

# A NOVEL IMPLEMENTATION OF ICP ALGORITHM APPLIED TO THE MULTIMODAL REGISTRATION OF THE LEFT VENTRICLE OF THE HEART

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## ABSTRACT

Image registration is a valuable technique for medical diagnosis and treatment. In this paper, we present an enhanced implementation of the popular iterative closest point (ICP) algorithm developed for the registration of 3D free-form closed surfaces. The main step of the ICP consists of finding the closest points between data sets which are then used to estimate the parameters of the global rigid transformation. We propose a new technique based on the use of a look up matrix for finding the best correspondence pairs. The algorithm, called Comprehensive ICP (CICP) algorithm, is then successfully applied for the registration of 3D data of the left ventricle of the heart, acquired using two different medical imaging modalities.

## 1. INTRODUCTION

3D data registration is a common problem in medical imaging. In particular, surface registration is used for the determination of correspondences between different sets of free-form structured data points. It involves the estimation of transformation parameters needed to align or visualize the different data sets into a common coordinate system. An overview of image registration techniques can be found in [1].

In clinical practice, robust image registration techniques are crucial in a large number of applications. It is used to merge complementary information obtained from various imaging modalities, in order to improve diagnosis and treatments. For instance, registration is helpful when surgery instruments are visualized in 3D close to tumors to be detected or treated. An extensive review of registration techniques used in the context of medical application can be found in [2].

In the case of mono-modal registration, where data is obtained from a single imaging technique, but at different instants, image registration can be used to follow the

evolution or remission of a disease, or to measure the impact of a treatment over a period of time.

Multimodal registration, on the other hand, takes benefit from the complementary information obtained from two or more imaging modalities (Computed Tomography, Magnetic Resonance Imaging, Angiography, Ultrasound, etc.) of the same patient [3]. It is also used to validate new imaging technologies or to compare two or more surface reconstruction methods.

This paper focuses on the validation of a new imaging modality in which 4D data of the left ventricle (LV) of the heart are acquired within one cardiac cycle using an ultrasound system [4]. For comparison reason, data of the same organ have been acquired quasi-simultaneously using Nuclear Medicine (NM) as a reference imaging modality. Prior to the comparison of the two reconstructions, the two data sets have to be registered.

The original iterative closest point algorithm (denoted OICP in this paper), proposed by Besl and McKey [5], is one of the most widespread algorithms used for 3D data registration. It is particularly valuable in the case of medical imaging registration, since it addresses situations where only few data are available. This is the case for NM images of the LV of the heart, where images are usually noisy and only 64 by 64 pixels. In this case, all the data of the targeted organ should be taken into consideration to ensure the maximum use of available information.

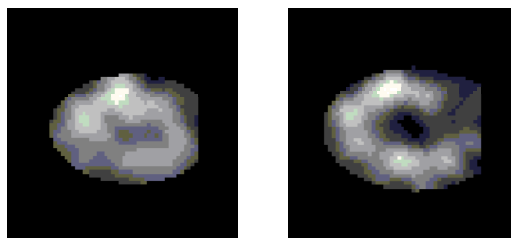


Figure 1. Example of NM slides of the LV of heart.

The OICP algorithm is designed to register *rigid* data sets. So, it is well adapted for the medical application addressed in this paper. In fact, we focus more on surface comparison than on surface fitting, which means that only parameter estimation of rigid transformation is required, without introducing deformation or modification of the organs (only translation, rotation and/or scaling are allowed).

The original ICP, algorithm is an iterative algorithm that consists generally of three main steps, as presented in Figure 2. The objective is to find a transformation that properly matches the scene surface ( $M$ ) with the reference one ( $P$ ) and minimizes the distance between them.

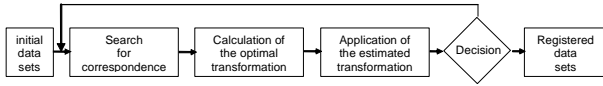


Figure 2. Overall ICP function steps.

The first step of the OICP algorithm is based on the search of pairs of nearest points between the two sets. The second step includes the estimation of the optimal rigid transformation that aligns the two data sets. Then, in the last step, the rigid transformation is applied to the points of the scene data. The procedure is iterated until convergence is achieved.

Widespread interest in 3D surface registration using the OICP algorithm has motivated the scientific community to propose new techniques for enhancing the different steps of the original algorithm. Many variants have been developed for speeding up the convergence and/or improving the performance of the different phases of the algorithm. A good review of these variants can be found in [6]. Additional features, such as curvature and moment invariants, can also be used to improve the correspondence search.

A drawback of the previously proposed ICP variants comes from the difficulty to produce a one to one match between the points of the two data sets to be registered. This leads to multiple assignment problems that we propose to solve by introducing a new matching process based on a complete lookup matrix.

## 2. MULTIPLE ASSIGNMENT PROBLEM

In previous variants of the OICP algorithm, the search procedures of corresponding pairs of points are based on a line-by-line (vector) search within a  $P$ - $M$  distance matrix described in Table 1. In this table, the 1<sup>st</sup> row describes the indices of the reference data points and the 1<sup>st</sup> column describes the indices the scene data points.  $d$ 's are the distances between the corresponding reference-scene points.  $d_1$  is less than  $d_2$  and  $d_2$  is less than  $d_3$  and so on.

For each point  $p_i$ , the OICP considers the closest point from  $M$  as a correspondence pair. For example,  $m_1$  is the closest point to  $p_1$ , and then  $p_1$  is assigned to  $m_1$ ; and so on for the rest. This might yield to correspondences that are surjective, where two or more scene points are assigned to a common reference point, as seen from the example of Table 1 where points  $p_2$  and  $p_3$  are assigned to the same point  $m_2$ .

	<b>m1</b>	<b>m2</b>	<b>m3</b>	<b>m4</b>	<b>m5</b>
<b>p1</b>	$d_1$	$d_5$	$d_{10}$	$d_{22}$	$d_{21}$
<b>p2</b>	$d_{11}$	$d_3$	$d_4$	$d_{18}$	$d_{23}$
<b>p3</b>	$d_9$	$d_2$	$d_{17}$	$d_{20}$	$d_{24}$
<b>p4</b>	$d_{12}$	$d_{13}$	$d_5$	$d_6$	$d_{19}$
<b>p5</b>	$d_{16}$	$d_{25}$	$d_7$	$d_{14}$	$d_8$

Table 1. Matching using OICP.

To overcome this drawback, the Picky ICP [7], or PICP rejects all points previously estimated to correspond to one reference point, except the one with the smallest distance,. In the given example,  $d_2$  is less than  $d_3$ , then the pair  $p_2$ - $m_2$  is rejected from the transformation estimation process. While this reduces convergence problems of the OICP algorithm, this might affect negatively the performance of the algorithm in noisy situations, since many points might be discarded in the estimation step, as presented in Table 2. In addition, as the bijectivity property of the rotation is respected.

	<b>m1</b>	<b>m2</b>	<b>m3</b>	<b>m4</b>	<b>m5</b>
<b>p1</b>	$d_1$	$d_5$	$d_{10}$	$d_{22}$	$d_{21}$
<b>p2</b>	$d_{11}$	$d_3$	$d_4$	$d_{18}$	$d_{23}$
<b>p3</b>	$d_9$	$d_2$	$d_{17}$	$d_{20}$	$d_{24}$
<b>p4</b>	$d_{12}$	$d_{13}$	$d_5$	$d_6$	$d_{19}$
<b>p5</b>	$d_{16}$	$d_{25}$	$d_7$	$d_{14}$	$d_8$

Table 2. Matching using PICP.

## 3. THE PROPOSED METHOD

Taken the bijectivity property into consideration, we propose a novel effective evaluation metric introduced for correspondence search, called comprehensive lookup matrix measure. This measure ensures that every selected point on the scene surface has a unique match in the reference surface.

The proposed algorithm is called Comprehensive ICP (or CICIP) algorithm. The CICIP is different in that it sorts the distances in ascending order within the entire  $P$ - $M$  distance matrix. Moreover, the point  $m_j$  is not considered to be a correspondence to  $p_i$  if either  $m_j$  or  $p_i$  has been previously assigned a correspondence. This ensures that each point in the scene surface will have a different association in the reference surface. In this case, the points ( $p_1$ - $m_1$ ) corresponding to the minimum distance ( $d_1$ ) are chosen as a match. Without using the rows and columns of

the previously selected pairs, the points (p3-m2) corresponding to the minimum distance ( $d_2$ ) of the resulting matrix are then chosen as another match, and so on.

As illustrated in Table 3, this method will ensure the bijectivity of the resulting matching pairs.

	m1	m2	m3	m4	m5
p1	$d_1$	$d_5$	$d_{10}$	$d_{22}$	$d_{21}$
p2	$d_{11}$	$d_3$	$d_4$	$d_{18}$	$d_{23}$
p3	$d_9$	$d_2$	$d_{17}$	$d_{20}$	$d_{24}$
p4	$d_{12}$	$d_{13}$	$d_5$	$d_6$	$d_{19}$
p5	$d_{16}$	$d_{25}$	$d_7$	$d_{14}$	$d_8$

Table 3. Matching using CICP.

#### 4. OVERVIEW OF THE CICP ALGORITHM

Assume that the given two surfaces to be registered can be described as point sets; the scene data points,  $\mathbf{P}$ , with  $N_p$  points,  $\{p_i, i=1, \dots, N_p\}$ , and the reference data points,  $\mathbf{M}$ , with  $N_m$  points,  $\{m_i, i=1, \dots, N_m\}$ . Depending on the accuracy of the constructed surfaces,  $N_p$  is not necessarily equal to  $N_m$ . Furthermore, the point  $p_i$  of the scene surface does not necessarily represent 3D correspondence to the point  $m_i$  of the reference surface. The search space, however, is determined by the size of the scene data set; i.e.,  $N_p$ .

When the number of points in the two sets to be registered is not the same, the CICP algorithm considers the one with a smaller number of points as a scene data set to ensure bijectivity of the resulting correspondence pairs. To reduce computation time introduced by matrix search procedure, fast assignment algorithms can be used. The CICP algorithm can be summarized as follows:

##### I. Initialization:

- 1) Let the initial scene surface  $\mathbf{P}_0$  be equal to  $\mathbf{P}$ .
- 2) Define the maximum number of iterations  $\mathbf{k}_{\max}$ .
- 3) Initialize the translation vector  $\mathbf{Tt}_0$  and the rotation matrix  $\mathbf{Tr}_0$  as follows:

##### II. Iterations:

- 1) For each point  $p_i \in \mathbf{P}$ , ( $i=1, \dots, N_p$ ), the algorithm computes the Euclidian distance to each point  $m_j \in \mathbf{M}$ , ( $j=1, \dots, N_m$ ). Then, for  $N_p$  times, the algorithm:
  - A. looks for the location ( $i, j$ ) that corresponds to the minimum distance in the current look up matrix,
  - B. assigns  $p_i$  to  $m_j$  as a correspondence pair,
  - C. removes this correspondence pair by eliminating the  $i^{\text{th}}$  row and  $j^{\text{th}}$  column
- 2) Using the selected correspondence pairs, compute the transformation, rotation ( $\mathbf{Tr}_k$ ) and translation ( $\mathbf{Tt}_k$ ), that minimises the mean square error (MSE) of these pairs:

$$\text{MSE} = \frac{1}{N_p} \sum_{i=1}^{N_p} \|y_i - R(p_i) - T\|^2 \quad (1)$$

The resulting transformation from the minimization of the above equation will be denoted  $\mathbf{Tt}_k$  and  $\mathbf{Tr}_k$ . This step provides also the minimum distances  $d_{i,j}$  which correspond to the matched pairs.

- 3) Transform  $\mathbf{P}$  according to ( $\mathbf{Tr}_k, \mathbf{Tt}_k$ )

$$\mathbf{P}_k = \mathbf{Tr}_k \times \mathbf{P}_0 + \mathbf{Tt}_k. \quad (2)$$

and restart a new iteration if the change in the MSE is above a predefined threshold  $\zeta$ , and if the maximum number of iterations  $\mathbf{k}_{\max}$  is not reached. If not, stop the iterations and exit.

#### 5. RESULTS AND DISCUSSION

We consider here the registration of two sequences of four surfaces of the left ventricle of the heart, acquired from two different imaging modalities. The sequences are reconstructed within one cardiac cycle. Examinations were carried out on a same patient within a short period of time, in order to assume the LV deformations to be reproducible and then medical comparisons applicable. The first sequence is composed of four LV surfaces obtained after automatic segmentation from nuclear medicine imaging, known to be a ‘‘gold standard’’ examination for cardiac observation (Figure 3a). The second LV sequence is provided by a new multidimensional ultrasound technique (US) called LV4D for Left Ventricle in 4 Dimensions [4], (Figure 3b).

The objective is to use the NM examination as a reference to validate the new ultrasound method. The evolution of the NM and US LV volumes as a function of time provides a global but not a local comparison of the reconstructed surfaces. This lack of registration does not allow local comparisons, since the two surface absolute orientations are not known.

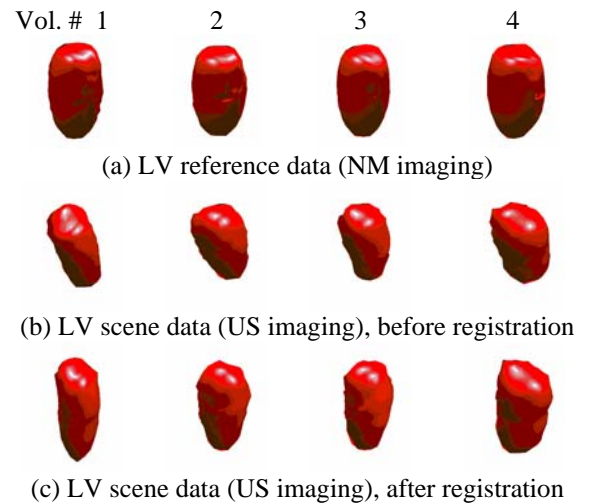


Figure 3. Registration of two sequences of LV surfaces acquired from Nuclear Medicine and Ultrasound imaging.

Even though the patient relative orientation varies inevitably between NM and US examinations, it can be considered that it remains the same relatively to an absolute reference system of coordinates during each examination. Thus, the transformation parameters to estimate are expected to be equivalent for all registered pairs of the corresponding surfaces. Differences of parameter values may occur because of the noise level that alters data, usually with a significant ratio in medical imaging. This is due for example to the resolution of the imaging techniques or the quality of the segmentation algorithms that produce surfaces.

Table 4 indicates the  $(\alpha, \beta, \gamma)$  Euler angle values (columns 3 to 6), estimated respectively using the OICP, PICP and CICP algorithms with the four NMI and US LV volumes shown in Figure 3a and Figure 3b. The last two columns (7 and 8) give the mean and standard deviation of the four corresponding angle estimations. Results obtained for each pair of surface are globally coherent, except for the  $\gamma$  Euler angle.

	Algo.	Vol. #				$\mu$	$\sigma$
		1	2	3	4		
$\alpha^\circ$	OICP	23.0	21.4	18.3	22.2	<b>21.4</b>	<b>2.3</b>
	PICP	24.7	21.5	18.4	22.2	<b>21.7</b>	<b>2.6</b>
	CICP	20.7	21.7	17.8	22.4	<b>20.7</b>	<b>2.0</b>
$\beta^\circ$	OICP	2.3	1.5	6.5	8.0	<b>4.6</b>	<b>3.2</b>
	PICP	5.6	0.2	6.9	7.7	<b>5.1</b>	<b>3.4</b>
	CICP	10.2	6.9	7.0	6.5	<b>7.7</b>	<b>1.7</b>
$\gamma^\circ$	OICP	1.9	4.1	0.6	-4.0	<b>0.7</b>	<b>3.4</b>
	PICP	-7.2	6.5	0.0	-3.8	<b>-1.1</b>	<b>5.9</b>
	CICP	-23.2	-11.5	-2.3	0.2	<b>-9.2</b>	<b>10.6</b>

Table 4. The estimated Euler angles used as rotation parameters for the registration of left ventricular surfaces.

The  $\alpha$  and  $\beta$  angles are evaluated correctly (with  $\sigma_\alpha < 2.6$  and  $\sigma_\beta < 3.4$ , respectively) since estimating the rotation angles around the X and Y axes is somewhat straightforward for LV shapes. On the contrary,  $\gamma$  angle is founded with a high degree of incertitude ( $\sigma_\gamma$  up to 10.6), yielding to non significant  $\gamma$  estimations without further study. This result is due to the shape of the LV, usually modeled by a semi-ellipsoid or a bullet, which presents a rotational symmetry around the Z axis and gives undefined  $\gamma$  angle values. Some shape discontinuities (observed for pathological cases such as ischemia, left ventricle shape irregularities, local deformations due to the right ventricle influence, overdeveloped papillary muscles, etc.) might be

helpful to estimate the  $\gamma$  angle. Moreover, post signal processing can be applied on the available  $\gamma$  angle values in order to refine coarse estimations. In this case, disposing of more than four different  $\gamma$  estimations would certainly be a prerequisite.

## 5. CONCLUSION

In this work, a multimodal data registration of the LV of heart using a novel enhanced implementation of the ICP algorithm is presented. The use of the complete look-up distance matrix during the point association procedure guarantees that unique matches are obtained for all points from the scene data, in agreement with the bijective property of the rotation. Promising results have been shown for 3D real medical data registration. After registration, the data of the two modalities considered are set to be compared locally. Further experiments will be conducted soon to describe and quantify more precisely the benefits of the CICP algorithm.

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