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Cooperative fusion of distributed multi-sensor LVM (Large Volume Metrology) systems

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Large Volume Metrology (LVM) tasks often require the concurrent use of several distributed systems. Competitive or cooperative methods can be adopted for fusing multiple system data. Nowadays, competitive methods are by far the most diffused in LVM; these methods basically perform a weighted mean of 3D position measurements carried out by individual systems, with respect to the relevant uncertainties. This paper proposes a cooperative approach relying on the combination of angular and distance measurements (and relevant uncertainties) yielded by the sensors of each individual system. Preliminary simulations and experimental results concerning the application of this method are presented and discussed.

Metrology; Sensor; Data fusion

1. Introduction

Large Volume Metrology (LVM) often involves the simultaneous use of multiple systems (for instance two or more laser trackers, or one 3D scanner combined with a photogrammetric system, etc.) [1-3]. The reasons behind this practice are different: (i) using systems based on various technologies can be practical for overcoming the drawbacks of single systems and improving measurement accuracy; (ii) taking advantage of the available equipment; (iii) reducing the risk of measurement errors; etc.

Typical industrial applications are reconstruction of curves/surfaces for dimensional verification and/or assembly of large-sized mechanical components.

The concurrent use of multiple systems requires the definition of suitable data fusion strategies. To this purpose there are two possible approaches [4, 5]:

- *Competitive fusion*. Each system performs an independent measurement of the 3D coordinates of the point of interest and the resulting measurements are fused into a single one [6]. For example, this principle is implemented in the SpatialAnalyser®, which is one of the most diffused software solutions for LVM applications [7].
- *Cooperative Fusion*. Data provided by two or more independent sensors, belonging to the same system and/or different ones, are used to achieve information that otherwise would not be available from individual sensors [6]. For example, data from two sensors of a system, which performs distance measurements, and data from one sensor of a system, which performs angular measurements, can be combined for determining the 3D coordinates of the measured points. With this cooperative logic, data derived from sensors equipping different systems concur in a unique overall localization of the points of interest.

Compared to the competitive fusion approach, the cooperative one has some disadvantages: it is more difficult to implement, as it requires "open" measurement systems, which return the angular and/or distance measurements provided by the system sensors; it is based on a more complicated fusion model. However, a cooperative fusion approach could potentially make a more efficient use of the available information, resulting in improved metrological performance. Also, it is the only option when using sensors that are unable to perform independent localizations of the points of interest (for instance a laser interferometer combined with a single photogrammetric camera).

While competitive fusion approaches are described in the literature [6], cooperative ones are almost totally ignored or confined to specific measurement applications.

The aim of this paper is to introduce a generalized cooperative fusion approach for 3D position measurement by LVM systems based on distance and angular measurements. The method takes into account the accuracy of the individual sensors, assigning more importance to the more accurate ones.

The remainder of the paper is structured as follows. Section 2 introduces and formalizes the problem of cooperative fusion for LVM systems. Section 3 describes the software developed for implementing the method and simulating different sensor configurations. Section 4 proposes an experimental benchmark for different configurations of the cooperative approach, using a distributed LVM system that integrates a laser tracker and several photogrammetric cameras.

2. Definition of the problem

The problem herein discussed is to define the 3D position of a measured point according to the cooperative approach, when a set of LVM systems is available.

Schematically, the architecture of the problem consists of N LVM systems $(D_1, D_2, \ldots, D_N)$, which are distributed over the measurement volume, so that each system is able to identify the measured point ($P \equiv [X, Y, Z]^T$), and a centralized data processing unit (DPU), which receives local measurement data from the systems. Each i-th system consists of M_i sensors. O-XYZ is a global Cartesian coordinate reference system.

Each of the sensors has its own spatial position and orientation and, for each j-th sensor in the i-th system, a local coordinate reference system o_{ij}-$x_{ij}y_{ij}z_{ij}$, roto-translated with respect to O-XYZ, is defined. The (six) location/orientation parameters related to the j-th sensor in the i-th system (i.e., $X_{0_{ij}}, Y_{0_{ij}}, Z_{0_{ij}}$ and $\omega_{ij}, \phi_{ij}, \kappa_{ij}$) are treated as known parameters, since they are estimated, together with their uncertainties, in an initial calibration process. It must be remarked that the i-th measurement system (D_i) is able to measure the position of the point of interest, independently from the other systems.

Let S_{ij} be the generic set of measurements given by the j-th sensor of the i-th system and $\mathbf{\Sigma}_{S_{ij}}$ the related covariance matrix.

According to the current technology, S_{ij} can be of three types:

A. $S_{ij} = \{\hat{d}_{ij}\}$, in case of sensors performing distance measurements (for instance, Absolute Distance Meters (ADMs), interferometers, ultrasound sensors, etc.), where $\hat{d}_{ij}$ is the distance measurement provided by the j-th sensor of the i-th system;

B. $S_{ij} = \{\hat{\theta}_{ij}, \hat{\varphi}_{ij}\}$, in case of sensors performing angular measurements (for instance, optical/magnetic encoders, photogrammetry cameras, iGPS sensors, etc.), where $\hat{\theta}_{ij}$ and $\hat{\varphi}_{ij}$ are respectively azimuth and elevation angles;

C. $S_{ij} = \{\hat{d}_{ij}, \hat{\theta}_{ij}, \hat{\varphi}_{ij}\}$, in case of hybrid sensors, able to measure one distance and two angles (for instance, laser trackers, 3D scanners, or a combination of other sensors).

The cooperative approach estimates the position of point $P \equiv [X, Y, Z]^T$ using the angular or distance measurements by the individual sensors and the relevant uncertainties.

Based on the previous classification, the following sets may be defined:

$$\begin{aligned} I_A &= \left\{(i,j) : S_{ij} = \left\{\hat{d}_{ij}\right\}\right\} \\ I_B &= \left\{(i,j) : S_{ij} = \left\{\hat{\theta}_{ij}, \hat{\varphi}_{ij}\right\}\right\} \quad , \qquad i = 1 \ldots N, \qquad j = 1 \ldots M_i \ . \\ I_C &= \left\{(i,j) : S_{ij} = \left\{\hat{d}_{ij}, \hat{\theta}_{ij}, \hat{\varphi}_{ij}\right\}\right\} \end{aligned} \tag{1}$$

Specifically, I_A, I_B and I_C are the sets of index-pair values (i,j), relating to the measurements performed by distance, angular and hybrid sensors respectively.

The problem may be decomposed according to the following linearized model:

$$\begin{bmatrix} \mathbf{M}^A \\ \mathbf{M}^B \\ \mathbf{M}^C \end{bmatrix} \mathbf{X} - \begin{bmatrix} \mathbf{b}^A \\ \mathbf{b}^B \\ \mathbf{b}^C \end{bmatrix} \equiv \mathbf{MX} - \mathbf{b} = 0 \ , \tag{2}$$

being:

$$\mathbf{M}^A = \begin{bmatrix} \vdots \\ \mathbf{L}_{ij} \\ \vdots \end{bmatrix}_{(i,j)\in I_A} , \ \mathbf{M}^B = \begin{bmatrix} \vdots \\ \mathbf{A}_{ij}\mathbf{R}_{ij}^T \\ \vdots \end{bmatrix}_{(i,j)\in I_B} , \ \mathbf{M}^C = \begin{bmatrix} \vdots \\ \mathbf{R}_{ij}^T \\ \vdots \end{bmatrix}_{(i,j)\in I_C} \tag{3}$$

and

$$\mathbf{b}^A = \begin{bmatrix} \vdots \\ \mathbf{b}_{ij} \\ \vdots \end{bmatrix}_{(i,j)\in I_A} , \mathbf{b}^B = \begin{bmatrix} \vdots \\ \mathbf{A}_{ij}\mathbf{R}_{ij}^T\mathbf{X}_{0_{ij}} \\ \vdots \end{bmatrix}_{(i,j)\in I_B} , \mathbf{b}^C = \begin{bmatrix} \vdots \\ \mathbf{t}_{ij} + \mathbf{R}_{ij}^T\mathbf{X}_{0_{ij}} \\ \vdots \end{bmatrix}_{(i,j)\in I_C} \tag{4}$$

where:

$\mathbf{X} = [X, Y, Z]^T$ is the position vector of point $P \equiv [X, Y, Z]^T$ in the global coordinate system *O-XYZ*;

$\mathbf{L}_{ij}$ and $\mathbf{A}_{ij}$ are the *design matrices* (or Jacobian matrices) for distance sensors and angular sensors respectively, referring to the global coordinate reference system *O-XYZ*;

$\mathbf{R}_{ij}^T$ is the rotation matrix, which aligns the local coordinate reference system $o_{ij}\text{-}x_{ij}y_{ij}z_{ij}$ to the global one *O-XYZ*;

$\mathbf{b}_{ij}$ is the vector of the *reduced measured observations* (i.e. the difference between sensor measurements and calculated ones) for distance sensors;

$\mathbf{t}_{ij}$ is the vector of the *measured observations* for hybrid sensors, referring to the global coordinate reference system *O-XYZ*;

$\mathbf{X}_{0_{ij}}$ is the vector containing the coordinates of the origin of the local coordinate reference system $o_{ij}\text{-}x_{ij}y_{ij}z_{ij}$ in the global one.

A solution to the problem in Eq. (2) may be obtained by applying a generalized least squares approach, using the overall covariance matrix Ω as a weighting matrix [8].

The Ω matrix can be estimated by the application of the MLPU (Multivariate Law of Propagation of Uncertainty) [9] to the system in Eq. (2), using the covariance matrices ($\mathbf{\Sigma}_{S_{ij}}$) of the measured observations and the covariance matrix ($\mathbf{\Sigma}_{\xi}$) of the sensor parameters ($\boldsymbol{\xi}_{ij}$) of the systems in use.

The elements of the $\mathbf{\Sigma}_{\xi}$ matrix can be estimated experimentally in two different ways: (i) by performing a separate calibration process for each i-th system, under the assumption of independence between the systems; (ii) by performing a joined calibration (e.g. by bundle adjustment techniques) of the whole set of sensors belonging to the totality of the systems.

Hence, the estimate of the position vector $\mathbf{X}$ is obtained by reversing Eq. (2) and including Ω as a weighting matrix:

$$\hat{\mathbf{X}} = \left(\mathbf{M}^T\Omega\mathbf{M}\right)^{-1}\mathbf{M}^T\Omega\mathbf{b} \tag{5}$$

3. Software development

A specific software was developed in Matlab®, in order to implement the proposed method for on-the-field LVM applications.

Main input data are: angular/distance measurements by sensors, sensor parameters (i.e. position and orientation in the measurement volume, calibration parameters, etc.), and relevant uncertainties. Output results are the 3D coordinates of each measured point, with an estimate of the related uncertainty.

The software includes also a simulation routine for estimating the metrological performance of different system configurations, before performing the experimental setup. This routine is very helpful, especially in the design phase, for pointing out: (i) how many systems and/or individual sensors should be placed in the measuring volume, (ii) which are the most suitable typologies of devices (when different technologies are used), and (iii) which are their suitable positions for reducing the measurement uncertainty.

Section 4 shows an example of the advantages of the simulation routine for a variety of configurations referring to the combined use of a photogrammetric system and a laser tracker.

4. Experimental case study

The method was implemented considering a specific combination of two LVM systems: (i) a photogrammetric system (PS) OptiTrack V120-TRIO™ [10] equipped with 38.1 mm reflective spherical markers, and (ii) a laser tracker (LT) API Radian™ [11]. The experiments have been conducted in the laboratories of Microservice S.r.l., which also provided the LT.

The PS consists of a set of 3 cameras fixed on a line frame (see Fig. 1), each of which is able to provide azimuth (θ_{PS}) and elevation (φ_{PS}) angular measurements of the target point. Using these data, the PS is able to estimate the position of each point $P \equiv [X,Y,Z]^T$ [10].

The LT is equipped with an ADM or a laser interferometer (performing distance (d_{LT}) measurements) and by angular encoders (performing azimuth (θ_{LT}) and elevation (φ_{LT}) angular measurements). Using these data, the LT is able to estimate the position of each point [11].

The proposed cooperative fusion approach is able to estimate the 3D position of each point based on the measurements performed by the sensors equipping the two systems (i.e. $\hat{\theta}_{PS}$ and $\hat{\varphi}_{PS}$ for each camera of the PS, and $\hat{d}_{LT}$, $\hat{\theta}_{LT}$ and $\hat{\varphi}_{LT}$ for the LT).

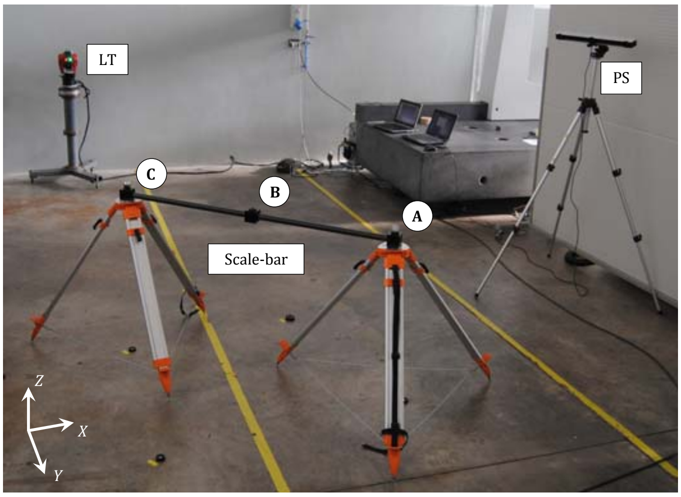

Figure 1. Measurement layout (A, B and C are the reference points of the scale-bar).

The experiments were conducted in two steps: (i) the first simulation-based step is aimed at defining the optimal layout of the two systems and obtaining a predictive estimation of the uncertainty in the position of the measured points; (ii) a second step, based on the acquisition and analysis of experimental data, highlights the advantages of the cooperative fusion approach, when joining data coming from the totality or a portion of the sensors of the two systems.

In order to obtain an optimal alignment between the coordinate systems of the LT and the PS respectively, according to the typical approaches reported in the scientific literature, 16 points, randomly distributed in the measuring volume, plus 3 specific points on a calibrated scale-bar (see Fig. 1) were measured using both the LVM systems [4, 5].

4.1. Layout simulation

The simulation was conducted for understanding the optimal relative position of the PS and LT.

In practical applications, the LT is generally positioned at a sufficiently large distance from the measured object, in order to "cover" most of the measured points, without requiring additional repositioning. On the other hand, the PS is repositioned at the optimal distance (specified by the manufacturer in the user manual) from the measured object, in order to "cover", position by position, all the points of interest. According to this approach, the coordinate system of the LT is used as global reference system and the 3D coordinate measurements obtained by the PS are therefore aligned to it.

In the simulation, the position and orientation of the PS are not changed. Precisely, the distance between the PS and the barycentre of the measured points is set to the optimal distance of 6 m [10]. The position of the LT is varied along the Y axis of the global Cartesian coordinate reference system O-XYZ, so that the LT distance from the measured points is changed, while the LT orientation remains unchanged. In detail, 15 total different positions of the LT are simulated. For each of the 19 points, in the 15 LT positionings, 100 replications are considered.

Regarding cameras (which are nominally identical), the simulated angular measurements (in rad) of azimuth and elevation ($\hat{\theta}_{PS}$, $\hat{\varphi}_{PS}$) are obtained by adding a Gaussian noise to the nominal values [10]:

$$\begin{aligned} \hat{\theta}_{PS} &= \theta_{PS} + \varepsilon_{\theta PS} \quad with \ \varepsilon_{\theta PS} \sim \mathrm{N}(0, \sigma_{\theta PS} = 3 \cdot 10^{-4}) \\ \hat{\varphi}_{PS} &= \varphi_{PS} + \varepsilon_{\varphi PS} \quad with \ \varepsilon_{\varphi PS} \sim \mathrm{N}(0, \sigma_{\varphi PS} = 3 \cdot 10^{-4}) \end{aligned} . \tag{6}$$

The same logic is extended to the LT simulated measurements (angles in rad and distances in mm) [2]:

$$\begin{aligned} \hat{d}_{LT} &= d_{LT} + \varepsilon_{d_{LT}} \quad with \ \varepsilon_{d_{LT}} \sim \mathrm{N}(0, \sigma_{d_{LT}} = 2.5 \cdot d_{LT} \cdot 10^{-3}) \\ \hat{\theta}_{LT} &= \theta_{LT} + \varepsilon_{\theta LT} \quad with \ \varepsilon_{\theta LT} \sim \mathrm{N}(0, \sigma_{\theta LT} = 1.396 \cdot 10^{-5}) \\ \hat{\varphi}_{LT} &= \varphi_{LT} + \varepsilon_{\varphi LT} \quad with \ \varepsilon_{\varphi LT} \sim \mathrm{N}(0, \sigma_{\varphi LT} = 1.396 \cdot 10^{-5}) \end{aligned} . \tag{7}$$

The standard deviations of the Gaussian noise were defined according to technical specifications of the two LVM systems and the typical values reported in the scientific literature [2, 10].

The above defined measurements are assumed to be uncorrelated. Next, the positions of the points are calculated assuming the metrological characteristics of the sensors (i.e. their calibration parameters $\boldsymbol{\xi}_{ij}$ and the related covariance matrices $\boldsymbol{\Sigma}_{\xi_{ij}}$) to be known.

Simulation results are analysed by comparing the simulated 3D coordinate measurements of the points ($\hat{\mathbf{X}}$) and their nominal positions ($\mathbf{X}$). To this purpose, the mean absolute error is used as indicator of accuracy:

$$e = \frac{\sum_{k=1}^{19 \cdot 100} \left\| \mathbf{X}_k - \hat{\mathbf{X}}_k \right\|}{19 \cdot 100} . \tag{8}$$

Fig. 2 shows a semi-log plot of the mean absolute error value in different measurement configurations, for both the cooperative and competitive approach.

The plot shows that the integrated use of the two systems (PS and LT) produces a significant improvement in measurement accuracy. The cooperative and competitive approaches show roughly the same performance when the two LVM systems are using all the sensors (see the overlapping profiles).

Excellent results are obtained when using only one or two cameras of the PS in cooperation with the LT. It is remarked that when combining the LT and a single camera, cooperative fusion is the only possible approach, since single cameras are not able to provide independent 3D measurements. Furthermore, the accuracy resulting from the cooperative fusion approach tends to stabilize when LT distances are higher than 15 m.

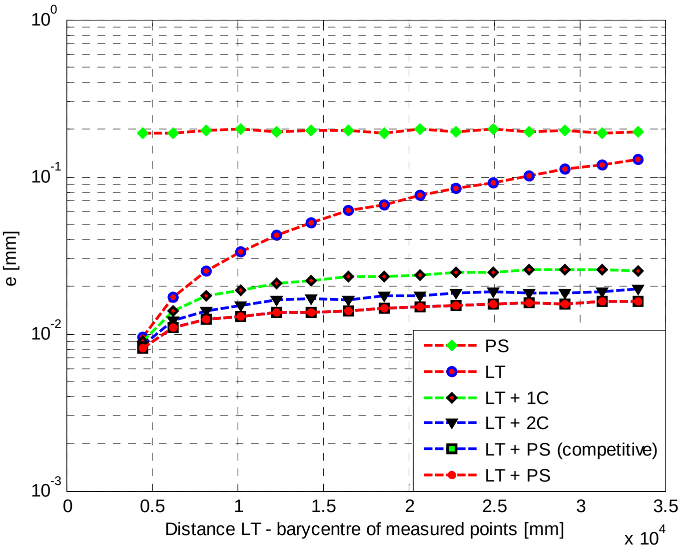

Figure 2. Simulated mean absolute position error (e) versus the distance between the LT and the barycentre of measured points (LT: Laser tracker; PS: photogrammetric system; 1C: central camera of the photogrammetric system; 2C: two lateral cameras of the photogrammetric system).

4.2. Experimental data acquisition and analysis

Data were acquired positioning the LT and the PS, according to the layout reported in Fig. 1, i.e. at 10 m and 6 m from the barycentre of the measured points respectively.

The position measurements of three reference points on the scale-bar were replicated 30 times, obtaining the results in Table 1. The mean values of the distances measured on the scale-bar and the related standard deviations are reported for all the possible sensor configurations. The nominal values of these distances were obtained by a calibration procedure using a DEA SCIROCCO 251310 Coordinate Measuring Machine (CMM), performing 10 replications for each distance.

Results are compared with those obtained using (i) the LT and the PS individually, and (ii) the competitive approach implemented by the SpatialAnalyser® software.

Table 1 Distances measured on the scale-bar (values reported in mm), using different sensor configurations (LT: Laser tracker; PS: photogrammetric system; 1C: central camera of the photogrammetric system; 2C: two lateral cameras of the photogrammetric system).

Config.	d_{A-B}	$\sigma_{d_{A-B}}$	d_{B-C}	$\sigma_{d_{B-C}}$	d_{A-C}	$\sigma_{d_{A-C}}$
Nominal	728.294	0.003	727.703	0.003	1455.996	0.003
Individual systems						
LT	728.317	0.032	727.668	0.034	1455.984	0.032
PS	728.320	0.077	727.664	0.116	1455.984	0.111
Competitive						
LT + PS	728.313	0.016	727.663	0.015	1455.976	0.015
Cooperative						
LT + PS	728.308	0.016	727.669	0.015	1455.977	0.015
LT + 2C	728.318	0.019	727.665	0.018	1455.982	0.017
LT + 1C	728.298	0.022	727.676	0.023	1455.974	0.021

Table 1 and Fig. 2 suggest three main considerations: (i) considering the overall uncertainty, including both the position error and measurement repeatability contributions, the results in Table 1 are compatible with the nominal distances at a 95% confidence level for all configurations, (ii) the cooperative fusion improves the system performance, both in terms of mean absolute error and precision, and (iii) the sensor configuration LT + PS drives to the same result, both when implementing the competitive and the cooperative data fusion, however, differently from the competitive approach, the cooperative one can be also profitably applied for the LT + 2C and LT + 1C configurations.

This last finding is particularly important since it demonstrates that when implementing the cooperative data fusion, the metrological performance of relatively accurate systems (such as LTs) may be further increased combining them with other sensors of lower accuracy (such as photogrammetric cameras).

5. Conclusions

This paper presented a new approach for cooperative fusion of data obtained from different LVM systems. This approach uses angular and distance data, measured by the sensors equipping each system, so as to compute the 3D position of the measured points. Input data of this model are: (i) the measurements obtained by the individual sensors, with the relevant uncertainties, and (ii) the calibration parameters of the individual sensors with the relevant uncertainties. A dedicated software, which implements the proposed method, was developed; this software is able to compute 3D coordinates of measured points and perform simulations for assisting in defining the measurement system layout.

The main advantages of the proposed approach, in comparison with that based on competitive data fusion, are: (i) it potentially makes a more efficient use of data available from system sensors, (ii) it is the only option when using systems that do not provide independent position measurements (e.g., laser interferometers or a single cameras), (iii) it is the only option when only a portion of the sensors of individual systems work correctly (for instance, a laser tracker in which only distance – not angular – measurements are performed), (iv) when using systems with redundant sensors (i.e. photogrammetric systems with a large number of distributed cameras), point localization tends to be better than that obtained through the competitive data fusion approach, (v) simulations can be used in the design phase of the measurement process, in order to identify the optimal combination of systems (or sensors) and their layout.

A limitation of the proposed method is that it works only for sensors which perform angular and distance measurements, referring to the 3D position of the measured points. For this reason, it cannot be used for fusing data concerning systems like mechanical CCMs or CMM arms.

The method was applied in some real and simulated experiments, in which data obtained from a laser tracker and a photogrammetric system are fused. Future research aims at applying the new method to other configurations, which reflect realistic industrial applications.

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