# Fast and robust diaphragm detection and tracking in cardiac x-ray projection images

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## ABSTRACT

A number of image analysis tasks of the heart region have to cope with both the problem of respiration and heart contraction. While the heart contraction status can be estimated based on the ECG, respiration status estimation must be based on the images themselves, unless additional devices for respiration measurements are used. Since diaphragm motion is closely linked to respiration, we describe a method to detect and track the diaphragm in x-ray projections. We model the diaphragm boundary as being approximately circular. Diaphragm detection is then based on edge detection followed by a Hough transform for circles. To avoid that the detection algorithm is misled by high frequency image content, we first apply a grey-level morphological closing operator. A Canny edge detector is then applied to the preprocessed images. In the edge images, the circle corresponding to the diaphragm boundary is found by the Hough transform. To restrict the search in the 3D Hough parameter space (parameters are circle center coordinates and radius), prior anatomical knowledge about position and size of the diaphragm for the given image acquisition geometry is taken into account. In subsequent frames, diaphragm position and size are predicted from previous detection and tracking results. For each detection result, a confidence measure is computed either by analyzing the Hough parameter space with respect to the goodness of the peak giving the circle parameters or by analyzing the coefficient of variation of the pixel that form the circle described by the maximum in Hough parameter space. If the confidence is not sufficiently high - indicating a poor fit between the Hough circle and true diaphragm boundary - the detection result is optionally refined by an active contour algorithm.

**Keywords:** respiration phase, image alignment, Hough transform, Active contours

## 1. INTRODUCTION

A couple of tasks in medical image registration require the estimation of the patient's respiration status.[1 2] To find the correct respiration phase e.g. temporal gray level variations in certain regions of interest are analysed.[3] In this paper we propose a new method to extract the respiration information by detecting and tracking the diaphragm in x-ray projection images of the chest. The diaphragm is a muscular membranous partition separating the abdominal and thoracic cavities and its observed motion is directly linked to respiration. However the diaphragm is not always visible[†] in x-ray images displaying the heart. While applicable only when the diaphragm is visible this algorithm based on the explicit detection and tracking of an anatomical organ is a robust and real-time capable alternative to current respiration detection methods.

Provided that some assumptions are met (e.g. table and patient movements are compensated beforehand), we describe the diaphragm using the boundary of its projection which we assume to be approximately circular in shape. Diaphragm detection is then based on edge detection[4] followed by a Hough transform[5 6 7] for circles. To avoid that the detection algorithm is mislead by spurious edges we remove structures smaller than a certain size (i.e. potential vessels) by morphological closing.[8] At the same time we also eliminate x-ray shutter edges. To restrict the search in the Hough parameter space and thus provide real time capabilities to our algorithm,

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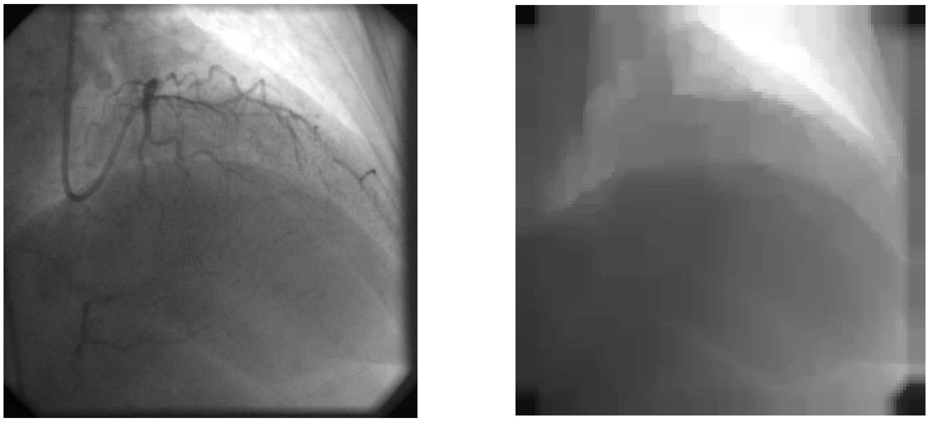
[†]For certain projections the diaphragm is not visible in the acquired X-ray images



(a) (b)

**Figure 1.** Original cardiac x-ray image (a) and result of morphological closing (b).

prior anatomical knowledge about position and size of the diaphragm is considered. In subsequent frames, approximative diaphragm position and size are predicted from previous results.

There are also cases when the computed Hough circle does not correctly approximate the diaphragm (e.g. when the optimum circular fit could not be found due to the restricted Hough search space). To deal with such difficulties, for each detection result a confidence measure is computed. If the confidence measure is not sufficiently high indicating a poor fit between the Hough circle and the diaphragm, the result can be optionally refined by an active contour algorithm.[9] After finding the diaphragm, its position is described by a 2D vector. This vector can then be used for image registration with respect to the respiration phase.

The paper is structured as follows: in Section 2 we describe the theoretical backgrounds of the diaphragm tracking while observing the main steps of the algorithm. In Section 3 we describe the experiments made to verify our assumptions and demonstrate the validity of this respiration information extraction method by presenting the results obtained on sequences acquired in clinical routine. In Section 4 we discuss algorithm related particularities and present our conclusions.

## 2. METHODS

### 2.1. Preprocessing

To improve the algorithm performance with respect to speed the input images are first down-sampled by a factor of 16, thus we work on 128x128 pixels large images down from the original resolution of 512x512 pixels. The circular approximation of the diaphragm is found starting from its edge points, by means of a Hough transform. The procedure can be mislead by non-diaphragm edges given by e.g. vessels or the x-ray shutter. Thus, every image is preprocessed to eliminate such edges.

A gray-level morphological closing operator is applied to the analyzed image prior to edge points selection, to eliminate vessels (see Figure 1). Since the vessels (once contrast agent is introduced) and the diaphragm are stronger x-ray absorbents than their surroundings they will appear darker in the analyzed images. Thus, we start by applying a sliding maximum filter. Choosing the filter size slightly larger than the largest expected vessel diameter will eliminate the vessels and erode the diaphragm. To remove the undesired diaphragm erosion a sliding minimum filter of the same size is subsequently applied. The results are shown in Figure 1.

To eliminate the influence of shutter edge points we have applied two methods. The first most straightforward method is to simply ignore all the edges at a certain distance away from the image borders. However, it is difficult to properly establish this distance as there is no universally valid shutter setup. Alternatively, by analyzing the edge maps obtained for a number of images one can identify the shutter edge points as those belonging to objects

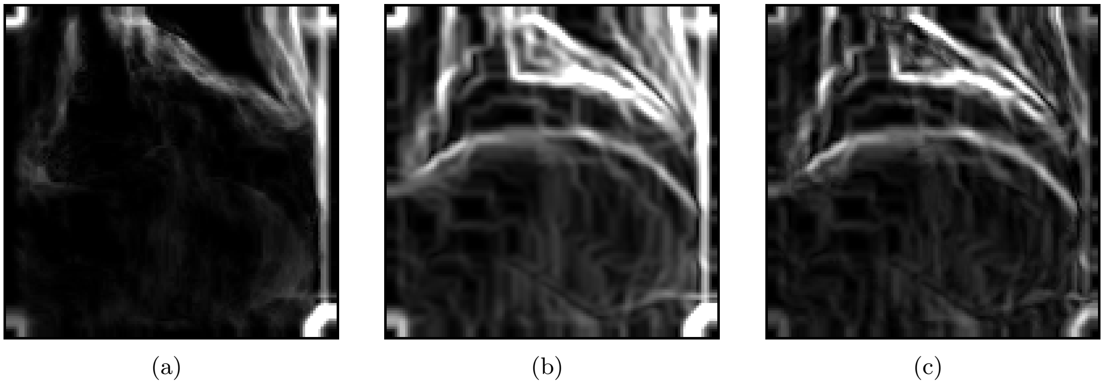



**Figure 2.** Still edges computed for a cardiac x-ray sequence (a), edge map for one frame of the sequence (b) and the edge map of the same image after subtracting the still edges (c).

which remain static. The edges of static objects are obtained by observing the minimum intensity projection of the edge maps of a number of previously acquired images. These edges are then subtracted from the edge maps of each analyzed image before computing the circular diaphragm fit (see Figure 2).

## 2.2. Tracking

### 2.2.1. Hough Transform

The Hough transform was originally developed to detect straight lines in black and white images.[5] Since then it has become a general accepted tool for detecting parametric[6] and also arbitrary[7] curves in images. The key idea is to replace the complicated problem of finding the instances of a certain curve among contour points obtained e.g. at the output of an edge detector, with the more simple problem of detecting a peak in a transformed space. The axis of the transformed space (accumulator) are the free parameters of the curve.

After eliminating the spurious edges given by vessels and shutter, we proceed to diaphragm detection by applying a Hough transform for circles on the binary edge image. The parametric representation of a circle is:

$$(x - a)^2 + (y - b)^2 = r^2 \tag{1}$$

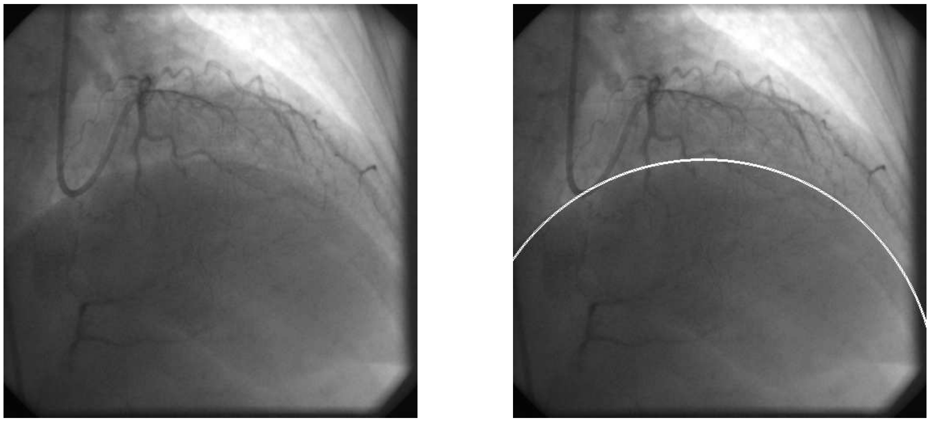
where $(a, b)$ are the center cartesian coordinates and $r$ is the radius.

The Hough accumulator for detecting circles will be a 3D space whose axes are the two center coordinates and the radius. To each presumptive circle point in the original plane corresponds a sphere in the Hough transformed space which contains the parameters of all possible circles passing through that point. Under the simplifying assumptions that the Hough space is discrete and finite a point on the circle in the original plane casts a vote on each accumulator cell which belongs to its sphere. Thus, the accumulator cell corresponding to the parameters of the circle passing through a majority of the investigated points will get the highest number of votes. The desired circle is represented by the maximum in the accumulator.

The size of the accumulator increases exponentially with the number of curve parameters and the time needed to find the maximum becomes rapidly unacceptable. To speed up the computation in the case of diaphragm tracking we make use of prior knowledge on where the diaphragm can be expected. Typically we start with a large ROI to detect the diaphragm in the first frame. The ROI is then reduced and kept constant as the diaphragm can not travel far between consecutive frames. Figure 3 shows the results of Hough based diaphragm detection for a high-dose sequence.

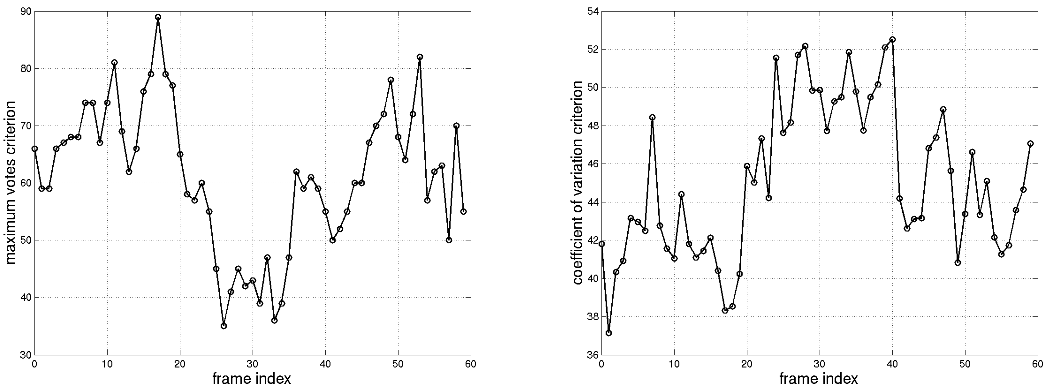
### 2.2.2. Confidence measure

The Hough transform may fail to correctly capture the diaphragm if it does not have a circular form or due to an insufficiently small ROI. To detect such cases we define a measure of confidence in the Hough result which is



(a) (b)

**Figure 3.** Original x-ray image (a) and result of diaphragm detection by Hough circular approximation (b).




(a) (b)

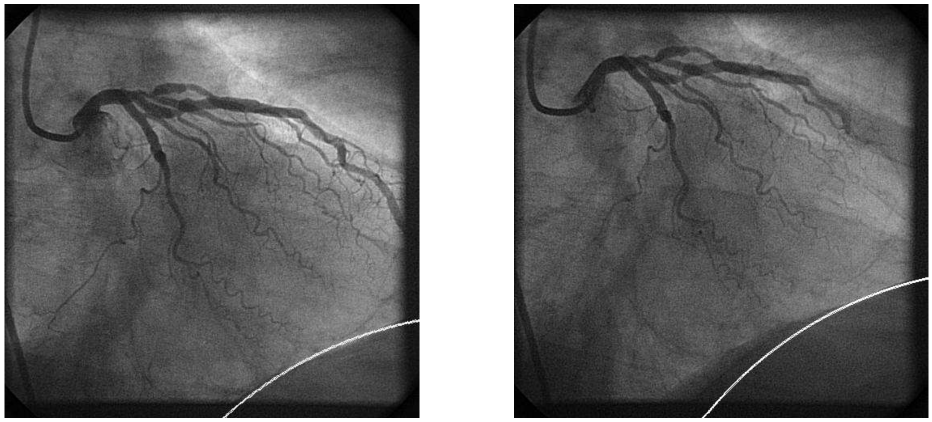
**Figure 4.** Accumulator based confidence measure (a) and image based confidence measure (b) for a sequence where the visible diaphragm border remains constant in length.

evaluated for each frame. If the confidence measure lies below a certain threshold then the corresponding result is inappropriate. In such a case an active contour is used to refine the tracking result (see Section 2.2.3).

We propose two confidence measures: one is based on the Hough accumulator while the other one is image based. The accumulator based confidence measure is simply the number of votes obtained in the ROI by the best circular fit (i.e. the ROI maximum). Assuming that the observable diaphragm border length remains approximately constant during the entire analyzed sequence, the accumulator maximum should vary only within a small interval over the frame index. A large decrease indicates then that the corresponding Hough circle does not correctly approximate the diaphragm. Under such circumstances the quality of the peak may be additionally characterized by relative confidence measures which show how well the peak is expressed in the accumulator like e.g. the entropy ‡. In Figure 4a the accumulator based confidence measure is plotted against the frame index for a sequence where the observable diaphragm border length remains approximately constant.

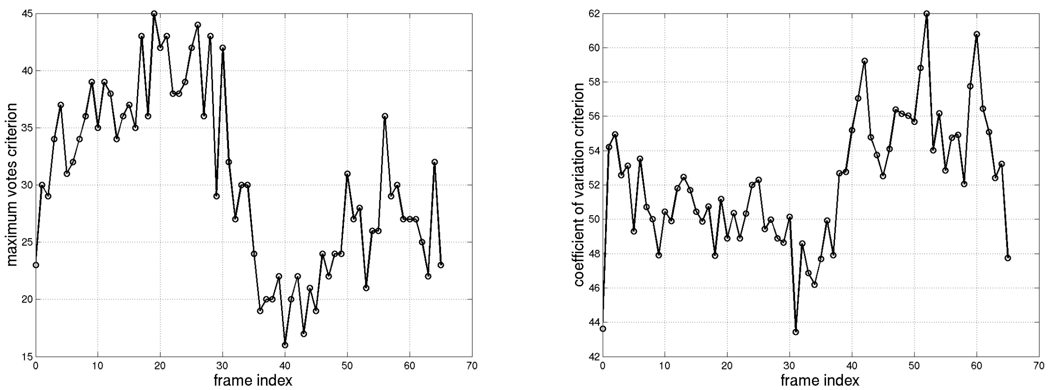
The accumulator based confidence measure will fail if the assumption with respect to the constancy of the observable diaphragm border length is not fulfilled. Such a case occurs for certain x-ray projections. Then, the accumulator based measure will exhibit low values both in the case of a poor fit in an image where the visible diaphragm border length is large and in the case of a good fit in an image where the visible perimeter is small (see

‡It is assumed that in this case that the Hough space is appropriately sampled. We observe that a very dense sampling of the accumulator will always produced well expressed peaks.



(a) (b)

**Figure 5.** Two images where the accumulator based confidence measure has signaled a poor circular approximation of the diaphragm. Such a conclusion is false for image (a) and correct for image (b).




(a) (b)

**Figure 6.** Accumulator based confidence measure (a) and image based confidence measure (b) for a sequence where the visible diaphragm border is no longer constant in length. The results obtained with the image based confidence measure correspond better to reality.

Figure 5). This is why we also propose another confidence measure which is not based on the Hough accumulator but on the image itself. This confidence measure is computed as the variation coefficient of the pixels along the detected circular approximation of the diaphragm in the corresponding edge map. A high variation coefficient signals a poor fit irrespective of the visible diaphragm perimeter. The variation coefficient is defined as:

$$V = \frac{s_x}{\overline{x}} \tag{2}$$

where $s_x$ is the standard deviation of the samples $x_i$ and $\overline{x}$ is their mean.

In Figure 6 the image based confidence measure is plotted against the frame index for a sequence where the visible diaphragm border length varies. For comparison the accumulator based confidence measure is also plotted. Unlike in the previous case (See Figure 4), the two measures are now less correlated (correlation coefficient $q = -0.3140$ compared to $q = -0.6907$).

In our experiments we have primarily used the image based confidence measure as it has a better generalization performance, although it has a smaller dynamic range. To decide if the Hough based tracking has failed, the confidence measure is compared with a threshold. Since the accumulator based confidence measure is an increasing function of the quality of the fit a value below the threshold indicates a poor result. The image based confidence measure being a decreasing function of the quality of the fit behaves in the opposite way.

We can not make any prior assumptions on the success of the tracking and thus on the confidence measure evolution in a certain sequence and we have no access to a labeled training set of confidence measures. We therefore use heuristics to find the desired threshold. This threshold is set using the confidence measure curve computed for a sequence acquired in similar projection geometry at the same patient, but with different dose. We propose two methods for establishing the threshold. In the first case, the threshold is based on the mean confidence measure over the entire analyzed sequence. For the accumulator based confidence measure we consider (on empirical basis) a value which is 15% less than the mean value while for the image based confidence measure we consider a value which is 10% above the mean value. Alternatively instead of basing the threshold on the mean we consider the extreme confidence measure value corresponding to the best possible fit (i.e. the maximum for the accumulator based measure and the minimum for the image based measure). In this case for the accumulator based confidence measure we consider (also on empirical basis) a value which is 40% less than the maximum while in the case of the image based confidence measure we consider a value which is 25% above the minimum. In our experiments both thresholds proved successful, however the one based on the extreme confidence measure value is more robust.

### 2.2.3. Active contours based refinement

Active contours (snakes) are energy minimizing curves able to lock on to prominent image features such as edges, ridges, etc. The active contours paradigm describes the behavior of an elastic curve which travels on the image plane under the influence of internal and external energies to that position where the weighted sum of these energies is minimized. Minimizing this energy yields internal and external forces. There are two types of internal forces: the elastic force which holds the curve together and the bending force which keeps it from bending too strongly. The external forces are image based and attract the curve towards the desired features. For an active contour represented by the parametric curve $\mathbf{v}(s) = (x(s), y(s))$ the energy functional to be minimized is written as:

$$E(v) = \frac{1}{2}\int_0^1 (\alpha(s)\Big|\frac{\partial \mathbf{v}}{\partial s}\Big|^2 + \beta(s)\Big|\frac{\partial^2 \mathbf{v}}{\partial s^2}\Big|^2)ds + \int_0^1 P(\mathbf{v}(s))ds \tag{3}$$

The first order derivative term describes the elasticity of the curve while the second derivative term its rigidity. Together they define the internal energy. The weights $\alpha(s)$ and $\beta(s)$ can be used to control elasticity and rigidity along the curve. In our implementation however they were chosen to be constants. $P(\mathbf{v}(s))$ is the external (potential) energy along the curve. To improve a dissatisfactory Hough based tracking result, we need a snake which is attracted by edges and thus will lock on the real diaphragm edge. In such a case, the external energy function is defined as:

$$P(x, y) = -w_e\big|\nabla\big[G_\sigma(x, y) * I(x, y)\big]\big|^2 \tag{4}$$

where $w_e$ is a positive weighting parameter, and $G_\sigma(x, y)$ is a 2D Gaussian low-pass kernel with standard deviation $\sigma$ which is convolved with the image $I(x, y)$ to increase the attraction range of the sought contours. The curve which solves this minimization problem is found by variational calculus, i.e. by solving the corresponding Euler-Lagrange equation:

$$\frac{\partial}{\partial s}\big(\alpha(s)\frac{\partial \mathbf{v}}{\partial s}\big) - \frac{\partial^2}{\partial s^2}\big(\beta(s)\frac{\partial^2 \mathbf{v}}{\partial s^2}\big) - \nabla P(\mathbf{v}) = 0 \tag{5}$$

We obtain thus the force formulation of active contours. If the confidence measure indicates a poor fit an active contour is initialized using the computed Hough circular approximation. It then evolves to the correct diaphragm boundaries. The result obtained with this approach for an image where the Hough based tracking has failed is shown in Figure 7.

## 2.3. Diaphragm position description

We describe the diaphragm position in the image starting from the edge oriented tracking result. For fast and robust comparison of tracking results it is important to have a unique and compact representation of the diaphragm position. The diaphragm position is encoded in a 2D vector. In computing this vector we assume

(a) (b)

**Figure 7.** X-ray image with erroneous circular approximation of the diaphragm (a) and the result of the active contours based refinement (b).

that the diaphragm edge meets the image border always in two points only and we establish an image coordinate system whose origin lies in the upper left corner. One component of this vector is the angle which the line underlining the diaphragm (from one point where it meets the image border to the other one) makes with the $Y$ axis and the second component is the $y$ coordinate of the middle point of the diaphragm border. The descriptive value of this 2D representation was confirmed in our experiments (See Figure 9).

## 3. EXPERIMENTS AND RESULTS

We assume that in general a circular approximation is well suited for the diaphragm border. To verify this assumption, we compared the hand segmented diaphragm border to an optimal circular approximation[§]. We have observed the approximation error (i.e. minimum mean distance) for a number of 96 frames from six sequences at a resolution of 512x512 pixels. The mean error was 0.24 pixels (standard deviation 8.05).

To show that the Hough transform is able to correctly find the diaphragm, using the same experimental setup as above we have compared the hand segmented diaphragm border to the circular fit found by the Hough transform. The mean error was 2.37 pixels (standard deviation 9.35) in this case.

We have tested our respiration information extraction by diaphragm tracking method on several appropriate sequences in our data base. The results obtained for two representative cases, one with high-dose images and the other one with low-dose images are shown within this section.

In the first case, the length of the visible diaphragm border remains constant in the analyzed sequences. Figure 8a and b shows the image based confidence measure for both high-dose and low-dose images plotted against the frame index. The image based confidence measure threshold computed using the extreme value over a high-dose sequence was 46.42. Using this threshold, for a number of 24 high-dose images out of a total of 60 and for a number of five low-dose images out of a total of 126 it was necessary to improve the Hough circle fit by active contours.

In the second case, the length of the visible diaphragm border varies in the analyzed sequences. The confidence measure plots for both high-dose and low-dose sequences are shown in Figure 8c and d. In such a case, the accumulator based confidence measure is not able to provide resonable results (see also Figure 5). The image based confidence measure threshold was in this case 54.30. With this threshold for a number of 18 high-dose images out of a total of 66 and for a number of 18 low-dose images out of a total of 111 it was necessary to improve the Hough circle fit by active contours.

[§]The optimal circular approximation was taken as the one having the minimum mean distance to the hand segmented diaphragm border.

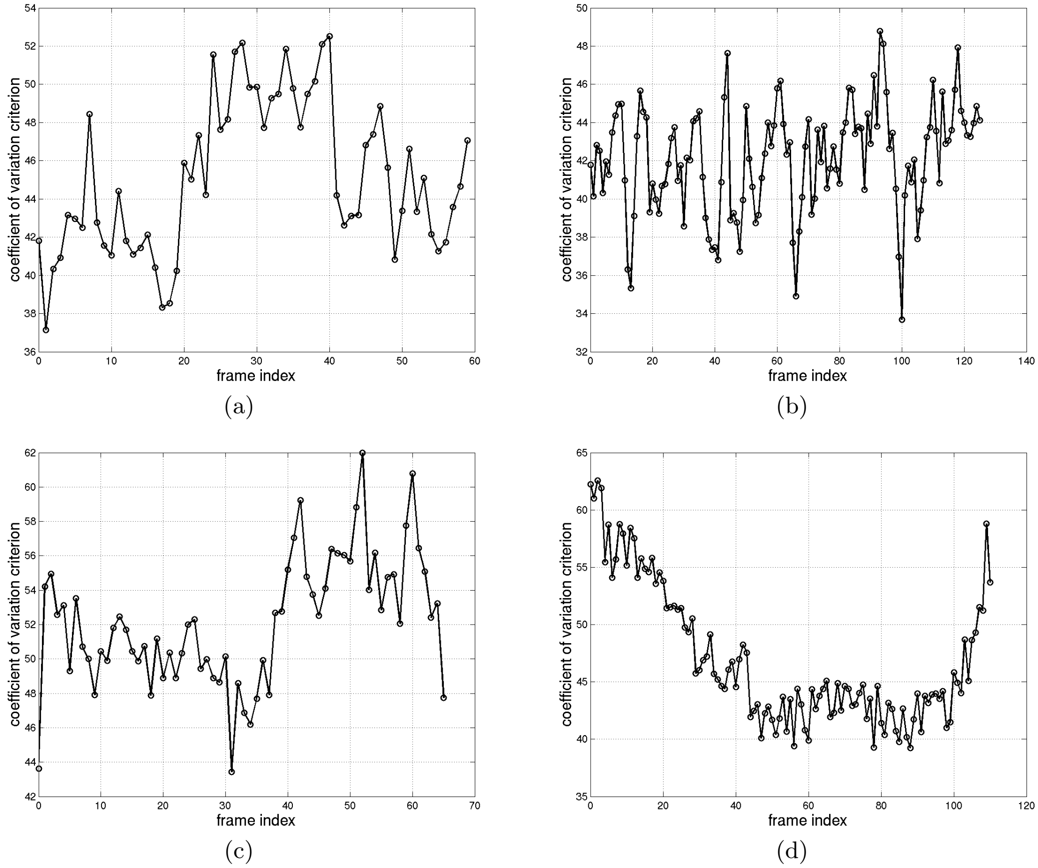


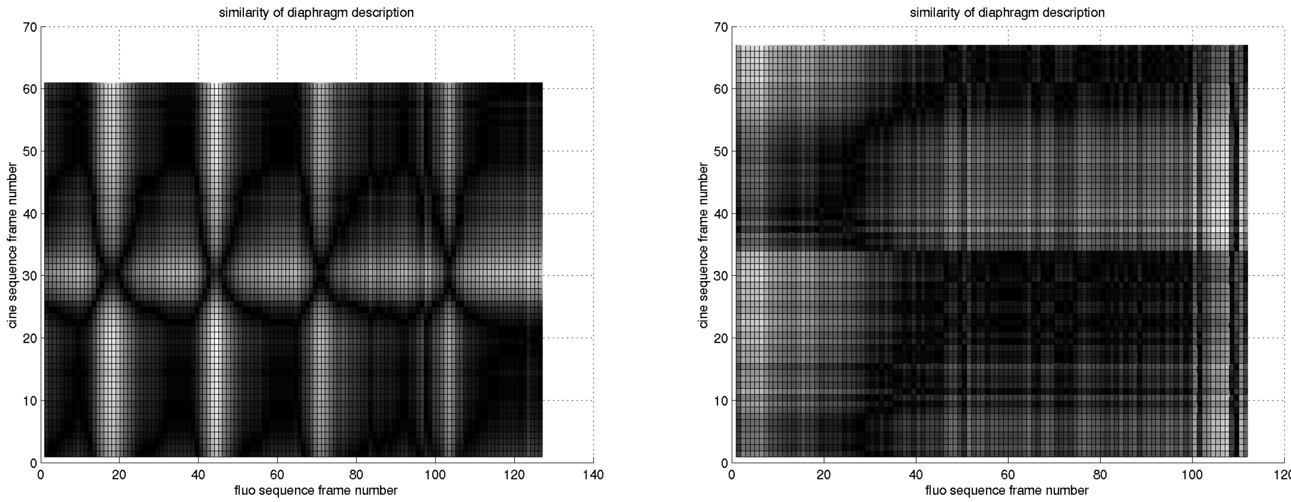

**Figure 8.** The image based confidence measure for the high-dose sequence (a) and for the low-dose sequence (b) when the length of the visible diaphragm border was constant and the image based confidence measure for the high-dose sequence (c) and for the low-dose sequence (d) when the length of the visible diaphragm border was not constant.

In Figure 9 the similarity (Euclidian distance) between the tracked diaphragm positions in a low-dose and a high-dose sequence of the same patient for both analyzed cases is shown. The brighter the gray level the lower the similarity. The repetitive pattern which may be observed is linked to the respiration frequency and to how many respiration cycles were recorded in the analyzed sequences. In the first case (Figure 9a), the high-dose sequence showed one and a half respiration cycles while the low-dose sequence showed four and a half respiration cycles. In this case the patient was allowed to breath freely. In the second case (Figure 9b), the patient was allowed to breath freely during the acquisition of a high-dose sequence and he was told to hold breath for a while during the acquisition of a low-dose sequence. Figure 9 illustrates that by tracking the diaphragm and specifying its position as described in our algorithm pairs of images with similar respiration status can be found. Thus, our approach represents a viable method of extracting image based respiration information.

## 4. DISCUSSION AND CONCLUSIONS

This paper addresses the problem of respiration information extraction. Earlier approaches have been based on an analysis of the temporal gray-level variations in certain regions of interest without invoking anatomical segmentation. We propose to describe the respiration phase using the explicit diaphragm position in the image. Our algorithm yields thus two-fold results: first it provides the respiration status and second the diaphragm is segmented starting from its boundary.

For respiration information extraction we need to track the diaphragm in the analyzed sequences. In doing so we assume that:




(a) (b)

**Figure 9.** Respiration phase information using diaphragm tracking when the visible diaphragm length is constant (a) and when the visible diaphragm length is not constant (b).

1. The diaphragm is present in all analyzed images
2. Both the high-dose and the low-dose images are acquired with the same projection geometry.
3. Potential table and patient movements are compensated beforehand
4. At least one respiration cycle is present in the high-dose sequence

The diaphragm appears in the observed images as a dark large circular pattern whose position we describe by a two dimensional vector starting from its edges. To avoid misleading effects from vessel and shutter edges we eliminate them by morphological filtering in the image and minimum intensity projection in the edge map respectively. We then find the diaphragm by a Hough transform for circles. To allow on-line usage of this algorithm, we use prior anatomical and image acquisition system knowledge to speed up the diaphragm tracking process. Knowing the typical respiration frequency and the frame rate at which images are acquired we assume that the diaphragm can not travel far between consecutive frames. Thus, we do not analyze the whole Hough accumulator to find the best fit but only a small region of interest (ROI) around the previous best fit. The whole procedure is initialized with a large ROI and continues then with a smaller one.

In some cases the Hough based tracking may fail. There are mainly two reasons for this:

1. A sudden move of the diaphragm which causes an accumulator maximum which is out of the investigated small ROI
2. The diaphragm edge has no longer a circular pattern

In such cases an active contour is initialized using the already found circular approximation and it is allowed to iterate until it finds the true diaphragm edge. To determine when the tracking has failed we describe the quality of the fit by a confidence measure which we then compare to a threshold. We have experimented with two different confidence measures.

The first one is based on the Hough accumulator and is computed as the absolute peak value found in the ROI. The Hough accumulator may be further harvested to collect also relative information related to how well this peak is expressed. However, an accumulator based measure may provide resonable results only as long as the length of the visible diaphragm border (i.e. the visible perimeter) remains relatively constant over the analyzed sequences. If this is not the case, then establishing a confidence measure using the accumulator is a difficult problem as the maximum will exhibit small values both in the case of a good fit for an image where the visible perimeter is small and in the case of a poor fit for an image where the visible perimeter is large.

Thus, we propose another confidence measure which is image based and gives sensible results in such cases also. This measure is computed as the variation coefficient of the pixel gray level values along the detected circular approximation of the diaphragm in the corresponding edge map. Our algorithm is based on the assumption that for a large majority of images the Hough circle is sufficient to correctly approximate the diaphragm. Thus, we can not say beforehand that in the high dose sequence which we analyze to establish the confidence measure threshold, there are enough (if any) poor Hough fit results to allow setting the threshold using standard unsupervised classification algorithms. On the other hand we can not be sure that no poor Hough fit appears. Thus, the confidence threshold is established using heuristics.

To speed up the algorithm we use a small, constant Hough accumulator ROI. This strategy however may lead to poor fit results in the case of sudden diaphragm motion. Such cases are detected using the confidence measure and corrected by the snake which in turn takes extra time. For further implementations, a variable size ROI could be used. In such a case the ROI size would decrease constantly as long as the confidence measure is 'clearly' above the threshold. If this is no longer the case, the ROI is reinitialized to a large size and the tracking continues. The decision interval within which the confidence measure is nolonger assumed to be 'clearly' above the threshold as well as the ROI reinitialization size may be set empirically and will directly influence the algorithm's performance with respect to speed.

Due to the Hough ROI based diaphragm tracking our algorithm is fast enough to allow on-line implementations and the confidence measure ensures the robustness needed in medical applications. We have tested our algorithm on several appropriate sequences from our data base and an initial visual inspection has shown good results.

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