# Profile and Surface Monitoring Methods for Shapes

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**Abstract**
In discrete part manufacturing, quality depends on the final geometry of the product, which is usually constrained by geometric tolerances. This is why appropriate tools for shape monitoring can highly reduce scraps and reworking. A review of approaches for monitoring the shapes of manufactured objects is given. We start from the simplest case of bi-dimensional curves (i.e., traditional profiles) to move to tri-dimensional surfaces. Critical issues of modeling and monitoring this specific type of profiles and surfaces are explained. Directions for future research are highlighted.

**Key Words:** profile monitoring, shape, geometric tolerances, surfaces, Gaussian processes

## 1. Introduction

Starting from the seminal papers on linear profile monitoring (Kang and Albin (2000), Kim et al. (2003), Mahmoud and Woodall (2004)), the literature on profile monitoring has now covered many application domains. Reviews of the literature on profile monitoring can be found in Woodall *et al*. (2004) and Woodall (2007) and in the book recently edited by Noorossana *et al*. (2012).

In this scenario, one stream of research focused on monitoring profiles corresponding to physical shapes obtained on the machined workpiece (Colosimo and Pacella (2007, 2010), Colosimo *et al*. (2008), Colosimo and Senin (2011)). These profiles are usually related to geometric tolerances, i.e. requirements that concern the physical shape of an object, such as straightness and roundness or circularity. Most of these specifications concern 2-dimensional (2D) curves, i.e. profile that lie in a plane. In case where 3D curves are of interest, for example when the straightness of an axis is the quality feature of interest, different approaches for profile modeling have to be considered (Colosimo and Pacella, 2011). Similarly, when moving from profiles to surfaces, appropriate extensions of methods and tools developed for profile monitoring have to be developed (Colosimo *et al*. (2008, 2010)).

This paper summarizes the main results and the current state of research on methods and tools for monitoring profiles and surfaces representing shapes obtained on an object. Directions for future research are outlined in the conclusions of the paper.

## 1. Profile monitoring for shapes

Very often the final shape of a machined workpiece is constrained by geometric tolerances. Sometimes, these tolerances concern 2D profiles. As an example, Figure 1 shows a technical drawing where a circularity or roundness tolerance of 0.2 mm is specified. In this case, the constraint refers to the circular profile measured at each cross-section of the cylinder. Figure 2 shows on the left 100 profiles measured on a cross-section of turned specimens. As it is clear from the figure, all the real profiles are not perfect circles and this is why the circularity constraint allows one to judge wether the observed difference from a perfect circle has to be "tolerated", i.e., the workpiece is conforming to requirements.

Figure 2 on the right shows how the specification has to be checked. Starting from the real profile (passing through the dots), the form error is measured as the radial distance between two concentric circles including between them the real profile observed. This form error is called "out-of-roundness" (OOR) and has to be compared with the tolerance $t$ specified on the technical drawing (Figure 1). If the OOR is lower than the tolerance $t$, the workpiece can be considered as conforming to this requirement.

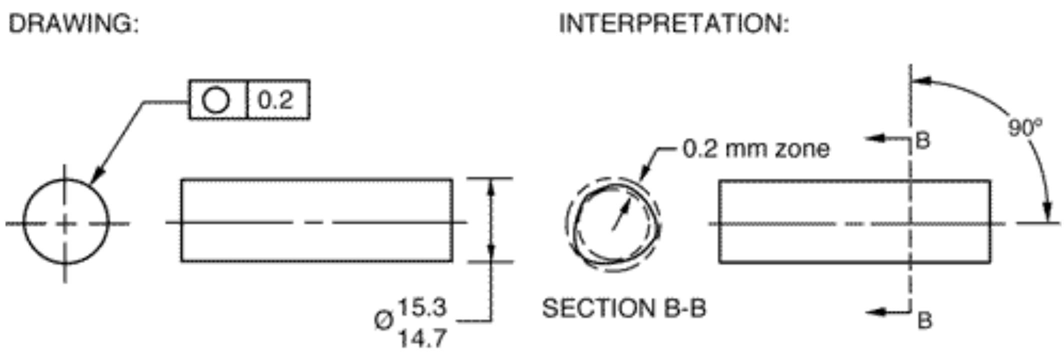


**Figure 1:** Technical drawing specifying a circularity tolerance equal to $t$=0.2 (GDT, 2013).

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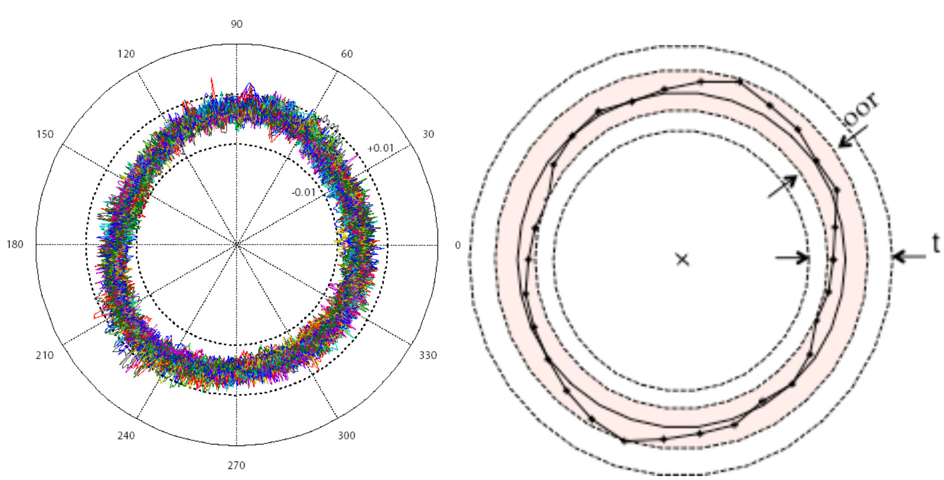



**Figure 2:** On the left: examples of 100 roundness profiles. On the right: the real profile is included between two concentric circles, whose radial distance is equal to OOR (out-of-

roundness). The maximum form error allowed is *t*, which is the tolerance specified on the technical drawing (Figure 1).

A common approach for monitoring the circular profile consists of summarizing all the information contained in the profile in one synthetic indicator (the OOR) and then monitoring it using a simple univariate control chart, as shown in Figure 3. A clear drawback of this approach is that the profile can deviate from its natural or in-control shape in many different ways, while remaining within the band defined by the OOR - shown in Figure 2 on the right. In these cases, the control chart should in principle issue an alarm because the change of the final shape can be due to problems with the materials or the manufacturing process that is machining the workpiece.

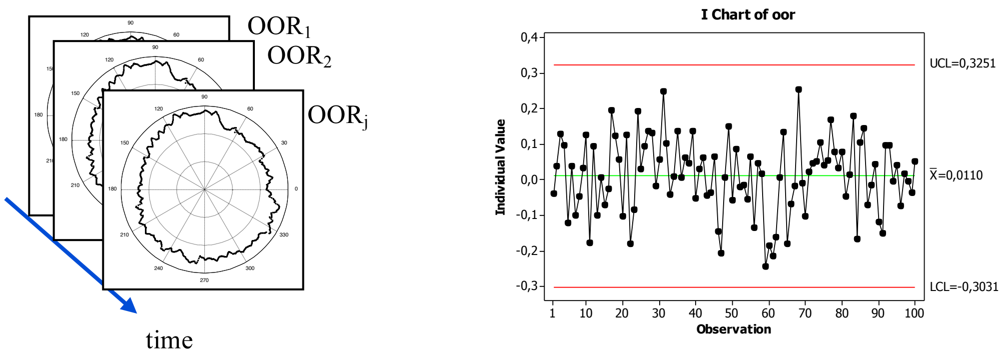



**Figure 3:** A common approach for monitoring circural profiles: on the left – compute the OOR for each profile observed with time and – on the right - design and use a univariate control chart on the OOR values.

Starting from the simple OOR control chart, many different approaches have been proposed in order to enhance roundness profile monitoring, namely:

- a location control chart reproducing the approach proposed by Boeing (1998) – named “LOC cc” in Figure 4;
- a profile monitoring method combining linear regression with harmonic regressors to a spatial autoregressive model for the residuals (Colosimo *et al*, 2008)– named “REG cc” in Figure 4;
- a profile monitoring method based on principal component analysis (Colosimo and Pacella, 2007) – named “PCA cc” in Figure 4;
- a profile monitoring method based on a one-class classifier adaptive resonance theory neural network (Pacella and Semeraro, 2011) – named “ART NN” in Figure 4.

Figure 4 shows comparison of performance achieved by using different methods for circular profile monitoring. In particular, 95% confidence intervals of the overall Averge Run Length (ARL) when different out-of-control states are considered (bi-lobe, tri-lobe, quadri-lobe, half-frequency) are shown. Details of the comparison procedure are described in Colosimo and Senin (2011).

The main conclusions of the performance comparison study can be summarized as follows:

- Profile monitoring methods (based on regression or principal component analsysis, i.e., REG cc or PCA cc) outperform competing methods.

- Other approaches based on artificial neural networks – ART NN - can be effective, especially when profile-to-profile randomness is present – see Colosimo and Senin (2011 – chapter 11). However, these approaches are not suitable for Phase 1 because they are sensitive to otulying profiles in the training set.
- Profile monitoring methods, as the REG cc and the PCA cc, are worth because they include a phase of profile modeling, which is then used as baseline for the monitoring procedure. The model of the profile is useful to gain knowledge on the manufacturing process behind the workpiece and to design a process optimization procedure (Colosimo and Pacella, 2011).

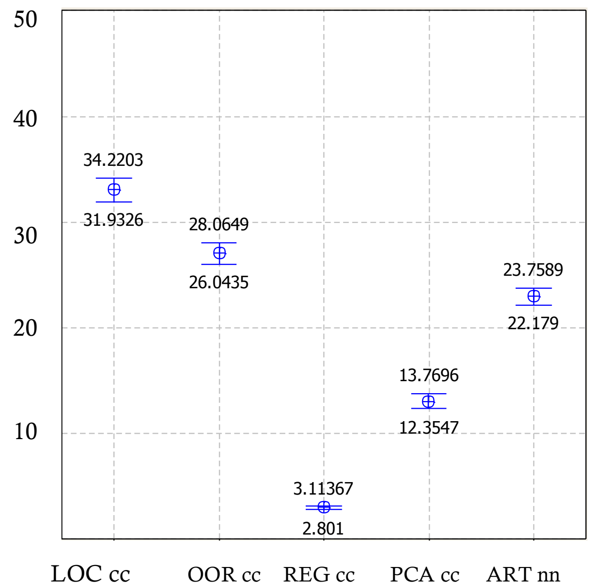



**Figure 4:** Confidence interval (95%) on the Average Run Length performance of different approaches for roundness profile monitoring.

## 2. Surface monitoring

Surface monitoring can be faced using an approach similar to the one used for profile monitoring: i) modeling the target shape and estimating the unknown coefficients; ii) monitoring the estimated coefficients via control charts.
However, when moving from profiles to surfaces different issues moving from 2D profile to 2.5D or even 3D surfaces have to be solved. As an example, monitoring of cilindrical surfaces is discussed in the following.

### 2.1 A cylindrical shape

A cilindricity requirement is shown in Figure 5. Similarly to what we showed with respect to the circularity, this tolerance is requiring to the machined surfaces to lie within two concentric cylinders whose radial distance is equal to 0.2 mm.

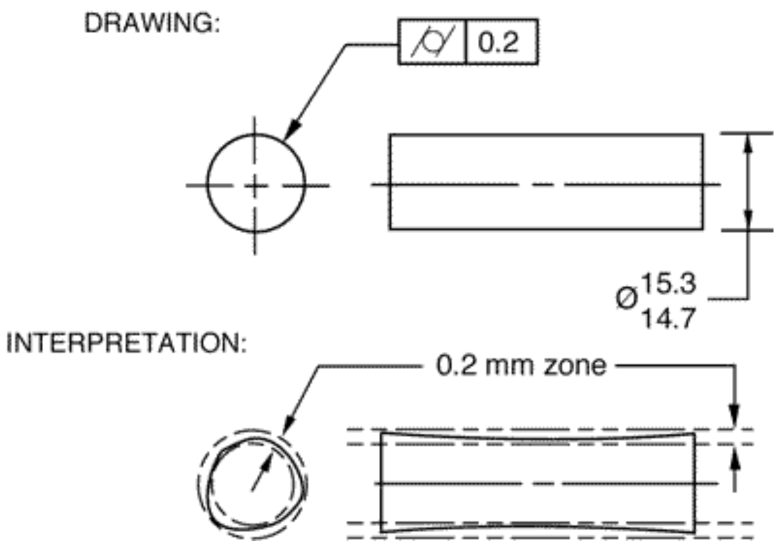



**Figure 5:** A technical drawing showing the cylindricity requirement (GDT, 2013).

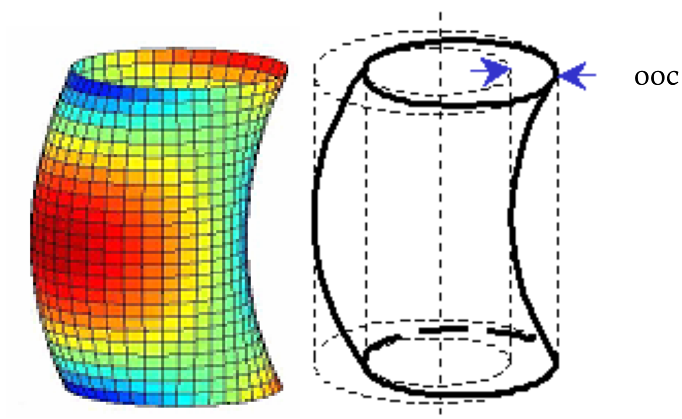



**Figure 6:** Reconstruction of a cylinder and the corresponding form error (OOC).

Figure 6 shows a possible shape of a real cylindrical surface and the corresponding form error, the out-of-cilindricity (OOC), which has to be lower than the tolerance shown in the technical drawing in order to let the shape be considered as conforming to requirements.

## 2.2 A parametric approach for monitoring cylindrical surfaces

When Coordinate Measuring Machines (CMMs) are used as measurement systems, surfaces are usually inspected at a regular grid, as the one shown on the right of Figure 7. In this case, a viable solution consists of using a Spatial Autoregressive Regression (SARX) model (Cressie, 1993) to reconstruct the obtained shape. SARX models are used in spatial statistics to represent the spatial correlation in regular lattices and are constituted by a large-scale model, representing the main shape of the machine feature, and a small-scale model, representing the spatial correlation of the residuals.
Colosimo *et al*. (2010, 2013) explored the use of SARX model for modeling cylindrical features obtained by turning. In their models, the deviation from a perfect cylinder

observed at location $\boldsymbol{s}_i = (\theta_i, z_i, R)$ (see Figire 7) is modeled by combining Chebyshev polynomials and Fourier (periodic) functions to represent axial errors and circular errors, respectively. Then, the remaining errors are modeled considering a spatial autoregressive structure linking residuals observed at neighboors.
The model allows one to represent the typical patterns shown in Figure 8.
Once the in-control model of the cylindrical surface is identified, the monitoring approach consists of estimating all the unknown coefficients, store them in a vector, which is then monitored via multivariate control charting (Colosimo *et al*. 2010, 2013).

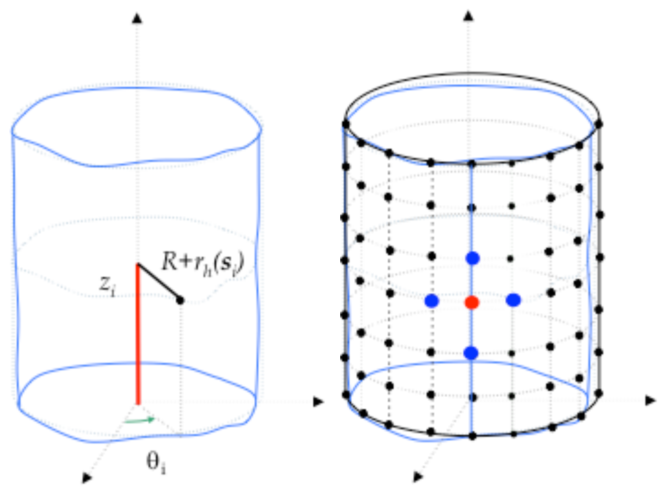



**Figure 7:** On the left: Cylindrical coordinates to represent the deviation from a nominal cylinder at a given location. On the right: grid showing the first-order neighbours for modeling the small-scale component of the SARX model.

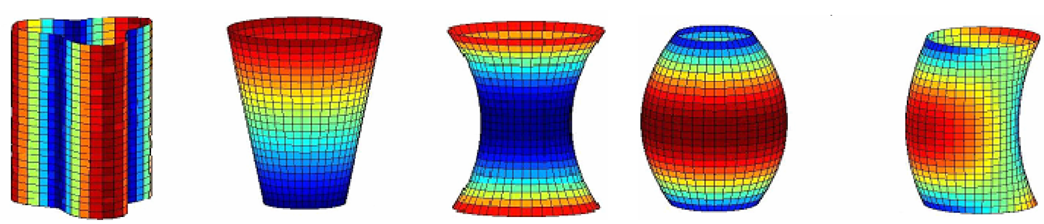


**Figure 8:** Typical patterns of cylindrical component (Henke *et al.*, 1999; Zhang *et al.*, 2005).

## 2.3 Surface monitoring via Gaussian processes

When the surface is not inspected on a regular grid and/or defining the appropriate regressors is not an easy task, Gaussian processes (GPs) can be used for modeling surfaces (Cressie, 1993).
In this case, the deviation from a perfect cylinder is modeled using a GP with a constant mean and a covariance function that represents the similarity between measured points as a function of their distance (isotropic assumption). Colosimo *et al.* (2013) tried comparing different correlation functions (namely squared ecxponential vs. Matern) for

fitting the in-control cylindrical surface shown in Figure 9. No significant difference was found for the case study at hand, as shown in Figure 10.

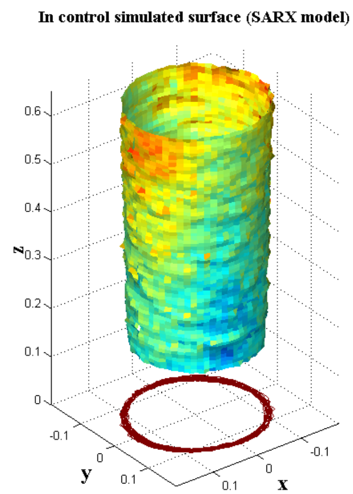



**Figure 9:** The in-control cylindrical surface (Colosimo *et al*. 2013).

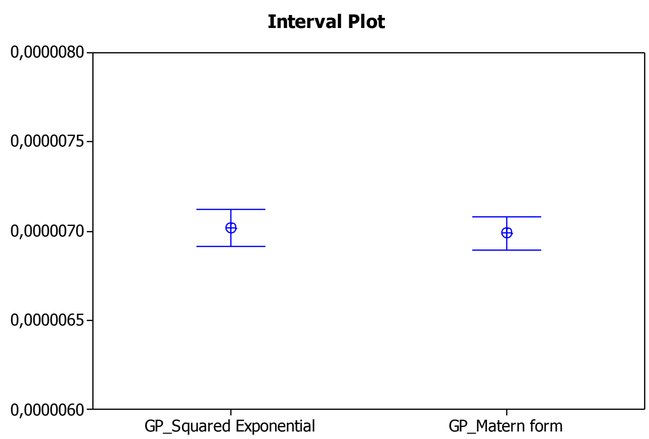


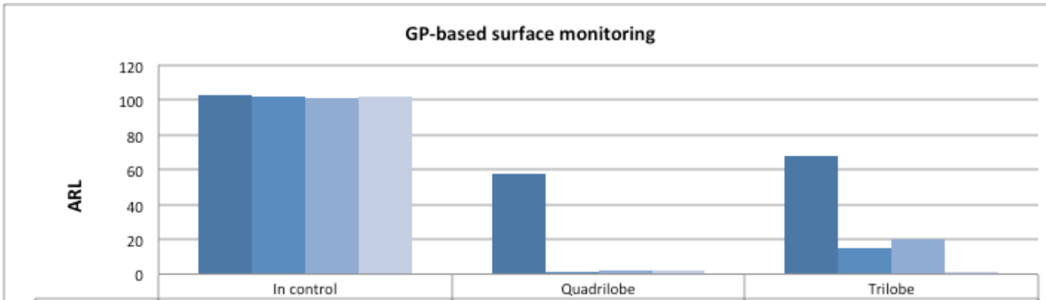

**Figure 10:** Confidence interval of the prediction error obtained via GP when using the squared exponential and the Matern correlation functions.

After fitting the surface, the problem of how to control its stability with time has to be solved. Colosimo *et al*. (2013) tried different methods:

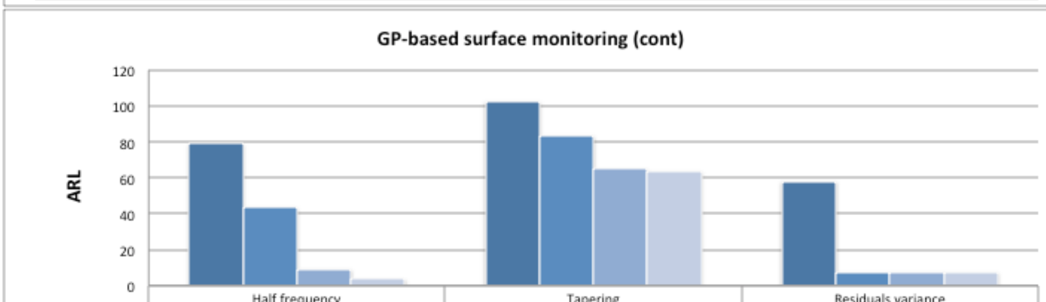
1) a control chart on the GP parameters estimated on each new surface; - “GP_par”;
2) a Hotelling $T^2$ control chart built on the differences between the target surface pattern and the GP-predicted values at all the N=460 available locations – “GP_all”;
3) an approach similar to the one used in 2) but based on predictions done at a subset of n=25 uniformly placed locations – “GP_unif”;

4) an approach similar to the one used in 2) but based on predictions done at a subset of n=25 locations placed according to a latin hypercube (lh) design – "GP_lh".

Figure 11 shows the performance obtained using all the aforementioned procedures for cylindrical surface monitoring. As it is clear from the figure, all the approaches have been designed to achieve the same in-control Average Run Length (ARL) but have very different out-of-control ARLs. In particular, the GP-lh method outperforms the other GP-based approaches in all the simulated out-of-control scenarios.




| | In control | Quadrilobe | Trilobe |
|---|---|---|---|
| GP_par | 102,83 | 57,18 | 68,08 |
| GP_all (N=460) | 102,29 | 1,61 | 15,1 |
| GP_unif (n=25) | 101,28 | 2,46 | 19,71 |
| GP_lh (n=25) | 101,6 | 1,99 | 1,35 |




| | Half frequency | Tapering | Residuals variance |
|---|---|---|---|
| GP_par | 78,96 | 102,53 | 58,17 |
| GP_all (N=460) | 43,59 | 83,6 | 7,29 |
| GP_unif (n=25) | 9,15 | 64,87 | 7,52 |
| GP_lh (n=25) | 3,8 | 63,55 | 7,4 |

**Figure 11:** Average Run Length performance considering different in-control and out-of-control states (quadrilobe, trilobe, half-frequency, tapering, increase of the residual variance) of the cylindrical surfaces.

Eventually, Figure 12 shows the comparison of ARL performance when different methods for cylindrical surface monitoring are considered, namely:

- a univariate control chart on the out-of-clindricity (OOC);
- a control chart based on the SARX model of the cylindrial surfaces;
- a control chart based on the GP-model of the cylindrical surfaces when using a uniform or lh sampling strategy.

As it is clear from the figure, the GP-lh method and the SARX method outperforms competitor approaches.

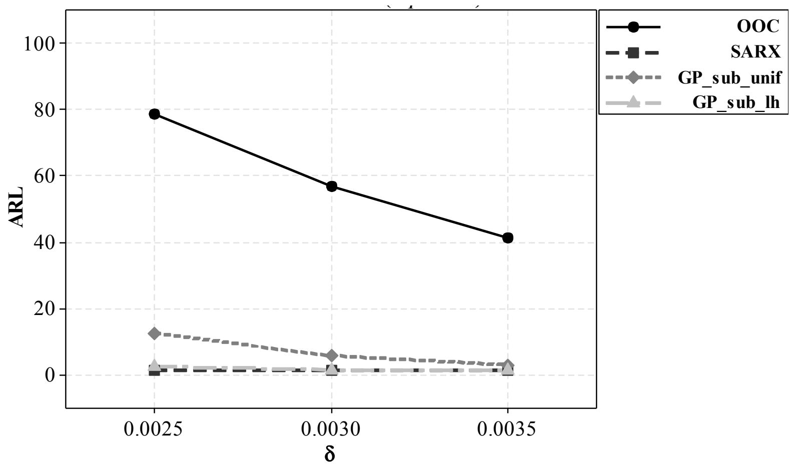



**Figure 1:** Average Run Length performance of different approaches for cilindrical surface monitoring (OOC, SARX, GP-based methods with uniform or latin hypercube locations of points) – on the abscissa the size of the simulated shift (trilobe pattern). Similar perfromance have been obtained for other out-of-control scenarios.

## 3. Conclusions and concluding remarks

This paper summarized methods for monitoring surfaces and profiles representing shapes of machined objects. In particular, we showed that both regression-based and GP-based methods can be effectively used to detect unwanted changes of the shape of the machined features.

Different directions for future research can be outlined and are summarized below.

1) Registration or alignment of machined features is a very important pre-processing step (Senin *et al*., 2013). Significant attention should be devoted to register shapes before detecting whether they are in control or not.
2) Surfaces can have complex shapes and – furthermore – all the three spatial coordinates can be affected by measurement errors. Different approaches as the Geodesic Gaussian process (del Castillo *et al*., 2013) should be considered for surface modeling.
3) A new generation of non-contact measurement systems is going to replace existing contact sensors. In this scenario, high-dimension data will be available to reconstruct the surface. Appropriate tools for "big data" should be considered.

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