Aorta detection in ultrasound medical image sequences using Hough transform and data fusion

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Abstract - Nowadays, information fusion constitutes a challenging research topic. Our study proposes to achieve the fusion of several knowledge sources, in order to detect the aorta artery, in ultrasound slices of the esophagus area. After a brief description of information fusion concepts, we propose a system architecture including both model and data fusion. Two primary models compose the algorithm: a fuzzy model, based on data fusion of three different information sources extracted from slices, and a Hough Transform (HT) model, which is often employed for pattern recognition. A global fusion model combines their complementary aspects and advantages. Along the sequence, spatial aorta matching is achieved by parameters propagation and controlled using a 3D-trajectory model. Simulation results, obtained from echo-endoscopic sequences, are presented.

Key Words: Hough Transform, knowledge sources fusion, echo-endoscopic image sequences, spatial matching.

I. INTRODUCTION

Many engineering research domains use imaging processing architectures that often include fusion modules. In medical imaging and particularly in ultrasound imaging, data fusion is a must. Original data image usually contains insufficient information to develop robust segmentation algorithms, because of noise and distortion introduced by the acquisition system. Unfortunately, numerous medical imaging systems are not based on a multi physical sensor architecture that offers complementary information, to improve the efficiency of a posteriori numerical computation.

In this study, our particular interest is the detection of the aorta position and shape, estimated on a sequence of ultrasound transversal slices of the esophagus area. This detection is a module within a larger project intended to achieve a realist esophagus 3D reconstruction based on anatomical context information, in order to use the whole reconstruction as a diagnosis aid tool to evaluate digestive system pathologies [1].

As numerous anatomical human objects, an ellipse can first approximate the general shape of the esophagus wall. On ultrasound slices, the aorta has significant shape and position variations during all the sequence acquisition, as a consequence the condition of continuity is not always satisfied. Despite the small distance between two consecutive slices (1mm), strong shape and position variations can be produced by the patient breath activity, blood stream, natural anatomical orientation, and sensor displacements. Otherwise the contour is imprecise, noisy and is usually opened.

After the section II, which presents general fusion concepts, we propose in section III an aorta detection system based on data fusion, model fusion and on the Hough Transform (HT). In this section are first discussed the different knowledges which are able to complete the poor numerical information of ultrasound images. In a second time, method to combine their complementary aspects is precised. At the end of this part, model fusion to improve HT efficiency is proposed and ways to include knowledge at different level of HT are presented. In the section IV, results from a sequence acquired in real conditions of a medical exam are presented and commented. The conclusion evokes possible work perspectives.

II. INFORMATION FUSION

A definition of data fusion, given in [2] can be generalized to information fusion as follows: 'A multilevel, multifaceted process dealing with
automatic detection, association, correlation, estimation, and combination of information from single and multiple sources'.

II.1 Information fusion concepts

Information fusion appeared when researchers have had the necessity to solve problem classes requiring to imitate the human intelligence. A possible classification of the fusion [3] introduces three conceptual levels corresponding to the three kinds of information:

- **Data Fusion** - is the first conceptual level. It usually consists in the merging of low level information, as primitives, in order to deduce a decision less noisy than with only one information source.

- **Decision fusion** - acts at the decision space level. Decision fusion achieves the combination of elaborated information as decision hypothesis, or results issue from a data fusion.

- **Model fusion** - is the case where information to be merged are strategies, processing methods or reasoning modes. A model fusion uses complementary aspects of two or more approaches in the case that just one isn’t able to lead to the solution of a given problem. In [4], edge detection problem and model fusion are considered through the use of the Canny-Derich algorithm.

II.2 General fusion system architecture

This subsection intends to summarize the two major fusion system architectures. Due to some historical reasons, the first available scheme that we have when discussing information fusion systems, is that of a multi-sensor system. This scheme constitutes a partial view of the reality where several "physical" sensors are needed, in order to access several information issues of an object from the real world scene. In fact, two main architectures of information fusion systems can be distinguished:

The first, Figure 1.a, (referred to as the mono-sensor architecture) is based on the use of a single sensor and, the application of a priori knowledge, to obtain a new set of information data. The use of the probability set theory or the fuzzy set theory is generally performed through this step. The second system architecture (Figure 1.b) corresponds to the intuitive multi-sensor situation, where the "analyzed" object is observed through different physical sensors (or the same sensor, but with different geometric observation positions as is in the case of stereovision). The first system architecture has not been considered, for a long time, as being a real information fusion system. Anyhow, this is the main architecture used in several applications where the use of different sensors remains an obstacle and where an important amount of knowledge can be formulated as a priori knowledge sources of information. This is the case, for instance, in medical applications where the processing system can use a huge amount of a priori anatomical and expert-based sources of knowledge, to analyze medical images.

### III. AORTA DETECTION

As previously mentioned, the aim of this study is to accomplish the aorta detection, using an ultrasound image sequence, acquired by an echo-endoscopic system. The sensor, called endoscope, is introduced through the mouth in the patient digestive system (Figure 2). Generally, a doctor assumes the sensor control but, in our particular case, endoscope progress through the esophagus lumen is entirely controlled by a mechanical system [1]. The obtained precision on z coordinate, which is about one millimeter, is enough to acquire all structures useful for a diagnosis elaboration (esophagus, aorta artery, and ganglions...).

![Figure 2](image_url)

**Figure 2:** (a) Position of aorta in anatomical general scheme: aorta artery is always in contact with the esophagus. (b) Echo-endoscopic imaging system: endoscope progresses along the esophagus lumen and, thanks to ultrasound waves, an esophagus area image can be computed.

An echo-endoscopic image is shown in Figure 3. Detailed analysis shows that the image quality depends mainly on two phenomena: speckle noise (due to the ultrasound imaging acquisition approach) and a concentric wave reflections network created...
by the protection surrounding the ultrasound transducer. These different factors show the extreme difficulties encountered in the detection of the aorta section \[1\][5][6][7][8].

![Figure 3: Echo-endoscopic 2D-slice views of the esophagus area. Aorta lumen is uniformly black and contour is clearly visible (a). Aorta lumen becomes noisy and the contour is practically invisible (b).](image-url)

III.1 Global architecture

Concerning the numerical images processing, we propose a mono-sensor information fusion system based on the use of echo-endoscopic image slices of the esophagus and of a priori knowledge to detected the aorta section.

We have taken into account the following constraints: (i) it is necessary to preserve medical information contained in the slices. (ii) Numerical information is completed by means of models and a priori knowledge to make algorithms more robust. (iii) A slice by slice processing is applied, given the characteristics of the acquisition system. (iv) Aorta’s shape uncertainty is handled knowing that semi-major axis (a), semi-minor axis (b) and orientation (γ) are set according to a variation Δ. Considering the above constraints, two different approaches are used:

- FUZZY LOGIC: allows integrating knowledge from different sources, simplifying data fusion thanks to fuzzy operators properties.
- HT: detects parameterized shapes, handling uncertainty. This transformation can also include a priori knowledge at different levels of its implementation. Finally, HT is robust on noisy images because it is based on co-operative vote and on the notion of Accumulation Kernel (AK) \[9\].

III.2 Considered knowledge

- **Aorta visual appearance**: A doctor easily denotes aorta presence in echo-endoscopic slices, but he can’t precisely draw its contour. In fact, on ultrasound slices, aorta contour is very noisy. The following scheme shows elements, which perturb the artery detection.

![Figure 4: Pixels of interest for the aorta detection are contained in the hyper-echoic contour. Pixel within the halo must be eradicated to achieve a right detection.](image-url)

The part of the aorta ellipse called hyper-echoic contour, which is opposite to the ultrasound sensor, is the primary knowledge we use. Otherwise, independently to the approach of detection that will be adopted, it is necessary to privilege hyper-echoic pixels, and contribution of the halo pixel must be less important.

- **Aorta position**: Specialists usually consider that the aorta artery is invariant in term of position relatively to the anatomical context. Real medical exams and sequences observation leads to think that the aorta has to be searched in a region surrounding the esophagus. It is a precious information, which avoid to confuse aorta with others encountered elliptical anatomical structures (harmonics, ganglions, artery...).

- **Scalable trajectory model**: Aorta 3D shape can be considered to be invariant with a linear transformation. Both, doctors considered a 3D model as an information we have to take in account to perform a good detection. As, for the moment, a slice by slice processing was retained, only the 3D-model projection is of great interest to be use as knowledge.

III.3 Fuzzy model

The fuzzy set theory pioneered by L. Zadeh \[10][11\] provides us with a powerful mathematical tool for modeling the human ability to reach conclusions when the information available is imprecise, incomplete, and not totally reliable. The major characteristic that distinguishes fuzzy set theory from traditional crisp set theory is that it allows intermediate grades of membership. A fuzzy set \(A\) over \(Ω\) is defined as the set of ordered pairs \(A=\{ (X, \mu_A(X)), \ X\inΩ\}\), where \(\mu_A(X) (\in[0,1])\) is termed the grade of membership, or simply the membership value, of the element \(X\) to the fuzzy set \(A\).

Let’s introduce, first, the useful concept of fuzzy images. A fuzzy image is defined as the
transformation of an original image (considered as a MxN array of gray level associated with each pixel) into an image with the same dimensions but where each pixel is associated with a value denoting the degree of possessing a fuzzy property:

\[ A: \{0,1\} \rightarrow P(x,y) \rightarrow \mu_A(P) \]  \hspace{1cm} (1)

where, \( \mu_A(P) \) reflects the appropriateness or the validity of the fact that the pixel \( P \) possesses the fuzzy property “A”. Concerning the application of the esophagus inner wall detection, four fuzzy images are defined:

**Fuzzy position image**: fuzzy image representing the more reliable position of the aorta section

**Fuzzy intensity image**: fuzzy image representing the “brightness” of different pixels.

**Fuzzy gradient image**: fuzzy image representing the gradient computed at each pixel.

**Fuzzy region image**: fuzzy image representing the contrast of each pixel relatively to the dark region of the esophagus light.

**Fuzzy Position Image**: In a sequence, reliable aorta position information is introduced through a manually built fuzzy image \( \mu_p(P) \) where pixels gray level traduces the membership value to the aorta contour. More a pixel is far from the center i.e. the location of the esophagus, more its membership value is important (Figure 5.a).

**Fuzzy Intensity Image**: Physical consideration on the tissue nature lead to conclude that a large part of the aorta contour is generally hyper-echoic. Therefore, contour pixels have a high intensity. The S-shape function is applied over the gray level values in order to construct the fuzzy intensity image, \( \mu_i(P) \). The S-shape parameters selection method is considered as a normalization process of the image brightness values and, thus, the visualization parameters tuning has no influence on the fuzzy intensity image (Figure 5.b).

**Fuzzy Gradient Image**: The edge information constitutes an important element in the determination of the aorta contour. Therefore, the fuzzy gradient image, \( \mu_g(P) \), (representing the degree of membership of each pixel \( P \) to the “ill-defined” or ambiguous concept of an edge) is of great interest. For this purpose, a 5x5-gradient filter, similar to the Sobel operator, is used. The horizontal and the vertical masks of this filter are given as follows:

\[
G_x = \begin{bmatrix}
0 & -1 & 0 & 1 & 0 \\
-1 & -2 & 0 & 2 & 1 \\
-1 & -2 & 0 & 2 & 1 \\
0 & -1 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0
\end{bmatrix}, \\
G_y = \begin{bmatrix}
0 & 1 & 0 & 1 & 0 \\
-1 & -2 & -2 & -2 & -1 \\
-1 & -2 & -2 & -2 & -1 \\
0 & 0 & 0 & 0 & 0 \\
1 & 2 & 2 & 2 & 1
\end{bmatrix}
\]  \hspace{1cm} (2)

Therefore, the x-y gradient of an image \( I(x,y) \) is given through the following expressions:

\[
\frac{\partial I}{\partial x}(x,y) = G_x \ast I(x,y) \\
\frac{\partial I}{\partial y}(x,y) = G_y \ast I(x,y) \]  \hspace{1cm} (3)

The module of the gradient is given by:

\[
G_r(x,y) = \sqrt{(G_x \ast I)^2(x,y) + (G_y \ast I)^2(x,y)} \]  \hspace{1cm} (4)

Finally, we use the S-shape function to perform the ‘fuzzification’ operation (Figure 5.c).

**Fuzzy Region image**: aorta halo introduces imprecision in the contour detection cause of its hyper-ecoicity and area. Also, the use of a \( \Pi \)-function, which performs a progressive threshold as well as the ‘fuzzification’, seems to be adapted to limit influence of pixels corresponding to this region. In a fuzzy region image \( \mu_r(P) \), each pixel is represented by a coefficient (i.e. membership value) denoting the degree of possessing the property: Do not be in “touch” with the region of the aorta halo (Figure 5.d).

**Figure 5**: An example of knowledge sources extraction: position fuzzy image (a), intensity fuzzy image (b), fuzzy region image (c) and fuzzy gradient image (d).

**Fuzzy Reasoning**: The fuzzy reasoning step aims at the concentration of all the information previously mentioned in order to produce a single membership value, for each pixel in the analyzed image, to the aorta inner wall. The wide range of combination operators proposed in fuzzy set literature (see, for instance, [12]) reflects the power as well as the flexibility of the use of fuzzy concepts. In this study, the simple fuzzy intersection operator (i.e. a "conjunctive-type" combination operator) is used:

\[
\mu_m(P) = \text{Min}(\mu_p, \mu_i, \mu_g, \mu_r) \]  \hspace{1cm} (5)
where \( \mu_w(P) \) denotes the “global” degree of membership of the pixel \( P \) to the aorta wall. On the Figure 6, an example of fuzzy decision is presented. We can notice that the halo has disappeared, as well as harmonics and speckle noise.

![Figure 6: Decision fusion obtained from a given image of an echo-endoscopic sequence. We note that the information is less noisy and that only pixels belonging to the aorta contour has significant membership degree.](image)

III.4 HT Model

Hough has introduced a detection method (HT) in 1962 for identification of straight lines [13]. Duda and Hart have extended the same method to extract parameterized curves in general [14].

**General idea:** Let \( f(X, V) = 0 \) be an analytic expression defining a parameterized curve, where \( X = (x, y) \) define a pixel coordinate and \( V \) a parameter vector. The HT is accomplished in two steps:

- The first aims to the definition of the parameter \( V \) and the quantification of the parameter space into rectangular n-dimensional cells called Hough Space. The last expression signifies that if we are given a parameter vector \( V \), then, the curve of interest is formed by pixels in the image plane satisfying the analytic curve expression. The application of an HT consists in considering the inverse situation where we have a contour pixel \( E_k \) included in a parameterized curve and we are looking for the set of parameter vectors \( V \) that pass through this considered pixel which verify the following expression: \( f(E_k, V) = 0 \). The locus of these vectors in the Hough Space (HS) is called Accumulation Kernel (AK) as in [9]. Let consider for a set of pixel of the same contour the set of the parameter-associated vector. In theory, as these pixels are members of the same parameterized curve, among the set of parameter associated vector, only one is in common. This vector entirely defines the search curve. Given that, each pixel can be considered as an elementary expert, which contributes to the global object detection.

**Particular ellipse case:** In the ellipse case, five parameters are necessary to entirely define the curve. On each slice, aorta section can be modeled as an elliptic shape according to these parameters: ellipse center coordinates \((x_0, y_0)\), semi-major axis \( a \), semi-minor axis \( b \) and orientation \( \gamma \).

We don’t directly discuss in five dimensions HS. In a first time, only a restriction space of two dimensions, corresponding to ellipse center position space, is considered.

As previously mentioned, HT needs to know curve parameters. Thus, an initialization of these parameters is required. This problem will be discussed in the next sub-section.

This operation achieved, the slice gradient is computed using a large convolution kernel. From the gradient image, two informations are extracted: the gradient magnitude, which is a criterion to accomplish a first selection of pixels implicated in the algorithm (using a threshold), and the gradient direction, which is exploited to limit the search space.

![Figure 7: \((x_0, y_0)\) is the center of the ellipse, \(\Phi\) the angle to the ellipses center, \(\Theta\) the direction of the gradient.](image)

In the case where the searched ellipse parameters are \(a, b, \gamma\), the geometric relation between the gradient angle and the angle relative to the center is given by the following relation (Figure 7):

\[
\Phi = \gamma + \arctan\left(\frac{b}{a}\tan(\Theta)\right)
\]

**Imprecision handle:** Handle of imprecision on direction radius introduced in [9] was useful to take in account fluctuation of aorta shape.
In the case of total ignorance accumulation, from a pixel edge $E_k$, the whole space is explored (Figure 8.a).

![Figure 8: Total ignorance accumulation (a), and total knowledge accumulation (b).](image)

In total knowledge accumulation, a precise direction for given distance $d$ is observed (Figure 8.b). In the case of imprecise direction/radius accumulation, imprecision on the definition of semi-minor and semi-major axis is introduced as well as in the direction exploration (Figure 9.a). For each contour pixel, an area so called AK, corresponding to a set of parameter vectors, is computed (Figure 9.b).

The aorta center estimation is obtained computing the max of the accumulation. Finally, considering the set of pixels $S=\{E_1, E_2, ..., E_n\}$, which have contributed to this estimation, $a$ and $b$ parameters are re-estimate with the following method:

Given $b$ member of the interval $[b-\Delta b, b+\Delta b]$, $a$ is computed from each pixels of $S$. The $b$ which corresponds to the minimal standard deviation of $a$ can be considered as a good estimation of the semi-minor axis. The retained semi-major axis is given by the mean of the obtained $a$. Given $x, y, a, b, \gamma$, ellipse is entirely defined. Then parameters are propagated to the next slices assuming that a continuity hypothesis satisfied.

III.5 HT and Information fusion

The proposed general architecture is presented in Figure 10. We can see that others knowledges as numerical information have been introduced at three levels of the HT implementation to improve the efficiency of our method:

![Figure 10: Aorta detection architecture based on fuzzy logic and HT. A fuzzy model based on data fusion of information extracted from a priori knowledge is merged with a HT based model.](image)

**Initialization of parameters:** For the moment, initialization of ellipse searched parameters is assumed considering typical anatomical measures. But we can easily imagine a human-assist tool, which is able to assume this task for the first slice of the sequence. Once the first ellipse detected i.e. parameters evaluated, these ones are propagated to initialize the detection on the next slice.

**Fuzzy decision fusion:** At the level of accumulation elaboration, fuzzy decision image is used to weigh pixel vote (see [15] for a ponderation by the gradient). This method has the advantage to take in account, in the HT, both the numerical information contained in a slice, elaborated considerations as the halo problem and a priori knowledge on the aorta position.

![Figure 11: From aorta trajectory 3D model, we just consider the projection on the slice plan. The model is first adjusted to the data and then used as knowledge.](image)
Scalable 3D model: Recall the proposed solution is based on a slice by slice processing, the coefficients derive problem must be considered. Even if a continuity hypothesis is considered by introducing parameters propagation, it is a relatively local consideration, which is insufficient to assure a correct detection along the sequence. The proposed solution is based on the use of a 3D model of trajectory to assure the global coherence of the elaborated reconstruction. Cause of the 2D nature of processing, only the 2D-model projection seems useful (Figure 11). The model is first adapted to the data considering a linear transformation (in fact a similitude). Then, when the error is inferior to a given threshold, the model can be fully considered as real knowledge source.

IV. RESULTS

Images given in Figure 12 and Figure 13 come from a real sequence acquired in a medical context. We can notice the aorta contour vanishing in several parts. Finally, it is worthwhile to notice the important problem due to the harmonics presence, which can introduce error on the detection of aorta.

On Figure 12, we can see the detected aorta at different levels of the sequence. The stability of the detection is due to trajectory 3D model. This knowledge source adds a fundamental information on the aorta global shape, which fully compensates defects of a slice by slice processing sequence.

On Figure 13, two magnified views prove that the use an elliptical model is judicious to approximate the aorta contour. Such a model assures a correct precision despite its relative simplicity.

V. CONCLUSION

Obtained results are very encouraging. Simulations have shown that the processing sequence is robust enough against the noise (Figure 13), thanks to Hough Transform. Imprecision on $a$ and $b$ estimation at the level of the aorta bend, should be compensated by the introduction of a full 3D model taking in account both the trajectory of the center, semi-minor and semi-major axis.

In term of image processing, ultrasound slices relative positions can be corrected from this reconstruction considering shape regularity conditions.

Actual studies are conducted in order to generalize the proposed HT based information fusion system to the case of spherical anatomical structures 3D detection as ganglions.

The whole system will be soon integrated in a blackboard architecture that seems to be promising.

REFERENCES


