Universidade do Minho

Escola de Engenharia

Semana da Escola de Engenharia
October 24 - 27, 2011

FUZZY CLUSTERING FOR SEGMENTATION OF 1ST TRIMESTER ULTRASOUND FETAL IMAGES

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KEYWORDS
Fuzzy clustering, Segmentation, Ultrasound images.

ABSTRACT

The work herein presented is a part of a broader set of tasks included in a PhD thesis which main objective is to develop an automatic measurement system for the crown-rump, nuchal translucency and biparietal measurements in ultrasound fetal images. These measurements are of extreme importance to evaluate the possible abnormal conditions of the fetus, namely chromosomal anomalies like Down's syndrome, also known as Trisomy 21. To achieve this objective the task of segmentation, which consists inidentifying the relevant objects/structures in the ultrasound images and separate them from the non relevant ones, is of utmost importance. In this work different fuzzy clustering approaches for segmenting 1st trimester ultrasound fetal images are presented and applied for the crown-rump measurement. Results are compared with other methodologies to evaluate their performance.

INTRODUCTION

The present work is part of a set of tasks included in a PhD thesis work, which main objective is to develop an automatic measurement system for 1st trimester ultrasound fetal images. It resulted from a direct challenge from an obstetrician and intends to automatically obtain the measurement values of the crown-rump, nuchal translucency and biparietal diameter for diagnose purposes.

Ultrasonography is probably the most widely used pregnancy observation method because it is relatively cheap, noninvasive and gives physicians enough information to evaluate the fetus condition. In case of doubts, other methods can be applied to confirm or deny initial suspicions. In general, these exams are invasive and more aggressive for both the fetus and pregnant and, for these reasons, only used in specific cases. Although ultrasound exams are widely used, measurements are not fully automatic. The process always requires specialized human intervention to mark with calipers the points of the regions to be measured, in order to obtain distances, perimeters and other measurements. The ultrasound image observation combined with the obtained measurements is of extreme importance as it allows specialists to diagnose devitalized and ectopic gestations, to perform precocious evaluation of the gestational age, to identify major congenital malformations and possible chromosomal disorders, and other anomalies (Nicolaides et al. 2000). The Down's Syndrome (trisomy 21) is one of the chromosomal abnormalities for which ultrasonography is commonly used as an important diagnostic auxiliary tool in order to access the risk of disease (Snijders et al. 1998).

For a low risk pregnancy, medical organizations and physicians recommend the performance of 3 ultrasound scans. The first one should be performed between the 11th and the 14th week, the second between the 18th and the 23rd week and the third between the 28th and 32nd gestational week. The first scan is of great importance since it allows identifying possible problems with the fetus within a period that gives physicians and parents enough time to decide treatments or, in drastic situations, pregnancy interruption (if this is the parents option). At this period, obstetricians can observe the gestational vitality, multiple pregnancy, gestational age, major malformations and nuchal translucency size (used as a marker for screening chromosomal abnormalities) and use their observations to guide possible invasive techniques, such as amniocentesis.

Three important measurements are made at the first scan: crown-rump length, biparietal diameter and the nuchal translucency size. The first two are used to evaluate the gestational age and to monitor the fetus growth. The last measurement performed at the first scan, the nuchal translucency, is being used as a marker for chromosomal abnormalities since the 90s, as its size is related with some chromosome anomalies such as the Down's syndrome or the Turner's syndrome. This measurement, crossed with the maternal age and the crown-rump length, revealed to be particular efficient in the identification of this kind of disease (chromosome anomalies). The need to cross the results with the crown-rump length, arises from the fact that the nuchal translucency increases with the gestational age and a relative high value of the nuchal translucency could indicate an abnormal chromosome situation. This screening method has revealed to be particularly efficient since it allowed the identification of approximately 75% of the affected fetus with a false-positive rate of about 5% (Nicolaides et al. 2000). The percentage rises to 90% of Down's syndrome cases detection when combined with data from maternal serum markers (obtained from current blood analysis) (Souka et al. 2001). Even in the presence of a normal karyotype (i.e, no anormal number of chromossomes), a bigger nuchal translucency thickness can be associated with structural defects and genetic syndromes (Nicolaides 2004). Thus, the measurement of nuchal translucency is probably the most important of the three referred measurements in the way that is not used to evaluate fetal growth or physical development but to screen severe chromosome disorders. An illustrative example of each of the three measurements can be observed in Figure 1.

a) b) c)

Figure 1 – Measurements of the a) Crown-rump Length, b) Nuchal Translucency and c) Biparietal Diameter (Courtesy of Hospital de São Marcos)

A major problem concerning the manual obtention of these measurements is the intra-operator variability. Measuremnts tend to be different, and sometimes significativelly different, among specialists (Nicolaides et al. 2000). Moreover, motivation is another factor that affects the quality of the measurements obtained by specialists. Measurements performed with interventional purposes tend to be more accurate than the ones made with merely observational objectives. A study demonstrated that the measurement was successfully done in 100% of the cases in the first situation and only 85% in the second (Nicolaides et al. 2000). To reduce the impact of these factors in the measurement accuracy, medical organizations recommend that: (i) before performing the measurement (crown-rump and nuchal translucency), an adequate sagittal cut should be obtained and the fetus should occupy about 75% of the image, in order that every caliper movement represents 0.1mm; (ii) measurements should be made with the fetus in the neutral position and attention given to the position of the umbilical cord (Nicolaides et al. 2000). However, even in these situations intra-operator variability is observed and the measurement quality tend to decay with the increase of the working load.

In this context, a fully automatic system able to perform the above-mentioned measurements represents an important tool for obstetricians. Such a tool could improve the everyday workflow, increase patient throughput, improve consistency of the measurements and reduce the risk of repetitive stress injury that can happen with the specialists who perform the exams (Carneiro et al. 2008).

The major task to achieve this objective is to automatically perform a good separation and identification of the relevant structures in the ultrasound images. This task (segmentation) is dificult to achieve mainly due to the great variability of images (even for the same measurement) and to the ultrasound image quality. Ultrasound images are very noisy, with low contrast and very dependent of the operator experience. These aspects affect the segmentation algorithms ability to successfully perform their work and especially their generalization capacity. Thus, the segmentation problem is the focus of this work.

In the last years, several segmentation algorithms were developed and successfully applied to different types of images, including the ones obtained by ultrasonography. A special mention should be made to the Fuzzy Clustering techniques since they will be the focus of this work. Segmentation consists in grouping image information (data) according to its similarity in order to separate the different objects in an image, which is precisely the concept of clustering. The application of clustering algorithms to the ultrasound images will help to separate the structural information and proceed to the identification of the relevant structures of the ultrasonography exam. Fuzzy Clustering algorithms provide a fuzzy description of the discovered structure. The main advantage of this description is that it captures the imprecision encountered when describing real-life data. Thus, the user is provided with more information about the structure in the data compared to a crisp, non-fuzzy scheme (Shihab 2000). The Fuzzy Clustering algorithms associated with edge-detection and image descriptors algorithms could represent a valuable tool to correctly identify the fetal ultrasound images structures and therefore an efficient solution in the attempt to solve the presented problem.

STATE-OF-THE-ART

Until the present moment, most works found on medical image analysis don't refer to ultrasound fetal image processing. In fact, the great majority of them are in the cardiology domain for identification of vascular problems (Ozbay, 2006; Ibrahim, 2008), cancer detection (Hwang et al., 2007; Karabatak and Ince, 2009) and neurology field for analysis of the nervous system and determination of psychotic behaviors (Pennec et al., 2003; Chattopadhyay et al., 2008). Nevertheless, some works are found in the obstetric field, mainly for morphological and physiological analysis of fetal images (Lu et al., 2005; Grobbelaar and Douglas, 2007). The number of published works regarding fetal image analysis is very small when compared to the other above mentioned areas of application. This aspect is thought to be closely related to the ultrasound images quality, with low signal-to-noise ratios, and to the large intra class variation because of differences in the fetus age and the dynamics of the fetal body (Carneiro et al. 2008).

Regarding the ultrasound fetal image analysis, several works with different approaches are available in the literature. For the biparietal diameter measurement most of them are based on morphological operators and involved the application of edge detection, edge linking, Hough transform, among other standard computer vision techniques, to provide head segmentation (Thomas et al., 1991; Hanna and Youssef, 1997; Matsopoulos and Marshall, 1994; Carneiro et al., 2008). These methods presented good correlation factors but had to be modified when identifying different anatomies, showing great lack of generalization (Carneiro et al. 2008). Other works (Chalana et al., 1996, Chalana and Kim, 1997; Pathak et al. 1997) proposed an active contour based approach for segmentation of the fetal head and abdomen. The obtained results were satisfactory, but the system could get stuck at local minima and manual correction required. Another disadvantage was that an initial guess was needed, which makes the algorithm semi-automated. Similar problems were found in the work of Lu et al. (2005), where the authors introduced an iterative randomized Hough transform for the fetal head measurement. In fact single strategies tend to present severe problems for ultrasound image analysis. Because of this some authors used combined strategies (Yu et al. 2008), trying to take advantage of the best of each one and trying to improve the generalization ability of the algorithm.

An important work in this field is the one performed by Carneiro *et al*. (2008). In this work the authors proposed a strategy to perform several measurements in the fetal image. In fact, they refer some success in measuring the biparietal diameter, head circumference, abdominal circumference, femur length, humerus length and crown-rump length. They proposed a system for fast automatic detection and measurement of fetal anatomies that exploited a large database of expert annotated fetal anatomical structures in ultrasound images. The method automatically learned to distinguish between the appearance of the object of interest and the background by training a constrained probabilistic boosting tree classifier. The system was able to produce the automatic segmentation of several fetal anatomies using the same basic detection algorithm. To our knowledge, this was the only fully automatic system found to detect the crown-rump measurement.

The nuchal translucency measurement is very difficult to perform. The prove of that is the few papers published on this subject and the fact that none of the presented methodologies is fully automated (Lee et al., 2007; Deng et al., 2008; Nirmala and Palanisamy, 2009; Moratalla et al., 2010) withhuman intervention being always required to define the region of interest. Once the region is conveniently identified there are several possible strategies that can be applied. Nirmala and Palanisamy (2009) presented a strategy based on the Mean Shift algorithm for segmenting the region of interest, followed by a Canny operator to detect the limits of the nuchal translucency and a Blob operator to estimate the thickness. Lee *et al*. (2007) describe a semi-automatic method of fetal nuchal translucency thickness measurement using a coherence enhancing diffusion filter to enhance the border and reduce noise, followed by detection of the nuchal translucency by minimization of a cost function, which combines intensity, edge strength and continuity, using dynamic programming. Although results were satisfactory, the method is semi-automatic and can only be applied when fetal position is as horizontal as possible. Deng *et al.* (2008) presented a a scheme based on morphologic filtering that establishes the edge map and extracts a preliminary contour by the gradient vector flow snake.

Then an algorithm based on the dynamic programming is proposed to compound the edge map and the preliminary contour to obtain the nuchal translucency contour. Finally, parameters of the nuchal translucency, such as the thickness and the area, are calculated. Once again the process is not entirely automated since it needs two artificial points inside the nuchal translucency to begin the scheme and there is no warranty that the final contour will converge to the optimal one.

The literature revision reveals to important facts. First, that fetal image analysis is a complex task, especially if the system is intended to be fully automated and with a good generalization capacity. Second, that none of the authors tried to introduce a Fuzzy approach. Considering that Fuzzy Logic has proven to be an efficient tool for several tasks, including segmentation, this could represent a capable solution in the attempt to solve the presented problem.

Although the above literature review focused on the intended three measuremnts this paper only gives attention to the crown-rump measurement. In the next sections different fuzzy clustering techniques applied to the fetal images segmentation will be presented. The measurement process will not be addressed mainly because the segmentation task isn't cocluded.

Since this work is on an initial stage, results are preliminary and improvements are needed to guarantee a good structure identification and good generalization ability.

FUZZY CLUSTERING FOR SEGMENTATION OF ULTRASOUND FETAL IMAGES

Clustering techniques aim to group data from a dataset into several subsets based on a similarity criteria. This way, similar data (according to the criteria used) is grouped into the same subset (cluster). Hard clustering techniques create a hard partion of the dataset so that every point in the dataset is included in only one cluster with a membership value of 1. Using a Fuzzy strategy the same point could belong to several clusters simultaneously, creating a fuzzy partition of the data. The believe of that point belonging to each cluster is reflected by the membership value.

Recent research shows that new analysis and clustering methodologies based on Fuzzy Logic and applied to images and medical diagnostic data present an appreciated successful rate compared to the existing ones (Suri et al., 2002; Ibrahim et al., 2008). In this section, the Fuzzy Clustering methodologies applied for the crown-rump measurement are presented.

Fuzzy C-Means

Fuzzy C-means (FCM) has been applied with great success to data clustering. Most of the Fuzzy Clustering algorithms are based on the Fuzzy C-means, which groups data by minimization of a cost function based on the Euclidean distance. The objective is to determine the best partition matrix that minimizes the distance between the cluster prototypes and the sample according to:

$$J_m = \sum_{k=1}^{N}\sum_{j=1}^{C}\left(\mu_{jk}\right)^m \left\|x_k - c_j\right\|^2 \qquad (1)$$

where m is a weighting factor ($1 \leq m < \infty$), N represents the number of observations, C the number of clusters, c_j the center of the j^{th} cluster and x_k the k^{th} observation. The resulting partition matrix is formed by the best μ_{jk} found in the minimization of the objective function. μ_{jk} represents the degree of membership of the point x_k to cluster j. Although this method is very effective in image segmentation, cluster attribution is only based on the distribution of pixel attributes in the feature space. Sometimes the spatial distribution of pixels in an image should be taken into consideration to improve the segmentation results, especially in the presence of noise.

Fuzzy C-Means with Spatial Information

Typical FCM algorithms use a distance measure to aggregate data into the respective cluster. As mentioned above, sometimes this is not sufficient to obtain good results. Wang and Bu (2010) proposed a FCM scheme that uses the local contextual information and the high inter-pixel correlation inherent.

Firstly, a local spatial similarity measure model is established. A local image feature, F_{ij}, is computed based on both local spatial relationship and the local gray-level relationship for a given window according to:

$$F_{ij} = \begin{cases} F_{ij}^S \times F_{ij}^G, & j \neq i \\ 0, & j = i \end{cases} \qquad (2)$$

where i is the center pixel of the local selected window (5×5), j is the set of the neighbors pixels within the local window (Ω_i). and represent the local spatial relationship and the local gray-level relationship, respectively, calculated by Equation (3) and Equation (4):

$$F_{ij}^{S} = e^{\left(\frac{-\max\left(\left|x_j - x_i\right|,\left|y_j - y_i\right|\right)}{\lambda_S}\right)} \quad (3)$$

where (x_i,y_i) and (x_j,y_j) are the spatial coordinates of the ith and jth pixel and λ_S is the scale factor of the spread of F_{ij}^{S} .

$$F_{ij}^{G} = e^{\left(\frac{-\left\|g\left(x_j,y_j\right)-g\left(x_i,y_i\right)\right\|^2}{\lambda_G \times \sigma_i^{G^2}}\right)} \quad (4)$$

where $g(x_i,y_i)$ is the gray value of the central pixel within the selected window, $g(x_j,y_j)$ is the gray value of the jth pixels in the same window. (x_i,y_i) and (x_j,y_j) are the spatial coordinates of the ith and jth pixels. λ_G is a global scale factor of the spread of F_{ij}^{G}. σ_i^{G} is a function of the local density surrounding the central pixel representing the gray value homogeinety degree of the local window and its calculated according to Equation (5):

$$\sigma_i^{G} = \sqrt{\frac{\sum_{j\in\Omega_i}\left\|g\left(x_j,y_j\right)-g\left(x_i,y_i\right)\right\|^2}{N_{\Omega_i}}} \quad (5)$$

Based on an initial partition and on the local image feature (Equation (2)) a new membership function is calculated, corresponding to a new partition that includes the spatial and gray-level relationships. It can be calculated by Equation (6).

$$\mu_k\left(x_i,y_i\right)' = \frac{\mu_k\left(x_i,y_i\right)^p h_k\left(x_i,y_i\right)^q}{\sum_{j=0}^{c-1}\mu_j\left(x_i,y_i\right)^p h_j\left(x_i,y_i\right)^q} \quad (6)$$

where p and q are parameters to control the relative importance of both functions. $\mu_k(x_i,y_i)$ is the membership value of the ith pixel to the k cluster and h_k is a spatial function defined as:

$$h_k\left(x_i,y_i\right) = \sum_{j\in\Omega_i}\mu_k\left(x_j,y_j\right) \quad (7)$$

where $\mu_k(x_i,y_i)$ is computed by equation (8) and is the result of an initial segmentation.

$$\mu_k\left(x_i,y_i\right) = \frac{\left(w_i - v_k\right)^{-2/m-1}}{\sum_{j=0}^{c-1}\left(w_i - v_j\right)^{-2/m-1}} \quad (8)$$

The initial centers are given by:

$$v_k = \frac{\sum_{i=0}^{q-1} r_i \mu_k\left(x_i,y_i\right)^m w_i}{\sum_{i=0}^{q-1} r_i \mu_k\left(x_i,y_i\right)^m} \quad (9)$$

with r_i as the number of pixels having the gray value equal to i.
w_i is given by:

$$w_i = \frac{\sum_{j\in\Omega_i}\left(F_{ij}\cdot g\left(x_j,y_j\right)\right)}{\sum_{j\in\Omega_i}F_{ij}} \quad (10)$$

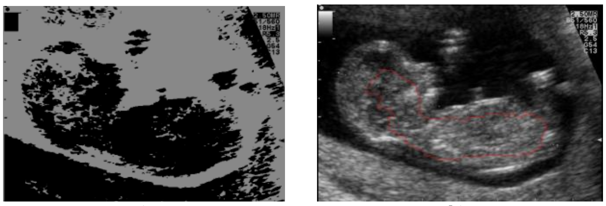
Based on the initial segmentation, new membership values and cluster centers are recalculated using equation (6) and Equation (7) until the termination criteria is satisfied.
This approach tends to present better results because it includes more information for the segmentation and because it is less vulnerable to the presence of noise.

RESULTS

In the last section two different fuzzy clustering approaches where presented, namely the FCM and the FCM with spatial information. These strategies were applied to a ultrasound fetal image used for the crown-rump measurement and the results compared with two other approaches: to a hard clustering approach, K-means algorithm, and to an active contour approach.
The original image is presented on Figure 2 and the results of the applied methodologies in Figure 3 and Figure 4. In Figure 3 we can observe the results obtained with 2 non-fuzzy approaches and in Figure 4 with the described fuzzy clustering techniques.
The K-means algorithm (Figure 3 a)) presented a similar result to the FCM. This was expectable because although the FCM creates a fuzzy partition of the dataset, it is required to choose one cluster to include the

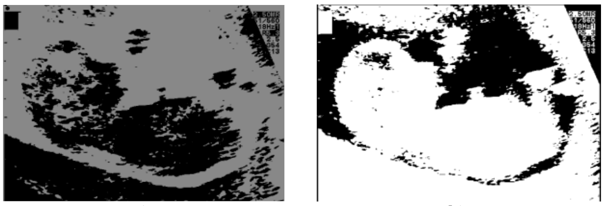
Figure 2 – Original Image for the Crown-rump Measurement (Courtesy of Hospital de São Marcos)

pixel. In this work the maximum membership value was used to decide to what cluster associate the pixel.
Both methods are sensitive to noise and, consequently, several pixels inside the fetus body tend to be included in the wrong cluster as the result of the distance criteria used.



a) b)
Figure 3 – Segmented Image a) Using K-means Algorithm and b) Using an Active Contour Algorithm

The active contour method used, based on the gradient, presented the worst segmentation result. This can be explained also with the presence of noise in the image which creates high gradient values along the image. Although the initialization was made inside the fetus body, the algorithm was unable to correctly identify the fetus edge. This happens because the threshold gradient value is found before the real edge is identified.
A more flexible threshold value could be used. However, this would detiorate the edge identification in the regions where the fetus body is closer to the uterus wall.
Finally, the results obtained by the FCM with spatial information, presented in Figure 4 b), shows an improvement compared to the other presented methods. This is due to the fact that the partition of the data space is not only based on the gray-level information but also on the location information of each pixel. Every pixel attribution to a cluster depends on the neighbors information. However, the method could be problematic in the touching regions of two different tissues.



a) b)
Figure 4 – Segmented Image a) Using FCM Algorithm and b) Using FCM with Spatial Information Algorithm

CONCLUSIONS

In this work two different fuzzy approaches were applied to an ultrasound fetal image for the crown-rump measurement. As mentioned in the initial section, these results are preliminary and several changes are needed to improve the performance of the fuzzy approach. However, results showed that the fuzzy clustering approach presents similar or even better results than other approaches known as good segmentors, indicating that by introducing several modifications or even combining this methodology with others good results could be obtained.

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Semana da Escola de Engenharia
October 24 - 27, 2011

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