Kalman-Filter-Based Block Matching for Arterial Wall Motion Estimation From B-Mode Ultrasound

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Abstract-**The motion of the carotid artery wall has been previously estimated from ultrasound image sequences using block matching. In this paper, this conventional method was extended through its combination with Kalman filtering in two distinct scenarios; (a) by renewing the reference block and (b) by updating the estimate of the conventional algorithm. Both procedures were evaluated on synthetic image sequences through the estimation of the warping index. The results showed that incorporation of the Kalman filter in conventional block matching slightly improved the accuracy in arterial wall motion estimation. Updating the estimate of the conventional algorithm using Kalman filtering was the most efficient procedure and could be used to study further the displacements of the arterial wall in an attempt to obtain useful knowledge about arterial biomechanics.**

Keywords- Adaptive block matching; Kalman filter; motion analysis; ultrasound; arterial wall

I. INTRODUCTION

B-mode ultrasound is widely used in the diagnosis of arterial disease because it allows non-invasive assessment of arterial wall morphology. Arterial wall motion during the cardiac cycle can also be estimated from B-mode ultrasound by recording image sequences and subsequently applying a motion estimation algorithm.

Block matching has been previously used in estimating carotid artery wall motion from B-mode ultrasound [1]. The method relies on the use of a reference block of pixels in the first image of the sequence and the identification, in each subsequent image, of a block that shows the highest similarity to the reference block. Examples of applications of block matching in carotid artery wall motion include the estimation of the vessel diameter in systole and diastole, the arterial wall distensibility in two directions [1], the average motion amplitude and the shear strain within the wall [2]. The method was also used by Bang et al [3] to study motion dynamics of carotid atheromatous plaque.

Adaptive block matching is an extension of the algorithm which updates the reference block using one or more of the previous frames. Four update strategies have been proposed, namely single-frame, multiframe, finite impulse response (FIR) filtering, and Kalman filtering, and it was shown that the use of Kalman filtering was the most robust strategy which minimized the mean tracking error [4]. The methods were also used to extract motor activity signals of selected anatomical sites from video recordings of neonatal seizures and the best performance was again achieved when Kalman filtering was used [5]. Kalman filtering has also been used in a dynamic contour tracking approach to reinforce the accuracy in tracking the myocardial boundaries from echocardiographic image sequences [6].

Based on the above, this work was undertaken in an attempt to further improve the performance of block matching-based arterial wall motion estimation, by incorporating an adaptive methodology. More specifically, in this paper the conventional block matching algorithm was combined with Kalman filtering in two distinct scenarios: (a) the algorithm was extended to adaptive block matching by introducing an update reference block strategy based on the Kalman filter and (b) Kalman filtering was used to renew the estimate of the conventional algorithm.

II. BASIC PRINCIPLES OF KALMAN FILTERING

Kalman filter is an efficient recursive filter that estimates the current state of a linear dynamic system from a series of noisy measurements [7]. Kalman filter assumes that the true state of the system at time k is related to the state at time (k-1) according to the model:

$$\boldsymbol{x}_k = \boldsymbol{A}\boldsymbol{x}_{k-1} + \boldsymbol{B}\boldsymbol{u}_k + \boldsymbol{n}_k \tag{1}$$

where $\boldsymbol{x}_k$ is the state at time k, $\boldsymbol{A}$ is the state transition matrix applied to the previous state $\boldsymbol{x}_{k-1}$, $\boldsymbol{B}$ is the control-input matrix applied to the control vector $\boldsymbol{u}_k$ and $\boldsymbol{n}_k$ is the process noise with a zero mean normal distribution described by the covariance matrix $\boldsymbol{Q}$. At time k an observation, or measurement, $\boldsymbol{z}_k$ of the true state $\boldsymbol{x}_k$ is made according to the model:

$$\boldsymbol{z}_k = \boldsymbol{H}\boldsymbol{x}_k + \boldsymbol{v}_k \tag{2}$$

where $\boldsymbol{H}$ is the observation matrix that relates the measurement of the true state with the true state and $\boldsymbol{v}_k$ is the observation noise the distribution of which is described by the covariance matrix $\boldsymbol{C}$. To use Kalman filtering one should model the process according to the above equations.

Because Kalman filter is a recursive estimator, only the estimated state from the previous time step ($\hat{\boldsymbol{x}}_{k-1}$) and the current measurement ($\boldsymbol{z}_k$) are needed to compute the estimate for the current state ($\hat{\boldsymbol{x}}_k$). Kalman filter acts in two distinct phases: prediction and update. The prediction phase produces an a priori estimate of the state ($\hat{\boldsymbol{x}}_k^-$) and the filter's error, the distribution of which is represented by the covariance matrix ($\boldsymbol{P}_k^-$).

$$\widehat{\boldsymbol{x}}_k^- = \boldsymbol{A}\widehat{\boldsymbol{x}}_{k-1} + \boldsymbol{B}\boldsymbol{u}_{k-1} \tag{3}$$

$$\boldsymbol{P}_k^- = \boldsymbol{A}\boldsymbol{P}_{k-1}\boldsymbol{A}^T + \boldsymbol{Q} \tag{4}$$

In the update phase, the a priori estimate is considered a linear combination of the a priori state estimate and the difference (multiplied with an appropriate factor) between the observation and the prediction of the observation:

$$\widehat{\boldsymbol{x}}_k = \widehat{\boldsymbol{x}}_k^- + \boldsymbol{K}(\boldsymbol{z}_k - \boldsymbol{H}\widehat{\boldsymbol{x}}_k^-) \tag{5}$$

This factor is represented by the Kalman gain $\boldsymbol{K}$:

$$\boldsymbol{K} = \boldsymbol{P}_k^-\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}_k^-\boldsymbol{H}^T + \boldsymbol{C})^{-1} \tag{6}$$

In case of high process noise the Kalman gain gives priority to the update, whereas in case of high observation noise the term of the a priori state estimate dominates. The improved estimate is termed the a posteriori estimate of the current state ($\widehat{\boldsymbol{x}}_k$) and the filter's error is updated according to the following equation:

$$\boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}\boldsymbol{H})\boldsymbol{P}_k^- \tag{7}$$

III. METHODS

A. Block matching

Block matching assumes that a block of pixels remains constant over motion and that all its pixels have the same velocity. The algorithm consists in finding a block (best-matched block) in an image that shows the highest similarity to the reference block which is chosen by the user in the first image. The search for the best-matched block is performed in a limited image region, called search window, around the best-matched block of the previous image.

In this work block matching methods were implemented in Matlab (The MathWorks, Natick, Massachussetts, USA), using the correlation coefficient as the similarity measure, 25x17 pixels reference blocks selected in the first frame and 10x10 pixels search windows. This size of the search window was suggested in [1] as the most appropriate for this application.

B. Adaptive block matching using Kalman filtering

In adaptive block matching the reference block is updated to take into consideration the changes in the appearance of the target [4]. Kalman filtering can be used in adaptive block matching because it can estimate the reference block which is used for image *k* by modeling the process as:

$$\boldsymbol{x}_k = \boldsymbol{R}_k = \boldsymbol{R}_{k-1} + \boldsymbol{n}_k \tag{8}$$

$$\boldsymbol{z}_k = \boldsymbol{M}_{k-1} = \boldsymbol{R}_{k-1} + \boldsymbol{v}_k \tag{9}$$

where $\boldsymbol{R}$ is the reference block and $\boldsymbol{M}$ is the best-matched block. With reference to (1) and (2) $\boldsymbol{A}$=$\boldsymbol{H}$=$\boldsymbol{I}$ and $\boldsymbol{B}$=0. Consequently, (3)-(7) are valid for $\boldsymbol{x} \equiv \boldsymbol{R}$ and $\boldsymbol{z}_k \equiv \boldsymbol{M}_{k-1}$.

Matrices $\boldsymbol{Q}$ and $\boldsymbol{C}$ were considered proportional to the identity ($\boldsymbol{Q}=q\boldsymbol{I}$, $\boldsymbol{C}=c\boldsymbol{I}$) and the method was optimized in terms of the multiplication factors q, c. Experimentation with these parameters showed that the method maximized its performance when $c \gg q$. Therefore in this study q=0.1 and c=100 were used. This observation shows that the error is minimized when each image tends to maintain the a priori estimate, which means to use the previous reference block as a reference block, with a slight improvement derived from the difference between the best-matched block and the reference block of the previous image.

C. Updating the estimation of conventional block matching using Kalman filtering

Kalman filtering can be used to improve the motion detection of the conventional block matching algorithm, by modeling the process as:

$$\boldsymbol{x}_k = \begin{bmatrix} Y(k) \\ X(k) \\ dY(k) \\ dX(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Y(k-1) \\ X(k-1) \\ dY(k-1) \\ dX(k-1) \end{bmatrix} + \begin{bmatrix} nY \\ nX \\ ndY \\ ndX \end{bmatrix} \tag{10}$$

where X, Y are the coordinates of the centre of the best-matched block in the longitudinal and radial direction, respectively, and dX, dY are the displacements in relation to the previous image. The estimate of conventional block matching for the coordinates of the centre of each best-matched block found in the images of a sequence is considered as observation information:

$$\boldsymbol{z}_k = \begin{bmatrix} ZY(k) \\ ZX(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} Y(k) \\ X(k) \\ dY(k) \\ dX(k) \end{bmatrix} + \begin{bmatrix} vX \\ vY \end{bmatrix} \tag{11}$$

This idea can be implemented during (version 1) or after (version 2) the execution of the algorithm.

In this case performance is still dependent on matrices $\boldsymbol{Q}$ and $\boldsymbol{C}$ which are defined in the same way as before. Consequently the method was again optimized in terms of the multiplication factors q and c. The experimentation showed that it minimized its deviation from real motion when the process error was double the observation error. Therefore the evaluation of the two versions was made by selecting q=4 and c=2. This choice shows that the method requires "confidence" in the estimate of the conventional block matching algorithm, leaving room for improvement coming from the Kalman filtering.

D. Performance evaluation

The methods described above were optimized and evaluated by applying them to four synthetic 87-image sequences of the common carotid artery, corresponding to three cardiac cycles. The first synthetic sequence ("synthetic") was created by distorting a real ultrasonic B-mode image (Fig. 1(a)) according to a mathematical motion model [8]. Two additional sequences were created by adding noise levels of 25 decibels ("synthetic25") and 15 decibels ("synthetic15"), respectively, to the first sequence. The fourth synthetic sequence ("field") was constructed using the Field II software package and a mathematical motion model [8]. Fig. 1 presents the first image of the four synthetic sequences.

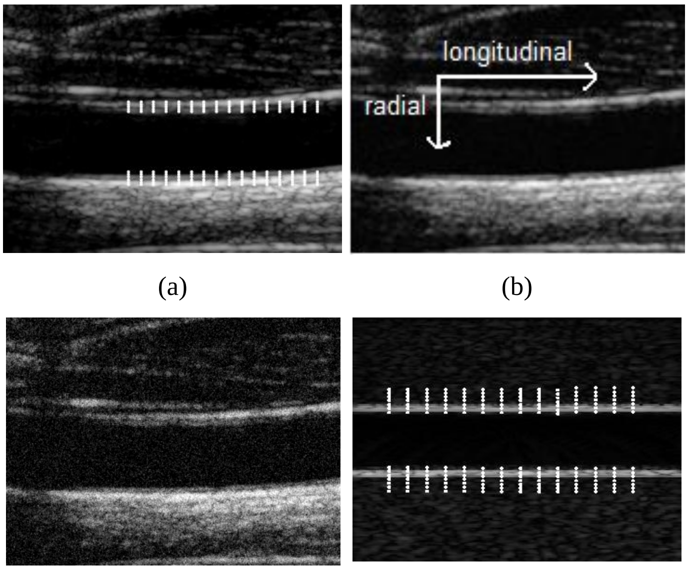
Performance was assessed by means of the warping index defined by (12) and (13), separately for the longitudinal and radial directions as well as for the whole movement.

$$w_{longitudinal} = \sqrt{\frac{\sum_{k=1}^{m}\sum_{i=1}^{n}\left(long_{real\ (k,i)} - long_{est\ (k,i)}\right)^2}{n \cdot m}} \quad (12)$$

$$w_{radial} = \sqrt{\frac{\sum_{k=1}^{m}\sum_{i=1}^{n}\left(radial_{real\ (k,i)} - radial_{est\ (k,i)}\right)^2}{n \cdot m}} \quad (13)$$

$$w = \sqrt{w_{longitudinal}^2 + w_{radial}^2} \quad (14)$$

where m is the number of selected blocks and n is the number of images of each sequence. The warping index was computed by choosing 176 block centres for sequences "synthetic" (Fig. 1(a)), "synthetic25" (Fig. 1(b)), "synthetic15" (Fig. 1(c)) and 196 block centres for the sequence "field" (Fig. 1(d)).



(a) (b) (c) (d)

Figure 1. Examples of images of the common carotid artery wall of synthetic sequences (a) "synthetic", (b) "synthetic25", (c) "synthetic15" and (d) "field". The white marks represent the selected block centres.

IV. RESULTS

Table 1 shows the warping index values for each synthetic sequence when motion was estimated by conventional block matching (BM), adaptive block matching using Kalman filtering (KF), update of BM's estimation applying Kalman filtering during tracking (K1) and update of BM's estimate applying Kalman filtering at the end of tracking (K2). As we can see, errors were generally greater in the longitudinal direction probably because of relatively higher homogeneity of image intensities in that direction. In most cases the Kalman filter minimized the warping index, which means that it improved motion estimation for the majority of selected blocks. Highest performance was achieved by the use of Kalman filtering to update the BM's estimate after tracking (K2). Fig. 2 shows examples of radial and longitudinal displacements, respectively, of a block located in the lower wall-lumen interface in the first image of the sequence "synthetic25" using the four investigated methods, BM, KF, K1, and K2. The root-mean-square errors for these cases were 1.42, 1.31, 1.34 and 1.16 pixels, respectively.

TABLE I. WARPING INDEX VALUES IN PIXELS FOR BM, KF, K1 AND K2 FOR THE SEQUENCES "synthetic", "synthetic25", "synthetic15", AND "field"

"synthetic"	w	w_{radial}	$w_{longitudinal}$
BM	1.1938	1.0753	0.5185
KF	1.1939	1.0749	0.5196
K1	1.1893	1.0753	0.508
K2	1.1758	1.0703	0.487
"synthetic25"	w	w_{radial}	$w_{longitudinal}$
BM	3.8863	2.267	3.1567
KF	3.9102	2.3921	3.0931
K1	3.3553	2.2668	2.4738
K2	3.8484	2.258	3.1164
"synthetic15"	w	w_{radial}	$w_{longitudinal}$
BM	13.9839	3.7012	13.4852
KF	13.9136	3.89	13.3587
K1	14.0717	3.6509	13.5895
K2	13.9327	3.6282	13.452
"field"	w	w_{radial}	$w_{longitudinal}$
BM	1.6476	1.1313	1.1979
KF	1.6485	1.1353	1.1952
K1	1.6374	1.1317	1.1834
K2	1.6266	1.1254	1.1744

The method that generally produced the lowest error, K2, was applied to a real ultrasound image sequence of the carotid artery of a young normal subject. The first frame of this sequence is shown in Fig. 1(a). Fig. 3 shows examples of radial and longitudinal displacements, respectively, of a block located in the lower wall-lumen interface in the first image of this sequence using K2 and BM. K2 differs from BM mainly in the radial direction while maintaining both the periodicity and the expected motion pattern.

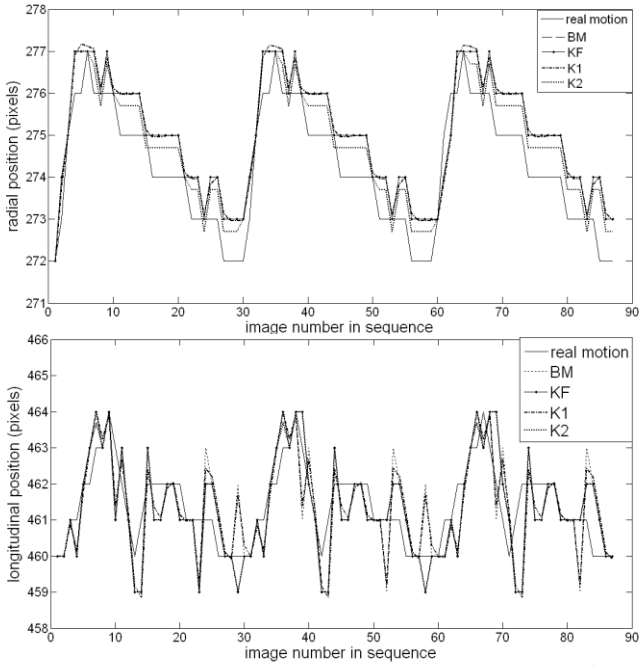


Figure 2. Radial (top) and longitudinal (bottom) displacements of a block located in the lower wall-lumen interface in the first image of the sequence “synthetic25” using BM, KF, K1 and K2.

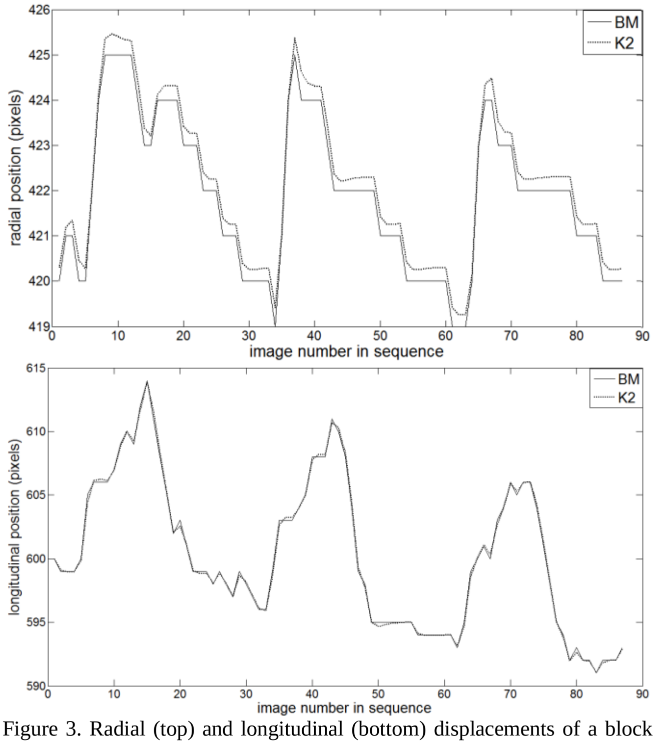


Figure 3. Radial (top) and longitudinal (bottom) displacements of a block located in the lower wall-lumen interface in the first image of the real sequence using BM and K2.

V. DISCUSSION

Kalman filtering managed to slightly enhance motion detection accuracy when it is used for either renewing the reference block, or updating the estimate of the conventional algorithm. In the first case the error is smoothed because the algorithm takes into consideration changes in brightness of the image, which would be essential under real conditions where these changes may stem from the patient's movement or errors during the processing of images. In the second case Kalman filtering limits the displacements estimate according to the defined models and prevents the transmission of considerable errors in the subsequent images. However, the improvement does not respond to Kalman filter potential, especially in case of noisy sequences. KF creates a better reference block for each image, but it searches for the best-matched block within a search window around the best-matched block of the previous image, without preventing error transmission. K2 limits error transmission, whereas it still uses the reference block of the first image as a reference block for all images.

The fact that Kalman filtering reinforces the conventional algorithm, without entailing high complexity or high computational cost, makes the methods worth implementing. Taking into consideration the reasons which limited the improvement range, it is recommended to use the above methods in combination to study the movement of important anatomical areas of the carotid artery, correlate motion with structural and mechanical properties of the wall and create a user-friendly software to visualize the results.

VI. CONCLUSION

Kalman filtering for updating the estimate of the conventional block matching algorithm may be efficiently used for arterial tissue motion estimation. Systematic application of this sophisticated form of the algorithm in additional samples of real data, including different image areas, would provide new knowledge about the mechanical deformations of the arterial wall during the cardiac cycle.

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