

## Heart Localization from Magnetic Resonance Images Sequence

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**Abstract: Problem statement:** Heart localization is an important step in cardiac Magnetic Resonance Images (MRI) analysis. This study aims to locate the moving heart region from MRI sequence of images. **Approach:** The idea is to use the motion detection techniques to isolate the heart region from the background image and then apply morphological operations to construct a moving heart region mask. The mask is then applied to the MRI image to separate the Region Of Interest (ROI) that includes the heart. The K-means clustering algorithm is applied to the ROI to segment the heart walls. **Results:** Experimental results have shown that the performance of the proposed technique is superior to other MRI heart segmentation techniques in both complexity and accuracy. **Conclusion:** The proposed technique can be used as a pre segmentation step in any other future heart segmentation techniques to increase their accuracy through the localization of the moving heart region. The presented technique is fully automated technique and superior compared to other segmentation techniques.

**Key words:** Heart segmentation, K-means, morphological operations

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### INTRODUCTION

Cardiac Magnetic Resonance Imaging (CMRI) provides information about the cardiac anatomy and cardiac function in a noninvasive way. It is considered to be the reference standard (Deserno, 2011b). MRI is more accurate than echo-cardiology in the calculation of the ejection fraction and also shown superior results in endo-cardium border segmentation (Narin *et al.*, 2010). CMRI is one of the most important imaging modalities for investigating cardiac anatomy and pathophysiology in clinical applications. Accurate functional analysis from CMRI images needs accurate and unbiased segmentations. However, whole heart segmentation is currently challenging due to the image noise and artifacts, low tissue contrast and the indistinct boundary information between the cardiac atria and major vessels.

Accurate identification of boundaries of heart muscle lets the cardiologist determine important physiological parameters like the left-ventricular ejection fraction, volume of the left ventricle and regional heart wall thickening; all of which aid in better diagnosis of heart diseases, so the segmentation of the heart and its walls specially the Left Ventricle (LV) across a cardiac

cycle is a problem of interest because of the cardiovascular diseases are the leading cause of death in the world (Allender *et al.*, 2008; Lloyd-Jones *et al.*, 2010).

CMRI segmentation algorithms can be classified into three main categories: manual, fully and semi-automated methods. The level of information used in the segmentation process is correlated to the type of segmentation method and the level of user interaction (Petitjean and Dacher, 2011).

The manual segmentation is one of the most reliable methods in clinical applications; however the segmentation results are subjective to inter- and intra-observer errors. The manual segmentation techniques have several disadvantages: (1) it requires a high level of knowledge, (2) it is time and labor consuming, (3) it is subjective and therefore not reproducible and (4) it lacks the accuracy of the segmentation process, so researchers always try to find automated methods.

Semi-automated methods have been developed in order to further aid the cardiologist in the segmentation process (Jonge *et al.*, 2011; Gerard *et al.*, 2002; Mazonakis *et al.*, 2010). These methods require user intervention, for example: placing an initial contour around the LV or moving the cursor around the LV wall while the border attaches itself to the high gradient points.

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Although these approaches considerably reduce the time taken to manually segment the myocardium boundary it is still subject to inter- and intra-observer variability. Active contour algorithm or snakes (Zhang *et al.*, 2010a) are curves that move toward the sought-for shape in a way that is controlled by internal forces such as rigidity, elasticity and an external image force. The external force should attract the contour to certain features, such as edges in the image (Santarelli *et al.*, 2003; Spreeuwers and Breeuwer, 2003; Neubauer and Wegenkittl, 2003). Initialization of the contour is the key to its success. Bad initialization can draw the curve away from the left ventricle to edges that best fit its predefined parameters. Snakes and active contours have difficulty working on images with low contrast and may not be able to flag important features such as wall thinning.

Level-set methods have become well established methods for segmentation. Level-sets have also become a widespread method in medical image segmentation (Reis *et al.*, 2008; He *et al.*, 2008; Jayadevappa, *et al.*, 2009). Level-sets have gained popularity due to their implicit nature and ability to perform well in noisy data. They also have the ability to split and re-join throughout the deformation without the need for re-parameterization. Similar to active contours, they rely on the first initialization step and can fall into the trap of local minima.

Active Shape Models (ASMs) (Brunet *et al.*, 2009; Hamarneh and Gustavsson, 2000; Rogers and Graham, 2002) are a model driven segmentation approach. The model is built up using a priori knowledge about the left ventricle shape, usually hand-annotated segmentations from a training set of data. This shape model is then compressed, usually using Principle Component Analysis (PCA), to find the common modes of shape variation. The mean shape then searches an unseen image and converges over the most likely set of features. The mean shape is then deformed using the PCA modes. The accuracy of the segmentation relies heavily on the amount and variation of images in the training set. If the training set is too small with low variation, there is a limited number of unseen images that the model is applicable to. On the other hand, if the model is large with large variation it may easily choose some erroneous points. The hand annotation of the training set can also be very time consuming and introduce bias.

Active Appearance Models (AAM) ((Brunet *et al.*, 2009) are similar to ASMs but texture of the shape is added to the model and they perform a combined shape-appearance statistical analysis. (Stegmann, 2000) showed how these active appearance models could be applied to analyze short axis MR images of the heart. Mitchell *et al.* (2001) addresses the problems that AAMs have with attaching the model with the gradient

information by formulating a hybrid approach which combines ASMs and AAMs. Lelieveldt *et al.* (2001) introduces a time factor into his active appearance motion models and minimizes the appearance-to-target differences. Again all AAMs suffer the same limitations as the shape models with regards to the variation and building of the training sets. Strengths of AAM and ASM can be combined in a hybrid model (Mitchell *et al.*, 2001; Zambal *et al.*, 2006; Zhang *et al.*, 2010b).

Recently, in the field of medical image processing, many model-based segmentation approaches have been studied in (Deserno, 2011b). Geometrically deformable models (Dougherty, 2011) are parametric representations of the desired shape to be segmented. These parametric models can enhance the local properties of an image such as grey level or texture to aid the delinearization in poor quality images.

This study introduces a new fully automated heart segmentation technique that uses the motion detection techniques to isolate the heart region from the background image, then apply morphological operations to construct a moving heart region mask instead of user intervention step. After automatically identifying the moving ROI, the k-means segmentation technique is applied to segment heart walls.

## MATERIALS AND METHODS

**Morphological process:** There are several applications of Morphological Processing (MP) in many areas of biomedical image processing. Noise reduction, smoothing and other types of filtering, segmentation, classification and pattern recognition are applied to both binary and gray-scale images. As one of the advantages of MP, it is well suited for discrete image processing and its operators can be implemented in digital computers with complete fidelity to their mathematical definitions. Another advantage of MP is its inherent building block concept, where any operator can be created by the composition of a few primitive operators (Deserno, 2011a).

MP operations are affecting the form, structure or shape of an object. Applied on binary images (black and white images-Images with only 2 colors: black and white) and color images. They are used in pre or post processing (filtering, thinning and pruning) or for getting a representation or description of the shape of objects/regions (boundaries, skeletons convex hulls).

The two principal morphological operations are dilation and erosion (Umbaugh, 1997). Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries. These

operations can be customized for an application by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded.

**The dilation:** Dilation adds pixels to the boundaries of objects in an image. It is performed by laying the structuring element B on the image A and sliding it across the image in a manner similar to convolution. It is best described in a sequence of steps:

- If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel
- If the origin of the structuring element coincides with a 'black' in the image, make black all pixels from the image covered by the structuring element

Formally, the dilation of set A by B, denoted by  $A \oplus B$ , is defined by:

$$A \oplus B = (A^- \ominus \bar{B})$$

where,  $A^-$  denotes the set-theoretic complement of A and  $\bar{B} = \{-b: b \in B\}$  is the reflection of B.

The structuring element can have any shape. Typical shapes are presented in Fig. 1.

**The erosion:** The erosion process is similar to dilation, but we turn pixels to 'white', not 'black'. As before, slide the structuring element across the image and then follow these steps:

If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel.

If the origin of the structuring element coincides with a 'black' pixel in the image and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image (corresponding to the position on which the center of the structuring element falls) from 'black' to a 'white'. Formally, the erosion of set A by B:  $A \ominus B$  and defined by:

$$A \ominus B = \{x : B_x \subset A\}$$

where,  $\subset$  denotes the subset relation and  $B_x = \{b+x: b \in B\}$  the translation of set B by a point x.

**K-means clustering algorithm:** K-means clustering is a simple unsupervised learning algorithm that divides a collection of objects into K groups.

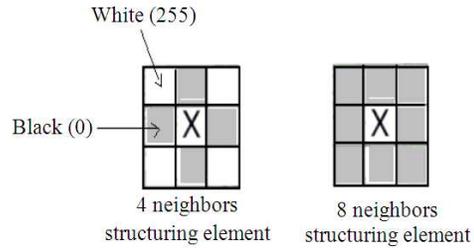


Fig. 1: Typical shapes of the structuring elements (B)

The algorithm iterates over three steps: (1) Compute the mean of each cluster. (2) Compute the distance of each point from each cluster by computing its distance from the corresponding cluster mean. Assign each point to the cluster it is nearest to. (3) Iterate over the above two steps till the sum of squared within group errors cannot be lowered any more.

The initial assignment of points to clusters can be done randomly. In the course of the iterations, the algorithm tries to minimize the sum, over all groups, of the squared within group errors, which are the distances of the points to the respective group means. Convergence is reached when the objective function (i.e., the residual sum-of-squares) cannot be lowered any more. The groups obtained are such that they are geometrically as compact as possible around their respective means.

The K-Means can then be used to segment the image into three clusters-corresponding to two scripts and background respectively. For each additional script, one more cluster is added. Here, each feature is assigned a different weight, which is calculated based on the feature importance as described in the previous section. Once the image has been segmented using the K-Means algorithm, the clustering can be improved by assuming that neighboring pixels have a high probability of falling into the same cluster. Thus, even if a pixel has been wrongly clustered, it can be corrected by looking at the neighboring pixels.

**The proposed technique:** The idea of the proposed technique is to use a motion detection technique to isolate the heart region from the background image of the moving heart and then apply morphological operations to construct a moving heart region mask. The mask is then applied to the MRI image to separate the region of interest that includes the heart. The K-means clustering algorithm is applied to the ROI to segment the heart walls. Figure 2, shows the main block diagram of the proposed technique.

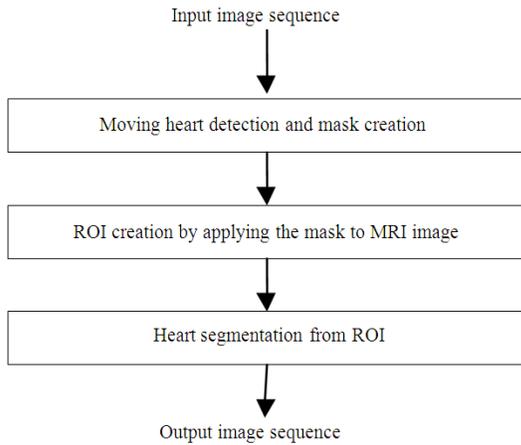


Fig. 2: Proposed technique

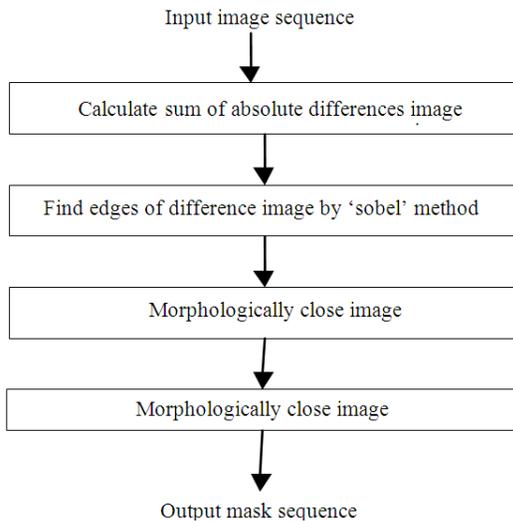


Fig. 3: Flowchart for mask of moving objects detection

**Step1: Moving heart detection and mask creation:**

The objective of this step is to isolate the heart region from the rest of the MRI image. The idea is using the simple technique of subtracting the observed image from the background image. It is a commonly used technique for segmenting moving objects in a scene for applications as sports analysis.

In this study we used the subtraction idea with a little bit modification as follows:

```

FramesList=LoadSequenceFramesFromDisk();
For i=1 to number of frames.
MovingHeartMask=HeartMask+abs(Frames{i}-
Frames{i+1}); End
    
```

Figure 3, shows the mask of moving of objects detection.

**Mask region creation:** To create a moving region mask we do the following steps

**Edge detection:** Apply sobel edge detection algorithm on the Moving Heart Image. it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image.

Edge detection is extensively used in image segmentation to divide the image into areas corresponding to objects. Representing an image by its edges help in calculation most of image information.

**Closed region creation:** In this step a closed region around edges is created by doing the following:

**Dilate the edge image:** The Dilation rule is value of the output pixel is the maximum value of all the pixels in the input pixel's neighborhood. In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1.

**Image eroding:** To obtain the edges of the heart walls, the dilation operation followed by the erosion operation were used on the binary image.

Eliminated small Objects by removing from the binary image all connected components (objects) that have fewer than 400 pixels as the heart region is greater than this area in such image resolution. This guarantees the removal of any noise generated small objects.

Step2: Apply Mask to Original MRI Image to isolate the ROI: This is done by multiplying the Mask Matrix with the Original image matrix.

Step3: Apply K-means clustering algorithm to the resulting image

**RESULTS**

We applied the proposed technique to the database provided by the cardiac atlas project (<http://www.cardiacatlas.org/web/guest/overview>, 2011; Fonseca *et al.*, 2011). Figur 4, shows the result of the first step of the proposed technique after applying the technique to image sequence of first case in the database. The sequence contains 30 frame of the moving heart.



Fig. 4: Result of first step of the Moving Heart detection technique

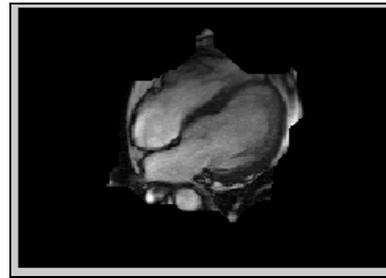


Fig. 8: Heart region after applying the Mask

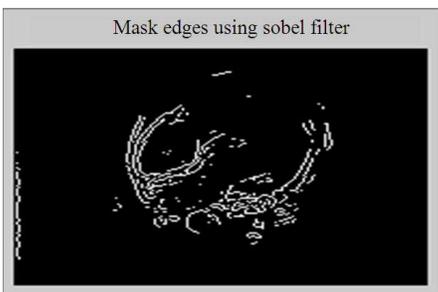


Fig. 5: Result of sobel filter

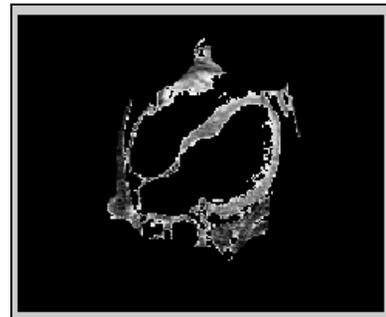


Fig. 9: Result after applying the proposed technique

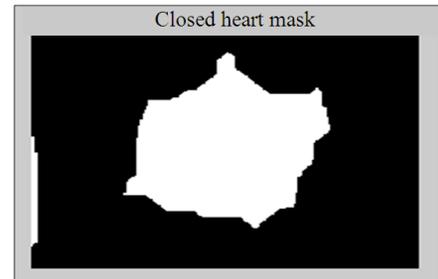


Fig. 6: Result of morphological operators

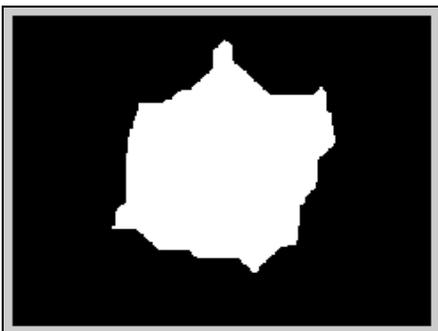


Fig. 7: Heart region mask

Table 1: A comparison between the proposed technique complexity and active contour algorithm

Technique	Execution time (sec)
Proposed technique	0.205664
Active contour	21.149772
Standard k-means	0.193827

Figure 5, shows the result of the sobel filter that is applied to the moving mask image. The results of applying the morphological operations are presented in Fig. 6 and 7, shows the Heart region mask after removing small objects that results from image noise. Fig. 8, shows the resulted image after applying the ROI mask on the MRI image. Figur 9, shows the segmented heart walls after applying the k-means algorithm to the masked ROI.

Table 1 shows a comparison between the proposed technique complexity, standard k-means and active contour algorithm. The comparison was made on a machine with the following specifications: CPU Intel core 2 T5600, 1.86 GHz clock speed, 1.5 GB ram and windows 7 32 bit operating system.

### DISCUSSION

From the above results, it is clear that only the moving heart region is present in the resulting difference mask. This is the main advantage of the presneted research in this study. From Fig. 5, we

conclude that only the edges of the moving objects are clearly determined. But there still exist some noises at the bottom left of this image. The location of noise may vary in some other images. The rest steps of the technique are capable of removing these noises. The result of applying the morphological operations is removing such noise. Figure 7, shows that the proposed technique is capable of removing the resulting small artifacts irrespective of their location. After applying the ROI mask on the MRI image, only the heart region is present which will enhance the output of the following segmentation algorithm. After applying the k-means algorithm to the masked ROI, the resulting image shows that the heart walls are successfully segmented with a very high accuracy. The main advantage of the proposed technique is that it is totally automatic without any user intervention. From Table 1, it is noted that, the proposed technique is superior to other techniques such as active contour and k-means. It has less complexity compared to the active contour although it is a fully automated technique and not a semi-automated one. The proposed technique has more accuracy than standard k-means because it focuses the k-means segmentation algorithm only to the heart region and removes all other objects and artifacts.

### CONCLUSION

A fully automated segmentation technique is proposed in this study. The technique is applied to cardiac atlas database and the experimental results showed that the technique successfully increase the accuracy of the standard k-means segmentation algorithm as can be concluded after reviewing Fig. 9 and 10. The proposed technique can be used as a pre segmentation step in any other future heart segmentation techniques to increase their accuracy through the localization of the moving heart region. The presented technique is superior compared to other segmentation techniques.

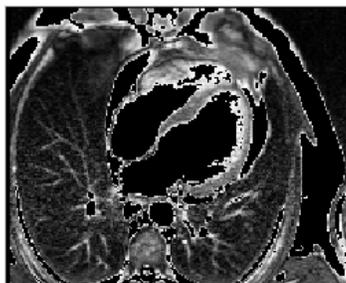


Fig. 10: Result of applying the standard k-means algorithm on the same image

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