IMAGE ENHANCEMENT USING COLOR AND SPATIAL INFORMATION

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ABSTRACT

In this paper, a new filter that is performing color image enhancement is presented. The filter is achieving this through the minimization of a weighted cost function. The weights are determined using potential functions which are calculated in such a way as to convey spatial information. Application of the proposed filter on a real blurred and noisy color image is performed to verify its enhancement capabilities.

1. INTRODUCTION

Many of the signals available for processing nowadays are of vectorial nature and for optimal output results vector techniques have to be employed. Color images is another example of vector valued signals. These images compared to grey scale ones contain more information and are more appealing to the human observer. Are thus used more and more in several scientific applications as well as in every day life.

Vector processing methods exhibit significant advantages over single channel approaches, preserving the existing correlation between the channels. Order statistics type filters play a key role in the processing of these signals and several multivariate ordering techniques have been proposed in the literature[1,2]. Another similar approach to solve the vector ordering problem is by means of the minimization of an appropriate cost function[3,4].

Cost functions based on different distance measures find an ever increasing number of applications in several areas of multichannel signal processing. Vector ordering is controlled by certain parameters of the cost function.

In this work the minimization of the combination of two different distance functions is used in order to select the output vector for the case of color images. Although in most cases the two functions have similar characteristics, in certain cases, due to particular signal features and cost function's parameter setting, their outputs differ. In addition the two functions do not have exactly the same spatial domain of application. The combined information given by the two cost functions is used advantageously to achieve edge enhancement and noise suppression at the same time.

2. THE NEW COST FUNCTION

Pixels in color images can be represented as vectors in the RGB space. Thus a single pixel can be defined as:

$$\mathbf{X}_i = [r_i, g_i, b_i]^T \quad (1)$$

where r_i ,g_i ,b_i are the red, green and blue components of pixel i. In this representation however, valuable information about the pixels' distribution on the image plane is ignored. Attempts to incorporate this type of information can be found also in other works [5].

Given a rectangular filter window W_N of size N, scanning the color image plane, for each window position a set of N vectors is used in the filtering process.

The proposed new algorithm for image enhancement is based on the selection of the vector within each W_N (closeness is assumed) that minimizes the following weighted aggregate distance formula:

$$d(\mathbf{X}_i) = g(\mathbf{X}_i) * \sum_{j=1}^{N} \left\| \mathbf{X}_i - \mathbf{X}_j \right\| \qquad (2)$$

where $\mathbf{X}_i$ is one of the vectors in W_N and $\|.\|$ is the L_2 vector norm.

In the above formula the weight $g(\mathbf{X}_i)$ is the conveyor of the spatial information and the new function $g(\mathbf{X})$ is defined over a new local window W_M, centered on vector $\mathbf{X}_i$. The size of the new window is M and in general $N \neq M$. An illustration of the enlarged window used, is given in Figure 1 below, in this case N=M=9.

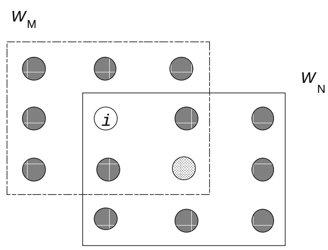

Figure 1: Enlarged filter window.

The potential functions[6] (PFs) are utilized to define $g(\mathbf{X}_i)$. According to potential function theory, each pixel is being regarded as an energy source creating a homogeneous, decreasing with distance, field around it. The function describing this field may not be restricted to the conventional, well known from physics, ones (i.e. gravitational), but can be any monotonically decreasing function of distance [7].

As such the following exponential function is chosen:

$$p(\mathbf{X}_i) = \sum_{k=1}^{M} \exp\left[-\frac{1}{2h^2} \left\| \mathbf{X}_i - \mathbf{X}_k \right\|^2 \right] - 1 \qquad (3)$$

where, the parameter h is a constant determined globally and its value selection is based on the image noise content. M is the number of pixels contained in the neighbourhood of pixel $\mathbf{X}_i$. In the above formula -1 is included in order to exclude contribution from pixel $\mathbf{X}_i$.

The calculation of the PF in the neighbourhood of each pixel makes it embody spatial information as was desired. Then $g(\mathbf{X}_i)$ is set equal to:

$$g(\mathbf{X}_i) = \frac{1}{p(\mathbf{X}_i)} \qquad (4)$$

Obviously, if

$$g(\mathbf{X}_i) = 1 \quad \text{for } i=1,\dots,M \qquad (5)$$

the minimization procedure will lead us to the selection of the well known vector median.

3. METHOD OF OPERATION

As seen from eq. (1), the described filtering process is the product of two different distance functions, defined over adjacent filter windows. In this section the operation and basic properties of each one are analysed separately.

The behaviour of the scalar function $f(\mathbf{X})$:

$$f(\mathbf{X}_i) = \sum_{j=1}^{N} \left\| \mathbf{X}_i - \mathbf{X}_j \right\|$$

(6)

has been extensively examined in the literature. Of particular interest is its response to steps, impulses, ramp signals and random noise. Although its minimum value selection is the optimum in the case of biexponentially noisy conditions this is not so for other noise distributions and non stationary signals. An improvement is thus sought in these cases.

Potential functions are basically probability density function estimators in the neighbourhood of each $\mathbf{X}_i$ [8] and are used in eq. (2) to include this additional information, along with the spatial, modulating the cost function f. This action is illustrated in the following example.

In Figure 2a a noisy three-component one-dimensional edge is shown. For the pixels of this edge, the function $f(\mathbf{X})$ has been calculated through (6) and using a window W_N spanning all the pixels, which means N=11. Its minimum value, as can be observed in Figure 2b, corresponds to one of the pixels in the transition area of the edge (pixel number 6), which is the vector median.

Next, the function $p(\mathbf{X})$ is calculated using (3). The window W_M has a size of M=3 pixels, which means that for each pixel $\mathbf{X}_i$ two neighbouring pixels determine its potential. Since the potential's value is high in areas of high pixel consentration in the RGB space and, correspondingly, low for low consentration, it is expected that flat area pixels will exhibit high values of $p(\mathbf{X})$ and transition area pixels, as well as impulses, low values. It should be pointed out that these statements may not hold if parameter h is not chosen correctly. Its value depends on the window size M and on the noise variance. A detailed study on the method for choosing h can be found in [2] and [8]. Assuming gaussian distribution noise with variance σ^2, it is found that h should be of the order of $M^{-1/7}$[2]:

$$h = \sigma\left(\pi\sqrt{\pi}/3M\right)^{1/7} \tag{7}$$

$g(\mathbf{X})$, which is the inverse potential function, will be low in flat areas and high in transition areas, as displayed in Figure 3c (normalized). Thus, acting as coefficient in (2) it is modulating (6), decreasing the cost function value for flat area pixels and increasing it for transition area ones. At the same time, the cost remains high for impulses. The final cost function $d(\mathbf{X}_i)$ for the pixels of Figure 2a is shown in Figure 2d. It can be seen now that d's minimum has moved to one of the flat area pixels.

Thus, by following the procedure of choosing as output $\mathbf{Y}$ of the filter the pixel with minimum d:

$$\mathbf{Y} = \arg(\min\{d(\mathbf{X}_i)\}) \tag{8}$$

will result in edge enhancement and impulsive noise suppresion. Decrease in gaussian noise in flat image areas is also expected, since the potential function p will yield maximum (g will correspondingly be minimum) for the pixel with higher probability, as it acts as an estimator of the pixels' probability density function[2,8].

4. APPLICATION TO IMAGES

The edge enhancement and noise attenuation properties of the presented method have also been visually verified. In Figure 3a the image 'peppers' is shown, blurred with an averager of window size 3x3 and corrupted with gaussian noise of variance 100 and impulsive 1% in each channel. In Figure 3b the same image is displayed after enhancement with the proposed method. As can be seen, the blurred edges have been enhanced. Also, the impulses have been removed and the gaussian noise has been reduced.

Acknowledgements

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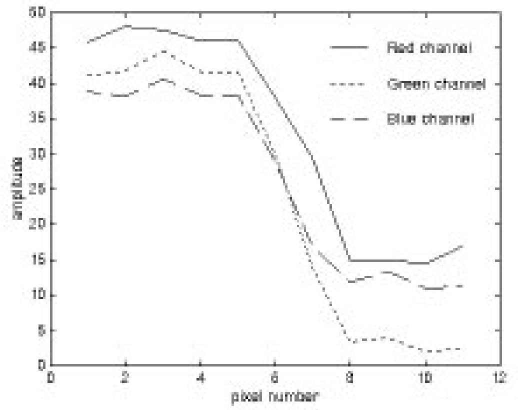

Figure 2a

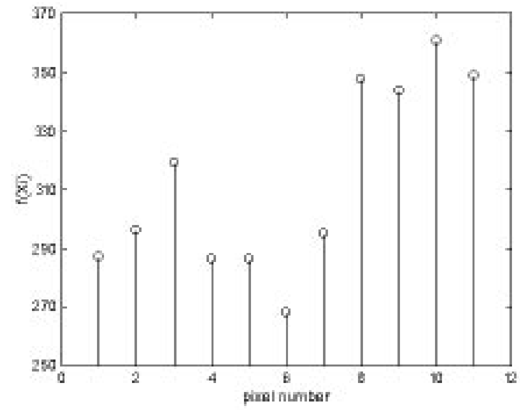

Figure2b

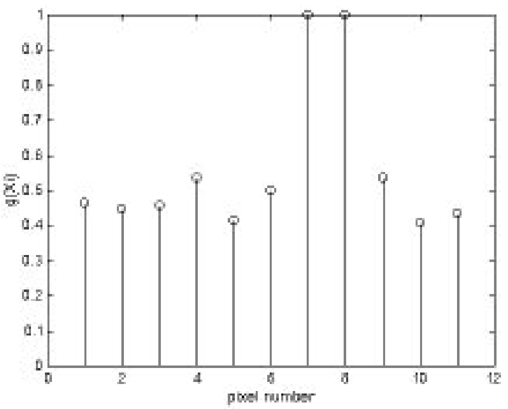

Figure 2c

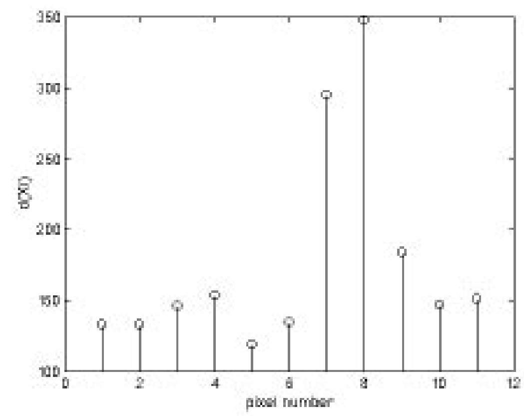

Figure 2d

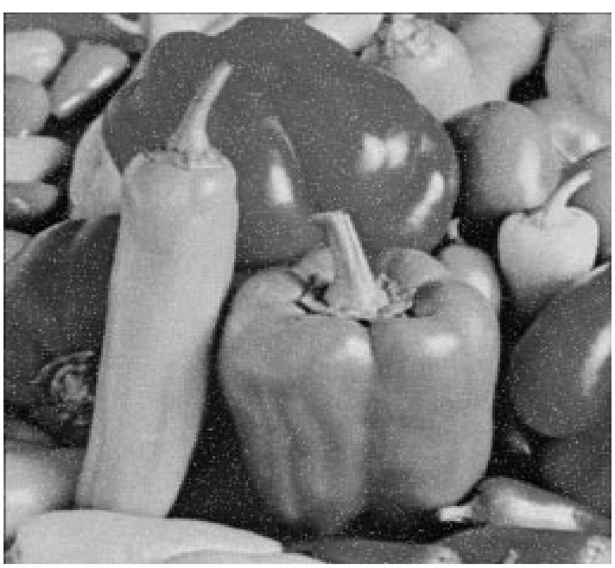
Figure 3a


Figure 3b