Non-rigid Shape Registration using Curvature Information

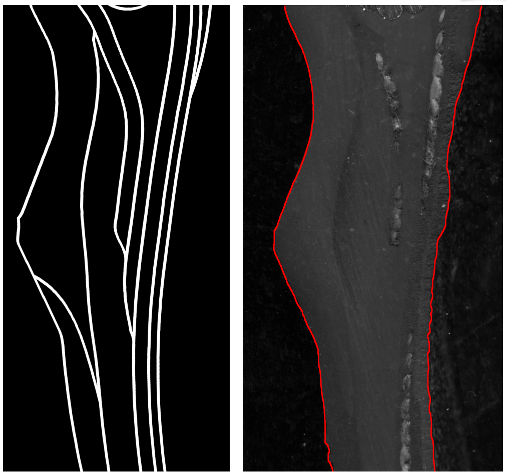
Albane Borocco and Beatriz Marcotegui
MINES ParisTech, PSL Research University, CMM - Centre for Mathematical Morphology,
35, rue St. Honore, 77305 Fontainebleau, France

Keywords: Non-rigid Registration, Shape Registration, High Curvature, Industrial Quality Control.

Abstract: This paper addresses a registration problem for an industrial control application: it meets the need to registrate a model on an image of a flexible object. We propose a non-rigid shape registration approach that deals with a great disparity of the number of points in the model and in the manufactured object. We have developed a method based on a classical minimization process combining a distance term and a regularization term. We observed that, even if the control points fall on the object boundary, the registration failed on high curvature points. In this paper we add a curvature-based term in order to improve the registration on object extremities. We validate our approach on a real industrial application. The addition of this curvature term reduces by two the error of the inner boundaries location on the previously problematic cases of our database.

1 INTRODUCTION

Manufacturing industry requires inspection tools for controlling industrial processes. This control usually relies on images of the manufactured objects and on a prior knowledge of them. In our application the previous knowledge consists in the theoretical model in the form of a set of boundaries of different object components.



(a) model (b) manufactured object

Figure 1: Example of the data used.

Figure 1(a) shows a theoretical model from our application. It contains the boudaries between the different object components. The visual appearance of the inner parts (the textured appearance) is unknown. Figure 1(b) shows an image of an object manufactured according to this model. The segmentation of the whole object is relatively easy. It is performed by a marker-based watershed approach (Beucher and Meyer, 1992). The segmentation result is overlayed in red on figure 1(b). This step is out of the scope of this paper. The automatic location of the inner boundaries is much harder, as several object components have a very similar visual appearance.

In order to control the quality of the manufactured object, we need to perform the registration of the model (2D shape) on the image of the object. This registration relies on the external shape of the model and the object image. The object is flexible. A non-rigid registration method of the model on the objects image is required.

The main contribution of this paper is the inclusion of a curvature term in a non rigid registration framework that avoids spurious deformations in high curvature zones. The approach is validated in an industrial context.

The rest of the paper is organized as follows. Section 2 briefly reviews the state of the art of registration methods, describes the principle of the selected method that better fits our requirements and discuss its performances in different situations. Section 3 proposes a solution that solves the observed problems. In section 4 we validate our solution in a industrial con-

Borocco, A. and Marcotegui, B.
Non-rigid Shape Registration using Curvature Information.
DOI: 10.5220/0007354903340340
In *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2019)*, pages 334-340
ISBN: 978-989-758-354-4

text. Qualitative and quantitative results are given. Finally section 5 concludes this paper.

2 REGISTRATION

The registration literature is very rich and offers many different registration methods. Interesting surveys can be found in: (Zitova and Flusser, 2003) (Sotiras et al., 2013). We focus on the techniques relevant to our application. Our model contains only the boundaries of the object's components and the visual appearance of the inner parts is unknown. Thus image-based registration techniques are not suitable for our application.

Also the object is made of nearly incompressible material and suffers only large scale deformations. Thus, the inner parts move coherently with the object boundary. Therefore we perform a shape registration between the 2D model and the object external boundary, and then apply the computed deformation to the entire model. The same strategy is used by Peterlik (Peterlík et al., 2017).

Our aim is then to register the model 2D shape to shape of the manufactured object. Because of the flexible nature of our objects, we need a non-rigid 2D shape registration. Many methods exist in the literature for this purpose.

Among them there are many well known methods such as the ICP (Iterative Closest Point) method introduced par Besl and McKay (Besl et al., 1992), but even its variants later developed (Rusinkiewicz and Levoy, 2001) (Pomerleau et al., 2013) are inappropriate for cases where the sampling step is not uniform. This is the case in our application, because the model is discretized so that there are more points in areas of strong curvature while the object boundary is regularly sampled according to the resolution of the image acquisition device. Also it is very sensitive to the initialization step. Another widespread method is the Coherent Point Drift (CPD) algorithm, (Myronenko and Song, 2010) (Myronenko et al., 2007). It is a probabilistic method, for both rigid and non-rigid point set registration that considers the alignment of two point sets as a probability density estimation problem.

The method developed by Rouhani (Rouhani and Sappa, 2012) is particularly suitable for our purpose. Indeed, it can cope with the not even discretization step of the model's border. Also it exploits a quadratic distance approximation which allows each iteration of the algorithm to be linearly solved. Hence, the registration process has a fast convergence. Because of those reasons we choose to use Rouhani's method.

2.1 Principle of Rouhani's Registration

Let us describe the Rouhani's registration principle introduced in (Rouhani and Sappa, 2012). Let $S = \{s_i\}_1^{N_s}$ be the set of data points of the model shape and $C = \{c_i\}_1^{N_c}$ the points of the object boundary. The registration is done by minimizing an error term in an iterative process. This error relies on the sum of the distance of points s_i belonging to the model, to the border of the object C:

$$SD(s_i, C) = \frac{d_i}{d_i - \rho_j}[(s_i - c_j)^T T_j]^2 + [(s_i - c_j)^T N_j]^2 \quad (1)$$

with s_i the considered point belonging to the model, c_j the closest point to s_i belonging to C, T_j and N_j, the unit tangent and outer normal at c_j, d_i , the signed distance between s_i and c_j, ρ_j , the curvature radius at s_i.

The use of this distance makes this registration method it suitable for a different number of points on registered shapes. Figure 2 shows an illustration of the considered distance: In low curvature zones the considered distance is close to the normal distance to the shape, and so the minimizing process is not affected by the different number of points. Whereas in high curvature zones, the considered distance is equivalent to the euclidean one.

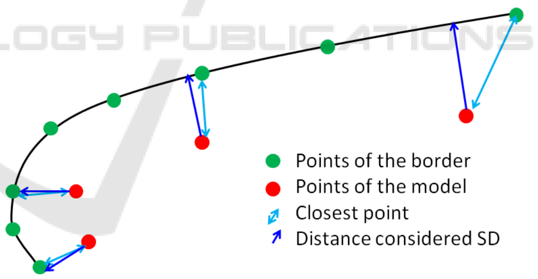


Figure 2: Illustration of the considered distance.

A squared control lattice, P, is defined and its deformation, L,is regularized by a global tension term , $T(P)$, measured by its curvature over the whole domain:

$$T(P) = \int\int_{XY} [\|L_{xx}\|^2 + 2\|L_{xy}\|^2 + \|L_{yy}\|^2] dxdy \quad (2)$$

with L, the vector field representing the deformation of the control lattice.

In each iteration, we optimize the deformation field L in order to minimize the error E:

$$E = \lambda T(P) + \sum_{i=1}^{N_s} SD(L(s_i), C) \quad (3)$$

with $L(s_i)$ the position of s_i after deformation of the control lattice L, $L(s_i)$ is initialized as s_i.

And $\lambda T(P)$ a regularity term in order to assure that the local deformation is not too important.

λ represents the registration rigidity, and is automatically tuned during the registration. It starts with a high value ($\lambda = 10^6$), which intends to cope with the alignment problem. Then, once the ratio of registration error between consecutive iterations is below a given threshold, λ is divided by 10, until $\lambda = 1$.

Because of the chosen distance, the whole registration function in equation 3 is linear in terms of the control lattice coordinates. The optimal control lattice deformation is obtained by iterating the resolution of a system of two linear equations. The reader is refered to (Rouhani and Sappa, 2012) for a detailled description of this method.

The results obtained on our data using that method are generally good: we observe that the external contours coincide, but also, the internal ones, obtained by the application of the deformation computed on the external contour to the whole object, correspond to the ones we observe in our objects, as it is shown in figure 3.

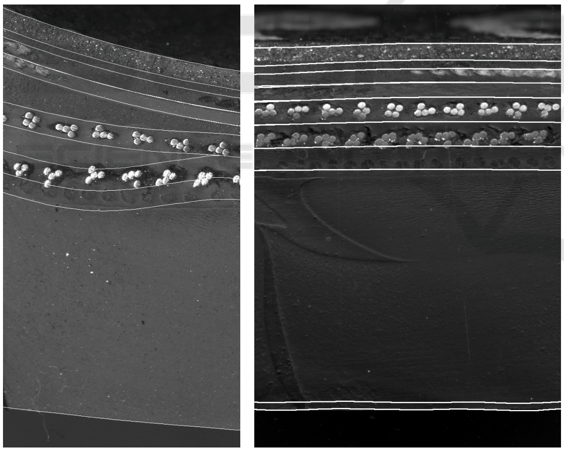


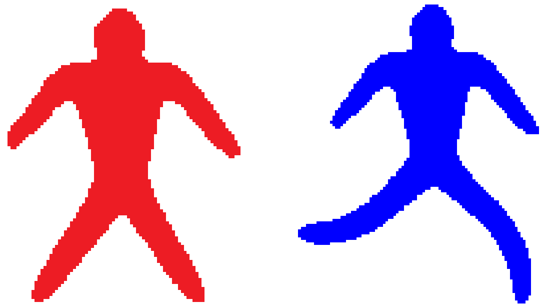
Figure 3: Good registration results on objects 6 and 16 using Rouhnani's method (Rouhani and Sappa, 2012).

2.2 Problems Encountered

Using that method we have performed registration of 2D shapes, obtained from the database (Ralph, 2009).The blue shape is the model that is registered to another instance of the object, the red shape.

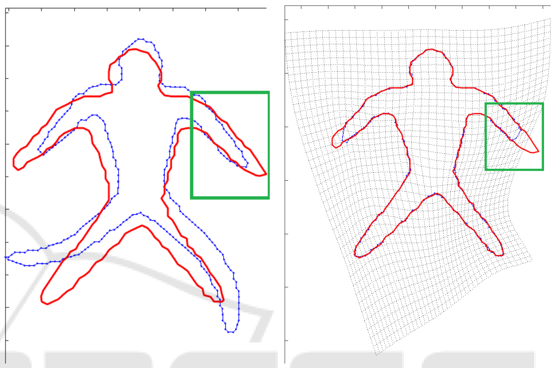
Figure 5 illustrates the results obtained after Rouhani's registration. We can observe that every point of the model is, after registration, projected on the contour of the image. Based on this observation, it may be considered as a good result. However the contours do not actually coincide: If we connect the dots, as shown in the figure 5(c), we observe that even if the points were moved so that they belong to the image contour after registration, the registration fails, specially on the dude's arms. We can observe that phenomenon on the figure 5(d).

This phenomenon occurs because this registration technique tends to minimize a criterion that is only related to the distance between the model points and

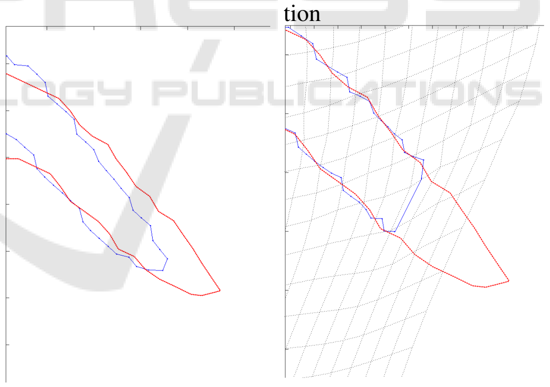


(a) object: dude 0 (b) model: dude 7

Figure 4: 2D Shapes used for registration.



(a) before registration (b) after Rouhani's registration



(c) before registration, zoom from 5(a) (d) after Rouhani's registration, zoom from 5(c)

Figure 5: Registration results on 2D Shapes: dude7 and dude0.

the contours. In the case of the dude's arms, the point located at the end of the arm in the model is closer to a point located in the forearm of the image than to the extremity. This error appears mainly in high curvature zones.

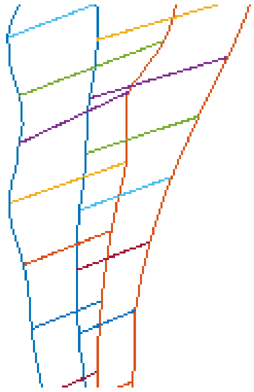
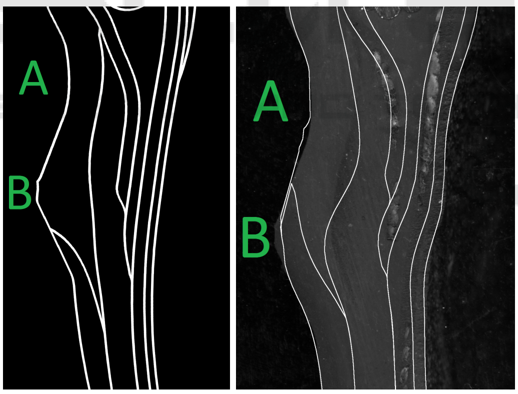


Figure 6: Mapping between model points and their location after registration.

We also face this problem in our images. This phenomenon can be observed in figure 6: the contours coincide but there is a shift between them. The final error achieved by the algorithm is close to zero but the registration still fails.



(a) model (b) registration of the model on the object

Figure 7: Registration results on object 18: the deformation due to registration introduces non-physical curvatures on the internal contours.

This is problematic in our case because it induces distortion in the internal contours, as shown in figure 7. The observed distortions of the internal contours are due to a shift between the obtained registration result and the expected one. This is in our case a major mistake: such a distortion corresponds to a stretching in the lower area (B) and a compression in the upper area (A), as in figure 7, inducing a curvature in the internal contours. Those two physical transformations could not happen in the case of nearly incompressible material, and thereby this solution is not possible.

3 PROPOSED SOLUTION

Our solution relies in the fact that the distortion between the object and its model is global. Because of that, high curvature zones present in the model will remain in the object.

The solution we propose is to favor the pairing of similar high curvature points by adding a term in the error equation (3).

This term would avoid shifts between the contours, but also prevent the case where model points belong to the object's contour after registration but the contours do not coincide as seen on figure 5, which happens mainly in high curvature zones.

First we detect high curvature points on the model. We name them the characteristic points cp. Those characteristic points are identified using the curvature radius. For our experiment we defined a point as high curvature point if its curvature radius ρ_j is the local minimum of a zone where the curvature radius is smaller than 50 pixels.

Then we detect high curvature points on the image. By definition, high curvature points of the model are also present in the object and no additional high curvature points are created. Therefore we select the same number of characteristic points N_{cp} as detected in the model, within the high curvature points in the image.

We match each characteristic point from the model cp_i to the closest characteristic point of the object $C(cp_i)$.

We add a term in the error equation in order to minimize the distance between characteristic points of similar curvature.

$$E = \lambda T(P) + \sum_{\substack{i=0 \\ i \notin cp}}^{N_s} SD(L(s_i), C) + \sum_{i \in cp} \mu d(L(cp_i), C(cp_i))^2 \quad (4)$$

with cp characteristic points, cp_i being paired with $C(cp_i)$, d the distance between those points and:

$$\mu = \frac{k}{1 + |\rho_{C(cp_i)} - \rho_{cp_i}|} \quad (5)$$

with k, being a weight to give the curvature term more or less impact, and ρ_{cp_i} and $\rho_{C(cp_i)}$ being respective curvature radius. In our application we observed experimentally that variations of this parameter has a low sensitivity as long as it has values between 20 and 200. We decided to use k = 50.

Then as each iteration tends to reduce the global error, the distance between those points will decrease.

4 EXPERIMENTAL RESULTS

4.1 Database

The study we conducted was for an industrial purpose: an industrial partner provided us with images of objects and the models according to which the objects were manufactured. Our database contains 80 images of size 14000 by 8000 pixels, of objects produced according to 31 different models.

In order for us to quantify the improvement on the problematic cases of our obtained results, images of objects with areas of strong curvature have been annotated by a specialist: we have a ground truth of the real inner frontiers of the objects corresponding to 4 different models.

The method we've developed aims to be deployed in factories, it must therefore must cope with a wide variety of objects and models.

4.2 Results

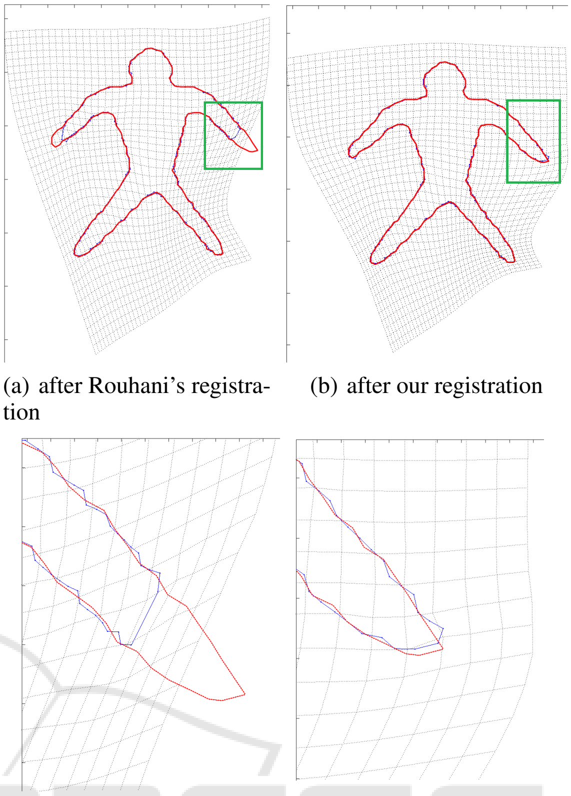
Figure 8 compares the results between Rouhani's original method and our proposed improvement. We observe that after Rouhani's registration every point of the model is projected on the image but that the contours do not coincide.

Using our method, as the extremities of the arms are high curvature points, those points are well registered.

Adding this constraint on high curvature points improves the registration: in both cases every point of the model is, after registration, projected on the contour of the image, which leads to a small error term. But the use of high curvature points pairing allows contours to coincide even in high curvature zones.

This method improves the registration of the model on the object produced: not defining characteristic points induces a shift between contours which corresponds to a not physical deformation (cf. figure. 7), whereas those deformations do not occur with our method cf. figure 9.

Figure 9 shows the performances of our method on other problematic images. We observe on all the objects that the inner borders are less curved using our method in comparison with Rouhani's method. These



(a) after Rouhani's registration (b) after our registration

(c) extremity of the arm after Rouhani's registration (d) extremity of the arm after our registration

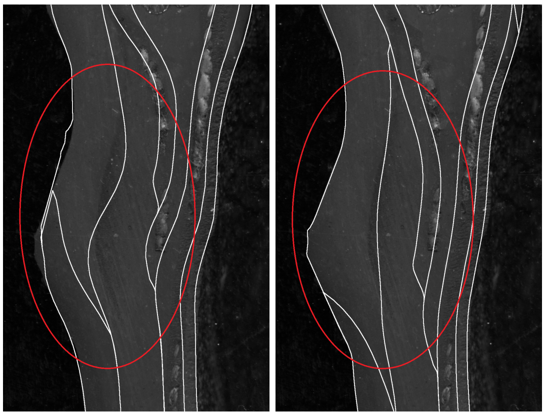
Figure 8: Comparison of registration results on 2D Shapes before and after adding the curvature term.

curvatures are not present in the model before registration, they where induced by the registration and do not correspond to any physical deformation of the object. Therefore our registration method improves the registration.

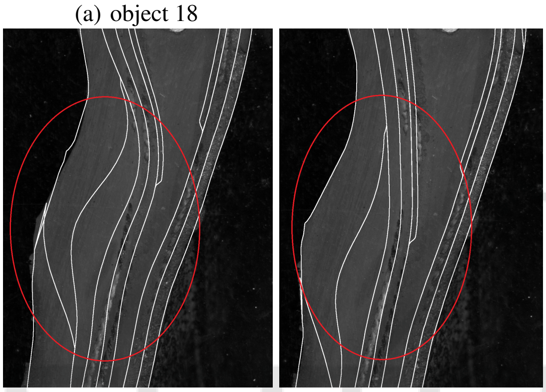
The quantitative evaluation of the registration is not easy. As illustrated hereinbefore, a perfect correspondence of registered points is not a guarantee of a perfect registration. In order to quantify the quality of the registration in an objective way, we introduce a distance measure between the inner frontiers of the object annotated by an expert, and their corresponding frontiers registered: To each point of the registered inner frontier is associated the distance to the closest point in the annotated frontiers.

As the objects are not perfect, even if the registration was perfect the inner contours in the image might not correspond with those in the model. However, a huge average distance between the annotated and the registered frontiers reveals a failure in the registration.

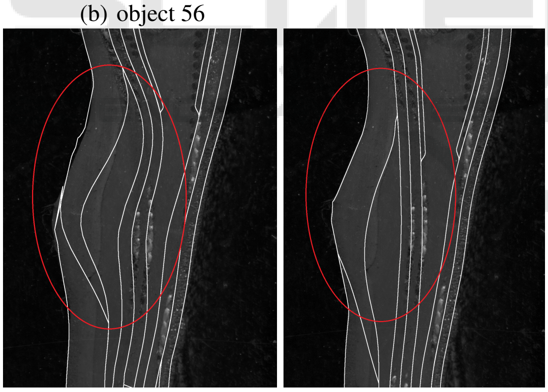
The average distance to the ground truth is signif-



(a) object 18



(b) object 56



(c) object 75

Figure 9: Comparaison of the results obtained before (left) and after adding the curvature term (right) on objects 18, 56 and 75.

icantly lower for our result than for Rouhani's result. The quantitative evaluation of the results shown in figure 9 are the following.

For object 18, shown in figure 9-a the average distance between the annotated and the registered frontiers is 24.11 pixels using Rouhani's method whereas we obtain an average distance of 11.49 pixels using our method. It corresponds to an improvement of 52 %.

We obtain similar results for objects 56 and 75 shown in figures 9-b and 9-c. For object 56, before adding the curvature term, the average distance to ground truth is 22.13, whereas with that term the average distance is 12.53, which correspond to an improvement of 43%. Also for object 75, before adding the curvature term, the average distance to ground truth is 39.78, whereas with that term the average distance is 20.94, which correspond to an improvement of 47%.

Over all the annotated objects, the mean distance using Rouhani's registration is 28.9 pixels, whereas using our method we obtain an average distance of 14.2 pixels, wich corresponds to an improvement of 51%. Those results highlight the improvement made by our method: the average distance on all annotated objects is divided by 2.

By the use high curvature points pairing, this method allows us to get better results: a curvature on the inner contours is not induced by this registration. The registered model's contours are closer to the object's without any non physical deformation induced. This method has been applied on our whole database and similar results have been obtained.

5 CONCLUSION

This paper presents a method to cope with registration mistakes of 2D shapes that are common in high curvature regions. It is done by first identifying and pairing the high curvature points, then by adding a term that favors the rapprochement of these pairs.

This method allows us to get better results that are consistent with the physics inherent to the manufactured object. It has been used in an industrial context, and good results have been obtained on the set of images provided by the manufacturer. This method is intended to be deployed in factories to allow a quality control of the produced objects.

From the methodological point of view, we propose a non-rigid shape registration method, able to handle correctly extremities registration. Our process avoids significant deformations of objects, that can not be seen if we verify only the contour correspondence.

REFERENCES

Besl, P. J., McKay, N. D., et al. (1992). A method for registration of 3-d shapes. *IEEE Transactions on pattern analysis and machine intelligence*, 14(2):239–256.

Beucher, S. and Meyer, F. (1992). The morphological approach to segmentation: the watershed transformation. *OPTICAL ENGINEERING-NEW YORK-MARCEL DEKKER INCORPORATED-*, 34:433–481.

Myronenko, A. and Song, X. (2010). Point set registration: Coherent point drift. *IEEE transactions on pattern analysis and machine intelligence*, 32(12):2262–2275.

Myronenko, A., Song, X., and Carreira-Perpinán, M. A. (2007). Non-rigid point set registration: Coherent point drift. In *Advances in Neural Information Processing Systems*, pages 1009–1016.

Peterlík, I., Courtecuisse, H., Rohling, R., Abolmaesumi, P., Nguan, C., Cotin, S., and Salcudean, S. (2017). Fast elastic registration of soft tissues under large deformations. *Medical Image Analysis*.

Pomerleau, F., Colas, F., Siegwart, R., and Magnenat, S. (2013). Comparing ICP variants on real-world data sets. *Autonomous Robots*, 34(3):133–148.

Ralph, R. (2009). Mpeg-7 core experiment ce-shape-1 test set.

Rouhani, M. and Sappa, A. D. (2012). Non-rigid shape registration: A single linear least squares framework. In *European Conference on Computer Vision*, pages 264–277. Springer.

Rusinkiewicz, S. and Levoy, M. (2001). Efficient variants of the ICP algorithm. In *3-D Digital Imaging and Modeling, 2001. Proceedings. Third International Conference on*, pages 145–152. IEEE.

Sotiras, A., Davatzikos, C., and Paragios, N. (2013). Deformable medical image registration: A survey. *IEEE transactions on medical imaging*, 32(7):1153–1190.

Zitova, B. and Flusser, J. (2003). Image registration methods: a survey. *Image and vision computing*, 21(11):977–1000.