

Model Acquisition by Registration of Multiple Acoustic Range Views

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Abstract. This paper deals with the three-dimensional reconstruction of an underwater environment from multiple acoustic range views acquired by a remotely operated vehicle. The problem is made challenging by the very noisy nature of the data, the low resolution and the narrow field of view of the sensor. Our contribution is twofold: first, we introduce a statistically sound thresholding (the X84 rejection rule) to improve ICP robustness against noise and non-overlapping data. Second, we propose a new global registration technique to distribute registration errors evenly across all views. Our approach does not use data points after the first pairwise registration, for it works only on the transformations. Therefore, it is fast and occupies only a small memory. Experimental results suggest that ICP with X84 performs better than Zhang's ICP, and that the global registration technique is effective in reducing and equalizing the error.

1 Introduction

In this paper we address the problem of registration of many three-dimensional (3D) point sets, coming from an acoustic range sensor. Typically, the term *registration* is used for the geometric alignment of a pair or more 3D data point sets, while the term *fusion* indicates the recovery of a single surface representation from registered 3D data sets.

The registration of two point sets is usually addressed by means of the Iterated Closest Point (ICP) algorithm [2,5]. ICP is based on the search of pairs of nearest points in the two sets, and estimating the rigid transformation which align them. Then, the rigid transformation is applied to the points of one set, and the procedure is iterated until convergence. ICP assumes that one point set is a subset of the other. When this assumption is not verified, false matches are created, that negatively influence the convergence of ICP to the solution. In order to overcome this problem, many variants to ICP have been proposed, including the use of closest points in the direction of the local surface normal [5], the use of thresholds to limit the maximum distance between points [25], rejecting matching on the surface boundaries [23], Least Median of Squares estimation [22].

In this paper we propose to use the X84 outlier rejection rule [10] to discard false correspondences on the basis of their distance. This is an improvement over

[25], because the threshold is set automatically, and a larger basin of attraction is achieved.

A widely used approach to the registration of many views is to sequentially apply pairwise registration until all the views are combined. Chen and Medioni [5] proposed an incremental approach in which two views are registered and merged building a *metaview*. The next view is then registered and merged with the metaview and the process is repeated for all the views. This approach was taken also by [21] and [12]; the latter proposed to incrementally build a surface model, onto which new views can be registered and already registered views can be adjusted. In [4], couples of images are incrementally registered together with a final registration between the first and last view, by using the inverse calibration procedure of the range-finder to relate a point in the 3D space corresponding to a point in the range image.

These schemes do not use all the available information, and do not compute the optimal solution, because of the accumulation of registration errors, as pointed out by [19] and [1]. Multiview registration could exploit information present in the unused overlapping view pairs, distributing the registration error evenly between every pairwise registration. Bergevin et al. [1] registered multiple range images simultaneously, using an extended ICP algorithm. They converted the sequential registration relationship into a star-shaped relationship, and then imposed the *well-balanced network* constraint. A network of range views is well-balanced when the registration error is similar for all transformation matrices, and the transformation matrix between any two views is uniquely defined regardless of the path chosen to link the views. Pulli [18] proposed to use the pairwise alignments as constraints that the multiview step enforces while evenly diffusing the pairwise registration errors. In such a way, computational time is reduced as well as memory storage. He introduces the concept of *virtual mate* to enforce the pairwise alignments as constraints.

Some works focus on computing the global registration given the correspondences among many views (this is called the *N-view point set registration problem*). To this end, in [20] and [8], a force-based optimisation approach is proposed. Assuming the points' correspondences among the data sets are known, interconnections using springs between corresponding points is simulated. Pennec [17] introduces an iterative algorithm based on the concept of *mean shape*. Benjema and Shmitt [19] use a quaternion approach similar to [3]. In [9] a statistical model is introduced, and the problem is solved using the EM algorithm. In a recent work, Williams and Bennamoun [24] proposed a new technique for the simultaneous registration of multiple point sets, in which rotations are first computed iteratively, and then translations are obtained as the solution of a linear system. The method have been integrated in a generalized multiview ICP. Three of these techniques, namely [20],[17], and [19], have been compared in [6], and the result is that, not considering speed, Pennec's method is the best one, whereas [19] is the fastest.

All the multi-alignment methods need to keep data of all – or at least some – views in memory at the same time, reducing drastically performance, especially when aligning large data set. Our global registration approach differs from all the

others because we enforce the constraints arising from the pairwise registration directly on the transformation matrices, without the need to process data points again, after the initial pairwise registration between all the overlapping views. The idea comes from [7] where it was applied to the construction of planar mosaics from images. Here we propose to extend the technique to the registration of multiple 3D point sets. In our case we end up with a non-linear system of equations, because of the parametrization of the rotations. Following [16,3,19] we used quaternions to represent rotations, because of their well-known good properties [15].

In the field of 3D registration, the closest work to our approach is [18], because both are based on the simultaneous satisfaction of constraints provided by the pairwise registration, and both do not rely on the solution of the N-view point set registration problem. Our work differs in the formulation of the constraints (which do not use data points) and because we cope with overlapping between any number of sets, not just pairs.

Our final goal is the reconstruction of a scene from a sequence of cluttered, noisy, and low resolution 3D data, aimed at building a 3D model. Such model is then displayed to a human operator of an underwater remotely operated vehicle (ROV), in order to facilitate the navigation and the understanding of the surrounding environment. Our data come from a high frequency acoustic camera, called Echoscope [11] with a typical resolution of 3 cm. Moreover, speckle noise affects data due to the coherent nature of the acoustic signals. With such operative conditions, the registration problem is much more demanding, and, although a large literature addresses this issue, no work dealt with this particular kind of 3D data. Further, due to lack of tight hypotheses about the sensor motion and the direct manipulation of the transformation matrices instead of 3D points, our approach results particularly suitable to real-time applications.

The rest of the paper is structured as follows. In Section 2, the pairwise registration stage is described outlining the X84 outlier rejections rule. Section 3 introduces the multiview registration focusing on the global transformation adjustment. Results are shown in Section 4 for both synthetic and real images and conclusions are drawn in Section 5.

2 Robust Pairwise Registration

Pairwise registration was addressed using the classical Iterated Closest Point (ICP) algorithm [2] to which we added an outlier rejection rule (X84) [10] in order to cater for non-overlapping areas between views.

2.1 Two View Point Set Registration

Let us suppose that we have two sets of 3-D points which correspond to a single shape but are expressed in different reference frames. We will call one of these sets the model set X , and the other the data set Y . Assuming that for each point in the data set the corresponding point in the model set is known, the *point set registration problem* consist in finding a 3-D transformation which, when applied

to the data set Y , minimizes the distance between the two point sets. The goal of this problem can be stated more formally as follows:

$$\min_{\mathbf{R}, \mathbf{t}} \sum_{i=1}^N \|\mathbf{x}_i - (\mathbf{R}\mathbf{y}_i + \mathbf{t})\|^2, \quad (1)$$

where \mathbf{R} is a 3×3 rotation matrix, \mathbf{t} is a 3×1 translation vector, and the subscript i refers to corresponding elements of the sets X and Y . Efficient, non-iterative solutions to this problem were compared in [14], and the one based on Singular Value Decomposition (SVD) was found to be the best, in terms of accuracy and stability.

2.2 Iterated Closest Point

In general, when point correspondences are unknown, the Iterated Closest Point (ICP) algorithm may be used. For each point \mathbf{y}_i from the set Y , there exists at least one point on the surface of X which is closer to \mathbf{y}_i than all other points in X . This is the *closest point*, \mathbf{x}_i . The basic idea behind the ICP algorithm is that, under certain conditions, the point correspondence provided by sets of closest points is a reasonable approximation to the true point correspondence. The ICP algorithm can be summarized:

1. For each point in Y , compute the closest point in X ;
2. With the correspondence from step 1, compute the incremental transformation (\mathbf{R}, \mathbf{t}) ;
3. Apply the incremental transformation from step 2 to the data Y ;
4. If the change in total mean square error is less than a threshold, terminate. Else goto step 1.

Besl and McKay [2] proved that this algorithm is guaranteed to converge monotonically to a local minimum of the Mean Square Error (MSE).

ICP can give very accurate results when a set is a subset of the other, but results deteriorate with outliers, created by non-overlapping areas between the two sets. In this case, the overlapping surface portions must start very close to each other to ensure convergence, making the initial position a critical parameter.

Modifications to the original ICP have been proposed to achieve accurate registration of *partially* overlapping point sets [25,23,22]. We implemented a variation similar to the one proposed by Zhang [25], using robust statistics to limit the maximum allowable distance between closest points.

2.3 Robust Outlier Rejection

As pointed out by Zhang, the distribution of the residuals for two fully overlapping sets approximates a Gaussian, when the registration is good. The non-overlapped points skew this distribution: they are *outliers*. Therefore, good correspondences can be discriminated by using an outlier rejection rule on the distribution of closest point distances.

To do this, we employ a simple but effective rejection rule, *X84* [10], which use robust estimates for location and scale of a corrupted Gaussian distribution to set a rejection threshold. The median is a robust location estimator, and the Median Absolute Deviation (MAD), defined as

$$\text{MAD} = \text{med}_i \{ |\epsilon_i - \text{med}_j \epsilon_j| \} \quad (2)$$

is a robust estimator of the scale (i.e., the spread of the distribution). It can be seen that, for symmetric (and moderately skewed) distributions, the MAD coincides with the *interquartile range*:

$$\text{MAD} = \frac{\xi_{3/4} - \xi_{1/4}}{2}, \quad (3)$$

where ξ_q is the q th quantile of the distribution (for example, the median is $\xi_{1/2}$). For normal distributions we infer the standard deviation from

$$\text{MAD} = \Phi^{-1}(3/4)\sigma \approx 0.6745\sigma. \quad (4)$$

The X84 rule prescribes to reject values that are more than k Median Absolute Deviations away from the median. A value of $k=5.2$, under the hypothesis of Gaussian distribution, is adequate in practice (as reported in [10]), since it corresponds to about 3.5 standard deviations, and the range $[\mu - 3.5\sigma, \mu + 3.5\sigma]$ contains more than the 99.9% of a Gaussian distribution. The rejection rule X84 has a *breakdown point* of 50%: any majority of the data can overrule any minority.

3 Multiview Registration

We now turn our attention to the simultaneous registration of several point sets.

3.1 Chaining Pairwise Transformations

Assume that there are M overlapping point sets (or views) $V^1 \dots V^M$, each taken from a different viewpoint. The objective is to find the best rigid transformations $\mathbf{G}^1 \dots \mathbf{G}^M$ to apply to each set, bringing them a common reference frame where they are seamless aligned.

Let \mathbf{G}^{ij} be the rigid transformation matrix (in homogeneous coordinates) that registers view j onto view i , i.e.,

$$V^i = \mathbf{G}^{ij} V^j \quad (5)$$

where the equality holds only for the overlapping portions of the two points sets V^i and $\mathbf{G}^{ij} V^j$.

If we choose (arbitrarily) view k as the reference one, then the unknown rigid transformation $\mathbf{G}^1 \dots \mathbf{G}^M$ are respectively $\mathbf{G}^{k,1} \dots \mathbf{G}^{k,M}$. As customary, we will take $k = 1$.

These rigid transformations are not independent each other, being linked by the composition relationship:

$$\mathbf{G}^{k,j} = \mathbf{G}^{k,i} \mathbf{G}^{i,j}. \quad (6)$$

We can therefore estimate the alignment \mathbf{G}^j of image V^j on the reference view (defined by the image V^1), by first registering V^j onto any view V^i and then using \mathbf{G}^i to map the result into the space of V^1

$$\mathbf{G}^j = \mathbf{G}^i \mathbf{G}^{i,j} \quad (7)$$

This relationship, can be used to compute \mathbf{G}^i when all the matrices $\mathbf{G}^{i-1,i} \dots \mathbf{G}^{1,2}$ are known, by simply chaining them

$$\mathbf{G}^i = \prod_{j=2}^i \mathbf{G}^{j-1,j} \quad (8)$$

The global registration matrix \mathbf{G}^i will map V^i into the space of V^1 (the reference view).

As it is well known, the combination of pairwise registration does not yield the optimal result. For example, if $\mathbf{G}^{k,i}$ and $\mathbf{G}^{i,j}$ are optimal on the sense that they minimize the mean square error distance between the respective sets, then $\mathbf{G}^{k,j}$ computed with Eq. (6) does not necessarily minimizes the mean square error between views V^j and V^k . Small registration errors accumulate so that images near the end of a sequence have a large cumulative error.

3.2 Global Transformations Adjustment

In order to improve the quality of global registration, let us suppose we have locally registered all spatially overlapping image pairs, in addition to those that are adjacent in the image sequence. Especially for underwater images, in which the ROV moves back and forth we can find significant overlapping also between distant views in the temporal sequence.

The aim of our method is to optimize the information coming from every pairwise registrations, obtained by the alignment of all overlapped range images. The original contribution consists in obtaining a global registration by introducing algebraic constraints on the transformations, instead of data points.

We first perform pairwise registration between every view and each of its overlapping views, thereby computing the $\mathbf{G}^{i,j}$ whenever it is possible. By considering many equations as (7), we can build a system of equations in which the $\mathbf{G}^{i,j}$ are known quantities obtained by pairwise image registration, and the matrices $\mathbf{G}^{i1} = \mathbf{G}^i$ ($1 \leq i \leq N$) are unknowns to be found. By decomposing the homogeneous transformation matrices \mathbf{G} into a rotation and translation, Eq. (7) splits in two:

$$\begin{cases} \mathbf{R}^j = \mathbf{R}^i \mathbf{R}^{i,j} \\ \mathbf{t}^j = \mathbf{R}^i \mathbf{t}^{i,j} + \mathbf{t}^i \end{cases} \quad (9)$$

where \mathbf{R} is a rotation matrix and \mathbf{t} is a translation vector. Although this system of equations is essentially linear, a number of problems arise when formulating solutions that account for the non-linear constraints on the components of \mathbf{R} . In order to respect these constraints, the rotation matrices must be suitably parametrized, ending up with a system of non-linear equations.

This non-linear least squares problem can be cast as the minimization of the following objective function:

$$\min_{i,j} \sum \left(\left(\frac{\text{angle}(\mathbf{R}^i \mathbf{R}^{i,j} (\mathbf{R}^j)^\top)}{\pi} \right)^2 + \left(\frac{\|\mathbf{R}^i \mathbf{t}^{i,j} + \mathbf{t}^i - \mathbf{t}^j\|}{\|\mathbf{t}^i\|} \right)^2 \right) \quad (10)$$

where $\text{angle}(\cdot)$ takes a rotation matrix and returns the angle of rotation around a suitable axis. Starting from the global registration obtained by chaining pairwise transformation (Eq. (8)), a solution is found using a Quasi-Newton method.

The estimated transformation $\mathbf{G}^1 \dots \mathbf{G}^M$ are influenced by all the pairwise observed transformations, and the registration error is distributed over all the estimated transformations. In this sense, the network of the views after the final registration is very close to be *well balanced* as defined in [1].

Moreover, the complexity of the proposed algorithm is *independent from the number of points involved*. Because the objective function includes only the matrix components, the complexity depends only on the number of (overlapping) views.

3.3 Dealing With Rotations

A number of techniques have been developed to represent rotations. One of the most convenient is the quaternions representation. They have a number of mathematical properties that make them particularly well suited to requirements of iterative gradient-based search for rotation and translation [15].

Rotations are represented by unit quaternions. Instead of requiring the quaternion $\mathbf{q} = [u, v, w, s]$ to be a unit vector, we can enforce the constraint that the rotation matrix is orthogonal by dividing the matrix by the squared length of the quaternion [15]:

$$\mathbf{R}(\mathbf{q}) = \frac{1}{\mathbf{q} \cdot \mathbf{q}} \mathbf{R}_u(\mathbf{q}) \quad (11)$$

where $\mathbf{R}_u(\mathbf{q})$ is the rotation matrix given by

$$\mathbf{R}_u(\mathbf{q}) = \begin{pmatrix} s^2 + u^2 - v^2 - w^2 & 2(uv - sw) & 2(uw + sv) \\ 2(uv + sw) & s^2 - u^2 + v^2 - w^2 & 2(vw - su) \\ 2(uw - sv) & 2(vw + su) & s^2 - u^2 - v^2 + w^2 \end{pmatrix} \quad (12)$$

This constraint is necessary in general to ensure the gradient accurately reflect the differential properties of a change in the quaternion parameters.

3.4 Summary of the Algorithm

Finally, the multiview registration algorithm is defined as:

- Step 1.** calculate pairwise registration for all the overlapped images using ICP algorithm, with X84 rejection rule;
- Step 2.** if the pairwise registration is good, accept the registration matrix $\mathbf{G}^{i,j}$;
- Step 3.** compute a starting guess for the global registration by chaining pairwise transformation (Eq. (8));
- Step 4.** minimize the objective function defined in Eq. (10) with the BFGS Quasi-Newton method with a mixed quadratic and cubic line search procedure¹; At each step enforce orthogonality of rotation matrix with Eq. (11)
- Step 5.** apply the transform defined by \mathbf{G}^i to the view V^i , $i = 1, \dots, M$.

Registered sets of points must be fused in order to get a single 3D model. Surface reconstruction from multiple range images can be addressed as the problem of surface reconstruction from a set of unorganized 3D points, disregarding the original organization of the data. We used the public domain implementation of Hoppe and De Rose algorithm [13].

4 Results Description

In this section we show results obtained on synthetic and real acoustic images.

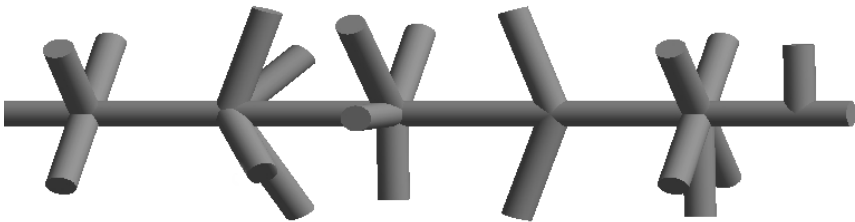


Fig. 1. 3D synthetic model representing pipes structure

In synthetic experiments we simulated the movement of an underwater ROV around the external part of an offshore rig using the OpenGL library to generate synthetic range images. Given a 3D model of part of the rig (Fig. 1),

¹ MATLAB `lsqnonlin` function

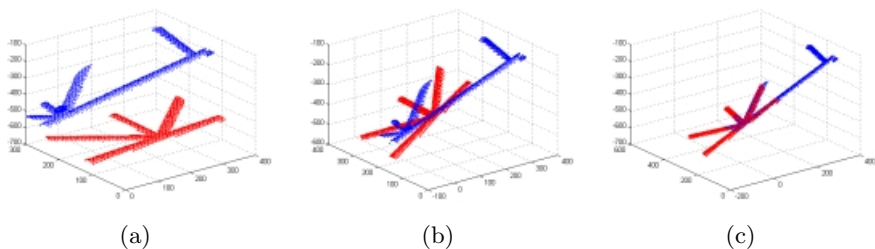


Fig. 2. In Figure (a) the two point sets are in the start position, Figure (b) shows the result of Zhang’s ICP algorithm and Figure (c) shows the result of ICP with X84

range images are obtained by moving a (virtual) camera and extracting the *z-buffer* for each view. In order to assess the final registration, we made the last view to coincide with the first one.

In real experiments the acoustic data are acquired by an underwater ROV using the Echoscope acoustic camera, which outputs a 64×64 range image [11]. The noise corrupts sensibly the acoustic signals and decreases the reliability of the estimated 3D measures. Moreover, there is a trade off between range resolution and field of view. Resolution depends on the frequency of the acoustic signal (it is about 3 cm at 500 KHz): the higher the frequency, the higher the resolution, the narrower field of view. Consequently, we are forced to operate with a limited field of view.

4.1 Pairwise Registration

In Fig. 2, we show an example of two point sets that Zhang’s ICP fails to align. Instead, our ICP algorithm with X84 rejection rule recovers the correct rigid transformation.

4.2 Global Registration

In order to evaluate the performance of our global registration algorithm, we computed the *registration error* as the closest points mean square distance between each view and the mosaic composed by all the already registered views (outliers are discarded according to the X84 rule). The improvement over the chained pairwise alignment is shown as an histogram depicting, for each view, the difference between the registration errors of the two techniques (a positive value means an improvement of our method).

In experiment n. 1 we generated a synthetic sequence, of 29 range images. The benefit brought by the global registration can be appreciated in Fig. 3a-b. The histogram in Fig. 3c shows that the global registration improves especially in near the end of the sequence (as expected).

In experiment n. 2 we generated a sequence composed by 37 range images. We wanted to test the performance of the global registration algorithm in the

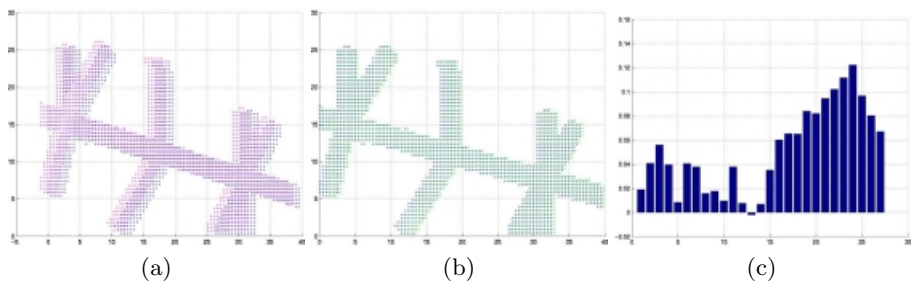


Fig. 3. Experiment n. 1. Alignment between view n. 1 and view n. 29 for chained pairwise registration (a) and global registration (b). Histogram of the differences of the registration error (c)

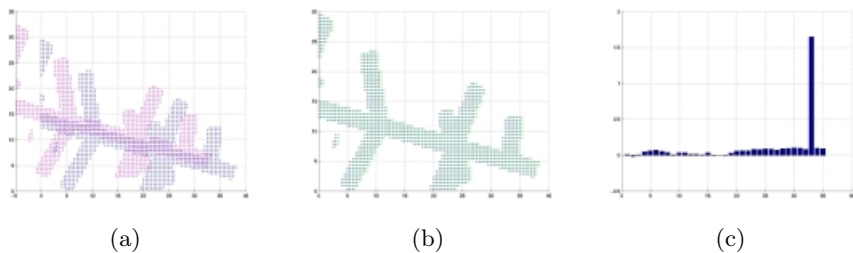


Fig. 4. Experiment n. 2. Alignment between view n. 1 and view n. 37 for chained pairwise registration (a) and global registration (b). Histogram of the differences of the registration error (c)

presence of an incorrect pairwise registration (n. 35). In this case the chaining of pairwise transformations inevitably propagates the error. In our global multiview registration, thanks to the information coming from the other pairwise transformations linking (indirectly) view n. 35 and n. 34, the correct registration is achieved, and the error is distributed over the whole sequence. Fig. 4c shows the improvement obtained by optimal global registration, which is concentrated on matrix n. 35, as expected. The improvement brought by the global registration is also clearly visible in the Fig. 4a-b and also in Fig. 5 where the reconstructed surfaces are shown for both techniques.

In experiment n. 3 and n. 4 we introduced Gaussian white additive noise with different standard deviation ($\sigma = 0.02$ and $\sigma = 0.045$, respectively) on the synthetic images of experiment n. 1. The relative histograms are shown in Fig. 6.

Experiment n. 5 uses a sequence of 15 real acoustic images (Fig. 7) that are partial views of a tubular structure. The images are rather noisy and the scene is quite difficult to understand from a single view. The histogram shown in Fig. 8c confirms the improvement obtained by the global multiview registration.

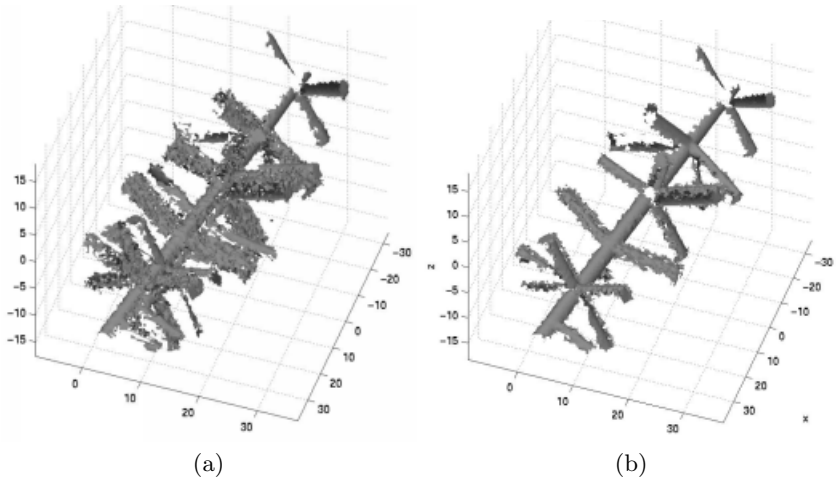


Fig. 5. Surface reconstruction using Hoppe and De Rose algorithm. Chained pairwise registration (a) and global multiview registration (b)

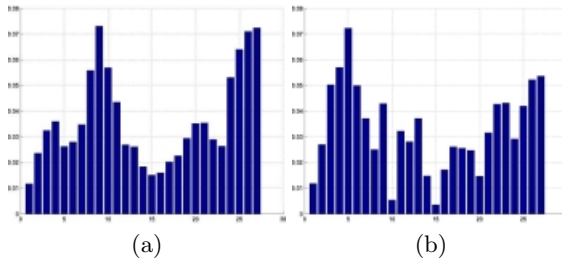


Fig. 6. Histogram of the differences between the registration error for the chained pairwise registration and the global registration, in experiment n. 3 (a) and n. 4 (b). A positive value correspond to an improvement over chained pairwise registration.

The light worsening of the first views registration is compensated by the good improvement of the last ones. A more accurate evaluation is not possible in real case because true correspondences are not known (as in synthetic experiments). Nevertheless, Fig. 8a-b visually confirm the effectiveness of the global multiview registration in building the mosaic of the scene.

Tables 1 and 2 summarizes the numerical results obtained in all the experiments. Table 1 reports the average (over the views) registration errors for both algorithms. In Table 2 a more meaningful evaluation is obtained by calculating the registration error (misalignment) between the first and the last view (which should coincide). In this case we know exactly the corresponding points and error evaluation is more accurate.

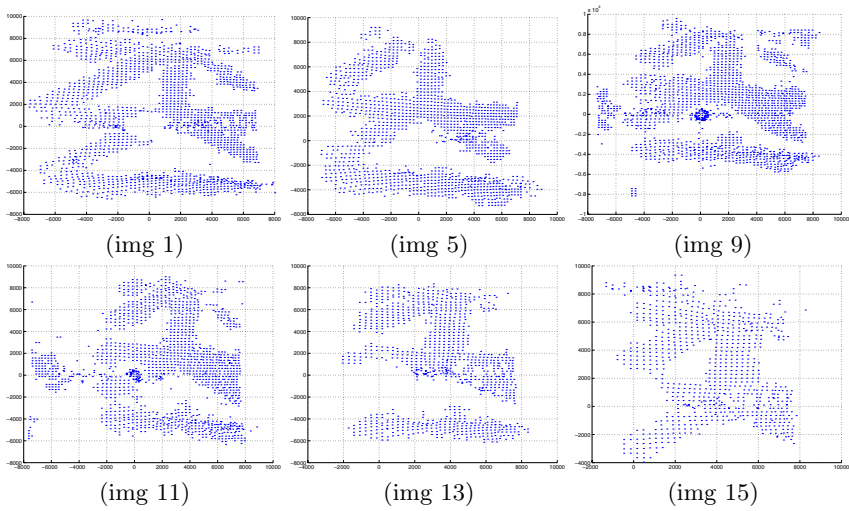


Fig. 7. Experiment n. 5. Selected views from the real sequence.

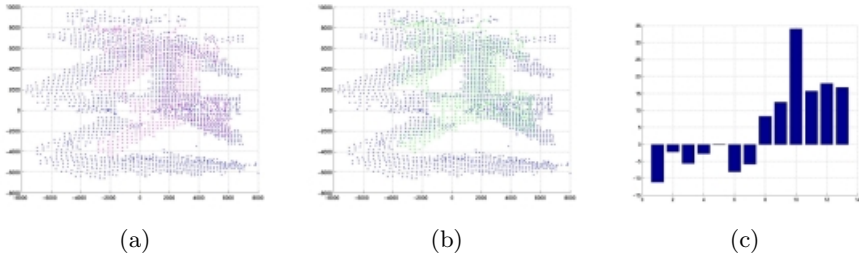


Fig. 8. Experiment n. 5. First and last views of the mosaic. The images are aligned using chained pairwise registration algorithm (a) and global registration algorithm (b). Histogram of the differences of the registration error (c).

Table 1. Average registration error (cm).

Experiment	Chained pairwise reg.	Global registration	% difference
exp 1	0.24095	0.19258	20,0740 %
exp 2	0.28960	0.19630	32,2168 %
exp 3	0.36328	0.32936	9,3371 %
exp 4	0.50290	0.47200	6,1443 %
exp 5	15.47955	15.01574	2,9963 %

Our global multiview registration algorithm always improves over pairwise registration. When the noise level was increased in the experiments on synthetic

Table 2. Misalignment between the last and the first view (cm).

Experiment	Chained pairwise reg.	Global registration	% difference
exp 1	1.9584	0.1340	93,1577 %
exp 2	29.8662	0.1362	99,5440 %
exp 3	4.0279	2.1979	45,4331 %
exp 4	13.8420	11.1094	19,7413 %

data, our algorithm continued to perform better. Improvement was also seen in the experiment involving real data.

In another set of experiments we reproduced those reported by [19] and [24]. We evaluate the error on the rotations by comparing the result of the global registration with the ground truth. As a measure of the discrepancy between two rotations \mathbf{R}^1 and \mathbf{R}^2 we take $\text{angle}(\mathbf{R}^1(\mathbf{R}^2)^\top)$.

A set of six random transformations $\mathbf{G}^{2,1}, \mathbf{G}^{3,1}, \mathbf{G}^{4,1}, \mathbf{G}^{5,1}, \mathbf{G}^{6,1}$ are generated, as in [24]. By composing these transformations we simulate the output of the pairwise registration of 12 overlapping views, namely 1-2, 2-3, 3-4, 4-1, 1-5, 2-5, 3-5, 4-5, 1-6, 2-6, 3-6, 4-6. The rotation components are perturbed by a random rotation in the range $[-5,5]$ deg., The pairwise transformations are composed to obtain the perturbed $\mathbf{G}^{i,1}$, and the error on the rotations is computed as detailed above. Then we run our algorithm, and compare the average error and its variance over the views. Results, shown in Table 3, demonstrate that our global multiview registration technique is effective in reducing the variance of the error on the rotations, and also it improves the average error.

Table 3. Rotation error.

	Chained pairwise reg.	Global registration	% difference
average error	0.0463	0.0381	17.7%
average error variance	0.00243	0.00108	55.6%

5 Conclusions

In this paper we propose a technique for 3D object reconstruction from multiple acoustic range views, acquired by an underwater ROV. As data coming from the acoustic sensor is noisy, low resolution, and the field of view is narrow, we want to provide the human operator(s) with a synthetic 3D model of the scene, in order to facilitate the navigation and the understanding of the surrounding environment. To this end, we address the problem of registering many 3D views, starting from pairwise registration between all the overlapping views.

Our contribution is twofold. First we modified Zhang's ICP by introducing the X84 rejection rule, which does not depend on user specified thresholds and is more effective in achieving a larger convergence basin.

Moreover, we propose a new global multiview registration technique to distribute registration errors evenly across all views. Our approach differs from all the others because we enforce the constraints arising from the pairwise registration directly on the transformations, and we do not rely on the solution of the N-view point set registration problem. The complexity of our technique does not depend on the number of points involved, but only on the number of views. The drawback is that the error is only spread among the views, but does not get reduced significantly. Consequently, this technique is well suited for all the application where speed can be traded for accuracy.

Future work will be aimed at automatically detecting the degree of overlap between views and introducing a weight for each term of Equation (10), depending on the amount of overlap.

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