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DEVELOPMENT OF A PRACTICAL PHOTOGRAMMETRIC NETWORK DESIGN USING EVOLUTIONARY COMPUTING

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Abstract

Photogrammetric network design is the process of optimising a network configuration in terms of the accuracy of object points. This accuracy is improved by selecting the best set of intersection rays in a bundle adjustment. This paper explains the approach followed to achieve the development of a practical network design using a real robotic system. The aim is to integrate a simulation-based network design into a practical vision metrology system. The simulation is carried out with a population search metaheuristic inspired by the evolutionary computing paradigm. The proposed approach uses an analytical criterion to search for a suitable first-order design in a fraction of the computational time required by the evolutionary approach using a rigorous bundle adjustment. The combination of an evolutionary algorithm simulation with the very well-established bundle adjustment provides a straightforward approach to network design. An example of a photogrammetric network design is provided to illustrate the result of a complete network design.

KEYWORDS: camera placement, evolutionary algorithms, network design, sensor planning, vision metrology

INTRODUCTION

THE LEVEL OF AUTOMATION achieved in digital close range photogrammetry has allowed the effective integration of vision metrology systems into industrial environments (Fraser, 1997; Ganci and Hanley, 1998). Indeed, the advances in coded targets, exterior orientation devices and intelligent cameras, as well as software systems that integrate these technologies, have eliminated the need for user intervention during the image measurement and orientation stages. However, the automated determination of an optimal datum, an optimal imaging geometry, the optimal distribution of observational work in a fixed configuration, as well as the improvement of a network through the inclusion of additional points and/or observations, remain as unresolved problems in photogrammetry. Network design addresses all these aspects in accordance with the widely accepted classification scheme of Grafarend (1974). Given the practical importance of these problems, the automation of the network design stage is receiving renewed interest from the photogrammetric community (Mason, 1995a, b; Fraser, 1996; Olague, 2002; Saadatseresht et al., 2004, 2005).

The network design problem in photogrammetry is normally stated as follows: *given* the required quality (precision and reliability) of a set of parameters that are to be estimated, *find* the set of measurements that will achieve this with the least cost. This problem is known as photogrammetric network design (PND). Today it is widely accepted that the process of designing a photogrammetric network should be done through simulation. A truly optimal network would achieve the highest possible precision and reliability in the most economical manner. Nowadays the link between design cost and number of camera stations is considered as being effectively removed (Saadatseresht et al., 2004). This is true from the standpoint of carrying out the photogrammetric project. However, the cost of obtaining a suitable network design depends on the strategy by which the decision-making process is automated. Moreover, from a practical standpoint, network design is still carried out mostly by photogrammetric experts. Expertise is involved in deciding the arrangement and number of cameras to gain the strongest network, setting the lighting to obtain strongly contrasting targeted features, and suitable arranging of the feature targets. Finally, the expert should run a program with all the above information and decide if the results are within some predetermined limit, or make some change, check for errors and repeat it with new values until the objectives are achieved. Therefore, although close range photogrammetry is considered as a mature technique for mapping and measurement, it could be said that there are still opportunities for improving the level of automation. In this way, PND remains a specialised subject that requires non-trivial expertise. On the other hand, network design in the case of a multi-image real-time photogrammetric system needs to consider novel aspects such as object recognition and pose estimation, path planning and obstacle avoidance, control of each exposure, target and feature localisation, to mention but a few. Therefore, the costs of designing a photogrammetric network should not be overlooked.

Nowadays, vision metrology is actively used in conjunction with computer vision, robotics, computer graphics and other visual related disciplines to solve problems in areas such as medicine, biology, architecture, industrial engineering, aerospace technology and in other more traditional fields. The motivation for this research is to reduce the cost of vision system design and to equip autonomous inspection systems with photogrammetric network capabilities like those provided by measurement robots, as illustrated in Fig. 1.

Network design by simulation is often approached using an optimisation technique. From the first such work through to the present day (for example, Brown, 1980; Zinndorf, 1989; Mason, 1995a, b; Fraser, 1996; Olague, 2002; Saadatseresht et al., 2004; Fraser et al., 2005) network design optimisation has been understood as the search for a satisfactory configuration. Thus, the design process is concluded once a network achieves the desired accuracy, within the limit of cost and/or time. This research is about how evolutionary computing could be applied to design a photogrammetric network for industrial inspection tasks. Evolutionary computation (EC) should be understood as a general adaptable concept for problem solving, especially well suited for solving difficult optimisation problems such as PND, instead of a collection of related and ready-to-use algorithms. Computer simulation of the natural evolutionary process results in a set of stochastic optimisation techniques known as evolutionary algorithms. The application of evolutionary computing to PND provides the benefit of a natural interaction between both research areas in order to achieve the common goal of obtaining a suitable solution. It is known that solving a network design through a unique sequence of mathematical steps, possibly involving iteration, is not a viable technique (Mason, 1994). However, analytical design is deeply employed in order to describe the criteria that are applied within the

FIG. 1. Typical sensor planning research is carried out with a robot manipulator and a CCD camera in what is known as a hand–eye configuration.

optimisation approach. Thus, the most significant advantage of using evolutionary search lies in the gain of flexibility and adaptability to the task at hand, in combination with robust performance and global search characteristics.

The aim of this paper is to present the mathematical modelling that has been applied to achieve the simulation, as well as a practical implementation with a real robotic system. Firstly, the projective camera model is reviewed in order to explain a much faster criterion used for modelling the uncertainty instead of a rigorous photogrammetric approach. This simplification is useful because evolutionary computing needs a high computational effort when running multiple bundle adjustments, even on workstations, which may reduce the applicability of the technique. This modelling is also applied to obtain the interior and exterior orientation parameters of each recorded image. However, this model is not suitable for computing the bundle adjustment, because some derivatives vanish when considering a Euclidean coordinate system. Instead of the projective model, collinearity equations are used and in order to maintain a consistent approach a transformation between the two functional models is applied. Secondly, the evolutionary algorithm is introduced in order to illustrate the optimisation process giving emphasis to genetic representation, constraint handling and genetic operators. Aspects such as convergence angle, visibility and workspace constraints are considered in the robotic measurement system. Finally, a set of experiments are discussed to illustrate the practical approach proposed in this paper using a calibration grid, as well as a 3D complex object.

COUPLING AN EVOLUTIONARY NETWORK DESIGN WITH A BUNDLE ADJUSTMENT

This section presents the mathematical modelling used to couple an evolutionary network design system with a real photogrammetric system. In previous work (Olague and

Mohr, 2002), an approach based on a genetic algorithm was presented to solve the camera placement problem with the goal of obtaining highly accurate 3D measurements. The main advantage of that approach was the short computational time employed to obtain a network configuration. That work was later improved with the incorporation of a bundle adjustment (Olague, 2002). Nevertheless, the ensuing increase in computational cost could limit the application of the evolutionary approach. The motivation of coupling both approaches is to achieve the benefits of a reduced computational time and rigorous photogrammetric analysis. In order to obtain a practical network configuration system, two different models are considered to describe the imaging geometry of a digital camera mounted on a robot manipulator. The first is the projective model expressed in homogeneous coordinates. This model is used to obtain the camera calibration for each recorded image, as well as to obtain an estimation of the uncertainty for the case of a multi-station camera network (Olague and Mohr, 2002). The second is based on the collinearity equations used in the classical bundle adjustment approach (Brown, 1958). The pinhole camera model (central projection) underlies both the projective approach and the collinearity-based approach. This model is based on the fundamental assumption that the exposure centre, the ground point and its corresponding image point, all lie on a straight line. In order to apply both approaches simultaneously the mathematical transformation between the two models is described. In this work the target points will be represented by error ellipsoids describing the uncertainty of the position. In this way, the orientation and size of the error ellipsoids are changed with respect to the network distribution.

Modelling of Cameras

In computer vision the camera network is commonly modelled from a geometric standpoint according to the projective model. It describes the projection of the world points $\mathbf{P}_j$, $j = 1, \ldots, n$ of homogeneous coordinates $(X_j, Y_j, Z_j, 1)^{\mathrm{T}}$ onto the image points $\mathbf{p}_{ij}$. The photo coordinates $\mathbf{p}_{ij} = (u_{ij}, v_{ij})$ of the image point j in photograph i are described by the following algebraic parameterisation $\mathbf{p}_{ij} = \mathbf{M}_i\mathbf{P}_j$. This system of equations assumes that light rays travel in straight lines, that all rays entering a camera lens system pass through a single point and that the lens is distortion-free or, as is usual in highly accurate measurement, that distortion has been cancelled out after having been estimated. In this way, a projection matrix $\mathbf{M}_i$, $i = 1, \ldots, k$, of size 3×4 corresponding to the ith image, is defined up to a scale factor s. The matrix can be computed from the relative positioning of the real-world points and the camera centre, and from the interior orientation parameters; however, it can also be computed directly from image-to-world point correspondences. Each matrix $\mathbf{M}$ represents a mapping composed of a transformation $W \rightarrow C$ from the world coordinates W to the camera coordinates C followed by the perspective projection from the 3D world coordinate system to the 2D image coordinate system as follows:

$$\begin{pmatrix} su \\ sv \\ s \end{pmatrix} = \begin{bmatrix} -K_u f & 0 & u_0 & 0 \\ 0 & K_v f & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R}_{WC} & \mathbf{T}_{WC} \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \tag{1}$$

where f is the focal length of the camera, (K_u, K_v) are the horizontal and vertical pixel sizes on the image plane, and (u_0, v_0) is the principal point measured in image coordinates. These parameters describe the interior orientation of the camera. On the other hand, the rotation matrix $\mathbf{R}_{WC}$, which is a function of three rotation parameters (α, β, γ) and the translation vector $\mathbf{T}_{WC}$, also of three degrees of freedom, characterise the camera's orientation with respect to the world coordinate frame.

Camera Calibration and Bundle Adjustment

In computer vision, calibration is the process of estimating the interior and exterior orientation parameters of a camera. It can be thought of as a two-stage process in which the matrix $\mathbf{M}$ is first computed and then the intrinsic (interior) and extrinsic (exterior) parameters from $\mathbf{M}$ are computed (Faugeras, 1993). The approach used in that work was specially developed for the case of a digital camera. In photogrammetry the camera calibration is understood as the process of determining the interior orientation parameters. This definition is also becoming accepted in computer vision (Hartley and Zisserman, 2003). Beside the camera constant and the location of the principal point this may also include the parameters of lens distortion. The approach used in that work provides the camera calibration and the exterior orientation by resection in one single step. This is also a well-established procedure in photogrammetry. Thus, the camera calibration approach proposed by Faugeras and Toscani (1987) is applied to each recorded image. This approach provides a high level of automation even if it cannot provide great accuracy. The application of solid-state cameras for real-time photogrammetry is considered to help significantly in the level of automation. Moreover, the quality of such systems for the problem of vision metrology has been effectively demonstrated since the work of Beyer (1992). He presents a digital system based on the collinearity equations that achieves results comparable to small to medium format film cameras. Nowadays, the determination of the attitude, the position and the intrinsic geometric characteristics of the camera and of the coordinates of object space points measured on photographs are recognised as standard procedures that solve the fundamental photogrammetric problem (Grussenmeyer and Al Khalil, 2002).

In this work, the aim is to achieve the highest possible level of automation. Therefore, the calibration (interior and exterior parameters) obtained by the Faugeras–Toscani approach is used as the initialisation of a classical bundle adjustment in order to achieve the best estimation of the uncertainty that is provided by a rigorous approach. Indeed, in previous work (Olague and Mohr, 2002) the projective model was used to derive an analysis of the uncertainty that is useful in the determination of a camera configuration. The idea is to use the camera distribution in a robotic hand–eye configuration to perform a bundle adjustment. In photogrammetry the bundle method accords simultaneous consideration to all sets (or "bundles") of photogrammetric rays from all cameras. The bundle method is based on a mathematical camera model composed of separate functional and stochastic models. The functional model is represented as $F(x, b, a) = \mathbf{0}$, where x is a vector representing the u elements whose values are required, b is a vector of measurements and a is a vector representing the elements whose values are known constants. In this work it is considered that the cameras have undergone prior calibration and that these values could be included in a. The projective approach and the collinearity-based approach could be used simultaneously if the transformation between both parameterisations is defined appropriately. In this way, the camera constant usually expressed by f is described as two projections along the main directions $\alpha_u = -K_u f$ and $\alpha_v = -K_v f$; and the image coordinates of the principal point are simply expressed as $x_p = u_0$ and $y_p = v_0$ Therefore, the analysis could be simplified to obtain the following models based only on the exterior orientation parameters:

(a) Computer vision

$$\mathbf{P}'_j = \begin{bmatrix} \mathbf{R}_{WC} & \mathbf{T}_{WC} \\ \mathbf{0}_{1\times3} & 1 \end{bmatrix} \mathbf{P}_j. \tag{2}$$

(b) Photogrammetry

$$\mathbf{P}'_j = \mathbf{R}(\mathbf{P}_j - \mathbf{P}_c). \tag{3}$$

However, the last equation is expressed in non-homogeneous coordinates. In order to state this equation as in the computer vision model it can be written as

$$\mathbf{P}'_j = \mathbf{R}\mathbf{P}_j - \mathbf{R}\mathbf{P}_c \tag{4}$$

to obtain

$$\mathbf{P}'_j = \begin{bmatrix} \mathbf{R}_{3\times3} & -\mathbf{R}\mathbf{P}_c \\ \mathbf{0}_{1\times3} & 1 \end{bmatrix} \begin{pmatrix} \mathbf{P}_j \\ 1 \end{pmatrix} \tag{5}$$

where $\mathbf{P}_c = -\mathbf{R}^{\mathrm{T}}\mathbf{T}_{WC}$.

Uncertainty Assessment through Error Propagation

Currently, rigorous bundle adjustment procedures can be performed on a standard laptop. However, the PND, proposed in previous work, requires considerable computational resources due to the EC technique (Olague, 2002). Fraser (1987) has shown that a simplified model called "limiting error propagation" closely approximates the covariance matrix generated for the object point *XYZ* coordinates of the rigorous approach known as "total error propagation". This simplification is valid for strongly convergent multi-station photogrammetric networks in the case of the "first-order design". The vision metrology algorithms rely on applying a set of non-linear transformations to the image measurements to compute world measurements. Since the input quantities and the transformations are uncertain, the output measurements are also uncertain. In order to determine how the uncertainty propagates from input to output of the computation chain a much faster analytical approach can be applied to estimate the 3D measurement accuracy (Olague and Mohr, 2002). The analytical method takes account of the fact that the 3D measurement point $\mathbf{P}_j$ is related to the input data $\mathbf{p}_{ij}$ by a non-linear analytical function f. This relationship is approximated with a linear one by means of a first-order Taylor series expansion. By assuming noise only on the input data $\mathbf{p}_{ij}$ and not on the transformation, the following relationship is obtained:

$$f(\mathbf{p}) = f(E[\mathbf{p}]) + \frac{\partial f(E[\mathbf{p}])}{\partial \mathbf{p}}(\mathbf{p} - E[\mathbf{p}]) + \Theta(\mathbf{p}) \tag{6}$$

from which, ignoring the second-order terms, it is easy to compute the mean value of the output measurements and consequently the covariance of the measurements:

$$\mathbf{\Lambda P} = \frac{\partial f(E[\mathbf{p}])}{\partial \mathbf{p}} \mathbf{\Lambda p} \frac{\partial f(E[\mathbf{p}])^{\mathrm{T}}}{\partial \mathbf{p}}. \tag{7}$$

This analysis allows the 3D measurement accuracy to be estimated as a function of the disposition of multiple cameras and the image measurement uncertainty. This analysis is equivalent to the limiting error propagation normally used in photogrammetry. On the other hand, the coupling between the projective model and the collinearity-based model allows the rigorous approach to be computed once the convergence of the evolutionary algorithm is achieved. This is the key to simulating networks of complex objects and testing the best solution in the real world with the aid of a standard laptop computer.

EVOLUTIONARY COMPUTING FOR NETWORK DESIGN

Evolutionary computing techniques have previously demonstrated their value in the design of photogrammetric networks (Olague, 2002; Olague and Mohr, 2002). The methods based on evolutionary computing are stochastic heuristic search techniques following the natural evolutionary principles proposed by Darwin. These techniques operate over a set of parameterised solutions through a set of stochastic heuristic functions. The evolution is applied concurrently to the set of solutions using population-based metaheuristics. The evolutionary computing approach could manage a number of constraints and design decisions, avoiding the local minimum, and making it well suited as a global optimisation approach. The evolutionary computing approach offers a powerful paradigm to address three main challenges found in network design:

(1) The search space is non-linear. The relationship between the imaging geometry of multiple cameras and reconstruction accuracy present in a multi-station sensor configuration is modelled by a complex mathematical model that is difficult to address by analytical or numerical means.
(2) The search space offers discontinuities. Concave 3D objects present the problem of self-occlusion for visual sensing, giving rise to a combinatorial optimisation process.
(3) The search space is multi-modal. There exist multiple configurations, with very different geometrical topology, that provide similar results. This is in concordance to the generic network theory.

Therefore, the flexibility of the evolutionary computing paradigm allows the study of PND to be extended beyond a purely geometrical design problem into a simulation-based approach. The EPOCA (Evolving Positions of Cameras) is an example of a system that has been developed using these principles. EPOCA is a CAD-based planning system, which incorporates camera network design algorithms with a 3D simulation environment and interface. The system takes as input a 3D CAD model of the object and determines automatically the location and attitude of a set of cameras converging to the object. The ongoing development of EPOCA has extended this basic scenario to include the operation of an active vision system, as well as a rigorous photogrammetric approach using different evolutionary optimisation techniques.

Designing an Optimal Camera Network for 3D Measurements

There is a special nomenclature used in the EC literature for the basic algorithmic elements used in the development of an evolutionary algorithm. For example, the set of solutions is called a population while each single solution is called an individual. Also, the set of stochastic functions are called genetic operators while the criterion to optimise is termed a fitness function. In this work, such concepts are used in the EPOCA system to evolve a population of camera configurations in order to solve the PND problem. The first algorithmic aspect to be addressed is the definition of a suitable genetic representation.

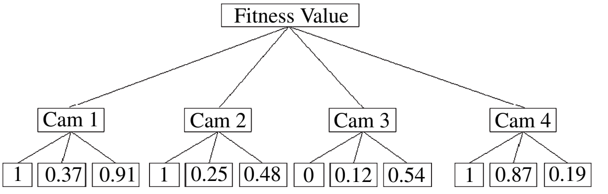


FIG. 2. The original tree structure was improved to incorporate real values, as well as a control bit for each camera. In this example the third camera will be excluded since the corresponding control bit is turned off.

Genetic Representation

The design of an optimal camera network is considered as a problem of determining an optimal imaging geometry. Hence, the main issues to be addressed are the convergence angle of each camera with regard to the object features, as well as the relative orientation of each camera with respect to the other sensing stations. The evolutionary approach requires a parameterisation of the network design that effectively represents these aspects. The viewing sphere model is adopted in order to have a representation that provides 3D convergent networks while maintaining a parameterisation of reduced dimensionality. The original representation of the EPOCA system was modified by adopting a real value encoding in order to increase the resolution of the camera placement parameterisation. Moreover, the original multi-cellular genetic algorithm (Olague, 2002) was further improved by adopting an additional binary encoding similar to the Hierarchical Genetic Algorithm or Linear Genetic Programming, see Fig. 2.

Constraint Handling

A valid camera configuration should provide sufficient image measurements to effectively reconstruct all the object features under study. Visibility constraints are incorporated into the EPOCA system by means of an offline ray-tracing module that evaluates the visibility of each object feature from the different camera positions available in the viewing sphere model. Data sufficiency for optical triangulation is computed from the visibility analysis for the entire network. This is done in order to ensure sufficient redundant measurements. The results of each visibility evaluation are stored in a database for online query during the evolutionary process. This process requires that every camera observes a non-empty subset of the object features. However, depending on the object being studied, it is possible for the evolutionary process to produce invalid camera positions. Such positions are validated and corrected if necessary. Moreover, the incidence angle constraint is enforced during fitness evaluation. For a single feature, only those cameras that comply with this constraint contribute to the feature reconstruction process. EPOCA validates these constraints and penalises the invalid configurations assigning a predetermined fitness value. These constraints are stored in an internal database that keeps a record of which camera positions are able to observe a given object region as shown in Fig. 3.

The integration of a robotic arm into the image acquisition system requires the consideration of the kinematics restrictions of the manipulator since they can limit the space of attainable camera positions. These restrictions are evaluated offline, through a simulation environment that solves the inverse kinematics problem, and at the same time storing the results in a database for online query.

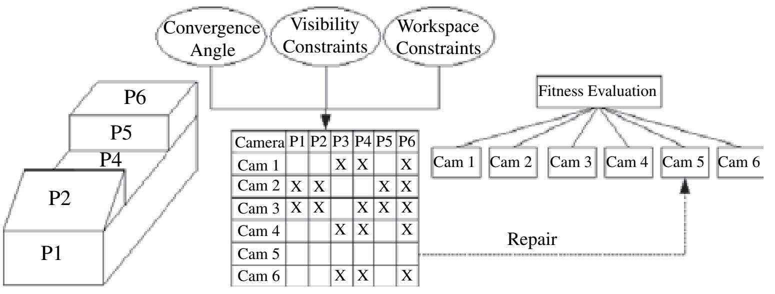


FIG. 3. Different constraints are integrated in the methodology using an internal database.

Recombination and Mutation

The genetic (recombination and mutation) operators used in real-valued encoding are different from those used for the binary representation. The simulated binary crossover (SBX) emulates the working principle of the single point crossover operator on binary strings. From two parent solutions P_1 and P_2, two children C_1 and C_2 are created as follows:

$$\begin{aligned} C_1 &= 0{\cdot}5[(1+\beta)P_1 + (1-\beta)P_2] \\ C_2 &= 0{\cdot}5[(1-\beta)P_1 + (1+\beta)P_2] \end{aligned} \quad \text{with } \beta = \begin{cases} (2u)^{1/(\eta x+1)} & \text{if } u < 0{\cdot}5 \\ \left(\frac{1}{2(1-u)}\right)^{1/(\eta x+1)} & \text{otherwise} \end{cases}. \tag{8}$$

The spread factor β depends on a random variable $u \in [0, 1]$ and on a user-defined non-negative value ηx that characterises the distribution of the children with respect to their parents. The mutation operation turns a parent P into a child C using the boundary values P^{LOW} and P^{UP} of each of the decision variables in the following manner:

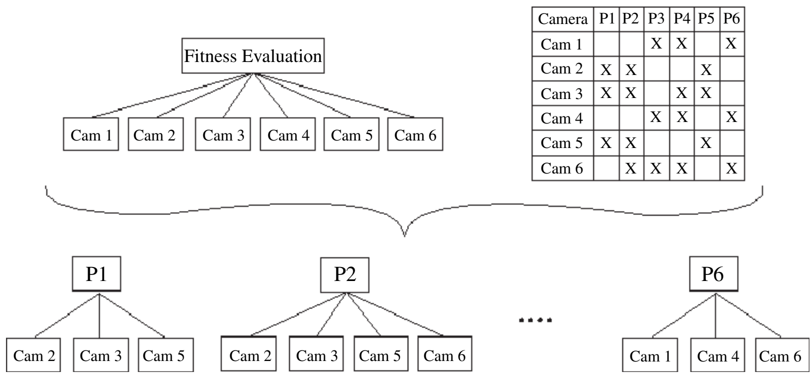
$$C = P + (P^{\mathrm{UP}} - P^{\mathrm{LOW}})\delta \text{ with } \delta = \begin{cases} (2u)^{1/(\eta m+1)-1} & \text{if } u < 0{\cdot}5 \\ (1 - [2(1-u)])^{1/(\eta m+1)} & \text{otherwise} \end{cases}. \tag{9}$$

Evaluation

Natural selection is based on the principle of survival of the fittest. In the evolutionary algorithm, the measure of an individual fitness is given by the quality of the 3D measurements expressed by the error propagation approach described by equation (7). The evaluation process partitions the objects into separate regions of interest. The mathematical model for 3D measurement is built for each object region considering a subset of cameras observing the object. In this way, the fitness evaluation is a dynamic process that depends on the topology of the object, as well as on the camera network distribution (Fig. 4).

VALIDATION THROUGH REAL-WORLD EXPERIMENTATION

A number of experiments were carried out on the calibration grid of Fig. 5 to verify the bundle adjustment software developed in-house. The real bundle adjustment implementation shows how the determination of point precision is reflected by variations in the shape and dimensions of the (scaled) error ellipsoids with respect to the network geometry. Fig. 5 shows



Camera	P1	P2	P3	P4	P5	P6
Cam 1			X	X		X
Cam 2	X	X			X	
Cam 3	X	X		X	X	
Cam 4			X	X		X
Cam 5	X	X			X	
Cam 6		X	X	X		X

FIG. 4. A mathematical model is dynamically formulated for each object region.

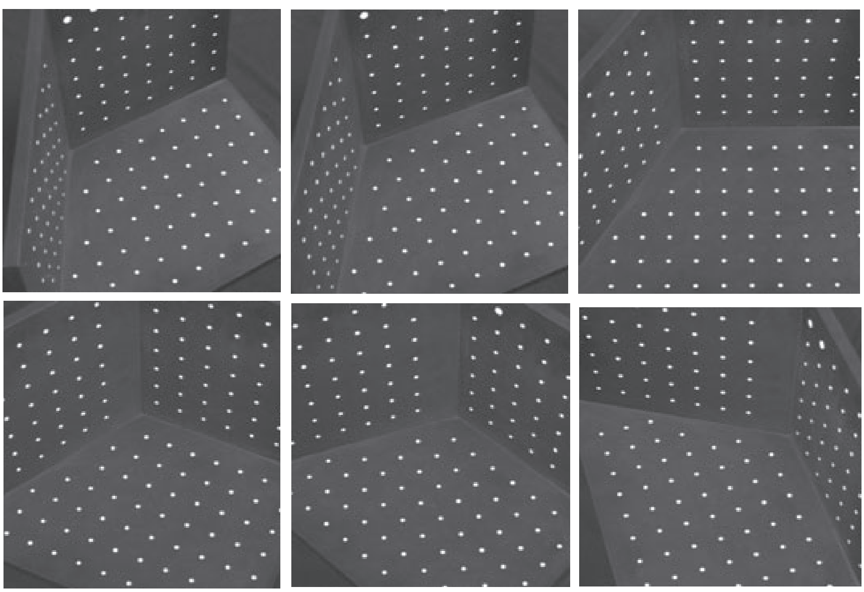


FIG. 5. The calibration grid used in the experiments of camera calibration and bundle adjustment.

6 out of 20 images that were used in the experiments. The grid is composed of 160 retro-reflective targets within a volume of $33{\cdot}7 \times 26{\cdot}2 \times 26{\cdot}2\ \text{cm}^3$. The images have been acquired with a Pulnix TM-6EX camera and a Kinoptik lens of focal length 12·5 mm. The frame grabber is an "Imaging Technology 150".

Each retro-reflective target was measured up to sub-pixel accuracy using an approach similar to one proposed by Gruen (1985). The basic idea is to propose a parametric model and then fit the model directly to image intensities. These image measurements along with the corresponding 3D data were used for camera calibration following the approach of Faugeras and Toscani (1987). The results of the calibration were applied to the bundle adjustment to obtain the error ellipsoids that are shown on Figs. 6, 7 and 8. The relationship can be

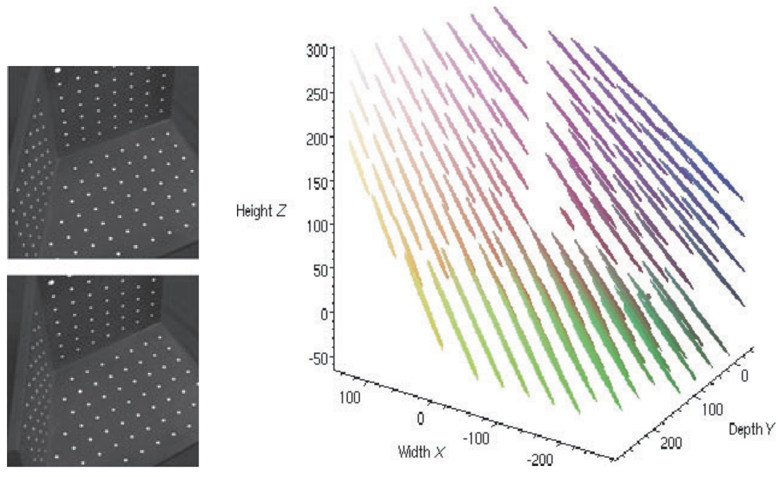


FIG. 6. The first two images of the sequence were selected to compute the error ellipsoids.

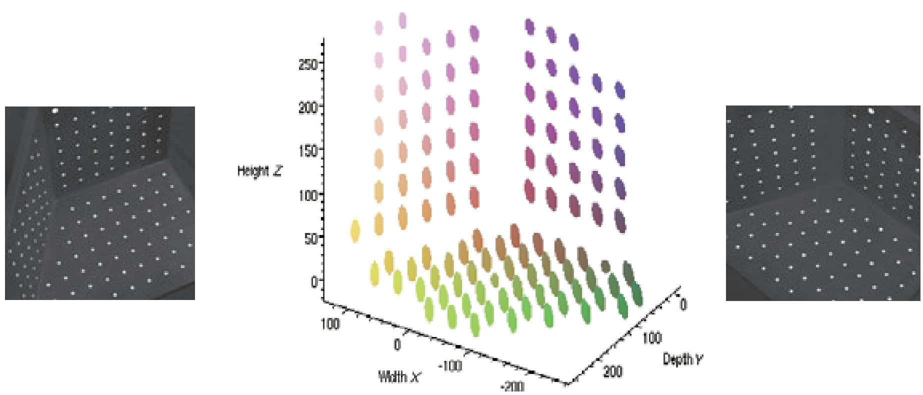


FIG. 7. The second and fifth images of the sequence were used to compute the error ellipsoids.

appreciated between the imaging geometry and the volume of the error ellipsoids for the case of two images taken close to each other, and for the case of a convergent configuration of two images. The changes in size and orientation of the error ellipsoids illustrate the compromise of configuring a suitable imaging geometry. Fig. 8 shows the problem of visibility that produces a lack of uniformity on the error ellipsoids because some of the points were only acquired by two photographs. These experiments validate the practical implementation of the in-house bundle adjustment and camera calibration software. Next, the PND for a complex object will be shown.

SIMULATION AND PRACTICAL DESIGN OF PHOTOGRAMMETRIC NETWORKS

The previous experiments have been performed to verify the practical implementation of the bundle adjustment procedure. In this way, it is now possible to show the simulation and

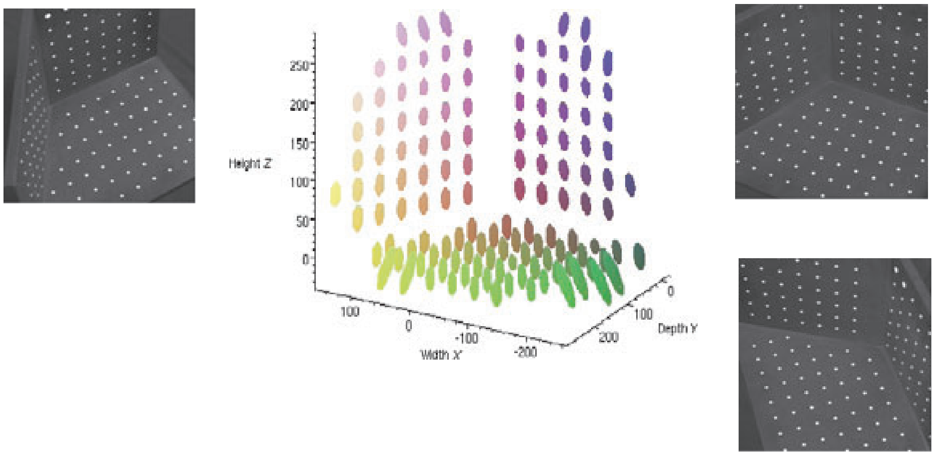


FIG. 8. The first, fourth and sixth images of the sequence were used to compute the error ellipsoids. Note that some of the (scaled) error ellipsoids are bigger due to the visibility problem.

practical implementation of a PND considering a multi-image real-time photogrammetric system. The robotic facility consists of an RX-60B Stäubli robot manipulator with 6 degrees of freedom. This robot is equipped with a Pulnix TM-9701d digital camera of 768 × 484 pixels in size and a nominal 16 mm C-mount Fujinon lens. The simulation was programmed following the nominal characteristics of the manipulator. The measurement analysis was applied over a complex 3D object similar to one that was previously used in the simulation. Quadrangular patterns were applied to the surface of the object and the corners of these patterns were used as the features to be measured. The motivations for using this kind of feature are the low cost and relative simplicity of producing them on a laser printer. Image measurements were obtained up to sub-pixel accuracy using an L-corner model in combination with an evolutionary ridge regression approach (Olague and Hernández, 2005). The image measurements and camera calibration parameters, as well as the 3D CAD information, were given as input to the PND system detailed in this paper.

The manipulator in a hand–eye configuration was used to implement multiple network configurations. Figs. 9, 10 and 11 show the experiments that were carried out with the real-world system. Note that a minimum of four images is needed in the case of the 3D complex object used in the experiments in order to achieve redundant measurements for all object surfaces.

The first scenario consists of four images presenting weak convergence due to the reduced baseline separation among sensing viewpoints. The error ellipsoids are neither homogeneous nor isotropic as is shown by the rigorous photogrammetric approach. Fig. 10 improves this minimal configuration in terms of accuracy through the enhancement of network design. Note the improvement obtained in the uncertainty of the 3D measurements as a result of properly selecting the imaging geometry. This network provides an improved set of reconstructed error ellipsoids in terms of homogeneity and isotropy. However, to obtain a strongly convergent imaging geometry it is necessary to use a greater number of images in the network design. Fig. 11 shows a network design that was obtained with the EPOCA system considering 29 convergent images. The error ellipsoids depicted on Fig. 11 are significantly more homogeneous and isotropic than those presented in the previous minimal configurations. As

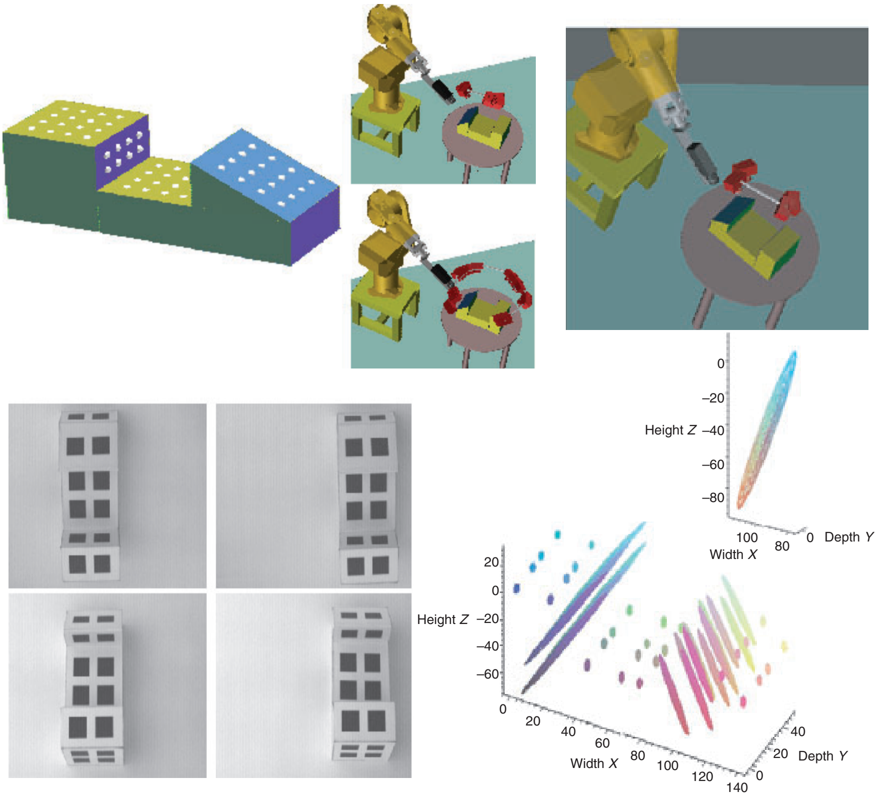


FIG. 9. Real-world experiments were conducted with the robotic facility and the camera planning system. Four images were acquired by a camera configuration presenting weak convergence.

a result of the approach proposed in this paper the computer processing time for running the simulation of 29 images was obtained in under 5 min, while the bundle adjustment to test the accuracy of 3D measurements was obtained in approximately 150 min. These computations were executed on a Pentium IV at 2·4 GHz with 512 MB of RAM running RedHat Linux 9.2.

In general the 3D measurements of the object features require a suitable set of intersection rays with strong convergence. The visibility constraint presents a conflict between convergence angle and data sufficiency that must be solved through the determination of an optimal imaging geometry. As the complexity of the object and the total number of images increases, the conflict to obtain the *optimal* design is magnified due to the high combinatorial aspects of the problem. In this paper, a practical evolutionary network design system has been presented that successfully addresses the conflicts inherent in PND.

CONCLUDING REMARKS

This paper has shown the practical development of a PND using concepts from computer vision, close range photogrammetry and evolutionary computing. This work has presented an additional step towards a general approach to solve the PND due to the ability to measure complex objects (self-occlusion) with a large number of images in a reasonable amount of

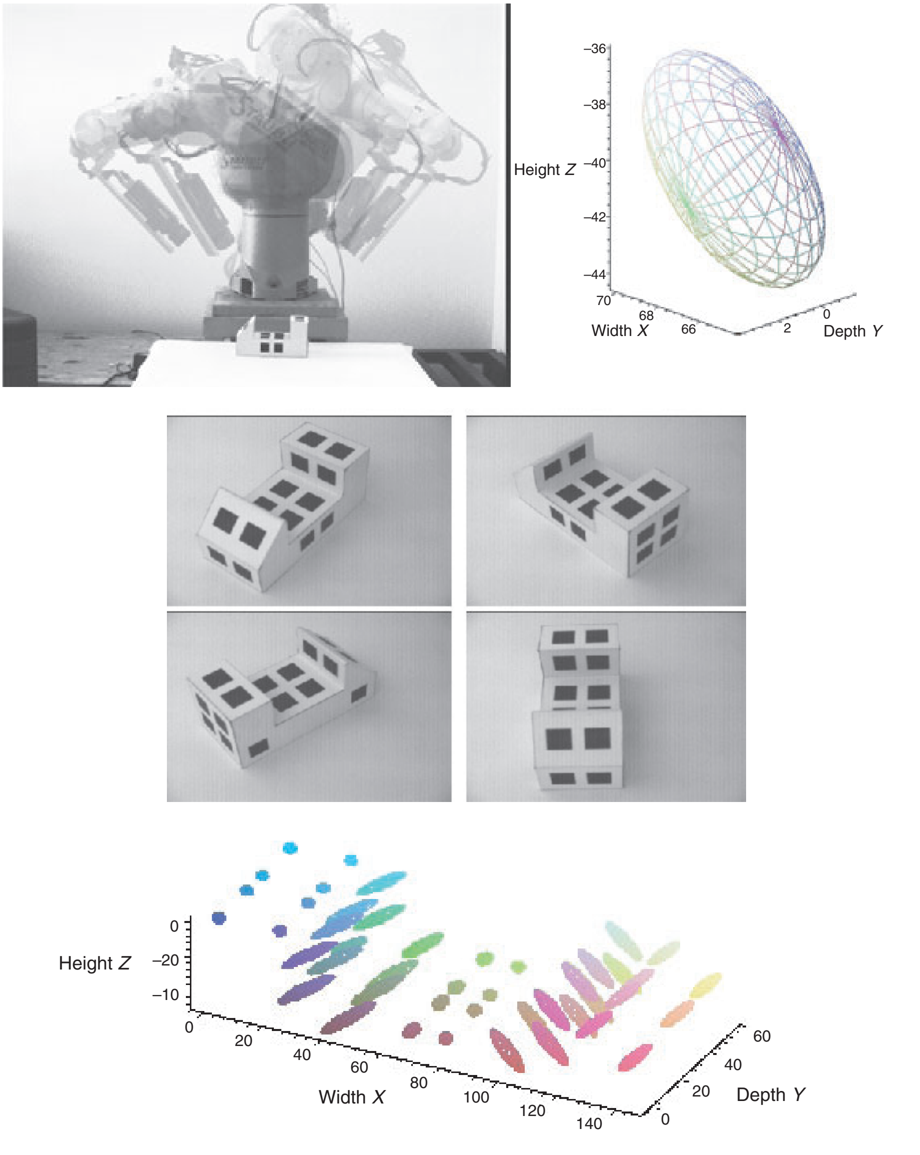


FIG. 10. The robotic infrastructure was used to test an improved network configuration of four convergent images, with a larger baseline separation among the sensing viewpoints. Due to self-occlusion some object features were not appropriately sampled.

time. Network design presents challenging problems produced by the non-linear set of equations, as well as the optical, visibility and environmental constraints. These problems are logically incorporated into the evolutionary computing strategy reported in this work, through a simulation and a practical system working on a real robotic facility. The strategy reported in this paper provides the ability to adapt the system according to the complexity of the problem

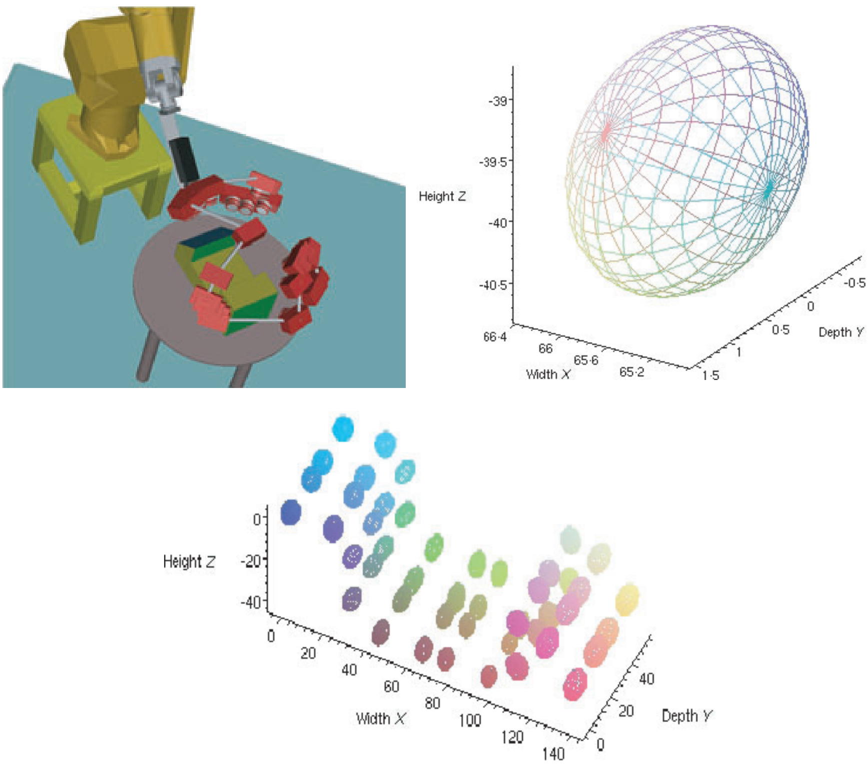


FIG. 11. A strongly convergent network of 29 images was obtained with the simulation-based approach. The design generated by EPOCA was tested with the robotic facility to obtain the (scaled) error ellipsoids.

to produce a suitable multi-image configuration for each new inspection task. Future research will be focused on the operational aspects and the reliability of network design.

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Résumé

Lorsque l'on conçoit un réseau photogrammétrique on vise à son optimisation en ce qui concerne la précision de détermination des points de l'objet. Pour une configuration donnée, on améliore cette précision en ne retenant dans la compensation par faisceaux que les jeux de rayons perspectifs présentant les meilleures intersections. On montre dans cet article le chemin suivi pour réaliser en pratique un tel réseau en se servant d'un véritable système robotique. On conçoit d'abord ce réseau à base de simulation puis on l'intègre dans un système pratique de métrologie robotique. On obtient cette simulation par une recherche métaheuristique s'inspirant d'un paradigme de calcul évolutif. On utilise pour cela un critère analytique d'où sortira une conception de réseau de premier ordre dans une fraction du temps nécessité par le calcul évolutif qui lui se base sur une compensation rigoureuse par faisceaux. La combinaison de cette simulation algorithmique *évolutive avec une compensation réelle par faisceaux débouche directement sur la finalisation de ce réseau. Un exemple de conception d'un tel réseau photogrammétrique est fourni, accompagné des résultats obtenus dans un système complet.*

Zusammenfassung

Ein photogrammetrisches Netzdesign optimiert eine Netzwerkkonfiguration mit Hinblick auf die Genauigkeit von Objektpunkten. Diese Genauigkeit wird durch die Wahl der besten Schnitte von Strahlenbündeln in einer Blockausgleichung noch gesteigert. Ein Netzwerkdesign basierend auf Simulationen soll in ein reales Bildmesssystem integriert werden. Anhand eines Robotersystems wird dieser Ansatz für ein Netzdesign vorgestellt. Die Simulation wird über einen Suchprozess mit evolutionärer Metaheuristik realisiert. Der vorgeschlagene Ansatz benützt ein analytisches Kriterium für die Suche nach einem geeigneten Design erster Ordnung. Dies erfolgt in einem Bruchteil der Rechenzeit, die mit einem evolutionären Ansatz mit einer strengen Bündelausgleichung benötigt wird. Die Kombination einer evolutionären algorithmischen Simulation mit einer klassischen Bündelausgleichung stellt einen einfachen Ansatz für ein Netzdesign dar, der am Beispiel eines photogrammetrischen Netzes illustriert wird.

Resumen

El diseño de redes fotogramétricas implica un proceso de optimización de la configuración de la red en términos de exactitud de los puntos-objeto. Esta exactitud se mejora seleccionando el mejor conjunto de rayos que intersecan en un ajuste por haces. Este artículo explica el enfoque seguido en el diseño de una red práctica usando un sistema robótico real. El objetivo es integrar un diseño de redes basado en la simulación dentro de un sistema de metrología basado en la visión de una forma práctica. La simulación se lleva a cabo mediante una búsqueda metaheurística basada en poblaciones inspirada en el paradigma de computación evolutiva. El enfoque propuesto utiliza un criterio analítico para alcanzar un adecuado diseño de primer orden en sólo una fracción del tiempo de cálculo requerido por el algoritmo evolutivo utilizando un método riguroso de ajuste por haces. La combinación de una simulación basada en un algoritmo evolutivo con el afianzado ajuste por haces aporta un procedimiento directo para el diseño de redes. Se proporciona un ejemplo de diseño de red fotogramétrica para ilustrar el resultado de un diseño de red completo.

