A Bio-inspired Interpolation Kernel for Medical Image Processing Implemented on DSP Processor

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Abstract **Post processing of medical images often needs interpolation. Taking cues from human visual system, we propose here an interpolation kernel consisting of linear combination of Gaussians at different scales. We compare the efficacy of the proposed kernel with other interpolation kernels, particularly in the processing of medical images. The basic algorithm has been implemented on a TI DM642 based hardware platform for real-time filtering and programmed for post-processing of ultrasound video frames (20fames/s) from the commercially available Siemens Medical Ultrasound Scanner.**

Key Words: multi-scale Gaussian; image interpolation; real-time processing; DSP processor

I. INTRODUCTION

In the post processing of medical images, the Laplacian based edge detection and image enhancement is a well-known technique. This approach is a direct consequence of the psychophysical findings of Mach [1], who pointed out that the derivatives of light intensity form the basis of human visual system (HVS) at the retinal level. Marr and Hildreth [2] used the Laplacian operator along with a Gaussian smoothing operation for the purpose of edge detection. This was termed as the Laplacian of Gaussian or the LOG ($\nabla^2 G$) operator, where G is a zero-mean Gaussian, whose standard diviation will later be denoted by σ . In this paper we propose a new multi-scale model of HVS, that generalizes the above-mentioned findings in order to compute general even order rotationally-symmetric Gaussian derivatives and combinations thereof, that yield a new class of filters for the purpose of edge detection and image enhancement. In this paper, the usefulness of such higher order Gaussian derivatives as interpolation kernel would be investigated. Use of interpolation kernels consisting of combinations of Gaussian and its partial derivatives was first proposed by Appledorn [3]. He exploited the near ideal spatial and frequency domain behavior of those filters. Such kernels are locally compact in the space and have excellent frequency domain characteristics. We propose, in this paper a novel approach for the generation of interpolation kernel from the linear combinations of Gaussians at different scales taking inspiration from a theorem of Ma and Li [4], that expresses the sum of (n/2+1) Gaussians of different scales as the n^{th} order derivative of a Gaussian function.

II. PROPOSED METHOD

It has been shown [5], with the help of Ma and Li's theorem [4] that in one dimension the fourth order Gaussian derivative filter can represent retinal receptive field (non-classical) by combining center, surround, extended surround as a combination of three multi-scale Gaussian functions, so that in two dimensions we finally arrive at:

$$\nabla^4 G(r,\sigma) = m\nabla^2 G(r,\sigma^{/}) + \nabla^2 G(r,\sigma^{//}) \qquad (1)$$

This means, the fourth order derivative can in fact be expressed as a linear combination of two second order derivative operators.

Again, following similar procedure it has also been shown [6]:

$$\nabla^6 G(r) = m\nabla^2 G(r) + n\nabla^2 G(r) + \nabla^2 G(r) \qquad (2)$$

so that with the help of equation (1), we get:

$$\nabla^6 G(r) = m\nabla^2 G(r) + \nabla^4 G(r) \qquad (3)$$

So proceeding in the same way,

$$\nabla^8 G(r) = m\nabla^2 G(r) + \nabla^6 G(r) \qquad (4)$$

As in the previous deductions [5, 6], if we assume that the Laplacian of Gaussian in Equation (4) is computed at a very narrow scale ($\sigma \rightarrow 0$), then

$$\nabla^8 G(r) = m\delta(r) + \nabla^6 G(r) \qquad (5)$$

Therefore using (3),

$$\nabla^8 G(r) = m\delta(r) + n\nabla^2 G(r) + \nabla^4 G(r) \qquad (6)$$

So for any intensity distribution I , for an insignificantly wide smoothing function i.e. $\sigma \rightarrow 0$, from equation (6) we may write:

$$\nabla^8 I = I + n\nabla^2 I + \nabla^4 I \quad (7)$$

Whereas by taking $m = 1$, in equation (1) (here $\sigma^{/} \rightarrow 0$), we may in the same way arrive at Mach's model [1] in a new light:

$$\nabla^4 I = I + \nabla^2 I \quad (8)$$

In this new light, equation (7) may be perceived as a more generalized version of Mach's model, that implies a computation of still higher order derivatives as a linear combination of lower order ones. Kernels derived from such combinations of derivatives by using finite difference

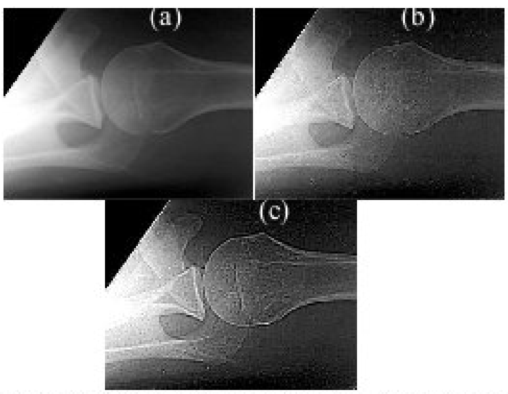

Fig. 1 An X-ray image (a) enhanced by (b) Laplacian kernel and (c) a kernel derived from a linear combination of Laplacian and Bi-Laplacian

approximation, can be very useful in edge enhancement of medical images compared to Laplacian kernel based image enhancement (popularly known as unsharp masking). Fig. 1 shows the superiority of the proposed model with an example from a medical x-ray image. The same may also be shown for ultrasound images [7].

On the other hand, interpolation is a very important technique in medical image processing in application areas such as translation, rotation, warping, magnification, reduction of the image for the purpose of registration and visualization. Particularly, zooming and rotating medical images, with least error, after their acquisition may be of enormous help in computer aided diagnosis (CAD) and surgery (CAS). The purpose of interpolation is to construct a two-dimensional continuous signal $c(x, y)$ from the discrete sample $d(i, j)$ with $c, x, y \in \Re$ and $i, j \in \mathrm{N}^0$. This is obtained by convoluting the discrete samples with a continuous response function of a filter as

$$c(x, y) = \sum_i \sum_j d(i, j) \cdot h(x - i, y - j).$$

Interpolation kernels are, generally symmetrical and separable, so that $h(x, y) = h(x) \cdot h(y)$. Considering the 1-D case we can generally write a kernel with a linear combination of n Gaussians as:

$$h(x) = \sum_{i=1}^{n} (-1)^{i+1} k_i G(x, \beta_i), \quad (9)$$

where $G(x, \beta) = e^{-x^2/2\beta}$ is the Gaussian function with zero mean and variance β [8].

If we consider the case for n=4 only, then:

$$h(x) = k_1 G(x, \beta_1) - k_2 G(x, \beta_2) + k_3 G(x, \beta_3) - k_4 G(x, \beta_4).$$

Using Ma-Li's theorem [4], the above equation can easily be expressed as a sixth order derivative of Gaussian or as a linear combination of Gaussian derivatives as in equation (3) and as proposed in Appledorn's interpolation method [3]. We shall next see the performance of the proposed kernel in interpolation of medical images as compared to Appledorn's Gaussian derivative based kernel and other well-known interpolators.

III. Results

In Fig. 2, we demonstrate the results of using the interpolator proposed in the previous section on an ultrasound image [7] for the purpose of zooming and compare these with those obtained with the help of the standard interpolators namely the 'nearest neighborhood' and 'bi-cubic' interpolator. Visual inspection reveals that results from the proposed method is at least comparable to bi-cubic interpolation and definitely outperforms the 'nearest neighborhood' interpolator.

In Fig. 3, an attempt has been made to compare the interpolation errors in two different types of images using bi-cubic interpolator, Appledorn's interpolator and the proposed interpolator [9]. One of these is a simple constant-intensity synthetic image, while the other is an X-ray image of chest. The images in Fig 3a and Fig 3c are down-sampled by exclusion of points and then interpolated back to the original size by the above-mentioned methods, the scale being reflected by the abscissa in Fig. 3b and Fig. 3d, while the ordinate represents the square of the departures of the gray levels in the final image from the original image. A two-fold down-sampling implies eliminating three pixel values from a 2×2 array of pixels and so on. In case of the constant intensity image of gray value 0.502 in Fig. 3a, we find that the Fig. 3b clearly shows that the performance of the bi-cubic interpolator far exceeds the other two, though the proposed interpolator performs better as compared to Appledorn's interpolator. However in case of the X-ray image of the chest in Fig. 3c, it is clearly evident from Fig. 3d that the performance of the bi-cubic interpolator gradually falls with increasing value of sampling frequency as compared to the other two, where again the proposed interpolator performs slightly better. So the "near-ideal" interpolator derived in this work may be of particular help for producing less number of artifacts in vital instances of image registration. For a simple synthetic image the ideal dc-constancy behavior of the bi-cubic interpolator plays the dominant role, which is why the proposed function also performs better as compared to Appledorn's kernel, which is only an "approximator". However for the medical image, particularly for a sampling frequency in excess of 2, the poor

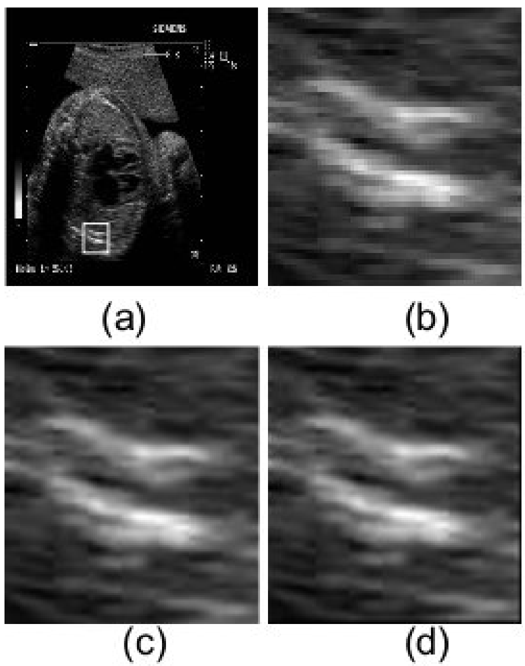

Fig. 2 A selected region (marked by white outline) from (a) an ultrasound image of four-chamber heart has been zoomed eight times by (b) nearest neighborhood method (c) bi-cubic method and (d) the proposed interpolator

frequency domain behavior of bi-cubic interpolator as compared to both Appledorn and the proposed kernel, results in its bad performance, where again the proposed kernel is marginally better as compared to Appledorn's kernel. Only one of the cases has been reported here, although similar behavior has been noted in many other medical images.

The methodologies proposed in this work therefore provide us with new kernels that are applicable both in Edge based Image Enhancement and Interpolation of medical images. The kernels are of finite length and are therefore very suitable for hardware implementation. General FIR filter implementation techniques are also applicable for these kernels. We shall deal with these hardware aspects and real-time applications of our proposed methodologies, including real-time processing of images acquired from an ultrasound imaging system used for medical diagnosis, in the next section.

IV. HARDWARE IMPLEMENTATION

Post processing of captured images is an essential part of any imaging system used for diagnostic purpose. This is especially true for ultrasound images because of its lower SNR, poor contour representation and lower contrast. Most of the image based diagnostics are carried out by visibly evaluating the diagnostically relevant features. Post processing of images is therefore used to primarily increase the SNR and enhance the diagnostically relevant features. In this endeavor we have

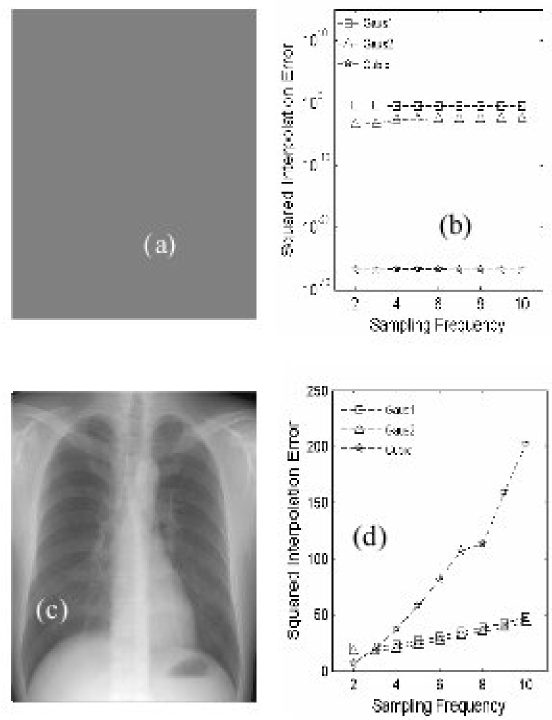

Fig. 3 Comparative interpolation error for bi-cubic interpolator (cubic), Appledorn's interpolator (Gaus1) and the proposed interpolator (Gaus2) (a) Constant gray image, (b) interpolation error for the image in (a), (c) chest X-ray image and (d) interpolation error for the case of the image in (c)

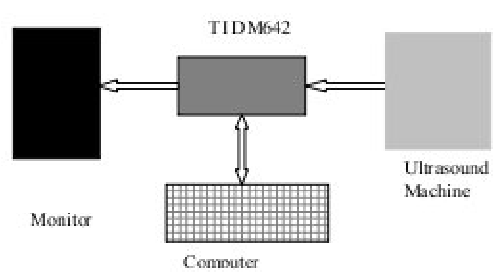

Fig. 4. Schematic for the real-time processing setup. Input for DM 642 board is from a Ultrasound Machine. Processed output is displayed on a RGB monitor in real-time. The computer controls the hardware and downloads processing algorithms.

Fig. 5. The experimental real-time processing setup is shown in this figure. Input for the DM 642 based hardware (marked (b)) board is given from a Siemens Medical Ultrasound Machine (marked (a)) on the right of the figure and the processed output is being displayed on a separate RGB monitor (marked(c)) in real-time on the left of the figure. The board in front of the RGB monitor is the DM 642 based hardware.

implemented the basic algorithm proposed in this paper for Edge Detection, Image Enhancement and Interpolation on a TI DM642 based hardware platform for real-time filtering and programmed for post-processing of Ultrasound video frames (20fames/s) from any standard Ultrasound machine. The schematic of the experimental setup is shown in Fig. 4 and the real setup is shown in Fig. 5. The real-time processing is performed on DM 642 processor because of the huge computational requirement of processing of ultrasound video frames at a rate of 20-30 frames/s. We have been able to handle this high rate of processing with our optimized C/C++ code embedded on TI DM642 based prototype hardware platform. We have also exploited the positive symmetries of the kernels to reduce the number of multiplication operation. This prototype platform is capable of accepting video with PAL/NTSC/RGB coding. The input video is decoded, processed frame-by-frame on the TI DM642 hardware, encoded and finally displayed on a suitable RGB monitor. Fig. 5 shows the complete prototype setup. The Ultrasound video was taken from a commercially available Siemens Medical Ultrasound Scanner (on the right of the picture) and the processed ultrasound video was displayed on a RGB computer monitor (center of the picture). Though we have made the system external to the ultrasound machines, to make it flexible enough to be machine independent the best scenario would be to incorporate the techniques in the ultrasound machines.

V. CONCLUSION

We have proposed an interpolation kernel consisting of a linear combination of Gaussians, which gives comparable performance as compared to Appledorn's kernel. The performance of the proposed kernel is worse than bi-cubic kernel at low sampling frequency, but outperforms the latter at high sampling frequency. Bi-cubic interpolation is computationally costly and difficult to be implemented in real time processing. Considering the low computational complexity of the proposed kernel, it is an ideal candidate for online real time medical image processing. We have designed a prototype hardware platform to test the algorithm by performing an online image processing of medical images from an ultrasound imager. We are able to process real time data at the rate of 25 frames/s. In future the hardware will be incorporated in the machine itself.

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