Pair-wise Registration of 3D/Color data sets with ICP

Lounis Douadi, Marie-José Aldon, André Crosnier

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Lounis DOUADI, Marie-José ALDON, André CROSNIER

LIRMM

UMR CNRS/UM II n° C55060

Montpellier - FRANCE

douadi@lirmm.fr, aldon@lirmm.fr, crosnier@lirmm.fr

***Abstract* - The ICP (Iterative Closest Point) algorithm remains a very popular method for the registration of 3D data sets, when an initial guess of the relative pose between them is known. The purpose of the work presented in this paper is to improve performance of classical ICP. We address, here, the problem of pair-wise registration of color range images. Many variants of ICP have been proposed for the registration of 3D data sets. However, there are only a few solutions dealing with color range images. In this paper, we have adapted some variants of ICP to take into account color information in the closest point research. Two approaches of color data integration have been evaluated with real 3D/Color data sets.**

Index Terms – model reconstruction, color range images, registration, Iterative Closest Point.

I. INTRODUCTION

Automatic building of 3D computer models of real-world objects and scenes has found application in many fields like: building 3D environment maps for robot navigation, creating virtual reality models through observation of real objects, digitizing historical buildings for restoration planning, or archiving heritage objects from museums or cultural organizations.

Creating a 3D model requires generally the acquisition of multiple partially overlapping views captured with different sensor locations. The number of views increases with the sensor resolution and it depends on the object complexity and on the object size. So, building the complete 3D model requires the registration of multiple views that are assumed to be pair-wisely overlapping [3,11]. The registration of 3D data sets can be defined as the process of estimating the rigid transformation that places these 3D data sets in a common coordinate system. This is often considered as an optimization problem in which the cost function to minimize is based on distances between the 3D data sets placed in a same frame [1]. Most of registration techniques proceed with two main steps: the data matching stage followed by the rigid transformation estimation stage.

The ICP (Iterative Closest Point) algorithm [2] remains a very popular method for the registration of 3D data sets, when an initial guess of the relative pose between them is known. Many variants of ICP have been proposed for the registration of 3D data sets. However, there are only a few solutions dealing with color range images [6,8,11].

The use of color data, when available, can provide constraints necessary when 3D information is not relevant enough to provide a correct solution (flatness, periodicity, symmetry, etc.). Morever, color information can be used to reduce the cost of the expensive closest point finding, and to make registration more robust against false pairings.

3D/color data can be acquired in two different ways. The first one is to capture range and color data with the same sensor (stereovision, structured light vision, …). In this case, 3D and color data are provided in the same coordinate system. The second approach consists in acquiring range and color separately. For instance, range data can be captured with a laser range finder, and a CCD camera can provide color information.

Our research work has been carried out in the context of creation of high-resolution 3D/color models of heritage objects for museums. Our purpose was to improve performance of classical ICP approaches by taking into account color information for point matching. We address here the problem of pair-wise registration of dense color range images provided by a structured light sensor.

This paper is organized as follows. In section II we describe the ICP algorithm and the problem statement. In section III, we evaluate three variants of ICP including our new variant, for the registration of a pair of 3D/color images. These variants are used, in section IV, for real data registration. In section V, we study the effect of the color space on the algorithm performance.

II. ICP ALGORITHM AND PROBLEM STATEMENT

The ICP algorithm [2] is an iterative method for the registration of 3D data sets. This algorithm computes, in an iterative way, the transformation matrix T (a rotation matrix R and a translation vector t) that best aligns two 3D data sets (3D points, 3D curves or surfaces). A rough estimate T_i of the transformation matrix is needed for the initialization of ICP. This algorithm repeats the two registration main stages: the data matching and the transformation estimation. Many variants of ICP have been developed [7]. Rusinkiewitcz & Levoy [12] have classified most of these variants and evaluated their effect on the algorithm convergence. According to the Rusinkiewitcz classification, we consider that the variants proposed for ICP concern the different steps of the algorithm: selection of points to be registered [8,10,12], matching technique [4, 6, 7, 11, 13], weighting of the matched pairs [7, 9], outliers rejection [10, 11, 15] and transformation estimation [1, 2, 4, 5, 9, 14].

The problem considered in this paper is to register two sets D1 and D2 of 3D/color points. These data sets are partially overlapping. They are captured with two different sensor locations (or with different object positions). A 3D/color point P_i is defined by its 3D coordinates (x_i, y_i, z_i) and its color components (c_{1i}, c_{2i}, c_{3i}). We need to compute the rigid transformation matrix T that best aligns D1 and D2 using ICP.

A summary of the basic ICP algorithm [2] is given below. It uses only 3D information to achieve the registration of D1 and D2.

Initialize: k = 1; $T_k = T_i$; convergence = 0;

WHILE (k<Kmax or convergence == 0)

1. Point Matching: For each point P2' from D2' (P2' = T_k.P2) find its closest neighbour in D1. We obtain the matched points list [CP1, CP2],

2. Compute the transformation matrix $\hat{T}$ with a mean squares estimator. This estimator needs CP1, CP2 and T_k as inputs in order to minimize error:

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\left\| \hat{T} * cp_2(i) - cp_1(i) \right\|^2 \quad (1)$$

3. Update: $T_k = \hat{T}$, k = k + 1,

if convergence condition is satisfied $\Rightarrow$ convergence = 1,

END While, T = T_k.

In the following sections, we will compare three variants of ICP with this basic algorithm when registering a pair of 3D/color images.

III. Comparative Study

The comparative study performed here concerns two well known versions of ICP using only 3D data [2, 15], and two new variants using 3D and color data in order to improve the speed of the matching step and to help the rejection of bad pairs. So, we will compare performance of the following algorithms:

- *ICP (classical algorithm) [2],*
- *ICP_GAT (G: geometric distance, AT: adaptive threshold) [15],*
- *ICP_MAT (M: mixed distance, AT: adaptive threshold) [6],*
- *ICP_GCT (G: geometric distance, CT: color threshold).*

Experimentations described in section III have been achieved with a data set provided by the MINOLTA sensor from Ohio State University [16]. We use a part (2000 points) of a 3D/color image called Image1. We obtain the Image2 to be registered with Image1 by moving the latter with a simulated motion Ts (figure1). No additional noise has been added to the second image.

The simulated motion Ts is a translation along the X-axis: tx = 15 mm. The overlapping between the two images is 40%. We add a noise to the rigid transformation Ts in order to obtain the initial guess Ti used by the evaluated algorithms. The bias on the three translations is 5 mm and the bias on the three rotations is 5°.

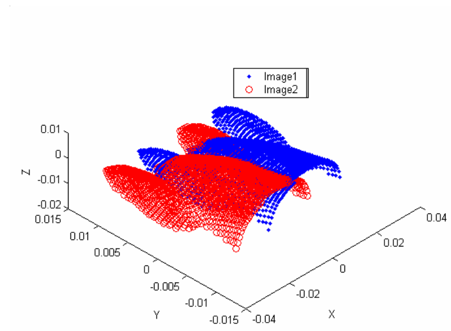


Figure.1: Image1 and Image2 before registration

A. *ICP_GAT*

ICP_GAT is a variant of ICP algorithm using an Euclidian geometric distance in the matching stage and a statistical adaptive threshold [15] to remove outliers. This threshold is named Dmax is defined as follows :

if $(\mu < D) \Rightarrow D_{\max} = \mu + 3\sigma \Leftrightarrow$ The registration is quite good (2)

else if $(D < \mu < 3D) \Rightarrow D_{\max} = \mu + 2\sigma \Leftrightarrow$ The registration is good (3)

else if $(3D < \mu < 6D) \Rightarrow D_{\max} = \mu + \sigma \Leftrightarrow$ The registration is not so bad (4)

else $\Rightarrow D_{\max} = \xi \Leftrightarrow$ The registration is bad (5)

μ is the mean distance of the matched points, σ is the distance standard deviation, D is a constant near of the sensor resolution. We chose D = r / 5, where r is the geometric sensor resolution. The points pairs with a distance larger than Dmax are systematically rejected.

Figure.2 shows the evolution of the distance residual error between matched points in the case of ICP and ICP_GAT, compared to the sensor resolution. For ICP the residual error decreases monotonically to a local minimum. It is reached in about 16 iterations. We can see that, for ICP_GAT, the error does not fall monotonically to a local minimum. This error increases during the four first iterations, then it is stable during more than 25 iterations and, finally, it falls below the error obtained with classical ICP. In ICP_GAT the non-monotony of the error in the first iterations is due to the adaptive threshold that we force to an exaggerated value equal to 50.D. This is done in order to avoid the rejection of all the pairs during the fist iterations.

In ICP_GAT the parameter D, which must be supplied by the user, has a big impact on the convergence of the algorithm. When D is too big, the algorithm can converge to a bad solution (local minimum) because some false matches have not been rejected. If, D is too small, the algorithm does not converge because many good points pairs have been discarded. So, the difficulty to adjust D is a real drawback for this method.

We can notice that here, the residual error reaches a value less than the sensor resolution. This is only due to the fact that we have no additional noise in the second image.

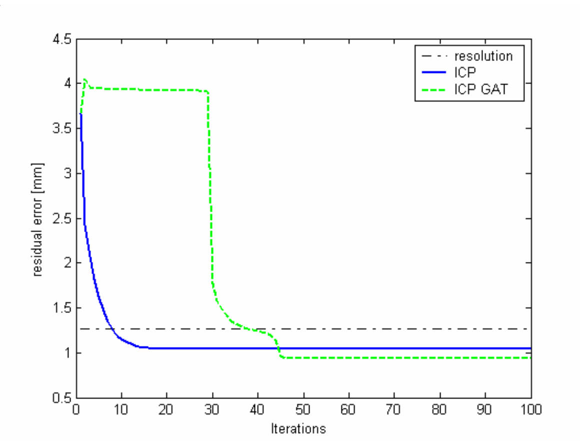


Figure.2: Residual error: ICP vs. ICP_GAT

B. *ICP_MAT*

ICP_MAT is a variant of ICP that uses color data in a mixed distance in the closest point research. Johnson and Kang used a 3D/color distance in [6]. We follow a similar approach by using an adaptive threshold to remove outliers.
The mixed distance includes a geometric term A and a photometric term B :

$$d_m = \sqrt{[A+B]} \tag{6}$$

$$A = (1-\alpha).\left((x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2\right) \tag{7}$$

$$B = \alpha.\left((c_{11} - c_{12})^2 + (c_{21} - c_{22})^2 + (c_{31} - c_{32})^2\right) \tag{8}$$

(x_i, y_i, z_i) and (c_{1i}, c_{2i}, c_{3i}) are, respectively, the coordinates and the color components of a point in image i. α allows us to adjust the respective weights of color and 3D data. This coefficient, included between zero and one, reflects the confidence in color data with respect to geometric data of the digitized object. When the shape of the object is not significant (e.g. on a painting), we give more importance to texture, α is taken near to one. This coefficient is also adjusted according to data quality, which depends on the acquisition noise. Figure.3 depicts the residual error in the case of ICP_GAT and ICP_MAT. We can easily observe that ICP_MAT gives better results than ICP_GAT.

Besides the need to adjust the parameter D, ICP_MAT requires the definition of the color weight α. In figure.3 this coefficient is equal to 0.5. Because of the nature of the digitized object, we give the same weight to color and range data. We will see that, generally, it is difficult to fix α in a relevant way. In order to avoid the difficulties induced by the need to adjust parameters D and α, we propose another variant named ICP_GCT where color is used in a different way.

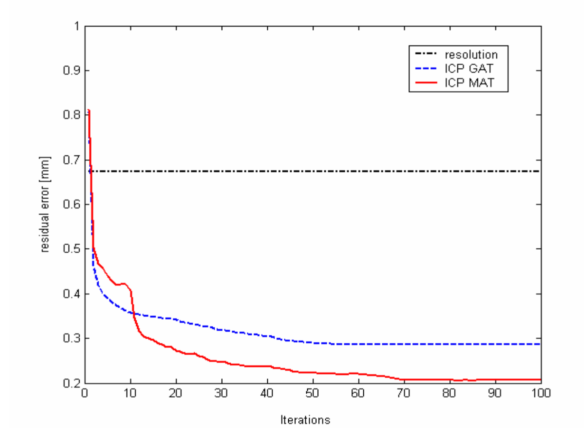


Figure.3 Residual error: ICP_GAT vs. ICP_MAT

Experimental results presented in fig. 2 and fig.3 have been obtained from the same original data sets, but with a different resolution. In fig. 3 we have used all available points, while in fig.2 a uniform subsampling has been achieved to use only 50% of points.

C. *ICP_GCT*

ICP_GCT takes into account color and range data separately. In the matching stage of the algorithm, we use only range data to find the 3D closest points. So, the criteria used during the matching stage consists in a simple geometrical euclidian distance.
Color data occurs in an euclidian color distance constraint applied to the pairs resulting from the geometrical matching step. So, a color threshold is used instead of an adaptive geometrical one to remove outliers. This color threshold applied on color distances between matched points is equal to the median of color distances.

Figure.4 shows residual error for ICP_GAT, ICP_MAT and ICP_GCT. We see that ICP_GCT is the most efficient. This result seems to confirm that, color data is not correctly used with ICP_MAT (bad choice of α). Moreover, outliers have not been rejected in an efficient way for ICP_GAT and ICP_MAT, because of an incorrect value of D.

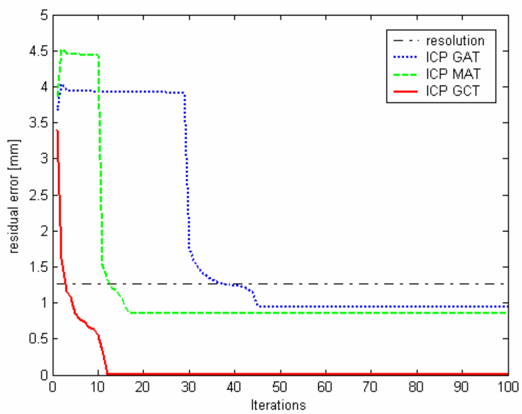


Figure.4 Residual error: ICP_GAT vs. ICP_MAT vs. ICPGCT

TABLE I
REGISTRATION ERRORS AT CONVERGENCE

Algorithm	ICP_GAT	ICP_MAT	ICP_GCT
tx [mm] error	1.7856e-005	1.163e-005	~0
ty [mm] error	1.7382e-005	4.0619e-005	1.9516e-018
tz [mm] error	7.1254e-005	6.6131e-005	1.3878e-017
rho [d°] error	0.024365	0.21428	5.7645e-015
theta [d°] error	0.065573	0.044336	1.7493e-014
phi [d°] error	0.27072	0.23403	9.5417e-015
Convergence iteration	45	18	12

Table 1 contains the pose estimation errors between the correct pose (ground truth) and the estimated pose for each algorithm. We consider errors at the convergence iteration. These errors have been estimated for each of the six motion components (translations components and roll-pitch-yaw angles). One can remark errors near to zero in the case of ICP_GCT. These errors are very close in the case of ICP_GAT and ICP_MAT. Nevertheless, errors with ICP_MAT are, generally, slightly lower than errors with ICP_GAT. On the other hand, when comparing the number of iterations required to reach the convergence of the estimation process, we notice that only 12 iterations are necessary for ICP_GCT. This algorithm remains the most efficient with respect to residual and pose estimation errors, and to convergence rate.

IV. REAL DATA REGISTRATION

In this section, we will not use a simulated motion to generate the second view to be registered with the first one. We will achieve the registration of two real 3D/color images provided by the MINOLTA sensor from OSU [17].

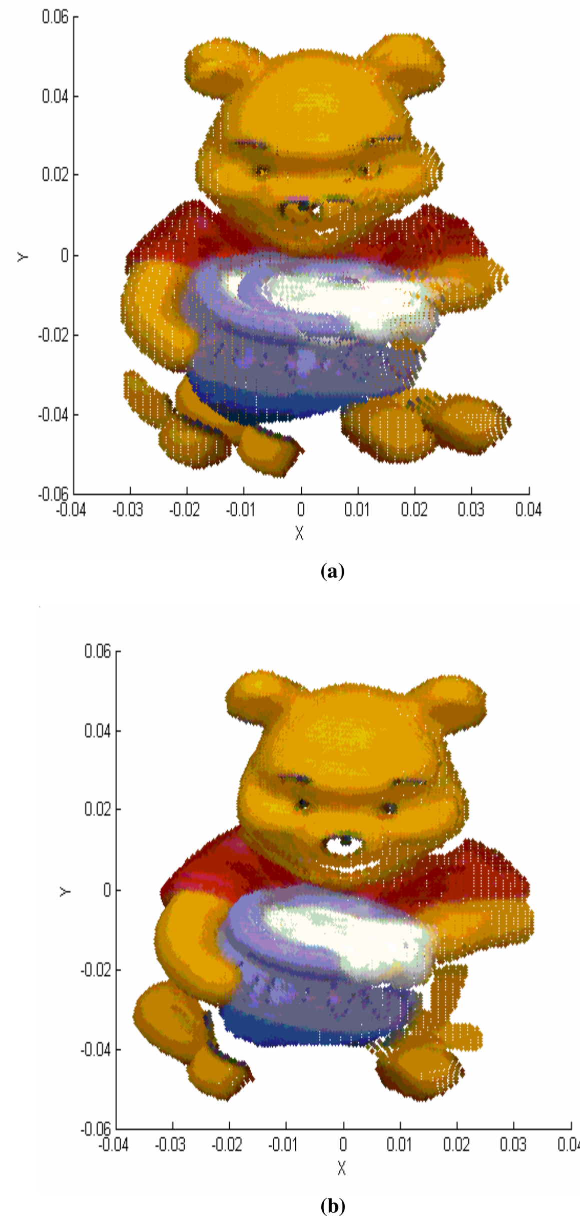
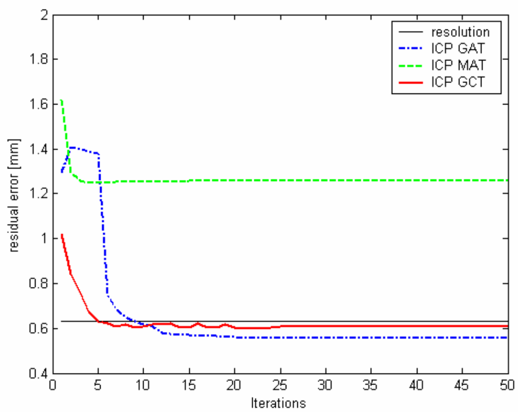


Figure 5: Image1 and Image 2:
a) registered with the initial transformation
b) registered with ICP_GCT

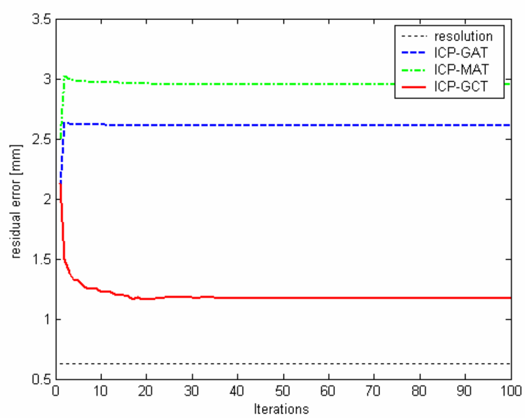
These partially overlapping views are captured with two different object locations. The object was placed on a turntable rotating with a step of 20° around a vertical axis. Figure.5a shows the two images to register: Image1 and Image2. The second is mapped on the first one using the transformation matrix provided by the OSU. One can see that this transformation does not fit the two images correctly. This transformation matrix is used as the initial guess in the evaluated algorithms.
Figures 6a and 6b present the mean residual error given by the algorithms evaluated in the previous sections. These

registration results are obtained by using two different subsets of the whole data set provided by the sensor:

- In figure 6a, registration has been achieved by using only the first 2000 points in each 3D/color image, which corresponds approximately to the upper part of the head where color data is not very significant,
- In figure 6b, registration has been achieved by using the following 2000 points in each 3D/color image that corresponds to a middle zone including the lower part of the head and the shoulders (see figure 7). In this part, color images are more textured.



(a)



(b)

Figure 6: Residual errors with registrations using two different data subsets: (a) upper part of the images, (b) middle part of the images.

In figure.6a, we can see that ICP_GAT has the lowest error compared to ICP_MAT (with α = 0.5) and ICP_GCT. Nevertheless, the last one provides a residual error very close to that of ICP_GAT. This error is less than the sensor resolution for these two algorithms. However, ICP_GCT presents the best convergence rate.

These results show that, in the upper part of the two images, which are used for registration, color data is not significant compared to 3D data. It is obvious that, for ICP_MAT, we should attribute a lower weight for color. Figure.5b displays Image1 and Image2 registered with ICP_GCT. We can check the registration quality by comparing this result with the registration given by the initial transformation (figure 5a).

In figure 6b where more significant color data are used, ICP_GCT produces the best results in terms of residual error and of convergence rate. The mean residual error is twice the sensor resolution, and the convergence requires less than 20 iterations. We can observe that ICP_GAT and ICP_MAT reach a local minimum, which can be explained by a bad choice of the parameter D.

V. CHOICE OF THE COLOR SPACE

On figure 8, the residual error in the best case (for ICP_GCT) is approximately twice the sensor resolution. This is due to noise in color and range data. Color variations between two viewpoints may occur, due to variations in shading. Shading generally affects the intensity of light coming from an object, but not its intrinsic color [6]. We can reduce the effect of intensity variation in the matching process by using a color representation system, which separates the intensity and chromatic components. Instead of the RGB color space, we work in the YIQ space (Y is intensity, I and Q are chromatic components). Equation (6) giving the mixed distance in ICP_MAT becomes:

$$d_m = \sqrt{[A + C]}$$

$$C = \alpha.\left(a.(c_{11} - c_{12})^2 + b.(c_{21} - c_{22})^2 + c.(c_{31} - c_{32})^2\right).$$

The Euclidian distance used in ICP_GCT to remove outliers is defined below:

$$d_c = \sqrt{\left[a.(c_{11} - c_{12})^2 + b.(c_{21} - c_{22})^2 + c.(c_{31} - c_{32})^2\right]} \; .$$

a, b and *c* are weights corresponding to each color component. They take values between 0 and 1. Through these weights we can control the contribution of each color component in the distances d_m and d_c. In this experimentation, we have chosen:

a = b = c = 1, for the RGB color space,

a = 0.1, b = 1, c = 1, for the YIQ color space.

We evaluate the impact of the color space on performance of ICP_GCT. Figure 8 shows residual errors for ICP_GCT_RGB and ICP_GCT_YIQ applied to the registration of images shown on figure 7. It appears that the residual error is lower in the case of ICP_GCT_YIQ. Using a perceptual color space helped us to reduce the impact of intensity variations and to improve the performance of ICP_GCT.

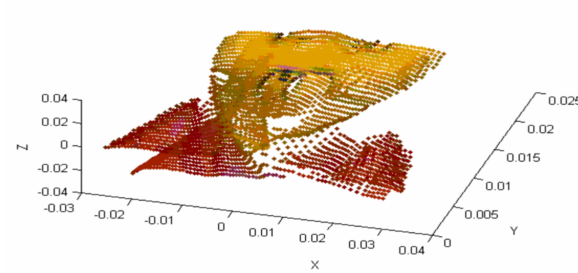


Figure.7 Image1and Image2 before registration

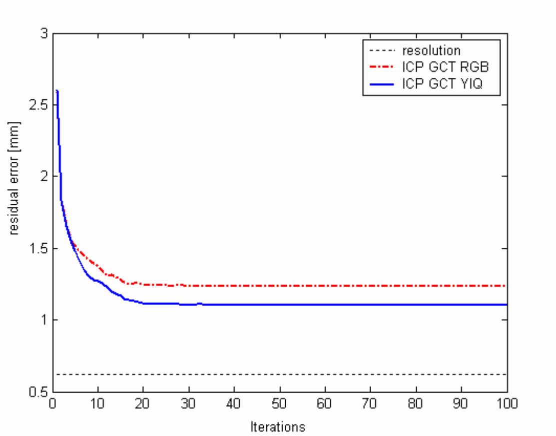


Figure.8 Effect of the color space on the residual registration error.

VI. Conclusion

We have developed two variants of the Iterative Closest Point algorithm for the registration of 3D/color data sets. The aim of this work was to show the importance of color information to increase the matching performance. We compare these variants with a well-known version of ICP that does not use color data. This method proposed by Z. Zhang [15] uses an adaptive threshold to remove outliers.

In our first algorithm, the point matching uses a mixed distance and a 3D adaptive threshold. In the second approach, we use a simple Euclidian geometric distance for the matching, and we reject false pairs that do not verify a constraint on color distance. This last solution remains the most efficient of the three evaluated variants for noise free data. We have noticed that the adaptive threshold was very sensitive to the choice of parameter D. Also, adjusting the weight α of the color makes the use of a mixed distance difficult enough. The test achieved with real data helped us to see the behavior of these algorithms in presence of noise (noisy color and noisy range data). We concluded that when color data is not as significant as the geometric data, the method of Zhang provides the best results. But for data with significant colors our method was the most efficient.

Finally, we showed that it was possible to reduce the drawbacks of intensity variations by choosing a perceptual color space like YIQ where intensity and chromatic components are separated.

Being a local optimisation method, ICP is very sensitive to a bad initial transformation estimate. So, our current research aims to propose a solution for determining automatically a rough estimate of the initial transformation of ICP. Then, we will generalize our method to the problem of multiview registration.

References

[1] K. Arun, T. Huang and S. Blostein, "Least Squares Fitting of two 3D Point Sets", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 9, n° 5, pp. 698-700, 1987.

[2] P.J. Besl and N.D McKay, "A Method for Registration of 3D Shapes", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 14, n° 2, pp.239-256, 1992

[3] G. Blais and M.D. Levin, "Registering Multiview Range Data to Create 3D Computer Objects", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 17, n° 8, pp. 820-824, 1995.

[4] Y. Chen and G.Medioni, "Object Modelling by Registration of Multiple Range Images", Image and Vision Computing, Vol. 10, n° 3, pp. 145-155, 1992.

[5] O. Faugeras and M. Hebert, "The Representation, Recognition and Localisation of 3D Objects", International Journal of Robotics Research., Vol. 5, n° 3, pp. 27-51, 1986.

[6] Andrew Johnson and Sing Bing Kang, "Registration and Integration of Textured 3D Data", Cambridge Research Lab, Technical Research Series, CRL 96/4, October 1996.

[7] Timothée Jost, "Fast Geometric Matching for Shape Registration", PhD report, Faculté des Sciences de l'Université de Neuchâtel, 2002.

[8] G. Godin, D. Laurendeau, R. Bergevin, " A method for the registration of Attributed Range Images", 3DIM, pp. 179-186, Québec, 2001.

[9] Jason Luck, Charles Little and William Hoff, "Registration of Range Data Using a Hybrid simulated Annealing and Iterative Closest Point Algorithm", IEEE International Conference on Robotics and Automation, San Francisco, pp. , 2000.

[10] Takeshi Masuda and Naokazu Yokoya, "A Robust Method for Registration and Segmentation of Multiple Range Images", Computer Vision And Image Understanding, Vol. 61, n° 3, pp. 295-307, May 1995.

[11] Kari Pulli, "Multiview Registration for Large Data Sets". 3DIM, pp. 160-168, Ottawa, 1999.

[12] Szymon Rusinkiewicz and Mark Levoy, "Efficient Variant of the ICP Algorithm". 3DIM, pp. 145-152, Québec, 2001.

[13] Gregory C. Sharp, Sang W. Lee and David K.Wehe, "ICP Registration Using Invariant Features", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, n° 1, pp. 90-102, 2002.

[14] M. Walker, L. Shao and R. Volz, "Estimating 3D Location Parameters Using Dual Number Quaternions", CVGIP: Image Understanding, Vol.5, n° 3, 1991.

[15] Zhengyou Zhang, "Iterative Point Matching for Registration of Free Form Curves", IJCV, vol. 13, n° 2, pp 119-152, 1994.

[16] http://sampl.eng.ohiostate.edu/~sampl/data/3DDB/RID/minolta/.