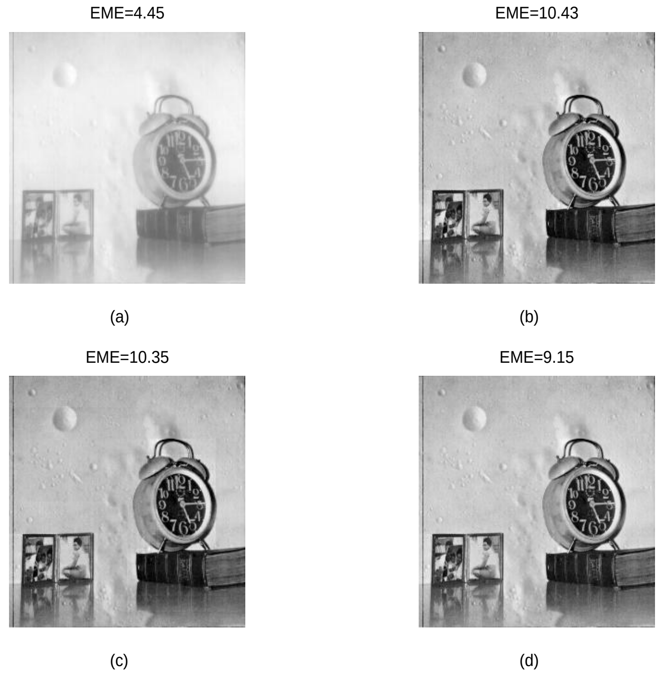

Fig. 3. Enhancement of the original image (a) via α-rooting based on the Fourier (b), Hadamard (c), and cosine (d) transforms when $\alpha = 0.92$.

duction techniques and design new one. The wide range of characteristics can be obtained from a single transform by varying enhancement parameters. The proposed algorithms are simple for design, which makes them practical. A number of experimental results illustrate the performance of these algorithms. The comparative analysis of transforms based image enhancement algorithms has been described, too.

References

[1] A. Rosenfeld and A.C. Kak, *Digital Picture Processing,* vol. 1, New York: Academic, 1982.

[2] W.M. Morrow and all., "Region-Based Contrast Enhancement of Mammograms," *IEEE Trans. on Medical Imaging,* vol. 11 (3), Sep. 1992.

[3] S.S. Agaian, "Visual Morphology," *Proceedings of SPIE,* Nonlinear Image Processing X, San Jose CA, vol. 3304, pp. 153-163, Jan. 1999,

[4] R. Kogan, S.S. Agaian, and K.P. Lentz, "Visualization Using Rational Morphology and Zonal Magnitude-Reduction," *Proceedings of SPIE,* vol. 3304, pp. 153-163, Nonlinear Image Processing IX, San Jose, 1998.

[5] R. Kogan, S.S. Agaian, and K.P. Lentz, "Visualization Using Rational Morphology and Magnitude-Reduction (2)," *Proceedings of SPIE,* vol. 3387, Visual Information Processing VII, 1998.

[6] T.L. Ji, M.K. Sundareshan, and H. Roehrig, "Adaptive Image Contrast Enhancement Based on human Visual Properties," *IEEE Trans. on Medical Imaging,* vol. 13 (4), Dec. 1994.

[7] A. Khellaf, Azeddine Beghdadi, and H. Dupoiset, "Entropic Contrast enhancement," *IEEE Trans. on Medical Imaging,* vol. 10, no. 4, Dec. 1991.

[8] G.X. Ritter and J.N. Wilson, *Handbook of Computer Vision Algorithms in Image Algebra,* CRC Press, 1996.

[9] K.R. Castleman, *Digital Image Processing,* Prentice-Hall, New Jersey, 1996.

[10] S. Aghagolzadeh and O.K. Ersoy, "Transform Image Enhancement," *Optical Engineering,* 31 (3), pp. 614-626, 1992

[11] J. K. Kim, J.M. Park, K.S. Song, and H.W. Park, "Adaptive Mommographic Image Enhancement Using First Derivative and Local Statistics," *IEEE Trans. on Medical Imaging,* vol. 16 (5), Oct. 1997.

[12] S.W. Hang, Y-H. Chan, and Wan-Chi Sin Subband, *Adaptive regularization methods for removing blocking effect.*

[13] A. Beghcladi and A.L. Negrate, "Contrast enhancement technique based on local detection of edges," *Comput. Vision, Graphic, Image Processing,* vol. 46, pp. 162-274, 1989.

[14] J.S. Leim, *Two-dimensional Signal and Image Processing,* Prentice Hall, 1990.

[15] I.E. Gordon, *Theory of Visual Perception,* John Wiley & Sons: New York, 1989.

[16] G.T. Fechner, *Elements of Psychophysics,* Vol. 1, Rinehart & Winston: New York, 1960.

[17] J.A. Saghri, P.S. Cheatham, and H. Habibi, "Image quality measure based on a human visual system model," *Opt. Eng.,* vol. 28 (7), 1989.

[18] P. Duhamel and M. Vetterli, "Fast Fourier transforms: A tutorial review and state of the art," *Signal Processing,* vol. 19, pp. 259-299, 1990.

[19] A.M. Grigoryan and S.S. Agaian, "Split manageable efficient algorithm for Fourier and Hadamard transforms," *IEEE Trans. on Signal Processing*, vol. 48, no. 1, pp. 172-183, Jan. 2000

[20] N. Hu and S. Luoh, "Adaptive Discrete Cosine Transform Based Image Coding," *Opt. Eng.,* 35 (4), pp. 989-996, 1996.