New Matching Scheme for Panorama Image : A Simulation Study

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Abstract

This paper presents a new matching scheme for creating a single panoramic image from a sequence of partially overlapping images of the same object or scene. This matching scheme is based directly on the searching algorithm, using a multiscale approach to the Hooke-Jeeves algorithm. Matching scheme evaluation was performed using simulated pattern images. The proposed matching scheme reveals good results and could be effectively applied to real ultrasound applications.

Key words : ultrasound panoramic image, image matching, hooke-jeeves algorithm, multiscale optimization

I. INTRODUCTION

Compared with other methods, such as computed tomography (CT) and magnetic resonance imaging (MRI), sonographic transducers are small and mobile. They can be used in every position and for every view, which allows application to any part of the body. However, the field of view, especially with high-resolution linear arrays, is small and usually excludes identification landmarks. Consequently, sonography may have some limitations in comparison with CT and MRI.

The developed panoramic imaging facilitates possible extended field-of-view with no loss in resolution by the manual movement of a real-time ultrasonic probe in the direction of the transducer array[1]. This imaging-processing technology estimates translation and rotation of the probe by comparing successive images during probe movement. No probe position-sensing mechanism is necessary. The images are transformed geometrically according to estimated probe motion and entered into the panoramic image buffer and combined with previous images to produce a panoramic image. Extended field-of-view images enable the acquisition and recording of a panoramic image and offer new possibilities for viewing topographic anatomic structures. Larger organs or pathologic structures can be displayed in one image together with their surroundings. The generation of panoramic images can be described as follows: given a sequence of partially overlapping images of the same object or scene, one tries to rearrange the images in such way that they form a compound panoramic image. This procedure can be split into two steps. In the first step, imaging matching is done to search for the displacement between two successive images. In the second step, the result is visualized by an appropriate combination of joint image information.

The imaging matching that is also referred to registration in connection with ultrasound image can be introduced into some kind of method [2,3], such as the feature based method [4,5], which compute the displacement of a small number of characteristic features, and intensity based method, which are based on the optimization of some similarity measure. The image registration technique for probe motion estimation was such that in two successive image frames, the previous frame was treated as a reference image and the current frame was divided into a gird of nonoverlapping blocks. Each image block in the current frame was matched with the previous frame to obtain a local motion vector. This searching process was applied to all image blocks in the current frame. A complete local motion vector map was obtained and the overall probe translation and rotation was found by calculating these local vectors [1]. But the evaluation of the overall (global) motion averaging these local vectors in curve type probes created a slight problem in deriving the displacement of successive images from the near field to the far field. In the curved type case, the usage of the computing of local motion vector at several positions does not represent the accurate displacement of probe motion in that the variation of local motion vectors caused by the lack of anatomical structure, or

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the low signal-to-noise (SNR) for each local geometry, has influence on the estimation of a global vector. The new matching scheme using the direct searching method could help solve the problem at the expense of excess computation time. So the direct search method is introduced, based on the Hooke-Jeeve algorithm [6] with multiscale optimization reducing computation time.

II. MATERALS AND METHODS

A. Ultrasound Panorama Imaging

A compound panorama image was basically produced by frame correlation that compares a part of the image in the present frame to the same part of the image in the previous frame. Image features within the area that overlap between one frame and the next frame are very similar. The probe motion can be found by matching similar image features in successive frames and visualizing the result using an appropriate combination of joint image information.

B. Image Matching

Let $u, v: f \subset R^n \rightarrow R$ be two intensities that are defined on the spatial domain R^n. Image matching finds transformation as $\tau: R^n \rightarrow R^n$. This matches the two images, i.e.,

$$u(\tau(x)) = v(x) \tag{1}$$

In reality, a solution (1) may not exist, due to noise and different acquisition conditions. Therefore, instead of looking for a solution in (1), the similarity measure between $u(\tau)$ and v is aimed to be minimized in a suitable class of transformation τ.

The application of image matching considered in this paper is the generation of panoramic images i.e., different views of a single static object have to be confounded. In this setting it makes sense to restrict the admissible mappings to the set of isometric affine transformations, which are compositions of a rotation and translation, i.e.,

$$\{\tau = \tau(\varphi, b) R^n \rightarrow R^n,\ x \rightarrow R(\varphi)x + b\}$$

This in particular means that all admissible mappings τ can be parameterized by the tuple (φ, b). Here $b \in R^n$ and, if 2D images are considered, with Eulerian angles $\varphi \in (-\pi, \pi)^t$, which denote the rotation angles around the x_1, x_2 axis. This setting in particular means that all considered transformations are due to the motion of the acquisition system. Ultrasound data is given on a finite domain $f \subset R^n$. Thus, after transformation the displayed image $u(\tau)$ is defined on the set $\tau^{-1}(f)$, which, in general, is different from f. Thus the similarity of two images u and v can be measured using the relative L^2-error functional

$$\varepsilon(\tau) := |f(\tau)|^{-1} \| u(\tau) - v \|^2_{L(f(\tau))}.$$

In the domain of overlap of the images u and v, i.e.,

$$f(\tau) := \tau^{-1}(f) \cap f.$$

If both images contain the entire object surrounded by an identical background (e.g., horizontal CT slices), then the dependency of the functional ε from the overlapping domain $f(\tau)$ can be eliminated by extending data sets accordingly. Matching problems of this kind are tackled by solving the Euler equation[7].

In practical applications image data is usually given in terms of samples on a rectangular grid, the so-called pixels. The discretized version ε of the functional ε reads as

$$\varepsilon(\tau) := |f(\tau)|^{-1} \sum_{x \in f_z(\tau)} (u(\tau(x)) - v(x))^2$$

C. Multiscale Processing

For two data sets u and v, a series of approximations is computed, in this case $M = 4$

$$u_m := P_m u,\ v_m := P_m v,\ (m = 0, \ldots\ldots M)$$

of decreasing resolution m; here P_m denotes the projection onto the space V_m, where $\{V_m\}$ is multiresolution analysis generated by the scaling function. $P_m u$ can be calculated by the fast wavelet transform (Mallat transform)[8]. The functional ε can be depicted as $\varepsilon(\tau) := \varepsilon_{u_m, V_m}(\tau)$ at the scale parameter m.

This approach has the significant advantage that the computational effort for evaluating ε_{u_m, V_m} is significantly smaller than that compared to the effort for evaluating ε, since the projected data sets u_m, v_m are significantly smaller (by a factor of 4^m in 2D at level m).

D. The Hook-Jeeves Algorithm

This algorithm shows that the objective (image matching) is evaluated on a stencil referenced by the searching area and the function values used to compute the search direction. The algorithm begins with base points x and pattern size h, which is like the scale factor. In the phase of the algorithm, called the exploratory move in [6], the function is sampled at successive perturbations of base point in the search direction $\{v_j\}$, where v_j is the jth column of direction matrix V.

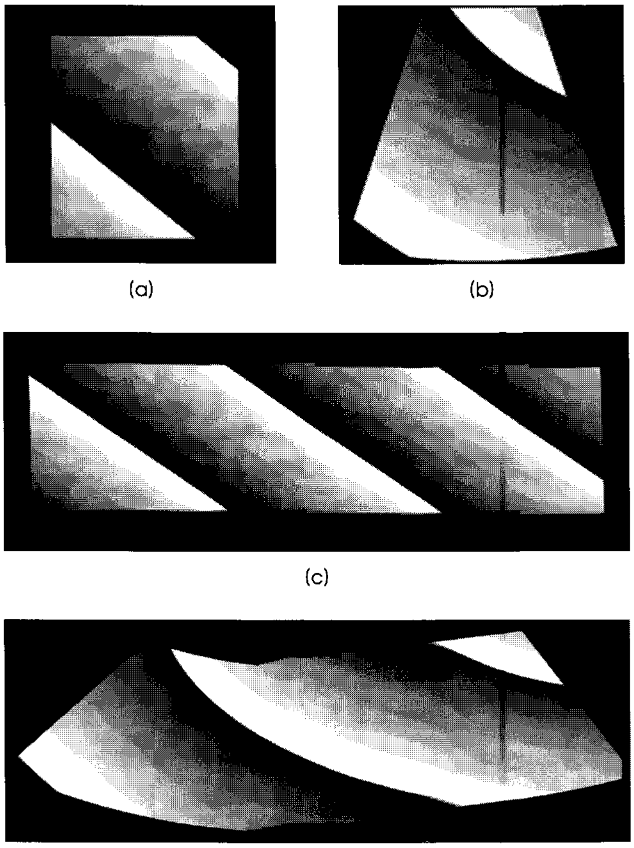
Table 1. The number of iterations, CPU-time, and relative error according to each scale.

	m =0	m =1	m =2	m =3	m =4
iterations	4.21±0.6	9.33±1.3	13.19±2.7	21.8±4.2	42.18±8.7
CPU–time (second)	2.76	0.73	0.19	0.046	0.0051
Relative error (%)	0.13±0.07	0.85±0.32	1.4±0.62	9.2±2.82	36.2±6.83

Table 2. The CPU-time, and relative error on the condition of two simulated pattern series for the comparison of performance between the proposed method (A) and the method using local vectors (B).

	Linear type pattern		Curved type pattern	
Method	A	B	A	B
CPU–time (second)	0.19	0.04	0.21	0.06
Relative error (%)	1.4±0.62	1.5±0.29	1.6±0.72	3.9±1.54

The current best value $f_{cb} = f(x_{cb})$ and best point x_{cb} are recorded and returned. x_{cb} is initialized to x. The sampling is managed by first evaluating f at $x_{cb} + v_j$ and only testing $x_{cb} - v_j$ if $f(x_{cb} + v_j) \geq f(x_{cb})$. The exploratory phase will either produce a new base point or fail (meaning that $x_{cb} \approx x$). Note that this phase depends on the ordering of the coordinates of x. Applying a permutation to x could change the output of the exploration. If the exploration phase has succeeded, the search direction is $d^{HJ} = x_{cb} - x$ and the new base point is x_{cb}. The subtle part of the algorithm begins here. Rather than center the next exploration at x_{cb}, which would use some of the same points that were examined in the previous exploration, the Hooke-Jeeves pattern move step is aggressive and tries to move further. The algorithm centers the



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

Fig. 1. (a) Simulated rectangle pattern image, (b) Simulated curved type pattern image, (c) Panorama image generated from 28 simulated pattern series images at rectangle type, and (d) Panorama image generated from 28 simulated at curved type pattern series.

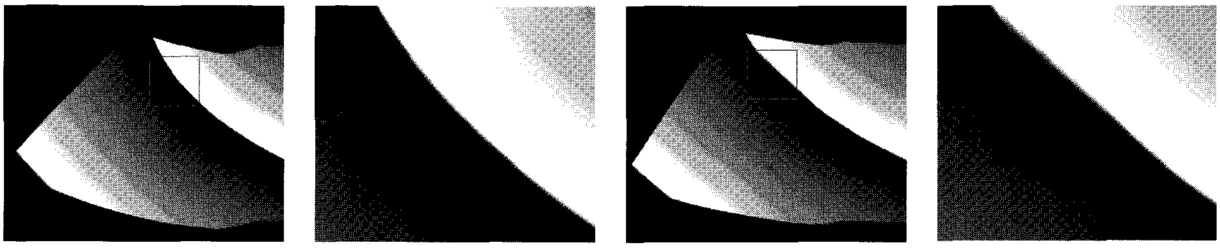


Fig. 2. In the curved type pattern panorama image, the accuracy of the proposed method for estimated track pattern was better than that of the conventional method using local vectors as shown Table 2. (a) The proposed method in the simulated curved type pattern panorama image, (b) The pattern of zoom-in the interesting area at (a), (c) The conventional method using local vectors in the simulated curved type pattern panorama image, and (d) The pattern of zoom-in the interesting area at (c).

next exploration move at $x_c = x + 2d^{HJ} = x_{cb} + d^{HJ}$. If this second exploratory move fails to improve upon $f(x_{cb})$, then an exploratory move with x_{cb} at the center is tried. If that fails, h is reduced, x is set to x_{cb}, and the process is started over. Note that when h has just been set, the base point and the center of the stencil for the exploratory moves are the same, but afterward they are not. If, after the first exploratory move, $x_{cb} = x$ (i.e., as x is the best point in the pattern), then x is left unchanged, and h is reduced. Therefore, whenever h is reduced, the stencil centered at x has x itself as the best point. This is exactly the situation that leads to a convergence result.

See Appendix for concrete implementation of this algorithm. There are other considerations, such as the budget (the number of evaluation), and tolerance for function evaluations, that should trigger a return from the exploratory phase in implementation. In the experiment the budget and tolerance ε to 300 and 1e-8 are used respectively. This algorithm could be speed up, by keeping the most recent iterations in memory to guard against reevaluation, because some points may be sampled more than once.

III. RESULTS

Some numerical results obtained with the proposed image-matching algorithm are present using the Hook-Jeeves algorithm with mutliscale optimization (Table 1 and 2). In the experiment, the data set is displayed using isometric affine transformation with Eulerian angles of $\varphi = (5, 5)^t$ degrees and translation vector $b = (310, 320)^t$ pixels, and matched with simulated pattern data. Table 1 lists the number of iteration, CPU-time, and relative error according to each scale. The relative error was calculated for the measurement as (estimated moving distance - the distance of moving at the scrolled pattern/the distance of moving at the scrolled pattern). As can be seen in Table 1, this algorithm succeeds in approximating the optimal displacement within $\pm 2.5\%$ the relative error of the measured distance on the condition of, $m \leq 2$. The optimal scale can be decided as $m = 2$, on the performance of the relative error over the CPU-time. Fig. 1 shows a panorama of simulated patterns from pattern series at a scrolling rate of 28Hz. Computing the displacement between consecutive images takes about 0.19 CPU seconds on a 1.5Ghz Pentium M. Thus, the algorithm is capable of generating panorama ultrasound with a frame rate of approximately 5 ~ 10 Hz images per second. Table 2 shows the performance of the proposed matching scheme over the scheme using local motion vector. Here, the proposed matching scheme suffers from computation time, but this has better results for relative error in curved type (Fig. 2). The compound panorama was generated by bilinear interpolation and averaging the joint image information.

IV. DISCUSSION

A new matching scheme has been introduced for creating a single panoramic image from a sequence of partially overlapping ultrasound images. This matching scheme is based directly on the searching algorithm, using multiscale approach to the Hooke-Jeeves algorithm. Compared with matching method that estimates the over-all motion by computing each displacment of several local blocks, the proposed matching scheme gives superior result that compensates for the excess compoutational requirements in curved type. Thus, the proposed matching scheme can be helpful especially in situation where the anatomical structure is lack or SNR for each local geometry is low. The burden of computation time could be reduced by mutiscale appraching, in the simulation case, $m = 2$. Herewith, the improvement of CPU power will be more accurate and more robust than the motion estimation with the finer scale.

In the simulatiuon study, the consideration of any motion artifacts are not taken into account, but it is important to point out that panorma ultrasound imaging is based on the assumption that two sucessive frames are similar. Patient motion including respiratory movement and arterial pulsation that can decrease the image similiarity could cause performance problems with panorma ultraound imaging.

Future work will include experiments to evaluate further the robustness of the new appraching scheme with real ultrasound images. Additionally, 3D panorama ultrasound images will be extended to examine the performance of the new apprach method under a more realistic environment.

V. APPENDX

This method begins with an exploratory phase, which uses a base point x_b, base function value $f_b = f(x_b)$, and stencil center x_c. Note that in the algorithm $x_b = x_c$ for the first exploration and $x_c = x_b + d^{HJ}$ thereafter. Algorithm *hjexplore* takes a base point and scale and returns a direction and the value at the trial point $x+d$. $V=I$ is the matrix of coordinate directions, but any nonsingular matrix of search directions could be used. The status flag s_f is used to signal failure and trigger a shrink step.

Hjexplore(x_b, x_c, f, h_k, s_f)

1.$f_b = f(x_b); d=0; s_f=0; x_{cb}=x_b; f_{cb}=f(x_b); x_t = x_c$

2. $p = x_t + h_k v$, *if* $f(p) \geq f_b$ *then* $p = x_t - h_k v$;
   if $f(p) < f_b$ *then* $x_t = x_{cb} = p$; $f_b = f(x_{cb})$

3. *if* $x_{cb} \neq x_b$; $s_f = 1$; $x_b = x_{cb}$

The exploration is coupled to the pattern move to complete the algorithm for a single value of the scale. The inputs for algorithm hjserach are initial iterate x, objective function f, and scale h. On output, a point x is returned for which exploration has failed. The main procedure can be implemented in three steps.

hjserach(x, f, h_k)

1. $x_b = x$; $x_c = x$; $s_f = 1$
2. *Call hjexplore* (x, x_c, f, h_k, s_f)
3. While $s_f = 1$
   (a) $d = x - x_b$; $x_b = x$; $x_c = x + d$
   (b) Call *hjexplore* (x_b, x_c, f, h_k, s_f);
   if $s_f = 0$; $x_c = x$; Call *hjexplore* (x_b, x_c, f, h_k, s_f)

Step 3b requires care in implementation. If $s_f = 0$ on exit from the first call to *hjexplore*, one should only test f at those points on the stencil centered at x that have not been evaluated before. The Hook-Jeeves algorithm simply calls hjsearch repeatedly as h varies over a sequence $\{h_k\}$ of scales.

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