A method for vector displacement estimation with ultrasound imaging and its application for thyroid nodular disease

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Abstract

Ultrasound elastography is a promising imaging technique that can assist in diagnosis of thyroid cancer. However, the complexity of the tissue movements under freehand compression requires the use of a parametric displacement model and a specific estimation method adapted to sub-pixel motion. Therefore, the aim of this study was to develop a motion estimation method for ultrasound elastography and test its performances compared to a classical block matching technique. The proposed method, referred to as Bilinear Deformable Block Matching (BDBM), uses a bilinear model with eight parameters for controlling the local mesh deformation. In addition, a technique of motion initialization based on a triangle scan of the images adapted to ultrasound elastography is proposed. The BDBM method includes an iterative multi-scale process. This iterative approach is shown to decrease the absolute error of the displacement estimation by a factor of 1.4 when passing from 1 to 2 iterations. The method was tested on simulated images and the results show that absolute displacement estimation error was reduced by a factor of 4 compared to classical block matching. We applied the BDBM method on three experimental sets of data. In the first data set, a phantom designed for ultrasound elastography was used. The two other sets of data involve the thyroid gland and were acquired using freehand tissue compression by ultrasound probe of a clinical ultrasound scanner modified for research. A similarity measurement based on local cross-correlation shows that, for experimental data, the BDBM method outperforms the usual block matching.

Keywords: Parametric displacement modeling; Sub-pixel tissue motion estimation; Deformable block matching; Multi-scale approach; Ultrasound image; Elasticity imaging of thyroid

1. Introduction

Palpation is the oldest and the most frequently used screening method for thyroid tumor detection. The basis of this method lies in the significant difference in the elastic properties between normal and diseased tissues (Siperstein and Clark, 2000). Unfortunately, manual palpation is subjective, inaccurate, and highly user-dependent, especially in detecting and characterizing small or deeply located lesions (Tan et al., 1995). Ultrasound (US) examination is a sensitive method for detecting thyroid gland lesions (Wong and Ahuja, 2005). However, its accuracy in differentiating between benign and malignant thyroid gland tumors is relatively low (Castro and Gharib, 2005; Mitchell and...
Parangini, 2005; Reading et al., 2005). For patients with thyroid gland nodules, fine-needle aspiration biopsy (FNA) has proved to be an efficient tool for thyroid cancer diagnosis. Despite the advantages of FNA, it is an invasive procedure and subject to sampling and analysis uncertainties.

The potential of ultrasonography to diagnose thyroid cancer can be extended by various new techniques such as elastography. With this method, strain images are usually constructed by derivation of the estimated displacement induced by a compressive force applied to the tissue surface. Theoretically, all the existing techniques of motion estimation can be used to estimate this displacement. In practice, the correlation techniques that track the echo delays in segmented waveforms that are recorded before and after the quasistatic compression are the most widely used (Lerner et al., 1990; Ophir et al., 1999). In most clinical applications (Cochlin et al., 2002; Garra et al., 1997; Lyshchik et al., 2005a), imaging systems used for elastography compute a uni-axial displacement field (Fromeageau et al., 2007). Nevertheless, different reasons, such as load non-uniformity within the tissues which leads to speckle decorrelation (Kallel and Ophir, 1997b), especially for freehand compression (Hiltawsky et al., 2001), encourage the use of 2-D displacement estimation techniques. The conventional 2-D motion estimation method for ultrasound elastography is speckle tracking, known as block matching in video applications (Noguchi et al., 1999). The particular characteristics of ultrasonic images and of the ultrasound elastography require that the classical block matching be adapted to our application. (Yeung et al., 1998a) thus classify the challenges in speckle tracking for ultrasonic images, for example, tissue deformation (more complex than only translation and rotation), low signal-to-noise ratio of ultrasonic images, speckle decorrelation, out-of-plane motion, etc.

The aim of this study was to develop a tissue motion modeling and estimation method for ultrasound elastography and apply it to visualization of thyroid gland tumors. The complexity of the displacement to be estimated requires the use of deformable block matchings, using parametric motion models (de Haan and Biezen, 1998; Wei et al., 2004). For ultrasound elastography, deformable block matchings have already been proposed in (Yeung et al., 1998b) and (Zhu et al., 1999).

We propose herein a deformable block matching adapted for ultrasound elastography considering bilinear local displacement (Choi and Choi, 1999; Wechsler et al., 2004), referred to as Bilinear Deformable Block Matching (BDBM).

The algorithm we developed takes into account motion initializations based on a priori knowledge of the motion to estimate. The importance of search zone prediction in terms of precision and computation complexity for block matching has already been discussed in the literature. Xi et al. (2006) detail different methods for more accurately placing the search zone, adapted to video image sequences. In our case, we propose an original method to cover the entire image, developed for ultrasound elastography and allowing motion initialization. Moreover, this method ensures a regular dense motion field and, consequently, the non-use of an analytical function to regularize the estimated displacement. Such functions usually complicate the cost functions, as in the case of optical flow-based methods (Pellot-Bezak et al., 2004).

Another characteristic of our method is the iterative multi-scale approach, described in Section 2.3.4. It has been found to considerably improve the precision of motion estimation and refine the local estimation with no increase in the computation complexity of the cost function.

This paper is organized into six parts. In Section 2, the BDBM proposed is described. Section 3 presents a simulation result obtained with parameter tuning adapted to the RF ultrasound images, followed by results on phantom experiments in Section 4. Section 5 describes the experimental protocol for clinical data acquisition and provides results obtained with thyroid images from two clinical cases: a normal thyroid and one with a malignant tumor. Finally, the last section concludes the study.

2. Method

2.1. Local displacement modeling

We consider a pair of ultrasound images, \( I_1(x, y) \) and \( I_2(x, y) \), representing the same medium before and after the application of the compressive force. The relation between the reference image \( I_1(x, y) \) and the image after deformation \( I_2(x, y) \) is represented by

\[
I_2(x, y) = I_1(x + u(x, y), y + v(x, y))
\]

where \( u(x, y) \) and \( v(x, y) \) are the spatially varying displacement fields along the two directions of the images. The motion estimation problem consists in estimating these two components of the displacement in all the pixels of the reference image, in order to obtain the 2-D dense motion field.

2.2. Standard deformable block matching

Deformable block matching, sometimes referred to as generalized block matching in the literature (Seferidis and Ghanbari, 1994; Wei et al., 2005), in contrast to simple block matching, employs a different geometric transformation instead of pure translation. Fig. 1 shows how, for a collection of nodes, noted \( N(i, j) \), placed on top of the reference image, rectangular blocks of pixels are mapped on the deformed image onto irregular quadrilateral of pixels.

2.3. Bilinear Deformable Block Matching (BDBM)

With the proposed Bilinear Deformable Block Matching (BDBM) method, the parameters of the parametric motion...
model are estimated in rectangular regions of interest (noted \( R \)) of size \( L_u \times L_v \), chosen around the defined nodes \( N \) (Fig. 2). 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.

Fig. 3 shows a flow diagram of the proposed BDBM method. The algorithm starts by initializing the rectangular mesh on the reference image and limits the displacement search to the nearest neighbor pixels for each block \( B \) centered on one corner of the region of interest \( R \). The node \( N(i,j) \) has as an initial translation:

- in the axial direction, that of the nodes \( N(i, j-1) \) or \( N(i, j+1) \) (left or right neighbor previously calculated);
- in the lateral direction, that of the node \( N(i-1, j) \) or \( N(i+1, j) \) (above neighbor calculated previously).

2.3.2. Estimation of the region of interest’s corner translations

As shown on the flow diagram in Fig. 3, the spatial parametric transformation is estimated for each region of interest \( R \), considered around one node, by estimating the translations of its four corners (noted \( C \)). These four
Create the initial mesh on $I_1$ (cf. Figure 1)

Define regions of interest (R) around each node (cf. Figure 2)

Current node
Initial translations of the current node (cf. section 2.3.1)

Place the 4 search regions on $I_2$ considering the initial translations of the current R and interpolate them (cf. Figure 6)

4 x block matching to estimate the translations of the 4 corners of the current R (cf. section 2.3.2)

Compute the transformation parameters for the study zone around the current node (cf. section 2.3.3)

End iterative multi-scale?

Deform the current study zone (cf. Figure 7) with the estimated parametric model (cf. section 2.3.4)

Go to the next node

End iterative multi-scale?

Yes

Final node?

No

Compute the dense motion field (cf. section 2.3.5)

Yes

Fig. 3. Flow diagram of BDBM method.

Fig. 4. Scan of the image for displacement field computation. (a) The points represent the nodes $N$. The points are scanned in a triangle following the solid line and in numerical order. (b) Initialization of the translation values for a computation node of coordinate $(i, j)$.
estimations are made by classic block matching, considering rectangular blocks $B$ centered on each of the four corners.

Among block matching methods (Giachetti, 2000), those based on normalized cross-correlation have been shown to be well adapted to the speckle texture of ultrasound images (Bohs et al., 2000).

$$\rho(x, \beta) = \frac{\sum_{i=1}^{l_x} \sum_{j=1}^{l_y} [B(i, j) - \bar{B}] [B'(i + x, j + \beta) - \bar{B}]}{\sqrt{\sum_{i=1}^{l_x} \sum_{j=1}^{l_y} [B(i, j) - \bar{B}]^2 \sum_{i=1}^{l_x} \sum_{j=1}^{l_y} [B'(i + x, j + \beta) - \bar{B}]^2}}$$

(2)

where $\rho$ is the normalized correlation coefficient. $B$ is a block of the reference image considered around one corner of the region of interest and $B'$ a candidate block of the search region in the image after deformation. These blocks have a size $L_x \times L_y$ (lateral $x$ axial) and $(x, \beta)$ are the spatial shift variables of the block $B$ in comparison with $B'$. The mean grey levels of the pixels in blocks $B$ and $B'$ are noted $\bar{B}$ and $\bar{B}'$, respectively.

The function $1 - \rho(x, \beta) \in [0, 2]$ is minimum when the two blocks $B$ and $B'$ are spatially matched. By minimizing the coefficient $1 - \rho(x, \beta)$ defined in (3), over a given searching area, the displacement $(du, dv)$ of a node can be estimated.

$$d_u, d_v = \arg \min_{x, \beta} (1 - \rho(x, \beta))$$

(3)

Note that to search for the minimum of the correlation function, two approaches are considered. The first one is the Full Search, which is the most common block matching search and which finds the optimal motion vector among all candidates. The aim of reducing search complexity is achieved by using the Gradient Descend Search (Po and Ma, 1996). Simulation results show that this method is well adapted to our case and provide similar results as the exhaustive algorithm, reducing the processing time by 20%.

### 2.3.3. Motion model

A bilinear model of displacement was chosen to locally describe the displacement field (Seferidis, 1995). The lateral and axial components of the displacement vector are noted:

$$\begin{align*}
\{ u(x, y) = a_u x + b_u y + c_u x y + d_u \\
v(x, y) = a_v x + b_v y + c_v x y + d_v
\end{align*}$$

\quad (4)

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

Fig. 5 shows the deformation in a region of interest of the initial image. To simplify, the regions of the initial and final images are represented in the same coordinate system.

Considering the method described in Section 2.3.2, the four initial corners ($C_1, C_2, C_3, C_4$) are found to have been displaced in ($C'_1, C'_2, C'_3, C'_4$).

As we consider that the displacement of the region of interest fits a bilinear model, we can write two systems of four equations as follows:

$$\begin{align*}
dl_{C_1} &= -a_u \frac{1}{2} - b_u \frac{1}{2} + c_u \frac{1}{4} + d_1 \\
dl_{C_2} &= a_u \frac{1}{2} - b_u \frac{1}{2} + c_u \frac{1}{4} + d_1 \\
dl_{C_3} &= a_u \frac{1}{2} + b_u \frac{1}{2} + c_u \frac{1}{4} + d_1 \\
dl_{C_4} &= -a_u \frac{1}{2} + b_u \frac{1}{2} - c_u \frac{1}{4} + d_1
\end{align*}$$

\quad (5)

where $d = u$ or $v$ to write the two equation systems.

Since the translations of the four corners may be estimated by simple block matching, we can solve the two systems and find the bilinear parameters corresponding to the current region of interest. We find,

$$\begin{pmatrix} a_u \\ b_u \\ c_u \\ d_u \end{pmatrix} = M \begin{pmatrix} d_{C_1} \\ d_{C_2} \\ d_{C_3} \\ d_{C_4} \end{pmatrix}$$

\quad (6)

with the matrix $M$, depending on $L_u$ and $L_v$:

$$M = \frac{1}{2} \begin{pmatrix} -1 & 1 & 1 & -1 \\ -\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{pmatrix}$$

\quad (7)

### 2.3.4. Iterative multi-scale approach

As shown on the flow diagram in Fig. 3, the estimation of the bilinear parameters works iteratively, making the

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estimation more accurate. The accuracy of the bilinear parameter estimation depends directly on the accuracy of corner (noted C) translation estimations.

Since the displacement searched for is locally lower than the pixel size, a multi-scale approach is proposed. Several techniques of sub-pixel motion estimation are proposed in the literature, such as the quarter-pixel motion estimation of H.264 (Wiegand et al., 2003) in the video domain or improved derivations of this method (Zhang et al., 2004).

In our method, we propose that at each resolution level, the computation grid used to process the block matching be refined by a bilinear interpolation. Fig. 6 shows the principle of the multi-scale block matching approach. The interpolation of the search region in the image after deformation increases with the number of searching positions, while the size of the region B in the initial image is unchanged. For example, if at each iteration, the interpolation factor is 3, the search zone will be interpolated by a factor of 3 at the first iteration, and then by a factor of 9 at the second iteration, etc. However, the displacement estimated at the iteration \( i - 1 \) is used as a starting value at the iteration \( i \), and the new search region is located around the displacement value. Thus, at each iteration, the computation complexity of the correlation coefficient is the same, since the size of the block B is unchanged and only the matching candidates \( B^* \) are interpolated. This method is similar to a multi-scale search, with the difference that the scale levels are built with an interpolation of the search region.

We also propose that, after each iteration, not only the search region resolution be changed, but also the four blocks considered around the four corners of the region of interest. Since the bilinear parameters of the motion model are estimated at the previous iteration, a region of the reference image, noted ABCD in Fig. 7 and called study zone is deformed when Eq. (4) is applied. The study zone includes the current region of interest and the four blocks around its four corners. In this way, the next iteration starts with four new deformed blocks. This will make it possible to have more accurate corner displacement estimations using the classical block matching. Fig. 7 shows how the algorithm deforms the study zone between two iterations. The advantage of this iterative method is shown by the simulation results, such that the estimation error decreases with the advance in the iterations.

### 2.3.5. Dense motion field computation

The previous sections show how, for the mesh considered, the bilinear displacement is estimated in regions of interest around the nodes. As shown on the flow diagram in Fig. 3, the output of the BDBM is the dense motion field, so that the displacement is given in each pixel of the reference image. The size of the regions of interest is considered larger than the size of the mesh, so that we are in the configuration of Fig. 8. We can note an overlapping of the regions of interest of four neighboring nodes (the gray area around point A), as in the case of overlapped block matching (Orchard and Sullivan, 1994). Consequently, the displacements of the points belonging to this overlapped zone were estimated four times.

In Fig. 8, there is 30% overlapping in both axial and lateral directions. Point A indicates the center of the \( N_1 N_2 N_3 N_4 \) patch. Since it was estimated four times, the final displacement in pixel A will be the mean value of these four estimated displacements (in the axial and in the lateral directions). A criterion on the deviation of each of the four displacement values compared to the three others is considered in order to eliminate eventual poor estimations. The criterion consists in making the following operations. First, the mean and the standard deviation values of the four estimations are calculated. Then, only the values in the interval mean value plus/minus standard deviation value are retained to calculate the final displacement in A.

Finally, only the node and the point A displacements are considered to calculate the dense motion field by bilinear interpolation.

This method of obtaining the dense motion field has the advantage of introducing a regularization constraint for the final result and eliminating eventual aberrant estimations.

![Fig. 6. Block matching computation of blocks B and B* using the multi-scale approach. The block B is placed on the search region interpolated by a factor of 3. The circles represent the pixels of B, and the points represent the pixels of the search region.](image-url)
3. Simulation

3.1. Image formation

The performance of the bilinear deformable block matching (BDBM) was tested using two data sets of simulated images. The formation of the RF simulated images was based on the spatial convolution product over the variables $x$ and $y$, as shown in (8) (Yu and Acton, 2002), where $h(x, y)$ is the impulse response of the imaging system (Liebgott et al., 2007) and $d(x, y)$ is a discrete distribution of scatterers representing the medium (Bamber and Dickinson, 1980). The parameters used for the image simulation are those of the experimental data in Sections 4 and 5.

$$r(x, y) = h(x, y) \otimes d(x, y)$$

where $\otimes_{x,y}$ denotes the spatial convolution over both directions.

The form of the simulated PSF (point spread function) $h(x, y)$ is given by

$$h(x, y) = \exp \left( -\pi \left( \frac{x}{\sigma_x} \right)^2 \right) \exp \left( -\pi \left( \frac{y}{\sigma_y} \right)^2 \right) \cos(2\pi f_y y)$$

with $\sigma_x = 1.09 \text{ mm}$ and $\sigma_y = 0.36 \text{ mm}$ the full width at half maximum of the Gaussian envelopes in the axial and lateral directions and $f_y = 7.5 \text{ MHz}$ the central frequency of the simulated linear ultrasound probe.

![Fig. 7. Calculation of the displacement field for one region of interest (hatched region). (a) Iteration 1. Initial image. A study zone is selected (ABCD). (b) Iteration 1. Image after deformation. The block matching is performed for each block in the deformed image. The local displacement vector is calculated using Eq. (4). (c) Iteration 2. Initial image. The study zone (ABCD) is deformed using the displacement found in iteration 1. A new study zone is defined in (A'B'C'D'). (d) Iteration 2. Image after deformation. The block matching is performed for each block in the deformed image. The local displacement vector is calculated using Eq. (4).](image_url)

![Fig. 8. Dense motion field computation. Motion estimated in point A and nodes $N_1$-$N_4$ and then interpolated to the entire ultrasound image by bilinear interpolation.](image_url)
The image after deformation was calculated using the same convolution expression but with a locally displaced distribution of scatterers reported to the distribution of the initial image. This way of simulating the ultrasound provides true displacement between the images before and after deformation.

Three estimations of 2-D displacement between the reference and the deformed images performed each time and their performance were compared. The first two estimations dealt with the bilinear deformable block matching, as presented in Section 2, using or not using the gradient descent method for estimating the blocks translations (cf. Section 2.3.2). The third estimated 2-D displacement was obtained using simple block matching (BM) and was used as the classic method. In all cases the accuracy of the estimations was evaluated using the dense motion fields. With the BDBM method, the dense motion field was calculated as explained in Section 2.3.5. With the BM method, the step between two consecutive estimated nodes was considered the same as for BDBM. Moreover, the dense field was processed in BM case by piecewise spline cubic interpolation of the 2-D displacement estimated for the considered nodes. Thus, both BM and BDBM methods yield to displacement maps having the same spatial resolutions and equal to the original images resolution.

The first two simulated images corresponded to a 20 × 30 mm² homogeneous medium. On these images, one pixel was equal to 21.4 μm in the axial direction and 120 μm in the lateral direction. The deformation applied between the two images corresponded to 3% in the axial direction and 1.48% in the lateral direction, the equivalent as presented in Section 2, using or not using the gradient descent method for estimating the blocks translations (cf. Section 2.3.2). The third estimated 2-D displacement was obtained using simple block matching (BM) and was used as the classic method. In all cases the accuracy of the estimations was evaluated using the dense motion fields. With the BDBM method, the dense motion field was calculated as explained in Section 2.3.5. With the BM method, the step between two consecutive estimated nodes was considered the same as for BDBM. Moreover, the dense field was processed in BM case by piecewise spline cubic interpolation of the 2-D displacement estimated for the considered nodes. Thus, both BM and BDBM methods yield to displacement maps having the same spatial resolutions and equal to the original images resolution.

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3.2. Confidence measure

The absolute error (Fitzpatrick et al., 2000) between the simulated and the estimated displacements (since the true displacement for the case of simulated images is available) was chosen to characterize the quality of the strain estimations. It was also used to evaluate the influence of different parameters of the BDBM algorithm, such as the sizes of the mesh and of the regions of interest, the number of iterations and the final resolution level, on the quality of the estimated displacement. This study led us to optimize these parameters to our images.

For the experimental data, since the true displacement was not available, a different measure of displacement estimate accuracy was used. For this, we applied the estimated 2-D displacement to the image after deformation \(I_2(x, y)\) in order to map it onto the reference image \(I_1(x, y)\). We thus obtained the registered version of \(I_2\), which we noted \(\tilde{I}_2\). Further, we calculated the normalized cross-correlation coefficient defined in (2) between each patch of the rectangular mesh on \(I_1\) (see Fig. 1) and its corresponding patch on \(\tilde{I}_2\). We obtained a cross-correlation coefficients map and our similarity measurement was defined as the mean of all these values, noted \(\xi\) in the subsequent sections. Note that \(\xi\) takes values in the range 0–100. Moreover we can notice that \(\xi\) equal to 100 corresponds to an estimation without error.

3.3. Parameter values of BDBM method

The following parameter values were used: the step between two consecutive nodes 15 pixels = 0.32 mm in the axial direction and 12 pixels = 1.44 mm in the lateral direction; the size of a region of interest \(R\) 40 pixels = 0.85 mm in the axial direction and 20 pixels = 2.4 mm in the lateral direction. With the BDBM method, local displacement was computed with two iterations and an interpolation factor of 3 by iteration. This means that the precision of the result was 1/9 of a pixel in both axial and lateral directions. With the classic BM, the size of the blocks was 40 × 20 pixels and the deformed image was interpolated by a factor of 9.

3.4. 2-D vector displacement estimation

Fig. 9 shows the true and the three estimated 2-D displacement vectors, superimposed on the B mode simulated image. BDBM gave similar results with and without using the gradient based method. As the use of this method reduced the computation time, the following BDBM results used this optimization.

The histograms of the absolute errors are given in Fig. 10. With our method, the standard deviation of the error was 0.27 μm in the axial direction and 2.3 μm in the lateral direction, while the classic BM gave 1.8 μm and 15.1 μm, respectively. These results show a decrease by a factor of 6 between our method and classic BM.

As the simulated medium was homogeneous and the deformation applied was uniformly distributed, the lateral displacement was the same at each depth for a given lateral distance. Fig. 11 shows the mean value and the standard deviation of the estimated lateral displacement in each column, for both our method and the classic BM. We can see that the displacement estimated with our method is considerably more accurate and more regular. The standard deviation was always 6–7 times smaller with our method than with the classic BM.

The simulated medium of the second data set was made of a surrounding homogeneous medium of 20 × 30 mm and a cylindrical inclusion in the center 10 mm in diameter (Fig. 12).

The inclusion had a Gaussian shape as shown in (10), where \(x\) and \(y\) are the lateral and axial directions and \(E\) the Young Modulus. The Young Modulus value in the center was set to 100 kPa (twice as hard as the surrounding medium) and the Poisson coefficient is 0.49,

\[
E(x, y) = 50 + 50 \exp\left(-\pi \times \left(\frac{x}{4}\right)^2\right) \times \exp\left(-\pi \times \left(\frac{y}{4}\right)^2\right)
\]  
(10)
These values were selected to be in agreement with the Young Modulus contrasts measured in the thyroid (Lyshchik et al., 2005b). The deformation applied was 2% in the axial direction and 0.98% in the lateral direction. The true displacements were obtained with a finite element method, using the software tool Femlab (COMSOL AB, Sweden).

Fig. 9. 2-D displacement: (a) true, (b) estimated with classic BM, (c) estimated with BDBM using exhaustive search, and (d) estimated with BDBM using the gradient descent method.

Fig. 10. Histograms of the error between true and estimated displacement (a) axial, estimated with BDBM, (b) axial, estimated with BM, (c) lateral, estimated with BDBM, and (d) lateral, estimated with BM.
The ultrasound images were simulated like those of the first data set, using the same parameters as for the clinical exam (cf. Section 5).

The estimation parameter adjustment had the same values as those used in the first simulation, since the ultrasound images were obtained using the same physical parameters.

Fig. 13 shows the true (a), estimated (b) and (c) 2-D displacements. The presence of the hard inclusion is visible in the center of the images.

The axial strain was calculated by derivation of the true and the estimated displacements, using a 1-D filter with finite impulse response (Kallel and Ophir, 1997a). With this filter, the pixel size on the strain maps is the same as for the dense motion field maps. Moreover, the filter length is chosen as a trade off between the noise generally introduced by a derivative filter and the smoothing related to the filter length. Note that for the results shown in Fig. 14 the length of the filter was set to 20% of the image axial size. The strain images clearly show the hard inclusion, which in our case presents a deformation of $-1.4\%$.

Fig. 15 shows the histograms of the absolute errors between the true and the estimated axial and lateral displacements. For this data set, in the axial direction the standard deviation values were $0.39\mu m$ for the BDBM, versus $1.1\mu m$ with classic BM, and in the lateral direction $2.7\mu m$, and $13.4\mu m$, respectively.

All the results on the standard deviation of the absolute errors obtained for the simulated ultrasound images are grouped in Table 1.

### 3.5. Results on the iterative multi-scale approach and dense motion field computation

The influence of the multi-scale approach on the accuracy of results is shown in Fig. 16. Several estimations on the simulated RF images presented below were made for different numbers of iterations and interpolation factors. The level of resolution, corresponding to the interpolation factor at the final iteration, is shown for each point of the 2-D displacement: (a) true, (b) estimated with BDBM (2 iterations, 1/9 final resolution level), (c) estimated with BM (1/9 resolution level).

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It can be seen that the mean and the standard values of the absolute error decrease with the increase in iterations. Thus, for 1 iteration and an interpolation by a factor of 9, the mean absolute error was 1.4 times larger than for two iterations and the same level of resolution. This result shows the advantage of the iterative process for the multi-scale approach and explains our choice of making two iterations.

Moreover, it can be seen that for a fixed absolute error, it was more efficient, in terms of computation, to increase the iterations than to decrease the resolution value. For example, in half the computation time, with three iterations and a resolution level of 1/8, we have the same absolute error as with two iterations and a 1/16 resolution.

Fig. 17 shows the influence of the mesh and region of interest sizes on the accuracy of the motion estimation in the axial and lateral directions. For regions of interest comprising 40 × 20, 20 × 10 and 60 × 40 pixels, we show how the displacement estimation depends on neighboring regions of interest overlapping (Fig. 8). As the displacement we estimate is corresponding to an axial compression and a lateral dilatation, the axial motion variation is larger than in the lateral direction. Therefore, to have a constant displacement inside the block, in our case smaller ROI sizes are more advantageous for the axial displacement accuracy, while small ones provide better accuracy in the lateral direction.

Table 1
Comparison of standard deviations of the absolute error for BDBM and BM methods

<table>
<thead>
<tr>
<th>Phantom</th>
<th>Axial</th>
<th>Lateral</th>
<th>Axial</th>
<th>Lateral</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BDBM</td>
<td>BM</td>
<td>BDBM</td>
<td>BM</td>
</tr>
<tr>
<td>Homogenous</td>
<td>0.27</td>
<td>1.8</td>
<td>2.3</td>
<td>15.1</td>
</tr>
<tr>
<td>With inclusion</td>
<td>0.39</td>
<td>1.1</td>
<td>2.7</td>
<td>15.4</td>
</tr>
</tbody>
</table>

Fig. 15. Histograms of the error between true and estimated displacement (a) axial, estimated with DBM, (b) axial, estimated with BM, (c) lateral, estimated with BDBM, (d) lateral, estimated with BM.

Fig. 14. Axial strain image in %: (a) true, (b) and (c) calculated with the displacement estimated with BDBM (2 iterations, 1/9 final resolution level) and BM (1/9 resolution level), respectively.
direction. Moreover, we show that the displacement estimation error decreases as the percentage of overlapping area increases and it increases as the overlapping area becomes too large. In Fig. 17, we observe that a ROI size of 60 × 40 pixels and no overlapping produce a very large estimation error. That is because in this case the number of considered nodes is too small and consequently not sufficient to obtain an accurate dense motion field. Seeking a trade off between the axial and lateral errors, we chose 40 × 20 pixel regions of interest, 62% overlapping in the axial direction and 40% in the lateral direction. This overlapping percentage corresponds to a mesh size of 15 × 12 pixels. The optimal size of the regions of interest is close to twice the values of the full width at half the maximum of the PSF Gaussian envelope we have chosen to simulate the images (cf. Section 3.1).

4. Results on experimental phantom data

First, an experimental result with phantom data was presented so that an elastogram in a simple case could be visualized. The test object was made of porcine-hide gelatine (type A, approx. 300 bloom, Sigma Chemical, St. Louis, MO, USA), graphite powder (3.25%, Kanto Chemical, Tokyo, Japan), formaldehyde (0.05%, Kanto Chemical, Tokyo, Japan) and 1-propanol (7.7%, Kanto Chemical, Tokyo, Japan) (percentage of total phantom weight) (Hall et al., 1997). The phantom measured 50 × 50 × 50 mm, with a cylindrical inclusion 5 mm in diameter. The axis of the inclusion was perpendicular to the imaging plane. The inclusion is roughly three times harder than the background. A small 5% precompression was applied to the phantom to ensure good contact between the ultrasound probe and the surface of the phantom. The step compression between two consecutive ultrasound images was 1.25% of the initial phantom thickness.

Fig. 18 shows the displacement vectors superimposed on the ultrasound B-mode image and the axial strain images obtained with displacement estimated with our method. The length of the derivative filter was set to 15% of the image axial size. The hard inclusion is easily distinguishable on the elastogram, whereas it is barely visible in the ultrasound B-mode image. The difference in visibility of the inclusion between the two images is explained by low acoustic contrast between the inclusion and the surrounding medium, whereas the elasticity contrast is high. Because of its stiffness, the inclusion is less deformed (axial strain close to −0.8%) under the external compression applied to the phantom with the ultrasound probe.

Fig. 18c shows the estimation accuracy versus the number of iterations, the final resolution level and compared to classical block matching. We show how, with the BDBM method, the similarity measure $\xi$ defined in Section 3.2 is larger than the classical method even for smaller interpolation factors. Moreover, the accuracy of the displacement estimation increases with the number of iterations.

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5. Clinical application

5.1. Experimental protocol

5.1.1. Patients

The methods of strain image reconstruction proposed were tested on the clinical data of two patients. The first 31-year-old male patient had a normal thyroid gland. The second 48-year-old female patient had papillary thyroid cancer. The study protocol was approved by the Kyoto University institutional review board. Before enrollment, each patient gave written informed consent as required by the Kyoto University Human Study Committee.

5.1.2. Ultrasound examination

In both cases, US was performed using a clinical scanner (Sonoline Elegra) that was modified for research and a 7.5-MHz linear probe (Siemens Medical Systems, Issaquah, WA, USA). The US images were acquired, reviewed, and interpreted by two radiologists (A.L. and T.H.) who were blinded to the patients’ final diagnoses. For both patients, the US examination started with B-mode imaging. The patients were positioned for imaging following the standard clinical thyroid gland US protocol: on the back with the neck slightly extended over a pillow. During B-mode US, thyroid gland lesions were identified and a region of interest for elastography was identified.

For each patient examined a new set of RF echo data was acquired during one compression cycle. Using the US probe, light compression was applied to the anterior neck above the examined lesion to fix the position of the thyroid gland and limit its lateral movement. Then light compression was applied to the same area again. During the second compression, digitized frames of in-phase and quadrature echo data consisting of 312 sample sequences (each sequence was an A line separated by a 0.12-mm transducer pitch) were recorded at 16 frames per second and stored in the system memory of the US scanner. The RF signals were initially digitized at 36 Msamples per second, demodulated, and decimated by a factor of 2 to yield in-phase and quadrature data for electronic transfer and storage. Then the in-phase and quadrature data were upsampled by a factor of 4 and remodulated to form RF data for off-line processing.

5.2. Clinical results

The image of the axial strain or axial elastogram was obtained by calculating the displacement between four pairs of RF images of the thyroid gland using the BDBM method. The four pairs of images are coming from the freehand acquisition sequences obtained as explained in Section 5.1.2 and the choice was handmade by a specialist doctor. In each case, the axial strain image was obtained using the derivative filter, whose length was 15% of the axial size of the images. The final elastogram is then obtained as the mean of the four estimated axial strains. For each result presented, the elastogram was compared to the usual B-mode image obtained after envelop detection and logarithmic amplification of RF signals. In both cases, the contours of the organs were hand-drawn by a specialist doctor. The results focus on the two patients introduced in Section 5.1.1.

Fig. 19 shows the transverse B-mode sonogram, the displacement vectors estimated with our method and the elastogram of a thyroid gland with a malignant tumor (papillary adenocarcinoma) located in the central part of the right thyroid lobe. On the elastogram, the tumor is highly visible and has a strain level (\(-0.05\%\) deformation) that

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is different from the surrounding tissues (−0.5% to −0.2% deformation). The tumor is also characterized by a regular and distinct margin.

Fig. 21 shows how, for both cases of normal thyroid and thyroid with malignant tumor, the BDBM method is more accurate than the simple block matching, even for larger final resolution levels. It is also shown that the iterative multi-scale approach provides good results for experimental data. For the same resolution level, but with more iterations, the accuracy measure increases as when passing from 1 to 2 iterations.

Our preliminary results show that the diagnostic performance of US elastography depends greatly on the quality of the freehand compression data acquired and on the specifications of the image reconstruction algorithm used. The overall quality of thyroid strain images is significantly affected by decorrelation noise caused by the non-axial and out-of-plane motion of the lesion examined. In thyroid

Fig. 19. Transverse B-mode sonogram (a), estimated 2-D displacement (2 iterations, 1/9 final resolution level) (b) and strain image (c) of a 31-year-old male patient representing a normal right lobe of the thyroid gland with no lesion. T – thyroid gland; C – carotid artery; V – jugular vein; M – anterior neck muscles; Tr – trachea, As – anterior surface, Ps – posterior surface, Ms – median surface, Ls – lateral surface.

Fig. 20. Transverse B-mode sonogram (a) of a 48-year-old female patient representing an 18-mm solid malignant thyroid tumor (papillary adenocarcinoma) in the central part of right thyroid lobe and estimated 2-D displacement (2 iterations, 1/9 final resolution level) (b). On elastogram (c) the tumor is clearly visible and dark with respect to surrounding tissues. It has a regular and distinct margin. T – thyroid gland; Tm – tumor; C – carotid artery; V – jugular vein; M – anterior neck muscles; Tr – trachea.

Fig. 21. Displacement accuracy measurement versus number of iterations and final resolution level, compared to block matching method (dashed lines) for (a) normal thyroid gland and (b) thyroid with malignant tumor.

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gland elastography, two main sources of noise can be pinpointed: the first source is pulsation of the carotid artery. The second major source of noise is the out-of-plane motion of the lesion examined under compression. The anatomy surrounding the thyroid gland consists of numerous movable structures such as the trachea and the jugular vein, so it is difficult to restrict the movement of the thyroid gland to the imaging plane. In general, the operator can control and limit the out-of-plane motions of the lesion examined using different levels of precompression load, varying directions and speed of freehand compression applied with the ultrasound probe. In addition, this problem may be solved by a substantial increase in the computational capability of US systems to a point where high-quality primary images at high frame rates can be attained, and by using the more sophisticated image reconstruction algorithms based on the parametric model of displacement and a thyroid-specific estimation method adapted to subpixel displacement. Despite a few obstacles, ultrasound elastography can provide valuable diagnostic information in patient with thyroid nodule. It is well known that pathological changes are generally correlated with changes in tissue stiffness, mainly due to the changes in the mechanical properties of their molecular building blocks and the microscopic and macroscopic structural organization of these blocks. Therefore, many tumors in cancers of the breast, prostate, and thyroid, for example, all showing significant disruption of normal cell architecture, appears stiffer than normal non-diseased tissues. Results of biomechanical studies revealed a significant difference in the stiffness on normal and diseased thyroid tissues. This difference in elastic properties, if accurately visualized on the US elastograms, can provide a valuable tool for initial diagnosis and clinical management of patients with thyroid nodular disease.

6. Conclusion

Tissue strain imaging with ultrasound applied to the thyroid was investigated. The experimental method consisted in gradually compressing the patient’s thyroid gland with the ultrasound probe to obtain a strain image rendering the elastic characteristics of tumors and surrounding soft tissues.

The complexity of the motion to analyze, the freehand compression and the constraints induced by the ultrasound images required the development of a novel method of motion estimation, referred to as Bilinear Deformable Block Matching in this paper. This method uses a bilinear motion model and proposes a technique to locally estimate the eight parameters of the model. In addition, a motion initialization approach adapted to ultrasound elastography and an iterative multi-scale algorithm are proposed. Estimating the displacement in an iterative manner is shown to decrease the absolute error estimation and to be more computationally efficient than increasing the resolution level. Additionally, a technique for calculating the dense motion field that takes into account the overlapping areas between the regions of interest is presented and shown to improve estimation accuracy.

The performance of the BDBM method was tested on two pairs of simulated ultrasound images on which the displacement to be estimated was controlled. The results showed an error reduction by a factor of 4 compared to classical block matching method. Moreover, we tested this method on phantom experimental data and on clinical images of the thyroid gland, showing encouraging results. In future work, a temporal model of the displacement parameters can be added to the method proposed. Rather than estimating the displacement field between two frames, the aim will be to time track parameters along the ultrasound image sequence of the thyroid when compression is gradually applied to it. Three-dimensional displacement estimation will also be considered, since one of the major problems in processing experimental data is the out-of-plane motion.

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