CONTRAST ENHANCEMENT IN NOISY IMAGES USING RATIONAL BASED OPERATORS

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ABSTRACT

This paper is devoted to a new method for image contrast enhancement in noisy environment. The corresponding algorithm contains two cascaded sub-functions: (1) The preprocessing block is formed by a new class of nonlinear filters called Median-Rational Hybrid Filters (**MRHF**) based on Rational Functions (**RF**), and (2) is the modified linear unsharp masking, by introducing a rational control operator of the local input data. The parameters of the control term can be fixed according to the noise statistics, and/or the type of application at hande to avoid the noise amplification and limit the overshoot effects on sharp edges. The proposed MRH Filters have the inherent property that on smooth areas they provide good noise attenuation whereas on changing areas the noise attenuation is traded for good response to the change.

Experimental results demonstrate a significant subjective improvement in the restored image quality as well as a consistent contrast enhancement improvement in comparison to other methods.

Keywords: Rational Filters, Median Rational Hybrid Filters, Image enhancement, Unsharp Masking.

1. INTRODUCTION

Various contrast enhancement algorithms have been proposed in the literature, and they are often employed in an interactive fashion with the choice of the algorithm and the setting of its parameters dependent on the specific application on hand, to improve the visual appearence of the image. Some include the use of local statistics, histogram equalisation, quadratic or cubic filters unsharp masking; the latter being the popular one. It is based on the addition of an amplitude-scaled linear highpass filtered version of the image itself. This scheme yields pleasent results by utilising an effect called *Simultanous contrast* [3]. However, the highpass filter which is traditionaly used also enhances noise components present in the image. Improvement in the quality of the enhancement has been obtained using a fairly simple quadratic filter in place of the linear highpass filter [3]. The filter output depends on the local background brightness, and as a result, it follows another property of the human visual system called "weber's law". This quality makes the new filters very attractive for image enhancement. Another modification proposed in [8] was to place, after the linear highpass filter, a polynomial operator formed by the parallel connection of a linear smoothing filter and a cubic sharpening component. In such a way the behavior of the filter becomes amplitude-sensitive: for small input amplitude changes, which can be interpreted as noise, the lowpass linear component dominates and a smoothing effect is obtained; whereas, large input variations representing relevant details and captured by the highpass are further amplified due to the cubic term. To ashieve enhancement in noisy environments, a prefiltering process may be required. In order to derive a rational filter for dealing with various kinds of noise such as Gaussian noise, impulsive noise and mixed Gaussian-impulsive noise, we propose a new class of nonlinear rational hybrid filters for signal and image processing called Median-Rational Hybrid (**MRH**) Filters. The MRH Filter is based on three subfilters in which two FIR subfilters and one standard median operator. Also we develop a new family of nonlinear operators (has similar behaviour than in [7] based on rational functions (the ratio of two polynomials)[2], able to enhance images and performs better than a number of methods in the literature. These operators are introduced in the correction path and replace the block edge-sensor in [6]. The noise amplification is very limited and steep edges, which do not need further emphasis, remain almost unaffected.

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2. MEDIAN-RATIONAL HYBRID FILTERS

Consider the real-valued 2-D sequence $\{x(\mathbf{n})\}$ containing $(2N+1)$ observation samples at each location $\mathbf{n}$, and a 3x3 window mask centered around $x(\mathbf{n})$ shown in Fig. 1, in order to filter the sample $x(\mathbf{n})$ at the central position. The corresponding output $y(\mathbf{n})$ is the result of a rational operation using two FIR substructures and one based on standard median operation of length $(2T+1)$ (with $T \leq N$ and $N \geq 1$) and written as:

$$y(\mathbf{n}) = \frac{\Phi_0(\mathbf{n}) + \Phi_1(\mathbf{n})}{h + k(\Phi_0(\mathbf{n}) - \Phi_1(\mathbf{n}))^2} + x_{med}(\mathbf{n})[1 - \frac{2}{h + k(\Phi_0(\mathbf{n}) - \Phi_1(\mathbf{n}))^2}]. \quad (1)$$

In Eq.(1),

$$\Phi_0(\mathrm{n}) = \sum_{i=1}^{4} h_0(i) x_i(\mathrm{n}). \quad (2)$$

$$\Phi_1(\mathrm{n}) = \sum_{i=5}^{8} h_1(i) x_i(\mathrm{n}). \quad (3)$$

Where the filter coefficients satisfy the following condition: $\sum_{i=1}^{4} h_0(i) = \sum_{i=5}^{8} h_1(i) = 1$.

$$x_{med}(\mathrm{n}) = 0.5 * \Big(median(x_1(\mathrm{n}), x_4(\mathrm{n}), x(\mathrm{n}), x_5(\mathrm{n}), x_8(\mathrm{n})) + \mathrm{median}(\mathrm{x}_3(\mathrm{n}), x_2(\mathrm{n}), x(\mathrm{n}), x_7(\mathrm{n}), x_6(\mathrm{n})) \Big). (4)$$

h and k are some positive constants. The parameter k is used to control the amount of the nonlinear effect.
The three subfilters Φ_0, Φ_1 and x_{med} are chosen so that an acceptable compromise between noise reduction and edge preservation is obtained. It is easy to observe that this Median-Rational Hybrid Filter differs from a linear low-pass filter mainly in the scaling, which is introduced in Φ_0 and Φ_1. Indeed, such terms are devided by a factor proportional to the output of an edge-sensing term characterized by $(\Phi_0(\mathrm{n}) - \Phi_1(\mathrm{n}))^2$. The weight of the median-operation output term is accordingly modified, in order to keep the gain constant. Let us examine its behaviour for different positive values of the parameter k.

1: $k \simeq 0$, we have a linear operation of the three output suboperators cited above: $y(\mathrm{n}) = \frac{\Phi_0(\mathrm{n}) + \Phi_1(\mathrm{n}) + (h-2) x_{med}(\mathrm{n})}{h}$.

2: $k \to \infty$, the output of the filter is identical to the median suboperator output: $y(\mathrm{n}) = x_{med}(\mathrm{n})$.

3: For intermediate values of k, the $(\Phi_0(\mathrm{n}) - \Phi_1(\mathrm{n}))^2$ term perceives the presence of a detail and accordingly reduces the smoothing effect of the operator.

In this way, the MRH Filter acts as a linear operator between three suboperators the coefficients of which are modulated by the edge-sensitive component.

$x_1(n)$	$x_2(n)$	$x_3(n)$
$x_4(n)$	$x(n)$	$x_5(n)$
$x_6(n)$	$x_7(n)$	$x_8(n)$

Figure 1: Elements of 3x3 sliding window centered around the pixel $x(n)$ for nonrecursive implementation

3. RATIONAL ENHANCEMENT OPERATOR

According to Fig.2 the unsharp masking (UM) scheme can be expressed as follows:

$$y(n) = x(n) + \lambda z(n). \quad (5)$$

where $x(n)$ and $y(n)$ represent the restored signal by the MRH Filter and the enhanced signal, respectively. $z(n)$ is the sharpening term and λ is a positive scaling factor. We

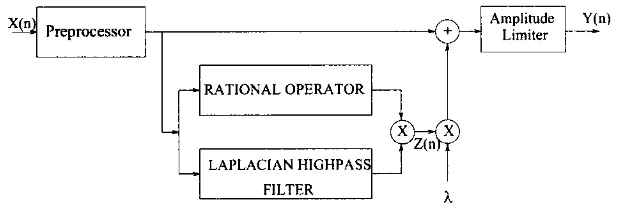

Figure 2: The proposed enhancement scheme

propose a new correction term $z(n)$ given by the product of the Laplacian $L(n)$ and a control function $\Gamma(n)$ of the local activity measure, which is inturn function of the "*edge − sensing*", $g(n) = (x(n-1) - x(n+1))^2$. The control function has the following rational form:

$$\Gamma(n) = \Gamma(g(n)) = \frac{g(n)^p}{a + b g(n)^q} \quad (6)$$

where $p, q \in N$ and $p \leq q$, Fig.3 shows the representative behaviour of the control function $\Gamma(n)$, with different selected parameters.

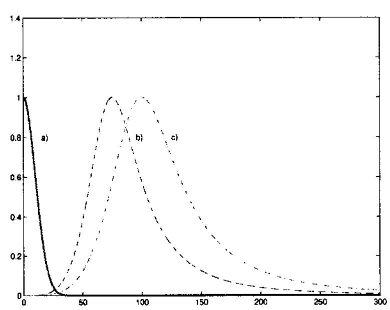

Figure 3: Behaviour of the proposed rational control function with different parameter values: a) Gaussian(0,100), b) rational (p=2, q=4, $a = 1.6 * 10^7, b = 1.6 * 10^{-8}$) and c) rational (p=2, q=4, $a = 5 * 10^7, b = 5 * 10^{-9}$)

To avoid the noise amplification, our function $\Gamma(n)$ must obey some restrictions.

Constraints:

1: At the value of the standard deviation $\sqrt{2}\sigma$ of the Gaussian noise $\nu(n)$ described in the following paragraph, the function $\Gamma(n)$ has a small value; while,

2: Its maximum value must be located in the region of interest (characterized by its intensity luminance).

Control Function: First of all, let us characterize the statistics of our rational control function in presence of Gaussian noise.
We assume an observation model such as:

$$X(n) = X_0(n) + \eta(n) \quad (7)$$

Where $X_0(n)$ is the true signal and $\eta(n)$ is an additive white Gaussian noise (0, σ^2) which result from an i.i.d. process. Let $f(n)$ denotes the *edge − sensor*. It will be written as:

$$
\begin{aligned}
f(n) &= X(n+1) - X(n-1). \\
&= [X_0(n+1) - X_0(n-1)] + [\eta(n+1) - \eta(n-1)]. \\
&= f_0(n) + \nu(n).
\end{aligned}
$$

where $\nu(n) = [\eta(n+1) - \eta(n-1)]$ represents the noise in the activity measure function $g(n)$.

Based on the above assumptions $\nu(n)$ is also an additive white Gaussian noise (0, $2\sigma^2$).

We note by $\sigma_1 = \sqrt{2}\sigma$ the standard deviation of $\nu(n)$. For $g = 2\sigma_1$, the control function must have a neglected value,

$$\Gamma(2\sigma_1) = \frac{(2\sigma_1)^p}{a + b(2\sigma_1)^q} \ll 1 \qquad (8)$$

Hence, for a fixed parameter b, it is easy to find the corresponding parameter a which must obey the above condition.

For the second constraint, let us denote by I_0 the mid-range intensity of the desired region. If the maximum of the control function $\Gamma(n)$ is located at I_0, the first derivative of $\Gamma(n)$ at I_0 will be equal to 0.

$$\frac{\partial\Gamma(g(n))}{\partial(g(n))}\Big\|_{g(n)=I_0} = 0. \qquad (9)$$

From Eq.(9) and for a given parameter b, the parameter a will be expressed:

$$a = b(\frac{p}{q} - 1)I_0^q \qquad (10)$$

We can conclude that our control function is able to vary over the activity measure axis by an appropriate selection of the different parameters a, b, p and q, in order to enhance the region of interest characterized by its mid-range intensity and at the same time, the Gaussian noise is not enhanced.

In the two dimentional case and according to the window mask shown in Fig.1, the corresponding sharpening component $Z(n)$ has been written in two different ways

1: plus-shaped mask: $Z_+(n) = \Gamma_+^T(n)L_+(n)$.
$L_+(n) = [(2x - x_4 - x_5), (2x - x_2 - x_7)]^T$
$g_+(n) = [g_x, g_y]^T = [(x_4 - x_5)^2, (x_2 - x_7)^2]^T$
$\Gamma_+(n) = [\Gamma(g_x), \Gamma(g_y)]^T$

2: cross-shaped mask: $Z_{cr}(n) = \Gamma_{cr}^T(n)L_{cr}(n)$.
$L_{cr}(n) = [(2x - x_1 - x_8), (2x - x_3 - x_6)]^T$
$g_{cr}(n) = [g_{cr1}, g_{cr2}]^T = [(x_1 - x_8)^2, (x_3 - x_6)^2]^T$
$\Gamma_{cr}(n) = [\Gamma(g_{cr1}), \Gamma(g_{cr2})]^T$

4. EXPERIMENTAL RESULTS

The noisy part of image Lena 256x256 (mixed Gaussian(0,50) and impulsive(2%) noise) is presented in Fig.4, and then processed with several prefiltering operators in order to compare the performance. Two well known techniques have been selected, the standard median filter and the rational filter. The corresponding enhanced images with rational preprocessing, median preprocessing and the proposed MRH preprocessing are shown in Figs. 5, 7 and 8, respectively. One can conclude that using the new MRH preprocessing operator, one can obtain better image quality compared to the other preprocessors. This is due to its effective property that on smooth areas it provides good noise attenuation; whereas, on changing areas the noise attenuation is traded for good response to the change. Also, in presence of impulsive noise, the preprocessing block will be inevitably used, while, in noise free image, the new MRHF appears with neglegible effect, see Fig.13.

For the rational preprocessing case, the noise was attenuated at the expense of excessive blurring and degraded sharp edges.

For the median preprocessing case, the latter fails to remove Gaussian noise and the image remains degraded.

The effect of the MRHF preprocessing on noise free images is illustrated in Figs. 6 and 9. It is clear that the preprocessing block causes neglegible degradation.

To assess the performance of the proposed rational operator under both subjective and objective viewpoints, the above corrupted and preprocessed image Lena by MRH preprocessing is used and shown in Fig. 10. Figs.11, 12 and 13 show the processed images using MRHF preprocessing, by the cubic Unsharp Masking operator ($\lambda = 0.05$), the mean-weighted Laplacian operator ($\lambda = 0.01$) and the proposed rational control operator ($\lambda = 1$), respectively. Clearly, noise is amplified and the image quality is thus degraded by using the cubic operator and the mean-weighted Laplacian. On the other hand, with the rational operator, the noise amplification in background area is significantly avoided and the contrast enhancement effect is perceived.

For evaluating quantitatively the performance of an enhancement scheme, we use the method proposed in [10]. It is based on the evaluation of the local image variance using a 3x3 or 5x5 mask. Each pixel of the original image is assigned a label according to the local measured variance: if this variance is below a threshold we judge that the pixel belongs to a background area, otherwise to a detail. In this way, a binary map image is generated. Then the local variance is measured again in the processed images. Each variance sample is accumulated as *details variance* (DV) or *background variance* (BV) according to the label assigned to that pixel, and the two average values of DV and BV are obtained for each image. Qualitatively, it can be stated that an ideal enhancement method should yield a DV value significantly larger than the one measured on the original data, while the BV should remain almost constant. Of course, this is a general consideration and it is a useful tool to compare different techniques.

The above BV and DV method is used. The tabulated results (Table 4 for the contaminated image and, table 5 for the noise free image) indicate that the proposed control operator satisfies the requirements of large DV and small BV, while the other techniques prove to be less effective from the viewpoints of both detail sharpening and noise attenuation.

5. CONCLUSION

In this paper, we introduced an efficient scheme for image contrast enhancement in noisy environment. The new preprocessing operator is the Median-Rational Hybrid MRH Filter. Experimental results demonstrated that MRH preprocessor can effectively remove various kinds of additive i.i.d. noise such as Gaussian noise, impulsive noise and mixed Gaussian-impulsive noise. The performances of several conventional preprocessing operators have been tested and compared to the proposed one. In most cases, the MRH preprocessor outperforms all its counterpart. Also, the rational control operator can enhance the contrast of a specific region of interest, while, noise amplification can be avoided. Its performance is rely on the choice of its parameters according to the nature of the data at hand.

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Preprocessing	without		with	
#	**BV**	**DV**	**BV**	**DV**
Original(noisy)	52.95	430	19.24	485
Cubic(λ_1)	60.09	407	21.49	488
MW Laplacian(λ_2)	60.98	404	23.20	487
Proposed(λ_3)	53.10	1174	18.10	1320

Table 1: Quantitative measures of the performance of the different enhancement techniques ($\lambda_1 = 0.05$, $\lambda_2 = 0.05$ and $\lambda_3 = 1$) for image Lena contaminated by Gaussian noise(0,50)

Preprocessing	without		with	
#	**BV**	**DV**	**BV**	**DV**
Original	22.40	516	15.60	495
Cubic(λ_1)	44.07	503	23.12	506
MW Laplacian(λ_2)	21.40	478	23.12	506
Proposed(λ_3)	21.40	1413	14.40	1307

Table 2: Quantitative measures of the performance of the different enhancement techniques in the case of noise free image ($\lambda_1 = 0.05$, $\lambda_2 = 0.05$ and $\lambda_3 = 1$).

#	**BV**	**DV**
Original image	16.02	502
Cubic operator(λ_1)	17.36	506
Mean-weighted Laplacian(λ_2)	18.81	503
Proposed operator(λ_3)	15.00	1361

Table 3: Quantitative measures of the performance of the different enhancement techniques with median-rational hybrid preprocessing in the case of image Lena contaminated by mixed Gaussian and impulsive noise. ($\lambda_1 = 0.01$, $\lambda_2 = 0.01$ and $\lambda_3 = 1$)

Figure 4: Noisy image Lena with mixed Gaussian(0,50) and impulsive noise (2%)

Figure 5: Enhanced image by the proposed rational control operator with rational preprocessing

Figure 6: Enhanced noise free image by the proposed rational control operator with MRH preprocessing

Figure 7: Enhanced image by the proposed rational control operator with median preprocessing

Figure 8: Enhanced image by the proposed rational control operator with the proposed MRH preprocessing

Figure 9: Enhanced image by the proposed rational control operator without preprocessing

Figure 10: Processed image by the proposed MRH preprocessing

Figure 12: Enhanced image by the cubic operator

Figure 11: Enhanced image by the mean-weighted Laplacian operator

Figure 13: Enhanced image by the proposed rational control operator