Application of Image Registration Techniques to Medical CT and MR Images

تطبيق تقنيات تسجيل الصور على الصور الطبية (صور الأشعة المقطعية وصور الرنين المغناطيسى)

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الملخص: لقد أصبح تسجيل الصور واحدا من أكثر التقنيات إستخداما فى مجال الرؤية بالحاسب حيث تتضمن تطبيقاته التدفق البصرى وتحليل الحركة والتتبع وإكتشاف الوجه وتخزين الصور الطبية. وفى هذا البحث تم تنفيذ ثلاث تقنيات مختلفة لتسجيل الصور وتطبيقها على صور الأشعة المقطعية وصور الرنين المغناطيسى. ويعتمد أول هذه التقنيات على الإرتباط التقاطعى. ويعتمد الثانى على إختيار نقاط تحكم من كل من الصورة المرجعية والصور المدخلة. أما ثالث هذه التقنيات فيعتمد على تعظيم المعلومات التبادلية بين الصورتين.

وقد تم حساب قابلية الصور للتسجيل لكل صورة لقياس مقدرتها على إعطاء تسجيل غير مبهم وذلك عن طريق إعطاء قيم إرتباط عظمى واضحة عند تسجيل الصورة مع صورة أخرى. بعد ذلك تم تقييم تقنيات التخزين الثلاثة ومقارنتها باستخدام نسبة الإشارة إلى الشوشرة العظمى الموزونة وكذلك بإستخدام معامل الإرتباط التقاطعى القياسى. وقد بين تطبيق التقنيات المختارة على كل من صور الأشعة المقطعية وصور الرنين المغناطيسى أن التسجيل المعتمد على تعظيم المعلومات التبادلية أعطى أفضل النتائج ويمكن إستخدامه بكفاءة لتسجيل صور الأشعة المقطعية وصور الرنين المغناطيسى.

Abstract: Image registration has become one of the most widely used techniques in computer vision. Its applications include optical flow, motion analysis, tracking, face detection, and biomedical image registration. In the present work, three different techniques of image registration were implemented and applied to both Computed Tomography (CT) and Magnetic Resonance (MR) images. The first technique is based on Cross Correlation (CC). The second approach depends on Control Points' Selection (CPS) from both the reference and the input images. The last technique is based on Maximization of Mutual Information (MMI) between the two images. The registrability is calculated for each image to measure its ability to provide unambiguous registration, by providing clear correlation peaks when registered with another subimage. Then, the three registration techniques were evaluated and compared using both the Weighted Peak Signal to Noise Ratio (WPSNR) and the Normalized Cross Correlation Coefficient (NCCC). The application of the selected techniques to CT and MR images has shown that registration based on MMI has given the best results and can be used efficiently for alignment of CT and MR images.

Key Words: Image registration, mutual information, weighted peak signal to noise ratio, CT images, MR images, registrability.

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1 Introduction

Computed Tomography (CT) is a medical imaging method employing tomography where digital geometry processing is used to generate a 3D image of the internals of an object from a large series of 2D X-ray images taken around a single axis of rotation. The word "*tomography*" is derived from the Greek *tomos* (slice) and *graphia* (describing). During the test, the patient lies on a table that is hooked to the CT scanner, which is a large doughnut-shaped machine. The CT scanner sends X-ray pulses through the body area being studied. Each pulse lasts less than a second and takes a picture of a thin slice of the organ or area. One part of the scanning machine can tilt to take pictures from different positions. The pictures are saved on a computer [1].

Magnetic Resonance (MR) imaging is a radiology technique that uses magnetism, radio waves, and a computer to produce images of body structures. The MR scanner is a tube surrounded by a giant circular magnet. The patient is placed on a moveable bed that is inserted into the magnet. The magnet creates a strong magnetic field that aligns the protons of hydrogen atoms, which are then exposed to a beam of radio waves. This spins the various protons of the body, and they produce a faint signal that is detected by the receiver portion of the MR imaging scanner. The receiver information is processed by a computer, and an image is then produced [2].

It must be noted that a CT scanner uses ionizing radiation, X-rays, to acquire its images, making it a good tool for dense tissue (bone) exams. MR, on the other hand, uses radio frequency signals and a magnet to acquire its images. MR is best suited for soft (non-calcified) tissue exams.

It is common for patients to undergo multiple tomographic radiological imaging for the purpose of medical diagnosis. These images provide complementary information. However, it is difficult for doctors to fuse these images exactly due to the variations in patient orientation [3]. A common problem related with such systems is the misalignment in the acquired images due to the coordinate differences in the images. This misalignment is further complicated by camera and object movement that change camera geometry relative to the object, thus affecting object pose and view direction. Further, the images are acquired at different resolutions, at different times and often with significant tissue change [4]. Lastly, the sensors acquire fundamentally different tissue properties thus the measurements differ in their units. In systems that are not co-registered during image acquisition, the alignment of images is crucial and pivotal in the sensor fusion. Image registration is a precursor to sensor fusion and enables information extraction from multiple images [3].

The present study aims to selecting the best technique that aligns the float image (unregistered image) with the reference one. These techniques will be applied to CT and MR images. In addition, it is required to maximize the Weighted Peak Signal-to-Noise Ratio (WPSNR), and to minimize the Mean-Squared Error (MSE).

In Section 2, brief background about three image registration techniques that will be applied to CT and MR images is introduced. Section 3 presents the results of applying these techniques to real CT and MR images. The conclusions are presented in Section 4.

2 Image Registration Techniques

Image registration is one of the basic image processing operations in computer vision and remote sensing [5]. It can be considered as a computational method for determining point-by-point correspondence between two images of a scene. It may be used to fuse complementary information in the images or to estimate the geometric and/or intensity difference between the images [6].

The method involves determining a number of corresponding control points in the images. From correspondences, a transformation function can be determined to get correspondence between the remaining points in the images.

As an application, consider the problem of registering two CT images of brain taken from the same patient at different times. Alignment of the two images is useful for detecting, locating, and measuring pathological and other physical changes. In addition, registration of images that show anatomical structures such as CT and images that show functional and metabolic activity such as Positron Emission Tomography (PET), and MR has led to improved diagnosis, better surgical planning, more accurate radiation therapy, and other medical benefits [7].

A second application concerns radiotherapy treatment, where both CT and Magnetic Resonance (MR) can be employed. The former is needed to accurately compute the radiation dose, while the latter is usually better suited for delineation of tumor tissue. The use of different image types is known as multimodality registration [8]. Other application areas exist in mono-modality registration as treatment verification by comparing pre- and post-intervention images [7-8].

2.1 Registration based on CC

CC is the basic statistical approach to registration. It is often used for template matching or pattern recognition in which the location and orientation of a template or pattern is found in a picture. It gives a measure of the degree of similarity between an input image and a reference one. This method is useful only for images that are misaligned by translational motion. For a reference image *U*, and an input image *V*, with means $\bar{U}$ and $\bar{V}$ respectively, the 2-dimensional normalized CC function can be represented as:

$$K(i,j)=\frac{\sum_{x,y}[V(x,y)-\bar{V}][U(x-i,y-j)-\bar{U}]}{\left\{\sum_{x,y}[V(x,y)-\bar{V}]^2\sum_{x,y}[U(x-i,y-j)-\bar{U}]^2\right\}^{0.5}} \quad (1)$$

Where *x and y* are the pixel coordinates while *i and j* refer to the shift at which the CC coefficient is calculated. The resulting matrix K contains correlation coefficients with values between -1.0 and 1.0 [9].

To use CC for registration of two images, sub-regions are chosen manually from each image, then the normalized CC is calculated. The peak coordinates are determined, and then the total offset between the two images can be obtained.

2.2 Registration based on CPS

A transformation is a mapping of locations of points in one image to new locations in another. Transformations used to align two images may be global or local. A global transformation is given by a single equation that maps the entire image. Examples of such typical geometric transformations are the affine, projective, perspective, and polynomial. Local transformations map the image differently, depending on the spatial location [8].

The fundamental step in obtaining the best geometric transformation is to get control points from both the input image and the reference image. The control point pairs can be selected either automatically using a Matlab program or by the user on the monitor. Visual selection is a general and safe method, but it is time consuming and the location accuracy is not guaranteed. In order to obtain high accuracy, automatic selection techniques of control point pairs are adopted [10]. The number of selected control point pairs depends on the geometric transformation resulting from the misalignment model.

Table 1 summarizes the hierarchy of 2D coordinate transformations [11-13].

Table 1: The hierarchy of 2D transformations

Name	Degrees of freedom	The transformation preserves	Icon
Translation	2	Orientations	
Rigid	3	Lengths	
Similarity	4	Angles	
Affine	6	Parallelism	
Projective	8	Straight lines	

Based on the control point pairs, the spatial transformation model is fitted. It causes the input image to be matched to the reference one geometrically. After spatial transformation model is defined, refining the selection of control point pairs can enhance the registration accuracy [14]. The determination of the corresponding points from images acquired in different times is known as temporal registration. It can be considered as a problem of pattern reorganization.

2.3 Registration based on MMI

In some applications, particularly medical imaging, data from one type of sensor must be aligned with that from another. Classical registration methods, which were explained in the previous subsections, rely on an interpolation algorithm, which is needed to estimate the pixel intensities at non-grid positions, whenever the pixel grids of the images are not in exact alignment [15].

To minimize errors, it is desirable to use data-consistent interpolators, so that the pixel intensity at any grid position does not change after interpolation. As a result, errors are only introduced when interpolating at non-grid positions. However, this implies that the amount of interpolation errors will vary depending on the extent of grid alignment. The variation may lead to artifactual fluctuations in the match metric, which may affect registration accuracy. Therefore, for the purpose of registration, the effectiveness of an interpolator cannot be judged solely by the closeness of the interpolated image to the original image, but also by its effect on the match metric.

Mutual Information (MI) is a popular match metric for image registration. MI has become the match metric of choice due to its wide applicability and overall accuracy [8]. Here, MI will be applied to CT images taken at different times. Registration is achieved by adjustment of the relative position and orientation until the MI between the images is maximized.

MI [I( )] is defined in terms of entropy as follows [16]:

$$I(U(x),V(x)) = h(U(x)) + h(V(x)) - h(U(x),V(x)) \quad (2)$$

Where U denotes the reference image, V refers to the input image, while $h(.)$ is the entropy of a random variable, and is denoted as:

$$h(x) = -\int p(x)\ln p(x)dx \quad (3)$$

where $p(x)$ denotes the probability of a random variable X. The joint entropy of two random variables x and y is given by:

$$h(x,y) = -\iint p(x,y)\ln(p(x,y))dxdy \quad (4)$$

The MI defined by equation (2) depends on three components. The first one is the entropy of the reference image. The second is the entropy of the input image onto which the reference image projects. This part enhances the transformations that project U onto V. The third component is the joint entropy of U and V, which contributes when U and V are functionally correlated. The negative joint entropy encourages transformations where U explains V well. The last two components identify transformations that find complexity and explain it well. This is the essence of MI [15].

Since MI serves to describe the reduction in the uncertainty of U due to knowledge of V, MMI between the two images has been shown as an effective means to register images [8]. MMI can be used to find the rotations and translations between the registered images U and V. The steps are as follows:

1. Calculate the MI of U and V for each rotation (360 MI calculations for 1 degree increments).

2. For each rotation, calculate the MI for all possible translations of the input image to the reference image. In the present work, translations were taken pixel by pixel.

3. Find the overall MMI value. The coordinates of this maximum value give the rotation and translation.

3 Results

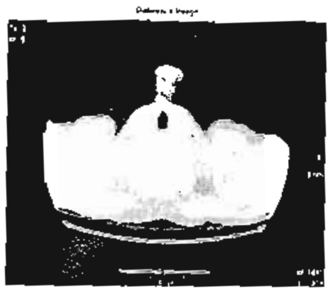
The ability of an image to provide clear correlation peaks when registered to another image is known as registrability (REG). It is computed from the variability of the autocorrelation values of the subimage against transformed versions of the subimage itself [12]. The top 50 % images that yield highest values of REG were selected for the registration process. Images with weak feature or less information have low REG, and thus they should be excluded. To perform registration, one image was marked as a reference image. The remaining images were considered as test images.

3.1 CT images

Database contains 48 CT images taken from the same patient at different times with a size of 804 pixels by 1005 pixels. Fig. 1 shows the reference image and one of the images.

The quality of the registration process was measured using the Weighted Peak Signal to Noise Ratio (WPSNR) because it is closer to perception than the PSNR [17].

Reference Image



Test Image

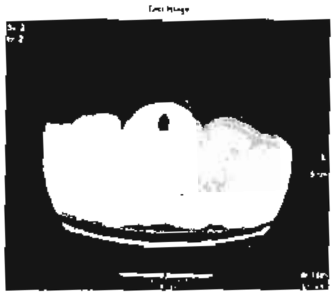


Fig. 1 Two different CT images for the brain

The weighted PSNR (WPSNR) weights each term of the PSNR by a local "activity" factor (linked to the local variance). The WPSNR takes into account the local human visual sense (HVS). It is a measure which holds account of the neighbors of the studied pixels [18-19]. Therefore, the WPSNR increases with variance increasing and vice versa following the equation:

$$WPSNR = 10 \log_{10}\left(\frac{MAX^2}{WMSE}\right) \quad (dB) \qquad (5)$$

The NCCC between the reference image and the test image had been selected as another measure of performance.

3.1.1 CC:

Registration was implemented using Matlab. The test image and the reference image have the highest NCCC at exactly the displacement between the test image and the reference one. Having this displacement, the test image is easily warped to the reference image. Fig.2 shows the result when CC is used. The process is repeated for all CT images. As shown in Table 2, the average value of the WPSNR is obtained. It is not high compared with MI maximization but it is higher than results obtained by CPS.

3.1.2 CPS:

CPS can be done both manually and automatically. Pairs of control points are used to infer a spatial transformation. Transform types can be linear conformal, affine, projective, polynomial, or piecewise linear. The selected number of control points depends on the used transformation. Affine transformation was selected, as it needs only three pairs of control points. In addition, applying affine transformation to CT images had given high values of the average WPSNR in comparison to other transformations. Fig.3 shows the results when CPS registration was applied. A Matlab program was designed to get the amount of scale and rotation of the test image from the reference one. As shown in Table 2, the average value of the WPSNR is lower than those obtained by CC and MMI registration.

3.1.3 MMI:

The entropies of both the reference image and the test image were calculated as well as their joint entropy. A Matlab program was implemented to get MI and maximize it. The maximum value occurs at a certain shift and rotation between the reference and the test images. Fig. 4 shows the results when MMI was applied. As shown in Table 2, the average value of the WPSNR is higher than those obtained by other techniques.

Table 2 Registration measures of performance

Registration Technique	Average WPSNR	Average NCCC
CC	26.971	0.9711
CPS	22.457	0.9507
MMI	27.769	0.9628

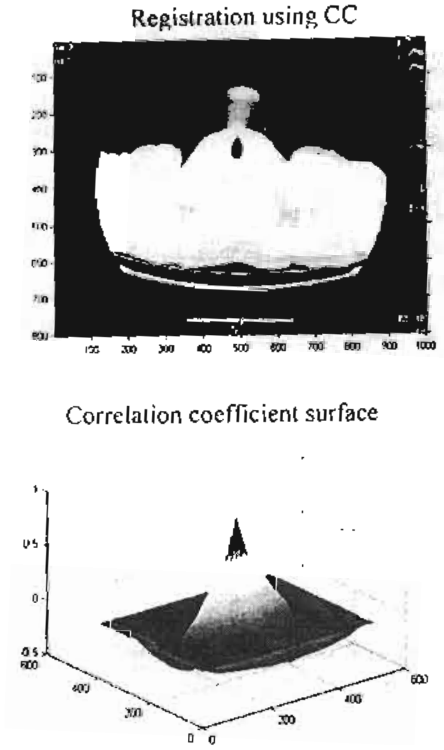


Fig. 2 Registration by CC

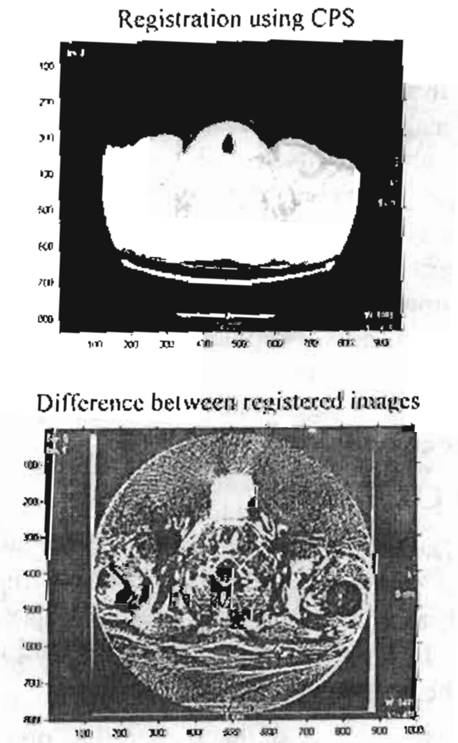


Fig. 3 Registration by CPS

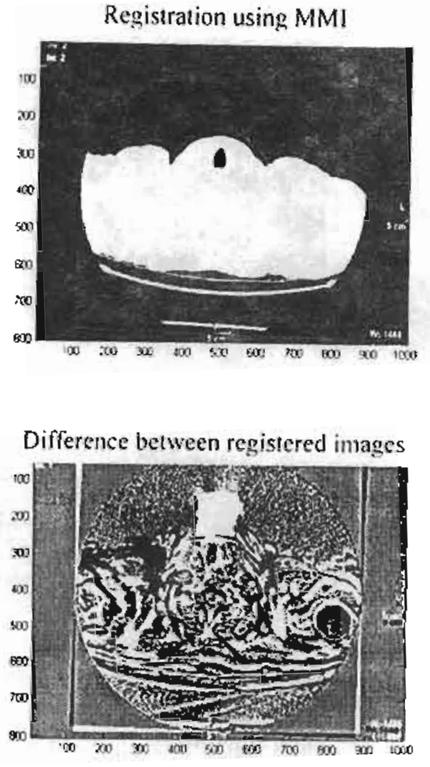


Fig. 4 Registration using MMI

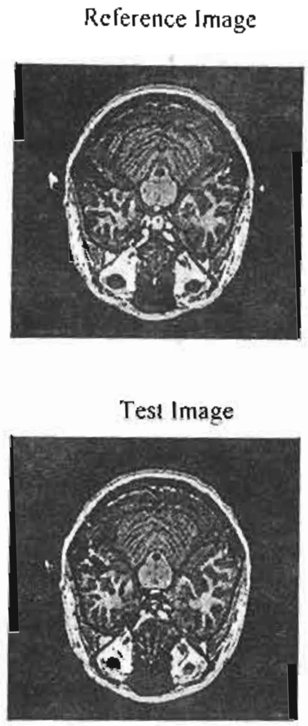


Fig. 5 Two different MR images for the brain

3.2 MR Images

Database contains 128 MR images taken from the same patient at different times with a size of 256 pixels by 256 pixels. Fig.5 shows the reference image and one of the test images.

3.2.1 CC:

Fig.6 shows the result when CC is used. The process was repeated for all MR images. As shown in Table 3, the average value of the WPSNR was obtained.

It is higher than that calculated for images registered using CPS. On the other hand, it is less than that calculated when MMI was used.

3.2.2 CPS:

Fig.7 shows the results when CPS registration was applied. A Matlab program was designed to get the difference of scale and rotation between the test image and the reference image.

As shown in Table 3, the average value of the WPSNR is the lowest among the three implemented techniques.

Table 3 Registration measures of performance

Registration Technique	Average WPSNR	Average NCCC
CC	25.843	0.9372
CPS	20.254	0.8645
MMI	26.543	0.9403

3.2.3 MMI:

Fig.8 shows the results when MMI was applied. As shown in Table 3, the average value of the WPSNR is higher than those obtained by other techniques. It must be noted that this result is due to the nature of MMI algorithm itself which takes all possible rotations and translations till we reach their best values that could maximize mutual information.

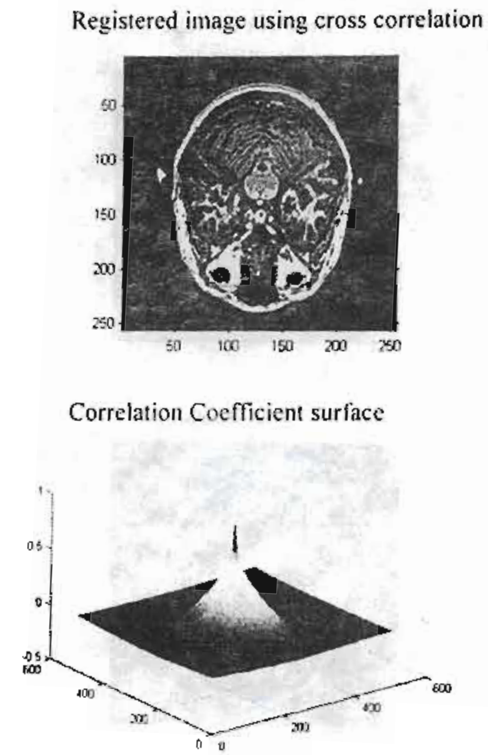


Fig. 6 Registration by CC

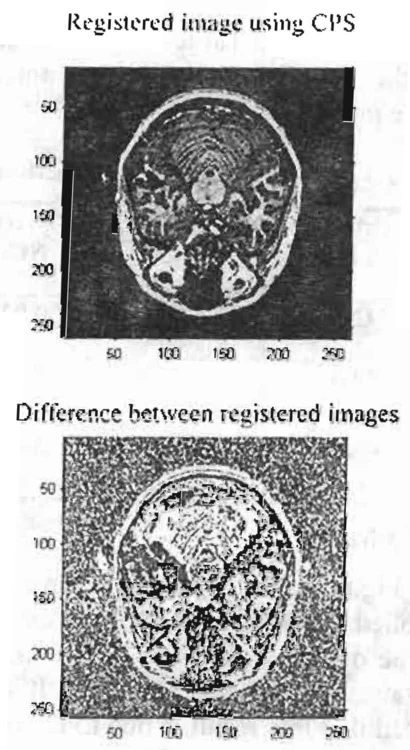


Fig. 7 Registration by CPS

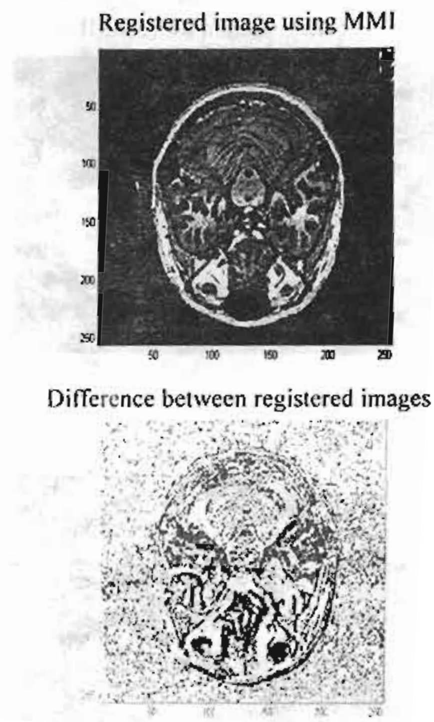


Fig. 8 Registration by MMI

4 Conclusions

The registration of CT and MR images is of high importance for surgical planning, diagnosis, and medical research.

NCCC has been shown to be an effective registration technique for both CT and MR images.

CPS has been shown to be a less effective registration technique for CT and MR images. This can be attributed to that this technique depends on both the used transformation and on the accuracy of selecting control points pairs.

Registration using MMI has given the best results. It has the following advantages:

(1) It does not require any assumptions about the nature of the imaging modalities.

(2) There is no need to information about the surface properties of the object.

(3) It is robust with respect to variations of illumination.

As a conclusion, MMI is an effective registration tool for medical applications involving both CT and MR images.

References

[1] Computed tomography From Wikipedia, the free encyclopedia, *available at:* http://en.wikipedia.org/wiki /Computed_axial_tomography

[2] Magnetic Resonance Imaging (MRI scan) Scanning information produced by medical doctors, *available at:* http://www. medicinenet.com/mri_scan/article.htm

[3] Lifeng Shang , Jian Cheng Lv, Zhang Yi , "Rigid Medical Image Registration Using PCA Neural Network," *Neurocomputing* Vol. 69, pp. 1717–1722, 2006.

[4]Graeme P. Penney, J"urgen Weese, John A. Little, Paul Desmedt, Derek L. G. Hill, and David J. Hawkes, "A Comparison of Similarity Measures for Use in 2-D–3-D Medical Image Registration," *IEEE transactions on Medical Imaging*, Vol. 17, No. 4, August 1998.

[5] L.G. Brown, "A Survey of Image Registration Techniques," *ACM Computer Survey*,. vol. 24, pp. 325-376, 1992.

[6] S. Baker and I. Matthews. Lucas-kanade 20 years on: A unifying framework: Part 1: "The Quantity Approximated, The Warp Update Rule, and The Gradient Descent Approximation," *International Journal of Computer Vision*. Vol. 56, No. 3, pp. 221–255, March 2004.

[7] B. Likar and F. Pernu, "Extraction of Corresponding Points for the Registration of Medical Images," *Medical Physics*, Vol. 26, No. 8, pp. 1678–1686, 1999.

[8] J. B. Antoine Maintz, Max A. Viergever, "A Survey of Medical Image Registration," *Medical Image Analysis*, Vol. 2, No. 1, pp. 1-37, 1998.

[9] Jeffrey Tsao, "Interpolation Artifacts in Multimodality Image Registration Based on Maximization of Mutual Information," *IEEE Transactions on Medical Imaging*, Vol. 22, No. 7, pp. 854-864, July 2003.

[10] J. P. Lewis, "Fast Template Matching," *Vision Interface*. pp. 120-123, 1995.

[11] Kennedy, R.E. and W.B. Cohen, "Automated Designation of Tie-Points for Image-to-Image Coregistration," *International Journal of Remote Sensing*, Vol. 24 No. 17, pp. 3467-3490, 2003.

[12] R. Szeliski and H.-Y. Shum., "Creating Full View Panoramic Image Mosaics and Texture-Mapped Models," *Computer Graphics (SIG-GRAPH'97 Proceedings)*, pp. 251–258, 1997.

[13] Prachya Chalermwat, "High Performance Automatic Image Registration for Remote Sensing," Ph.D. thesis, George Mason University, 1999, *available at*:

http://citeseer.ist.psu.edu/cache/papers/cs/24191/http:zSzzSzwww.science.gmu.eduzSz~prachyazSzthesis.pdf/high-performance-automatic-image.pdf

[14] R. Szeliski, "Image Alignment and Stitching," *A tutorial. Technical Report MSR-TR-2004-92, Microsoft Research*, 2004, *available at*:

http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/Papers/MSR-TR-2004-92-Sep27.pdf

[15] W. A. Davis and S. K. Kenue, "Automatic Selection of Control Points for The Registration of Digital Images," *Proc. Int'l J. Conf. Pattern Recognition*, pp. 936–938, 1978.

[16] P. A. Viola, W. M. Wells, "Alignment by Maximization of Mutual Information," *International Journal of Computer Vision*, Vol. 24 No. 2, pp. 137-154, 1997.

[17] Papoulis, A., "Probability, Random Variables, and Stochastic Processes," McGraw-Hill, Inc., 1991.

[18] Chaw-Seng Woo, Jiang Du, and Binh Pham, "Multiple Watermark Method for Privacy Control and Tamper Detection in Medical Images," *APRS Workshop Proceedings on Digital Image Computing*, February 2005.

[19] Voloshynovskiy, S., Pereira, S., Iquise, V. and Pun, T., "Attack Modeling: Towards a Second Generation Watermarking Benchmark" *Signal Processing - Special Issue on Information Theoretic Issues in Digital Watermarking*, pp. 1177– 1214, 2001.