16th IMEKO TC4 Symposium
Exploring New Frontiers of Instrumentation and Methods for Electrical and Electronic Measurements
Sept. 22-24, 2008, Florence, Italy

Cardio -Vascular Image Contrast Improvement via Hardware Design

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Abstract - In many circumstances software processing is the best and suitable way of improving image contrast, hence image quality. Different biomedical instrumentation and apparatuses encompass post processing units capable of optimal outcomes. However, in particular cases, especially for contour analysis, the above outcomes are not sufficient. Therefore, an alternative can be envisaged in designing image enhancer and intensifier to compensate image processing limitations. This aspect is very important regardless of computational costs of this alternative. This paper proposes some criteria of design image enhancer and intensifier for biomedical applications. Moreover, the hardware has been used for improving the quality of cardio-vascular image constrast with acceptable outcomes. The images come from different instrumentations, namely, diagnostic ultrasound and echocardiograph. In addition, a specific algorithm has been implemented by means of a variational approach based on Mumford & Shah functional to solve the *magnification or zooming* problem for a given digital image. The numerical solution of the system of elliptic PDEs associated with the MS functional can provide simultaneously noise suppression, extraction of shape and magnification of the image.

I. Introduction

Practical noise reduction methods often involve mutiple-sample averaging (*block averaging*) of a sequence of measured values, *x(n)*, to compute a sequence of *N*-sample arithmetic means, *M(q)*. As such, the block averaged sequence *M(q)* is defined by:

$$M(q) = \sum_{k=qN}^{(q+1)N-1} x(n)\,, \tag{1}$$

where the time index of the averaging process is q=0,1,2,3, etc. When *N*=10 for example, for the first block of data (*q*=0), time samples *x*(0) through *x*(9) are averaged to compute *M*(0). For the second block of data (*q*=1), time samples *x*(10) through *x*(19) are averaged to compute *M*(1), and so on [1]. The following impulsive-noise smoothing algorithm processes a block of time-domain samples, obtained through periodic sampling, and the number of samples, *N*, may be varied according to individual needs and processing resources. The processing of a single block of *N* time samples proceeds as follows: collect *N+2* samples of *x*(n), discard the maximum (most positive) and minimum (most negative) samples to obtain an N-sample block of data, and compute the arithmetic mean, *M*(q), of the *N* samples. Each sample in the block is then compared to the mean. The direction of each sample relative to the mean (greater than, or less than) is accumulated, as well as the cumulative magnitude of the deviation of the samples in one direction (which, by definition of the mean, equals that of the other direction). This data is used to compute a correction term that is added to the mean according to the following formula:

$$A(q) = M(q) + \frac{(P_{os} - N_{eg})\left|D_{total}\right|}{N^2} \tag{2}$$

where *A*(q) is the corrected mean, *M*(q) is the arithmetic mean (average) from Eq.(1), P_{os} is the number of samples greater than *M*(q), and N_{eg} is the number of samples less than *M*(q), and D_{total} is the sum of deviations from the mean (absolute values and one direction only). D_{total} , then, is the sum of the differences between the P_{os} samples and *M*(q).

The aforementioned algorithm can be combined with a morphological filtering process. The morphological filters [2] are the particular non linear filters based on the morphological maths. In this circles every signal is the morphological convolution of itself and a structural element. The main tools of morphological image processing are a broad class of nonlinear image operators, of which the two most fundamental are dilation [3] and erosion [4]. The space domain in which images are defined can be either continuous, $E = R^2$, or discrete, $E = Z^2$. For a binary image represented by a set $S \subseteq E$, its morphological dilation by another planar set B, denoted by $S \oplus B$, and its erosion, denoted by $S \otimes B$, are the Minkowski set operations

$$S \oplus B = \{x + b : x \in S, b \in B \} \qquad (1)$$

$$S \otimes B = \{x : B_{+x} \subseteq S \} \qquad (2)$$

where $x = (x, y)$ denotes points on the plane and $B_{+x} = \{x + b : b \in B\}$ denotes set translation by a vector. The corresponding signal operations are the Minkowski dilation and erosion or fan image function (fig.1)

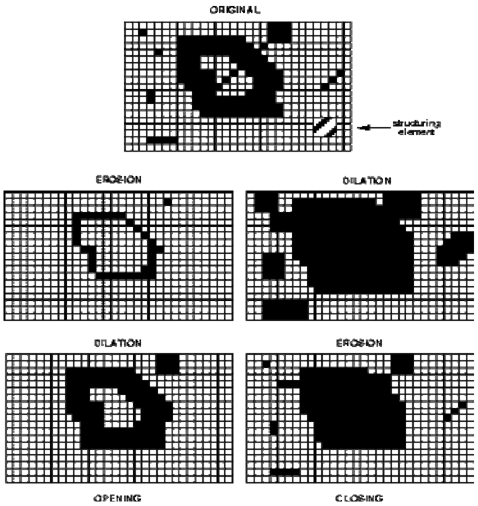


Fig. 1 Morphological image processing main tools

$f : E \rightarrow \overline{R}$ by another (structuring) function g:

$$f \oplus g(x) = \bigvee_{y \in E} f(y) + g(x - y) \qquad (3)$$

$$f \otimes g(x) = \bigwedge_{y \in E} f(y) - g(y - x) \qquad (4)$$

where $\vee$ and $\wedge$ denote supremum and infimum.

There is, however, a variety of nonlinear smoothing filters that can smooth while preserving important image features and can provide a multi scale image ensemble, that is, a nonlinear scale-space. A large class of such filters consists of the standard morphological openings and closings (which are serial compositions of erosions and dilations) in a multi scale formulation [5] [6] [7] and their lattice extensions, of which the most notable are the reconstruction openings and closings [8] [9].

II. Design

The preliminary employment of an amplification section has been necessary just because of the aforementioned characteristics. Thanks to the use of the amplifier a little improvement of the echographic image (see fig.2 and fig.3 for facility) has been obtained. In order to get a further important improvement, it was decided to update the processing card by designing and assembling a video amplifier-enhancer. A video enhancer, also called *crispener*, is a device which enhances the high frequencies of video signal. It does not bring to an actual "enlargement" of signal band, but the enhancement of the higher frequencies produces a better contrast in details. The used circuit layout is shown in fig. 4. After assembling and testing the enhancer, it has been connected to the amplifier through the connection shown in fig. 5.

Fig. 2 Instrumentation keyboard

Fig.3 Used linear probe

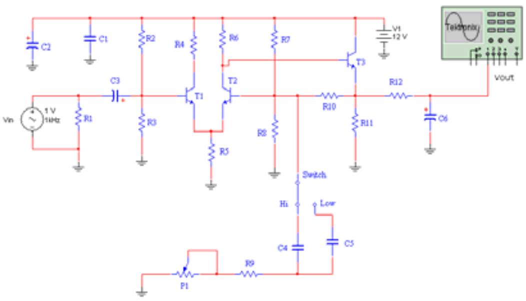


Fig.4 Video enhancer circuit layout

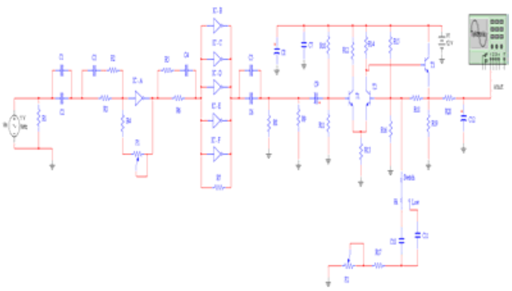


Fig.5 Video amplifier-enhancer circuit layout

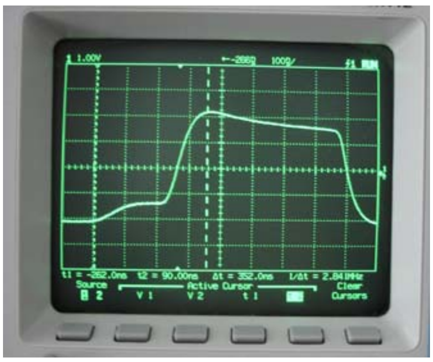


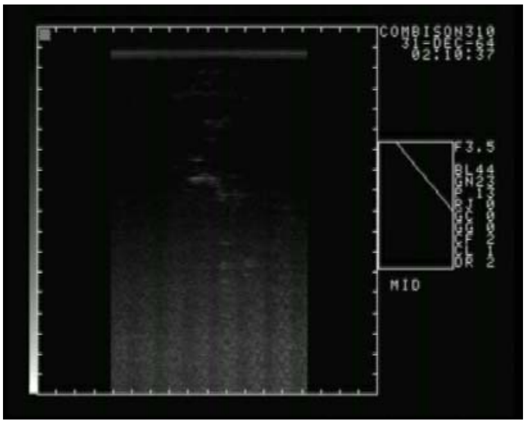
Fig. 6 Step response

Fig.7 HPE4411B spectrum analyzer

Fig,6 and fig.7 depict the step response of design video amplifier-enhancer circuit and the spectrum respectively.

III. Results and conclusion

The quality and improvement of the obtained images are very evident: in the starting image (fig.8) no object can be distinguished, whereas in fig. 9 a gland is seen. The research has traced out a way of designing an image processor implementing wavelet and nonlinear filtering as morphological one. It establishes some interesting and specific criteria for a correct compatibility between image processing and hardware treatment. Certainly, in presence of black and white image (for gland) of echographic scanner, the best results are obtained using a morphological filtering.



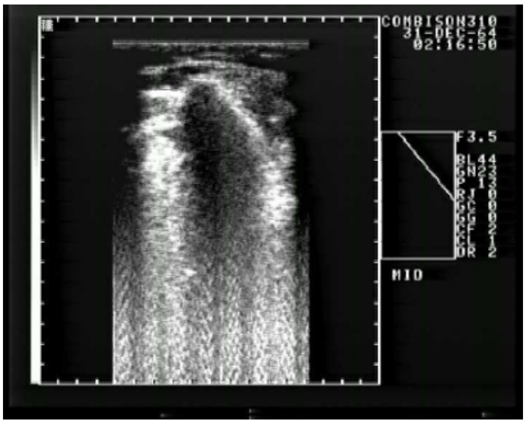
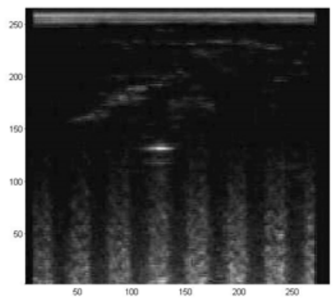


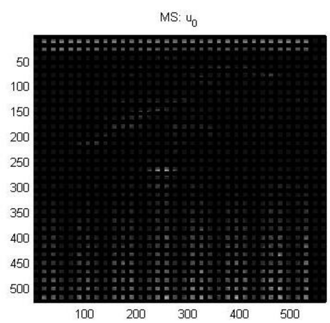
Fig. 8 Original image from the Combison 310 Fig. 9 Processed image via amplifier-enhancer

Our idea is to use for magnification of echographic images the variational approach based on the above Mumford-Shah model which provides simultaneously and in a single framework the image segmentation, denoising, and magnification. The numerical treatment of the above Mumford & Shah functional is not easy for the presence of the unknown set K. By the way, the functional *MS*(*K; u*) can be approximated in the sense of the Γ-convergence [10], Ambrosio & Tortorelli [11] by means of a sequence of elliptic functionals Fk. These elliptic functionals are more convenient because the associated system of Euler-Lagrange equations are more tractable from the numerical point of view. In order to apply the MS approach both for denoising and edge detection in a given image *g*, the authors of [12] have introduced a finite difference approximation of the elliptic PDE system together with an algorithm which varies the parameter *k* to perform a simulation of the Γ-convergence in the discrete framework. In this paper we aim to apply the same approach and the same numerical methods as in [12] for the *magnification problem* of a given noised image. Towards this goal, the MS approach can be easily applied by solving the above PDE system by simply denoising in a different way the so called *fidelity term* present in the functional, that is

$$\mu \iint_{\Omega\backslash D} \left|u(x,y)-g(x,y)\right|^2 dxdy = \mu_D \iint_{\Omega} \left|u(x,y)-g(x,y)\right|^2 dxdy \qquad (5)$$

where *D* is the region to be painted. In other words, this can be obtained also denoising the function *μD*(*x; y*) =μ if (*x; y*) Є Ω\D and and *μD*(*x; y*) = 0 otherwise.
The outcomes of the application of Mumford-Shah model, starting from the original image (fig.10), are shown in fig. 11 (for one iteration) and fig.12 (after two iterations). The MS approach can be replace the other approaches.





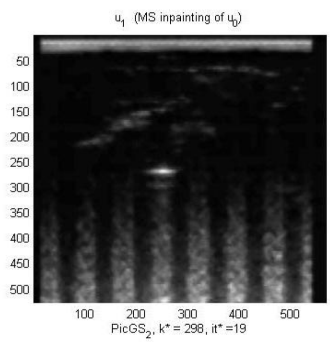


Fig. 10 Original image Fig. 11 MS - iteration 1 Fig. 12 MS - iteration 2

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