AUTOMATIC HEART LOCALIZATION IN ULTRASOUND FETAL IMAGES

Mozart Lemos de Siqueira and Philippe Olivier Alexandre Navaux
Institute of Informatics, Federal University of Rio Grande do Sul
PO Box: 15064, ZIP: 91501-970, Porto Alegre-RS, Brazil

Keywords: Medical Imaging, Fetal Cardiology, Ultrasound, Bhattacharyya Coefficient, Texture Feature.

Abstract: This paper presents the research developed in order to detect the cardiac structure in echocardiography gray images from the fetal heart. It is based on patten recognition and use a density probability function with the scales of gray. The function is also used for search of the similar cardiac structure, where it is applied on the whole image, and then compared with the pattern of structure in which one interested. In order to obtain the similarity that defines the choice of the structure of interest we use the Bhattacharyya coefficient.
The method uses texture features to isolate the region of interest inside the ultrasound image to improve the results and performance. A prototype was developed to evaluate the proposed method. The results of the experiments are also presented in this paper.

1 INTRODUCTION

Scientific Research in medical imaging area grows constantly and its results generate many benefits to people's health. Usually, these researches cover many aspects of image processing and medicine such as disease predicting and more accurate diagnostics. In this context, this article presents a computational technique for automatic localization of cardiac structure in images. The images used is fetal echocardiography and, more specific, fetal's ultrasound images (Duncan and Ayeche, 2000; Sheehan, 2000). Such images are important to the prenatal phase, because an early diagnosis of congenital cardiopathy can help the medical treatment. Therefore, this work may be used to help automatic analysis, mainly when the physician involved is not a heart specialist.

Although ultrasound images provide a lot of information about cardiac structures, the resulting images are contaminated by speckle noise, which corrodes the borders of the cardiac structures (Kang and Hong, 2002; Zong et al., 1998; Crimmins, 1985; Burckhardt, 1978). This characteristic turns difficult the automatic image processing, and specially the pattern recognition. Besides this kind of noise, other factors influence the outcome of fetal ultrasound image. For instance, the transducer[1] and the fetus positioning, the rotation and the scale variations in images of different patients and the composition of the tissue separating the fetus heart are issues that must be taken into account when dealing with heart images (Mattos, 1999).

The method presented in this paper makes use of a density probability function to obtain the mapping of the region of interest and generate a searching mold to be used in other target images. This mold is based on scales of gray image in the region where the cardiac structure is positioned. Besides, the mold calculation considers the distance of the pixels of the center.

The search for the region of interest begins with the mapping of the candidate regions in the target image. Each candidate region is compared to the searching mold using the Bhattacharyya coefficient (Djouadi et al., 1990). This calculated coefficient provides a index that defines the degree of similarity between the candidate region and the searching mold.

A prototype for the cardiac structure localization was developed in order to evaluate the automatic searching pattern. The search of the candidate regions was implemented using the mold and local-

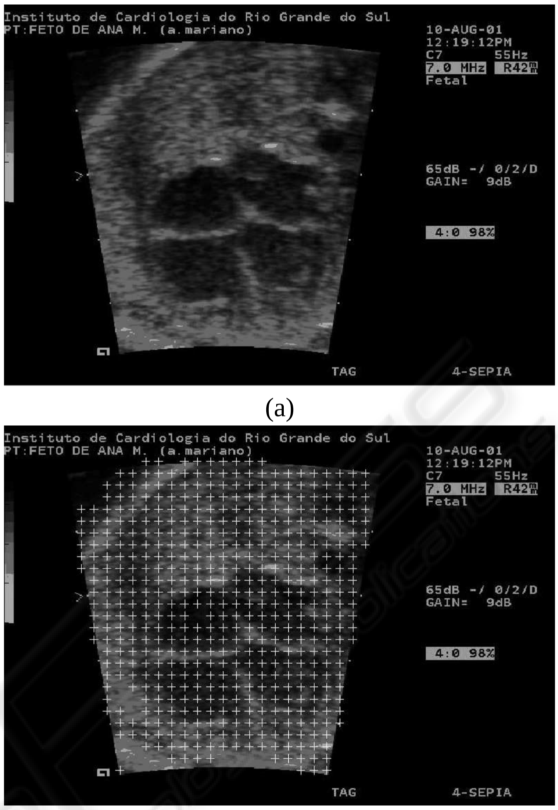
[1]The electronic device used to capture ultrasound images

Lemos de Siqueira M. and Olivier Alexandre Navaux P. (2007).
AUTOMATIC HEART LOCALIZATION IN ULTRASOUND FETAL IMAGES.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications*, pages 107-112
DOI: 10.5220/0002059101070112

ization in different images that was analyzed with a moving window shifted in 10 pixels along the image columns and lines. The moving window size was defined based on the mold size. Although this search covers the whole image and can provide an accurate result, the time to process on each image is usually greater than one minute considering a resolution of 640*x*480. Because this, it was necessary to find new manners to increase the search performance.

Allowing the search performance in consideration, we developed a module to images preprocessing and to isolate the region of interest (ROI). The entropy texture feature was used for selection of region of interest. The Figure 1 (a) presents an original image and a preprocessed image (b) with entropy texture feature to select the ROI. This approach improves the search performance because it does not need search regions out of ultrasound, i.e. the black frame on images. The use of texture features on this ultrasound images is justified by the specific characteristics of them, therefore many works about ultrasound processing using this features (Valdes-Cristerna et al., 2004; Brusseau et al., 2004; Hope et al., 2005).

The paper is organized in five sections. After this introduction, we present a brief section with related research. The Section 3 present the description of the proposed model. The Section 4 show the obtained results. Finally, the paper presents the conclusion section.



(a)

(b)

Figure 1: Fetal echocardiography obtained with ultrasound device. (a) Original image; (b) The regions of interest isolated with entropy.

2 RELATED RESEARCH

The pattern recognition in images is an area that has offered many results. The goal of pattern recognition is to automatically spot specific objects inside images, without the intervention from the user. There are many application possibilities for pattern recognition in medicine, since several medical routines generate images. In some routines, physicians look for image patterns in nodules, intern structures, the behavior of the heart (i.e. systole and diastole), for example. There are works that already address this routines (Lee et al., 2001; Brown et al., 2001; Bruijne et al., 2003; Salvadorls et al., 2003).

Jacob et al. (Jacob et al., 2002) and Sugioka et al (Sugioka et al., 2003) developed research using patterns to detect cardiac structures using active contours (snakes) in echocardiographic images. Comaniciu (Comaniciu et al., 2004) proposed a methodology to tracking cardiac edges in echocardiographic images using several information extract of the images.

One of the principal ways of searching objects in images is through patterns. In most of the cases, the objects of interest must be known, and their characteristics are searching in the image. When the object of interest is not previously known, the complexity of the search increases. The search algorithm performance is important to the processing time do not to be a bottleneck to the system.

3 PROPOSED MODEL

To developing the automatic localization of the cardiac structure was studied the approach proposed by Comaniciu (Comaniciu et al., 2003) for tracking down dynamic objects. We proposed a model inspired on Comaniciu and implement a prototype to evaluate our proposal. The prototype was applied in 640*x*480 fetal cardiac ultrasound images with four chamber cut plans (Nelson, 1998).

The searching pattern is calculated based on the gray scale histogram and the space location of pixels of a given object of interest. This gray scale was used as parameter in the calculation of the searching mold.

The method process is composing by three stages: the first, the second and the third. The first stage of the process consists in the selection of the region of interest to be found. This structure region is isolated, and then used in the calculation of the searching mold. This task is done by the user, who interacts with the prototype in order to select the limits of the structure inside of an image.

The second stage of the localization process is the search for regions that looks like the searching mold. In this search it is used the same calculation that generated the mold, applied to several regions of the image, which are called candidates. From the distributions generated in the candidate regions, it is estimated the position of the pattern that is more similar among the candidate regions and the searching pattern used.

The last stage of the process is the search for the region of interest inside the image. At this stage, the similarity is calculated through the Bhattacharyya coefficient. The whole process is shown in Figure 2.

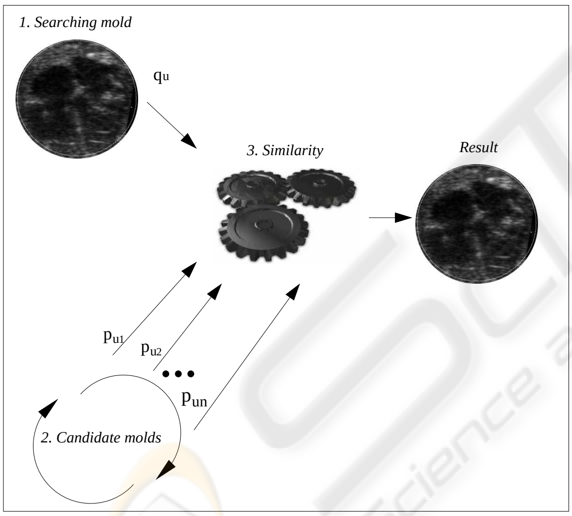


Figure 2: Prototype model (q_u is the searching mold and p_{un}, the candidate regions).

3.1 Calculation of the Searching Mold

To determine the mold of the cardiac structure, the method follows this procedure: a circular region, radius h, with center x_c, placed in the center of position of the desired structure of the region. For each point (or pixel), $x = (x_1, x_2)$, in the region, a vector of characteristics is extracted and categorized according to a discrete number of characteristics. This point receives an index of that characteristic, $u = b(x)$. The distribution of characteristics, $q = \{q_u\}_{u=1...m}$, which computes the occurrence of a given characteristic u in the region of the desired structure, is calculated by:

$$q_u = \frac{\sum_{i=1}^{n} k(|x_i - x_c|/h)\delta(b(x_i), u)}{\sum_{i=1}^{n} k(|x_i - x_c|/h)} \qquad (1)$$

Where x_c is the center of the region, and δ is the delta Kronecker function [2]. Notice that the distribution satisfies $\sum_{i=1}^{n} q_u = 1$.

The function $k(x)$ is an isotropic kernel that reduces the importance of characteristics removed from the center, in the distribution calculation q. Specifically, the important characteristic is the gray scale of the pixel. The distribution (q) represents an histogram of gray $q = \{q_u\}_{u=1,\dots,m}$ which incorporates spatial and color information of the image pixels.

Figure 3 shows a scheme with the stages of the generation process of the mold. In this figure, it is possible to see the window of the system, developed at Matlab (Gonzalez, 2004), with an echocardiographic image where the region of the image used for the calculation of the mold is selected. To this mold, it is applied the equation 1, and the vector q_u is calculated and stored for later use in searching for images of different patients. Figure 4 shows the distribution characteristic of the molds of cardiac structure of different patients.

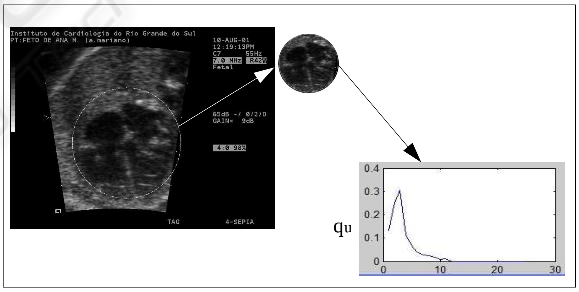


Figure 3: Calculation of searching mold.

3.2 Search in the Image of Interest

At this stage of the process, it is necessary to scan given image searching for a similar mold to the searching mold generated in the previous stage. The solution developed for searching was preprocessing the image with entropy texture feature to select only the ROI.

To search for the candidate region, it must be assumed that in this region of the image the distribution

[2] The Kronecker delta function returns 1 if its arguments are equal and 0, otherwise.

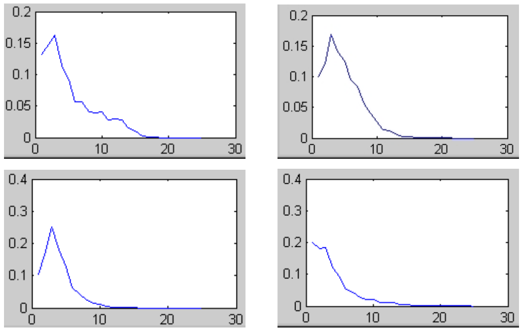


Figure 4: Distribution characteristic of the molds in different patients.

is similar to the searching mold of the structure. By doing this, the searching mold equation was used for the calculation of the candidate regions as in Equation 2.

$$p_u(y,h) = \frac{\sum_{i=1}^{n} k(|x_i - y|/h)\delta(b(x_i),u)}{\sum_{i=1}^{n} k(|x_i - y|/h)} \qquad (2)$$

In the search, the image is examined with a moving window and a set of candidates generated for later comparison with the mold. Figure 5 shows the process of searching in an image. The number of candidate patterns depends on the diameter of the searching pattern and the image processed.

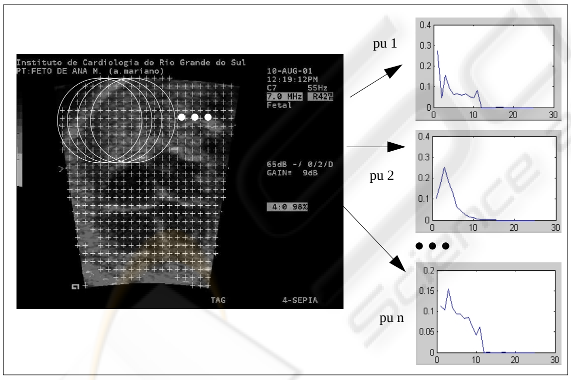


Figure 5: Process of searching for structures.

3.3 Finding of the Structure in the Image of Interest

Spotting the cardiac structure takes place by comparing the candidate mold found at the previous stage with the structure mold generated during the first stage of the process. The comparison is done using the Bhattacharyya coefficient (Djouadi et al., 1990), which provides an index of similarity between the mold distribution and candidate mold.

The Bhattacharyya coefficient is a measure of the statistical separability of classes, and gives an estimate of the probability of correct classification. It is a divergence-type measure that has a straightforward geometric interpretation. It is the cosine of the angle between n-dimensional vectors. The closer to 1 the provided value is, the more similar the vectors are. The calculation is presented in the Equation 3.

$$\rho(y) = \rho[p(y),q] = \sum_{u=1}^{m} \sqrt{p_u(y)}\sqrt{q_u} \qquad (3)$$

The method spots the searching structure through the patterns bearing more similarity. Only the candidate region bearing more similarity is selected; all the others are ignored. Even so, the calculation of the candidate region is done considering the whole image. The Figure 5 shows this process.

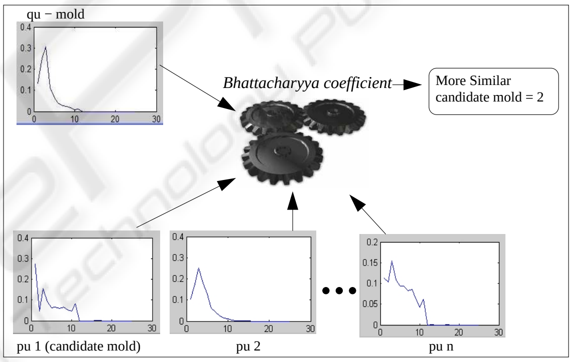


Figure 6: Finding of the cardiac structure.

4 RESULTS

The tests was applied in an image sample where the searching mold has been calculated from an image and the search occurred over 33 different images. In the sample showed in Table 1 we classified the results in three types: success (second column of table 1), find two chamber (third column of table 1) and fail (fourth column of table 1). The first class is the objective of work, i.e. success on the search for the heart structure on the image. When the method finds the heart, but not totally we classified with two chamber and when the method fail, the third class is select. The last line in the table shows the means of all tests results.

The Figure 7 shows images with the results, the first image showed in the Figure 7(a) is a instance of

(a) (b) (c) (d)

Figure 7: Results obtained on tests.

Table 1: Results obtained with the prototype tests.

Test data	sucess (%)	find two chambers (%)	fail (%)	number of images
mold1	69,7	30,3	0,0	33
mold2	59,4	34,4	6,3	32
mold3	64,5	25,8	9,7	31
mold4	54,5	36,4	9,1	33
mold5	30,3	45,5	24,2	33
mold6	73,5	23,5	2,9	34
mold7	38,2	47,1	14,7	34
mold8	57,1	31,4	11,4	35
mold9	67,6	26,5	5,9	34
mold10	50,0	34,4	15,6	32
mold11	79,4	14,7	5,9	34
mold12	26,5	47,1	26,5	34
mean	55,9	33,1	11,0	33,25

search mold and it localization on the image, the others two, Figure 7 (b) and (c) are instances of success, and the Figure 7 (d) is a search result instance of class ”find two chamber”.

5 CONCLUSION

This paper presents a model developed for pattern recognition of cardiac structure in echocardiographic images, as well as the necessary modifications for its improvement. One of reason that motives the research about echocardiographic images has been the dynamics feature. In reality, these images are extract of videos of the cardiac dynamics that allow working with these sequences on future. This approach can take advantage of the dynamics information on the heart test that nowadays does not be used.

The images used were kindly provided by the fetal cardiology team at Institute of Cardiology of Porto Alegre. Those images were captured with an echocardiographic machine produced by Siemens (Aspen). That machine allows the recording of images in DICOM format. The resolution of the images was 640x480 pixels.

It has been observed that the size of the searching mold influenced the results; larger molds showed better performance. A small region may not represent adequately the structure. This happens because of the noise, the size of the heart is variable, and the search is based exclusively on the intensity of gray.

The use of texture feature, to select the region of interest had been important to increase the performance of the method, because texture can separate the ultrasound image of the background.

The prototype developed can automatically extract the pattern of cardiac structure of echocardio-

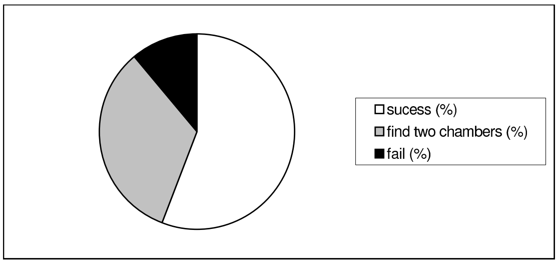


Figure 8: Trial obtained, only mean.

graphic images. Considering the graphic depicted in Figure 8 and the class ”find two chambers” as objective, we can confirm the success of the proposed method.

REFERENCES

Brown, M. S. et al. (2001). Patient-specific models for lung nodule detection and survellience in ct images. *IEEE Transactions on Medical Imaging*, 20(12):1242–1250.

Bruijne, M., Niessen, W. J., Maintz, J. B. A., and Viergever, M. A. (2003). Localization and segmentation of aortic endografts using marker detection. *IEEE Transaction on Medical Imaging*, 22(4):473–482.

Brusseau, E., de Korte, C. L., Mastik, F., Schaar, J., and van der Steen, A. F. W. (2004). Fully automatic luminal contour segmentation in intracoronary ultrasound imaging a statistical approach. *IEEE Transactions on Medical Imaging*, 23(5):554–566.

Burckhardt, C. B. (1978). Speckle in ultrasound *b*-mode scans. *IEEE Transactions on Sonics and Ultrasonics*, SU-25(1):1–6.

Comaniciu, D., Ramesh, V., and Meer, P. (2003). Kernel-based object tracking. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(5):564–577.

Comaniciu, D., Zhou, X. S., and Krishnan, S. (2004). Robust real-time myocardial border tracking for echocardiography: An information fusion approach. *IEEE Transaction on Medical Imaging*, 23(7):849–860.

Crimmins, T. R. (1985). Geometric filter for speckle reduction. *Applied Optics*, 24(10):1438–1443.

Djouadi, A., Snorrason, O., and Garber, F. D. (1990). The quality of training-sample estimates of the bhattacharyya coefficient. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(1):92–97.

Duncan, J. S. and Ayeche, N. (2000). Medical image analysis: Progress over two decades and the challenges ahead. *IEEE Transactions in Pattern Analysis and Machine Intelligence*, 22(1):85–105.

Gonzalez, R. C. (2004). *Digital image processing : using matlab*. Pearson Prentice Hall, Upper Saddle River, 1 edition.

Hope, T., Linney, N., and Gregson, P. (2005). Using the local mode for edge detection in ultrasound images. In *Proc of. Canadian Conference on Electrical and Computer Engineering*, pages 374–377, Canada. Los Alamitos: IEEE.

Jacob, G., Noble, J. A., Behrenbruch, C., Kelion, A. D., and Banning, A. P. (2002). A shape-space-based approach to tracking myocardial borders and quantifying regional left-ventricular function applied in echocardiography. *IEEE Transaction on Medical Imaging*, 21(3):226–238.

Kang, S. C. and Hong, S. H. (2002). A speckle reduction filter using wavelet-based methods for medical imaging application. In *Proc of. 14th International Conference on Digital Signal Processing, DSP2002*, volume 2, pages 1169–1172, Santorini, Greece. Los Alamitos: IEEE.

Lee, Y., Ishigaki, T., et al. (2001). Automated detection of pulmonary nodules in helical ct images based on an improved template-matching technique. *IEEE Transaction on Medical Imaging*, 20(7):595–604.

Mattos, S. S. (1999). *O Coração Fetal*. Revinter, Rio de Janeiro/RJ.

Nelson, T. R. (1998). Ultrasound visualization. In *Advances in Computers*, volume 47, pages 185–253. Academic Press, New York.

Salvadorls, A., .Maingourd, Y., Ful, S., and LeralluT, J.-F. (2003). Optimizaton of an edge detection algorithm for echocardiographic images. In *Proc. of the 25 Annual International Conference of the IEEE EMBS*, Cancun, Mexico. Los Alamitos: IEEE.

Sheehan, F. (2000). Echocardiography. In *Handbook of Medical Imaging*, volume 2, pages 609–674. Spie, Bellingham.

Sugioka, K. et al. (2003). Automated quantification of left ventricular function by the automated contour tracking method. *ECHOCARDIOGRAPHY: A Jornal of Cardiovascular Ultrasound and Allied Tech.*, 20(4):313–318.

Valdes-Cristerna, R., Jimenez, J., Yanez-Suarez, O., Lerallut, J., and Medina, V. (2004). Texture-based echocardiographic segmentation using a non-parametric estimator and an active contour model. In *Proc. of the 26th Annual International Conference of the IEEE EMBS*, San Francisco, US. Los Alamitos: IEEE.

Zong, X., Laine, A., and Geiser, E. (1998). Speckle reduction and contrast enhancement of echocardiograms via multiscale nonlinear processing. *IEEE Transactions on Medical Imaging*, 17(4):532–540.