AUTOMATIC OBJECT DETECTION USING SHAPE INFORMATION IN ULTRASOUND IMAGES

Pablo Cancela Fernando Reyes Pablo Rodríguez Gregory Randall Alicia Fernández

Instituto de Ingeniería Eléctrica, Universidad de la República, Uruguay
e-mail:pcancela@fing.edu.uy

ABSTRACT

A method is presented for segmentation of anatomical structures that incorporates prior information about shape. The method iteratively applies steps which find object's border considering its properties independently from shape. The boundary is regularized taking in account the shape being extracted. Detection is not directly performed in the image but in a "shape space" referred to the shape in each step. The problem is reduced to work in this new coordinate system where the border is approximately a horizontal line. Shape information is introduced through a higher dimensional map similar to a distance map of a mean shape. Segmentation results are demonstrated on ultrasound imagery to measure meat quality of bovine and ovine livestock.

1. INTRODUCTION

Segmentation in noisy images is an important topic specially in ultrasound imaging where object geometrical properties are critical for the applications [5][6].

Most of these problems consist in segmenting a closed shape in which different texture from the medium is observed or edges around the object define its boundaries [1][3][4][6].

In animal quality applications, the same basic problems are found. Animal profit can be predicted from measures taken with non-invasive techniques such as magnetic resonance imaging (MRI) or ultrasound. Ultrasound images allow the measurement of standard quality indicators as the Rib Eye Area [8][9]. Today these parameters are manually measured by experts on the ultrasound images to evaluate animal profit.

Automatic, real time measure of such indicators has several advantages over manual tracing measures. One of them is the possibility to classify animals in acquisition time. Besides, taking more objective measures, makes possible to establish well defined standards.

An important noise component is present in this kind of application images. Low image quality suggests the use of robust methods that consider additional information about the object being extracted.

An iterative algorithm based on the evolution of a curve for object segmentation in noisy images is proposed. In each evolution step, the curve is moved to object's border and its shape is adjusted.

The first part of each evolution step consists in looking for object's border and moving the curve towards it. The image is transformed into what we will call the "shape space". In this new coordinate system, borders are referred to the curve in that step (the reference border curve), making the processing in that step independent of object's shape.

In the shape space, a new curve is found. The next curve in the evolution is build using the edges and the reference border curve.

In the second part of each step, shape knowledge information is used. Curve pose, size and principal moments are calculated to fit a shape model. Shape is corrected according to the model.

Border detection and shape correction are iteratively applied until a stop condition is satisfied.

2. SHAPE SPACE

Border detection is obtained in a shape independent schema. This is achieved by transforming the image into a different coordinate system. This transformation is done referred to the Reference Border Curve (RBC) in each step.

2.1. Shape space transform

We will define a shape transform (ST) that maps R^2 to R^2 using a curve (the RBC). As a result, the plane is expressed in a new coordinate system, the shape space.

Consider a point P that we want to transform referred to RBC C. Let O be an arbitrary point in the curve that will be mapped to the origin in the shape space. Let Q be the nearest point to P in the curve. The coordinates of the transformed P, are the distance between O and Q along the curve as the abscissa and the distance from P to Q as the ordinate. See figure 1.

Formally, Q can be defined by

$$Q \in C, \forall Q' \in C \; d(Q,P) \le d(Q',P)$$

where d is the euclidean distance function.

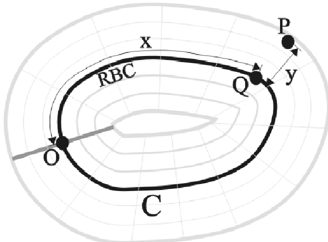

Figure 1. Transformation of point P. Distances from P to the curve y, and from O to Q along the curve are shown.

Assuming a constant speed parametrization C(t) of C, P coordinates in shape space are:

ST(P) = (x,y) where

$$x = \int_0^{t_Q} \left|\dot{C}(t)\right| dt \quad C(0) = P, C(t_Q) = Q \ , \ y = d(Q, P) \tag{1}$$

The inverse shape transform ST^{-1} is:

$$ST^{-1}(x, y) = C\left(\frac{x}{l}\right) + \vec{N}\left(\frac{x}{l}\right).y \tag{2}$$

where $l = \int_0^1 \left|\dot{C}(t)\right| dt$ and $\vec{N}(t) = \frac{\ddot{C}(t)}{\left|\ddot{C}(t)\right|}$ is the curve´s normal in Q.

It can be seen that in this space the RBC is mapped into the horizontal axis. Any curve parallel to the RBC will be also mapped into a horizontal line. A vertical coordinate is related to the distance to the RBC. Points in a normal to the curve are in a vertical line in shape space.

2.2. RBC considerations

Using the mapping, any problem can be seen in the new space as the detection of a horizontal border, with independence of shape. This is true if the RBC has exactly the shape of the searched object and is well posed. Under some constraints, the searched border curve has desired properties that enable its detection:

- RBC curvature is small enough. If the RBC curvature is too high, the mapping loses desirable smooth properties.
- RBC and the searched object shapes are similar.
- The initial RBC does not need to be so close to the target as soon as it intersects the searched object.

Using the shape space transform and working under these assumptions, border detection becomes independent of object's shape as it is normalized to it.

3. SEGMENTATION IN SHAPE SPACE

Each edges detection problem has it particularities. It comes natural to mention some considerations about general edge detection techniques that are easily implemented in shape space.

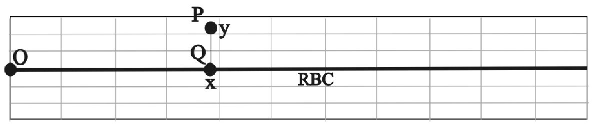

Figure 2. Point P in shape space. The same point as in figure 1, represented in the shape space.

3.1. Edges in shape space

It is difficult to detect continuous edges in noisy images. Some points would be surely detected as edges but the object border will be formed by not connected regions. In this kind of problems, more global and topological considerations about the searched borders have to be taken in account to improve the segmentation.

We extract edges by some image processing. We will caracterize the border combining the properties of these edges. Once edges have been detected, a set of regions is obtained. Some of these regions are part of the desired border and some not. Some border sections may have not been detected.

Border position estimation is done in such a way that each region adds information to the global solution. Regions with characteristics (orientation, etc.) compatible with the desired border shape must win over the other regions.

Some assumptions about the searched border have to be done, and based on them, the evolution is calculated:

- It is not too far from the RBC – It is reasonable to assume that the RBC is sufficiently near to the solution so that it can converge to it.
- Although noise is present, segmented border regions produced by the segmentation process are in general bigger than noise regions.
- Smooth borders are assumed.

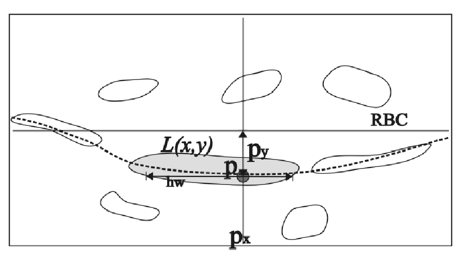

Figure 3. It is shown the horizontal width of a point in a region with label *L(x,y)*

3.2. Finding border curve in shape space

For each horizontal coordinate, the vertical position of the border in shape space is found.

This vertical position is calculated as a weighted mean of each point in that vertical line. The weights considered are the size of the region in which that point is (based in the assumption that noise regions are in general smaller), a weight that penalizes distance to the horizontal axis so that a more stable solution is found. Finally, a measure of how horizontal the region in each point is.

Let L be the label function, that gives the label of the region a point lies on, where label's domain is considered as natural numbers.

$$L : R^2 \rightarrow N$$

Let A be the area function that given the label of a region, gives its area.

$$A : N \rightarrow R$$

where $A(BackgroundLabel) = 0$

Let hw (horizontal width) be the length of the longest horizontal segment that contains the point P and is completely contained in the same region as P. This is a good measure of how horizontal the region is in the considered point.

$$hw(p_x, p_y) = máx \left\{ \begin{array}{l} x_2 - x_1 ; L(p_x, p_y) = L(x, p_y) \\ \forall x \; x_1 \leq x \leq x_2 ; x_1 \leq p_x \leq x_2 \end{array} \right\} \quad (3)$$

Now the border curve (BC) can be expressed as:

$$BC(x) = \frac{\int_{-d}^{d} y.F_1(|y|)F_2(hw(x,y))F_3(A(x,y))dy}{\int_{-d}^{d} F_1(|y|)F_2(hw(x,y))F_3(A(x,y))dy} \quad (4)$$

where F1, F2 and F3 define the weight assigned to each term.

This defines the border curve in shape space which is later smoothed to cut off spurious points generated by noise. In figure 4, segmented border regions are shown. The dashed line represents the smoothed border curve which is also shown with the reference curve in the original image space.

Border curve in the image space is

$$BC_{is}(t) = ST^{-1}(l.t, BC_{ss}(l.t)) \quad (5)$$

The RBC for the next step is calculated as a weighted mean of the RBC and the border curve in the current shape space. This can be expressed as:

$$BC_{is}(t) = ST^{-1}(l.t, 0) + \alpha.N(t).BC(l.t) \quad 0 \leq \alpha \leq 1 \quad (6)$$

4. SHAPE MODEL

We haven't introduced yet any information about how the shape information is taken in account. In this work it is assumed that the object being detected has a "mean shape", which can be extracted from the experts knowledge. Having a set of manually traced objects, shape can be extracted by different mechanisms.

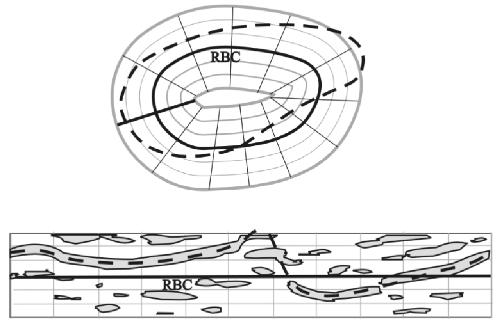

Figure 4. Segmented regions and the corresponding border curve (dashed line), in the original and shape space

The model used to represent shape is similar to a signed distance map of what is considered the mean shape. At zero-level is the mean shape curve. Non zero levels represent almost homotetic curves to the mean shape. A signed distance map could have been used as the model. Particularly, the blurred aligned over-imposition of the manually traced shapes was used. This function is noted mean shape model (MSM). See figure 5 and 6.

4.1. Correcting shape

At each step, the shape model is used to correct shape. The MSM is adapted with an affine transformation to fit the curve to be corrected. Position is adjusted in order to move the MSM center of mass to the RBC center of mass. Scale is adjusted considering the ratio between RBC and MSM mass. Finally, rotation is calculated considering the principal inertia axes of RBC and MSM.

$$MSM : R^2 \rightarrow R$$

Where mass center is calculated as:

$$MassCenter(MSM) = \frac{\iint_{R^2} \vec{x}.MSM(\vec{x})dx_1 dx_2}{\iint_{R^2} MSM(\vec{x})dx_1 dx_2}$$

Once the model is fitted, the zero level of the MSM is considered the curve with correct shape. This zero level curve is located in shape space. SeeFigure 6. Next step curve is built again as a weighted mean of the RBC and the zero level curve in shape space.

$$NextStepC_{is}(t) = ST^{-1}(l.t, 0) + \alpha.N(t).ZeroLevelC(l.t)$$
$$0 \leq \alpha \leq 1 \quad (7)$$

This corrects shape and allows small variations from the mean shape. In each step, competition between detected borders and shape correction leads to the solution. A similar approach can be seen in [6].

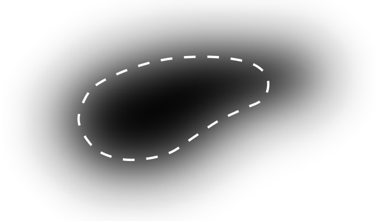

Figure 5. Mean shape and its model The dashed line is the zero level.

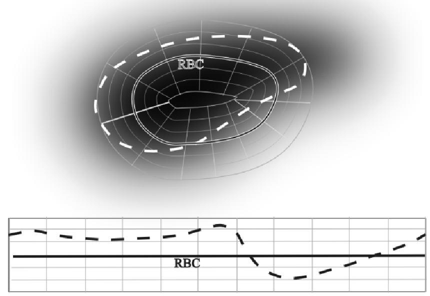

Figure 6. Mean shape (dashed line) referred to the RBC in shape space.

5. RESULTS

The method has been applied on real ultrasound imagery. The problem consists in measuring the area of a slice of longissimus dorsi muscle (rib eye area) in cattle.

The algorithm is fast enough to be applied in real time acquisition. The codified implementation performs about three steps per second which allows to have the result in less than a minute in a moder machine (PIII 1Ghz). It was tested in a set of 60 ultrasound images with good results. The achieved accuracy is comparable to expert traced measures, having a deviation of up to 15% in 80 % of the images.

Figure 7 shows some steps of the evolution process with the segmented shape space image.

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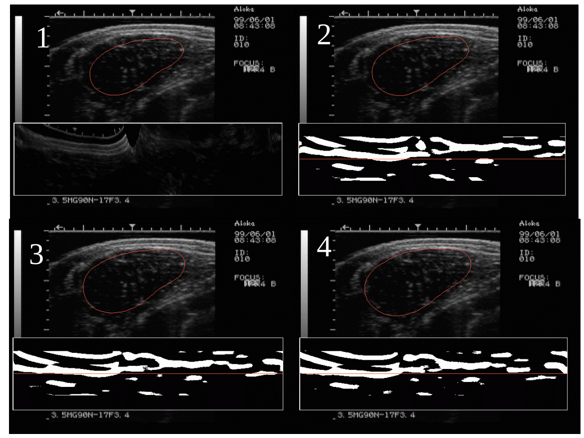

Figure 7. Different evolution steps. 1 The image in the original space and the shape space. In 2,3,4 it can be seen the curve and the segmented edges in shape space.

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