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Multi-Sensor Multi-Resolution Data Fusion Modeling

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Abstract

Inspection analysis of 3D objects has progressed significantly due to the evolution of advanced sensors. Current sensors facilitate surface scanning at high or low resolution levels. In the inspection field, data from multi-resolution sensors have significant advantages over single-scale data. However, most data fusion methods are single-scale and are not suitable in their current form for multi-resolution sensors. Currently the main challenge is to integrate the diverse scanned information into a single geometric hierarchical model. In this work, a new approach for data fusion from multi-resolution sensors is presented. In addition, a correction function for data fusion, based on statistic models, for processing highly dense data (low accuracy) with respect to sparse data (high accuracy) is described. The feasibility of the methods is demonstrated on synthetic data that imitates CMM and laser measurements.

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1. Introduction

Inspection analysis of 3D objects has progressed significantly due to the evolution of advanced sensors. Today's sensors facilitate surface scanning at both high and low resolution levels. Fusion of multi-sensor data has significant advantages over single source data [1-7]. The concept of data fusion is taken from the capability of living organisms to use multiple senses in order to learn their environment. The brain fuses all this available information to perform a decision task [2, 6]. For sensors, integrating this diverse information remains a major challenge. Most data fusion methods for multi-sensors are highly application-oriented, and their generalization is problematic.

The multi-sensors facilitate surface scanning for obtaining low density high accuracy (LD-HA) and high density low

accuracy (HD-LA) data. LD-HA data is usually acquired by a CMM touch probe, while HD-LA data is acquired by laser. Due to their different accuracies, these data sets can be referred as a multi-resolution data set. Applying data fusion methods on multi-resolution data yield an accurate model with detailed features. The HD-LA data is processed and its accuracy is improved according to the LD-HA data, resulting in an accurate preservation of the original 3D shape.

In this paper we present the Point of Interest approach, developed for multi-resolution data fusion (Technion). In this approach, Shape Histograms are used for point matching and data fusion [8, 22]. Further, we present here, a novel correction function based on statistic models (Politecnico di Milano- Polimi), which consists of locally correcting the HD-LA data using the few LD-HA data as local attractors. In this process, Kriging also known as Gaussian process is used as

correction model [9, 18, 23-24]. Hence, HD-LA data is corrected using this correction function before it is integrated with the LD-HA data and the improved 3D multi-resolution model is reconstructed.

The model reconstruction is presented in the scheme by the dotted blocks as shown in Fig. 1. The feasibility of the methods is demonstrated on a real windmill gearbox (provided by Gamesa [20]).

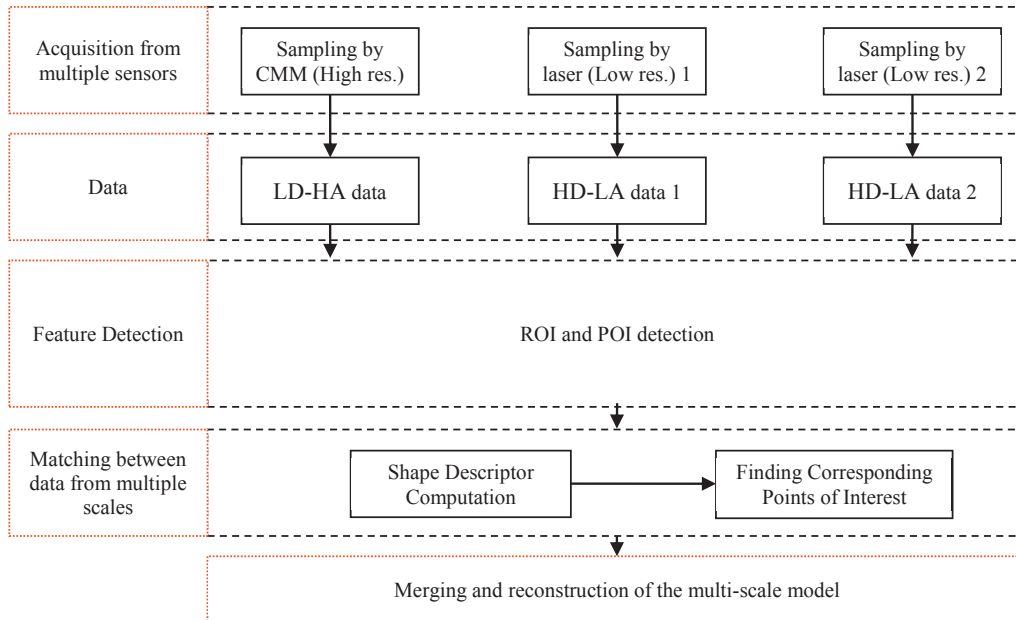


Fig. 1. Framework outline for Multi-Sensor Multi-Resolution Data Fusion.

2. Approach

In this paper, approaches developed for multi-resolution data fusion by Technion and Polimi, are described. First the HD-LA data is corrected (Polimi). Then, the corrected HD-LA data is integrated with the LD-HA data into a multi-resolution model (Technion).

2.1. Point of Interest Approach - Technion

In this section we present the Point of Interest multi-resolution data fusion approach that has been developed (Fig. 1). It is based on detection of Regions of Interest (ROI) and Points of Interest (POI). The POIs allow alignment between the different models and fusing the data efficiently. The ROIs on data sets are detected, based on Shmukler and Fischer [21]. POIs are then found for each data set. The sets of sampled data are matched using Shape Histograms [14]. Shells and spherical sectors are built for the POIs. For each POI, the surface area of the sub-shells is defined. The histograms are then calculated for each sub-shell and a correlation map between histograms is built.

The proposed approach deals with two types of noisy sampled data: (a) high resolution (LD-HA) data that is very accurate but sparse, and (b) low resolution (HD-LA) data that is less accurate but dense. Hence, LD-HA data is much more

reliable than HD-LA data. Two types of merging approaches were used: (a) selective merging and (b) retentive merging. In *selective merging*, only selective points from each set of sampled data are added to the merged model, based on Euclidian distances. In *retentive merging*, all points from both sets of sampled data are added to the merged model.

The multi-resolution data fusion method and preliminary results based on synthetic models generated in commercial CAD software (SolidWorks) were presented at the CIRP Design 2013 conference in Bochum, Germany [8]. In this work we demonstrate the implementation of the method on a CAD model of a mechanical part, windmill gearbox of Gamesa [20].

2.2. Gaussian Processes Approach - Polimi

Data from different sources are more and more often used for surface reconstruction [16]. The approach proposed by Polimi implements a merging process, where the LD-HA points are used as local attractors for the high density HD-LA points, in a two-stage hierarchical statistical model.

It is assumed that both the LD-HA and HD-LA data sets have already been correctly localized within the same coordinate system, i.e. that the registration problem has been solved. This task can be solved using the Technion approach

based on POIs (see 2.1) or an alternative method as the one proposed in [17].

This data fusion method originates from the approach proposed in [18] to register or align data provided by different measurement systems. Colosimo *et al.* [9, 23, 24] presented a similar approach to enhance surface reconstruction via multisensory data fusion. The approach consists of a two-stage model. At the first level, the Kriging Gaussian process is used considering HD-LA data only, similarly to what is proposed in [19] in the field of Statistical Process Control. At the second stage a correction model is used to locally adjust the first-stage surface reconstruction (based on HD-LA data only) taking advantage of the highest resolution offered by the LD-HA data. This correction stage improves predictions. The statistical method obtains uncertainty of the reconstruction at any location in terms of a prediction interval.

This approach was extended to the B-Spline correction function (Technion). In the CAD field, a B-Spline is a Spline function with local support with respect to a degree parameter [10-11]. Every polynomial function of a given degree can be uniquely represented as a linear combination of B-Splines of that same degree and smoothness. In fact, a B-Spline function can be considered a low-pass filter [12-13], so that B-Spline curves/surfaces can be used as a correction function for HD-LA data. Finally, mesh is created for reconstructing a hierarchical model from the multi-resolution cloud of points.

2.3. Joint Approach – Technion and Polimi

The two data fusion approaches, the Point of Interest approach and the Gaussian Processes Approach can be integrated to improve the mesh reconstruction process. For example, feature detection can be based on Shape Histograms and POIs/ROIs. Matching can be based on correlation maps by using the proposed Gaussian processes correction function. Matching between data sets can be based on combined correction function that includes statistic models. The feasibility of this joint approach can be seen from implementations of these stand-alone approaches sequentially on the same scanned data.

3. Implementation

The multi-sensor data fusion methods are applied on the CAD model of a real windmill gearbox with diameter of about 1300 mm and depth about 1200 mm, as demonstrated in Fig. 2 [20]. The POI process (Technion) consists of two main stages: (a) pre-processing (Section 3.1) and (b) data fusion (section 3.2). The Data Knowledge extraction and modelling by using multi-sensor data fusion (Section 3.3) was developed for multi-sensor data fusion (Polimi).

3.1. Pre-processing

To demonstrate the feasibility of the POI method, the CAD model was taken as a base (Technion). Next, two meshes were

generated, a sparse mesh containing approximately 10000 points, and a dense mesh containing approximately 30000 points. Note that the meshes were not uniformly distributed. A denser mesh was generated in areas containing small details, such as holes, fillets and corners, where a sparser mesh was generated in areas that were more flat. Noise was artificially added to both meshes. The noise was of uniform distributed magnitude in each axis and then projected to normal direction of each point. In order to mimic acquisition methods output of a laser scanner and a touch probe, the noise maximum magnitude in the dense mesh was four times larger (0.004mm) than the magnitude of the sparse mesh (0.001mm). The models containing the noise are depicted in Fig. 3 (a-b). Then, the error map of the noisy models with respect to the CAD model alongside a histogram of the error percentage is shown in Fig. 3 (c-d). High error values correspond to areas colored in red, and low error to areas colored in blue.

3.2. Data Fusion

In the second stage Points of Interest (POIs) were selected in an automated process relying on the topological properties of the models (Technion). POIs are represented as black points on the mesh in Fig. 4 (a-b). Next, a matching process was applied to select POIs that appear in both models. The corresponding POIs are depicted in Fig. 4 (c-d). Finally, an automated fusion algorithm was executed using both models and the extracted POIs. The output of this process is a merged model depicted in Fig. 5 (a).

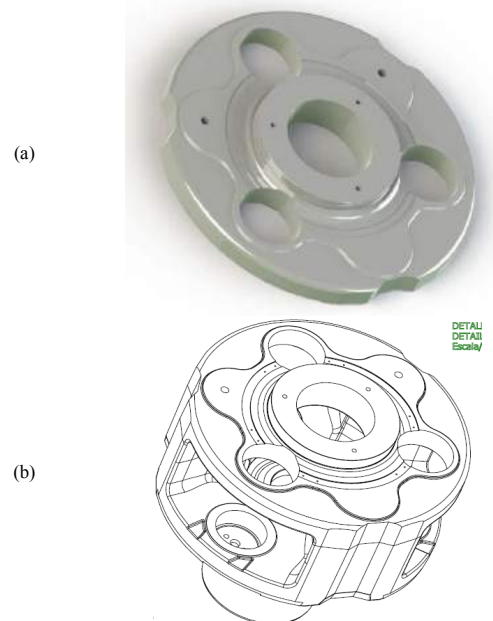


Fig. 2. Windmill gearbox of Gamesa (a) The upper part of the CAD model (b) Drawing of the part

The merged model essentially adopts the most accurate points from each of the models and achieves higher accuracy when compared to the CAD model. It can be seen that the merged model preserves all important features of the initial models. An error map and histogram of the merged model with respect to the CAD model is presented in Fig. 5 (b-c). It can be seen that when the framework is provided with high

quality scans from the multi-sensors, a high quality fused model is generated. A more detailed explanation can be found in [8]. The resulting mesh can be used as a model for analysis and visualization.

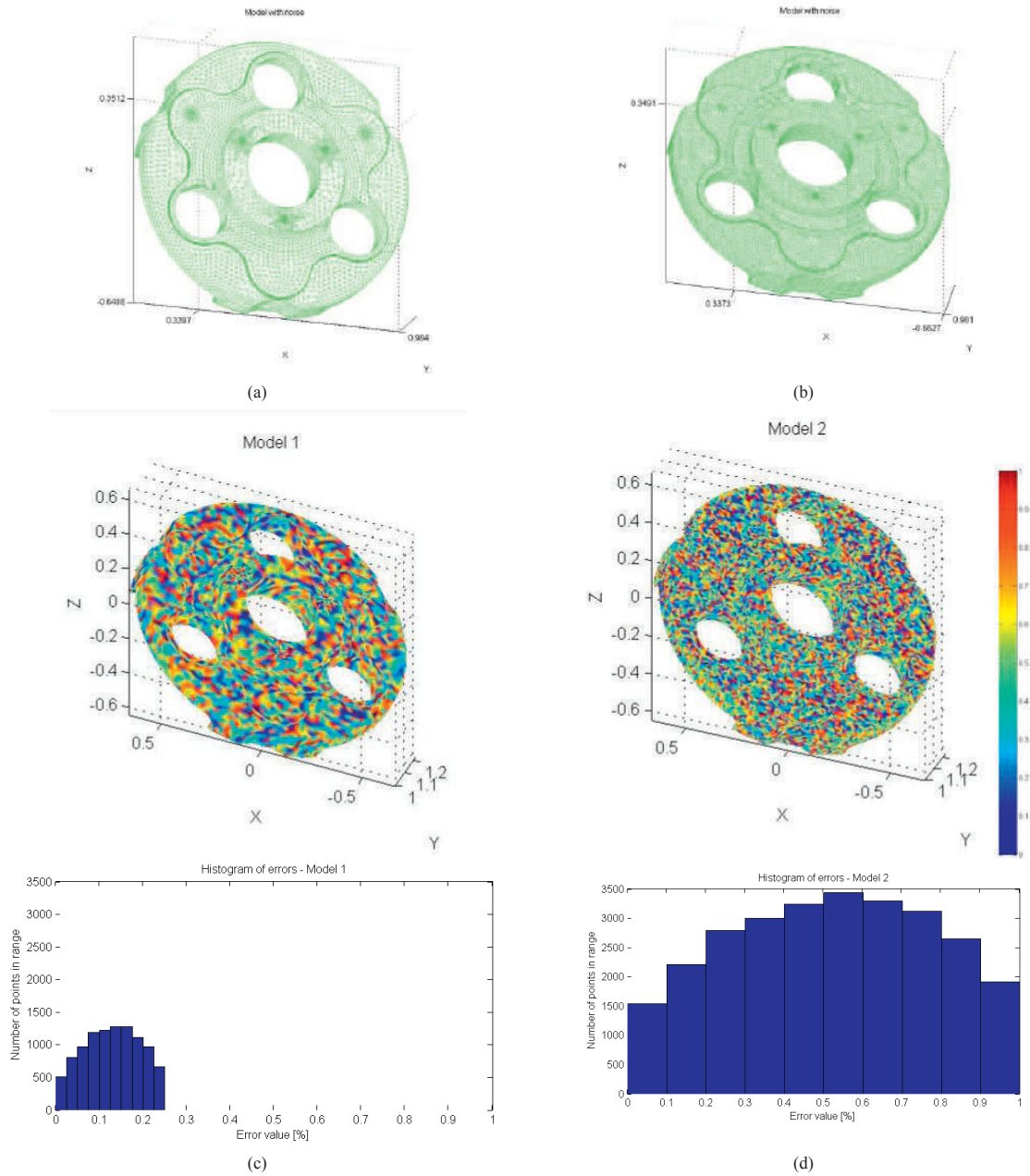


Fig. 3. Windmill gearbox of Gamesa (a) Sparse mesh with low noise, LD-HA data (touch probe sensor) (b) Dense mesh with high noise, HD-LA data (Laser scanner) (c) Error map and histogram of touch probe sensor (d) Error map and histogram of laser scanner.

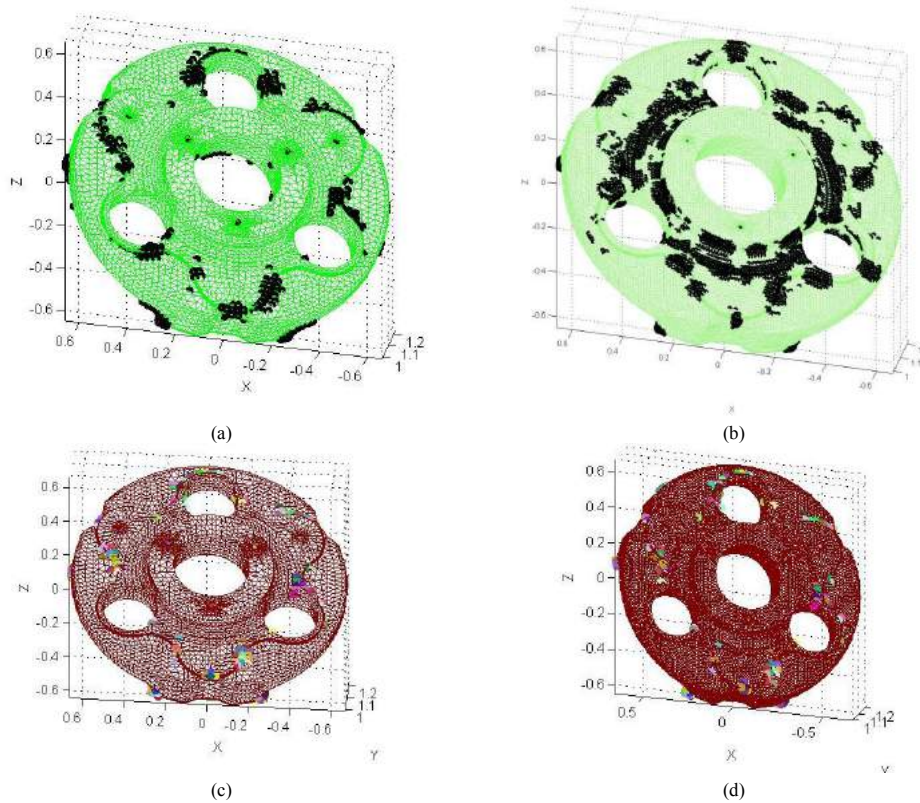


Fig. 4. Windmill gearbox of Gamesa Selected POI which were sampled by (a) a touch probe sensor (b) a laser scanner. Matching points of interest that were sampled by (c) a touch probe scan (d) a laser scanner.

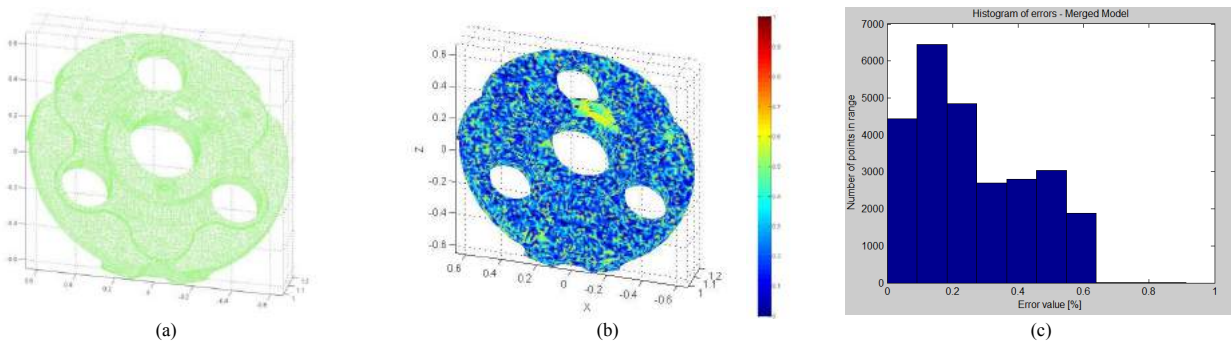


Fig. 5. Windmill gearbox of Gamesa : (a) Merged model (b) Error map of the merged model (c) Error histogram

3.3. Data Knowledge extraction and modeling by using multi-sensor data fusion

This section describes the approach that was for multi-sensor data fusion (Polimi). It was demonstrated on the windmill gearbox shown in Fig. 2 [20].

3.3.1. Multiresolution point cloud

Synthetic datasets were used as starting reference for the data fusion and refer to the work piece shown in Fig. 6 (a). Two points clouds obtained via laser scanner at different density were firstly available. We will refer to these data sets as HD and LD data, only. We will firstly fuse these data sets and then combine the result with (simulated) contact data,

referred to as LD-HA data.

Back to the two LD and HD data sets acquired via laser scanner, the approach proposed in [9, 23] to fuse point clouds was firstly used. In particular, data fusion was carried out with reference to the two cylindrical features shown in Fig.6 b-c.

Fig. 7 shows the results of the fusion approach. In particular, the fusion model attempts to connect the data at different resolution. The local discrepancy between the two data sets is shown in Fig. 7 as an error map, where it is clear that the error is high at regular angles of the cylinder. This discrepancy was due to way in which HD data were acquired. In fact, it was acquired as a set of four separate point clouds, each referring to a quarter of the original cylinder. Besides to the discrepancy observed at regular angles, a second effect was also observed along the cylinder height. This effect is shown in Fig. b, where the discrepancy map is illustrated on one quarter of the cylinder A. It can be observed that the discrepancy increases as one moves from the bottom to the top of the cylinder. A similar situation characterizes the discrepancy map obtained by fusing data sets measured on cylinder B (Fig. 8).

As a main result of the fusion procedure, we decided to concentrate the effort on a registration procedure aimed at realigning each quarter of the cylindrical surface, starting from the four HD point clouds.

3.3.2. Registration of HD point clouds

Fig. 9 shows the cylinder radius ρ observed along the cylinder height as a function of the angular position θ . In this plot, a perfect cylinder should correspond to a horizontal line, i.e. the radius should be constant, despite of the angular position and the height.

In order to realign the four point clouds, a feature-based procedure was used. For each cylinder quarter, the corresponding cylinder portion was fitted and the corresponding axis computed. Then the four axes were overlapped to achieve the final alignment of the four cylinder portions. Fig. 11 and Fig. 12 show the results of the alignment procedure.

3.3.3. Simulating contact and contactless data fusion

In order to show potential advantages of multisensor data fusion, contact LD-HA data points were simulated, as obtained by the touch probe that is going to measure the final shape on the lathe-machine and/or the CMM available on the shop floor. A sample of 50 contact data points were ideally measured on a perfect cylinder whose nominal radius is the average radius observed on the cylinder measured via noncontact HD-LA data. These 50 LD-HA points were placed

considering a Latin hypercube sampling. A random noise in all the x, y, and z directions with a null mean and variance equal to 0.0001 was added to represent measurement error of the contact system. The discrepancy map obtained by fusing the (simulated) LD-HA contact and the (real) HD-LA contactless data sets is shown in Fig. 13. As clear from Figure 14, data fusion allows one to define zones of the workpiece where the HD-LA data are biased, i.e., have a systematic error. This discrepancy map allows one to “correct” via data fusion the HD-LA data set, i.e. apply local corrections to the HD-LA data to achieve accuracy of the LD-HA data almost everywhere.

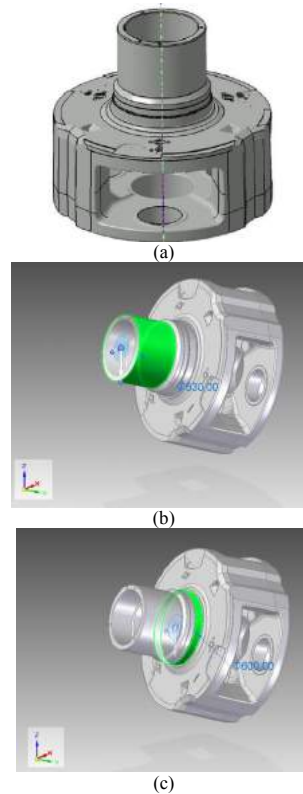


Fig. 6. Gamsa gearbox (a) first positioning (b) Cylinder A and (c) Cylinder B

4. Summary

This paper described a new integrated approach for data fusion from multi-resolution multi-sensors. The POI approach was used for merging sparse LD-HA data with dense HD-LA data, where The HD-LA data was modified by applying the correcting function that is based on a statistical model. The join approach has some major advantages: (a) integrating emerging and traditional inspection technologies such as CMM and laser scanner; (b) integrating unlimited number and types of sensors; (c) adaptive adding of diverse data with different accuracies; (d) merging multi-resolution data into a hierarchical model.

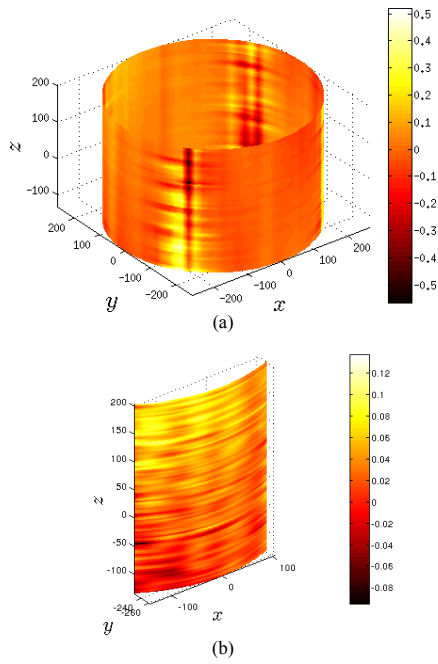


Fig. 7. Gearbox - Cylinder A: (a) Discrepancy map [mm] (b); A detail of the discrepancy map which is shown on a cylinder quarter

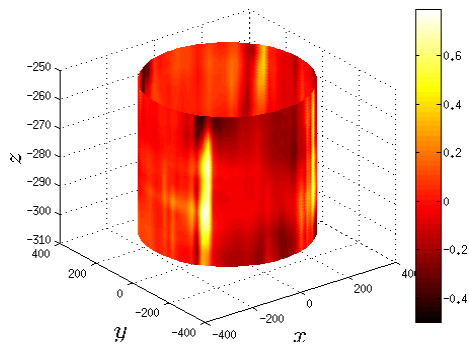


Fig. 8. Gearbox- Cylinder B: Discrepancy map [mm]

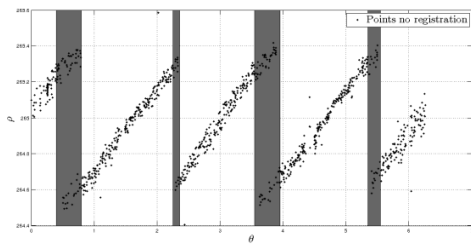


Fig. 9. Radii observed at different heights as a function of the angular position for the HD point clouds. Grey zones represent the borders between the four HD point clouds.

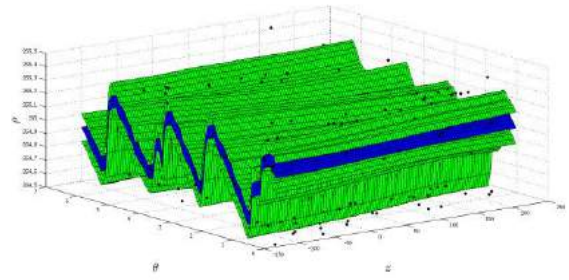


Fig. 10. Representation of the cylindrical surface in cylindrical coordinates (only 1000 LD data points selected according to a latin-hypercube sampling are shown).

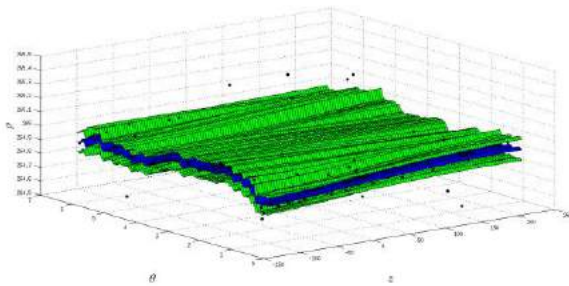


Fig. 11. After registration: Representation of the cylindrical surface in cylindrical coordinates.

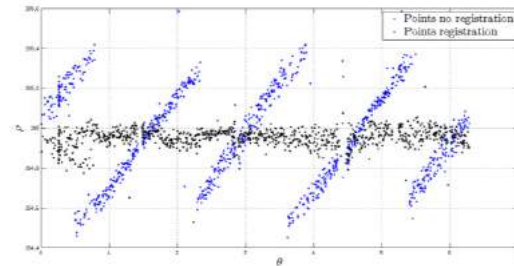


Fig. 12. Radii observed at different height as a function of the angular position before and after the registration procedure

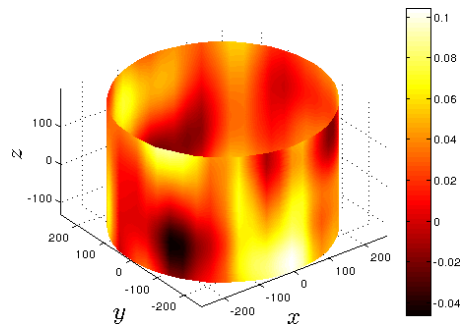


Fig. 13. Discrepancy map of real contactless and simulated contact data.

In the future, performance can be improved by using a hierarchical data structure for efficient storage and fast neighbor searching. Moreover, additional information, such as normals and color from the multi-sensors, can be incorporated.

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References

- [1] Hall, D. L., and Llinas, J., An Introduction to Multisensor Data Fusion. Proc IEEE. 1997. 85 (1): p. 6-23.
- [2] Esteban J., Starr A., Willetts R., Hannah P., and Bryanston-Cross P., A Review of data fusion models and architectures: towards engineering guidelines. Neural Computing & Applications, 2005. 14(4): p. 273-281.
- [3] Weckenmann A., Jiang X., Sommer K. D., Neuschaefer-Rube U., Seewig J., Shaw L., and Estler T., Multisensor data fusion in dimensional metrology. CIRP Annals-Manufacturing Technology, 2009. 58(2): p. 701-721.
- [4] Mandic D.P., Obradovic D., Kuh A., Adali T., Trutschel U., Golz M., De Wilde P., Barria J., Constantinides A., and Chambers J., Data Fusion for Modern Engineering An Overview. Lecture Notes in Computer Science, 2005. 3697: p. 715-721.
- [5] Gros X. E., NDT Data Fusion. 1996, Elsevier.
- [6] Raol J.R., Multi-Sensor Data Fusion with MATLAB. 2009, CRC Press.
- [7] Elmenreich, W., Sensor Fusion in Time-Triggered Systems, 2002, Institut für Technische Informatik, Technischen Universität Wien: Wien.
- [8] Tansky D., Fischer A., Data Fusion and 3D Geometric Modelling from Multi-Scale Sensors, Proceedings of CIRP Design Conference. 2013, Bochum, Germany.
- [9] Colosimo B. M. and Pacella M., On Integrating Multi-sensor Data for Quality Inspection and Monitoring, in X Convegno AITeM. 2011: Napoli.
- [10] Farin G., Hoschek J., and Kim M.-S., Handbook of Computer Aided Geometric Design. 1 ed. 2002, Amsterdam: North-Holland, Elsevier.
- [11] Bartels R. H., Beatty J. C., and Barsky B. A., An Introduction to Splines for Use in Computer Graphics And Geometric Modeling. 1987: Morgan Kaufmann.
- [12] Goshtasby, A., F. Cheng, and B.A. Barsky, B-spline curves and surfaces viewed as digital filters. Computer Vision, Graphics, and Image Processing, 1990. 52(2): p. 264-275.
- [13] Unser, M., A. Aldroubi, and M. Eden, B-spline signal processing. I. Theory. Signal Processing, IEEE Transactions on, 1993. 41(2): p. 821-833.
- [14] Ankerst M., Kastenmueller G., Kriegel H.-P., and Seidl T., 3D Shape Histograms for Similarity Search and Classification in Spatial Databases. Advances in Spatial Databases, Springer, 1999, pp. 207-226.
- [15] Ankerst M., Kastenmuller G., Kriegel H.-P., and Seidl T., Nearest Neighbor Classification in 3D Protein Databases, ISMB. 1999, 99. p. 34-43.
- [16] Campatelli G., Geometric Tolerance Evaluation Using Combined Vision – Contact Techniques and Other Data Fusion Approaches, Springer, 2010: p. 189-213.
- [17] Senin N., Pacella M., and Colosimo B.M., Point set augmentation through fitting for enhanced ICP registration of point clouds in multisensor coordinate metrology, Robot Comput Integrated Manuf., 2013. 29(1) pp. 39–52
- [18] Xia HF, Ding Y, and Mallick BK. Bayesian hierarchical model for combining misaligned two-resolution metrology data. IIE Trans. 2011. 43:p. 242-58.
- [19] Colosimo BM, Cicorella P, Pacella M., and Blaco M. From profile to surface monitoring: SPC for cylindrical surfaces via Gaussian Processes. To appear in Journal of Quality Technology. 2014.
- [20] Gamesa, wind technology industrial company. Available at: <http://www.gamesacorp.com/en/gamesaen/>
- [21] Shmukler, A., Fischer, A., Verification of 3D freeform parts by registration of multiscale shape descriptors. The International Journal of Advanced Manufacturing Technology, 2009. 49: p. 1093-1106.
- [22] Tansky D., Data Fusion and 3D Geometric Modeling for Multi-Scale Sensors, M.Sc. thesis, Faculty of Mechanical Engineering, Technion, Haifa, Israel. 2013.
- [23] Colosimo B.M., Pacella M. and Senin N., Multisensor Data Fusion via Gaussian Process Models for Dimensional and Geometric Verification, submitted paper to precision engineering. 99.
- [24] Dolci L. Bayesian Hierarchical Gaussian Process Model: an Application to Multi-Resolution Metrology Data, M.Sc. thesis, Faculty of Mathematical Engineering, Politecnico, 2011.