Optical Flow Algorithm for Cardiac Motion Estimation

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Abstract— **Diagnostic techniques in cardiology require complex image analysis of single images and image sequences obtained by a variety of medical imaging modalities such as ECG-gated MR, CT, and ultrasound. Cardiac motion estimation provides useful information about cardiac function. In this work, we present a novel brightness-based algorithm for computation of optical flow. The advantage of brightness-based techniques as opposed to shape-based techniques is that they do not require segmentation of images to obtain the shape of various heart regions. The proposed optical flow algorithm is applied to ECG-gated MR image sequence of the heart. The method used in this work is based on minimization of an energy function that is computed for two consecutive image frames. The energy function consists of two terms. The first energy term represents a measure of similarity between the regions in two image frames. The second energy term calculates the neighborhood influence and is increased based on the difference in velocities and the cross-correlation of neighboring regions. The regions are dinamically grown and are of variable size. The minimal energy state corresponds to the optimal solution of the optical flow estimation problem. The energy function minimization is based on a steepest descent algorithm. The proposed algorithm has been implemented in C language and tested on mathematical phantoms and real patient images. Experiments have shown encouraging results.**

Keywords— **cardiac image analysis, optical flow, velocity field, motion estimation, medical imaging**

I. INTRODUCTION

Diagnostic techniques in cardiology require complex image analysis of single images and image sequences obtained by a variety of medical imaging modalities such as ECG-gated MR, CT, and ultrasound. In particular, useful information about the cardiac function can be extracted from motion analysis of a beating heart. A number of approaches for motion analysis have been studied in literature [1], [2], [3]. The goal of these techniques is to compute an estimation of the optical flow representing the displacement vector for each image point. The estimation of optical flow is a challenging problem in image analysis because of a wide range of possible motions and the presence of noise. In addition to this, the non-rigid motion of the heart makes cardiac motion estimation a complex problem. The techniques used for cardiac motion estimation can be divided in shape-based and pixel brightness-based techniques. The shape-based approaches track the motion of some characteristic points of the heart. Physics-based deformable models have been used in this approach [4], [5], [6]. Pixel brightness-based techniqes use directly the brightness of individual pixels to estimate the motion [7], [8], [9].

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In this work, we present an algorithm for computation of optical flow which provides an estimate of cardiac motion. The optical flow is computed from ECG-gated MR image sequence of the heart. The proposed algorithm is described in Section II. Results and discussion are presented in Section III. Conclusion is placed under Section IV.

II. OPTICAL FLOW ESTIMATION

Optical flow algorithms provide estimation of the motion fields. In general optical flow information is not the same as the motion field. The motion field is represented by the field of vectors that show the displacement of points in the optical field relative to the observer. Optical flow shows a velocity field of pixels in the image. There are a number of ways to compute the optical flow. The basic classification of methods is into gradient-based ([2]), correlation-based, and energy-based methods([10]).

The method used in this work is based on minimization of the velocity field energy function that is computed for two consecutive image frames. The minimal energy state corresponds to the optimal optical flow estimation. The energy function minimization is based on steepest descent algorithm. The energy function E used in this algorithm consists of two terms.

$$E = E_1 + E_2$$

The first energy term E_1 represents a measure of similarity between the regions in two image frames. In this work, we have tested methods for measurement of region similarity. The first region similarity measure is obtained by comparing regions based on their average brightness and standard deviation of pixels brightness. The second measure that was tested is based on a correlation factor. The measure presented in this paper is correlation-based. The correlation factor is obtained by correlating the region pixels brightness from the first and the second image with given velocity. Every region contains a list of positions of its pixels. The correlation is performed between the original pixels location in the first image and the location in the second image that is formed by adding a velocity to the original location.

$$E_1 = corr(image1, image2, r, velocity)$$

The second term, E_2, calculates the neighborhood influence. The neighborhood factor is computed in the following way. The pixels in the region border are checked for neighborhood with the other region. For all neighboring pixels,

Choose initial region size S.
repeat
  for i=1, ..., N_{iter} **do**
    Choose random site in image $P = (x, y)$
    Build region r around point P with maximum size S
    Compute region r average velocity av
    Compute region r energy E_1 with velocity av
    Let $best\_vel = av$ and $lowest\_E2 = MAX\_FLOAT$
    for $i = -K_X, \ldots, K_X$ **do**
      for $j = -K_Y, \ldots, K_Y$ **do**
        Let $vel = (i, j)$
        Compute region r energy E_2 with velocity vel
        if $E_2 < E_1$ **then**
          $best\_vel = vel$ and $lowest\_E2 = E_2$
        end if
      end for
    end for
    if $lowest\_E2 < E_1$ **then**
      set velocity of all pixels in region r to $best\_vel$
    end if
  end for
  Decrease the region size S
until $S > MIN\_REGION\_SIZE$

Fig. 1. The algorithm for computation of optical flow.

the factor E_2 is increased based on the difference of velocities and the cross-correlation of neighboring regions. The neighborhood factor is introduced to serve as a smoothness factor of the velocity field.

The optical-flow algorithm is shown in Figure 1. The algorithm works with dinamically created regions. This is because working with single pixels tends to create a very diverse motion filed. Regions are created using a region growing algorithm. The pixels are included based on several parameters. The size of the region is limited and is lowered in time. For large regions it is highly probable that their motion will be correctly estimated. For small regions, that can even be a single pixel, it is necessary to have a correct neighboring information that will prevent the region from being given a wrong velocity. Large regions provide a good neighborhood information.

III. RESULTS AND DISCUSSION

The algorithm has been tested on artificially created image pairs with controlled and known amount of displacement between the images. The algorithm has shown excellent results on this test.

A real-world test has been performed using a real patient ECG-gated MR images. The image size was 100 by 100 pixels. The image sequence consists of sixteen volumes per heart cycle. The algorithm for optical flow computation has been implemented in C language.

Experiments have shown that the noise and reconstruction artifacts present is MR images cause errors in optical flow estimation. In order to overcome this difficulty, a preprocessing step has been introduced where the original input images are low-pass filtered using a Gaussian kernel in order to smooth the image. The size of the kernel is chosen so that high frequency noise is removed while preserving the relevant structure required for optical flow detection. Kernels of size 3×3 and 5×5 have shown satisfactory results.

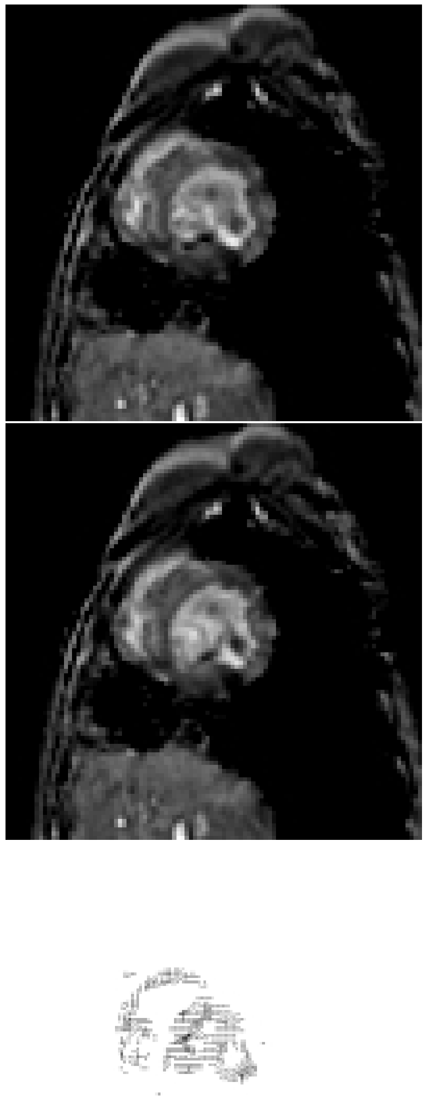

Fig. 2. Optical flow estimation results. Top: Two consecutive image frames. Bottom: The computed velocity field.

We have investigated and tested two different approaches for region similarity measurement. The first method compares regions using a number of region features such as average brightness and standard deviation of image brightness. While this technique has good properties with respect to noise it lacks the ability to accurately determine similarity of smaller sub-regions. The alternative measure that was tested is based on cross-correlation of pixel values in regions that are compared. This technique is able to better differentiate the sub-region details but is more sensitive to noise and image artifacts.

The execution time of the optical-flow algorithm on Pentium 200 based PC computer is about 2 minutes. The result for an example image pair is shown in Figure 2.

IV. CONCLUSION

In this paper, we have presented a novel brightness-based algorithm for computation of optical flow. The optical flow is computed from ECG-gated MR image sequence of the heart. The proposed method is based on minimization of the velocity field energy function that is computed for two consecutive image frames.

Experimental results have shown encouraging results. The algorithm executes relatively fast. Due to high noise level and reconstruction artifacts in MR images the algorithm has limited accuracy in determining optical flow and this problem will be further addressed in the future work.

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