

Affine with B-Spline Registration Based Retrieval Using Distance

Ayyachamy SWARNAMBIGA*

SACS MAVMM Engineering College, Madurai, Tamilnadu, India.
E-mail: aswarnambiga@gmail.com

* Author to whom correspondence should be addressed; Tel.: 0452-4522522098;

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Abstract

Developing a two stage framework is the purpose dealt in this paper. This rely on the Affine transformation and B –Spline for registration of medical images as the first stage of the framework and retrieval of medical images using distance metrics as the second stage in the framework. Affine with B-Spline registration based retrieval methods have been dealt in this paper. Evaluation of the framework using images extracted from the Affine with B-Spline registration are applied for the retrieval of medical images performing registration based retrieval. Quantitative analysis is performed to show the registration based retrieval methods perform well with comparable results and presents a summary of the results obtained. This work brings three major advantages as conclusion. First, medical images are conveniently retrieved from the database for effective clinical comparison, diagnosis and verification and also serving as a guidance tool. Second, coping registration techniques with monomodal medical images for more detailed view of images. Third, driving and tracking the entire lifecycle of this medical process would be easier with this application which permits immediate access to all patients' data stored in a medical repository. Conclusions drawn out of the proposed schemes are listed and justified.

Keywords: Medical image registration; Medical image retrieval; Clinical diagnosis; Medical image registration based retrieval; Medical imaging

Introduction

The image is one of the most important tool in medicine, since it provides see through information for diagnosis, monitoring drug treatment responses and disease management of patients with the benefit of being a very fast non-invasive procedure, having very few sideeffects and with an excellent cost-effect relationship. Computer assisted diagnosis has been proposed to support clinical decision making, and also supporting for evidence based and case based reasoning. The information gained from two images acquired in the clinical track of events is usually of complementary nature. Hence proper integration of useful data obtained from the separate image is often desired and needed for effective clinical diagnosis. Both in clinical diagnosis and in effective image guided surgery, registration of the image from practically any combination will always benefit the surgeon. Content based medical image retrieval is used to locate medical images in large databases. This scenario briefly describes the creation of medical images, categorization of medical images, and a content based access approach.

Pluim et al (2000) suggests that many registration algorithms involve iteratively transforming image A with respect to image B while optimizing a similarity measure calculated from the voxel

values. Interpolation errors can introduce modulations in the similarity measure with T . This is most obvious for transformations involving pure translations of datasets with equal sample spacing, where the period of the modulation is the same as the sample spacing. This periodic modulation of the similarity measure introduces local minima that can lead to the incorrect registration solution being determined. Vincent Arsigny (2004) presented geometrical transformation, like poly rigid and poly Affine transformation. A new and efficient numerical scheme for the practical implementation in any dimension especially in the poly rigid case is designed. A desired complete optimization strategy for non rigid registration of medical images is dealt. It is observed that the poly rigid transformations are exemplified successfully on 2D registration of histological slices. In order to make the poly rigid transformation more accurate, it should also be possible to define adaptive strategies progressively to refine the shape of regions when it is necessary.

Methodology

In the registration process, the measurer typically compares grayscale intensity values in the fixed image against the corresponding values in the transformed moving image. After the each iteration, matching degree between moving image and fixed image will be measured.

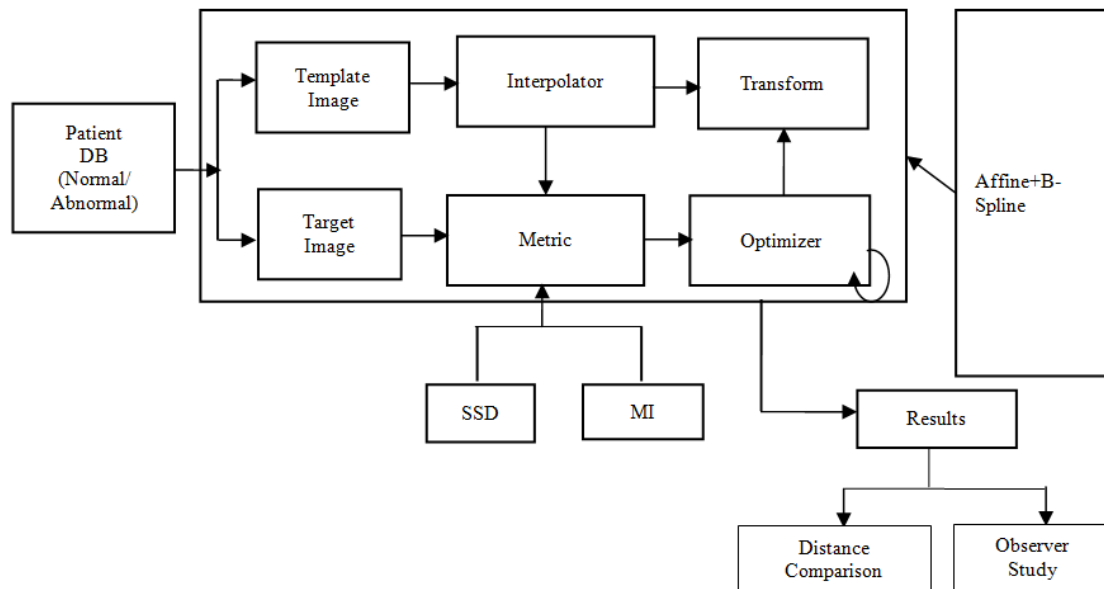


Figure 1. General image registration framework

When the difference between moving image and fixed image is quite big and maybe matching degree could not reach the threshold forever, and then set the maximum iteration number to avoid this instance. A geometrical transformation is applied to one of the two images to bring two images into spatial alignment. The measure of similarity between images or regions is a vital component in image registration along with the selection of the transformation function. Sum of Squared Differences (SSD) and Mutual Information (MI) are the two similarity metrics used in this paper. Figure 1 shows the general medical image registration framework which is utilized as a registration system module.

Affine Based Image Registration

Affine transformation is one of the most commonly used methods in registering two images. Although only in linear, it models a combination effect stemming from four simple transformations: translating, rotating, scaling and shearing. An Affine transformation corrects some

global distortions in the images to be registered. An Affine registration model assumes that the above transformation is linear and is given in Equation (1).

$$\varphi(\mathbf{X}) = \varphi_a(\mathbf{X}) = \begin{bmatrix} \varphi_{a_1}(\mathbf{X}) \\ \varphi_{a_2}(\mathbf{X}) \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} a_5 \\ a_6 \end{bmatrix} = \mathbf{A}\mathbf{X} + \mathbf{b} \quad (1)$$

where $\mathbf{A} = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix}$ and $\mathbf{B} = \begin{bmatrix} a_5 \\ a_6 \end{bmatrix}$ are the Affine transformation matrix and the translation vector respectively, for all $\mathbf{X} \in \Omega$. Here for optimization purpose, the vector $\mathbf{a} = (a_1, a_2, a_3, a_4, a_5, a_6)^T \in \mathbb{R}^6$ is used. Clearly the inverse transform is simply $\mathbf{X} = \mathbf{A}^{-1}(\varphi_a - \mathbf{b})$ if \mathbf{A} is invertible. Note that \mathbf{A} can be decomposed into a product of rotation, a scaling, a shear in x_1 – (and/or x_2 –) direction or a combination of these simple transformations and is given in Equation (2).

$$\mathbf{A} = \begin{bmatrix} a_1 & a_3 \\ a_2 & a_4 \end{bmatrix} = \underbrace{\begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}}_{\text{Rotation}} \underbrace{\begin{bmatrix} s_{x1} & 0 \\ 0 & s_{x2} \end{bmatrix}}_{\text{scaling}} \underbrace{\begin{bmatrix} 1 & S_{x1} \\ 0 & 1 \end{bmatrix}}_{\text{shear}} \quad (2)$$

θ is the rotation angle, s_{x1}, s_{x2} are the scaling parameters, and S_{x1} is the shear factor in x_1 – direction. It is clear that both a rigid-body transformation with $s_{x1} = s_{x2} = 1$ and $S_{x1} = 0$.

B-Spline Based Image Registration

However, most of the human body does not conform to Affine approximation. For respiratory motion correction, researchers widely used Affine image registration, but reported that it is sufficient only for a single organ and associated lesion. For effective motion correction usually requires nonrigid image registration, which enables more flexible matching of local details between two images than rigid registration. B-Spline bases are used frequently for non-rigid image registration because, locally supported basis function expansions. The displacements field $u(x,y)$ and $v(x,y)$ are two dimensional Splines controlled by a smaller number of displacements estimates \vec{u}_i and \vec{v}_i which lies on a coarse Spline control grid. The value of the displacement of pixel i and is given in Equation (3).

$$u(x_i, y_i) = \sum_j \vec{u}_j B_j(x_i, y_i) \quad (3)$$

where the $b_j(x,y)$ are called the basis functions. They are only non-zero over a small interval $W_{ij} = B_j(x_i, y_i)$ weights to emphasize that the (u_i, v_i) are known linear combinations of the (u_j, v_j) .

Database

The database is formed from personally collected medical images from clinics and health care centers and benchmarked web image databases especially for particular modalities. Different collections and several classifications based on modalities are concentrated while creating the database. The collections can grow as computing power increases, and as new issues are added. Before going for experimental analysis characteristics of medical image are once again discussed briefly which helps in justifying the results.

Distance Based Medical Image Retrieval

A lot of research work has been carried out on distance based image retrieval by many researchers, expanding in both depth and breadth. But analysis of various organs and modality of medical images using distance metrics implemented by the research community is found to be lesser. The distance metric can be treated as similarity measure, which is the key component in medical image retrieval is an effective technique. The retrieval of medical images is processed by using seven distance metrics and such as Euclidean, Manhattan, Mahalanobis, Canberra, Bray-

Curtis, Squared Chord, Chi-Squared and by using energy as a feature. The query image is more similar to the images in the database. If x and y are 2D feature vectors of database image and query image respectively. The distance metrics are defined as follows, where n represents the number of images.

1) The Euclidean (EU) distance measure (d_E) is defined in Equation (4)

$$d_E(X, Y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \tag{4}$$

x_i and y_i are the database image and Query image. The minimum distance value signifies an exact match with the query.

2) The Manhattan (MAN) measure (d_M) computes the similarity scores between two images and they are widely used in similarity calculation for medical images. Here x_i and y_i are the images of the database image and query image and is defined in Equation (5).

$$d_M(X, Y) = \sum_{i=1}^n |x_i - y_i| \tag{5}$$

3) The Mahalanobis (MAH) distance metric is appropriate when each dimension of the image feature vector is dependent of each other and has different importance in medical imaging. Here F_i and F_j are the images of the database image and query image and is defined in Equation (6) and (7).

$$D(i, j) = \sqrt{(F_i - F_j)^T C^{-1} (F_i - F_j)} \tag{6}$$

Where C is the covariance matrix of the feature vector. In this case, only the variance of each feature component c_i is used. Mahalanobis metric is represented as $D(i, j)$.

$$D(i, j) = \sum_{i=1}^N \frac{(F_i - F_j)^2}{c_i} \tag{7}$$

4) The numerator signifies the difference and the denominator normalizes the difference in Canberra (CAN) distance metric (δ_C) and is defined in Equation (8).

$$\delta_C = \sum_{i=1}^n \frac{|x_{ri} - x_{si}|}{|x_{ri}| + |x_{si}|} \tag{8}$$

5) The Bray-Curtis (BR) measure (δ_{BS}) usage on medical images found to be lesser. The numerator signifies the difference and the denominator normalizes the difference and is defined in Equation (9).

$$\delta_{BS} = \frac{\sum_{i=1}^n |x_{ri} - x_{si}|}{\sum_{i=1}^n x_{ri} + x_{si}} \tag{9}$$

6) The Squared Chord (SQ) distance measure (d_{sc}) is highly useful for image database applications. Distance values never exceed one and it is equal to one if any one of the attributes is zero. Here x_i and y_i are the images of the database image and query image and is defined in Equation (10).

$$d_{sc}(X, Y) = \sum_{i=1}^n \sqrt{x_i} - \sqrt{y_i} \tag{10}$$

7) Within the distance metrics the Chi-Squared (CHI) distance (d_{ch}) have been used with the lesser implementation in medical image retrieval. Here x_i and y_i are the images of the database image and query image and is defined in Equation (11).

$$d_{ch}(X, Y) = \sum_{i=1}^n \frac{(x_i - y_i)^2}{x_i + y_i} \tag{11}$$

Performance Measures

The performance of the medical image retrieval system techniques is analyzed by the measures Precision, Recall and Accuracy. The level of retrieval accuracy which is achieved by a system is important to establish its performance illustrated by Henning Muller (2004). In CBMIR, precision-recall is the most widely used measurement methods to evaluate the retrieval accuracy. Precision P is defined as the ratio of the number of retrieved relevant images r to the total number of retrieved

images n , i.e. $P = r/n$. Precision measures the accuracy of the retrieval and it is given in below Equation (12).

$$P = (\text{number of relevant images retrieved}) / (\text{total number of images retrieved}) = r/n \quad (12)$$

The recall is defined by Henning Muller (2004) and is denoted as R which is the ratio of the number of retrieved relevant images r to the total number of relevant images in the whole database (m), i.e., $R = r/m$. Recall measures the robustness of the retrieval and is given in Equation (13).

$$R = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in Database}} = \frac{r}{m} \quad (13)$$

Henning Muller (2004) defined, as many of the presented systems uses classifications of images, accuracy is very often used to evaluate the system. This is defined in Equation (14).

$$\text{Accuracy} = (\text{number of images classified correctly}) / (\text{total number of images classified}) \quad (14)$$

Registration Results

In most of the computer assisted intervention techniques, medical images are crucial for treatment planning and guidance during the surgery. However, images acquired in different stages of diagnosis and treatments are affected by the position of the patient, deformation of soft tissue and the orientation of the imaging device. Therefore, computer assisted interventions often involve a registration step in which coordinates systems of two images (of the same or different modalities) are matched. As a result, corresponding pixels in two images represent the same anatomical regions of the tissue being imaged. In this work it is aimed for that. Without any constraint, images are chosen for medical image registration depending on the user's selection ensuring the applicability of this developed system.

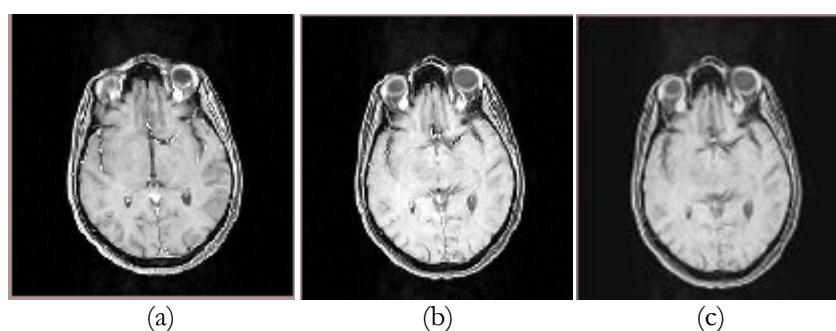


Figure 2. Monomodal registration of Brain image. (a) represents the reference image. (b) represents the test image to be registered. (c) represents the registered images using Affine with B-Spline registration respectively.

Figure 2 shows the registration of Brain images using Affine with B-Spline registration. Figure 3 shows the MR image of the Liver. This T2 weighted slice shows Liver, spleen, aorta, vena cava, stomach, kidneys and thoracic vertebra. Lesser variations in the intensity of images are found for Affine with B-Spline and Demons registered images.

Table 1. Measured performance parameters using Affine, Demons and Affine with B-Spline based registration for Brain, Liver and Knee images

Performance parameters	Before registration	After Registration Using Affine with B-Spline based registration
Registration of Brain image		
SSD	123.1011	98.5715
MI	1.7181	1.6902
Registration of Liver image		
SSD	240.5798	124.0495
MI	0.82015	0.2872
Registration of Knee image		
SSD	248.57	186.06
MI	0.8658	0.2019

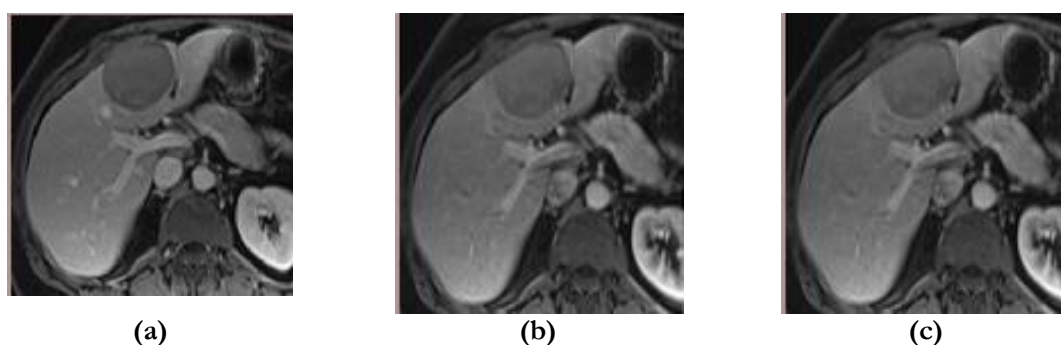


Figure 3. Monomodal registration of Liver image. (a) represents the reference image. (b) represents the test image to be registered. (c) represents the registered images using Affine with B-Spline registration respectively.

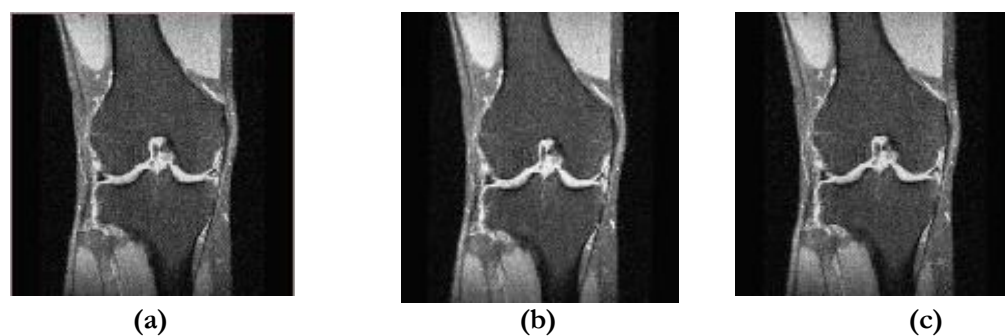


Figure 4. Monomodal registration of Knee image. (a) represents the reference image. (b) represents the test image to be registered. (c) represents the registered images using Affine with B-Spline registration respectively.

Figure 4 shows the MR image of the Knee. It depicts the femur, tibia, fibula, intracondylar notch and menisci with one meniscal tear. Affine with B-Spline registered images found to have lesser changes in the registered image than with the original image. Table 1 shows the measured performance parameters using Affine, Demons and Affine with B-Spline registration applied to the Brain, Liver, and Knee images. The value of SSD and MI before registration is higher while after registration for Affine with B-Spline found to be lesser confirming the best performance for Brain image.

Affine

with B-Spline Registration Based Retrival using Distance Metrics

In the first part of the Affine with B-Spline registration based retrieval have created a database with Affine with B-Spline registered images using Affine with B-Spline based registration. The second part of the technique implements medical image retrieval. Three main techniques are applied to check the applicability. Distance metrics based retrieval using Affine with B-Spline based registered images is implemented. The metrics used are Euclidean, Manhattan, Mahalanobis, Canberra, Bray-Curtis, Chi-Squared and Squared Chord by using energy as a feature. The simulated results using distance based medical image retrieval system is justified purely based on medical terms for effective clinical diagnosis in a detailed view. Topmost image is the query image shown in Figure from 5, 6 and 7. Also (a)-(g) represents the retrieved images using various distance metrics for Brain image images by distance based retrieval. (a) shows retrieved images using Euclidean distance metric. (b) shows retrieved images using Manhattan distance metric. (c) shows retrieved images using Mahalanobis distance metric. (d) shows retrieved images using Canberra distance metric. (e) shows retrieved images using the Bray-Curtis distance metric. (f) shows retrieved images using Squared Chord distance metric. (g) shows retrieved images using Chi-Squared distance metric. Table 2 shows the performance evaluation of the retrieved Brain, Liver and Knee images using distance metrics.

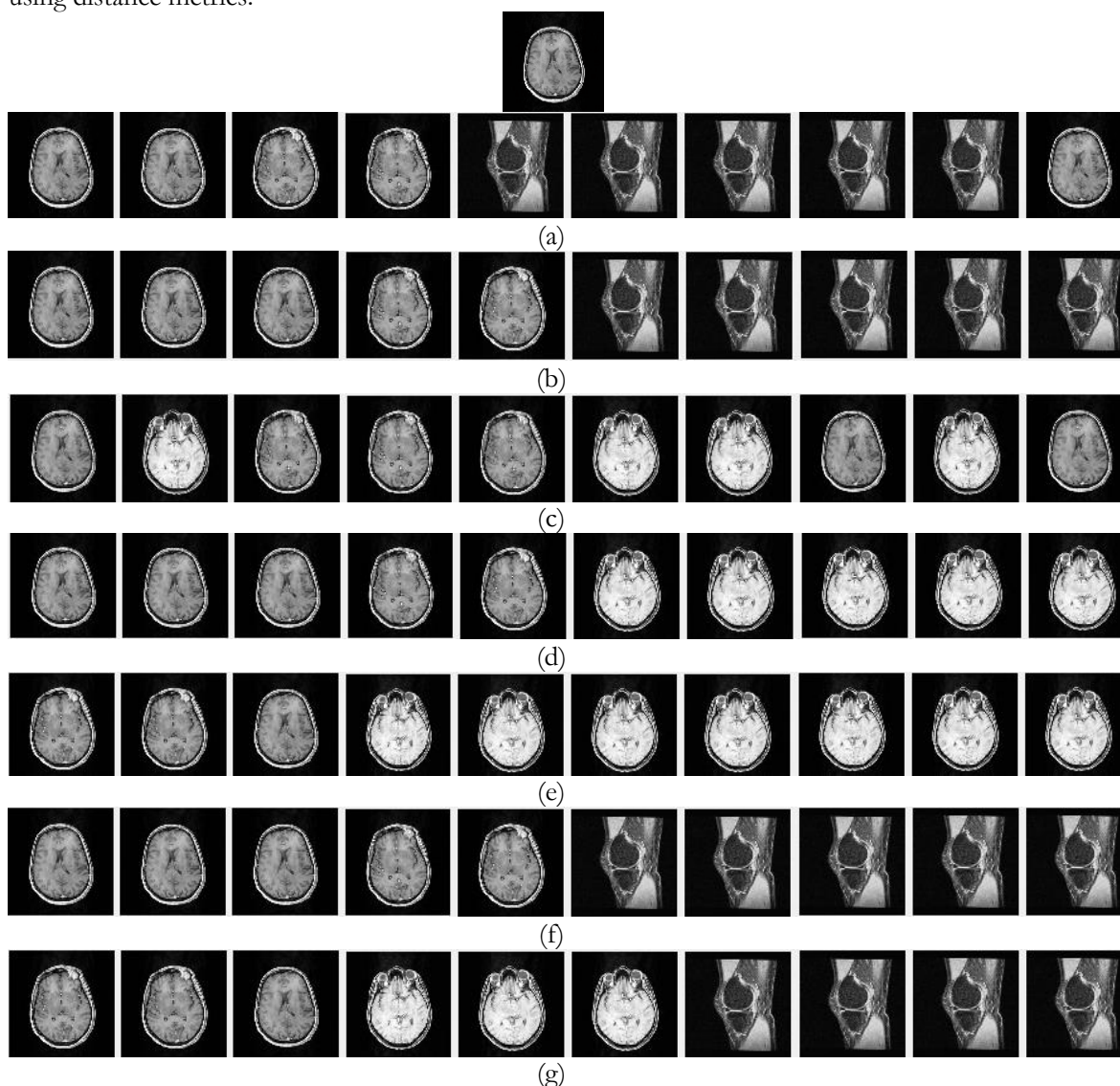


Figure 5. Affine with B-Spline registration based retrieval using distance metrics for Brain image

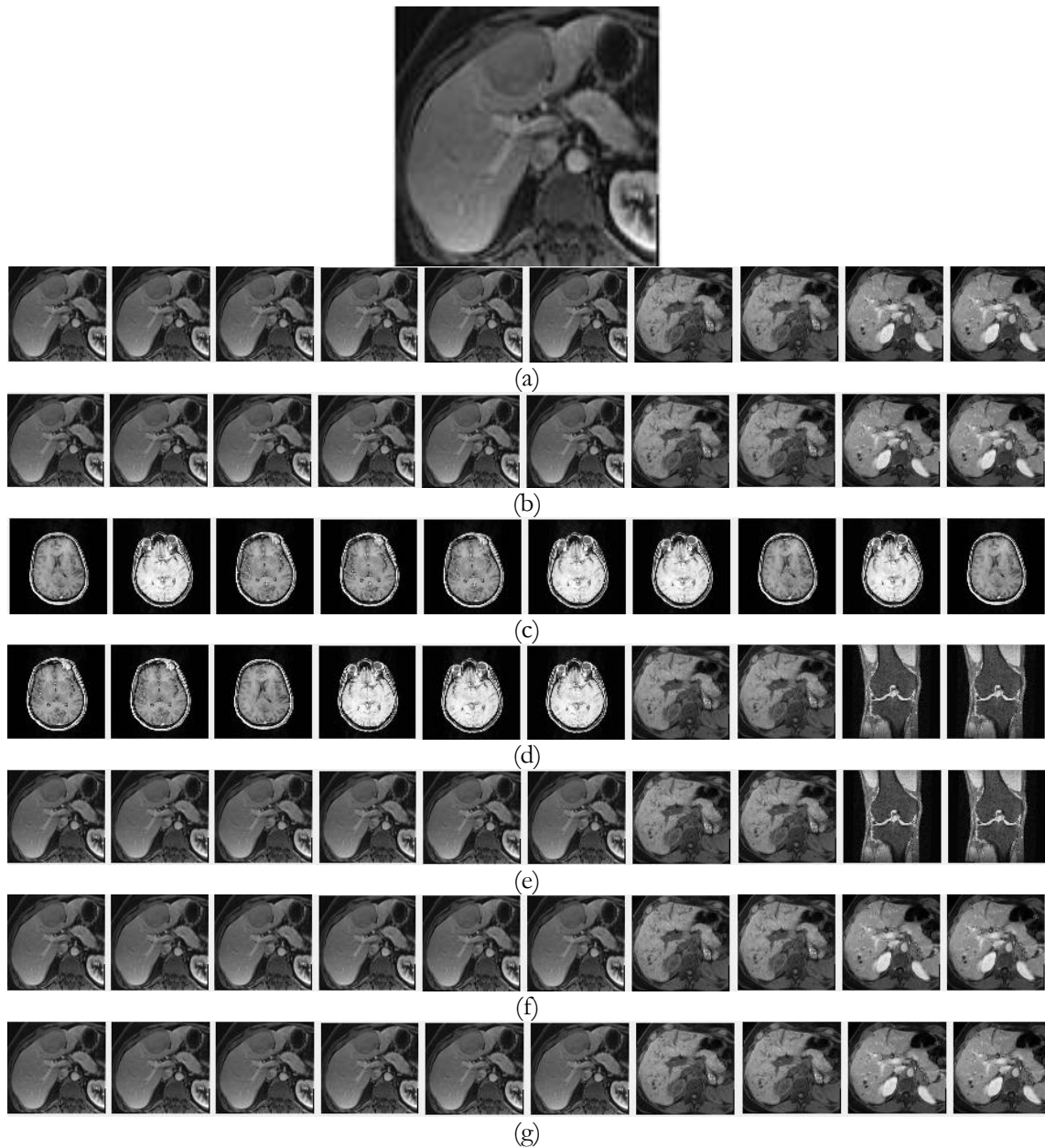


Figure 6. Affine with B-Spline registration based retrieval using distance metrics for Liver image

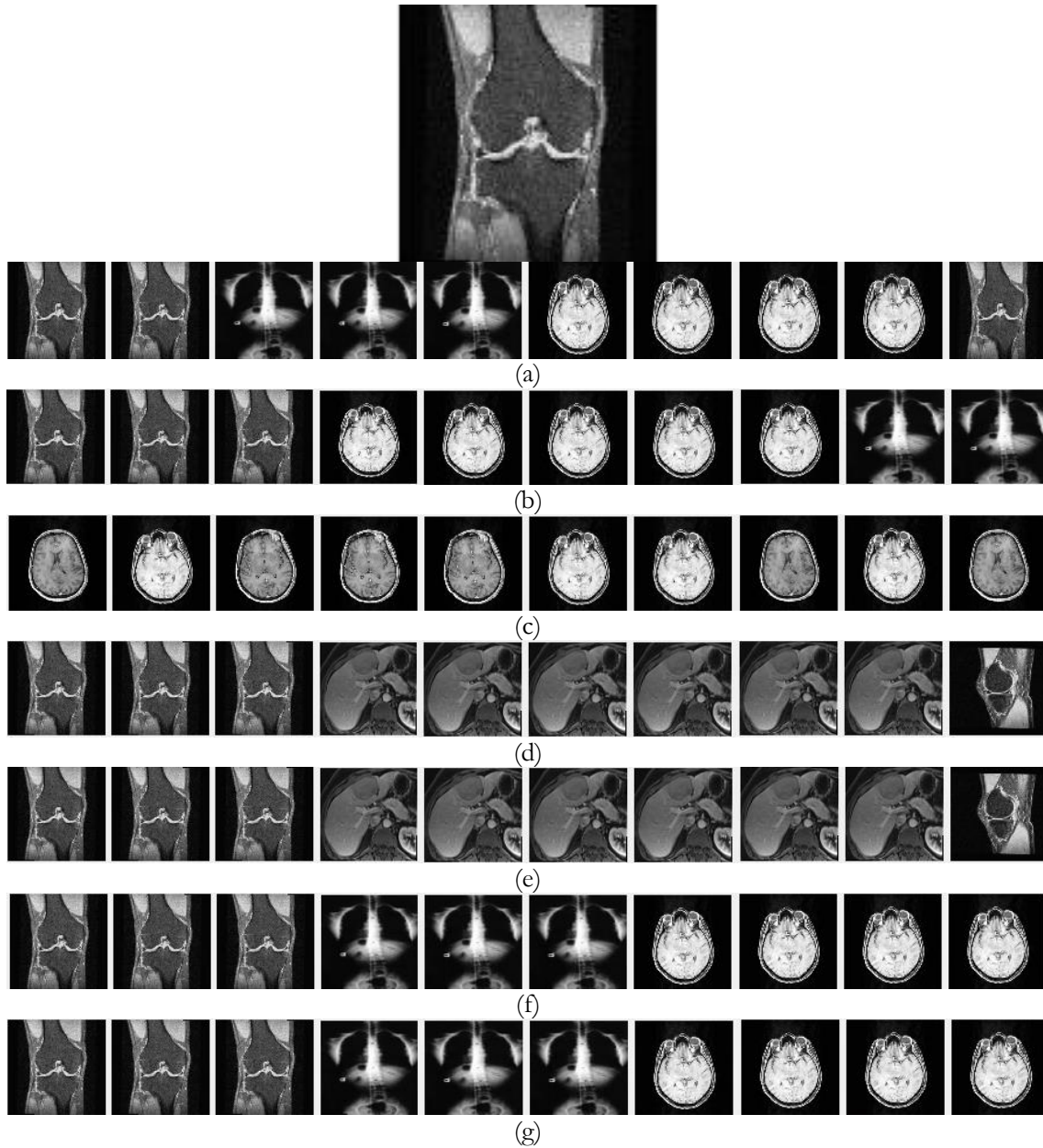


Figure 7. Affine with B-Spline registration based retrieval using distance metrics for Knee image

Table 2. Performance evaluation from retrieved Brain, Liver and Knee images using various distance metrics

Distance metrics	(Precision/Recall)	(Relevant/Irrelevant) images	Time in seconds	Accuracy
Retrieval results for Brain images				
Euclidean	50/25	5/5	0.5	50
Manhattan	50/25	5/3	0.5	50
Mahalanobis	100/50	10/0	0.5	100
Canberra	100/50	10/0	0.5	100
Bray-Curtis	100/50	10/0	0.5	100
Squared Chord	50/25	5/5	0.5	50
Chi-Squared	60/30	6/4	0.5	60
Retrieval results for Liver images				
Euclidean	30/15	3/7	0.5	30
Manhattan	30/15	3/7	0.5	30
Mahalanobis	0/5	0/10	0.5	0
Canberra	40/20	4/6	0.5	40
Bray-Curtis	40/20	4/6	0.5	40
Squared Chord	30/15	3/7	0.5	30
Chi-Squared	30/15	3/7	0.5	30
Retrieval results for Knee images				
Euclidean	100/50	10/0	0.5	100
Manhattan	100/50	10/0	0.5	100
Mahalanobis	0/0	0/10	0.5	0
Canberra	20/40	2/8	0.5	20
Bray-Curtis	80/40	8/2	0.5	80
Squared Chord	100/50	10/0	0.5	100
Chi-Squared	100/50	10/0	0.5	100

Table 3. Overall performance evaluation using (Precision /Recall) calculation from retrieved images by various distance metrics

Images	D1	D2	D3	D4	D5	D6	D7	APR	ARR
(Precision/Recall) values									
Brain	50/25	50/25	100/50	100/50	100/50	50/25	60/30	73	36
Liver	100/50	100/50	0/0	20/10	80/40	100/50	100/50	71	36
Knee	30/15	30/15	0/5	40/20	40/20	30/15	30/15	29	15
APR	60	60	33	53	73	60	63	-	-
ARR	30	30	17	27	37	30	32	-	-

Table 3 shows overall best performance for Affine with B-Spline registration based retrieval using distance metrics. The overall best performance is given by Bray-Curtis metric with (73/37)% of Average precision rate (APR) and Average recall rate (ARR). The next best performance is given by Chi-Squared, Euclidean, Manhattan, Canberra and Mahalanobis metric. For Bray-Curtis, the intensity difference is normalized and the sum of the intensities is taken than normalizing both numerator and denominator, and taking squared difference. The normalization of the intensity difference helps in retrieving more images for the particular metric than any other metrics. The combination of Affine with B-Spline has an added advantage of the properties of both Affine and B-Spline. B-Spline has the property of smoothness and when combined with Affine, more smoothed images get best results. Hence Brain images are retrieved more than Liver and Knee images.

Conclusions

An user friendly front end registration based retrieval system have been developed for routine clinical use. The results of the various experiments done under this work, found to coincide with clinical results. This framework helps in registration of images and retrieval of registered medical images with Average precision and recall rate of (73/37)% for Bray-Curtis metric. To be used as a diagnostic aid, the techniques proved their performance and they are accepted by the physicians' and radiologists' as an useful tool. This also implies an integration of the systems into daily clinical practice which is an easy task. There are two principal applications for supporting this developed clinical decision-making process. The first one is to supply the medical doctor with cases to offer a similar visual appearance. This will supply a second opinion for them and (s) he can perform the reasoning based on the various cases that are supplied by the system and the data that is available on the current patient.

List of abbreviations

Basis Spline (B-Spline)
Sum of Squared Differences (SSD)
Mutual Information (MI)
Precision (P)
Recall (R)
Accuracy (A)
Average precision rate (APR)
Average recall rate (ARR)

Conflict of Interest

The author declares that he has no conflict of interest.

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