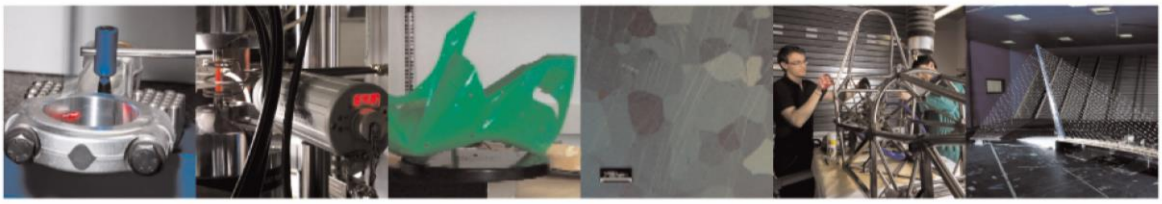

Modeling and monitoring methods for spatial and image data

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Modeling and Monitoring Methods for Spatial and Image data

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Short biographical note

Bianca Maria Colosimo is Professor in the Department of Mechanical Engineering of Politecnico di Milano (Italy), where she received her PhD degree in Industrial Engineering. Her research interest is mainly in the area of Quality Engineering (i.e. statistical process monitoring, control and optimization), with special attention to complex data modeling and monitoring (e.g., functional data, surfaces, signals and images) for advanced manufacturing processes. She is senior member of the American Society for Quality.

Modeling and Monitoring Methods for Spatial and Image data

Abstract

Intelligent sensing and computerized data analysis are inducing a paradigm shift in industrial statistics applied to discrete part manufacturing. Emerging technologies (e.g., additive manufacturing, micro-manufacturing) combined with new inspection solutions (e.g., non-contact systems, X-ray computer tomography) and fast multi-stream high-speed sensors (e.g., videos and images; acoustic, thermic, power and pressure signals) are paving the way for a new generation of industrial big-data requiring novel modeling and monitoring approaches for zero-defect manufacturing. Starting from real industrial problems, some of the main challenges to be faced in relevant industrial sectors are discussed. Viable solutions and future open issues are specifically outlined.

Keywords: Statistical quality monitoring; statistical process control, surfaces, shapes, images, additive manufacturing, signal, profile monitoring, functional data.

Introduction

There is a widespread consensus that smartness and big data availability are technological drivers of the fourth industrial revolution, i.e., Industry 4.0 (Figure 1). As in all previous revolutions, the fourth is driven by technological innovations. Water- and steam-powered mechanical manufacturing were driving forces for Industry 1.0; electricity and assembly lines drove Industry 2.0; and the introduction of computers for automation purposes catalyzed Industry 3.0. Unrivaled advances in data volumes, computational power and connectivity; new forms of human-machine interactions via augmented reality; and emerging advance in robotics and 3D printing are paving the way to the new generation of digital production in Industry 4.0. (Brettel, et al, 2014; Baur and Wee, 2015).

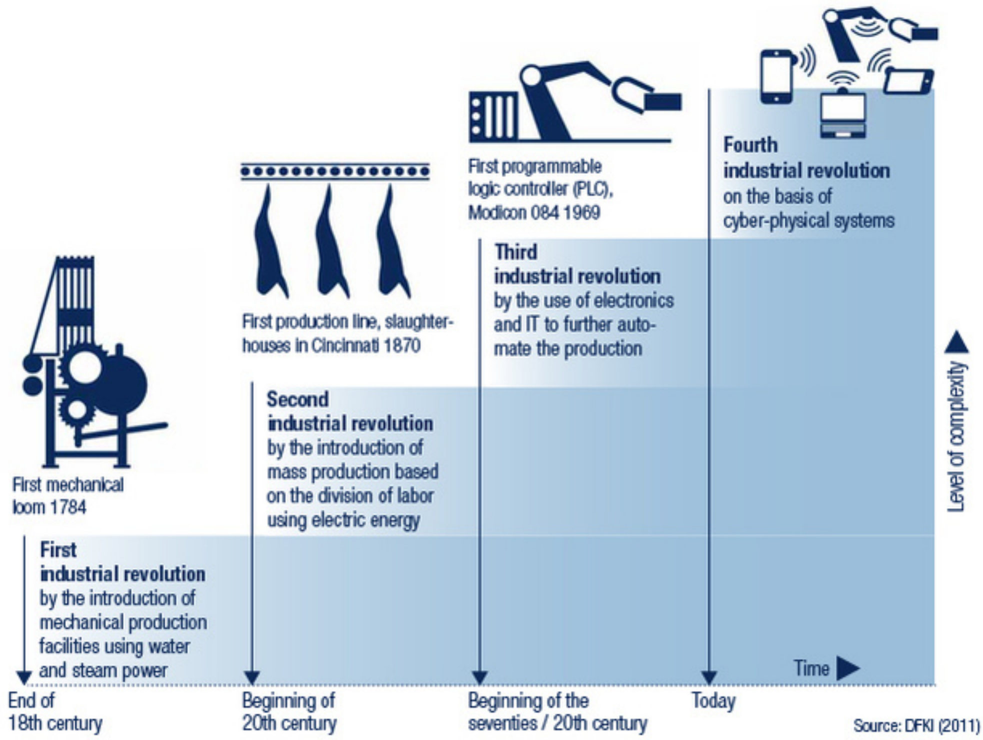


Figure 1: The four Industrial Revolutions[1]

Industry 4.0 involves many different technological advances (Rüßmann et al., 2015, Figure 2), which require novel approaches for data analysis (Lee, Bagheri and Kao, 2014 and 2015; Jazdi, 2014; Wang, Törngren and Onori, 2015). Overall, the increase of data volume, variety and velocity (i.e., the "big data" framework) poses several challenges for industrial statisticians and quality engineers (Steinberg, 2016; Megahed and Jones-Farmer , 2015; Jones-Farmer, Ezell and Hazen, 2014). For example, the highly interconnected cyber-physical systems (Lee, Bagheri and Kao, 2014 and 2015; Jazdi, 2014; Wang, Törngren and Onori, 2015) imply multiple streams of real and virtual data that have to be appropriately fused and analyzed. Cyber-security and industrial internet of things (Wells et al. 2014, Turner et al., 2015) ask for new approaches for data cloud monitoring and optimization (Aceto et al., 2015). Pervasive sensing of industrial processes and operators (to design machine-human interfaces) causes a huge amount of image and signal data that have to be appropriately studied.

[1] https://www.nrwinvest.com/fileadmin/_processed_/csm_industrial-revolution_997c038c69.jpg

Discussing all the effects of Industry 4.0 on industrial data modeling, monitoring and control is out of this paper scope. In this paper, the attention will be limited to challenges and opportunities in modeling and monitoring quality data of high-value-added mechanical products. Therefore, industrial sectors as the aerospace, automotive, tooling and machine-tools production will be specifically targeted. Furthermore, attention will be specifically devoted to the manufacturing stage of these products' lifetime.

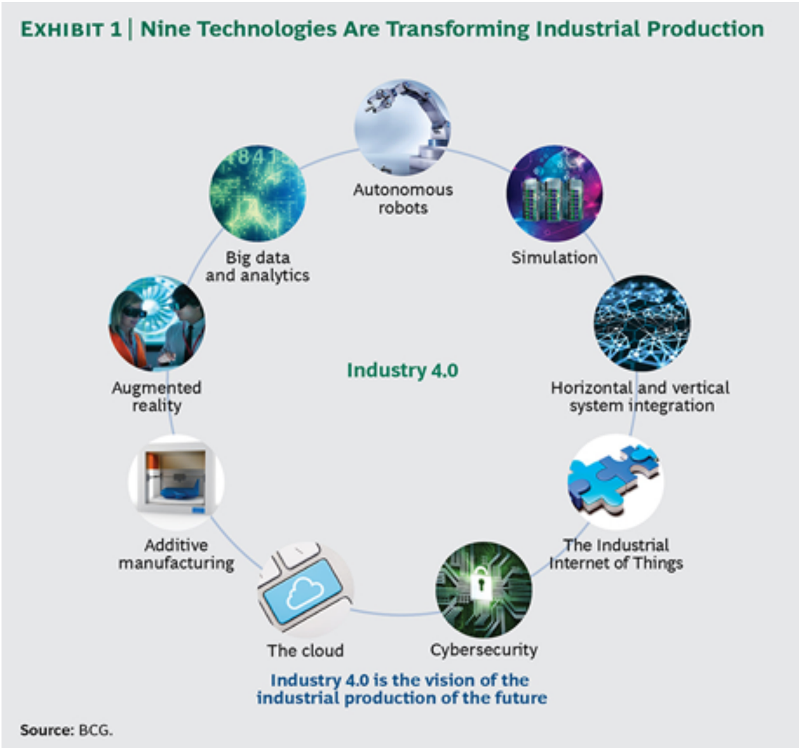


Figure 2: Technological pillars of Industry 4.0[2]

Throughout the paper, real industrial problems will be specifically introduced as motivating examples. Special attention will be devoted to some emerging manufacturing processes (3D printing or additive manufacturing – AM) and new dimensional and volumetric metrology solutions (i.e., non-contact metrology sensors, high-speed videos, X-ray computer tomography – CT).

[2] https://www.bcgperspectives.com/content/articles/engineered_products_project_business_industry_40_future_productivity_growth_manufacturing_industries/?chapter=2

For the sake of simplicity, the discussion will be organized in two main sections. The first will focus on quality features concerning **products**, while the second section will concern **process** data. In short, we will discuss approaches for modeling and monitoring product and process quality data, separately. This distinction is clearly artificial, as industrial practitioners are usually asked to face both the product and process data streams at the same time and link these two sources of information to define appropriate actions to drive the process toward zero-defect manufacturing.

The two sections will be organized following a similar structure. The industrial background and some motivating examples will be firstly introduced. Then, existing solutions for data modeling and monitoring will be briefly described. Eventually, directions for future research will be presented in the conclusions.

Modeling and monitoring product quality: Surface shapes and multi-sensor data fusion.

Quality of mechanical products can be related to different features: physical and mechanical properties; time-based performance (e.g. reliability, durability), functional performance and, possibly, aesthetic appearance. In this section, attention will be focused on technical drawings specifications, namely, dimensional and geometrical tolerances. The last decades have seen significant changes in the way in which these quality features are designed and inspected. From the design viewpoint, tolerances specifying form or location errors are increasingly accompanying traditional specifications on dimensions (e.g., diameter, length). Figure 3 summarizes typical geometric tolerances used in technical drawings of mechanical components (ASME Y14.5).

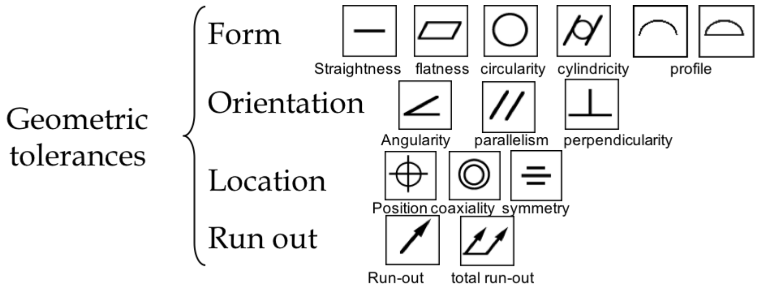


Figure 3 Some typical geometric tolerances

The reason why geometric specifications are important from a functional viewpoint is illustrated with a simple example in Figure 4. This shows a cylindrical pin mounted into a hole. In the case on the left, the pin has a constant diameter and a perfect cylindrical shape. On the right, the pin still has a constant diameter but a severe form error (named “out-of-cylindricity”). As the pin shape departs from its nominal pattern (moving from the left to the right), quality issues can arise in the assembly operation or during the functional operation of the assembled component. This is because the gap between the pin and the hole is not constant in the second case.

There are at least two main technological drivers underlying the increased attention given to geometrical specifications. First, advances in manufacturing processes are increasing the complexity of shapes achievable at reasonable costs. Figure 5 shows examples of products produced by metal AM. AM technology allows one to achieve “complexity for free”. Indeed, AM technology builds objects layer-by-layer by simply changing the track of the energy beam that melts the metal powder. This manufacturing procedure allows one to realize complex shapes “for free”, i.e., without the need of expensive tooling and molds.

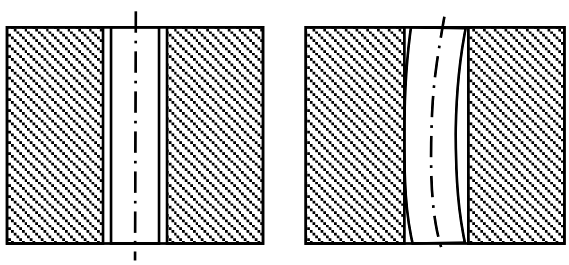


Figure 4: The effect of cylindricity form error on a pin-hole assembly.

The second technological driver favoring the use of geometrical tolerances can be found in the recent advance in metrology system technology. Non-contact systems (e.g., fringe projection, laser scanners, system based on interferometry) and multi-sensor solutions (combining traditional touch-probe and optical coordinate measuring machines (CMM)) are greatly reducing the acquisition time and improving dimensional accuracy.

On a different scale, a similar synergistic effect between advanced manufacturing processes and novel solutions for dimensional metrology is observed at the micro-scale level for engineered surfaces (Malshe et al., 2013). Although not covered in this contribution, surface manufacturing and metrology will play an important role in many application domains of engineering in the near future. In fact, appropriate surface engineering can greatly affect many different functional performance (friction and wear resistance, hydrophobicity, hydrophobicity, osseointegration, etc.).

Figure 5 Examples of AM product shapes (courtesy of EOS, Renishaw, Concept Laser)

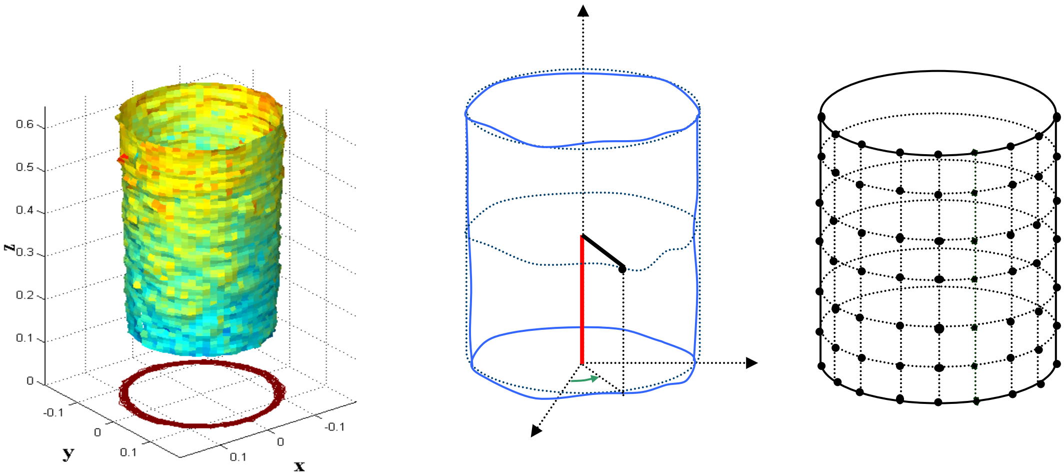
Product shape modeling and monitoring: Main challenges and possible solutions

In the last decade, many different approaches for monitoring geometric profiles have been proposed in the literature with specific applications for profile monitoring (Woodall, 2007, Noorossana et al 2011; Colosimo and Pacella, 2007, 2010, 2011; Colosimo Semeraro and Pacella 2008, Colosimo et al. 2008).

Surface monitoring represents a natural evolution of profile monitoring. However, modeling and monitoring surfaces entail specific issues that were not so relevant in profile monitoring. In particular, **spatial correlation** plays a major role. Spatial correlation refers to the way in which neighbors located on the surface are correlated in 3D directions and is strictly linked to the manufacturing process that produced the surface. Indeed, the manufacturing signature, i.e., the systematic pattern left by the process on the surface includes spatial correlation as an inner component. Modeling and monitoring the manufacturing signature is usually an effective way to indirectly monitor process stability.

Most of the surfaces in technical drawings of mechanical products are 2.5D surfaces, i.e., they can be represented as a projection of points lying on the 2D Euclidean space E^2 (plane) into the third dimension. In other words, the nominal pattern observed on the surface can be simply modeled as $z = z(x, y)$. This definition holds despite the specific Euclidean systems considered. In fact, a cylinder is a 2.5D surface when cylindrical coordinates are considered for surface modeling. In cylindrical coordinates, the radius of the surface acts as a z-coordinate while the angular and height locations act as x- and y-coordinates, respectively.

Without a loss of generality, we assume that the surface we are dealing with can be the result of one or more pre-processing steps. Typical pre-processing steps are: 1) registration or alignment consisting of roto-translating the observed surface to place it on a given coordinate system; and 2) subtraction of the nominal shape to the observed one, which is usually done to use the deviation from the nominal surface as response function.



a) b) c)

Figure 6: a) A cylindrical surface reconstructed by real data; b) a cylindrical coordinate system; and c) a regular inspection grid.

Models to represent the spatial correlation on surfaces are usually taken from spatial statistics (Cressie, 2015). When a regular inspection sampling grid is assumed (Figure 6), a Spatial AutoRegressive model with eXogeneous variables (SARX) can be used to represent the surface signature (Lesage and Pace, 2009). Colosimo, Mammarella and Petrò, (2008) and Colosimo, et al. (2014) used a SARX-based procedure for modeling and monitoring cylindrical surfaces.

Here, let $\boldsymbol{Z_h}$ represent the h-th surface point clouds, a SARX model of order 2 is given by

$$\begin{gathered} \boldsymbol{Z}_h = \boldsymbol{X\beta}_h + \boldsymbol{u_h} \\ \boldsymbol{u_h} = \left(\alpha_{1h}\boldsymbol{W}^{(\mathbf{1})} + \alpha_{2h}\boldsymbol{W}^{(\mathbf{2})}\right)\boldsymbol{u}_h + \boldsymbol{\varepsilon_h} \\ \boldsymbol{\varepsilon}_h \sim \boldsymbol{N}(\mathbf{0}, \sigma_h^2\boldsymbol{I}) \end{gathered} \tag{1}$$

where the first and second lines represent the large- and small-scale models, respectively (Cressie, 2015). $\boldsymbol{X}$ is the matrix of regressor functions; $\boldsymbol{W}^{(\mathbf{1})}$ and $\boldsymbol{W}^{(\mathbf{2})}$ are the 1st and 2nd order neighbors contiguity matrices; $\boldsymbol{\beta}_h$, α_{1h}, α_{2h} and σ_h^2 are parameters to be estimated (Colosimo et al, 2004 and 2010). Typical regressor functions for cylindrical patterns combine polynomial or Chebyschev functions along the axial direction to Fourier-based regression models along the angular direction (Figure 7).

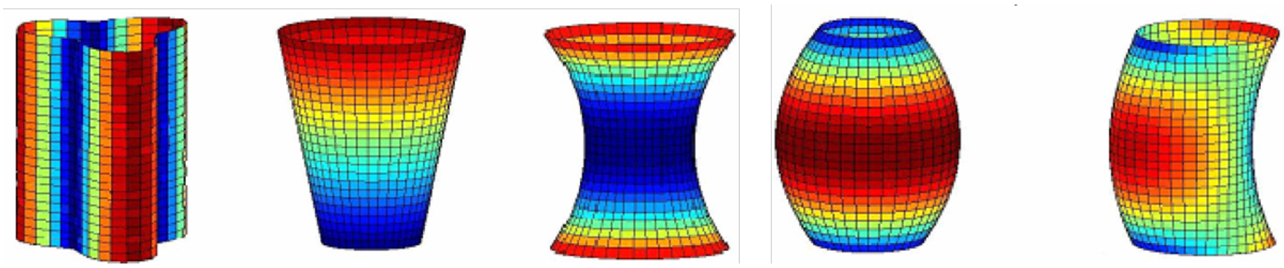


Figure 7: A typical large-scale shape of the cylindrical surfaces can be obtained by combining polynomial functions along the axial direction and Fourier-based regression model in the angular direction.

In this case, the spatial correlation structure uses lattice models where the discrete spatial autocorrelation is driven by some coefficients (α_{1h}, α_{2h} in equation 1) that act analogous to autoregressive coefficients for time-series models. Specifically, rook or queen contiguity matrices can be used to represent first-, second- ($\boldsymbol{W}^{(1)}$ and $\boldsymbol{W}^{(2)}$) or higher-order spatial autocorrelation. An example of rook-based contiguity structure in SAR(2) model is shown in Figure 8.

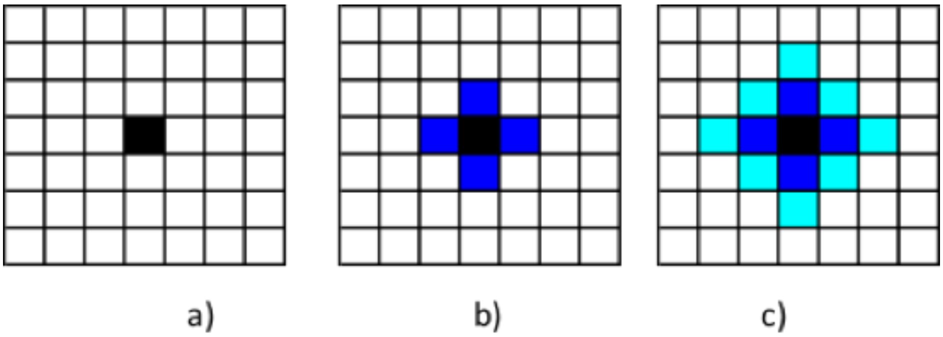


Figure 8: Rook-based contiguity in SARX model; a) the reference point (black); b) 1st-order neighbors of the central point (black); 2nd-order neighbors of the central point (black)

When a SARX(p) model is used for the manufacturing signature, the monitoring strategy can simply mimic profile monitoring. Indeed, a multivariate control chart can be used to monitor the estimated coefficients, while an additional univariate control chart monitors the residual variance (Colosimo, Mammarella and Petrò, 2008; and Colosimo, et al., 2014).

Regular sampling patterns are usually feasible when contact systems (i.e., traditional CMMs) are used. In fact, the CMM can locate the touch–probe at a given location on an ideal grid placed on the surface and then move the probe perpendicularly to the ideal surface (substitute geometry) and store the coordinates of the touched surface point.

When non-contact metrology systems are considered, uniform sampling strategies can no longer be assumed. Spatial correlation structure for unstructured point clouds can be modeled via Gaussian Processes (GPs) (Cressie, 2015; Colosimo *et al.*, 2014, Wand Wang and Tsung, 2014). In this case, the response observed at a given location $\boldsymbol{t} = (x, y)$ is given by:

$$z_h(\boldsymbol{t}) = f_h(\boldsymbol{t}) + n_h \tag{2}$$

where h represents the surface index, $f_h(\boldsymbol{t}) = \mathrm{GP}\big(\mathrm{m}(\boldsymbol{t}); \mathrm{k}(\boldsymbol{t}, \boldsymbol{t} + \boldsymbol{d})\big)$ is a GP with mean $\mathrm{m}(\boldsymbol{t})$ and covariance function $k_h(\boldsymbol{t}, \boldsymbol{t} + \boldsymbol{d}) = \sigma_\eta^2 R(\boldsymbol{d}, \nu, l \quad)$, where $\boldsymbol{d}$ is the Euclidean distance while different correlation structures can be considered to model $R(\boldsymbol{d}, \nu, l \quad)$ (e.g., squared exponential, Matern etc.).

In this case, the monitoring procedure cannot replicate traditional profile monitoring. In fact, similar values of the GP parameters can result in very different surface patterns; hence, different solutions for surface monitoring must be designed (Colosimo *et al.*, 2014). Appropriate procedures for GP-based surface monitoring are similar to those used for nonparametric profile monitoring (Qiu, Zou and Wang, 2010). A set of (x,y) checkpoints is used to compare the z-value predicted considering the actual surface points and the z-value predicted according to the in-control model. This vector of discrepancies is monitored to detect out-of-control states. Clearly, the number and location of the checkpoints affect the procedure performance.

In our experience, both approaches for surface monitoring (SARX- or GP-based) can be effective in detecting changes of the surface pattern. Figure 9 shows the Average Run Length (ARL) as a function of the size δ of a tri-lobed deviation from the in-control cylindrical shape. In this figure, competitor approaches are:

i) The industrial practice using a univariate control chart for monitoring the form error, i.e., the maximum deviation of the current surface from a perfect geometry;

ii) The SARX-based monitoring procedure;

iii) The GP-based one (using either a uniform or a Latin-hypercube sampling to locate the checkpoints) (Colosimo et al., 2014).

As shown in this example, approaches for surface monitoring based on spatial statistics (SARX- and GP-based methods) can be 80- to 40-times faster in detecting out-of-control states compared with industrial practice.

As a byproduct, knowledge of the manufacturing signature can bring a lot of advantages by itself. For example, modeling the manufacturing signature can investigate the effect of process parameters on the final shape.

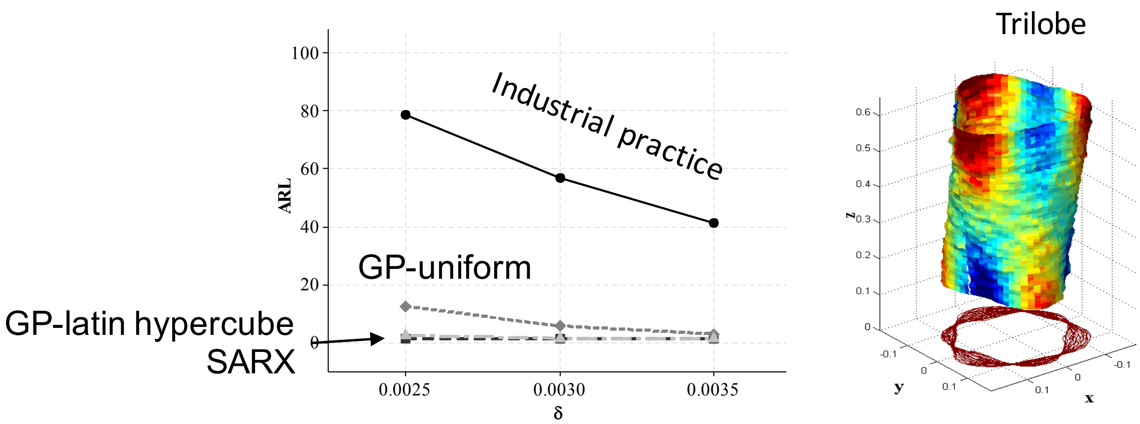


Figure 9 – ARL performance of surface monitoring using the industrial practice (monitoring the maximum deviation from the perfect shape, called out-of-cylindricity), SARX-based and GP-based procedures (the latter considering both uniform and Latin-hypercube designs) δ represents the size of the trilobe error affecting the in-control surface.

From 2.5D point to 3D points: The Geodesic Gaussian process

All models introduced in the previous section assume a similar structure to describe the surface shape, namely $z = z(x, y) + noise$. In this model, only one coordinate (z) acts as a random response variable, while the other two coordinates (x, y) are assumed to be deterministic. This assumption holds only in some specific conditions. Generally speaking, each point measured on the surface is defined by a triplet of (x, y, z) coordinates, which should be modeled as a multivariate GP model composed of three random variables. This is because randomness is due to the measurement error.

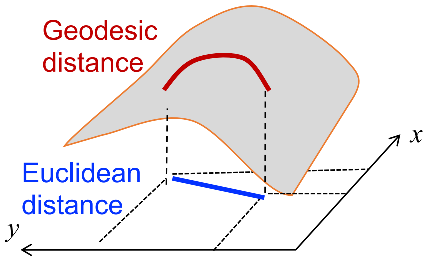


Figure 10: Euclidean and Geodesic distances

When traditional GP models are used for surface reconstruction, a second assumption considers Euclidean distances as drivers of the spatial correlation structure on the surface. There are several examples in manufacturing (e.g., stamping, casting, milling, etc.) where the spatial correlation signature is more likely to be guided by geodesic distances (i.e., distances measured along the surface) rather than Euclidean ones (Figure 10).

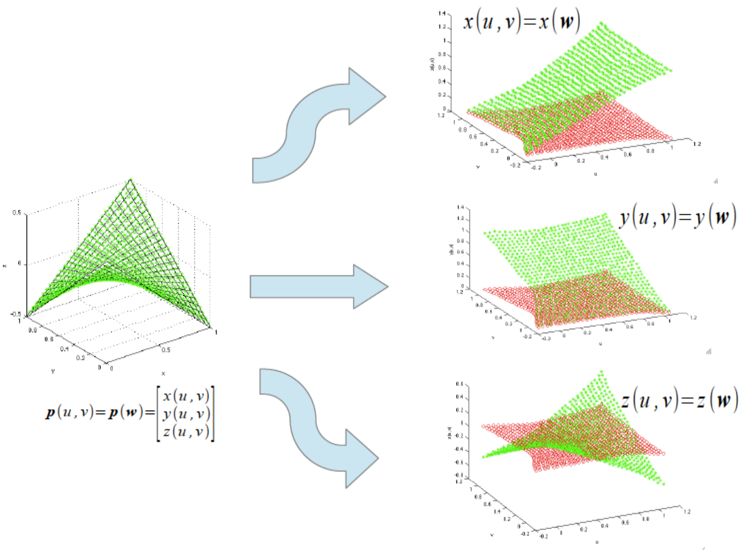


Figure 11: The Geodesic Gaussian process for surface reconstruction (del Castillo, Colosimo and Tajbakhsh, 2015)

When the two previous assumptions do not hold, *Geodesic Gaussian processes (GGP)* can be used for surface reconstruction (del Castillo, Colosimo and Tajbakhsh, 2015). The GGP approach performs near-isometric (ISO-MAP) parameterization mapping the original coordinates. This allows one to define a new (u, v) system where Euclidean distances (in the new space) correspond to the geodesic distances (in the original space). In principle, one could then model the three parametric surface components with a multivariate GP.

Such models require specification of the spatial cross-covariance matrix $\boldsymbol{C}(\boldsymbol{w}, \boldsymbol{w}')$ where $\boldsymbol{w} = (u, v)$, given by:

$$\boldsymbol{C}(\boldsymbol{w}, \boldsymbol{w}') = \begin{pmatrix} cov(x(\boldsymbol{w}), x(\boldsymbol{w}')) & cov(x(\boldsymbol{w}), y(\boldsymbol{w}')) & cov(x(\boldsymbol{w}), z(\boldsymbol{w}')) \\ cov(y(\boldsymbol{w}), x(\boldsymbol{w}')) & cov(y(\boldsymbol{w}), y(\boldsymbol{w}')) & cov(y(\boldsymbol{w}), z(\boldsymbol{w}')) \\ cov(z(\boldsymbol{w}), x(\boldsymbol{w}')) & cov(z(\boldsymbol{w}), y(\boldsymbol{w}')) & cov(z(\boldsymbol{w}), z(\boldsymbol{w}')) \end{pmatrix} \tag{3}$$

Here, $\boldsymbol{w} \neq \boldsymbol{w}'$, which as emphasized by Cressie and Wikle (2015), does *not* need to be symmetric. Specifying a non-symmetric cross-covariance has proven to be difficult. Methods that require symmetry are a multivariate Matern model and co-regionalization (see Banerjee et al., 2004), although Kleijnen and Mehdad (2012) indicate that co-regionalization usually does not outperform separate kriging predictions of each response.

As discussed by Cressie and Wikle (2015), the symmetry assumption is very strong, and this is particularly true for our surface modeling application. For these reasons, a possible solution consists of using a separate GP to fit each coordinate separately, i.e., assuming $\boldsymbol{C}(\boldsymbol{w}, \boldsymbol{w}') = diag(\boldsymbol{C}_x(\boldsymbol{d}), \boldsymbol{C}_y(\boldsymbol{d}), \boldsymbol{C}_z(\boldsymbol{d}))$ in (2) and $\boldsymbol{d} = \boldsymbol{w} - \boldsymbol{w}'$. Del Castillo, Colosimo and Tajbakhsh (2015) applied the GGP to reconstruct the real free-form surface shown in Figure 12, where the point cloud was acquired via structured light. In this case, the GGP approach outperformed traditional GP modeling by halving the mean squared prediction error.

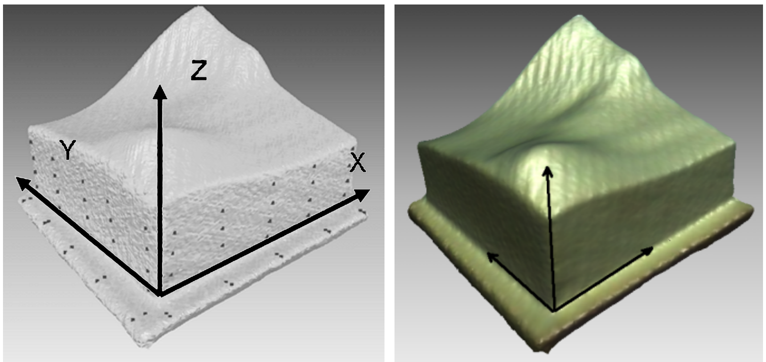


Figure 12: A real free-form surface and surface point acquisition via fringe projection (structured light).

Multi-sensor data fusion

Different and novel perspectives for surface modeling and monitoring arise in the field of multi-sensor data fusion (Hall and Llinas, 1997). This can be defined as "the process of combining data from several sources (sensors) … in order that the metrological evaluation can benefit from all available sensor information and data" (Weckenmann *et al.*, 2009).

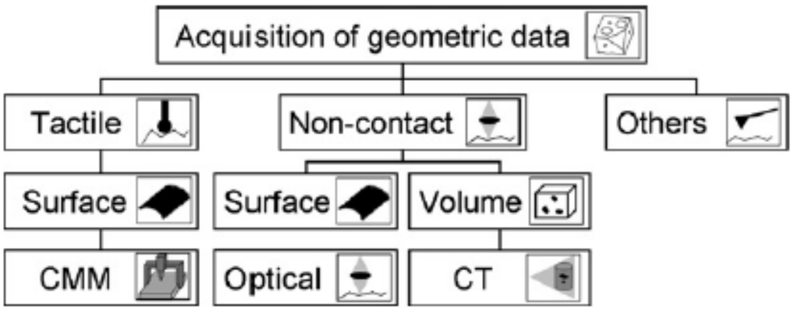


Figure 13: Summary of different systems for acquisition of geometric data (Weckenmann, et al. 2009).

Figure 13 summarizes the different types of metrology systems available for geometric data acquisition. The figure shows how surface data can be acquired using both contact and noncontact systems. It is known that measurement with noncontact sensors (e.g., laser scanners, fringe projections, photogrammetry) possesses some very desirable properties, specifically in terms of acquisition speed and low cost for obtaining a very large amount of points. However, the appeal of these techniques is somehow hampered by their poor metrological performance. This is why currently contact systems (the CMM touch-probes) are still considered the standard de-facto for metrological characterization.

In this framework, different authors have investigated advantages arising from combining contact and noncontact data sets to enhance surface registration, reconstruction and monitoring (Xia, Ding, and Mallick, 2011; Liu et al. 29016; Senin, Colosimo, Pacella, 2013; Suriano et al. 2015; Colosimo, Pacella and Senin, 2015, Wang et al., 2017). Most of these models have their origin in the approaches proposed by Qian *et al*. (2006), and Qian and Wu (2008) combine computer and real experiments for process meta-modeling.

In this case, the first stage of a GP model is used to reconstruct the surface using the HD (high-density) non-contact data only. Then, a second-stage GP-based model is used to correct the HD reconstructed surface using the low-density (LD) data point as “attractors”. This two-stage model allows one to have prediction anywhere by combining information provided by the two sensors in a structured way. This gives more trust to the (few) contact data points and less trust to the (large) set of noncontact data.

Using the free-form surface in Figure 12, inspected using both contact (CMM) and noncontact (structured light) systems, Colosimo, Pacella and Senin (2015) compared the performances of four different procedures for surface reconstruction, namely:

- LD: using a GP-based reconstruction of low-density (LD) contact data only;
- HD: using a GP-based reconstruction of high-density (HD) noncontact data only;
- ADD: using a GP-based reconstruction which uses contact and non-contact data sets merged into a single dataset as if they came from the same measurement system;
- FUSION: using the two-stage GP-based hierarchical data fusion approach previously described.

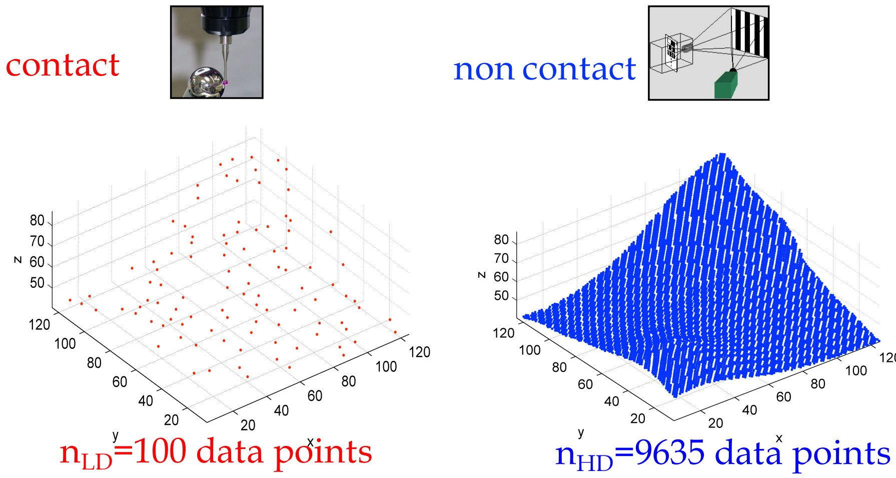


Figure 14: Contact and noncontact data points for multi-sensor data fusion

Figure 14 shows the original point clouds while

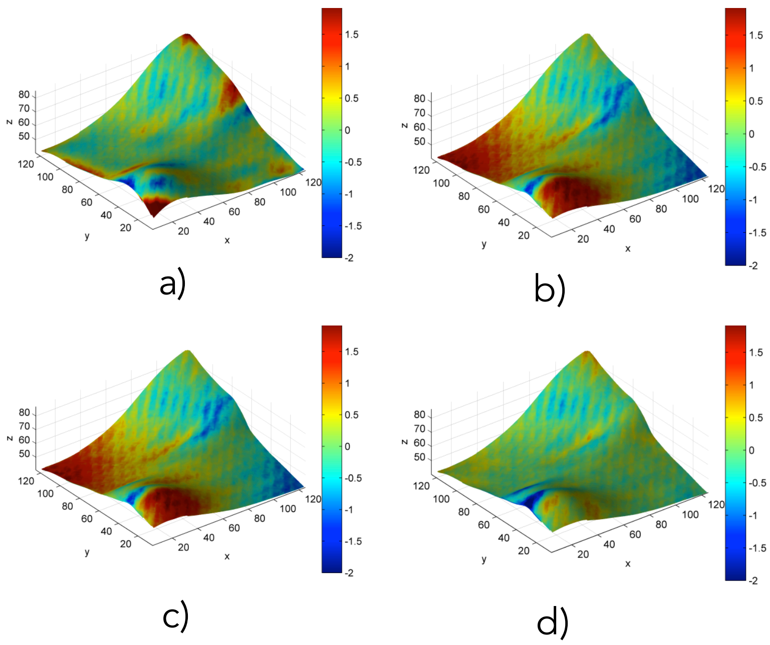


Figure 15 (cloud error map) and Table 1 (confidence interval on the mean prediction error of reconstruction) show results of the reconstruction procedures using the four approaches. It is clear that data fusion presents significant advantages over the other existing procedures.

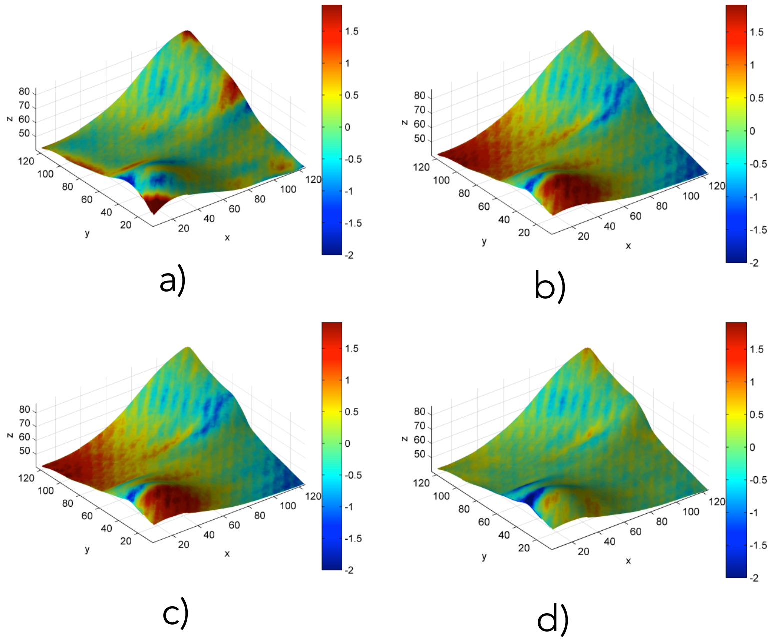


Figure 15: Color plot of the local prediction error (true minus predicted) for each method. 100 LD data points and feature-based alignment of data (all values in [mm]). LD model (a). HD model (b). ADD: LD+HD model (no data fusion) (c). Data fusion model (d)

Model	Mean squared prediction error	Confidence interval
HD only	0.442	(0.430-0.455)
LD only	0.235	(0.229-0.242)
Add	0.434	(0.422-0.447)
Fusion	0.103	(0.100-0.106)

Table 1: Mean squared prediction error and confidence interval when single and multisensor data fusion are considered to reconstruct a free-form surface (Colosimo, Pacella and Senin, 2015).

Future directions in product data modeling

Advances in manufacturing technologies and inspection systems will likely cause many different paradigms shifts in the near future including shifts from 2.5D to fully 3D surfaces. Other changes include moving from traditional to textured and functionalized bio-inspired surfaces (Malshe et al., 2013), from mono- to multi-material products, and from fully dense to functionally-graded structures (Miyamoto et al., Eds., 2013). Appropriate statistical methods should master these shifts by providing appropriate modeling tools.

Continuous improvement of measurement systems will easily cause reduction of the inspection times, possibly revealing autocorrelation between successive point clouds. Thus, approaches for spatio-temporal SPC will be needed (Megahed et al, 2012). Dimensionality reduction (Pacella and Colosimo, 2016) will become more and more common as an effect of the sample size increase of surface point clouds. Data fusion will represent the norm rather than the exception, as more and more systems will be available at reduced costs (Wells et al, 2013). Further attention should be paid to appropriate modeling of X-ray CT data, which will spread out in dimensional and volumetric metrology (Kruth, et al. 2011). As a matter of fact, complex internal geometries, porosity and functionally graded structures ask for X-Ray CT inspection to avoid destructive testing. Statistical approaches for modeling voxel data will tackle CT data denoising and aid uncertainty estimation. Thus, approaches developed in the field of statistical analysis of biomedical images could be useful.

Process signal and image data modeling and monitoring: Main challenges and possible solution

In recent years, continuously evolving sensor and information technologies have been shaping a new generation of data-rich industrial environments. The use of novel in-line sensing solutions (e.g., machine vision systems, non-contact in-line metrology, acoustic, force, thermal sensing technologies, etc.) allows one to link the quality and stability of processes to high-frequency data streams.

In this scenario, approaches for Statistical Process Monitoring or Control (SPC) should be appropriately redesigned to act on ***process*** (rather than product) data to take full advantage of all available information.

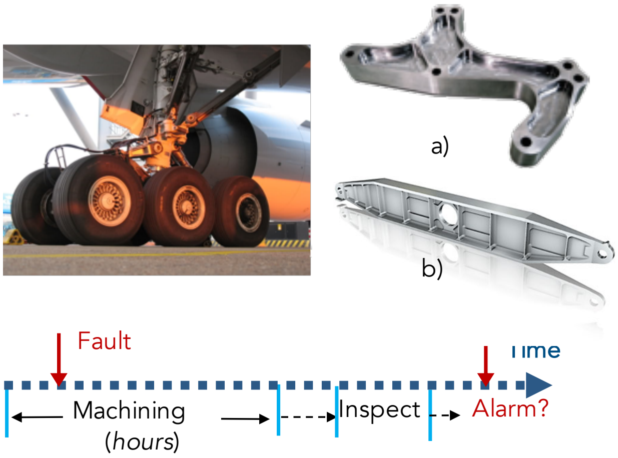


Figure 16: Landing gear (bracket (a) and beam (b). Processing and inspection time for this product in the aeronautic sector.

We emphasize that applying SPC to process data can have significant advantages, especially in the context of short production runs. Figure 16 shows two components of a landing gear—the bracket (a) and the beam (b). These two components are usually machined by milling starting from a solid block, which requires several hours because these components are made of hard-to-cut titanium alloys. In this situation, monitoring the final product quality translates to detecting possible process faults with hours of delay. This ultimately translates to an excessive waste of time, materials, and energy.

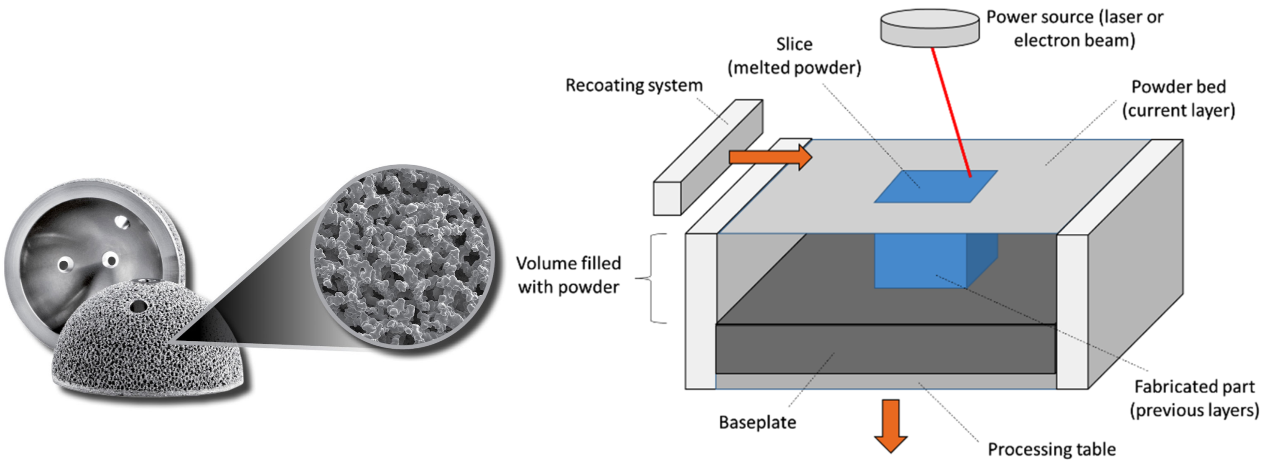


Figure 17: Additive manufacturing and hip implant (courtesy ARCAM).

A similar problem arises from customized product manufacturing. For example, consider hip implants made by additive manufacturing and shown in Figure 17. In this case, each single product is unique, and no phase-1 sample for control chart design is available.

In summary, when long-cycle time, high-value-added components, or customized products are manufactured, SPC on in-line process data represents an effective solution for quality monitoring.

In this scenario, traditional SPC should be appropriately revised to tackle specific data types—mainly signals and images. It is worth mentioning that these data types can sometimes offer an aid to process diagnosis after the alarm is issued (Chiang, Russell and Braatz, 2000).

Without being exhaustive, some of the main issues in SPC for in-line process data are summarized next.

Signal data - Many process data are characterized by cyclic patterns (Figure 18). Therefore, profile monitoring can be taken as a reference in developing SPC approaches for signal data (Jin and Shi, 1999 and 2001; Woodall et al., 2004).

For complex multi-scale signals, significant advantages can be achieved by including novel methods for signal decomposition (e.g., wavelet analysis, empirical-mode decomposition) in the profile monitoring procedure (Jin and Shi, 1999 and 2001, Ganesan, Das and Venkataraman, 2004; Ding, Zeng and Zhou, 2006; Grasso, Pennacchi and Colosimo, 2014; Grasso et al., 2016).

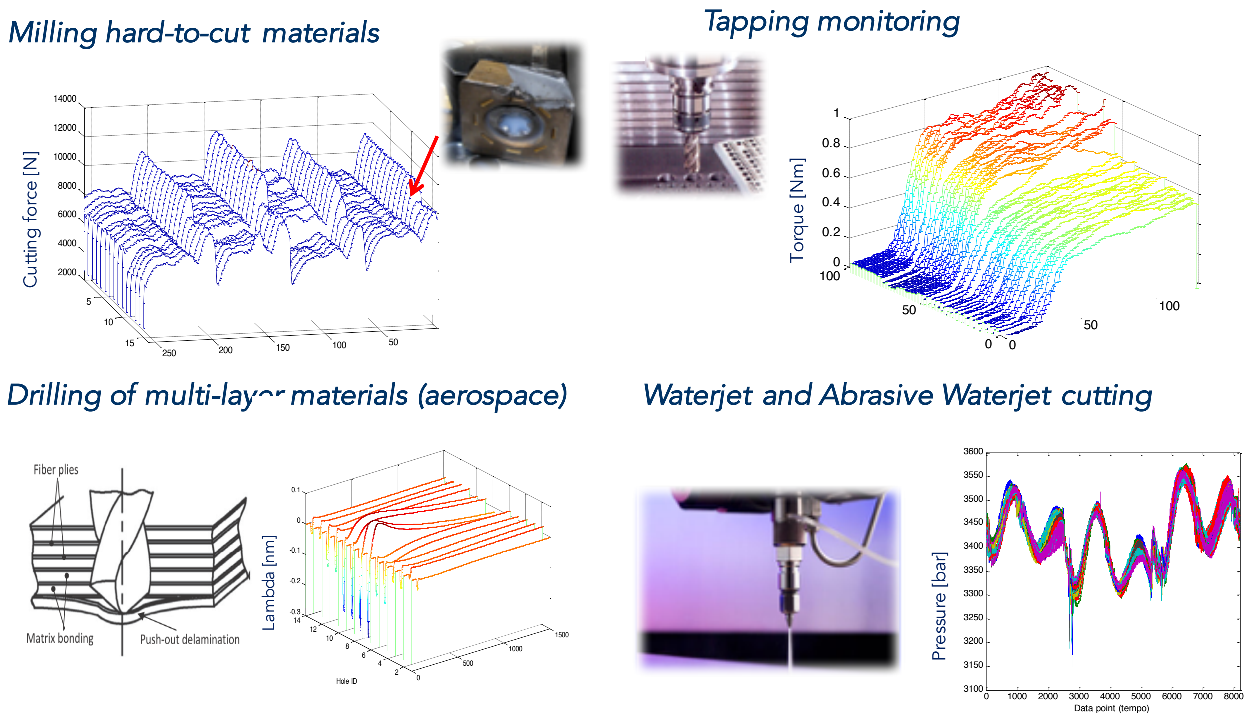


Figure 18: Examples of signals characterizing advanced manufacturing process quality (developed at the Department of Mechanical Engineering – Politecnico di Milano): a) force in milling of titanium alloys for aerospace applications; b) Torque signal in tapping; c) Force in multimaterial drilling; and d) pressure in water jet cutting.

All pre-processing steps (signal denoising and signal registration) can significantly affect the performance of the monitoring procedure. Hence, approaches combining pre-processing and control charting can be particularly effective (Grasso, Menafoglio and Secchi, 2016).

Distribution-free methods and machine-learning approaches can be used to create big data signals where traditional assumptions are violated (Grasso et al., 2015; Weese, et al, 2016).

New approaches for multi-stream signal data modeling and monitoring should be further developed to tackle the multivariate nature of in-line sensing (Paynabar, Jin and Pacella, 2013; Yang and Jin, 2012, Yoon and MacGregor, 2004, Guo, Jin and Hu, 2016).

Image data - Image data plays an increasing role in process monitoring and control. In fact, images represent an affordable, quick, and information-rich source of data in many industrial contexts. In manufacturing, cameras and video cameras are increasingly commonly for in situ data analysis (usually referred to as "in situ monitoring" among engineers). Unfortunately, when image or video data analysis comes to hand, no consolidated SPC procedures is available for practitioners. In recent years, many authors outlined the need of appropriate SPC procedures for image data (Megahed, Woodall, and Camelio, 2011; Megahed et al., 2012; Qiu, 2005; Xing and Qiu 2011; Qiu and Mukherjee, 2010, Yan, Paynabar and Shi, 2016). In this literature, little attention has been devoted to videos where the dynamic of the manufacturing process is recorded in real time. In the next section, a possible approach for in situ monitoring of metal AM is discussed.

In situ sensing via video-image data analysis in additive manufacturing

Metal AM represents a key enabling technology for Industry 4.0 because it paves the way to completely new production approaches and digitalized factories. The most attractive advantages of AM can be summarized in: 1) Digitalization of design and production processes; 2) Reduction of time-to-market compared with other technologies; 3) Supply chain transformation (AM enables, at least in principle, to produce a part when and where it is needed); 4) High flexibility and freedom for innovative design solutions (lightweight structures, functional surfaces, new materials); 5) Extended and more sustainable component life cycle thanks to the possibility of adding material to repair products.

Despite the continuous technological advances of metal AM systems, there are still important challenges to tackle. To achieve advanced industrial adoption, a first direction of intervention should be to reduce the high defective rates of current metal AM technologies. According to the National Institute for Standards and Technology (NIST), the poor quality of AM processes is the most urgent issue to be faced: "*the variability in part quality due to inadequate dimensional tolerances, surface roughness, and defects, limits its broader acceptance for high-value or mission-critical applications*" (Mani, et al., 2015).

Novel approaches for zero-defect AM represents a priority research area in metal AM for different issues:

- Processes are very long (several days for medium-sized parts), and the materials are very expensive. It is not affordable and acceptable to discover that the part is defective at the end of the process;
- Parts produced by AM exhibit complex shapes and internal structures that are difficult and expensive to measure with available metrological tools. Small internal defects may be difficult or impossible to find. Thus, post-process quality inspections alone are not sufficient;
- The key industrial sectors (e.g., aerospace and bio-medical) involve applications where defects are not tolerated. Thus, defects must be avoided or corrected as soon as they originate during the process.

Among the possible solutions for achieving zero-defect AM, in situ process monitoring via images and video analysis is particularly promising. For a complete review of sensors and solutions for in situ monitoring, interested readers can refer to Tapia and Elwany, (2014) and Grasso and Colosimo

(2017). Among the solutions for in situ data gathering, high-speed videos in the visible or infrared ranges are the most interesting (Repossini et al, 2017, Grasso et al., 2017).

Compared with SPC for images (Megahed, Woodall, and Camelio, 2011), SPC for video-images has an additional complexity, namely *speed*. Secondly, the in-control state that is videoed represents a *dynamic phenomenon*. In the case of selective laser melting (SLM), this phenomenon is laser processing, i.e., the laser beam moves at a high speed on a predefined trajectory to melt the metal powder.

Figure 19 shows the sequence of frames obtained by subsampling a video where one of the triangles shown in Figure 21, namely triangle 1, is manufactured via SLM. This video was acquired during an experimental study on in situ monitoring of metal AM carried out at the AddMe Lab of the Department of Mechanical Engineering of Politecnico di Milano[3]. In this study, some out-of-control conditions resulted in defects on the final shape of the triangles. These defects were mainly due to some "hot-spots" observed during the laser processing. Hot-spots are specific locations of the melted powder which remains at a high temperature for a long time.

[3] The metal object was processed using a Renishaw AM 250 industrial SLM system. An off-axis high speed camera CMOS Oylmpus i-speed 3 camera (frame rate 10kfps - spatial resolution 528x396) was used to acquire the video.

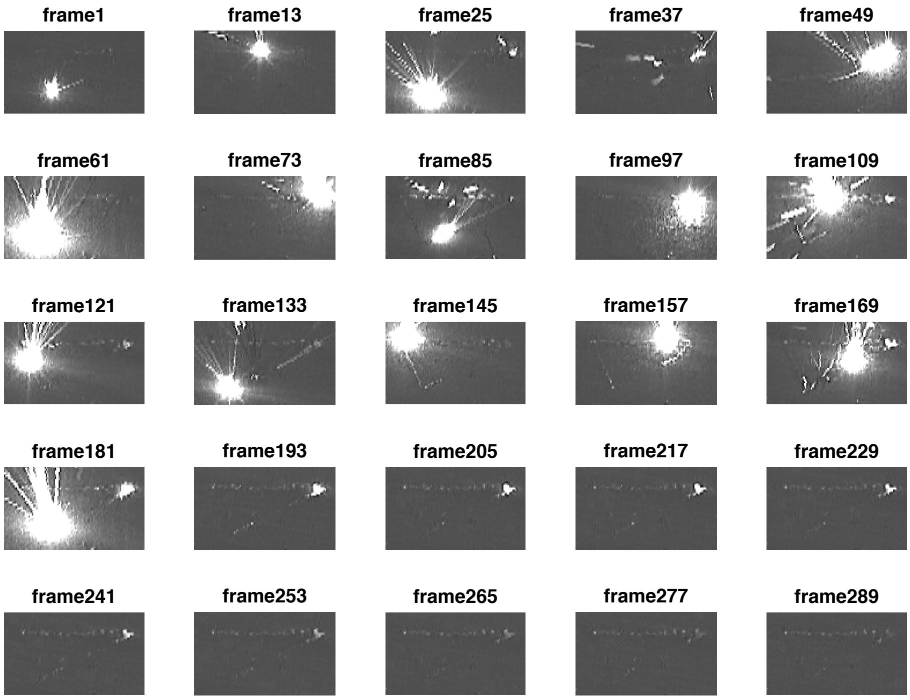


Figure 19: Frames sub-sampled by the video acquired during the AM processing of triangle 1.

One common approach in SPC for image data consists of using Principal Component Analysis (PCA) by unfolding the image frames using pixels as variable (columns of the data matrix) and frames as time points (rows of the data matrix) (Figure 20). The retained PCs can then be monitored using a multivariate control chart (Bharati and MacGregor, 1998). Grasso et al., (2016) showed that this approach is not effective in detecting hot-spots. The laser process dynamics dominates the hot-spot phenomena, thus preventing the PC-based control chart from detecting this out-of-control condition.

Starting from the literature on geospatial analysis and atmospheric science, an alternative approach known as T-mode PCA (Jolliffe, 2002) can also be sued. T-mode PCA works on the transposed data matrix where frames are treated as observations (columns) and pixels as time points (rows). In this case, T-mode PCA can capture the different dynamics of intensity registered at different locations (pixels) of the frame. Figure 22 shows an example of these different intensity patterns. Pixels taken at corners A and B show an in-control intensity pattern, while the pixel taken at corner C (hot-spot) shows an out-of-control pattern characterized by an intensity that remains high for a long time.

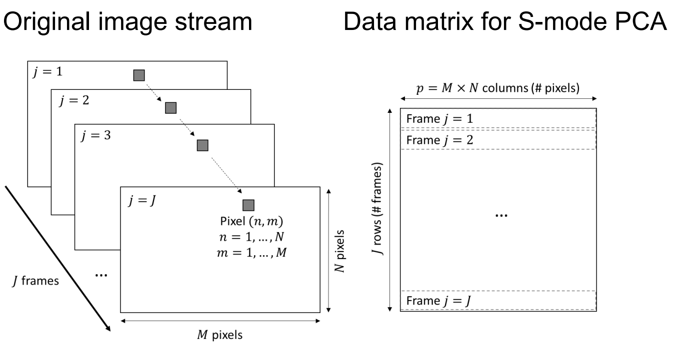


Figure 20 S-mode unfolding of the original image stream into a matrix.

Once T-mode PCA is computed, retained PCs are available at each pixel location in the frame and Hotelling T^2 can be used as a synthetic statistic to summarize the PCA result. Eventually, k-mean clustering can be used as an alarm rule.

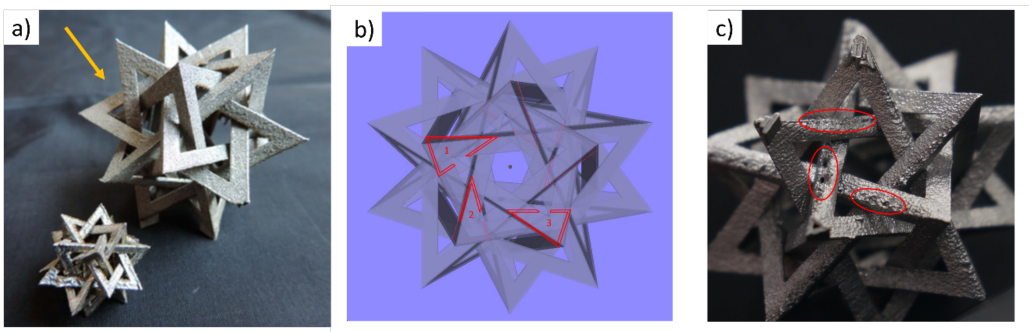


Figure 21: a) AM Complex shape; b) examples of triangular portions of the sliced CAD model; c) local defects in the acute corners of those triangles (details of non-conforming location of the triangles due to hot-spots).

Figure 23 shows k-mean clustering applied after T-mode PCA in the case of no defects (left) and hot-spot defects (right). In the first case, the optimal number of clusters is two: the first cluster represents the low-intensity background, the second cluster represents the high-intensity and high-frequency laser scanning path. When the hot-spot defect is present, a third cluster appears, which represents the high-intensity and low-frequency intensity path resulting from the extra-melting condition. In summary, video-image data analysis for SPC applications requires spatio-temporal modeling that can capture different dynamics and different spatial signatures of the observed phenomena.

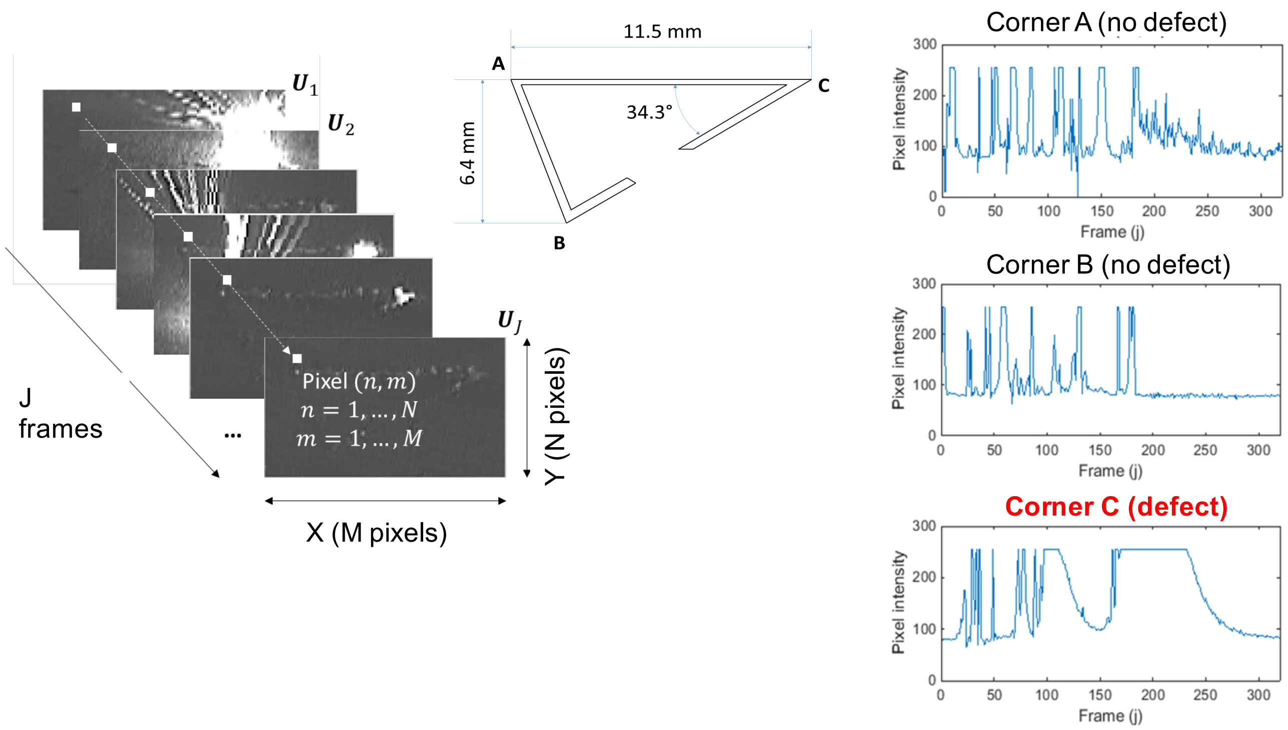


Figure 22: Pixel intensity along the video frames (i.e., time) for different pixel locations.

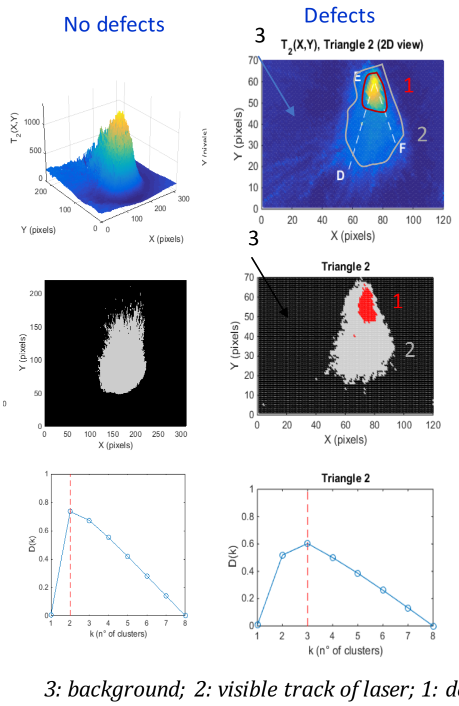


Figure 23: K-mean clustering applied after T-mode PCA when no defects (left) or hot-spot defects (right) are observed.

Conclusions

We are currently living in the "golden age" of data for industrial production (Steinberg, 2016). The golden age is driven from one side by recent advances in manufacturing and measurement technologies and by the extraordinary revolution of in situ sensing and computerized data analysis on the other. Both are available at reduced costs. This trend will be further emphasized via national and international policies aimed at sustaining the "industry 4.0" revolution to strengthen industrial competiveness.

Starting from real industrial problems, this paper has described some existing challenges and possible solutions for zero-defect manufacturing via product- and process data modeling and monitoring.

Many different directions for future research can be outlined.

- **Multisensor solutions** will spread because sensors are cheap and redundancy can aid robustness and spatial coverage. Novel methods for combining data from different sources at different scales and various frequencies will be needed. Redundancy could possibly aid in the identification of outliers to the manufacturing or the measurement processes.
- **Computational time**: Short computational time for in-line SPC procedures will act as a mandatory constraint. In fact, long computational times can make proposed approaches useless to real industrial practitioners.
- **From monitoring to control**: Process data acquired via in-situ sensing offer a great opportunity to move from statistical process monitoring to closed loop control. An appropriate combination of the two solutions will possibly characterize the new generation of tools for zero-defect manufacturing.
- **False-alarm rate:** An excessive false-alarm rate will act as huge enemy for SPC solutions applied at the factory floor. Attention to hypotheses violations and simultaneous testing should be emphasized to keep the overall false alarm rate low.
- **Aid to sensor design**: New approaches to aid sensor selection, location, and calibration will be needed. Industrial statistics should not only act on existing data but also support sampling design (spatio-temporal coverage and features to be extracted).

- **Multidisciplinary teamwork**: Solutions to actual and future problems will increasingly require a mixture of expertise from ICT to manufacturing—from mechanical to electrical engineering—from statistics to signal and image data processing. To this aim, multidisciplinary teamwork should be promoted as a fundamental goal of research training and professional education.

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