CLASSICAL IMAGE PROCESSING VS. COMPUTER VISION TECHNIQUES IN AUTOMATED COMPUTER-ASSISTED DETECTION OF FOLLICLES IN ULTRASOUND IMAGES OF OVARY

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1. INTRODUCTION

A complete understanding of follicle dynamics inside ovary is crucial for the field of genetic engineering. Monitoring follicles over entire cycle is especially important in human reproduction. In Gore et al. (1) is stated that the outcome of a pregnancy is dependent upon the quality of the embryo. This, in turn, is dependent in part upon the quality of the female gamete oocyte contained in the dominant follicle (dominant follicles are those that grow and have potential to ovulate at the end of the follicular phase) and, therefore, the quality of the follicle itself which supports oocyte growth and maturation. Not all dominant follicles ovulate and of those that do, not all are of sufficiently high quality to result in pregnancy.

Here the main task is successfully characterise dominant follicles from the set of follicles inside the ovary. To characterise successful dominant follicles, the follicles must be compared with unsuccessful dominant and subdominant follicles and their interactions examined. For a comparison to be possible, individual large and small follicles must be identified and their development monitored over a number of days. Follicles can be monitored in many different manners, the best way of monitoring is with non-invasive methods, e.g. ultrasonography. With frames of the ovary, grabbed on either way, and with appropriate criteria (right shape, antral edge quality, size and echogenicity) the follicles (and also its type) can be identified and required analysis accomplished.

Today, the monitoring of follicles is done non-automatic, with human interaction. For credible results, a doctor must examine over 30 women a day during their entire cycle (ultrascan woman, freeze the ultrasound image in the best position of the ovary, measure every follicle inside ovary by hand, repeat this procedure for both ovaries - left and right). This work can be very demanding and also inaccurate.

That was the main reason why we decided to develop an application for automatic location and analysis of follicles in the ovary. In the image processing sense, we are dealing with ultrasound image sequence of the ovary. Currently, we are analysing only one image from the sequence at a time. In the original ultrasound image (Figure 1), there can be found the ovary with the follicles in it (the edge of the ovary is very difficult to recognize), endometrium, blood vessels, and added noise due to the ultrasound device. Our aim is at locating follicles from this original image with the procedure that will, step by step, reduce the data to be processed.

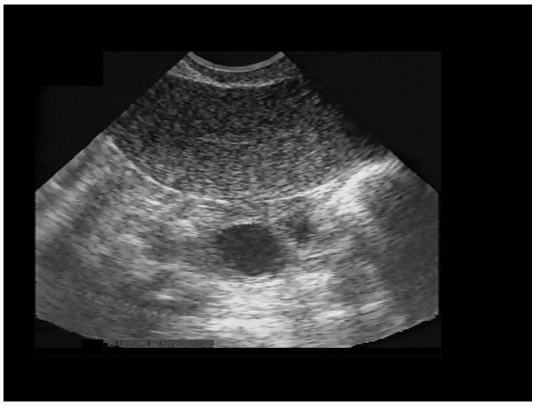

Figure 1: The original ultrasound image of an ovary. Image dimensions are 768x576 pixels with 256 greylevels. On the top of the image the endometrium can be seen, whereas the ovary with two follicles (black rounded region) is almost in the centre of the image. The edge of the endometrium is clearly seen, while the edge of the ovary can be located with forward and backward scanning of the image sequence. Speckle noise and noise due to ultrasound device are also noticeable.

We tried to locate follicles with two completely different approaches: with classical image processing techniques and with computer vision techniques. The fundamental difference between these two approaches is that processing an ultrasound image in the classical way we first want to isolate the ovary (generate subimage) and only then from the ovary recognize the regions which can be, with considerable likelihood, treated as follicles, while the computer vision techniques search for the follicles directly, without initial image segmentation. We are going to describe these two approaches more in detail.

The paper is organized as follows. In Section 2 the classical image processing algorithm for automated detection of follicles in ultrasound images of the ovary is briefly described, Section 3 brings the basis of Hough transform and its application for follicle detection, followed by the comparison of these two approaches, the paper concludes a short conclusion with some directions for future work.

2. CLASSICAL IMAGE PROCESSING

In Sonka et al. (2), Jähne (3), and Russ (4) the typical image processing scheme is defined. It has the following structure: the first step of this scheme is image acquisition (e.g. with frame grabber, scanning the photos). Next step is an image preprocessing stage where the image noise found is suppressed using filters or local operators (e.g. Gaussian, low-pass filter, edge detectors). Image segmentation follows, which can be done on many different ways; the most common methods are image segmentation based on thresholding, edge and region based segmentation. Each obtained region is then described by some features or parameters (area, perimeter, etc.). The last step of this scheme is classification, where these regions are usually compared to a praform (representative objects) and after that accepted as the right objects or rejected as the wrong one.

In our classical image processing algorithm, we adopt this recognition scheme. With this partial algorithm we are processing (analysing) only one ultrasound image from the image sequence at a time, without any additional knowledge from previous images. The main idea of the algorithm is that we first coarsely estimate the ovary boundaries (resulting in subimage containing the ovary) and after that this subimage is searched for the follicles. In the next subsections, a brief description of the classical algorithm is given, more about it could be found in Potoènik et al. (8).

2.1 Preprocessing stage

Because we are dealing with ultrasound images, we must be aware of noise present (noise due to ultrasound device). Especially disturbing type of noise found is speckle noise. For speckle noise suppression an accurate despeckle filter called homogeneous region growing mean filter (HRGMF) was used. This filter has one desirable feature, it namely preserves edges.

Image filtered by the HRGMF filter represents a basis for the whole subsequent analysis. From this image we try to estimate the ovary position. This task is accomplished as follows. First, the Kirsh's edge detector is applied (2,4). We experimented with a lot of other edge detecting operators (Sobel, Canny filter, etc.), but the Kirsh's one gave the most satisfying results respecting the time consumption and efficiency. After binarising the edge image (optimal threshold was used), a thinning algorithm is applied. Then, a simple heuristic method for edge filling is used. Starting and ending point of the connected component (partial boundary) are joined in the tangential direction with edge pixel from the other connected component.
From this image, the location of the ovary is estimated using the histograms. First, the two histograms are generated (along x and y direction). Then, the maxima in both histograms are obtained. After that, two minima, one on each side of the maximum (for each histogram), are searched for. With calculation of both minima (not necessarily global minima) along both directions, the rectangular area probably containing the ovary, is defined (subimage with ovary).

2.2 Segmentation stage

Follicles are dark (almost black) circular shapes, so our task is to find all the dark regions in the subimage and then verify if this regions could be follicles. Dark regions are obtained from the subimage using optimal thresholding. Thus, the binary subimage is generated followed by the processing of every region inside the ovary. Finally, each processed region is described with parameters (area, perimeter, moments, eccentricity, compactness, etc.).

2.3 Classification stage

We decide, on the parameter basis, about each region whether it is follicle or not. At this point, additional knowledge about the problem is introduced into the algorithm (minimum and maximum size of the follicles, expected shape, etc.). This knowledge influences the predefined thresholds needed and criteria for the regions classification. For the classification, we used three rules: area, compactness, and eccentricity. We also experimented with some other rules, but it was evident that they were correlated.

3. COMPUTER VISION TECHNIQUES

Parallel to the approach described in Section 2, we are experimenting with methods known from computer vision as well. The follicles are mostly of a circular shape, which gave us the idea to search ellipses (circles) directly in the edge image. We implemented this idea using the Hough transform.

3.1 Hough transform

Authors Illingworth and Kittler (5), and Leavers (6) provide a good survey of the Hough transform (HT). The HT was first introduced as a method of detecting complex patterns of points in binary images. The key idea of the method can be illustrated on example of searching parametrically defined image curve characterised by *n* parameters ($a_1,..., a_n$). This curve can be defined by the equation of the form

$$f((\hat{a}_1,\ldots,\hat{a}_n),\ (x,y)) \ = \ 0\ , \tag{1}$$

where (x,y) is the position of an image point. The hat symbol is used to denote quantities in the domain of the mapping. The HT uses the idea that parameters and variables can be swapped in Equation (1), thus defining the relation

$$g((a_1,\ldots,a_n),\ (\hat{x},\hat{y})) \ = \ 0\ . \tag{2}$$

The relation g (Equation (2)) maps image points to parameter space, thus producing hypersurface in the n-dimensional parameter space (also called accumulator array). The most probable parameters for image curves are indicated by the intersection of several of these hypersurfaces (local maxima in the accumulator). The HT converts a difficult global detection problem (of searching curves) in image space into a more easily solved local peak detection problem in parameter space.

The HT method has many desirable features. Each image point is treated independently, so HT can be implemented using more than one processing unit. Occlusion and addition of random data (noise) don't represent a severe problem for HT as for most other shape detection techniques. The principal disadvantages of the standard implementation of the HT is its large storage and computational requirements. If the curve described with n-parameters is searched and each of these parameters are resolved into k intervals, then required accumulator is of size k^n elements, which can be very large if either k or n is large (e.g. each ellipse is fully described with 5 parameters and if k=100, then accumulator has 10^{10} elements).

3.2 Ellipse location with Casasent and Krishnapuram method

Each ellipse is described with 5 parameters (centre point, major and minor axis - a and b, and rotation angle ϕ), thus requiring 5-dimensional accumulator. Casasent and Krishnapuram (7) proposed new method based on HT for ellipse location, which significantly reduce the computational effort and requires only 2-dimensional accumulator (Hough space - HS).

This method maps every white image point (from binary image) (x_0, y_0) in Hough space (Θ, p) using straight-line HT defined in Equation (3)

$$p \ = \ x_0 \cos\Theta \ + \ y_0 \sin\Theta\ , \tag{3}$$

where parameter p is normal distance from the origin to the line ($p \geq 0$) and parameter Θ is the angle of the normal with respect to the positive x-axis ($0 \leq \Theta \leq 2\pi$).

For a centered ellipse, a pattern in Hough space (after removing low entries-noise with thresholding) is known and described as

$$p \ = \ \mathrm{T_e}(a,b,\Theta) \ = \ \sqrt{a^2\cos^2\Theta \ + \ b^2\sin^2\Theta}\ . \tag{4}$$

Ellipse location is done with the following procedure (7). First, each image point is mapped with straight-line HT (Equation (3)) into Hough space (Θ', p'). After thresholding HS, this space is transformed into new space using the following equation

$$p \ = \ p' \ \mp \ \mathrm{T_e}(a,b,\Theta - \ \phi)\ , \tag{5}$$

in which ellipses appear as shifted sinusoids. In the space obtained the inverse HT is applied. Ellipses are determined with a simple search (e.g. local maxima) through inverse HS. Position of a peak in inverse HS point out the ellipse centre, while major axis a, minor axis b, and rotation angle ϕ must be known in advance. If this is not the case, then the "coarse-to-fine" processing strategy for obtaining unknown parameters a, b, and ϕ must be applied, meaning, that this procedure must be done through the entire scope of possible values for a, b, and ϕ, and then the highest peaks in inverse HS are selected as ellipse centres (for current parameters).

3.3 Hough transform for automated computer-assisted detection of follicles

As already described, we use idea that follicles are mostly of circular shape (very similar to ellipse), which direct us to search for ellipses in edge images. We implement this idea with the following procedure.

The preprocessing stage is the same as in the first algorithm described in Section 2 (despeckle filter, Kirsh's operator, optimal thresholding). Edge image is base for the subsequent ellipse searching. Ellipses are located with Casasent and Krishnapuram HT method (Subsection 3.2). The "coarse-to-fine" processing strategy is used. Ellipses (circles) are determined with a simple search (for global maximums) through inverse HT space (for current parameters). Isolated ellipses (ellipses which not satisfy predefined criterions are rejected) represent the first estimate for the follicle boundary. This boundary is then recalculated with active contour models (snakes) - initial boundary converge to the final position of the follicle. With the well defined boundary of the follicle, all other parameters can be easily obtained (area, perimeter, moments, etc.).

4. RESULTS AND COMPARISON OF METHODS

In this section, first the results are going to be presented, following by the comparison of the two methods observed.

Both algorithms are the core of our application called "xultra". Program "xultra" is written for X-windows system in the programming language C using Motif1.2 libraries. It has been tested on the HP 715/100XC and HP 712/80 systems with 128 MB RAM.

4.1 Results

Both algorithms will be demonstrated starting from Figure 1, the original ultrasound image of the ovary (Sections 2 and 3). Original images were obtained from VHS tape using simple software grabber. Image dimensions are 768x576 pixels with 256 greylevels.

First, the results of classical algorithm will be discussed. Original image (Figure 1) is initially processed with the HRGMF despeckle filter, followed by Kirsh's operator, binarisation and thinning. Intermediate result after this stage is shown in Figure 2. Then the ovary is estimated. After determination of subimage containing the ovary, each black region inside is processed and evaluated. All satisfying regions (possible follicles) are described with parameters (area, moments, eccentricity, etc.) and are finally superimposed to the despeckled image. The resulting image is depicted in Figure 3, while in Figure 6 the correct ovary and follicles location are hand encircled by an expert. Taking into account images with resolution of 768x576 pixels, an ovary processing and follicle detection last about 6 minutes on the mentioned HP machines (the majority of time is spent by despeckle filter, about two thirds). More detailed description of the results obtained with the classical algorithm could be found in (8).

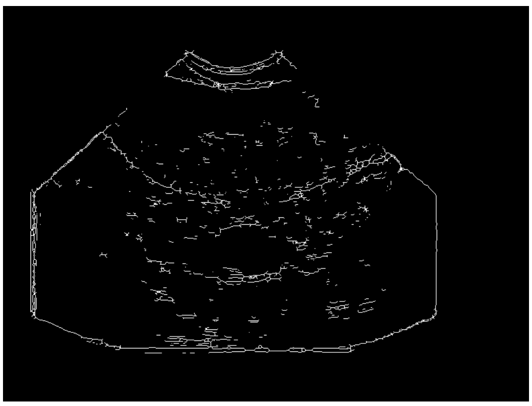

Figure 2: Despeckled image from Figure 1 processed by Kirsh's operator, followed by binarisation (threshold 40) and thinning.

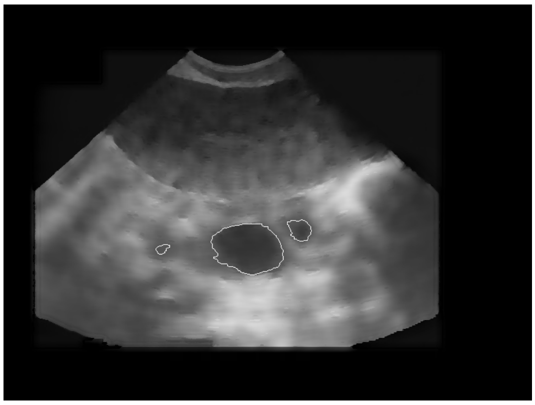

Figure 3: The result of classical algorithm for the image from Figure 1 - recognized follicles are rounded in white and are superimposed to the original speckled image. For the binarisation optimal threshold (89) was used.

Computer vision approach (Section 3) has the same preprocessing stage as the classical algorithm. Then the Casasent and Krishnapuram method for ellipse location (Subsection 3.2) is applied. Hough space (Θ, p) is of resolution 360x738 elements (parameter p is in range [1, length of subimage diagonal] and Θ is between $[0,2\pi]$, both parameters are resolved with step 1). Hough space obtained after applying straight-line HT on edge image (Figure 2) could be seen in Figure 4. It is clearly seen that each image point vote along sinusoid. This space is then thresholded (threshold is selected arbitrary at one fifth of the maximum value found in HS). Then the "coarse-to-fine" searching strategy is applied (parameters a and b are in range [10,100] - with step 5, rotation is not verified). In the inverse HS, only global maxima are evaluated. Isolated ellipses, satisfying certain criteria (current criterion is: each ellipse must be described with at least 15% boundary points), are superimposed to despeckled image. Unfortunately, we haven't implemented yet active contour models proposed above. Current result is shown in Figure 5. The entire processing with computer vision approach last approximately 8 minutes on the same HP machines (processing time is threshold selection dependent).

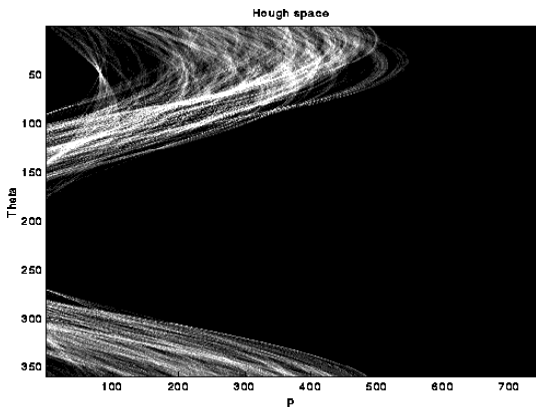

Figure 4: Image of Hough space obtained after applying straight-line HT on edge image (Figure 2).

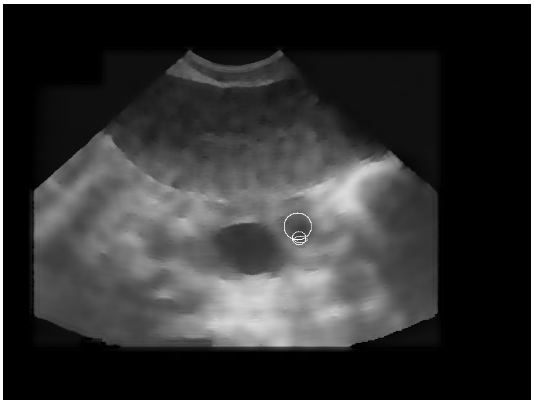

Figure 5: The results obtained using computer vision algorithm.

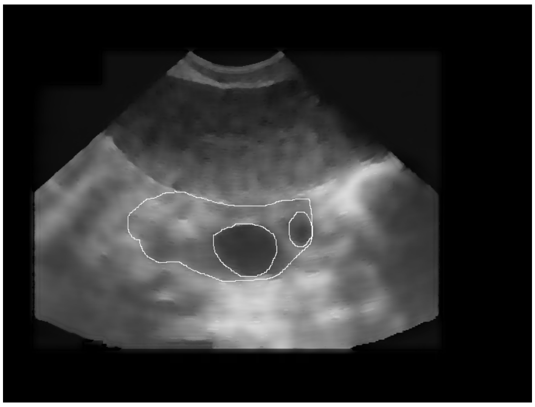

Figure 6: Ovary and two follicles as found manually by an expert (doctor).

4.2 Comparison of two approaches

Both algorithms have computational complexity of order $O(n^2)$, where n is the image dimension; despite this fact, the computer vision approach requires more processing time than classical algorithm. We also experimented with edge images not previously despeckled, but this trial leaded to yet a bigger required processing time, because also many noisy image points must be processed. Possible solution to cut down the processing time required is to first select random subset of pixels from edge image and only then apply Casasent and Krishnapuram method.

Classical algorithm has a few drawbacks. The ovary estimation using histograms is very poor (sometimes is also false). Second problem, which arises from the first one, is that a few regions are misidentified, because a few regions merge. In some cases the criteria are too lax (as in the example of the left region in Figure 3). Classical algorithm were tested on many images, the results returned were acceptable (recognition rate near 70%).

Equally good recognition rate cannot be reported for the current implementation of computer vision algorithm (without snakes). The HT is known as considerably superior in processing the noisy images (ultrasound images are very noisy), but follicle boundaries are usually too much corrupted to obtain good results (see edge image in Figure 2). Moreover, many identified ellipses don't completely fit to the follicles, but could actually be regarded as a coarse follicle estimation (inclusion of active contours is essential). Recognition rate of this algorithm is about 30%.

5. CONCLUSION

In this paper, a comparison between classical and computer vision techniques applied on detection of follicles in ultrasound images of the ovary was discussed. From results obtained we can conclude that classical algorithm (in real-application checked procedure) is more perspective that computer vision one, but we must not overlook the fact that current implementation of the latter algorithm has not been completed yet. Beside this, against computer vision approach work also very weak follicle edges (many of them are removed after binarysing edge image), which influence on ellipse (follicle) location with Hough transform (no distinctive maxima could be found in HS). Many follicles, good visible in the ultrasound images, remain undetected because of this fact.

Our future work will be oriented into study and inclusion of active contour models in computer vision algorithm.

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