HYBRID OPTIMIZATION FOR ULTRASOUND AND MULTIMODAL IMAGE REGISTRATION

Mark P. Wachowiak, Renata Smolíková, and Adel S. Elmaghraby
Computer Science and Engineering, University of Louisville, Louisville, Kentucky USA

Abstract-**Optimization of similarity metrics is an important component of many biomedical image registration applications that greatly affects registration outcome. Selection of an optimization approach is dependent on the modalities being registered, the characteristics of the similarity function, and available computational resources. This paper addresses optimization approaches for 2D and 3D rigid body intra- and multimodal ultrasound registration. Stochastic and direct techniques are compared for mutual information and correlation ratio functions. A new direct/stochastic hybrid approach based on the tabu search is also proposed. Visualization and experimental results suggest the usefulness of such an approach. Results also show that the tabu hybrid technique compares favorably with traditional techniques, based on accuracy and number of function evaluations.**
***Keywords* - Image registration, ultrasound, search, optimization**

I. INTRODUCTION

Rigid body registration of 2D-to-2D MRI and CT biomedical images can be performed efficiently and accurately with well-established methods. However, 2D-to-3D and 3D-to-3D ultrasound (US) registration and subsequent fusion is a relatively new and challenging field, as speckle and low signal-to-noise ratio (SNR) make both human and computerized analysis difficult. There are generally three major components in image registration: (1) definition of a search space; (2) selection of a similarity measure; and (3) choice of an optimization approach [1,2]. Rigid body, affine, and elastic transformations are common in US registration. Mutual information (MI) and its variants [3-5] and the correlation ratio (CR) [6,7] have been proposed as robust similarity metrics for biomedical images, including US B-scans. This paper compares optimization methods for US registration using these two functions. The global maximum of similarity functions is generally considered to correspond to correct registration. This assumption is made in the current study, although it is not true in all cases, and some degree of human intervention is often required.

An adaptation of the continuous tabu search, combined with a direct approach, is presented as an accurate hybrid method for global optimization. The search domain is the space of rigid body transformations.

II. STOCHASTIC AND DIRECT SEARCH TECHNIQUES

Many direct (deterministic) approaches are currently used to optimize registration functionals, including those requiring only function evaluations (e.g. Nelder-Mead simplex) and those requiring derivative information, such as gradient descent, and Powell-type algorithms [2,3,5-7]. They are primarily local optimizers that often rapidly converge to an exact local optimum. However, especially for multiextremal functions, they tend to converge to the first identified local optima [8]. Continuity, differentiability, and convexity constraints are placed on the functionals. Stochastic global optimizers and stochastic-direct hybrids are often used to address these problems. These methods, which include genetic algorithms, simulated annealing, and clustering methods [9], can converge to global optima of complicated functions. They are robust, can quickly locate global optima, and usually do not “get trapped” in local extrema. However, because they are probabilistic, they sometimes do not locate the true global optimum, but only nearby solutions. The search may be time-expensive because of the combinatorial nature of sampling multidimensional space. Nonetheless, stochastic methods have proven effective for biomedical image registration, where genetic algorithms [10,11] and simulated annealing [10,12] have been used. Another global optimizer, the tabu search (TS), has been successfully used to solve many discrete optimization problems [13]. The current work presents an adaptation of the continuous tabu search in which a likely area for the global optimum is determined, and Powell’s direction set algorithm (PDS) with Brent’s line optimization [14] identifies the global optimum. Continuous tabu search techniques have recently appeared in the literature [15-17], but, thus far, applications to image registration have not been reported. Results are compared with those of another powerful technique, adaptive simulated annealing (ASA) [18], also using PDS to find the global optimum.

III. HYBRID CONTINUOUS TABU SEARCH

The TS is an iterative combinatorial technique. Application-specific heuristics are implemented on top of a basic structure. One underlying concept of any TS approach is that “cycles” are avoided while searching for a potential new optimum value by placing previously visited solutions into a finite length first-in-first-out “tabu list”. The current study adapts the approach in [16] to image registration. The proposed tabu hybrid (TH) consists of the following stages:

1. The search space is discretized [15]. Discretization provides effective neighborhood generation and facilitates tabu list and promising list searches (see below). In the current study, each parameter is partitioned into 100 points.

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25OCT2001	N/A	-

Title and Subtitle Hybrid Optimization for Ultrasound and Multimodal Image Registration	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Computer Science and Engineering, University of Louisville, Louisville, Kentucky	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

2. In the diversification stage, k neighbors of the current n-D point $\mathbf{s}$ are generated at each iteration by randomly selecting $j \le n$ dimensions of $\mathbf{s}$, and perturbing the variables in those dimensions. A neighborhood $B(\mathbf{s};\, r)$ is a set of nested "balls" centered on the current solution $\mathbf{s}$, with maximum radius r. It contains all points $\mathbf{s}'$ such that $\|\mathbf{s}' - \mathbf{s}^k\| \le r$, where $\|\cdot\|$ denotes a Euclidean norm. The set of balls centered on $\mathbf{s}$ with radius $h_0, h_1, \ldots, h_k$ is defined as [16]:

$$B_i(\mathbf{s};\, h_{i-1}, h_i) = \{\mathbf{s}' \mid h_{i-1} \le \|\mathbf{s}' - \mathbf{s}^k\| \le h_i\},\ i = 1,\ldots.k. \quad (1)$$

3. The neighbor with the best function value is selected as the new starting point if it is not within a neighborhood of a point on the tabu list. If all k neighbors degrade the functional more than a threshold, the current point is added to a promising list. The current point is always added to the tabu list. The process continues until a specified number of iterations without a new promising area are reached (20 in this study), or until a maximum number of iterations is performed (here, 100).
4. Also in the diversification stage, the search is restarted from a randomly chosen reflection of the original (initial) solution if function evaluations do not improve beyond the best value obtained, after a fixed number of iterations (20 in this study).
5. An "affine shaker" algorithm [15] is applied to locate the best point in each promising area. The shape of the promising area is adapted during the search to include areas of the search space that may have been missed during diversification.
6. A direct local optimizer performs an intensified search on the best point from step (5). Powell's algorithm was chosen because of its accuracy and speed.

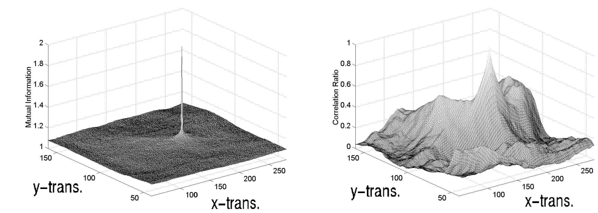
The tabu search is not a "brute force" approach. At each iteration, the point with the lowest function value in the neighborhood is selected as the new point; it need not be better than the current point. In this way, promising regions where the global optimum may exist are identified, and local optima are escaped. The tabu list prevents cyclic searching, and points on the promising list are explored more intensively with the affine shaker and PDS. In some implementations, a promising list is not used [17]. Search parameters can also be tuned to increase performance.

IV. Registration Metrics

Normalized mutual information is given as [4]:

$$I(A_T, B_T) = \frac{H(A_T) + H(B_T)}{H(A_T, B_T)}, \quad (2)$$

where $H(A_T)$ denotes the entropy of estimate of image A under transformation T, and $H(A_T,\, B_T)$ denotes the joint entropy estimate of images A_T and B_T. MI is commutative.



(a) (b)

Fig. 1. Similarity metrics for (a) MI and (b) CR for registration with a high SNR shoulder B-scan.

This metric is invariant under the size of image-to-volume overlap [4], and assumes values from 0 to 2.

The correlation ratio, $\eta(A_T|B_T)$, is given as [7]:

$$\eta(A_T \mid B_T) = \frac{\mathrm{Var}\left[\mathrm{E}(A_T \mid B_T)\right]}{\mathrm{Var}(A_T)}. \quad (3)$$

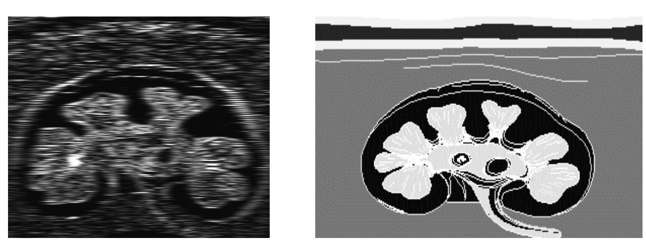
This metric, assuming values from 0 to 1, can also be generalized for gray level mapping and for weighting interpolation values [6]. In general, $\eta(A_T|B_T) \neq \eta(B_T|A_T)$.

In Fig. 1, plots of MI and CR as functions of translation are shown for a high SNR B-scan of a shoulder. The strong differences in the functions suggest that the metrics may produce different registration results, and should be considered in selecting an optimization method.

V. Experiments

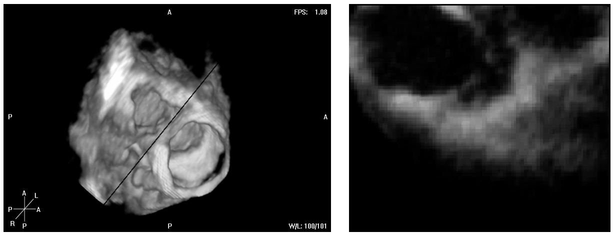
To empirically assess the differences in the functionals for B-scan registration, MI and CR surfaces were generated as functions of translation and rotation (see [3] and [7] for a theoretical discussion). 50×50-pixel regions of reference images were registered with the reference. This idealized situation provides an indication of the characteristics of US similarity metrics. Functionals were generated for: (1) A region of a low SNR kidney phantom (simulated with Field II Matlab software [19]) registered to the original 896×512 image, shown in Fig. 2(a); (2) A kidney phantom region registered to simulated MRI, shown in Fig. 2(b) (multimodal registration); and (3) The same as (2), but using biorthogonal wavelet filters to smooth the B-scan region.

In 2D-2D registration experiments, the low SNR kidney phantom region was registered to the simulated MRI image.



(a) (b)

Fig. 2. (a) Kidney US phantom. (b) Simulated MRI.



(a) (b)

Fig. 3. (a) 3DUS heart volume. (b) Extracted slice.

2D-3D registration was performed on US heart images. From a 148×160×141-voxel volume, shown in Fig. 3(a), a 64×64-pixel slice (Fig. 3(b)) was extracted at an arbitrary orientation and registered with the volume. This provides a "gold standard", as the correct registration is known, and exact values are sought. Five trials were performed with 10 initial points in 3D for 2D-2D registration (translation along the *x* and *y*-axes, rotation about the *z*-axis) and 6D for 2D-3D registration (translation along the *x*, *y*, and *z*-axes, rotation about the *x*, *y*, and *z*-axes), at varying distances from the true point. The optimization algorithms were PDS, the tabu hybrid, and adaptive simulated annealing with PDS.

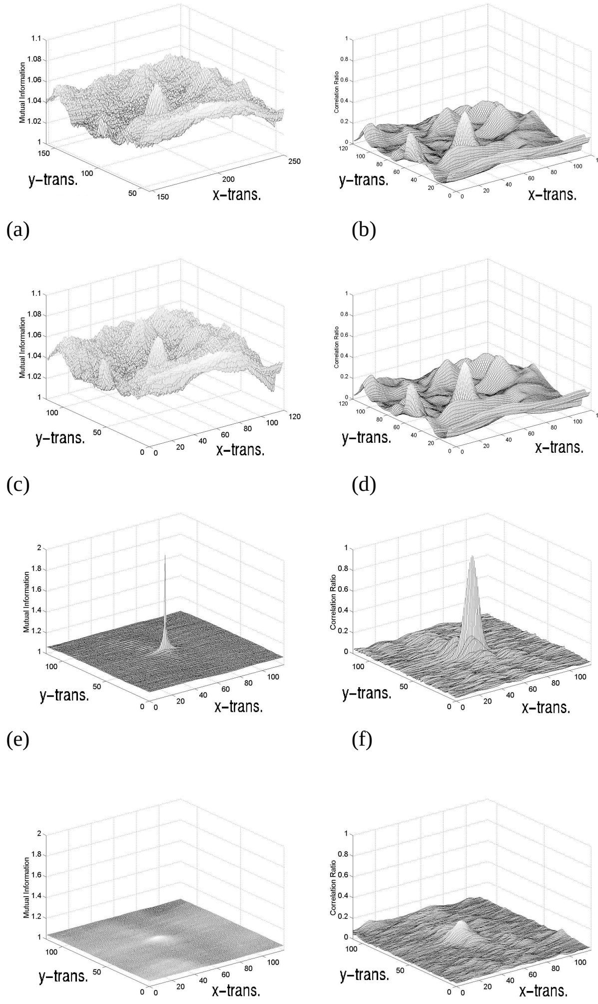
For all experiments, a registration is classified as "correct" if the Euclidean distance of the final translation from the true reference translation is less than 0.25 pixels and if the Euclidean distance of the rotation angles is less than 0.25°. Optimization was performed as minimization of the negative of the similarity metric.

VI. Results and Discussion

The MI and CR surfaces are shown in Figs. 4(a) – 4(h). MI is characterized by sharp narrow optima. The CR functions are smoother, but also contain many local extrema. Filtering the B-scan slightly increased the CR maximum, but had little effect on the maximum MI value.

Percentages of correct registrations for 2D-2D and 2D-3D are shown respectively in Tables 1 and 2. Registration accuracy clearly decreases with increasing distance of the initial point from the true point. Registration performed using only PDS on MI was very accurate for initial points close to the reference, but less accurate for the CR metric. This result is expected, as CR functions have more local extrema into which direct optimization can get trapped.

The tabu hybrid had a higher percentage of correct registrations for all experiments than PDS when the initial point is far from the reference, although these values are still relatively low. For 2D-3D registration, the tabu hybrid with CR produced the best overall results, although PDS was better for close initial points. ASA with CR did not have a good average accuracy, but it performed better than PDS and the tabu hybrid for distant initial points. ASA with MI was the worse performer. The narrow optimum in the MI functional is a plausible explanation. However, the tabu hybrid with MI was much better than ASA, indicating that the former more thoroughly samples the search space.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 4. Similarity metrics for: (a-b) MI/CR for low SNR phantom and simulated MRI. (c-d) MI/CR for low SNR phantom smoothed with a wavelet filter. (e-f) MI/CR for phantom-to-phantom registration at 0º rotation. (g-h) MI/CR for phantom-to-phantom registration at 12º rotation.

It is observed that MI outperformed CR for 2D-2D registration, but CR was the top performer for 2D-3D experiments. This result is expected, as the heart volume has a relatively high SNR with low speckle, so that the functionals are consistent with those in Figs. 1(a) and 1(b). For CR, there is a prominent and broad optimum with few local extrema, while the MI optimum is extremely narrow. In the multimodal 2D-2D experiments, local optima are present in both functionals, but those of CR are smoother and broader, and can be mistaken for promising regions.

The number of cost function (MI/CR) evaluations was also analyzed, and the mean values are shown in Table 3. As PDS examines only one region, it gives the fewest evaluations. Overall, successful registrations with the tabu hybrid method required fewer evaluations than ASA. Although the numbers of evaluations are relatively high, parallelization can greatly improve the efficiency of the tabu hybrid, which is inherently parallel.

TABLE I
CORRECT 2D-2D REGISTRATIONS FOR OPTIMIZATION TECHNIQUES. DISTANCES ARE MEASURED IN PIXELS, ROTATIONS IN RADIANS (5 TRIALS).

Dist. (trans)	Dist. (rot)	Percentage of Correct Registrations					
		PDS (MI)	PDS (CR)	TH (MI)	TH (CR)	ASA (MI)	ASA (CR)
4.47	0.30	100	100	100	100	40	40
7.00	0.00	100	100	100	100	20	40
13.00	0.20	100	0	100	100	40	80
14.14	1.10	100	0	80	100	60	20
14.87	0.20	100	0	60	40	40	60
15.13	0.40	0	0	60	60	0	60
17.00	2.10	0	0	40	20	40	40
35.34	0.40	0	0	60	0	40	40
42.04	0.20	0	0	40	20	40	80
61.85	2.10	0	0	0	0	60	60

TABLE II
CORRECT 2D-3D REGISTRATIONS FOR OPTIMIZATION TECHNIQUES. TRANSLATION DISTANCES ARE MEASURED IN PIXELS, ROTATIONS IN RADIANS (5 TRIALS).

Dist. (trans)	Dist. (rot)	Percentage of Correct Registrations					
		PDS (MI)	PDS (CR)	TH (MI)	TH (CR)	ASA (MI)	ASA (CR)
1.41	0.17	100	100	100	100	0	40
3.32	0.24	0	100	80	100	0	60
3.46	0.07	100	100	100	100	0	40
4.12	0.19	100	100	60	80	0	20
5.83	0.21	0	100	60	80	0	20
8.83	1.18	0	0	0	80	0	40
11.79	0.39	0	0	60	20	0	20
18.25	0.29	0	0	20	80	20	40
29.88	0.40	0	0	40	0	0	40
60.61	1.75	0	0	0	20	0	20

TABLE III
MEAN NUMBER OF COST FUNCTION EVALUATIONS ($\times$1000) FOR SUCCESSFUL REGISTRATIONS.

Type of Reg.	PDS (MI)	PDS (CR)	TH (MI)	TH (CR)	ASA (MI)	ASA (CR)
2D-2D	0.316	0.472	1.296	1.075	3.261	3.362
2D-3D	0.777	0.724	2.405	2.606	6.759	7.087

VII. CONCLUSION

This study demonstrates that US registration accuracy is sensitive to similarity metric, optimization method, and initial point. The experiments show that the tabu hybrid optimizer can potentially be used in intra- and multimodal US registration, and that stochastic methods, including ASA, combined with direct approaches, can improve registration accuracy. User interaction in selecting acceptable starting points is also shown to be important. Performance is expected to improve when these methods are integrated with multiresolution techniques, with feature extraction, or when used with combined spatial or gradient information [5]. The inherent parallellism of the tabu hybrid can be exploited to run on multicomputer systems.

Although existing direct and stochastic methods are effective in many situations, the continuous tabu search hybrid, along with other stochastic and hybrid techniques, can be used as a robust optimizer for ultrasound image registration, and further work on these techniques is warranted, especially for multimodal registration.

ACKNOWLEDGMENTS

The authors wish to thank TomTec, Inc., Germany, for supplying the ultrasound heart volume, and Dr. Craig Roberts of the University of Louisville Department of Orthopaedic Surgery for supplying the shoulder scans.

REFERENCES

[1] L. Brown, “A Survey of Image Registration Techniques,” *ACM Comp. Surv*., vol. 24, 1992, pp. 325-376.
[2] J.B.A. Maintz and M.A. Viergever, M.A, “A Survey of Medical Image Registration,” *Med. Image Analysis*, vol. 2, 1998, pp. 1-37.
[3] W.M. Wells III, P. Viola, H. Atsumi, S, Nakajima, and R. Kikinis, “Multi-Modal Volume Registration By Maximization Of Mutual Information” *Med. Image Analysis*, vol. 1, 1996, pp. 35-51.
[4] C. Studholme, D.L.G. Hill, and D.J. Hawkes, “An Overlap Invariant Entropy Measure of 3D Medical Image Alignment,” *Patt. Recog.*, vol. 32, 1999, pp. 71-86.
[5] J.P.W. Pluim, J.B.A. Maintz, and M.A. Viergever, “Image Registration by Maximization of Combined Mutual Information and Gradient Information,” *IEEE Trans. Med. Imag*., vol. 19, 2000, pp. 809-814.
[6] A. Roche, X. Pennec, M. Rudolph, D. P. Auer, G. Malandain, S. Ourselin, L. M. Auer, and N. Ayache, “Generalized Correlation Ratio for Rigid Registration of 3D Ultrasound with MR Images,” *Lecture Notes in Computer Science (Proc. Miccai'2000)*, vol. 1935, S. Delp, A.M. DiGioia, and B. Jaramaz, Eds. Springer Verlag, 2000, pp. 567-577.
[7] A. Roche, G. Malandain, X. Pennec, and N. Ayache, “The Correlation Ratio as a New Similarity Measure for Multimodal Image Registration,” *Lecture Notes in Computer Science (Proc. MICCAI'98)*, vol. 1496, Springer Verlag, 1998, pp. 1115-1124.
[8] P. Siarry, G. Berthiau, F. Durbin, and J. Hauusy: Enhanced Simulated Annealing for Globally Minimizing Functions of Many Continuous Variables. *ACM Trans. Math. Software*, vol. 23, 1997, pp. 209-228.
[9] L. Ozdamar, and M. Demirhan: Experiments With New Stochastic Global Optimization Search Techniques. *Comp. and Oper. Res*., vol. 27, 2000, pp. 841-865.
[10] G.K. Matsopoulos, N.A. Mouravliansky, K.L. Delibasis, and S.N. Konstantina, “Automatic Retinal Image Registration Scheme Using Global Optimization Techniques,” *IEEE Trans. Info. Tech. in Biomed*., vol. 3, 1999, pp. 47-60.
[11] N. Ritter, R. Owens, J. Cooper, R.H. Eikelboom, and P.P. van Saarloos, “Registration Of Stereo And Temporal Images Of The Retina,” *IEEE Trans. Med. Imag*., vol. 18, 1999, pp. 404-418.
[12] J.-M. Rouet, J.-J. Jacq, and C. Roux, “Genetic Algorithms for a Robust 3-D MR-CT Registration,” *IEEE Trans. Info. Tech. in Biomed*., vol. 4, 2000, pp. 126-136.
[13] F. Glover and M. Laguna, *Tabu Search*, Boston:Kluwer Academic Publishers, 1997.
[14] W. Press, S.A. Teukolsky, W.T. Vetterling, and B.P. Flannery, *Numerical Recipes in C*, Cambridge:Cambridge University Press, 1992.
[15] R. Battiti and G. Tecchiolli, “The Continuous Reactive Tabu Search: Blending Combinatorial Optimization And Stochastic Search For Global Optimization,” *Ann. of Op. Res*., vol. 63, 1996, pp. 153-188.
[16] R. Chelouah and P. Siarry, “Tabu Search Applied to Global Optimization,” *Euro. J. Of Op. Res*., vol. 123, 2000, pp. 256-270.
[17] P. Siarry and G. Berthiau, “Fitting of Tabu Search To Optimize Functions of Continuous Variables,” *Int. J. for Num. Methods in Eng*., vol. 40, 1997, pp. 2449-2457.
[18] Ingber, L., Rosen, B.: Genetic Algorithms and Very Fast Simulated Reannealing: A Comparison. *Math. and Comp. Model*, vol. 16,1992, pp. 87-100.
[19] J.A. Jenson, “Field: A Program for Simulating Ultrasound Systems,” *Med. and Biol. Eng. and Comput.* vol. 34, 1996, pp. 351-353.