Cardiac image segmentation using spatio-temporal clustering

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ABSTRACT

Image segmentation is an important and challenging problem in image analysis. Segmentation of moving objects in image sequences is even more difficult and computationally expensive. In this work we propose a technique for spatio-temporal segmentation of medical sequences based on K-mean clustering in the feature vector space. The motivation for spatio-temporalsegmentation approach comes from the fact that motion is a useful clue for object segmentation. Two-dimensional feature vector has been used for clustering in the feature space. In this paper we apply the proposed technique to segmentation of cardiac images. The first feature used in this particular application is image brightness, which reveals the structure of interest in the image. The second feature is the Euclidean norm of the optical flow vector. The third feature is the three-dimensional optical flow vector, which consists of computed motion in all three dimensions. The optical flow itself is computed using Horn-Schunck algorithm. The fourth feature is the mean brightness of the input image in a local neighborhood. By applying the clustering algorithm it is possible to detect moving object in the image sequence. The experiment has been conducted using a sequence of ECG-gated magnetic resonance (MR) images of a beating heart taken as in time so in the space.

Keywords: spatio-temporal image segmentation, clustering, optical flow, image analysis, motion estimation

1. INTRODUCTION

Image segmentation is a very challenging and demanding problem in image analysis. Because of the important role it plays in the modern image analysis, many authors have addressed this problem, but universal solution has not yet been found. Medical image analysis is an important part of image analysis applications. With development of complex medical imaging modalities which are capable of producing a large quantity of high-resolution image data, both two-dimensional (2-D) and three-dimensional (3-D), quantitative analysis of such data becomes almost impossible. Physicians would have to spend hours analyzing this data manually without assitance of computer-based methods. Because the patient life or health can be at stake, this programs must be fast and more important very accurate.

In motion analysis of moving object such as the beating heart we have two areas of interest. The first area is the background and surrounding tissue of the heart, and the second area is the heart itself. To make the problem even more complex, images are taken as three-dimensional, so what we are dealing with is the three-dimensional beating heart. Images like this can be taken using ECG-gated magnetic resonance scanning. It is obvious that analysis of such huge data sets is simply impossible by hand. So what we propose in this work is a novel method for three-dimensional motion image segmentation. Our method is based on spatio-temporal segmentation using clustering in the feature vector space.

The paper is organised as follows. In Section 2 an overview of optical flow algorithm is presented. In Section 3 segmentation using clustering method is presented. Experimental results are presented in Section 4 and the conclusion is given in Section 5.

2. OPTICAL FLOW COMPUTATION

In this work the algorithm proposed by Horn and Schunck [2] has been used. However, the original approach has been expanded to three-dimensions since the original Horn and Schunck algorithm produces two-dimensional vector.

The original two-dimensional algorithm equations for minimal error function are shown in Equations 1, 2a to 2e. Expanded, upgraded equations for three-dimension are shown in Equations 3, 4a to 4e.

The Horn and Schunck algorithm determines the optical flow as a solution of the following partial differential equation:

$$\frac{\partial E}{\partial x}\frac{dx}{dt}+\frac{\partial E}{\partial y}\frac{dy}{dt}+\frac{dE}{dt}=0 \tag{1}$$

The solution of Equation 1 is obtained by numerical procedure for error function minimisation. The error function *E* is defined in terms of spatial and time gradients of optical flow vector field and consists of two terms shown in Equations 2a-2e.

$$E=\iint(a^2E_c^2+E_b^2)dxdy \tag{2a}$$

$$E_b=E_xu+E_yv+E_t \tag{2b}$$

$$E_c^2=(\frac{\partial u}{\partial x})^2+(\frac{\partial u}{\partial y})^2+(\frac{\partial v}{\partial x})^2+(\frac{\partial v}{\partial y})^2 \tag{2c}$$

$$E_x=\frac{\partial E}{\partial x} \qquad E_y=\frac{\partial E}{\partial y} \qquad E_t=\frac{dE}{dt} \tag{2d}$$

$$u=\frac{dx}{dt} \qquad v=\frac{dy}{dt} \tag{2e}$$

E (x, y, t) represents luminance of the image in point *(x, y)* at time instant *t*. To solve the minimisation problem the steepest descent method is used which is based on computation of gradient to determine the search direction of search in the optimisation space.

When we want to compute three-dimensional optical flow vector we also need to involve the third dimension in original Equation 1, in other words we need to find gradient in three dimensions. The expanded partial differential Equation 1 becomes Equation 3:

$$\frac{\partial E}{\partial x}\frac{dx}{dt}+\frac{\partial E}{\partial y}\frac{dy}{dt}+\frac{\partial E}{\partial z}\frac{\partial z}{\partial t}+\frac{dE}{dt}=0 \tag{3}$$

The error minimisation function must also be modified in accordance to Equation 3. A new component in the error function must be added which covers the third dimension. The error minimisation function is shown in Equations 4a-4e.

$$E=\iiint(a^2E_c^2+E_b^2)dxdydz \tag{4a}$$

$$E_b=E_xu+E_yv+E_zw+E_t \tag{4b}$$

$$E_c^2=(\frac{\partial u}{\partial x})^2+(\frac{\partial u}{\partial y})^2+(\frac{\partial u}{\partial z})^2+(\frac{\partial v}{\partial x})^2+(\frac{\partial v}{\partial y})^2+(\frac{\partial v}{\partial z})^2+(\frac{\partial w}{\partial x})^2+(\frac{\partial w}{\partial y})^2+(\frac{\partial w}{\partial z})^2 \tag{4c}$$

$$E_x=\frac{\partial E}{\partial x} \qquad E_y=\frac{\partial E}{\partial y} \qquad E_z=\frac{\partial E}{\partial z} \qquad E_t=\frac{dE}{dt} \tag{4d}$$

$$u=\frac{dx}{dt} \qquad v=\frac{dy}{dt} \qquad w=\frac{dz}{dt} \tag{4e}$$

E (x, y, z, t) represents luminance of the image in point *(x, y, z)* at the time moment *t*. To solve the minimisation problem a steepest descent method is used which is based on computation of 3-D gradient to determine the direction of search for the minimum.

The optical flow algorithm has two main phases. In the first phase, gradient coefficients E_x, E_y, E_z and E_t are estimated from the input images. The coefficients represent the image gradients in space and time, and they are defined by Equation 4d. In the second phase, the optical flow vectors *u*, *v* and *w* defined by Equation 4e are computed. Depending on image content, the number of iteration steps must be chosen. If the moving object in the image has a big uniform area, the number of iterations must be large. If the image consists of small moving objects, the number of iterations can be small. In our case we have relatively small areas, so the number of iterative steps is relatively small. The number of iterations is directly related to the time required to compute the optical flow vector.

3. CLUSTERING-BASED SEGMENTATION

Classical image segmentation techniques rely only on a single frame to segment the image. However, motion is a very useful clue for image segmentation.

The main idea of this work is to develop a spatio-temporal image segmentation technique for image sequences. In this approach segmentation is not done on a simple frame-by-frame basis but utilises multiple image frames to segment the objects of interest. For this purpose we extract features both from the actual image that has to be segmented and from neighbouring image frames in the sequence. The extracted feature vectors are clustered using a clustering algorithm to determine the characteristic image regions. Research of various feature vectors is underway and here we present the currently used features.

The first feature is image brightness, which is useful for segmentation because the heart regions of interest are bright while the background is mostly dark. But however this data must not be taken as rule, because surrounding area around the heart has similar image brightness characteristic as the heart does.

The second feature is the Euclidean norm of the optical flow vector defined by Equation 5. With this information we can detect and isolate areas with higher and lower global motion characteristic, without considering the sign of individual motion vector components.

$$E_{of} = \sqrt{(u^2 + v^2 + w^2)} \qquad (5)$$

The third feature consists of three components. The first component represents motion in *x* direction, the second component represents motion in *y* direction and third one represents motion in *z* direction. This split of the optical flow vector allows us to control segmentation using motion specific for only one direction (or any other combination). In other words that means that we can detect only areas of the heart which move in only one direction, while other motion is ignored.

The fourth feature is the mean brightness in a window. We have to know that imaging modality used to acquire images of the beating heart, ECG-gated MR, produces noisy images. Because of that we decided to add extra feature in which this noise will be lowered using simple image averaging procedure. In this way we have disabled influence of the high peaks in the picture to the final result. In dark regions of the image with one or two high peaks, mean energy of the area is considerably higher than it should be. Computing mean brightness for such an area lowers the energy and improves the final result.

By using the above features, we obtain both the spatial and temporal information about the scene. K-means clustering algorithm has been used in this work [3]. The feature space is divided into four characteristic areas corresponding with four image regions. The first region is the static background and the initial cluster centre vector $center_1(0)$ for first group is set to (0, 0, 0, 0, 0, 0). The second image region represents the moving background and has the initial cluster centre vector $center_2(0)$ equal to (0, *m, 0, 0, 0, 0*), where *m* is experiment given percent of the maximum norm of E_{of} matrix computed by Equation 5. The third image region represents static objects with the initial cluster centre vector $center_3(0)$ equal to (*Mi*, 0, 0, 0, 0, *Mi*) where *Mi* is the maximum image brightness. And finally the fourth region represents moving objects and has the initial cluster centre vector $center_4(0)$ equal to (*Mi, m, mx, my, mz, Mi*) where are *mx, my* and *mz* maximums of optical flow vector components *u, v* and *w*. The rule for partitioning the feature space is defined by Equation 6.

$$x_i e R_k \Leftrightarrow d(x_i, u_k(n)) = \min\{\, d(x_i, u_j(n))\} \quad j=1...K \qquad (6)$$

where R_k is k-th cluster, K is the number of clusters (in our case $K=4$), and $u_k(n)$ is the centre of the k-th cluster. The clustering algorithm is computed using iterative sheme where in each cluster the membership for each feature vector is determined and then new cluster centres are computed by Equation (7).

$$u_k(n+1): \sum_{xeR_k} d(x_i, u_k(n+1)) = \min\{d(x_i, y)\} \quad k=1...K \tag{7}$$

The process is repeated until centres stabilise, i.e. until $u_k\ (n+1)$ becomes equal to $u_k(n)$. The resulting clusters correspond to four characteristic image regions in the segmented image. Computed results must be taken with reserve because it is possible that some pixels are mistakenly classified to a wrong cluster. This can happen if there is a very large motion in picture. With such a motion the object will be separated in two regions. The first region shows us the portion of the object that has very large motion, and the second region corresponds to the rest of the object. It is also important to mention that before the computation takes place, input features (image brightness, optical flow energy, optical flow vector and mean brightness) are normalised to the same range of values (in our case we normalised brightness according to optical flow energy).

In our case we have used two-dimensional clustering space for detection of moving objects of interest. Globally we can use multi-dimensional clustering space for isolating different areas of interest such is moving heart only in x dimension, or moving background with high motion characteristic.

4. EXPERIMENTAL RESULTS

Experimental results have been conducted using sixteen three-dimensional ECG-gated MR images of the heart. Each volume consists of sixteen two-dimensional images, covering the whole heart. The sixteen volumes are acquired during one heart beat. Due to the nature of the used optical flow algorithm, there are fourteen output volumes instead of sixteen (the first and the last volumes are used only for calculation of the optical flow for the neighboring volumes).

The computing procedure consists of two main steps. In the first step optical flow is calculated using three volume-images as input data. Using “past” and “future” volumes, together with the “current” volume, the three-dimensional optical flow field for the current volume is calculated. The process is repeated for all volumes. The first and the last one are not used. Calculated data is saved in a file, which is later, together with original image file, loaded by the program for clustering analysis that is run in the second step of calculation. Results consist of four binary images representing four areas of interest of the input image.

The first binary image represents the background that doesn’t have any movement and that is mostly black. The second image represents moving parts of the image that can not be clustered as background, but neither as any object of interest. The third and fourth images represent object of interest, in our case moving heart. The object of interest must be divided into two separate binary images because of the wide range of motion of the heart. By using only one cluster for the whole heart, probability that wrong segmentation is made is much larger than using two separate clusters. Using two separate binary images of the heart, we can distinguish between regions of the heart that have high velocity and between regions with low or zero velocity. This information can be used for analysis of heart function.

Results are shown on the Figures 1 to 7. On the left are original images of the heart and heart area, while on the right are calculated regions that include only heart. Using shown images we have tried to cover a wide scale of different types of input image data and results we have established using our segmentation method. It is important to emphasise that better results are accomplished for images where the heart motion is larger, because of the nature of used segmentation method. Figures 8 shows bad segmentation in cases without heart motion or region of the heart is very small.

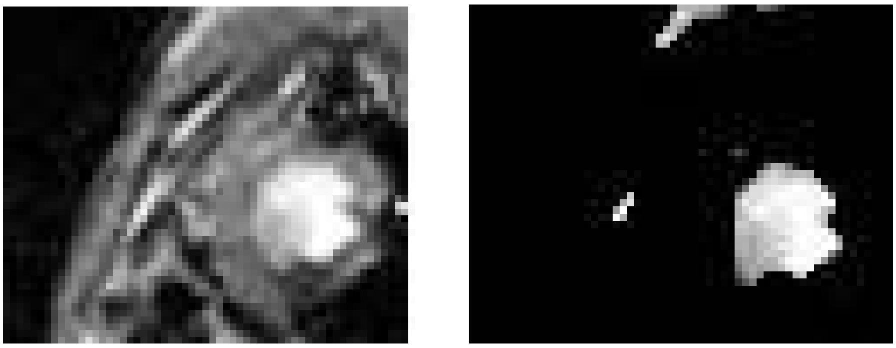

Figure 1 A small part of the image is heart. Motion is large. Image brightness is high.

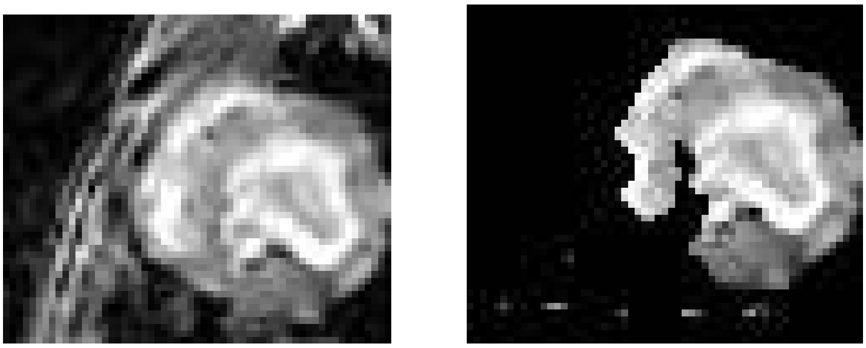

Figure 2 Large area of the image is heart. Motion is large. Brightness is medium.

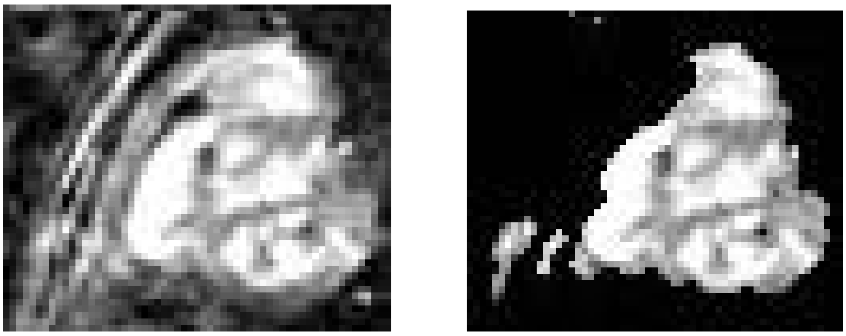

Figure 3 Same as Figure 2 but image brightness is very high.

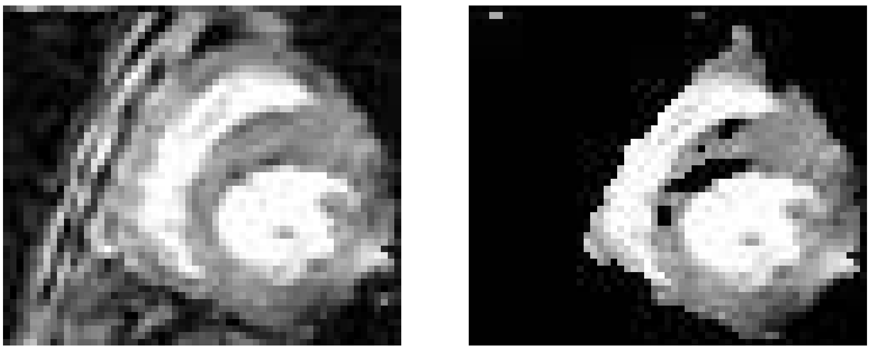

Figure 4 High motion with large range of brightness.

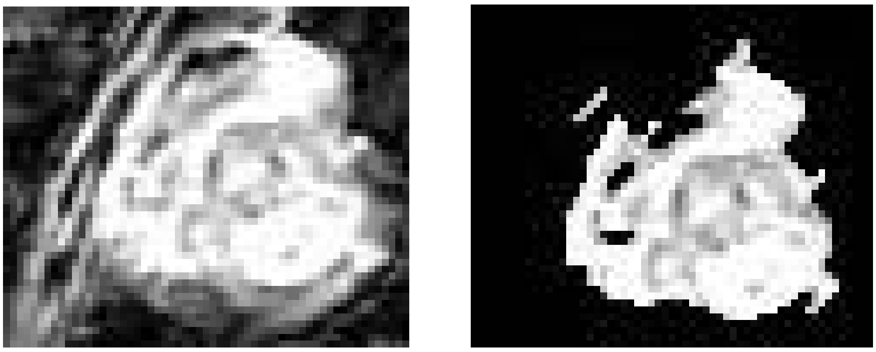

Figure 5 Large motion and brightness.

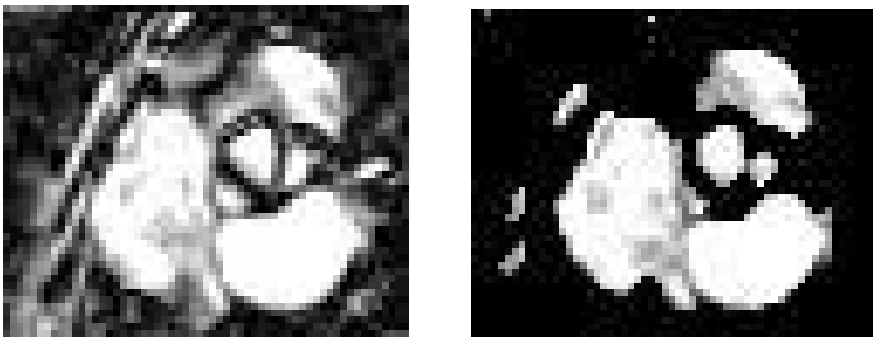

Figure 6 High brightness with background between heart areas.

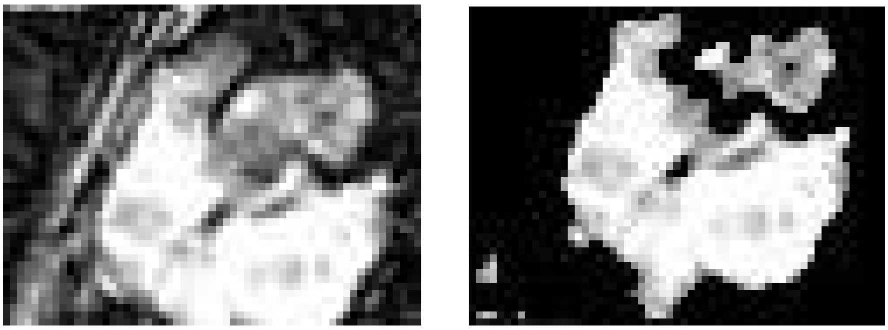

Figure 7 Medium motion with large range of image brightness.

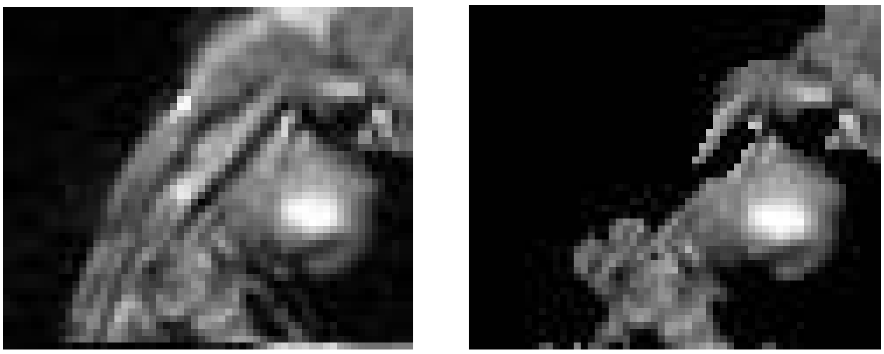

Figure 8 Small area of the heart without motion. Incorrect segmentation.

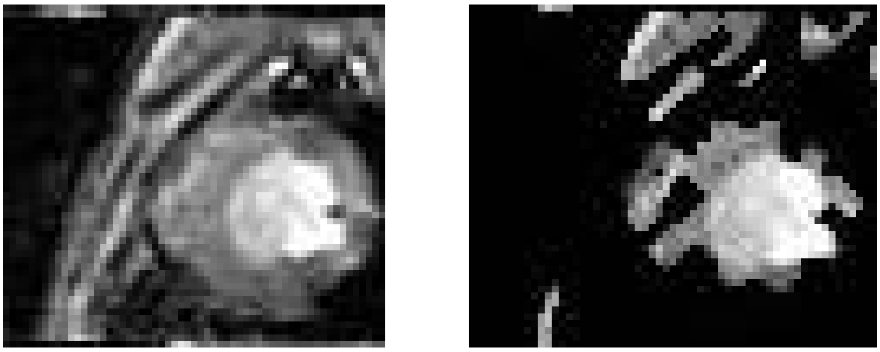

Figure 9 Large area of the heart without moving. Incorrect segmentation.

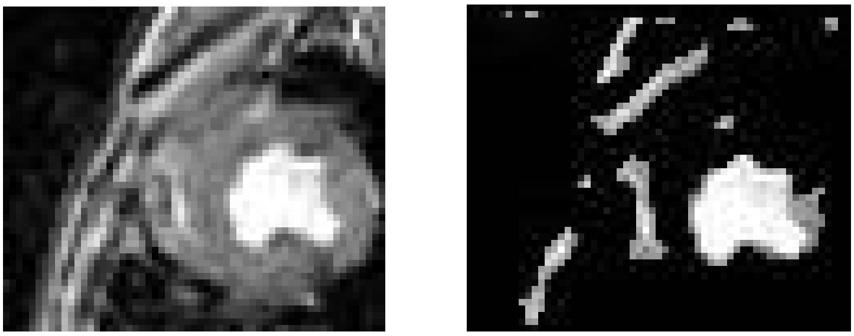

Figure 10 High-level heart brightness without moving. Incorrect segmentation.

We conclude that method works best for images with large level of motion (that means that motion difference between "past", "current" and "future" image is considerable) while image brightness is in the medium level of brightness. It is important to emphasise that images with low level of motion have higher level of error, as can be seen on Figure 8 and 9. Reason for such behaviour is directly connected to the nature of used clustering method. If image doesn't have motion feature, and its brightness is inside medium area, it is impossible to detect heart area. Area surrounding the heart has similar brightness as heart does, so algorithm cannot "decide" which area is the correct one. If brightness of the heart is higher than background area, while motion is at low level, the method will detect together with heart area and the area of the same characteristics that doesn't belong to the heart. Example is shown in Figure 10.

The software is written in C language to achieve fastest running of the program. Because of the large input image data (256 images), it was important to write the program in such way to optimize it for speed. Some new algorithms are developed especially for this purpose. In the final version of the program, we menage to reduce computation time 4 times than using the first version. Final computation time for calculating three-dimensional optical flow and clustering algorithm was around 100 seconds (the time depends on the number of iterative steps that further depends on the contests of the input data image). This means that we manage to make algorithm that calculates almost 2.5 frames per second. Experiments were performed using Pentium 3 processor on 500 MHz with 128 MB of memory.

5. DISCUSSION AND CONCLUSIONS

In this work we have presented a method for multi-dimensional spatio-temporal image segmentation which is based on clustering and optical flow computation. The experiments have been conducted using MR image sequence of the beating heart and have demonstrated the feasibility of the method. We have compared the results computed by clustering method with the results obtained by simple threshold segmentation method and with the results computed by applying optical flow vector as condition for detecting moving objects in the image.

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