13—32 Registration of Complex Free-Form Objects from 3D Edge Images Using the Hausdorff Distance

Antoine Escobar, Denis Laurendeau
Computer Vision and Systems Laboratory,
Department of Electrical and Computer Engineering
Laval University

Abstract

The Hausdorff distance [6] [7] is a max-min distance for comparing two sets. In fact, the Hausdorff distance can be considered as a metric to measure (quantify) the similarity between two sets of points, i.e. the extent to which each point belonging to a *model* lies near some point of an *image* set. In this paper, we describe an efficient registration method for computing the rigid body transformation of complex free-form moving objects from their 3D edge images. The registration problem is formulated as an optimization problem. Our method performs the minimization of a cost function based on the Hausdorff distance. What characterizes our approach is that it does not require explicit feature extraction, correspondence determination, or surface normal estimation, an operation that it is often sensitive to noise. Therefore, the choice of the Hausdorff distance allows us to deal with outliers, occlusion, appearance and disappearance. The proposed algorithm has been tested on real data, and the results show that it is efficient, robust and yields a good transformation estimate.

1. Introduction

The design of an intelligent robot, i.e. one that plans and executes actions intelligently, is one of the main goals of computer vision research. An intelligent robot must dynamically build models of its environment, detect any changes, and react properly in order to follow the execution of its assigned task. The design of a supervised or non-supervised intelligent robot is of interest for scientific purposes but also for applications, such as in automobile, energy, and space industries as well as in medicine. In many applications, the pose (the position and orientation) and motion of a robot relative to a target object can be important [1-11]. For instance, an autonomous car has to see the road and avoid any collisions. The work presented in this paper is based on the Hausdorff Dynamic Hill Climbing algorithm (HDHC) introduced in [4]. We can notice that no a priori knowledge on the object nor on its kinematic characteristics are required for computing the pose. Moreover, no constraints on the shape nor on the trajectory of the object are imposed. What characterizes our approach is that it does not require explicit feature extraction, correspondence determination, or surface normal estimation, an operation that it is often sensitive to noise.

Address: Computer Vision and Systems Laboratory, Department of Electrical and Computer Engineering, Laval University, Ste-Foy (Qc), Canada, G1K7P4.
E-mail: [escobar,laurend]@gel.ulaval.ca
http: //www.gel.ulaval.ca/~vision

2. Object registration strategy

As developed in [4], the registration problem may be formulated as an optimization problem.

Let us assume a set of $\boldsymbol{n}$ range views $\{ v_1, v_2,..., v_n \}$ of a given object describing the 3D structure of this object observed from different viewpoints. We want to find the $\boldsymbol{n}$ rigid transformations $\{ t_1, t_2,..., t_n \}$ that allow to transform each range view into one arbitrary view v_i chosen as the world reference frame. The new set of 3D points $\boldsymbol{S}$ representing the integrated surface model is thus the combination of all transformed 3D point sets $\boldsymbol{S}_i$ corresponding to their respective range view. In order to achieve an accurate registration, a cost function ζ is defined to quantify the quality of this registration. This means that two range view are registered for the rigid transformation t which minimizes the cost function ζ:

$$\exists\, t \in T \quad | \quad \zeta(t_x, t_y, t_z, \theta, \varphi, \alpha) \rightarrow \min \qquad (1)$$

Whereas the cost function which measures the quality of the overlap between the common part of two range images is often based on the sum of Euclidean distances between corresponding points in each view [2], or based on the average Euclidean distance between the first range image and the second range image along the normal to the surface at each overlapping point [8], we rather introduce a cost function based on the Hausdorff distance.

$$\begin{gathered}\exists\, t \in T \\ \zeta(t_x, t_y, t_z, \theta, \varphi, \alpha) = H(S_i, tS_k) \rightarrow \min\end{gathered} \qquad (2)$$

The Hausdorff distance [6][7] is a max-min distance for comparing two sets. For two given finite point sets M and I, corresponding respectively to the *model* and the *image* object, the Hausdorff distance is defined as:

$$H(M, I) = max(h(M, I), h(I, M)) \qquad (3)$$

where

$$h(M, I) = \max_{m \in M} \min_{i \in I} \|m - i\| \tag{4}$$

In others words, the Hausdorff distance between the two set M and I, $H(M,I)= \boldsymbol{d}$, means that all the points of M have to be within a distance $\boldsymbol{d}$ of some point of I, and there is at least one point of M at the distance $\boldsymbol{d}$ of its nearest point in I. Unfortunately, the Hausdorff distance, as define above, can be dramatically corrupted by outlier points (sensing errors, occlusions,...) which do not belong to any point of the object to track.

In order to reduce the effect of outliers, we used a rank order distance instead of the previous distance definition, where K^{th} denotes the K-th ranked value over the point set M. This takes care of the fact that a portion of M may not correspond to any portion of I.

$$h(M, I) = \underset{m \in M}{K^{th}} \min_{i \in I} \|m - i\| \tag{5}$$

In order to achieve an accurate registration, i.e. find the optimum transformation between two successive range images, we propose in [4] the Hausdorff Dynamic Hill Climbing algorithm. The basic idea behind the HDHC algorithm is that the direct partial Hausdorff distance, $h(M,I)$, measures the degree of similarity between the set M at a given time, and the set I in the next frame. The minimum value of this distance allows to identify the optimum transformation $\boldsymbol{t}^*$ in the space $\boldsymbol{T}$ of all rigid transformations in 6 DOF.

As shown in [4], the HDHC algorithm is efficient, robust and yields an accurate transformation estimate. However, it can be expensive in computation time when it is applied to a very large point set. For instance, the Haunch bone image can contain up 20500 points. Thus in order to reduce the computational load of the algorithm, we have implemented a 3D segmentation algorithm based on the classical Canny filter for the detection of 3D step discontinuities (Fig.1). The segmented Haunch bone image is approximately reduced to 3200 points, therefore reducing computation time by a factor of 6. The proposed range data algorithm, in opposition with methods based on the normal to the surface [3][8], -which cannot be used directly with 3D edge images-, remains efficient, robust and produces a good transformation estimate (Table 1, Fig.2) when applied to this 3D *compressed* image. The obtained transformation can then be used as an initial transformation when the HDCH algorithm is directly applied on a non-segmented image.

3. Experimental results

The proposed registration algorithm based on the Hausdorff distance, -the HDHC algorithm-, has been applied to several sets of range images of complex free-form objects with holes. The object presented in this paper is a haunch bone. Fig.1 shows the original Haunch bone image sequence and its corresponding segmented Haunch bone image sequence. The number in the view name represents the angle of rotation in degrees along the horizontal axe between two range views. A segmented haunch bone image is approximately reduced by a factor of 6 from its corresponding *non-segmented* image, reducing thus computation time by a same factor.

Table 1 shows results obtained from the Chen-Medioni algoritm and the HDHC algorithm applied to the same image sequence. One may note the difference between the ground truth transformation and the transformations estimated by the Chen-Medioni algorithm and the HDCH algorithm. This is due to the approach. Indeed, the actual transformation is made from the center of mass of the object whereas the estimated transformation is computed from the center of mass of the range data. Therefore, the difference in translation of the transformation is essentially due to this difference.

In Fig.2 each circle contains an segmented image sequence of a haunch bone at different time stamps. The inner circle corresponds to the original sequence of the moving segmented haunch bone. The second circle contains the transformed image sequence. Then, the outer circle contains the sequence of the transformed images in registration with the original images. At time $i+1$ (shadowed area), the transformation $\boldsymbol{t}_i$ between the image at the current and previous times is computed. Then, the past image is brought in registration with the image of the present time using the transformation $\boldsymbol{t}_i$ (2nd circle). Finally, in the outer circle, we show the two superimposed images.

4. Conclusion

A new approach has been presented to estimate the registration transformation for a set of scattered range data of complex free-from objects. The originality and the characteristics of our approach is that it does not require explicit feature extraction, correspondence determination, or surface normal estimation, an operation that it is often sensitive to noise. Therefore, the choice of the Hausdorff distance allows to deal with outliers, occlusion, appearance and disappearance. The proposed registration method, -the HDHC algorithm-, is efficient, robust, and produces a good transformation estimate. The transformation estimates from a 3D edge images can be used as an initial transformation for more accurate but more time consuming algorithms [3][4][11]. We can also add that our approach does not make any of the assumptions commonly made by others approaches. In fact, no *a priori* knowledge on the object nor on its kinematic characteristics are known. Moreover, no constraints on its shape nor on its trajectory are imposed.

5. Acknowledgments

The authors would like to thank M. Soucy of InnovMetric Inc. for providing the range images used in this work. The research work has been supported by

NSERC grant OGPIN 011. The authors also wish to acknowledge the support of the Networks of Centres of Excellence program of the Government of Canada, the Natural Sciences and Engineering Research Council and the participation of PRECARN Associates Inc.

6. Reference

[1] Besl, P.J., McKay, N.D., A Method for Registration of 3D Shapes, IEEE Trans. on PAMI, vol. 14, no. 2, 1992.

[2] Blais, F., Levine, M.D., Registering Multiview Range Data to Create 3D Computer Objects, IEEE Trans. on PAMI, vol. 17, no. 8, 1995.

[3] Chen, Y., Medioni, G., Object Modeling by Registration of Multiple Images, Proc. IEEE ICRA, Sacramento, CA, 2724-2729, 1991.

[4] Escobar, A., Laurendeau D., 3D Tracking using The Hausdorff Distance, Proc. Tenth IMDSP Workshop, Alpbach, Austria, 12-16 July, 77-84, 1998.

[5] Faugéras, O.D., and Hébert M., The Representation, Recognition, and Locating of 3-D Objects, Int. J. Robotics Research, 5, 3, 27-52, 1986.

[6] Huttenlocher, D.P., Noh, J.J., Rucklidge, W.J., Tracking Non-Rigid Objets in Complex Scenes, ICCV, 93-101, 1993.

[7] Huttenlocher, D.P., Rucklidge, W.J., A Multi-Resolution Technique for Comparing Images Using the Hausdorff Distance, Proc. CVPR 1993, N.Y., USA, June 1993.

[8] Laurendeau, D., Roth, G., Borgeat, L., Optimization Algorithms for Range Image Registration, Proc. VI'96, Toronto, Canada, May 1996

[9] Sabata, B., and Aggarwal, J.K., Estimation of Motion from a Pair of Range Images: A Review, CVGIP: Image Understanding, 54, 3, 309-324, 1991.

[10] Yamamoto, M., Boulanger P., Beraldin J.A., Rioux M., Direct Estimation of Range Flow on Deformable Shape from a Video Range Camera, PAMI, 15, 1, 82-89, 1993.

[11] Zhang, Z., Iterative Point Matching for Registration of Free-Form Curves and Surfaces, Int. J. of Computer Vision, vol. 13, n.2, 119-152, 1994.

Table 1 Statistical characteristic of the transformation computed by the HDHC algorithm from the sub-sequence [th45,th60]

	ground truth Transformation	Transformation (Chen-Medioni algo)	average Transformation (HDHC algo) for 100 runs	standard deviation
rot_x (degres)	15	14.713	13.913	0.292
rot_y (degres)	0	0.38548	0.552	0.444
rot_z (degres)	0	0.476986	-0.126	0.223
tr_x (mm)	0	-0.0630646	-0.867	0.335
tr_y (mm)	0	9.98921	7.499	1.132
tr_z (mm)	0	-2.76166	0.71	0.214

average Hausdorff distance (mm) over 100 runs of HDHC algo	standard deviation
2.2563	0.00124

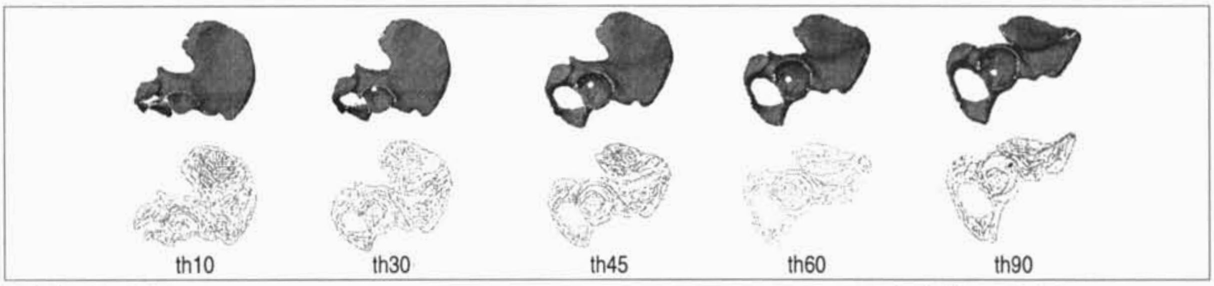

Fig.1 A full Haunch bone image sequence and its corresponding segmented Haunch bone image sequence.

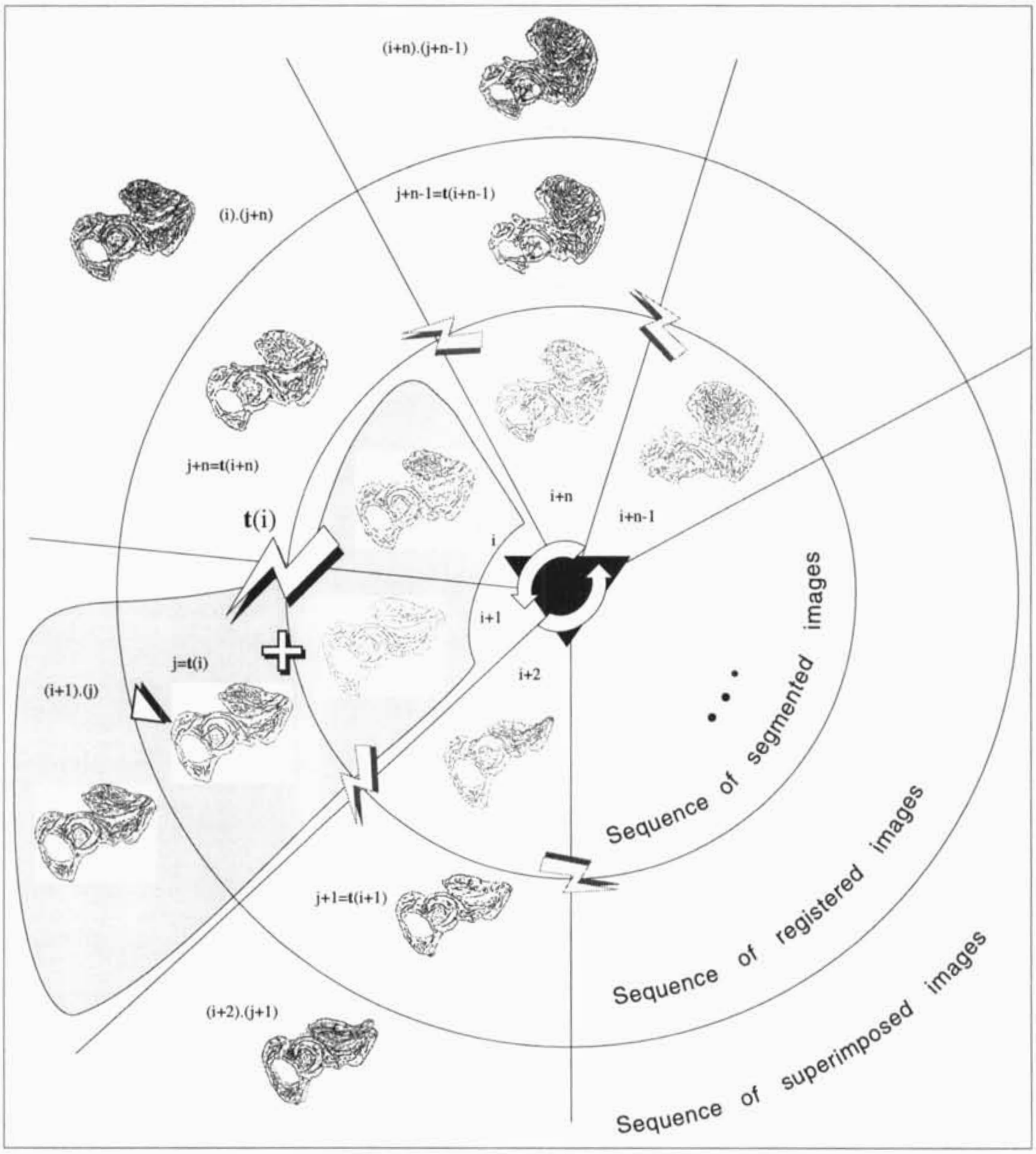

Fig.2 The Haunch bone Registration. Each circle contains an segmented image sequence of an haunch bone at different time stamps. The inner circle corresponds to the original sequence of the moving segmented haunch bone. The second circle contains the transformed image sequence. Then, the outer circle contains the sequence of the transformed images in registration with the original images. At time i+1 (shadowed area), the transformation t_i between the image at the current and previous times is computed. Then, the past image is brought in registration with the image of the present time using the transformation t_i (2nd circle). Finally, in the outer circle, we can see the 2 superimposed images.