Parisian Camera Placement for Vision Metrology

Enrique Dunn, Gustavo Olague

Centro de Investigación Científica y Educación Superior de Ensenada
División de Física Aplicada, EvoVisión Laboratory

Evelyne Lutton

INRIA - COMPLEX Team
Domaine de Voluceau BP 105 78153 Le Chesnay Cedex - France

Abstract

This paper presents a novel camera network design methodology based on the Parisian evolutionary computation approach. This methodology proposes to partition the original problem into a set of homogeneous elements, whose individual contribution to the problem solution can be evaluated separately. A population comprised of these homogeneous elements is evolved with the goal of creating a single solution by a process of aggregation. The goal of the Parisian evolutionary process is to locally build better individuals that jointly form better global solutions. The implementation of the proposed approach requires addressing aspects such as problem decomposition and representation, local and global fitness integration, as well as diversity preservation mechanisms. The benefit of applying the Parisian approach to our camera placement problem is a substantial reduction in computational effort expended in the evolutionary optimization process. Moreover, experimental results coincide with previous state of the art photogrammetric network design methodologies, while incurring in only a fraction of the computational cost.

Key words: , Camera Placement, Accurate 3D Reconstruction, Photogrammetric Network Design, Evolutionary Computation, Parisian Approach

Email addresses: {edunn,olague}@cicese.mx (Enrique Dunn, Gustavo Olague), Evelyne.Lutton@inria.fr (Evelyne Lutton).

1 Introduction

Planning a photogrammetric network with the aim of obtaining a high-accurate 3D object reconstruction is considered as a challenging design problem in vision metrology (1). This design problem offers an intricate combination of interactions between the sensor physical constraints, the mathematical modeling of the problem, as well as the numerical methods used to solve it (2),(3). Building on previous research on automated sensor placement, we develop a novel methodology for sensor placement based on the *Parisian* approach to evolutionary computation (EC). The Parisian approach of *individual evolution* considers that a single individual represents a partial solution to the considered problem. Hence, a process of aggregation of multiple individuals is needed in order to arrive at a solution. We incorporate such an approach to the camera network design problem by evolving a population of camera subnetworks. As a result, computational requirements are greatly reduced for individual fitness evaluation due to the reduced size of the total mathematical model. Parisian evolution is a complex optimization technique because multiple new aspects need to be considered in the evolutionary computation framework, such as: problem partitioning and representation, local fitness evaluation, global fitness evaluation and redistribution, population diversity preservation, and finally aggregation of individuals. In this paper, we attempt to combine widely accepted principals and techniques used in EC research. On the other hand, in the case of radical new concepts we provide a first solution based on the characteristics of the studied problem. Previous works have used what is called the Parisian approach. The work of Collet *et al.* (14) can be considered the first attempt to use the concept of individual evolution applied to the problem of iterate function systems within the domain of genetic programming. Louchet *et al.* (15) use also Parisian evolution for a problem of stereo vision, which could be seen as the first work in the evolution strategies domain.

Vision metrology addresses the attainment of accurate visual measurements from digital images. The choice of an adequate imaging geometry plays a major role in this process (1). The process by which the best possible configuration can be automatically determined, is still an open research area. Today, practitioners generally rely on heuristic means for making these crucial decisions. On the other hand, the problem of 3D reconstruction from multiple redundant image measurements is very well studied in photogrammetry and can be rigorously solved using iterative non-linear optimization techniques (5). Nevertheless, the lack of a widespread utilization of network design inside the photogrammetric community can be attributed to the inherent design complexity and its expensive computational requirements. Photogrammetric network design requires complex spatial reasoning about the geometrical characteristics of an object and the mathematical modeling of optical triangulation. This reasoning is by no means trivial and has been the topic of very diverse research.

For example, the work of Mason (6) solves the problem of camera placement by incorporating considerable *a priori* knowledge into an expert system. In this way, a set of heuristics based on the theory of *generic networks* is used to model the decision making process. On the other hand, the work of Olague and Mohr (9) uses an evolutionary computation approach, developing a criterion based on the error propagation phenomena, which was further extended considering a bundle adjustment (7). In this way, the required spatial reasoning is carried out by and adaptive system based on stochastic meta-heuristics that yield human competitive results. Recently, the work of Saadatseresht *et al.* (8) addresses the problem of improving an existing camera network by positioning additional sensing stations based on what they term "visibility uncertainty prediction modeling". This new modeling is based on the concepts of visibility uncertainty prediction and visibility uncertainty spheres. These concepts provide a mechanism to predict the visibility of current object target points in order to improve the overall certainty. All the above works give special attention to the usefulness of rigorous approaches such as bundle adjustment in order to characterize the quality of the photogrammetric network. In particular, the works of Fraser (4) and Olague and Mohr (9) have provided insight into how a mathematical modeling could be derived in order to simplify the network design. The aim of this work is to present a new network design simplification based on the numerical optimization approach. This work shows the ongoing development of the EPOCA sensor planning system and implements an evolutionary computation methodology based on the Parisian approach (10). This is accomplished in order to efficiently search the space of possible camera configurations while maintaining high-qualitative solutions of the photogrammetric adjustment process.

This paper is organized as follows. First we briefly introduce the quality criterion we have used to characterize a network configuration. Then, the paradigm of Parisian evolution is presented. A solution to the photogrammetric network design in terms of Parisian evolution is described together with implementation details about the problem partitioning, solution aggregation, individual fitness evaluation and diversity preservation techniques. Finally, experimental results are presented followed by discussion and conclusions.

2 Criterion for Accurate Reconstruction

Accuracy assessment of visual 3D reconstruction consists on attaining some characterization of the uncertainty of our results. The design of a photogrammetric network is the process of determining an imaging geometry that allows accurate 3D reconstruction. In order to estimate the 3D reconstruction error as a function of the disposition of multiple cameras, we will use an approach based on the error propagation phenomena as presented in (9). Under the pinhole camera model, each 3D point $P_i = (X_i, Y_i, Z_i)^t$, where $i = 1, \ldots, N$, is projected into an image point $p_{ij} = (u_{ij}, v_{ij})^t$ through a 3×4 projection matrix M_j, where $j = 1, \ldots, M$. This relationship is expressed by the collinearity equations

$$u_{ij} = \frac{m^j_{11}X_i + m^j_{12}Y_i + m^j_{13}Z_i + m^j_{14}}{m^j_{31}X_i + m^j_{32}Y_i + m^j_{33}Z_i + m^j_{34}}$$

$$v_{ij} = \frac{m^j_{21}X_i + m^j_{22}Y_i + m^j_{23}Z_i + m^j_{24}}{m^j_{31}X_i + m^j_{32}Y_i + m^j_{33}Z_i + m^j_{34}}$$

Using these equations, optical triangulation can be obtained solving a least squares system obtained from the projections of a 3D point in several images. In this way, given knowledge of each projection matrix M_j and the corresponding image measurements, we have a model of the form $P = f(p)$. Relying on the implicit function theorem, the covariance matrix ΛP of a 3D reconstruction can be obtained having knowledge of: 1) the 2D image measurement uncertainty Λp and, 2) a 3D reconstruction model from 2D image data of the form $P = f(p)$. Such relationship is stated as follows.

Proposition 2.1 *Given a random variable $p \in \mathbb{R}^m$, of Gaussian distribution, mean $E[p]$, and covariance Λp, and $P \in \mathbb{R}^n$, the random vector given by $P = f(p)$, where f is a function of class C^1, the mean of P can be approximated to a first-order Taylor expansion by $f(E[p])$ and its covariance by:*

$$\Lambda P = \frac{\partial f(E[p])}{\partial p} \Lambda p \frac{\partial f(E[p])^t}{\partial p}.$$

The 2D uncertainty Λp can be determined as a function of the incidence angle between the camera viewing direction and the surface normal of a 3D point. The function model of this phenomena in each image axis is obtained using experimental measurements of the projectively invariant cross-ratio. Multiple measurements of the cross-ratio for a set of collinear points were obtained varying the incidence angle of the observing camera. The resulting measurements were used for model fitting. The resulting model is given by the function

$$y = \beta \left(e^{\left(\frac{\alpha}{90-x}\right)} + e^{\left(\frac{\alpha}{90+x}\right)} \right) + \gamma,$$

where the best fit parameters are: α=79.74, $\beta = 1.31 \times 10^{-3}$, and $\gamma = 8 \times 10^{-3}$. Once an analytical expression for the reconstruction covariance matrix ΛP is obtained, in order to derive a criterion, a metric for comparing covariance matrices needs to be adopted. For this work, the maximum element of the main diagonal of ΛP was selected as our criterion:

$$f_1(M_j, p_i) = \max_{k=1\ldots3} \Lambda P_{kk} \tag{1}$$

The criterion presented above offers a highly discontinuous search space for imaging geometry. Moreover, the optimization method must take into account several interrelated constraints such as visibility, convergence angle and workspace limitations. However, optical constraints such as field of view, depth of field, resolution and image scale can be disregarded when deciding on imaging geometry. In this work, the cameras are placed according to the viewing sphere model, where viewing distance and camera's intrinsic parameter values can be determined *a priori* in order to fulfill the aforementioned optical constraints. On the other hand, the complexity is also due to the stochastic nature of the uncertainty assessment process which requires multiple redundant image measurements (11). Additionally, the dimensionality of our optimization problem increases with the number of desired sensing stations. Furthermore, the function landscape of our criterion is highly multi-modal. All the above aspects raise the need for a global optimization technique. The EPOCA system is an example of how evolutionary optimization has successfully addressed this problem (7). However, the computational burden of rigorous photogrammetric adjustments is still an open issue even for moderately sized networks due to the iterative and population based nature of EC techniques. It is in this respect that Parisian evolution becomes a viable alternative to improve our optimization approach.

3 The Parisian Approach: Evolutionary *Divide and Conquer*

The Parisian approach, originally proposed in (12), differs from typical approaches to evolutionary computation in the sense that a single individual in the population represents only a part of the problem solution. In this respect, it is similar to the Michigan approach developed for Classifier Systems (13), where a solution is a rule base obtained from an evolved population of individual rule subsets. Moreover, in this paradigm an aggregation of multiple individuals must be considered in order to obtain a solution for the problem being studied. Thus, the evolution of the whole population is favored instead of the emergence of only a single dominant solution. The motivation for such an approach is to make an efficient use of the genetic search process. This can be achieved from two different perspectives. First, the algorithm discards less computational effort at the end of execution, while considering more than a single best individual as output. Second, the computational expense of the fitness function evaluation is considerably reduced for a single individual.

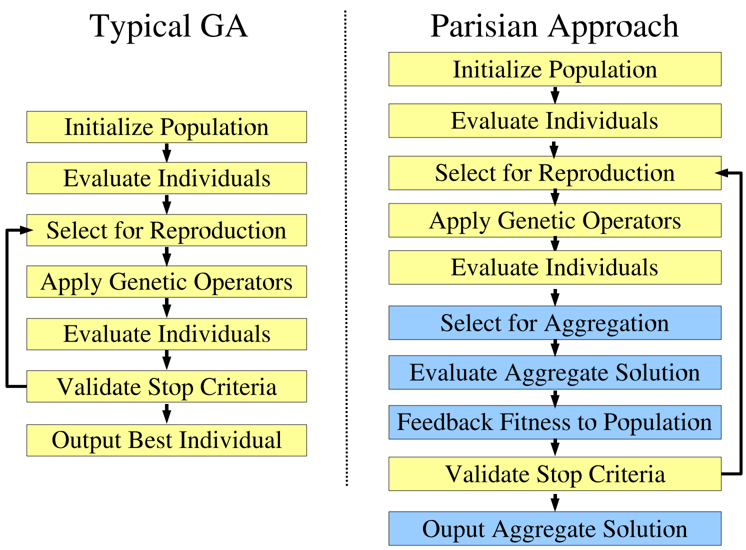

Fig. 1. Outline of our implementation of the *Parisian Camera Placement* approach. Fitness evaluation is modified in order to consider the local and global contribution of an individual.

Under the Parisian approach, many of the canonical aspects of evolutionary algorithms are retained, allowing for great flexibility in its deployment. From an algorithmic standpoint, Parisian evolution involves incorporating a set of specific heuristics to the fitness evaluation stage of an evolutionary algorithm, see Fig. 1. Accordingly, this approach can be adapted to encompass different evolutionary paradigms. However, the applicability of this approach is restricted to problems where the solution can be decomposed into homogeneous elements or components, whose individual contribution to the complete solution can be evaluated. Therefore, each implementation is necessarily application dependent, where the design of a suitable problem decomposition is determinant factor. Thus, the following implementation issues have been identified:

- **Partial Encoding**. The genetic representation used for a single individual encodes a partial solution.
- **Individual Aggregation**. A procedure by which a sample of a population, formed by partial solutions, is aggregated to form a complete problem solution.
- **Local Fitness**. A meaningful merit function must be designed for each partial solution. In this way, the worthiness of a single individual can be evaluated in order to estimate the potential contribution to an aggregate solution.
- **Global Fitness**. A problem defined merit function can be evaluated from a complete problem solution. However, the worthiness of this composite solution should be reflected on each partial solution.
- **Evolutionary Engine**. The evolution of the complete population should

promote the emergence of better aggregate solutions. The evolutionary engine requires a scheme for combining local and global fitness values. Also, it requires a diversity preserving mechanism in order to maintain a set of complementary partial solutions.

Successful examples of such an approach can be found in the image analysis and signal processing literature. The *Fly Algorithm* developed by Louchet *et al.* (15) is a real-time pattern recognition tool used in stereo vision systems. In such a work, the population is formed by individuals representing each a single 3D point. The evolutionary algorithm favors the positioning of each so called "fly" to a surface point in the observed scene using insightful problem modeling. The work of Collet *et al.*(14) incorporates the Parisian approach to the solution of the inverse problem for Iterated Function Systems (IFS). In this instance a Genetic Programming methodology was adopted and experimentation on 2D images presented.

In general terms, the Parisian approach makes the following assumptions:

(1) A complete problem solution $X \in S$ can be decomposed into n components $x_i \in S'$. Moreover, there exists a mapping $T : S' \times \ldots \times S' \to S$.
(2) There exists a meaningful merit function $f_{loc} : S' \to \mathbb{R}$ for evaluating each decomposed element.
(3) There exists a meaningful merit function $f_{global} : S \to \mathbb{R}$ for evaluating an aggregate solution.
(4) The fitness landscape defined by f_{loc} has sufficient structure to guide the evolutionary search process (i.e. if the problem solution is to be composed of a diverse set of components, then f_{loc} should provide a multi-modal function landscape).

Under these assumptions, evolutionary search is carried out over S' optimizing f_{loc}. However, the fitness values of the evolved individuals are systematically modified in order to promote the emergence of improved composite solutions in S. This is achieved by: 1) periodically sampling the evolving population to form aggregate solutions, 2) evaluating aggregate solutions through f_{global} and 3) adjusting the fitness values of the evolving individuals in S' accordingly. Figure 2 illustrates this process as well as the relationship between the different search spaces involved in the Parisian evolutionary approach. Depending on the interactions between f_{loc} and f_{global}, complex population dynamics can emerge.

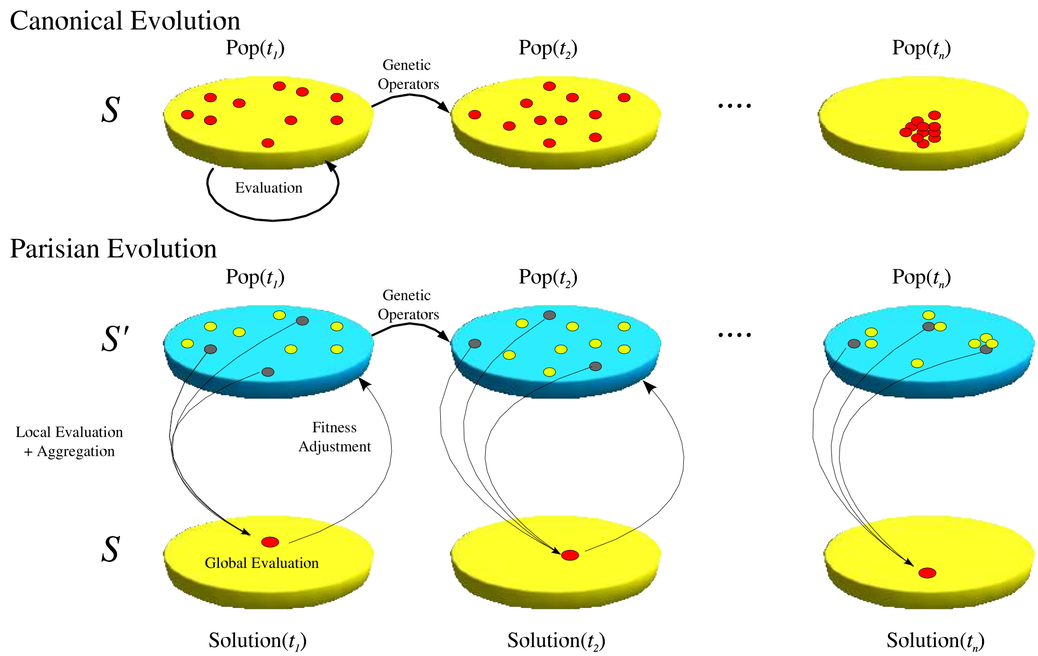

Fig. 2. Conceptual description of our Parisian Camera Placement approach. Interaction between different search spaces is based on adjusting the population fitness values in accordance to a global fitness evaluation.

4 Parisian Approach to Camera Network Design

Camera placement can be viewed as a geometric design problem where the control variables are the spatial positioning and orientation parameters of a finite set of cameras. In order to state such design problem in optimization terms the criterion expressed in section 2 is adopted. However, due to the sensor characteristics and mathematical modeling of the problem a strongly constrained optimization problem emerges. In this section we will discuss the different implementation issues involved in our incorporation of the Parisian approach into the camera placement problem.

4.1 Problem Partitioning and Representation

A viewing sphere model for camera placement is adopted in order to reduce the dimensionality of our search space. Therefore, given a fixed radius, each camera position is defined by its polar coordinates $[\alpha_i, \beta_i]$. A network of M cameras is represented by a real valued vector

$$\mathbf{\Psi} \in \mathbb{R}^{2M} \quad where \quad \alpha_i = \Psi_{2i-1}, \beta_i = \Psi_{2i} \quad for \quad i = 1, \ldots, M. \tag{2}$$

Our design problem allows the decomposition into individual elements since the complete camera network is formed by a set of homogeneous components. Nevertheless, a decision on the level of *granularity* of our decomposition is crucial. Here we have the choice of an individual representing a single camera or a camera subnetwork (i.e. a set of cameras). We have decided for the latter option since such an individual can be meaningfully evaluated in terms of its imaging geometry contribution to 3D reconstruction. Hence, each individual in the population represents a fixed size subnetwork of N cameras, denoted by a vector of the form

$$\psi^j \in \mathbb{R}^{2N} \quad where \quad \alpha_i = \psi^j_{2i-1}, \beta_i = \psi^j_{2i} \quad for \quad i = 1, \ldots, N. \tag{3}$$

where j is defined as the subnetwork population index. Accordingly, a complete camera network specification is given by the aggregation of J subnetworks

$$\mathbf{\Psi} \in \mathbb{R}^{2M} = \bigcup_{j=1}^{J} \psi^j, \quad where \quad M = J \times N \tag{4}$$

4.2 Local Fitness Evaluation

Section 2 presented a photogrammetric approach for estimating the variance of 3D point reconstruction using redundant measurements, see Eq. (1). Such methodology is generally applied to the complete measured object considering all cameras concurrently. Since in our representation we are working with camera subnetworks, it is unlikely that any single individual successfully captures the complete 3D object denoted by the whole set of 3D points $\mathbf{P}$. Hence, the object is also partitioned into R disjoint regions or subsets of points, in such a way that $\mathbf{P} = \bigcup_{i=1}^{R} P_i$. A single region of the object is considered visible by a camera network if at least two cameras capture it (i.e. there are no occlusions) and for each of these cameras the incidence angle constraint for 3D reconstruction is satisfied. Hence, the visibility of a camera subnetwork ψ^j is limited to a subset of the whole object, expressed by $\mathbf{V}(\psi^j) \subseteq \mathbf{P}$. These values are calculated *a priori* and stored in a database for on-line query during the optimization procedure. Accordingly, we define the visibility constraint in the form

$$C_{vis}(\psi^j, P_i) = \begin{cases} 1 & \text{if } P_i \subset \mathbf{V}(\psi^j) \\ 0 & \text{otherwise .} \end{cases}$$

Local fitness evaluation uses the idea of decomposing the problem in subnetworks which provide greater object coverage with higher precision in order to attain higher fitness values. Hence, the uncertainty for each of the sets P_i is evaluated for a single individual ψ^j accordingly to Equation (1), discarding the portions of the object not sensed by such a subnetwork. In order to reward camera subnetworks that provide greater coverage, the local fitness value is proportional to the number of data points sensed by that subnetwork, which is expressed as $\#[\mathbf{V}(\psi^j)]$. Thus, we define this fitness as

$$f_{loc}(\psi^j) = \frac{\#[\mathbf{V}(\psi^j)]}{\max f_1(\psi^j, P_i)} \quad \forall P_i : C_{vis}(\psi^j, P_i) = 1. \tag{5}$$

Here, $f_1(\psi^j, P_i)$ represents the 3D reconstruction uncertainty of a given region P_i, under observation by a subnetwork parametrized by ψ^j. Note that $f_1(\psi^j, P_i) > 0$, $\forall P_i : C_{vis}(\psi^j, P_i) = 1$. In the cases were an individual network does not cover any object region, its fitness is simply set to $f_{loc}(\psi^j) = 0$.

4.3 Global Fitness Evaluation

Once the local fitness of each individual has been evaluated, a process of aggregation is needed to obtain a solution to our camera network design problem. In order to achieve this, a *selection* of a group of individuals from the population must be made, see section 4.6 for details. Accordingly, at each generation t an aggregate solution $\mathbf{\Psi}(t)$ is obtained for global fitness evaluation. This global evaluation uses the same criterion in local fitness evaluation. Therefore, we obtain:

$$f_{global}(\mathbf{\Psi}(t)) = \frac{\#[\mathbf{V}(\mathbf{\Psi}(t))]}{\max f_1(\mathbf{\Psi}(t), P_i)} \quad \forall P_i : C_{vis}(\mathbf{\Psi}(t), P_i) = 1. \tag{6}$$

Such value describes the aptitude of the aggregate solution obtained at generation t. Note that here we also have $f_1(\mathbf{\Psi}(t), P_i) > 0$. On the other hand, aggregate networks which do not provide complete object coverage are penalized with $f_{global}(\mathbf{\Psi}) = 1$.

Obviously the goal of the algorithm is to foster the improvement of this global fitness along the course of successive generations. However, another purpose of this evaluation is to be able to reflect on the population the effect of the evolutionary process. The individuals that form part of the aggregate solution will be rewarded or punished based on its global fitness. Also, based on the complete solution characteristics, promising individuals not selected should be compensated so they might contribute in latter stages of the evolutionary process.

4.4 Global Fitness Redistribution

A valid solution to the network design problem is one that reconstructs accurately the complete object. An optimal solution is one that provides the best possible reconstruction accuracy. Under the Parisian approach this solution is formed by aggregating multiple individuals from an evolving population. Hence, individuals that contribute to attaining and improving valid solutions should be favored in the evolution process. This requires addressing the aspects of function optimization and constraint satisfaction. In this subsection we shall describe how global fitness evaluation is used to deal concurrently with both of these issues.

Our approach consists in periodically adjusting the local fitness values of individuals in the population based on the results of global fitness evaluations. In particular, the local fitness value of a single individual is incremented or decremented (as the case may warrant) in consideration of aspects such as: global fitness values of the aggregate solution, local fitness values of other individuals as well as the individual's potential for improving the aggregate solution. This is achieved by defining two different local fitness adjustment functions, one to promote global fitness optimization and another to promote global constraint satisfaction.

Function optimization will be addressed first. In order to reflect the quality of an aggregate solution $\mathbf{\Psi}(t)$ on each of the individuals ψ^j that compose it, we use the ratio of improvement in global fitness among successive generations. The magnitude of the adjustment of an individual's local fitness is proportional to this ratio as follows

$$g_1(\psi^j) = f_{loc}(\psi^j)\left[\frac{f_{global}(\mathbf{\Psi}(t))}{f_{global}(\mathbf{\Psi}(t-1))} - 1\right] \qquad \forall \psi^j \in \mathbf{\Psi}(t). \tag{7}$$

Now we shall consider constraint satisfaction. It is very likely that each individual subnetwork will only cover part of the object. It is also possible that a given aggregation of individuals will not provide full object coverage. In this respect, when a particular aggregate solution $\mathbf{\Psi}(t)$ does not cover some object region P_i (e.g. $C_{vis}(\mathbf{\Psi}(t), P_i) = 0$) it would be desirable to enhance the fitness value of those individuals on the population that indeed cover such region. The amount of enhancement of those individuals shall be proportional to their difference in fitness with respect to the best individual in the population. Hence, we have

$$g_2(\psi^j) = f_{loc}(\psi^{best}) - f_{loc}(\psi^j) \qquad \forall \psi^j : \mathbf{V}(\psi^j) \bigcap \overline{\mathbf{V}(\mathbf{\Psi}(t))} \neq \emptyset. \tag{8}$$

Note that this value is only calculated for those individuals that cover an object region not sensed by the aggregate solution formed at that generation.

Once both fitness adjustment functions are calculated, the global fitness is "fed-back" to the general population as follows:

$$f_{loc}(\psi^j) = \begin{cases} f_{loc}(\psi^j) + \lambda_1 g_1(\psi^j) & \text{if } \psi^j \in \mathbf{\Psi}(t) \\ f_{loc}(\psi^j) + \lambda_2 g_2(\psi^j) & \text{if } \mathbf{V}(\psi^j) \bigcap \overline{\mathbf{V}(\mathbf{\Psi}(t))} \neq \emptyset \\ f_{loc}(\psi^j) & \text{otherwise .} \end{cases}$$

Here, λ_1 and λ_2 are user defined parameters that reflect the relative importance given to each of the aspects involved in the global fitness redistribution.

4.5 Population Diversity Preservation

Maintaining a diverse set of individual solutions is a pre-requisite for our implementation of the Parisian approach. This is made more evident since our search for an optimal configuration is developed over a highly multi-modal space. In this work, the fitness sharing scheme is adopted (17). In this way, the fitness of an individual is adjusted by

$$f'_{loc}(\psi_j) = \frac{f_{loc}(\psi_j)}{\sum_{i=1}^{K} sh(\psi_i, \psi_j)}, \; where \; sh(\psi_i, \psi_j) = \begin{cases} 1 - \frac{\|\psi_i, \psi_j\|}{\sigma_{sh}} & \text{if } \|\psi_i, \psi_j\| < \sigma_{sh} \\ 0 & \text{otherwise .} \end{cases}$$

Since our individuals represent sets of spatially distributed cameras, the chosen metric was the Hausdorff distance. This metric is defined for our problem by

$$\|\psi_i, \psi_j\| = h(\psi_i, \psi_j) = \max_{a \in \psi_i} \{ \min_{b \in \psi_j} \{ d(a, b) \} \},$$

where a, b represent the 3D positions of each camera in a given network and $d(a, b)$ is the Euclidean distance among points. Geometrically, this metric expresses the maximum distance of a set to the nearest point in the other set. Based on such geometrical interpretation we can empirically define an appropriate sharing radius σ_{sh}. A related issue is the choice of a selection operator during evolution. One has the choice of using either ranking based selection or fitness proportional selection. It has been reported that tournament selection, is not adequate for fitness sharing approaches to multi-modal optimization due to the high selection pressure (16) . Hence, in our approach we use a stochastic remainder selection operator. This choice is also justified by the fact that we use proportional fitness adjustment during global fitness redistribution (see previous subsection).

As previously mentioned, at each generation a set of individuals is selected from the population in order to form a composite solution by means of aggregation. The manner by which such selection is carried out reflects directly on the quality of the solutions obtained by our approach. Moreover, such a procedure can be viewed as taking a sample of individuals from the population. A brute force approach which evaluates every possible combination of individuals is discarded from consideration due to its computational cost. Another alternative would be that of having a procedural mechanism by which a composite solution is incrementally built from the available population. This is in principle similar to incorporating local search in evolutionary techniques (e.g. memetic algorithms) and is necessarily application dependent. A more general approach is to use the individuals fitness values to influence the aggregation mechanism. In such a case we have the choice of either deterministic (i.e. elitist) or stochastic (i.e. roulette, tournament) selection procedures. In order to make such decision, the characteristics of the diversity preservation method must be taken into account. Fitness sharing mechanisms attempt to form and maintain clusters of individuals over each of the multi-modal function's local maxima (or minima as the case may be). The number of elements in each of this maxima should be proportional to it's magnitude. Hence, the selection of the best J individuals from the population is likely to produce very similar individuals (belonging to the same cluster), even for a well distributed population. Under such scenario, a clustering technique would be desirable in order to properly identify each local maxima for consideration into the aggregate solution (14). To avoid such calculations we have implemented the following simple procedure:

```
for i=1 to J
   Select the Best Individual in the Population
   Eliminate all Individuals whithin the Sharing Radius
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Naturally, special considerations need to be taken for the case where the population doesn't provide enough diversity for selecting J different individuals. However, this procedure takes advantage of the fact that distances among individuals have already been calculated in the fitness sharing stage. Heuristic provisions can be made to ensure that the selected individuals are maintained across several generations. This would correspond to elitist selection in typical genetic algorithms.

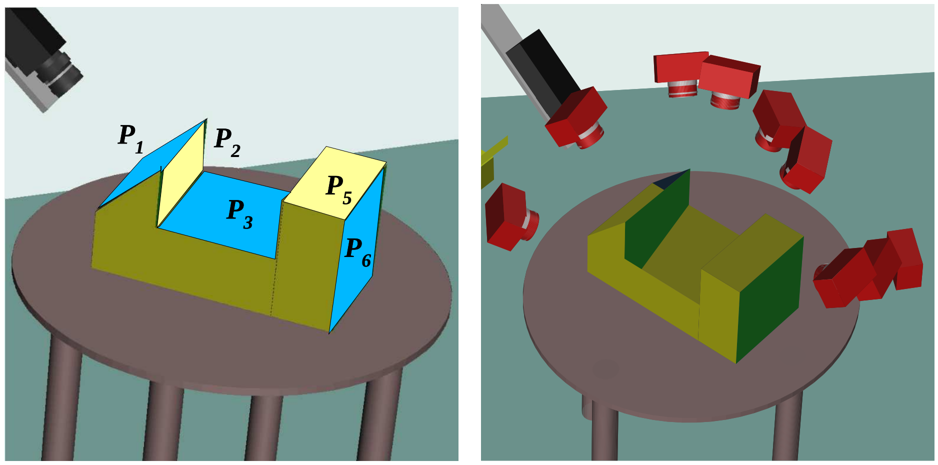

Fig. 3. The 3D object under observation. The concave object is partitioned into different regions in order to facilitate the fitness evaluation of sub-networks of small size. A photogrammetric network formed by 9 cameras is illustrated on the right.

5 Experimental Results

The reconstruction of a complex 3D object is considered in our experimentation. The goal is to determine a viewing configuration that will offer optimal results in terms of reconstruction accuracy. Here, we shall consider the design of a fixed size camera network of $M = 9$ stations. According to our approach, the level of granularity of our problem decomposition needs to be established. For these series of experiments we will use camera subnetworks of $N = 3$ cameras. In this way, each of the individuals in the population will consist of a vector $\psi \in \mathbb{R}^6$. Hence, a total of $J = 3$ subnetworks will need to be aggregated in order to form a complete solution to our network design problem. The convex polyhedral object under study, depicted in Figure 3, is partitioned into $R = 6$ regions. The selection of individuals for solution aggregation is based on their fitness value. Finally, the user defined valued λ_1 and λ_2 are set to $\lambda_1 = \lambda_2 = 1.0$ For all our experiments, SBX-crossover is utilized with a probability $P_c = 0.95$ along with polynomial mutation subject to $P_m = 0.05$. A sharing radius of $\sigma_{sh} = 0.75$ was utilized.

5.1 Algorithm Performance

We have used stochastic remainder selection for reproduction under generational replacement. Alongside of our methodology, the same global fitness function was optimized by a typical genetic algorithm (e.g. each individual encodes a complete solution). This was done in order to have some reference point in the assessment of our proposed methodology. Using a population of 30 individuals, both evolutionary algorithms were executed for 100 generations.

Figure 4 plots population performance measures (best, mean, worse fitness)

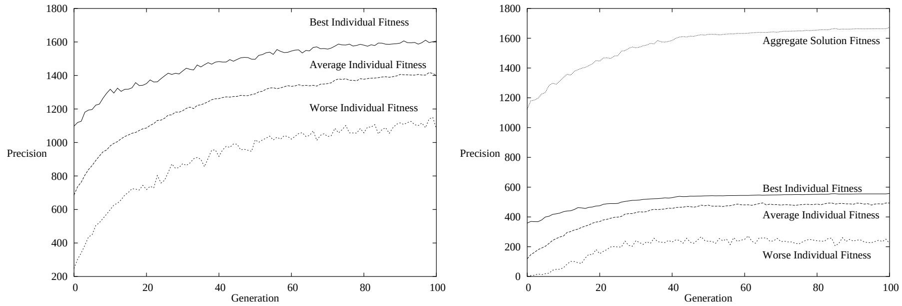

Fig. 4. Performance Comparison. On the left, the population evolution of a typical genetic algorithm is depicted. On the right, higher fitness values are consistently attained by the aggregate solutions of our proposed methodology. Plotted values reflect the averages over 20 executions with $\lambda_1 = \lambda_2 = 1.0$.

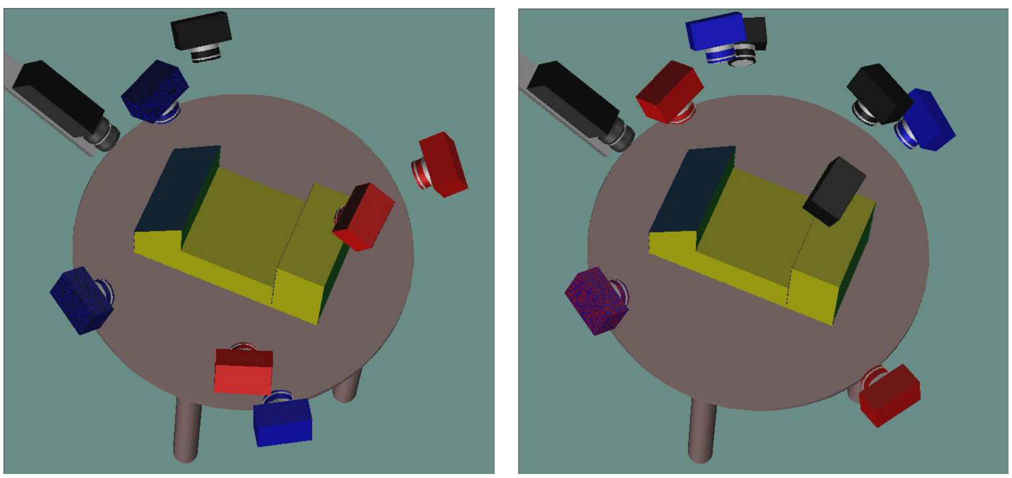

Fig. 5. These images show different imaging geometries obtained by our approach, which represents the best solutions found at different executions of our algorithm. Membership to a given subnetwork is depicted by camera color.

for a canonical GA on the left and also for our Parisian approach on the right. While these measures are descriptive of the dynamics of our population, the importance is on the *aggregate solution fitness* measure. In this respect, our approach slightly outperforms a canonical methodology in terms of solution quality. However, these results are made more relevant when considering the computational cost involved in fitness evaluation. For our studied object, evaluation based on criterion (1) of a complete network of 9 cameras is over 15 times more costly than that of a 3 camera subnetwork. Accordingly, by virtue of our problem decomposition, the total **execution time of the algorithm is reduced 10 times**. Clearly, a significant benefit in performance has been achieved.

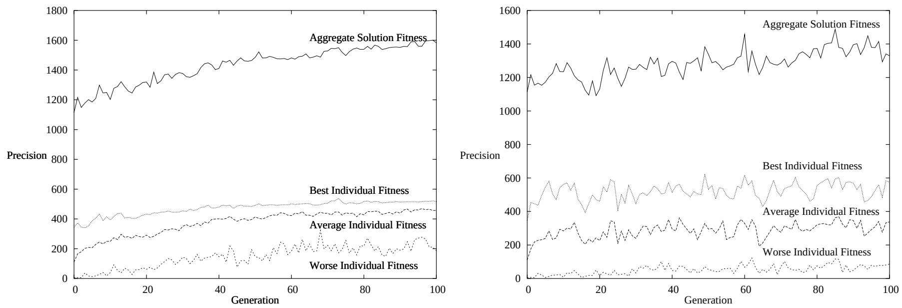

Fig. 6. Dependence on parameters λ_1, λ_2.The plot on the left corresponds to an execution with mixing values $[\lambda_1 = 0.8, \lambda_2 = 0.2]$. Performance is slightly deteriorated.The plot on the right represents an execution with values $[\lambda_1 = 0, \lambda_2 = 1.5]$. Note the almost random algorithm performance.

5.2 Imaging Geometry Configurations

Analysis and comparison among the best configurations found by our algorithm are comparable with the geometrical distributions reported in (7). Figure 5 depicts two of the configurations found by our algorithm. Note the geometrical similarities among both configurations. Each of these networks is composed of 3 subnetworks that are integrated by 3 cameras. Different color schemes depict the membership of each particular camera to a given subnetwork. These subnetworks correspond to a single individual in the population. In both configurations some of the cameras present mixed colors, indicating the composition of at least two cameras located in the same position. This corresponds to the Second Order Design stage in photogrammetric network design. The Parisian approach found similar geometrically configurations from an aggregation of distinct individuals in both cases. Nevertheless, the configuration on the right has an improvement of 4.2% on the fitness value in terms of precision. Such discrepancies illustrate the high non-linearity of our search space.

5.3 Parameter Setting

The choice of mixing values λ_1, λ_2 is an important aspect in the performance of the algorithm, as they determine the magnitude of the global fitness adjustment given to each individual. In order to exemplify such phenomena we have carried out different experiments varying the ratio and magnitude of these values. Experiments show a fairly robust behavior for similarly scaled values under 1.0. In general, performance deteriorates as magnitude and the ratio among parameters increases. The right plot of Figure 6 illustrates the scenario where constraint satisfaction is completely predominant over function optimization. As a result, the fitness value of aggregate solutions is decreased

Subnetwork Size	Best Fitness	Computational Speed-up
2	1666.43	29.72
3	1630.21	21.41
4	1310.84	11.48
6	1758.68	5.03
12	1702.05	1.0

Table 1
Results after 20 executions of our algorithm for different levels of granularity.

by weaker configurations that are unreasonably enhanced by the global fitness evaluations.

The level of granularity also plays a major role in the performance of our system. This is reflected in quality of our solutions as well as on the efficiency of our system. To illustrate this, the case of a 12 camera network is studied. Experiments for sub-networks of 2,3,4 and 6 cameras were carried out and results compared against a canonical evolutionary algorithm. For all experiments a population of 50 individuals was used. Also, mixing parameters where set to $\lambda_1 = \lambda_2 = 1.0$ and the sharing radius set to $\sigma_{sh} = 0.75$. The performance results after 20 executions are presented in table 5.4. The most accurate configuration was obtained by the canonical evolutionary approach. Among the results for different levels of decomposition by our Parisian approach, the results favor the choice of individual subnetworks of small size, as they give better fitness values along with the highest computational speed-up. The geometric disposition of these resulting camera networks is depicted in figure 7. While, in this scenario, the Parisian approach attained slightly lower fitness values than a canonical approach, note an almost **30 times reduction in execution time**. Again, a significant benefit in terms of performance has been achieved.

5.4 Problem Decomposition Granularity

6 Conclusions and Discussion

The Parisian approach to evolutionary computation offers an efficient way to address the problem of automated camera placement, while preserving the validity of photogrammetric procedures. In fact, by virtue of an adequate problem partition and decomposition, solution quality is improved with considerable reductions in computational effort for the considered scenarios. Future

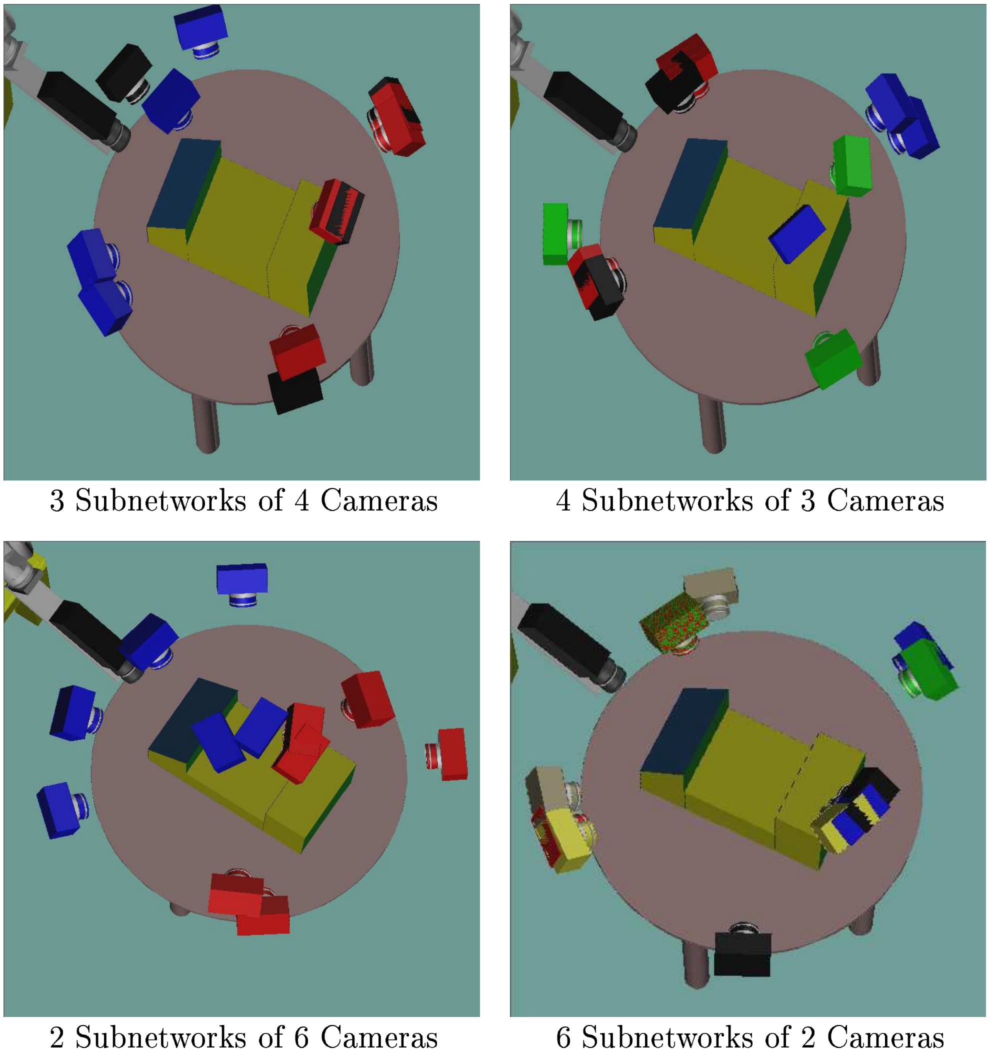

Fig. 7. Network configurations of 12 cameras with different levels of decomposition granularity.

work includes incorporating rigorous bundle adjustment procedures, where the computational savings should be even more dramatic. However, such research lines require careful considerations regarding Zero Order Design for photogrammetric networks, due to the need for a common datum in bundle adjustment procedures.

This work has developed an efficient optimization technique based an original conception of population based evolutionary optimum seeking. In particular, a novel application for the Parisian approach has been described and important application related aspects have been addressed. This work incorporated canonical evolutionary principals in order to achieve the goal of evolving a solution based on the evolution of its components. While promising experimental results are obtained, a lack of theoretical principals describing the algorithm behavior is still pending as in general evolutionary algorithms. Nevertheless, there are many specialized evolutionary approaches that could be used in conjunction with our proposed methodology, such as parallel evolutionary algorithms, co-evolution techniques or even multi-objective evolutionary algorithms.

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