Comparison and evaluation of registration methods of intra-oral radiographs images

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Abstract

This paper presents comparisons and evaluations of registration methods of intra-oral radiograph images. Several automatic and manual algorithms were examined. Three similarity functions for automatic registration are described and evaluated. In addition, the results of two manual registration tests are compared for both 3 and 10 control points marked interactively by the operator.

1. Introduction

In dental treatment, a set of images of the same intra-oral objects is taken over a certain time interval. A suitable comparison between a pair of radiographs is possible due to alignment of the images [1]. This alignment, known as registration, applies an image transformation to one of the pairs of images, which helps minimize misregistration [2,3]. To be more precise, the registration process transforms different sets of data into one coordinate system. A fixed, original image is often referred to as the reference image, while the transformed and registered moving one is known as the adjusting image. Image registration methods are often classified as either area-based or feature-based [4]. The area-based methods involve the entire image, using special correlation functions to determine image similarity. However, the feature-based algorithms take some features like lines, curves, textures or spatial relationship common to the objects into consideration during the registration process. Registration methods can be classified according to the extent of interaction needed for the determination of the transform, as manual, semiautomatic or automatic [4]. Manual registration requires interaction on both the reference and adjusting images, such as to mark the corresponding points interactively. The semiautomatic method has

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corresponding points located automatically on one of the registered images, while the automatic methods do not require any interaction on any image. Another useful classification [4] is the geometrical transformation used to adjust the moving image. For most cases a rigid body and scaling is sufficient for the transformation, but often shearing is added to form an affine transformation. Perspective and nonlinear transformation allow local warping of image features provided by local deformations, which are not desirable in medical imaging.

In this paper, the authors take both automatic and manual methods [5] into consideration. The registration procedure consists of a transformation function, a similarity function and an optimization algorithm. In this case, two-dimensional radiograph images are registered using the affine transformation:

$$[x,y] = S(s_x,s_y) R(\alpha) T(t_x,t_y) Sh(sh_x,sh_y) * [x',y'].$$ (1)

The quality of similarity measure is represented by the matching function parameterized by the geometric transformation:

$$f_m(s_x,s_y,\alpha,t_x,t_y,sh_x,sh_y): \Re^n \to \Re ,$$ (2)

where: $[s_x, s_y]$ – x-axis and y-axis scaling factor, α – rotation angle, $[t_x, t_y]$ – x-axis and y-axis translation factor, $[sh_x, sh_y]$ – x-axis and y-axis shearing factor.

An algorithm starts with the transformation parameters initially set. Following calculation of the transformation function (1), a process of iteration changes the optimization parameters using the Powell optimization algorithm [6] in order to minimize the similarity function (2). Iterations continue until the differences between similarity function values in the following iteration are lower than the assumed error. Based on the registration procedure the transformation parameters $T_{optimal}(s_x,s_y,\alpha,t_x,t_y)$ are determined, which establishes the optimal correspondence between the fixed and moving images. Using the $T_{optimal}$ transformation parameters, the moving image is transformed according to formula (1).

Two measures were used to evaluate the registration quality:

1) The mean image difference value:

$$\bar{v}_D = \frac{1}{M} \sum_{x,y \in M} abs\big(v_R(x,y) - v_O(x,y)\big).$$ (3)

2) The standard deviation of the histogram:

$$\sigma_r = \sqrt{\frac{1}{M} \sum_{x,y \in M} \big(v_D(x,y) - \bar{v}_D\big)^2} ,$$ (4)

where M is the number of pixels in superimposition, v_R represents intensities in the reference image, v_O represents intensities in adjusting image and v_D represents intensities in the difference image.

2. Automatic registration

The registration classification code for the automatic algorithm [4] used in this paper is denoted D(2)F(0.1.2)T(4.2.2)I(3), i.e. a two-dimensional D(2) transformation T(4.-.-), (affine), considered the global T(-.2.-) in iterative method T(-.-.2) for raw data F(0.1.2) searches the best match for the adjusting image. For this part, three similarity functions were compared:

1) Mean Square Difference (MD) [7]:

$$MD(v) = \frac{1}{M} \sum_{x,y \in M} \left[v_R(x,y) - v_O(x,y) \right]^2 , \tag{5}$$

where M is the number of pixels in superimposition, v_R represents intensities in the reference image and v_O represents intensities in the adjusting image.

2) Normalized Mutual Information (MI) [8]:

$$MI(v) = \frac{h_O + h_R}{h_{OR}} \tag{6}$$

where R represents the reference image and O represents the adjusting image.

$$h_O = -\sum p_O(x) \log(p_O(x)),$$
$$h_R = -\sum p_R(x) \log(p_R(x)), \tag{7}$$
$$h_{OR} = -\sum \sum p_{O,R}(x,y) \log(p_{O,R}(x,y)),$$

where h_O, h_R and h_{OR} are the single and joint entropies [8], p_O and p_R are the probabilities of each intensity in the intersection volume of both data sets and $p_{O,R}$ is a probability distribution of a scatter-plot histogram.

3) Cross-Correlation (CC) [7]:

$$CC(v) = \frac{\sum_{x,y \in M} \left(v_R(x,y) - \bar{v}_R \right) * \left(v_O(x,y) - \bar{v}_O \right)}{\sqrt{\sum_{x,y \in M} \left(v_R(x,y) - \bar{v}_R \right)^2} \sqrt{\sum_{x,y \in M} \left(v_O(x,y) - \bar{v}_O \right)^2}} , \tag{8}$$

where M is the number of pixels in superimposition, v_R represents intensities in the reference image and v_O represents intensities in the adjusting image.

To find the best matching function for the intra-oral radiograph images two tests were conducted: an identity registration test and a pair registration test.

2.1. Identity registration test

In this test a three-transformation set (listed in Table 1 as TI, TII and TIII) for the input image was applied. In the next step, this transformed image was registered with the described algorithm. Time and a number of iterations of registration were evaluated and compared for all similarity functions.

Table 1. Transformation parameters for the identity registration test

	TI	TII	TIII
Angle	0.1	0.3	0.3
Translation	[20; -20]	[100; 100]	[130; 130]
Scale	[1.1; 0.9]	[1.2; 0.8]	[0.8; 0.8]
Superimposition	0.89	0.63	0.40

In the consecutive transformation sets, the misregistration between the original image and the transformed image was greater, beginning from 40% to 89% of the common pixels. Table 2 presents the graphs of successive algorithm iterations for all transformation sets for all similarity functions. The best alignment is when the similarity function reaches its minimum.

Table 2. Similarity function values for successive iterations for the three transformation sets
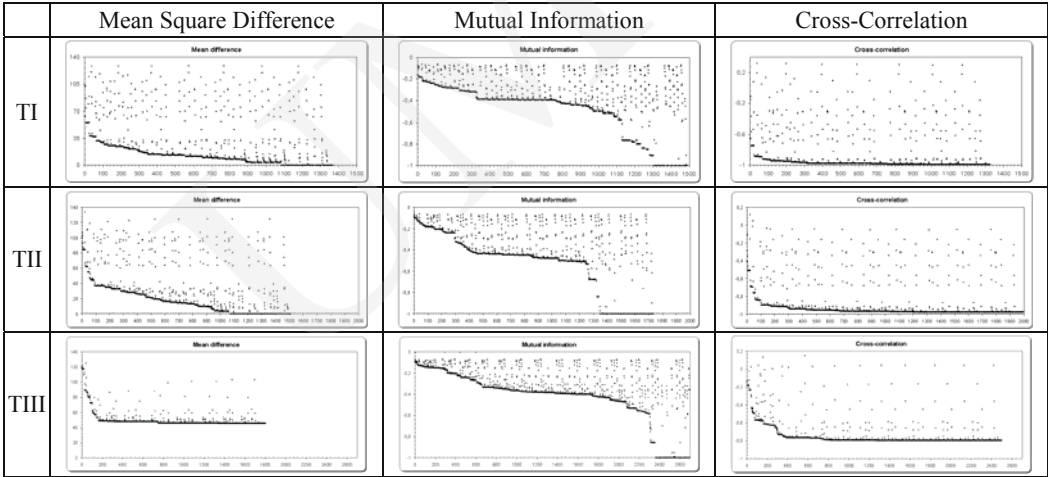

Table 3. Results for the identity registration test. The first number is the time in seconds, while the second number is the number of iterations. The fastest or the best method is shown in bold

	time, iter. T1	time, iter. T2	time, iter. T3
MD	**22s, 1370**	**24s, 1505**	31s, 2402
MI	48s, 1490	71s, 1733	**82s, 2696**
CC	48s, 1326	61s, 1997	69s, 2499

As follows from the results for this test (Table 3) for large misregistrations, simple similarity functions like MD do not converge to the original image but stick at a local minimum. The second conclusion is that for lower misregistrations this function is the fastest in both time and number of iterations. However, using only MI as the similarity function, the registration algorithm

was able to successfully complete this test despite requiring the most time and number of iterations. The graphs presented in Figure 1 confirm the convergence speed for all similarity functions. Only translations were used to calculate the values of these functions near the best fit.
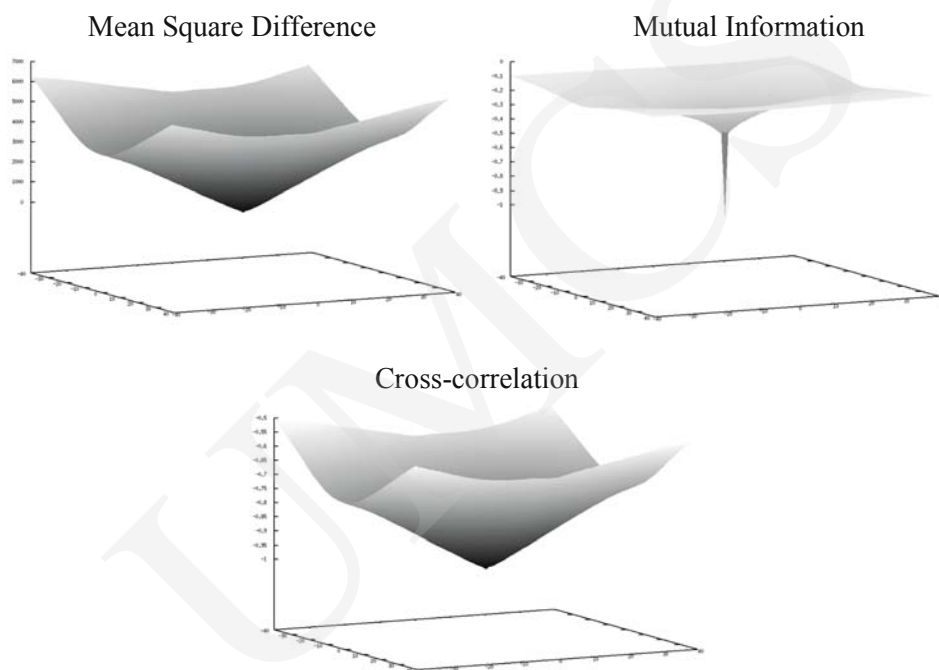
Mean Square Difference   Mutual Information

Cross-correlation

Fig 1. Similarity functions near the best fit in the identity registration test

2.2. Pair registration test

For the pair registration test, real intra-oral radiograph images were used. Ten pairs of images taken over a time interval were registered using three similarity functions MD (5), MI (6), CC(7). Two matching quality measures: the mean image difference value (3) and the standard deviation (4) are used to evaluate the effectiveness of the similarity functions used.

The results (Table 4) show the MI function to be the best method, but with only a little advantage over the MD function. The least success was obtained using the CC function. These results are compared in the next section to those obtained by manual registration, which is more accurate but requires operator interaction.

Table 4. Results for the pair registration test. The best results are in bold

	Mean Image Difference				Standard Deviation		
	MD	MI	CC		MD	MI	CC
1	**21.49**	21.66	21.76		32.49	33.21	**31.99**
2	**28.11**	44.14	43.49		**26.91**	46.59	42.10
3	**58.04**	60.73	62.11		**26.76**	33.26	33.96
4	31.03	**25.51**	30.54		45.25	**41.97**	44.83
5	40.15	**22.62**	38.61		40.81	**34.30**	38.82
6	36.53	**33.21**	34.28		36.82	**35.21**	36.98
7	**26.32**	28.91	29.85		**30.59**	31.09	31.82
8	62.01	**47.53**	63.97		61.89	**52.73**	63.46
9	39.11	**38.91**	40.02		48.01	**47.84**	47.92
10	52.18	53.58	**51.09**		43.18	43.96	**42.58**

3. Manual registration

The registration classification code for the manual algorithm according to [4] is denoted D(2)F(1.6.1)T(3.2.2)I(1). The goal for this registration procedure is to find a two-dimensional D(2) transformation T(3.-.-), (affine), considered globally T(-.2.-), which minimizes the Euclidian distance between the corresponding control points for the fixed and moving images. The reference image, the adjusting image and the set of control points positioned manually I(1) to several anatomical structures F(1.6.-) are input data for the algorithm. The number of control points for both images must be the same, each control point in the fixed image is a reference point for the specific control point in the moving image F(-.-.1). The similarity function was defined as the sum of distance squares between the corresponding control points in the fixed and moving images; however, the image transformation parameters were considered as the optimization parameters:

$$f_m\left(s_x, s_y, \alpha, t_x, t_y\right) = \sum_{i=1}^{n} d^2\left(p_i\right), \qquad (9)$$

where $d^2(p_i)$ is a square distance between *i-th* pair of control points, n – the number of control points and the transformation parameters are: $[s_x, s_y]$ – x-axis and y-axis scaling factor, α – rotation angle, $[t_x, t_y]$ – x-axis and y-axis translation factor.

The influence of the number of control points on the registration quality was examined next. Three and ten control points were marked by an operator on each of the image pairs. Table 5 shows the mean and the standard deviation results for 10 examined image pairs.

Table 5. Results for three and ten control point manual registration. The best results are in bold

	3 control points			10 control points	
	Mean	Std. dev		Mean	Std. dev
1	**23.58**	36.37		23.82	**36.33**
2	26.18	26.82		**26.02**	**26.11**
3	**37.63**	**35.67**		38.58	36.91
4	**27.84**	**35.21**		28.44	35.66
5	23.78	34.91		**23.61**	**34.48**
6	**23.63**	33.82		23.91	**32.97**
7	**27.57**	**41.79**		28.01	42.96
8	**27.91**	31.98		27.93	**31.56**
9	**21.02**	37.32		21.41	**37.18**
10	**34.10**	**43.63**		34.12	44.37

The results show that the number of control points does not influence the registration quality, in terms of either the mean or the standard deviation. In comparison with the automatic registration, the manual pair registration test shows slightly worse results in some cases. The explanation for this behaviour is that the automatic registration takes all pixel values into consideration while the manual registration depends only on a limited number of control points.

4. Conclusions and future works

Comparing the results in Tables 4 and 5, i.e. the automatic and manual registrations, it is clear that in some cases the automatic registration gives significantly worse matching results than the manual one. This may be due to weakness in the minimization procedure. The Powell optimization procedure is a simple, brute-force method that scans all space searching for local minima. The main advantage of this method is that the Powell function needs only the first order value for the similarity function, but not its first or second derivative. One of the main disadvantages is that it can become stuck to a local minimum and cannot unstick itself. Renewing the registration procedure often gives positive results but this is not a desirable solution. The main conclusion here is that a more complicated and effective minimization function is needed.

For all three similarity functions, MI and MD give similar results but MD is twice as fast as MI. However, while MI often leads to the global minimum, in the cases of extensive poor fit none of these simpler functions converges to the global minimum at all.

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