Surface registration by markers guided non-rigid Iterative Closest Points algorithm

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Abstract - *The problem of matching irregular surfaces was tested with additional markers as landmarks for the extension of the non-rigid Iterative Closest Points (ICP) algorithm. The general idea of presented approach was to take into account knowledge about markers' positions not only in computing transformation phase but also in finding correspondence phase in every algorithm's iteration. Four variants of retrieving correspondence were implemented and compared: the Euclidean distance, normal vectors with initial rigid registration, static and dynamic markers vectors. To evaluate different manner of computing correspondence the average correspondence assignment error of points nearest to the markers and the number of correspondences for every target points were defined. The presented approach was evaluated using abdominal surfaces data set, consist of captured clouds of points during free breathing of 6 volunteers. The modifications significantly improved results. To make the proposed changes more universal k-nearest neighbor method and radius constraint could be used.*

Keywords: markers guided geometry-based registration, finding correspondences, non-rigid Iterative Closest Points, surface registration quality, surface registration.

1 Introduction

Registration is a process to find correspondence between data sets, and generally could be divided into geometry-based or intensity-based methods [1]. Nowadays, in many multimedia application input data set are represented as point cloud (segmented surfaces of the objects etc.). Then in the processing pipeline data sets should be register, to find the correspondence between data sets. The most popular approach, in this case, is Iterative Closest Point algorithm (ICP) [2]. This algorithm was proposed by a few researchers independently Besl [3] and Chen [4]. The ICP is an iterative algorithm and consists of two steps. The first step is to find a correspondence between target and source points, based on Euclidean distance between points. In the second step, the updated version of result transformation is calculated using equation:

$$f(S,T) = \frac{1}{N_s}\sum_{i=1}^{N_s}\|T_i - Rot(S_i) - Trans(S_i)\|^2 \quad (1)$$

where: T, S are target and source set of points, Ns is number of source points (equals number of target points), and Rot, Trans are rotation and translation components of final transformation.

The updated version of final transformation in current iteration is based on close-form solution of mean square error problem. The classical approach used only one rigid or affine transformation for whole data sets. In literature the description of disadvantages of the classical ICP approach Rusinkiewicz [5] can be found:

- problem of finding global minimum of cost function depends on an initial guess of final transformation,
- the algorithm is sensitive to improper correspondences,
- long time of computation - one of the most time-consuming operation is retrieving correspondences.

Due to these disadvantages researchers proposed a lot of classical approach rectifications:

- registration only subsets of points,
- improvement of finding correspondence problem,
- quantity measure of proper correspondence,
- elimination of improper correspondence,
- modification of computing minimum of cost function.

The standard ICP approach cannot be used to track surface of objects that change their shape in time. Amberg [6] proposed non-rigid version of ICP, by the following equation:

$$E(X) = E_d(X) + \alpha E_s(X) + \beta E_l(X) \quad (2)$$

where:
X is the unknowns are organised in a 4n × 3 transformation matrix,
$E_d(X)$ is distance measure between all targets points and transformed source points, in contrast to classical ICP. X is not a single rotation or translation but a collection of affine transformation for each point,

$E_s(X)$ is stiffness regularization, topology matrix is created based on points neighbourhood to preserve the shape of object during iterations; we use square matrix topology (every point has four neighbours). α is stiffness vector, which influences the flexibility of cloud shape,

$\beta E_1(X)$ is a factor used for guiding registration, based on known position of landmarks in source and target sets of points. β is an weighting factor, used to fade out the importance of landmarks towards the end of the registration process.

The implemented non-rigid ICP algorithm consists of two iterative loops. In the outer loop, the stiffness factor α is gradually decreased with uniform steps, starting from higher values, which enables recovery of an initial rigid global alignment, to lower values, allowing for more localized deformations. For a given value of α, the problem is solved iteratively in the inner loop. The condition of changing stiffness vector is threshold norm of transformation difference from adjoining iterations. In our implementation β is constant and equals one. The above equation can be transformed into the system of linear equations, which is solved by computing pseudo-inverse matrix (see [6] for details). This is the iterative algorithm, where each iteration consists of two main steps, namely finding correspondences between source and target points and computing affine transformations for each source point. If the second step is modified by the solution proposed by Amberg, that causes better results, corresponding problem remains critical for final results.

2 Material and Methods

Improvement of finding correspondences was implemented. Classically finding correspondences is done by searching Euclidean distance between closest points in source and target or in normal vector of source point direction. The general idea of presented approach was to take into account knowledge about markers' positions not only in computing transformation phase but also in finding correspondence phase in every algorithm's iteration. Decision to test a few approaches of finding correspondences was done:

- searching along normal vectors in source points, following the initial rigid registration based on Horn algorithm [7],
- along static marker vector displacement, where marker vectors are calculated only once at the preliminary stage. Marker vector is defined by positions of specific marker in source and target point cloud,
- along dynamic marker vector displacement, where marker vectors are calculated in each iteration based on constant positions of nearest marker points in matrix topology. Transformed source point in each iteration is treated as a new origin of dynamic marker vector.

Classical Euclidean distance is treated as baseline to compare the obtained results. Generally it is challenging to verify registration approach. We used global and local criteria for evaluation:

- global measurement: average distances between nearest source and target points, average distances between correspondences,
- loocal measurement – quality of correspondences: average correspondence assignment error of points nearest to the markers and the number of correspondences for every target points.

Data set consists of abdomen surfaces acquired by 6 volunteers on free breathing using Time-of-Flight sensor Mesa SR4000 [8]. Intensity map example of input data is presented in Fig. 1. As markers 15mm white squares attached to the abdomen were used, which corners were manually segmented by two users.

Figure 1. Example of input data: intensity map for ToF camera of abdomen with nine square markers.

3 Results

For the different methods of finding correspondences, evaluation scores: surface distances, correspondence distances and average marker error, are presented in tables 1 and 2.

Table 1. Surface distances for four variants of ICP: the Euclidean distance (E), normal vectors with initial rigid registration (NH), static (SM) and dynamic markers vectors (DM).

ID	Surface Distance [mm]				
	Initial	E	NH	SM	DM
1	5.83	0,21	0.6	0.69	0.63
2	12.04	0.12	0.74	0.87	0.61
3	25.16	0.03	0.03	0.06	3.43
4	19.84	0.14	1.04	0.51	3.56
5	5.21	0.004	0.21	0.28	0.28
6	10.76	0.16	0.15	0.09	1.94

4 Discussion and Conclusions

The implemented non-rigid ICP algorithm showed average residual distance 0.68mm (Euclidean distance not included). A further analysis of registration accuracy was focused on finding correspondence problem. Four methods for this problem were tested: Euclidean distance treated as base line, normal shooting with initial rigid registration – marker based Horn algorithm, static marker vectors (computing only one at the beginning of registration process) and dynamic marker vectors (computing in every iteration). For “near” cloud, where stiffness vector is constant for almost every iterations in non-rigid ICP, Euclidean distance are good enough. Unlike "near" clouds, “far” clouds, where stiffness vectors are changing for few iterations, Euclidean distance seems to be not enough. There are a lot of gaps in registered source cloud – Fig. 2. To improve it, static and dynamic marker vectors were proposed. If marker is not only used in computing transformation step but also in computing correspondences step for each iteration, correspondence assignment error of points nearest to the markers decreased from 5.4 to 2.0 of confused neighbors. Normal shooting approach was also evaluated, but results were worse results than other cases, while combination normal shooting and initial rigid registration significantly improved results – Fig. 2. To use Horn algorithm at least three non collinear corresponding points in source and target should be known. It helps allows to overcome the problem of the relative displacement of the source and target point clouds, which is not taking into account when Euclidean distance is used.

Because it is difficult to measure directly the quality of correspondences, observation was proposed in a few steps. Correspondence map (Fig. 2) showed spatial distribution of the feature, number of correspondences assigned to every target point (desirable value is 1). It is easier to compare correspondence map globally with different cases using correspondence map histogram (Fig. 3). Average correspondence assignment error of points nearest to the markers allows to measure the quality of correspondence points from cloud, which are nearest to the markers. To make the proposed changes of finding correspondences more universal k-nearest neighbor method and radius constraint could be used, to apply marker information not to every point in cloud but only to for the nearest points to the markers. For points which are not the nearest to the marker, Euclidean distance or normal shooting could be used.

Presented approach may be used in different medical, entertainment and industrial applications, where non-rigid point clouds should be registered, when initial relative position of clouds is that finding correspondences by Euclidean distance or normal shouting is not enough. The proposed changes do not introduce complex calculations. Initial calculation of rigid registration allows to solve the problem of unknown transformation matrix initialization. Comparing to classical non-rigid ICP the disadvantage of proposed approach is that initial corresponding positions of markers in source and target point clouds are needed.

5 References

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Table 2. Correspondence distances and average marker error for four variants of ICP: the Euclidean distance (E), normal vectors with initial rigid registration (NH), static (SM) and dynamic markers vectors (DM).

ID	Correspondence Distance [mm]				Marker Error [number of unit]			
	E	NH	SM	DM	E	NH	SM	DM
1	0.26	0.18	0.25	0.58	12.42	10.81	4.45	0.76
2	0.12	0.27	0.33	0.87	7.02	6.28	2.12	1.49
3	0.04	0.03	0.03	1.7	2.57	2.9	1.86	0.44
4	0.14	0.22	0.15	0.88	4.3	4.63	3.6	0.72
5	0.04	0.07	0.1	0.1	4.05	2.61	3.11	4.69
6	0.16	0.07	0.06	0.53	2.25	1.89	0.75	0.09

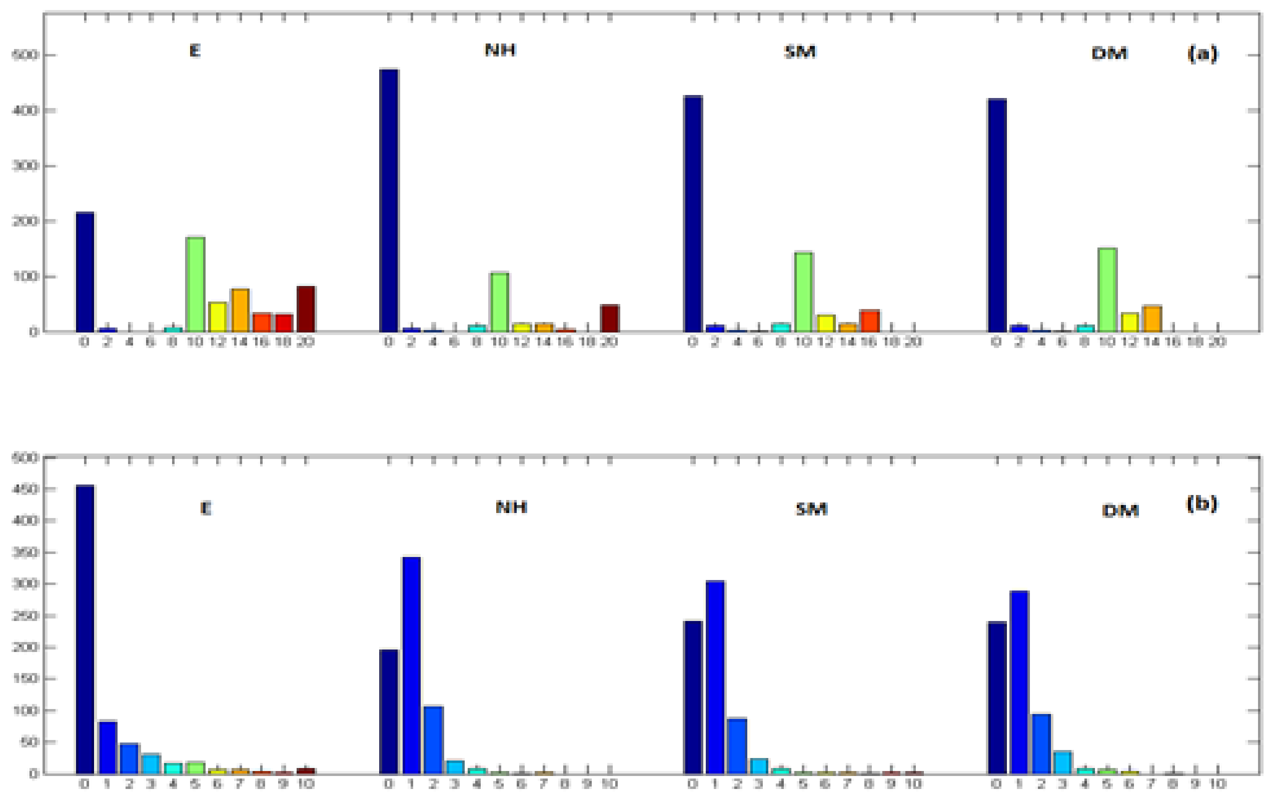

Figure 3. Distance map histogram [mm] (a) and correspondence map histogram [number of units] (b) in different modifications of ICP computing correspondence: Euclidean distance (E), normal shooting with initial rigid registration (NH), static marker vectors (SM), dynamic marker vectors (DM).

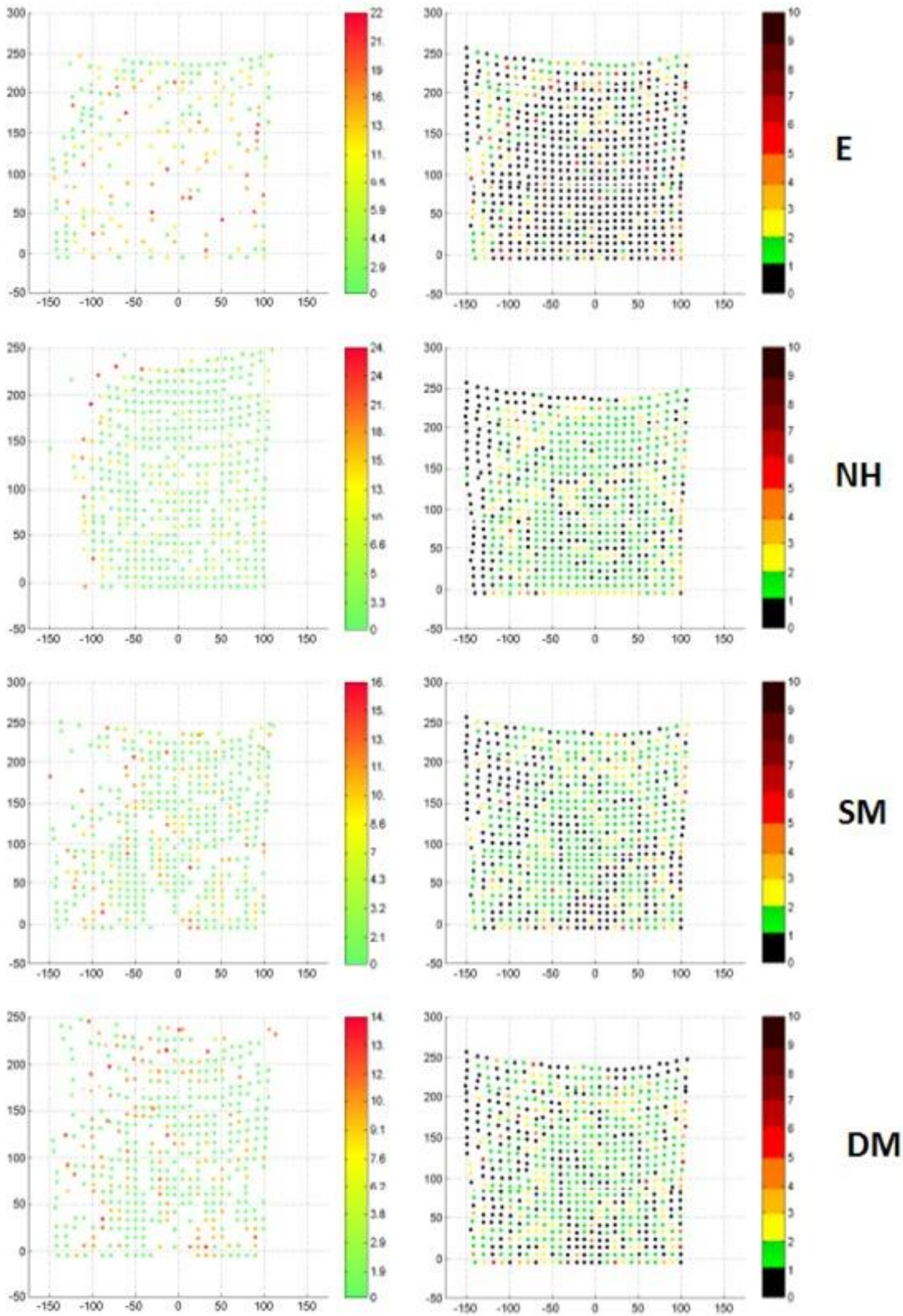

Figure 2. Distance map [mm] (left column) and correspondence map [number of units] (right column) for different modifications of ICP computing correspondence: Euclidean distance (E), normal shooting with initial rigid registration (NH), static marker vectors (SM), dynamic marker vectors (DM).