PARAMETRIC DEFORMABLE BLOCK MATCHING FOR ULTRASOUND IMAGING

Adrian Basarab[1], Walid Aoudi[1], Hervé Liebgott[2], Didier Vray[1], Philippe Delachartre[1]

CREATIS, CNRS UMR5220, Inserm U630, INSA-Lyon[1], Université de Lyon, Université Lyon1[2], F-69621, France

ABSTRACT

This paper investigates motion tracking for ultrasound imaging. The proposed method is adapted to ultrasonic images and uses a bilinear motion model for controlling the local mesh deformation. We use an iterative multi-scale approach which is shown to considerably decrease the estimated motion error when we pass from 1 to 2 iterations.
The proposed algorithm is tested in two medical applications. First, we use it to track tissue motion for ultrasound elastography. The second application is related to slow blood flow estimation with high frequency ultrasound imaging. In both cases, our technique considerably improves the quality of the results compared to classical block matching (BM).

Index Terms— parametric motion modeling, sub-pixel motion estimation, deformable block matching, multi-scale approach, ultrasound imaging.

1. INTRODUCTION

Motion estimation is used in different fields, like for example moving picture coding (H.264) or video manipulation (MPEG-4 framework) [1]. Among motion tracking techniques, those based on block matching are the most common.
In ultrasound imaging, motion estimation has its applications in different domains, such as ultrasound elastography and blood flow estimation which will be investigated here. Ultrasound images are characterized by a granular texture known as speckle. It is shown that, as in the case of video applications, ultrasound speckle provides temporal correlation when motions are small and in the plane of the image. Many techniques of ultrasound motion tracking are based on methods developed for digital video. However, Yeung et al. present in [2] a comparison between scene-oriented and ultrasonic image sequences, concluding that specific techniques adapted to ultrasound images are necessary. Among the challenges in block matching introduced by ultrasound images we can mention motion ambiguities in regions of image saturation or specular reflection, speckle decorrelation and low signal-to-noise ratio. Further explanations about the difficulties in motion tracking with ultrasound are given in [2].
In most video applications, local motion can be modeled by rigid translation and rotation. In medical applications it is shown that tissues are also deformed. Therefore, our generalized block matching is based on a bilinear local model. Motion tracking is then locally controlled by eight parameters, which will be estimated in regions of interest covering the entire image. Our parametric deformable block matching is developed for ultrasound applications and the iterative way of estimating is found to considerably improve the motion tracking. The proposed method is adapted to locally estimate small motions compared to the images resolution. In this way, the multi-scale approach is shown to provide good results when ultrasound images are interpolated.
The performances of the method are evaluated in two ultrasound applications, for tissue elasticity and blood velocity estimations.

2. METHOD

2.1. Local motion

We consider a pair of images $I_1(x,y)$ and $I_2(x,y)$. The relation between the two images is defined by:

$$I_2(x,y) = I_1(x + u(x,y), y + v(x,y)) \qquad (1)$$

where u(x,y) and v(x,y) are the spatially varying motion fields along the two directions (x and y) of the images. The 2-D motion tracking problem deals with the estimation of these two components in each pixel of I_1.

2.2. Algorithm description

Generalized block matching, also referred to as deformable block matching [3], employs a parametric transformation to describe the local motion. Thus, a collection of nodes on image I_1 (corresponding to a rectangular mesh) is tracked on image I_2 onto irregular quadrilateral of pixels.
In our case, we consider a bilinear model to locally characterize the motion (see section 2.3). With the proposed method, the parameters of the bilinear motion model are

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estimated in rectangular regions of interest (hatched region of pixels in Figure 1 and noted R) of size $L_u \times L_v$, chosen around the defined nodes N. The parametric estimation is made by estimating the translations of the four corners (noted C) of this region of interest. Corner translations are estimated considering rectangular blocks (noted B and having size $L_u \times L_v$) centered on each corner and joined in the current node N. Simple block matching is then used in order to estimate these four 2-D translations. We call study zone the image region (ABCD) that contains the region of interest and the four blocks around its corners. An asterisk denotes the nodes, corners and blocks after the local spatial transformation.
The main steps of our algorithm in tracking the motion between two images are given bellow.

1. Create initial rectangular mesh on I_1.
2. Define regions of interest R around nodes N.
3. For each node N_i, do steps from 4 to 12.
<u>Node N_i</u>:
4. Initialize the translations of region of interest R_i taking into account the estimation results of its neighbors.
5. For each iteration k, do steps from 6 to 11.
<u>Iteration *k*</u>:
6. Consider 4 rectangular blocks, noted B_{ij} around corners C_{ij} of R_i, with $j = 1..4$, and place 4 corresponding search regions on I_2.
7. Interpolate the search regions by factors of s_1^k in the axial direction and s_2^k in the lateral direction.
8. Estimate the translations of corners C_{ij} of current R_i (d_{uj}, d_{vj}) by 4 times simple block matching, maximizing the normalized cross-correlations defined in (2).

$$\rho_j(\alpha,\beta) = \frac{\sum_{m=1}^{L_u}\sum_{n=1}^{L_v}\left[B_{ij}(m,n)-\overline{B_{ij}}\right]\left[B_{it}^{*}(m+\alpha,n+\beta)-\overline{B_{ij}^{*}}\right]}{\sqrt{\sum_{m=1}^{L_u}\sum_{n=1}^{L_v}\left[B_{ij}(m,n)-\overline{B_{ij}}\right]^2\sum_{m=1}^{L_u}\sum_{n=1}^{L_v}\left[B_{ij}^{*}(m+\alpha,n+\beta)-\overline{B_{ij}^{*}}\right]^2}} \quad (2)$$

where B_{ij} is a block of the reference image considered around one corner of the region of interest R_i and B_{ij}^* a candidate block of the search region in the image after deformation. We have:

$$(d_{uj}, d_{vj}) = \underset{\alpha,\beta}{arg\,max}\left(\rho_j(\alpha,\beta)\right) \quad (3)$$

9. Compute the parameters of the bilinear model for the current study zone (which contains R_i and the four blocks B_i).
10. Deform the current study zone with the locally estimated bilinear model.
11. If final iteration, go to step 12, otherwise go to step 6.
12. If final node, go to step 13, otherwise go to step 4.
13. Compute the dense motion field.

For both ultrasound applications in section 3, a preliminary study allowed us to set the method parameters, as the mesh steps, the regions of interest size, the number of iterations and the interpolation factors.

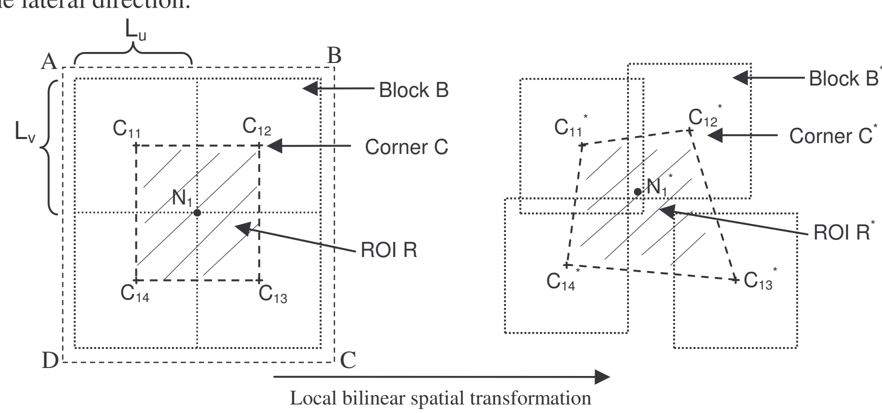


Figure 1. Parametric motion estimation for a given region of interest (hatched region) around one node.

2.3. Motion model

A bilinear model of displacement was chosen to locally describe the motion field [4]. The lateral and axial components of the motion vector are noted:

$$\begin{cases} u(x,y) = a_u.x + b_u.y + c_u.x.y + d_u \\ v(x,y) = a_v.x + b_v.y + c_v.x.y + d_v \end{cases} \quad (4)$$

where u and v are the displacements along x and y, in relation to the node N.

2.4. Local estimation

As we show in the algorithm description, we locally estimate the translation of the four corners of the region of interest. These four 2-D translations and the parametric motion model considered in 2.3 allow us to write two systems of four equations. The resolution of these two equation systems gives the relations between the parameters of the motion model and the translations of corners C_{ij}.

$$\begin{pmatrix} a_u \\ b_u \\ c_u \\ d_u \end{pmatrix} = M.\begin{pmatrix} d_{u1} \\ d_{u2} \\ d_{u3} \\ d_{u4} \end{pmatrix} \quad and \quad \begin{pmatrix} a_v \\ b_v \\ c_v \\ d_v \end{pmatrix} = M.\begin{pmatrix} d_{v1} \\ d_{v2} \\ d_{v3} \\ d_{v4} \end{pmatrix} \tag{5}$$

With the matrix M, depending on L_u and L_v:

$$M = \frac{1}{2}\begin{pmatrix} -\frac{1}{L_u} & \frac{1}{L_u} & \frac{1}{L_u} & -\frac{1}{L_u} \\ -\frac{1}{L_v} & -\frac{1}{L_v} & \frac{1}{L_v} & \frac{1}{L_v} \\ \frac{2}{L_u.L_v} & -\frac{2}{L_u.L_v} & \frac{2}{L_u.L_v} & -\frac{2}{L_u.L_v} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{pmatrix} \tag{6}$$

2.5. Iterative multi-scale approach

The algorithm description presented in section 2.2 shows that local estimation of the bilinear parameters works iteratively. Since we developed our method to track motion with sub-pixel precision, a multi-scale approach is proposed. We propose that at each resolution level the computation grid be refined by bilinear interpolation. For computation reasons, we propose to interpolate only the search regions and to maintain the initial resolution of blocks in I_1. Moreover, at each iteration, the current study zone of I_1 is deformed when equations in (4) are applied and using the bilinear parameters estimated at the previous iteration. In this way, the next iteration starts with 4 deformed blocks which allow better estimation of the current region of interest corners translations.
The interest of the iterative multi-scale approach is shown by the experimental results, as the motion tracking error decreases with the advancement in iterations.

2.6. Dense motion field

Steps 1 to 12 presented in section 1 describe the estimation of the 8 parameters of the bilinear motion model for each region of interest. The final step is to compute the dense motion field. With our method, the size of the regions of interest is considered larger than the distance between two neighboring nodes. Therefore, the pixels of the gray area in Figure 2 were estimated four times. Finally, only nodes and points A displacements are consider to calculate the dense motion field, by bilinear interpolation to the entire image. Motion in points A, as they were estimated four times, is the mean of these four estimated displacements. This way of obtaining the dense motion field has the advantage of introducing regularization constraints for the final result.

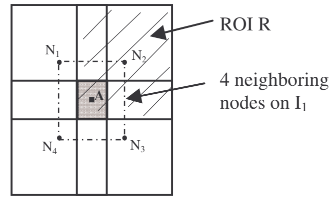


Figure 2. Dense motion field computation.

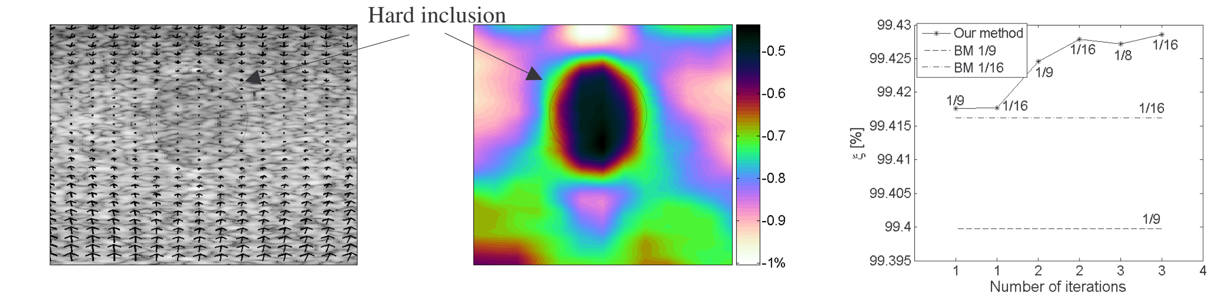
2.7. Confidence measure

As the proposed method is tested in this paper on experimental data, the true motion field between the ultrasound images is not available. Therefore, characterizing the quality of motion estimation requires a confidence measure. For this, we applied the estimated 2-D motion field to the image $I_2(x,y)$ in order to map it onto the reference image $I_1(x,y)$. We thus obtain the registered version of $I_2(x,y)$, which we note $\hat{I}_1(x, y)$. Further, we calculate the normalized cross-correlation defined in (2) between blocks in I_1 and their corresponding blocks in $\hat{I}_1$. We obtain a cross-correlation coefficients map and our similarity measure (ξ) is defined as the mean value of all these values.

3. APPLICATION TO ULTRASOUND

3.1. Elasticity imaging

The first experimental application deals with ultrasound elastography. Elastography is an approach of measuring the elasticity of soft tissues and was first introduced by Ophir in [5]. Its principle consists in acquiring images of the same medium for different levels of compression. In ultrasound, the compression is directly applied with the scanner probe and represents a few percents of the medium depth. Moreover, strain images are constructed by derivation of the estimated displacement between two acquired images.
The experimental result we present here is considered with phantom data. The phantom (Elasticity QA Phantom, model 049, by CIRS Tissue Simulation & Phantom Technology, USA) was designed for ultrasound elastography and presented a spherical 10-mm diameter inclusion of 62 kPa for a surrounding medium of 29 kPa. The images were acquired with a research scanner Sonix RP by Ultrasonix Medical Corporation, Canada, with a 8-MHz linear probe. The result is shown in figure 3(a) and 3(b). Note that the inclusion is clearly visible on the strain image whereas it is not the case on the B-mode image. On figure 3(c), our method is compared with classical block matching using the confidence measure in 2.7. We also notice that for the same final resolution level, making more iterations increases the estimation precision. When only one iteration is processed the multi-scale approach is not used. Thus, its influence can be evaluated when passing from one to two iterations.

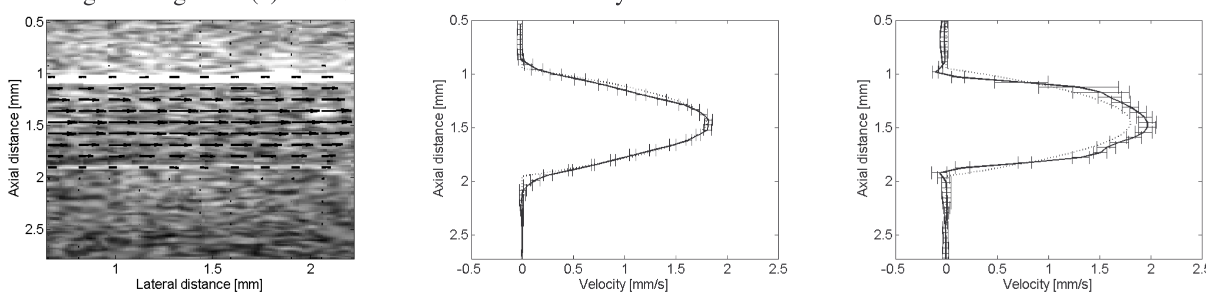


(a) (b) (c)

Figure 3. The B-mode image with estimated displacement vectors (2 iterations, 1/9 final resolution level) (a), the axial strain image in % (b), similarity measurement for BM and our method for different number of iterations and final resolutions (c).

3.2. Flow imaging

The second experimental application concerns the 2-D blood velocity estimation. For this, we use two B-mode images acquired on a gelatine phantom containing a vessel of 1 mm diameter. A blood mimicking fluid was injected with calibrated velocity of 1 mm/s. The angle between the ultrasound probe and the vessel was considered close to zero degree. Figure 4(a) shows the estimated velocity vectors superimposed to the B-mode image. Figures 4(b) and 4(c) show the axial velocity profiles estimated with our method and with classical block matching. For both cases the mean and standard deviation values are compared to the theoretical profile corresponding to a laminar flow. As expected the mean velocity is about 1 mm/s. It is shown that with our parametric block matching we decrease the standard deviations values by a factor of 3 reported to the classical method.



(a) (b) (c)

Figure 4. Blood velocity estimation: 2-D estimated motion vectors superimposed to ultrasound B-mode image (a), estimated mean and standard deviation (solid line) and theoretical (dotted line) axial profiles for (b) our method and (c) block matching.

4. CONCLUSION

In this paper, a parametric deformable block matching adapted to ultrasound images is presented. Our method was developed to locally estimate small complex motions. Therefore, a bilinear model was locally used to track motion between two ultrasound images and an iterative multi-scale approach of estimating was employed. Results on tissues and flow motion tracking with ultrasound are presented and show considerable improvements compared to classical block matching. In future work, a temporal model of the motion parameters can be added to the proposed method.

5. ACKNOWLEDGEMENTS

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