A New Measure of Image Enhancement

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Abstract— **A novel quantitative measure of image enhancement is presented. This measure is related with conceps of the Webers Low 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 (analysis, detection, segmentation, and recognition). Many methods proposed to enhance image are based on gray-level histogram modification [1], [2], [3], another methods are based on the local contrast transformation and edge analysis [4], [8], [9], or the "global" entropy transformation [10]. That is due to the absence of general standard of the image quality, which could be served as a design criteria for image enhancement algorithms [11].

It is fact that there is no general unifying theory of the image enhancement. Methods of the image enhancement techniques can be generally classified into two categories: spatial domain methods, which operate directly on pixels and frequency (transform) domain methods, which operate on transforms of the image (such as the Fourier, wavelet, and cosine transforms). The basic advantages of the transform image enhancement techniques are: (a) a low complexity of computations; (b) an important role of the orthogonal transforms in digital signal/image processing applications (c) they are easy to view and manipulate. In [13], a comparative analysis of transform based image enhancement techniques have been given, such as the alpha-rooting, modified unsharp masking, and filtering, which are motivated by the human visual response. The analysis of the existing transform based image enhancement techniques [7], [12], [13], [14], [15] 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, when image enhancement procedure is used as a preprocessing step for other image processing techniques such as the detection, recognition, and visualization. The use of the statistical measure of the gray level distribution measures of local contrast enhancement (for example, the mean, variance, or entropy) have not been particularly meaningful for many images (mammogram). A number of images, which clearly showed an improved contrast, showed no consistency, as a class, using these statistical measurement [16]. A measure which has proposed in [2] is based on the contrast histogram and has greater consistency than statistical measures.

This paper presents new quantitative measures of image enhancement and novel frequency domain based image enhancement methods for object detection and visualization. A number of experimental results are described to illustrate the performance of these algorithms. Comparative analysis of transforms based image enhancement algorithms are given.

II. Measure of image enhancement

In this subsection, we present a short servey of existing quantitative measure of the image enhancement and presented a new one. When analyzing the signals and systems, it is useful to map data from the time domain into another domain (in our case, the frequency domain). The basic characteristics of a complex wave are the amplitude and phase spectra. Specifying amplitude and phase spectra 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. To solve the corresponding problem, the real variable, t, is generalized to the complex variable, $(u+jv)$, which then is mapped back via the inverse mapping. For example, the Fourier transform maps the real line (time domain) into the complex plane, or real wave into the complex one. But, it has a high complexity of implementation which involves complex multiplications and additions.

The improvement in images after enhancement is often very difficult to measure. A processed image can be said to get an enhancement 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 the both objective and subjective validity of the enhancement method [16]. In practice, many definitions of the contract measure are used [2], [16], [9]. For example, the local contrast proposed by Gordon and Rangayyan [17] was defined by the mean gray values in two rectangular windows centered on a current pixel. Baghdan and Negrate [9] proposed another definition of the local contrast based on the local edge information of the image, in order to improve the first mentioned definition. In [9], the local contrast proposed by Beghdadi and Negrate have been adopted, in order to define a performance measure of enhancement. 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 [18]. 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 some modification of the the Webers and Fishers Lows. In the second image enhancement measure definition we will use the well known entropy concept: In Weber established its visual low, argued that the human visual detection depends on the ratio, rather than difference. The Weber definition of contrast is used to measure the local contrast of a single object (One usually assumes a large background with a small test object, in which case the average luminance will be close to the background luminance. If there are many objects this assumption do not hold). The Fisher Low, proposed the following relationship between the light intensity $i(x,y)$ and brightness:

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

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

We now introduce two new quantitative measures of image enhancement.

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, then we define

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

where $I^w_{\min;k,l}$ and $I^w_{\max;k,l}$ are respectively minimum and maximum of the image $X(n,m)$ inside the block $w_{k,l}$. 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 have been done after the study various examples of enhancement by transform methods using the different coefficients $C_i(p,s)$, $i=1,2,3$, which are described in the next section.

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

In the second image enhancement measure definition, we use the well known entropy concept.

Definition 2: Let an image $x(n,m)$ be split into k_1k_2 blocks $w_{k,l}(i,j)$ of sizes $l_1 \times l_2$. Then, the quantity

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

where

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

is called a *measure of enhancement by entropy.*

Definition 3: The best (optimal) image improvement transform-based enhancement algorithm is called a transform Φ_0 such as $EME(\Phi_0) = EME$, or $EMEE(\Phi_0) = EMEE$.

Definition 4: The best (optimal) image improvement transform-based enhancement algorithm is called a transform Φ_0 such as $EME(\Phi_0) = EME$, or $EMEE(\Phi_0) = EMEE$.

A. Enhancement in the frequency domain

Image enhancement in the frequency domain is straightforward. One simply perform the transform of the image to be enhanced, then manipulated the transform coefficient, and then perform the inverse orthogonal transform. Image transforms give the spectral information about an 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 the transform coefficients, for example the coefficients of the two-dimensional discrete Fourier transform,

$$F(p,s) = \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} x_{n,k} e^{-j2\pi(np+ks)/N} \qquad p,s = 0:(N-1), \quad j = \sqrt{-1}. \tag{4}$$

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

$$X_{p,s} = \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} x_{n,k} \cos\left(\frac{\pi}{N} [(n+\frac{1}{2})p + (k+\frac{1}{2})s] \right) \tag{5}$$

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

$$X_{p,s} = \sum_{n=0}^{N-1} \sum_{k=0}^{N-1} x_{n,k} a(p,n) a(s,k) \tag{6}$$

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

$$a(p,n) = (-1)^{n_0p_0 + n_1p_1 + \cdots + n_{r-1}p_{r-1}} \tag{7}$$

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 [7], [19]-[22].

Analyzing the existing transform-based enhancement algorithm (α-rooting and magnitude reduction methods [5], [6], [13], [15]), we can note 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 three steps:

Step 1. Perform the orthogonal transform.

Step 2. Multiply the transform coefficients by some factor, $O(k,m)$.

Step 3. Perform the inverse orthogonal transform.

The frequency ordered system-based method can bee represented as

$$x \to X \to \mathbf{O} \cdot X \to \mathbf{T}^{-1}[\mathbf{O}(X)] = \widehat{x}. \tag{8}$$

$\mathbf{O}$ 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 more 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*);

3) $C_2(p,s) = \log^\beta \left[|X(p,s)|^\lambda + 1 \right]$, $0 \le \beta$, $0 < \lambda$ [13];

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

$$X(p,s) = |X(p,s)| \exp[j\theta(p,s)] \tag{9}$$

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,

$$\mathbf{O}(X)(p,s) = \mathbf{O}(|X|)(p,s) \exp[j\theta(p,s)] \tag{10}$$

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 $0 \leq \alpha < 0.99$ 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 [13]. It is natural to ask what is 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 $\mathbf{a} = (\alpha, \beta, \gamma)$, i.e. $\Phi = \Phi_{\alpha,\beta,\gamma}$.

Definition 5: The best (optimal) Φ-transform-based enhancement image vector parameter (α, β, γ) is called the parameter $(\alpha_0, \beta_0, \gamma_0) \in \Omega$ such that $EME(\Phi_{\alpha_0,\beta_0,\gamma_0}) = EME$.

It should be noted here that the window size can be also included in the vector α as a parameter of optimal enhancement.

In the next section, the following problems are investigated: How to design the best improvement transform-based image enhancement algorithm? How to design the best Φ-transform-based enhancement image vector parameter (α, β, γ)?

III. Experimental results

In this section a number of experiments in order to evaluate the enhancement algorithm are described. For more clarity/visibility, we demonstrate the experimental results for 2-D signals such as moon plus clock image. We use classes of algorithms, namely, the transform based enhancement algorithms via respectively the operators $C_2(p,s)$. We present two classes of experiments. 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. A quantitative comparison of the provided methods is presented below, too.

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 [23], 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 were taken as the original, $x(n,m)$, with superimposed "moon" image, which gives an illegible image. Figure III illustrates an example of such kind of the illegible image. The result, $\widehat{X}(p,s)$, is an enhanced image, which can now be passed through a visualization algorithm.

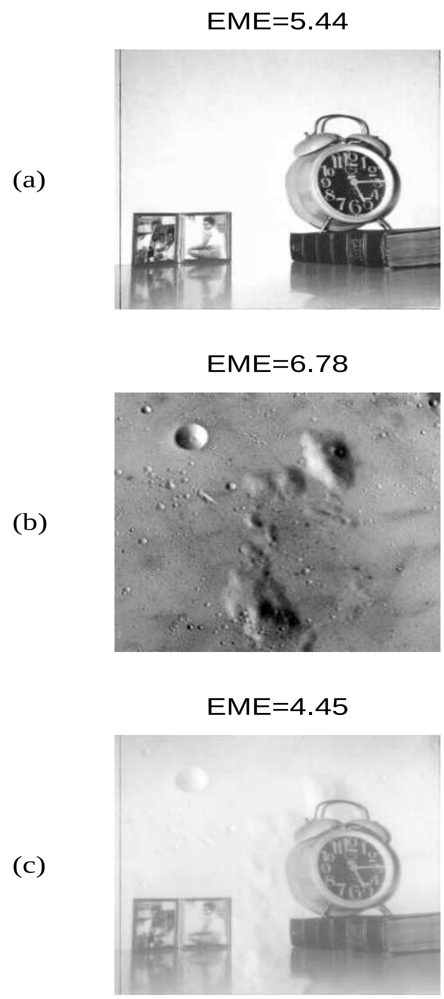

Fig. 1. Linear combination of the clock (a) and moon (b) images, which results in an illegible image (c).

Test 1 *(Choosing the best image enhancement transform for the given image).* Let $\widehat{x}(n, m)$ is identical to $x(n, m)$ after the normalization by a constant.

The enhancement measure of the original image shown in Fig. is 4.5, or $EME_I(X) = 4.5$, where I is the identical transform. Figures 4 shows four curves described the measure of the enhancement, when applying the Fourier, Hadamard, cosine, and Hartley transforms. We see that on the whole interval, where α varies, the maximal measure of enhancement is provided mostly by the cosine and Hadamard 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 best transform among above transforms). 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.

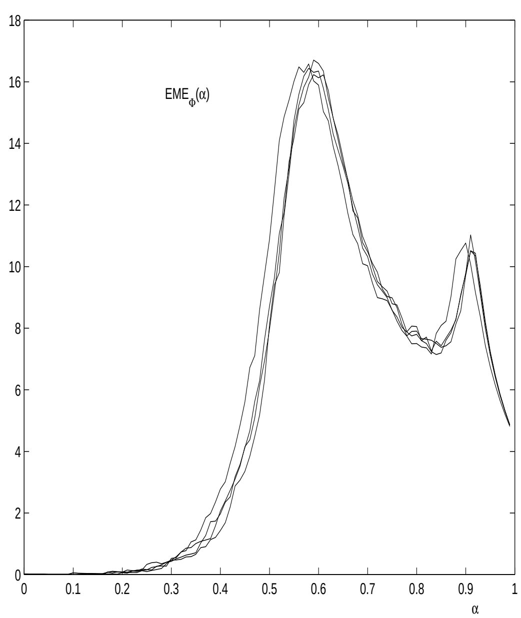

Fig. 2. α-rooting by the 2-D cosine (from the top to botton), Hadamard, Fourier, and Hartley transforms.

Transform based enhancement algorithm via operator $C_2(p, s)$.

Test 2 *(Choosing the best operator parameter).* Figure 4 illustrates the enhanced images by varying parameter α, when using the Fourier transform, (a)-(c), and Hadamard one, (d)-(f). The log-magnitude reduction using $C_2(p, s)$ served to enhance the edges around regions in the image.

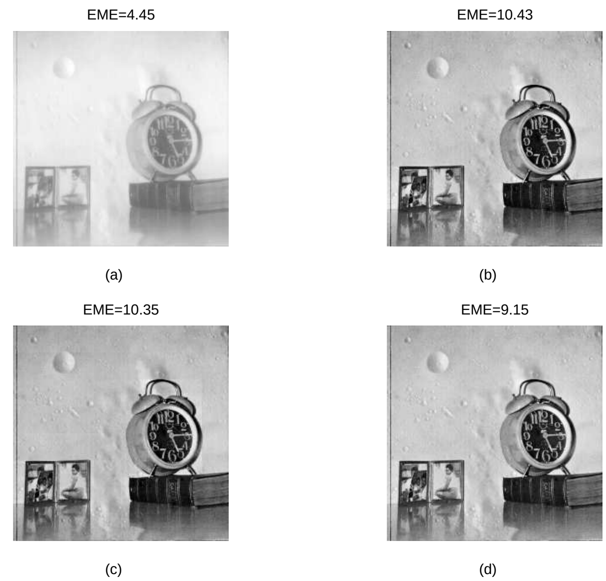

Fig. 3. Enhancement of the original image (a) via α-rooting based on the Fourier (b), Hadamard (c), and cosine (d) transforms when $\alpha = 0.92$.

Test 3 *(Choosing the best image enhancement transform for the given image).* Figures 5(a) and (b) illustrate the enhanced images by using different transforms and varying parameters λ and β respectively in the intervals $[0, 2]$ and $[0, 1]$. Figure 5(a) illustrates the surface of the measure for the Fourier method and (c) and (d) show the differences between the measures when the Fourier, Hadamard, and cosine transforms are used for enhancement. The results of the Fourier transform based image enhancement are shown in Fig. 6, for the boundary parameters. The 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.

Test 4 *(Comparison).* For completeunderstanding the above method of enhancement, Figure 7 illustrates the surfaces of measure $EME(\alpha, \lambda, \beta)$, when one of the parameter is fixed.

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 described and applied for detection and visualization objects within the image. A quantitative measure of signal/image enhancement was presented. This measure is related with conceps of the Webers Low of the human visual system. It helps to choose (automatically) the best parameters and transform.

We have improved upon the current magnitude reduction 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 were given illustrate the performance of these algorithms. The comparative analysis of transforms based image enhancement algorithms has been described, too.

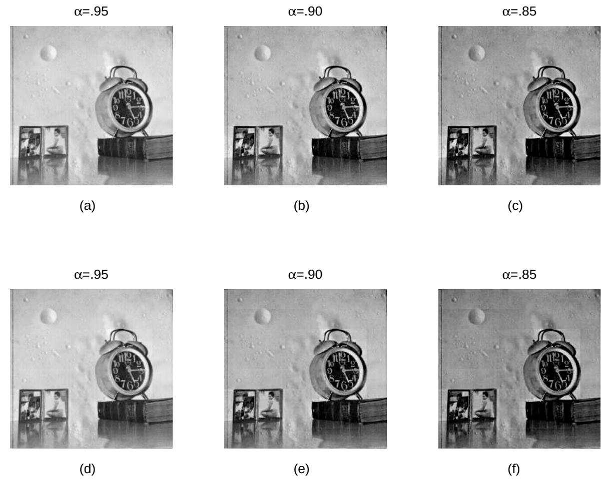

Fig. 4. Enhanced images via the α-rooting based on the Fourier transform, (a)-(c), and Hadamard transform, (d)-(f).

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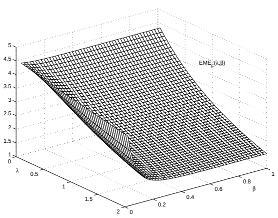
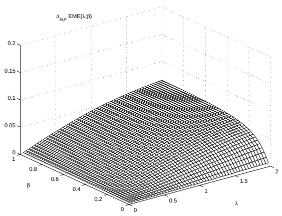
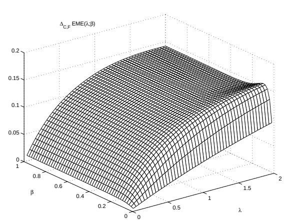


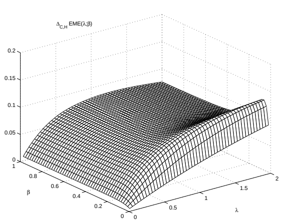
(a) Fourier enhancement



(b) Differnce $EME_H(\lambda, \beta)$-$EME_F(\lambda, \beta)$



(c) Differnce $EME_C(\lambda, \beta)$-$EME_F(\lambda, \beta)$



(d) Differnce $EME_C(\lambda, \beta)$-$EME_H(\lambda, \beta)$

Fig. 5. Measure of log-enhancement by Fourier, Hadamard, and cosine transforms.

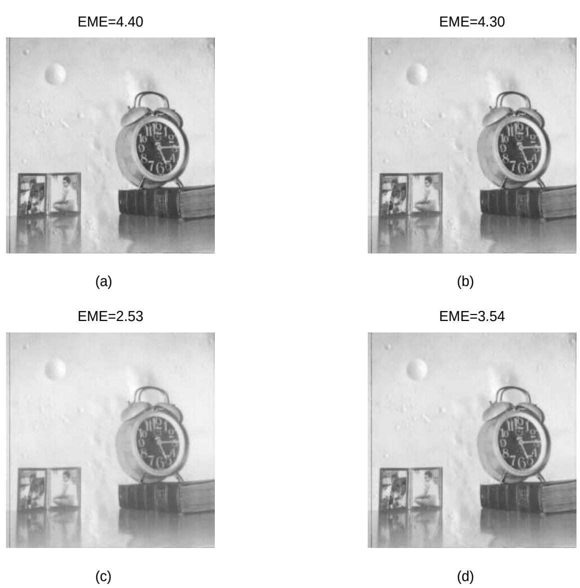
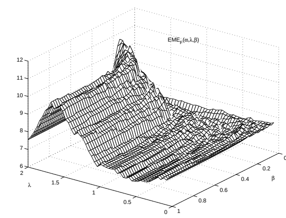
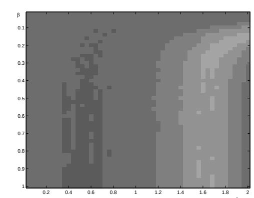


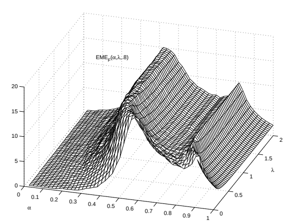
Fig. 6. The original image (a) and 2-D Fourier transform enhancements (b)-(d) when operating with C_3 coefficients for (λ, β) equal respectively to $(0.05, 0.05)$, $(1.9, 0.05)$, $(0.05, 0.9)$, and $(1.9, 0.9)$.



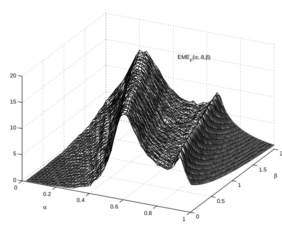
(a) Surface of the enhancement measure ($\alpha = 0.8$)



(b) Image of the enhancement measure



(c) Surface of the enhancement measure ($\beta = 0.8$)



(d) Surface of the enhancement measure ($\lambda = 0.9$)

Fig. 7. Fourier enhancement via log-reduction when coefficients $C_3(p, s)$ are calculated for one fixed parameter.