Shape extraction in fetal ultrasound images using a Hermite - based filtering approach and a Point Distribution Model

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ABSTRACT

In this work we present a segmentation framework applied to fetal cardiac images. One of the main problems of the segmentation in ultrasound images is the speckle pattern that makes difficult to model images features such as edges and homogeneous regions. Our approach is based on two main processes. The first one aims at enhancing the ultrasound image using a noise reduction scheme. The Hermite transform is used for this purpose. In the second process a Point Distribution Model (PDM), previously trained, is used for the segmentation of the desired object. The filtering process is then employed before the segmentation stage with the aim of improving the results. The obtained result in the filtering process is used as a way to make more robust the segmentation stage. We evaluate the proposed method in the segmentation of the left ventricle of fetal ultrasound data. Different metrics are used to validate and compare the performance with other methods applied to fetal echocardiographic images.

Keywords: Filtering Process, Segmentation Hermite Transform, PDM, Fetal Heart

1. INTRODUCTION

Among the medical image modalities, ultrasound is one of the most used for clinical applications. Ultrasound systems can provide anatomic distance and volume information. Motion study is other of the great advantages of ultrasound modalities [1, 2].

This technique has become the standard modality applied to fetal analysis because it is a non-ionizing and fast technique, provides extensive results and presents low risk for both the pregnant patient and her fetus. Diagnosis of congenital heart diseases using echocardiographic studies constitutes common applications of fetal ultrasound tests [3].

Computer-aided analysis can substantially improve the detection of abnormalities in fetal heart. In this case, the design of efficient segmentation algorithms constitutes a very valuable task. Major problems regarding the segmentation of ultrasound images arise from the low contrast, the poor definition of edges and the intrinsic artifact called speckle. Moreover, changes of the heart during periods of fetal development become a challenging problem for segmentation methods as well.

Many approaches have been designed to deal with the segmentation problem in cardiac ultrasound images [4, 5]. The left ventricular endocardium has been of main interest for segmentation applications [6-8]. Algorithms based on snake models [10], mathematical morphology [11], bayesian formulation [12], active shape model (ASM) [6, 7], active appearance model (AAM) [8] and level set [14] have been selected as alternatives to solve the segmentation task.

However, most of them fail to deal with the problem caused by noise and the characteristic speckle patterns of ultrasound images. Several authors proposed novel segmentation methods applied to fetal echocardiographic images [13, 14].

Active shape models, proposed by Cootes [8], present some advantages with respect to other techniques due the fact that it uses prior knowledge acquired through a training process. A point distribution model (PDM) is built in order to code the

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shape variations of the studied object. These variations are limited by the training set composed by previously annotated shapes. The main problem of ASM methods applied to medical ultrasound images is that the edge characterization using gray level profiles does not work well due to the intensive noise. Obviously, intensity profiles are not the best options to characterize the original ultrasound images. A good mechanism to improve this characterization is the implementation of a filtering process with the aim of reducing noise and enhancing edge details. The design of filtering techniques applied to ultrasound images is other task that researchers have tried to address for many years. Wavelet transform [15,16] and image decomposition are the most used mathematical tools for speckle reduction [19].

In this work we propose a semiautomatic segmentation method applied to the analysis of the left ventricle in fetal echocardiographic images. We use a filtering scheme in order to enhance the image which is advantageous to better characterize the profile used in the segmentation method. For the filtering process we employ the Hermite transform. The result of the transformation consists of several coefficients that code different image features. The Hermite-based filtering estimates a binary mask from the coefficients of the transform. The objective of this mask is to determine the pixels that correspond to noise which are subsequently smoothed. Afterwards, the PDM can perform the segmentation using features of the filtered image. Several images of fetal echocardiographic studies are used to evaluate the performance of the proposed algorithm. Synthetic images are also used to evaluate the filtering process. Simulated speckle noise with different characteristics was added to the synthetic images.

The rest of the paper is organized as follows. Section II presents a description of the proposed approach which includes a short definition of the filtering and segmentation techniques. The results of the segmentation process are described in section III. Finally, discussion and conclusions are presented in last section.

2. METHOD

The method consists of a filtering process followed by a segmentation stage in which a statistical shape model is used. One of the main problems of the segmentation in ultrasound images is the intensive noise that makes difficult to model image features such as edges and homogeneous regions.

Since the original ASM method uses gray level profiles for image characterization, it fails to correctly segment ultrasound images. The obtained result in the filtering process is used as a way to make more robust the segmentation stage. Figure 1 shows the general scheme of our technique. Descriptions of these processes are explained in the following sections.

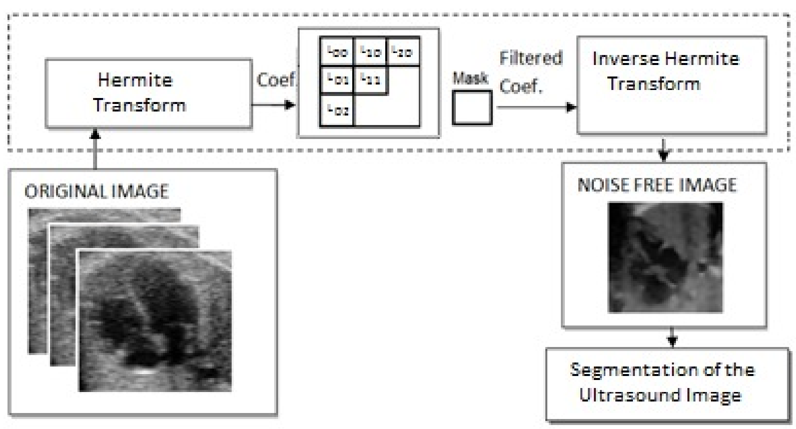


Figure 1. Scheme of the proposed Approach.

2.1 Hermite-based filtering

The filtering framework is based on a multiresolution decomposition using the Hermite transform. The approach consists of two parts: 1) the Hermite transform is applied to the input image, 2) Statistical parameters needed to reduce the speckle are found from the Hermite coefficients, the Hermite coefficients are then filtered and the inverse transform is calculated which results in the filtered image.

A. Hermite Transform

The Hermite transform is a mathematical tool that has demonstrated being very efficient for imaging analysis [17-19]. The Hermite polynomials are employed as base functions in the decomposition process. They are also orthogonal with respect to a Gaussian function:

$$\int_{-\infty}^{\infty} V^2(x,y)G_m(x,y)G_{n-m}(x,y)dxdy = \delta_{\mathrm{nm}} \tag{1}$$

Here, $V(x,y) = \frac{1}{(\sigma\sqrt{\pi})^2} e^{-(x^2+y^2)/\sigma^2}$, σ is the standard deviation of The Gaussian function and $G_n(x,y) = \frac{1}{\sqrt{2^n m!(n-m)!}} H_m(x/\sigma)H_{n-m}(y/\sigma)$ correspond to the normalized polynomials. The Hermite transform permits to obtain the decomposition of a function $L(x,y)$:

$$L_{m,n-m}(p,q) = \iint_{-\infty}^{\infty} L(x,y)G_{m,n-m}(x-p,y-q)V^2(x-p,y-q)dxdy \tag{2}$$

where $L_{m,n-m}(p,q)$ are the Hermite coefficients. The coefficients can be obtained by the convolution between the function $L(x,y)$ and the filters which are calculated as:

$$D_{m,n-m}(x,y) = G_{m,n-m}(-x,-y)V^2(-x,-y) \tag{3}$$

The Hermite coefficients up to the second order obtained for a fetal echocardiographic image are illustrated in Figure 2.

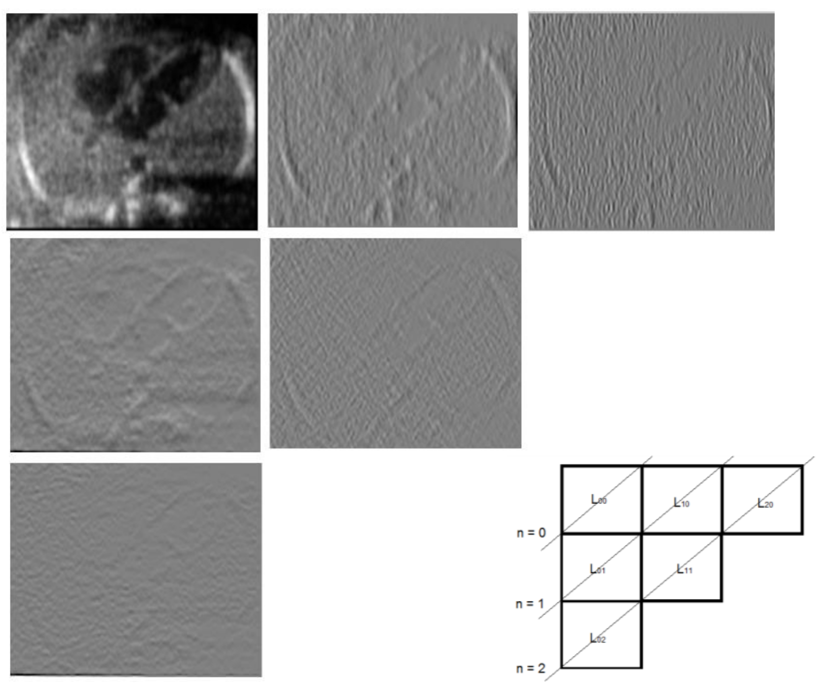


Figure 2. Coefficients up to second order of the Hermite transform using a four chamber view of a fetal echocardiographic image.

B. Statistical Parameters for pixel classification using the Hermite coefficients

The speckle presented in the fetal echocardiographic studies significantly degrades the images by affecting their quality. The modeling of this pattern has been considered in the literature as multiplicative noise [13, 15, 16]. The noise reduction algorithm adopted in this work and applied to fetal cardiac ultrasound images employs the energy coefficients of the Hermite transform to detect important image features [18, 19]. We have to compute an image energy from the first-order reference coefficients of the Hermite transform (L_{10}^2, L_{01}^2). These coefficients indicate the most relevant pixels and localization of the image edges. The image energy is defined as:

$$e = L_{10}^2 + L_{01}^2 \tag{4}$$

Specifically these coefficients, L_{10}^2 *and* L_{01}^2, determine the parameters that are subsequently used for the energy mask, which is calculated by thresholding the image energy e. It allows separating relevant details of the image, it means identifying noise and image features in order to perform the enhancement process. The threshold for each point of the image in this stage can be found by:

$$T(x, y) = \frac{2\vartheta(x,y)\, ln\left(\frac{1}{P_R}\right) L_{00}^2(x,y)}{AN} \tag{5}$$

where $\vartheta(x, y) = |R_L(x, y) * D_{10}(x, y) * D_{01}(x, y)|_{x=y=0}$, R_L is the autocorrelation function of L; P_R is the noise probability that we want in the image; L_{00}^2 is the zero-order coefficient; A is the signal-to-noise ration $(SNR_{1LooK})^2 \approx (1.9131)^2$ and N is the number of looks of the image L [18, 19]. Once the image energy e is thresholded using T, we obtain the energy mask M. Figure 3 shows an example of the energy mask obtained from the coefficients seen in Figure 2 and applied to each coefficient of the Hermite transform, except to the zero order coefficient.

Figure 3. The binary mask obtained from the coefficients in Figure 2. This mask indicates the region of interest.

Finally, each coefficient $L_{m,n-m}$ of the Hermite transform is multiplied by the mask M:

$$F_{m,n-m} = L_{m,n-m} * M \tag{6}$$

The result is the set of modified coefficients $F_{m,n-m}$ with the noise reduced (see Figure 4). The process of filtering ends with the inverse Hermite transform which is calculated by interpolation:

$$\hat{L}(x, y) = \sum_{n=0}^{N} \sum_{m=0}^{n} \sum_{(p,q)\in S} F_{m,n-m}(p, q)\, P_{m,n-m}(x - p, y - q) \tag{7}$$

where $P_{m,n-m}(x - p, y - q) = G_{m,n-m}(x, y)V(x, y)/W(x, y)$ are the interpolation patterns whose weighting function can be calculated through $W(x, y) = \sum_{(p,q)\in S} V(x - p, y - q)$ [17-19].

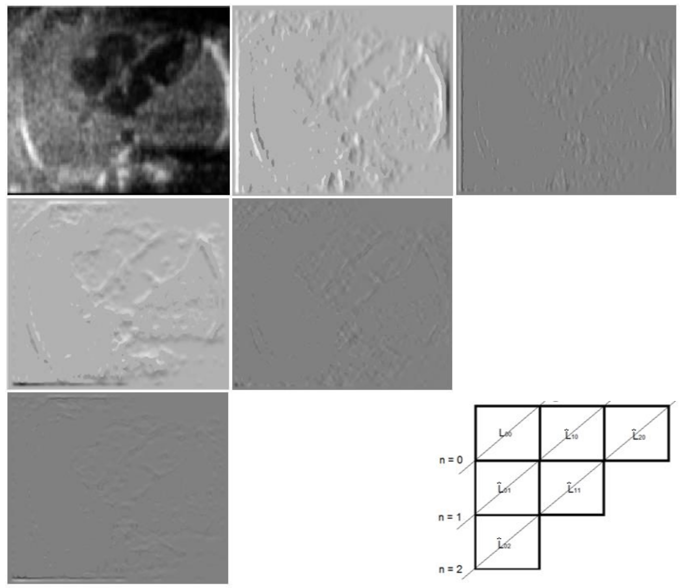


Figure 4. Modified coefficients of the Hermite transform using the energy mask.

2.2 ASM segmentation algorithm

ASM is one of the most used algorithms to segment medical images [7]. A statistical model is obtained from a training set in this technique. The objective of this method is to code possible shape variations of specific structures. To build the statistical model we require a number of sample shapes. These samples consist of the cardiac structures manually segmented. In this work we are evaluating the left ventricle of the fetal heart at different phases of cardiac cycle. The training result is point distribution model (PDM).

The PDM is therefore obtained from a set of N training shapes that have been previously noted. Each shape consists of a set of discrete points called landmarks. The training process follows several steps.

An aligning process of the shapes is firstly performed. We must select a reference shape and the training set has to be aligned with respect to this shape. Several aligning methods can be used for this purpose [7, 9].

Let S_i be the set of aligned shapes, $i = 1,2, \dots, N$. The mean shape $\bar{S}$ is obtained as:

$$\bar{S} = \frac{1}{N}\sum_{i=1}^{N} S_i \tag{8}$$

The principal axis of variation for each point can be obtained by applying principal components analysis (PCA) to the set of data. For this purpose the covariance matrix is needed:

$$C = \frac{1}{N-1}\sum_{i=1}^{N}(S_i - \bar{S})(S_i - \bar{S})^T \tag{9}$$

The set of eigenvectors p_k corresponding to the highest eigenvalues λ_k are selected to build the point distribution model. Therefore,

$$S = \bar{S} + Pb \tag{10}$$

where P is the matrix that contains the eigenvectors and b is a vector of coefficients named as shape parameters. They vary within the range $-3\sqrt{\lambda_k} \leq b_k \leq 3\sqrt{\lambda_k}$ [7].

In addition, it is necessary to build an appearance model that allows guiding the shape model during the segmentation. In the shape model we code the gray level of the landmarks. It is frequently to select gray level profiles along the normal direction to each landmark.

Once the statistical shape and appearance models have been obtained, they can be used for the segmentation of new images. The procedure can be reviewed with more details in [7].

The ASM algorithm is applied to the filtered images. Due to the speckle noise of the ultrasound data, image features such as edges and homogeneous regions are highly degraded. This is a disadvantage that makes more difficult to characterize the appearance of the shape landmarks using gray level profiles. In this work we demonstrate that using a very efficient algorithm, designed specially to enhance ultrasound images, we can substantially improve the performance of the ASM algorithm.

3. RESULTS

In this section we present the results of the proposed method. Evaluations of the filtering and segmentation processes are depicted. For the filtering process we compared the results with other methods. The segmentation is evaluated using the filtered and non-filtered images. Two types of data were used to evaluate the algorithms. In the filtering stage, we employed 9 synthetic images created for the fetal heart. They were added with simulated speckle noise.

We used a total of 38 real images of ultrasound fetal heart to evaluate the filtering and segmentation algorithms. They were acquired from 5 different patients. The acquisition of the fetal echocardiography images was obtained using a Voluson E8 system of GE which is used for the assessment of gestational age in the second trimester of pregnancy with a normal heart. We used quantitative and qualitative analysis for performance evaluation.

3.1 Filtering Results

In the quantitative analysis, we compared the method based on the Hermite transform with other approaches given in the literature [15, 16]. In table 1 is shown the results for several metrics calculated for each implemented filter. As evaluation metrics, we used the signal to noise ratio (SNR), the peak signal to noise ratio (PSNR) and the correlation coefficient (CoC). The assessment was made using the synthetic images, see Figure 5.

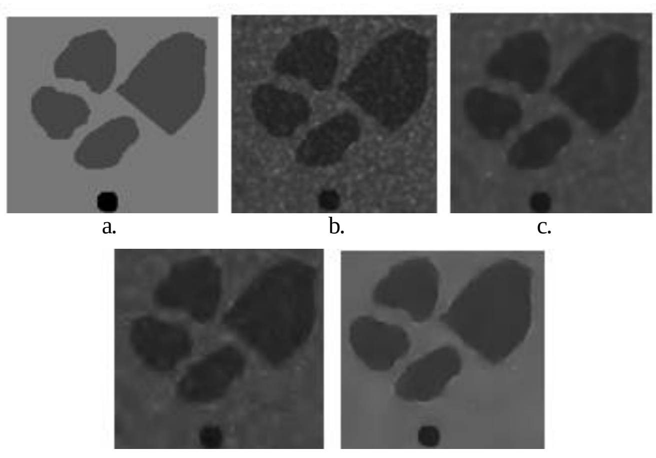
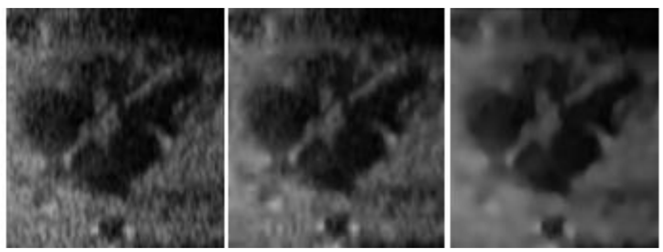


Figure 5. Filtering results for a synthetic image, a. Original image, b. Image with speckle noise, c. Filtered image using anisotropic diffusion, d. Filtered image with the approach proposed in [15], e. Filtered image with the Hermite-based method.

Table 1. Quantitative Performance of the filters used for the synthetic images.

Method	SNR(dB)	PSNR	CoC
	Evaluated Parameters		
	$\sigma = 0.4$		
Input Image with speckle noise	2.5384	12.7040	0.8545
Lee Filter	2.5908	12.8123	0.9203
Wiener	2.9807	12.8385	0.9238
Anisotropic diffusion	3.2135	12.8899	0.9606
Bayesian	2.9933	12.9461	0.9615
Hermite	**5.3023**	**19.2529**	**0.9779**

Figure 5 and 6 show the visual results of the filters applied to synthetic images and original fetal ultrasound images, respectively. The highest performance was obtained with the filter adopted in this work.



a. b. c.

Figure 6. Filtering results for a real ultrasound fetal image, a. Original image, b. Filtered image with the approach proposed in [15], c. Filtered image with the Hermite-based method.

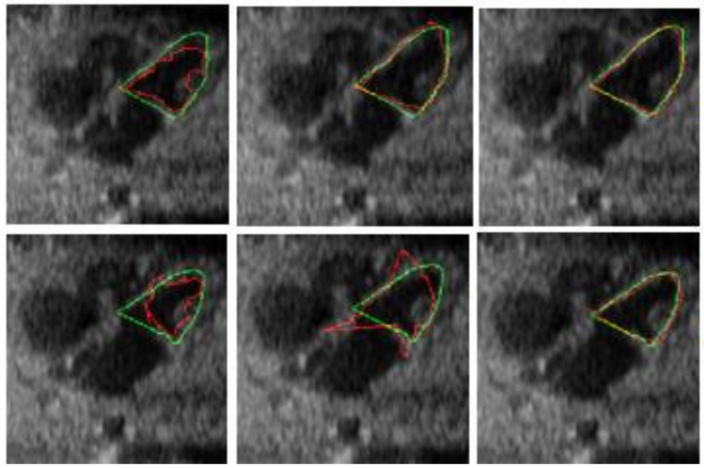
3.2 Segmentation Results

To analyze the performance of our segmentation technique, the point to curve distance was calculated. The ground truth is the expert segmentation. A leave one out method was used.

Figure 7 illustrates the results of the segmentation scheme proposed in this work compared with other methods. The algorithm was proved with the real ultrasound images. Table 2 presents the quantitative results of the segmentation scheme. It was compared with the classical snake method and the ASM approach applied to the original images.

Table 2. Quantitative Results (Means ± STD).

Cases	Evaluation Snake Method	ASM Method	Proposed Method
Patient 1 (5 Images)	5.40 ± 4.58	5.27 ± 3.62	2.35 ± 1.86
Patient 2 (11 Images)	4.76 ± 4.05	4.61 ± 4.23	2.42 ± 1.85
Patient 3 (7 Images)	4.13 ± 3.80	4.16 ± 2.09	2.03 ± 1.08
Patient 4 (3 Images)	6.37 ± 4.26	4.76 ± 4.22	1.55 ± 1.03
Patient 5 (12 Images)	6.36 ± 5.98	5.02 ± 4.11	2.21 ± 1.90



a. b. c.

Figure 7. Segmentation results for two images. The green line describes the manual segmentation and the red line is the segmentation using: a. classic snake, b. ASM applied to the original image, c. Our proposed scheme.

4. DISCUSSION AND CONCLUSIONS

We implemented a segmentation scheme applied to fetal ultrasound images. The left ventricle was the evaluated structure. A filtering process based on the Hermite transform combined with an ASM method is the proposed approach.

From the results in table II, we can see that the best performance was achieved with our scheme. The filtering process substantially improves the segmentation performance of the PDM. Table I also shows that the filtering method used in this work obtained better results than others methods proposed in the literature. From Figure 2 and 3 we can see that not only the speckle noise was reduced but also important features in the images were preserved. The results also demonstrate how the performance of the ASM method can be improved with the filtering process. Additionally, Figure 4 shows how the prior knowledge incorporated into the PDM method helps to preserve the shape of the left ventricle in the fetal images, which is not a characteristic of the snake model.

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