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Multisensor data fusion via Gaussian process models for dimensional and geometric verification

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ABSTRACT

An increasing amount of commercial measurement instruments implementing a wide range of measurement technologies is rapidly becoming available for dimensional and geometric verification. Multiple solutions are often acquired within the shop-floor with the aim of providing alternatives to cover a wider array of measurement needs, thus overcoming the limitations of individual instruments and technologies.

In such scenarios, multisensor data fusion aims at going one step further by seeking original and different ways to analyze and combine multiple measurement datasets taken from the same measurand, in order to produce synergistic effects and ultimately obtain overall better measurement results.

In this work an original approach to multisensor data fusion is presented, based on the development of Gaussian process models (the technique also known as kriging), starting from point sets acquired from multiple instruments. The approach is illustrated and validated through the application to a simulated test case and two real-life industrial metrology scenarios involving structured light scanners and coordinate measurement machines.

The results show that not only the proposed approach allows for obtaining final measurement results whose metrological quality transcends that of the original single-sensor datasets, but also it allows to better characterize metrological performance and potential sources of measurement error originated from within each individual sensor.

1. Introduction

1.1. Multisensor instruments for dimensional metrology

The combined use of multiple measurement sensors is becoming commonplace in dimensional metrology and an increasingly wider array of instruments equipped with multiple probes is becoming available. Popular commercial solutions for the measurement of parts include touch-probe CMMs equipped with additional optical and/or vision sensors [1–4], and measuring arms equipped with touch-probes and laser point or line scanners [5,6]. Even in surface metrology, where the aim is the characterization of surface texture at micro and sub-micro scales, 3D microscopes have recently become available equipped with multiple measurement heads implementing different measurement technologies (e.g. vertical scanning interferometry + focus variation [7]).

All such commercial offerings are based on the same conceptual approach: "one fixture, multiple sensors", i.e. all these instruments are designed to provide multiple measurement options within a single measurement setup, essentially letting the user select the proper sensor for each task, thus overcoming the limitations of each single measurement technology. Once the workpiece is mounted onto the instrument, depending on the type of characterization, part accessibility, time and accuracy requirements, the user is free to select the probe/sensor technology that is better suited to accomplish the inspection/verification task.

1.2. Multisensor data fusion

Multisensor data fusion tries to go one step further [8–13], and refers to the process of combining multiple sensor data sets with the goal of obtaining a result which either marks an improvement with respect to what obtainable from each data set taken

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singularly, or constitutes an entirely new piece of information, which could not be obtained by simply analyzing any of the individual datasets.

In multisensor data fusion, it is not necessary that all the datasets come from the same instrument, and data may have been acquired at different places and times. Combining multiple data sets may refer to combining data coming from different sensors and/or sensor types, but may also refer to combining data coming from the same sensor, used with different setups, or even used multiple times with identical operating conditions (i.e. combining replicate data sets).

Data types, which can be integrated in dimensional metrology, include:

- conventional digital images (RGB, gray scale): as acquired by digital cameras;
- range images (images whose pixels contain distance information): as acquired by structured light scanners, 3D microscopes and photogrammetry systems;
- point clouds (i.e. set of points in 3D space): as acquired by CMM, measuring arms, single-point laser trackers, laser radar, etc., and
- volume data (i.e. 3D matrices): as acquired by X-ray Computerized Tomography.

In general, the term *homogeneous integration* is used when combining the same type of data (e.g. 3D point clouds), while *inhomogeneous integration* is used in all the other cases.

Depending on the type of data to be integrated and on the overall characterization goal, many multisensor data fusion scenarios may be imagined; these can be categorized into three main classes according to a popular classification scheme [14]. In *competitive data fusion*, redundancy originated by replicate data sets acquired with the same sensor and in the exact same operating conditions is used to improve the metrological quality of the result. For example, multiple identical images of the measurand can be combined in order to extract an average image, more robust to noise. In *complementary data fusion*, homogeneous data sets, taken by the same sensor but in slightly different operating conditions, provide information so that each set is meant to complement the others. Fusion in this case is meant to take advantage of such complementarity. For example, digital images with the same magnification but slightly different localization may be stitched to obtain increased spatial coverage, or images taken at different magnification could be fused to obtain a result that covers a wider array of spatial resolutions (scales). Finally, *cooperative data fusion* gathers all the types of integration involving homogeneous/inhomogeneous data sets, which cannot be classified under competitive or complementary integration. A few scenarios of cooperative data fusion have already gained some popularity [9]: in dimensional and geometric verification, vision can be used to acquire global shape information needed to automatically produce an inspection path for the touch probe; in defect identification vision can be used to identify and localize a defect, then localization information can be used to drive a laser line scanner which performs the actual shape measurement of the defect; in reverse engineering, high-density point clouds obtained by an optical sensor can be stitched together with the help of a few reference points obtained by a touch probe to reconstruct the full-3D shape of an object. Some sensor technologies are intrinsically based on some form of cooperative integration [9]: for example, depth from focus, shape from shading and photogrammetry are 3D imaging technologies, which are based on fusing data obtained from conventional 2D images in order to obtain 3D information.

1.3. An overview of some notable approaches to multisensor data fusion

Some of the cooperative scenarios cited above can also be classified as sequential data fusion, an additional category where the first dataset is used to obtain the second, and then it is discarded. For example, in Ref. [12] high-density, low-quality information acquired by means of a vision system is used to guide the acquisition of a low-density, high quality dataset via a touch probe CMM. The dataset obtained by vision is discarded after the CMM dataset is available. An approach where both datasets are kept can be found in Ref. [15], where a laser scanner is used to acquire free-form surface patches, while a CMM is used to acquire patch boundaries only. Fusion is achieved by simply adding the two datasets together.

Fusion is also meant as a way to define the appropriate compensation (i.e., a roto-translation matrix) to be applied to a sensor to achieve information provided by the other one [16]. As in many applications of data fusion, this approach assumes that all the sensors acquire data at the same locations, an assumption that usually does not hold when measurement systems based on high-density optical scanning are considered.

In Ref. [17] a method is proposed for fusing high-resolution and a low-resolution data: after registration and elimination of redundant points, merging is achieved by remeshing all the acquired data points. No statistical models to represent measurement errors are considered in the merging procedure. On the contrary, in Ref. [18] the datasets acquired by different sensors are considered as different responses of a multivariate linear (or non-linear) model, and Bayesian estimates of the unknown coefficients are carried out. The statistical model is used specifically to correct laser trackers responses; the same locations are measured with all the available sensors (or multiple times by the same tracker) in order to compute the fusion step.

Most of the aforementioned approaches for data fusion either combine information by simply adding data points originated from different observations (after appropriate elimination of redundant data) or, assuming points are taken at the exact same locations, use one dataset to correct the other. Furthermore, most of the methods assume deterministic data fusion or statistics as a way to estimate unknown coefficients. A notable exception is the method presented in [19], aimed at multisensor data alignment. In this case, the main idea is to reconstruct the information provided by all the different sensors before performing the fusion step. This approach has the main advantages of (i) include statistical modeling while reconstructing the information provided by different data sets, providing prediction intervals for the local discrepancies between different data sets as well as on the final prediction of the shape at any given location; (ii) relaxing the assumption of acquiring all the data at the same location set. This approach is considered as starting reference for the fusion procedure presented in this work.

1.4. Multisensor scenarios involving 3D point sets with different densities and metrological performance

The specific data fusion scenarios investigated by this work involve multiple 3D point sets (point clouds, i.e. homogeneous data) acquired from the same measurand surface as part of an inspection/verification process [20].

In these scenarios, the datasets are supposed to belong to one of the two following main categories:

- *Points coming from touch-probe CMMs*: In a conventional CMM, point acquisition is generally very slow (acquisition in single point mode), or slightly less so (acquisition in profile mode); the localization of the points on the measurand can be accurately controlled by the operator, and variable point spatial density on the