Parisian Evolution with Honeybees for Three-dimensional Reconstruction

Gustavo Olague
EvoVisión Project, Computer Science Department
Applied Physics Division
CICESE, Mexico
olague@cicese.mx

Cesar Puente
EvoVisión Project, Computer Science Department
Applied Physics Division
CICESE, Mexico
puente@cicese.mx

ABSTRACT

This paper introduces a novel analogy with the way in which honeybee colonies operate in order to solve the problem of sparse and quasi dense reconstruction. To successfully solve increasingly complex problems, we must develop effective techniques for evolving cooperative solutions in the form of interacting coadapted subcomponents. A new adaptive behavior strategy is presented based on the "divide and conquer" approach used by the honeybee colony to solve search problems. The general ideas that explain the honeybee behavior are translated into a computational algorithm following the evolutionary computing paradigm. Experiments demonstrate the importance of the proposed communication system to reduce dramatically the number of outliers.

Categories and Subject Descriptors

I.2.10 [**Artificial Intelligence**]: Vision and Scene Understanding—*3D/stereo scene analysis, modeling and recovery of physical attributes, perceptual reasoning*; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*coherence and coordination.*

General Terms

Algorithms, Experimentation, Performance, Theory.

Keywords

Evolution Strategies, Evolutionary Computer Vision, Honeybee Search Algorithm.

1. INTRODUCTION

This paper presents a metaphor based on honeybee colonies that was applied to the problem of three-dimensional modeling. The problem of three-dimensional modeling is posed as a search process in which the cooperative coevolutionary behavior of honeybees is simulated with an evolutionary algorithm. Cooperative coevolution is implemented from the standpoint of individual evolution. The communication system of the honeybee colony allows an interactive process with a complex symbolic system that is achieved through the dance language. In fact, the honeybee dance language has been called one of the seven wonders of animal behavior and is considered among the greatest discoveries of behavioral science [5]. Moreover, their capacity to self-organize the colony to solve a number of tasks of increasingly complexity is shown on their ability to specialize the individuals for an optimal division of the work. In this way, a cooperative coevolutionary approach is applied based on the individual insect capacities and their communication system. Our work mimics this complex behavioral strategy using the principles of cooperative cooevolution of the Parisian evolutionary computational approach [4, 9].

This work could be considered as part of a more general research area called swarm intelligence. The major emphasis in swarm intelligence is to design adaptive, decentralized, flexible and robust artificial systems, capable of solving problems through solutions inspired by the behavior of social insects [1]. Research in the field has largely been focused on the working principles of ant colonies and how to use them in the design of novel algorithms for efficiently solving combinatorial optimization problems. The fundamental difference with our approach is that in ant algorithms, as well as in most computational intelligence approaches such as: evolutionary algorithms, tabu search, simulated annealing, etc.; each individual represents a complete solution to the problem. For example, in the ACO that is commonly used to solve the TSP, each ant attempts to find the shortest path. In contrast in the Parisian approach the individual should find only a part of the shortest path and a process of aggregation should group a suitable solution. In general, honeybee colonies, as social insects, follow a strategy where explicit notions of modularity are applied to provide reasonable opportunities for solutions to evolve in the form of interacting coadapted subcomponents. In the cooperative coevolutionary framework [26] two main aspects are reported by which traditional computational intelligence approaches are not entirely adequate for solving complex problems with high interactions between population members. Firstly, classical evolutionary approaches have a strong tendency to converge into a single solution in response to an increasing number of trials being allocated to observed regions of the solution space with above average fitness. As a result, computational effort is wasted in the search of a single solution. Secondly, individuals encoded by traditional computational intelligence approaches typically represent complete solutions that are evaluated in isolation. In this way, the interactions between population members are not modeled; and as a result, there is no evolutionary pressure for coadaptation to occur.

This work presents a novel strategy based on the individual evolution paradigm using the honeybee search strategy in which reasonable subcomponents "emerge" rather than being hand designed. Parisian evolution provides the key concepts to allow an adequate framework to identify and represent such subcomponents, provide an environment in which they can interact and coadapt, identify local and global fitness evaluations, and create mechanisms for population diversity preservation, in which the honeybee system could be applied to solve the difficult problem of three-dimensional reconstruction. A first attempt to apply the Parisian approach to the problem of three-dimensional scene modelling was reported in the work of Louchet [18, 3, 19] in which an individual evolution strategy was applied to obtain a three-dimensional model of the scene using stereo-vision techniques. The main characteristic of that work was the idea of applying the Parisian approach to the evolution of a population of 3D points, called flies, in order to concentrate those points on the object surface of the scene. The main drawback of that first attempt was the lack of applying the concepts of population interaction and coadaptation, as well as the identification of local and global fitness evaluations. Indeed, a high number of outliers were produced with their technique due to the overlook of these aspects. Moreover, the omission of these concepts produce a shortcoming of the paradigm to provide those 3D points with intelligent capabilities. We decide to explore the honeybee search behavior in order to develop an intelligent algorithmic process. Honeybees are considered to perform one of the most complex communication tasks, in the animal world. Indeed, concepts of memory attention, recognition, understanding, interpretation, agreement, decision-making, and knowledge, as well as questions about cognition and awareness, have appeared regularly in the honeybee literature. In this way, the honeybees are considered to achieve mental tasks like remembering, recognizing, searching, finding, understanding, and even disbelieving. All of these tasks are considered major subjects in computer vision and we believe that an algorithm inspired from the honeybee behavior could provide new insights in old problems not yet solved.

This paper is organized as follows: Section 2 introduces the honeybee search process in terms of the parisian evolutionary approach. Section 3 poses the problem of three-dimensional modeling. Section 4 provides an insight into the honeybee dance language and how these social insects are organized to perform complex behaviors. Section 5 explains the algorithm that we are proposing in this paper. Finally, section 6 provides a set of experiments to illustrate the capacity of the algorithm with real problems.

2. COOPERATIVE COEVOLUTION THROUGH HONEYBEE SEARCH

Parisian evolution originally proposed in [4], differs from typical approaches of evolutionary computation in the idea that a single individual of the population represents only a part of the solution. It is similar to the Michigan approach developed for Classifier Systems [17], where a solution is a rule base obtained from an evolved population of individual rule subsets. In this paradigm an aggregation of multiple individuals should be considered in order to obtain a solution to the problem being studied. This aggregation could be explicit or implicit. The motivation of such approach is to make an efficient use of the genetic search process. This is achieved from two complementary standpoints. Firstly, the algorithm discards less computational effort at the end of execution, while considering more than a single best individual as output. Secondly, the computational expense of the fitness function evaluation is considerably reduced for a single individual. The Parisian approach could be stated as cooperative coevolution with the aim to be applied in the general context of computational intelligence. The major difference with traditional cooperative coevolution is on the way of organizing the individuals. In traditional cooperative coevolution the individuals are divided in species that are genetically isolated. In other words, individuals only mate with other members of their species. Mating restrictions are enforced simply by evolving the species in separate populations. The only feedback is through a share domain model which produce a cooperative relationship. Contrary to this way of setting the framework for cooperative coevolution; the Parisian approach uses the idea of individual evolution to promote the exchange of genetic material based on the local and global fitness evaluations. This allows the coevolution of complex behaviors. However, as we will observe in our work those two viewpoints are not necessarily isolated, separated, or in conflict. Indeed, we decide to implement the idea of separate populations in the honeybee search algorithm in order to achieve the population interaction and coadaptation. It mimics the principle of individual specialization for an optimal division of the work found in honeybees. Under the Parisian approach, many of the canonical aspects of evolutionary algorithms are retained, providing great flexibility in its deployment. From an algorithmic viewpoint, Parisian evolution needs four aspects in their design which are implemented with different meta-heuristics. The reader should be aware that as other meta-heuristic approaches there are not mathematical models, which could yield the optimal parameter setting in each situation. Therefore, we decide to obtain the best set of parameters of our algorithm through statistical experimentation. Thus, Parisian evolution should consider the following aspects:

1. *Partial Encoding.* This is the fundamental concept that is need in cooperative coevolution. The genetic representation is achieved through a number of single individuals that encode a partial solution. Therefore an individual aggregation step is necessary in order to create a complete problem solution. This process of aggregation could be explicit or implicit according to the problem being studied. This concept provides the strength to decompose the problem by determining an appropriate number of subcomponents and the role that each subcomponent will play. In general the aggregation step has been defined by the human designer due to the difficulty of providing mathematical solutions. In the honeybee algorithm each honeybee represents a social insect as a three-dimensional point. Obviously, a single point is not enough to model a three-dimensional scene.

2. *The Environment*. The design of the system should provide an environment where different partial solutions interact and coadapt in order to allow the emergence of better aggregate solutions. Obviously, such a design interdict the evolution of subcomponents without interdependencies, in order to avoid the evolution of isolate subcomponents. In the honeybee search algorithm the scene where the artificial insect (three-dimensional point) is moving represents the landscape in which complex interdependencies and interactions emerge.

3. *Local and Global 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. The evolutionary engine requires a scheme for combining local and global fitness values. This could be explicit or implicit. In the honeybee search algorithm the worthiness of the final 3D model is a product of the interactions between the global evaluation, carried out by the explorers, and the local evaluation, carried out by the foragers, steps.

4. *Population Diversity Preservation*. In contrast to traditional computational intelligence approaches where diversity needs to be preserved only during enough time to perform a reasonable exploration of the search space; a cooperative coevolutionary approach requires that all subcomponents should be present in the final solution. In this respect, diversity preservation techniques need to be implemented. In evolutionary algorithms three different techniques could be applied: 1) heuristic modification of genetic operators in order to promote diversity, 2) fitness function penalization for crowded individuals, and 3) incorporation of some higher level algorithmic structure to generate and manage sub-populations. In this work, we apply the fitness sharing scheme [13].

3. STATEMENT OF THE PROBLEM

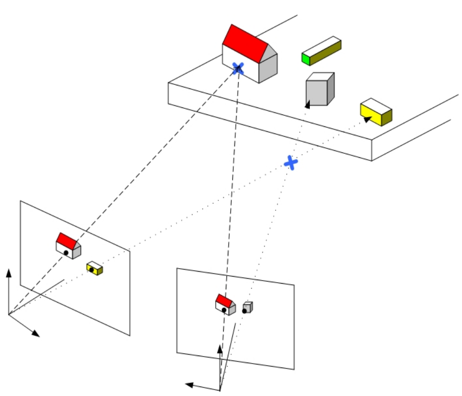


Figure 1: The fitness function of the honeybees' explorers is composed of two main criteria: 1) The contour information obtained with the sobel operator, and 2) The correlation between both images to estimate if the bee is posed on a surface.

Three-dimensional reconstruction has always been a fundamental research topic in computer vision and photogrammetry. Today the importance of image and vision computing tasks have gained relevance in the evolutionary computing community [25]. This paper proposes a bioinspired approach to tackle the problem of sparse and quasi-dense reconstruction using as model the honeybee search behavior. A common approach to obtain information about the three-dimensional world from digital cameras is performed with geometric knowledge about the scene and the images. The geometric relationships are translated into algebraic expressions that allow the computation of the 3D scene. The reconstruction that is obtained is related to the kind of scene knowledge that is used during the algorithmic process in what are known as the calibrated and uncalibrated approaches [14]. However, a major unsolved problem is related to finding the point correspondences among the scene and the images. The complexity of image acquisition, image size, feature extraction, and camera placement to mention but a few aspects that have driven the attention to study the problem considering specific cases. Here, we are interested in computing a sparse and quasi-dense stereo reconstruction using the honeybee's behavior. Normally, researchers attempt to obtain the 3D reconstruction from image correspondences using several stages. First, the fundamental matrix is computed from few and very reliable features points. Then, the 3D reconstruction is obtained with a triangulation stage in which the 3D model of the scene is produced as a sparse (with very few points), quasi-dense (with a bigger number of triangulated points), and finally a dense reconstruction (with all possible corresponding points). The reconstruction that is normally a projective reconstruction is further enhanced to provide metric information and a kind of bundle adjustment is performed to eliminate errors [27]. A different approach is to work directly from the projection matrix that models the transformation from the scene to the image, and this could be thought as a direct approach. The source of errors could produce misleading results on the calculation if not enough care is taken [23]. To eliminate those errors it is necessary to apply the best possible algorithm in the calculation of the projection matrix [20, 21]. The problem in this work is posed as a search process in which the 3D points are searched using the directed approach of projecting those points into the left and right images of a stereo pair instead of looking through the epipolar geometry. This idea represents a straightforward approach in which a 3D point with coordinates (X, Y, Z) on the Euclidean world is projected into two 2D points with coordinates (x_l, y_l) for the left camera coordinate system and (x_r, y_r) for the right camera coordinate system, see figure 1. A measure of similarity is computed with the *Zero Normalized Cross-Correlation* (ZNCC) and the image gradient is used to decide if both image points represent the same 3D point.

4. THE HONEYBEE DANCE LANGUAGE

Currently, most scientists in the honeybee behavioral community agree that the communication system of the bees is a language regarding insect capacities [5, 2, 10, 12]. The honeybee dance language has been used by researchers to solve machine vision problems [28, 29], as well as in robotics tasks [16]. In general, these works attempt to provide solutions based on the study of the honeybee capacities such as localization and vision. However, none of these works have used the adaptive behavior of the honeybee swarm. In this way, our work is also related to the ant colony optimization meta-heuristic and the more general field called swarm intelligence [7, 8]. However, our work is also strongly related to evolutionary computing, as we will explain later, because the search process is carried out with an evolution strategy. This work is part of our own effort to build new algorithms based on some basic principles taken by the observation of a particular natural phenomenon [22, 24]. Honeybees use a sophisticated communication system that enables them to share information about the location and nature of resources. If a sugar solution is placed outdoors a long time might elapse before they found the food. Soon after this first visit, however, bees soon begin swarming around the feeder. The communication among bees is performed using what is called the “dance language” as a means of recruitment. The dance language refers to patterned repetitive movements performed by bees that serve to communicate to their nestmates the location of food sources or nest sites. In this way, the dance is a code that conveys the direction, distance, and desirability of the flower patch, or other resource, discovered. The waggle dance of honeybees can be thought of as a miniaturized reenactment of the flight from the hive to the food or resource. Some honeybee scientists have correlated the distance to the site with the speed of the dance. As the flight to the food distance becomes longer, the duration of the waggle portion of the dance becomes longer. However, the detailed nature of distance communication has been difficult to determine, because the rate of circling and the length of the waggle run correlate with distance information. In this way, a question arise: if it is the finding that it is not distance *per se* the bees indicate, but rather the effort needed to arrive at the dance location. What is really important is that honeybees use the dance's symbolically encoded information to locate resources. Thus, honeybees use both dancing and odors to identify the location of resources, as well as the desirability of a resource. The desirability is expressed in the dance's “liveliness” and “enthusiasm”: the richer the source, the livelier the dance that can last many minutes, even hours. The dances are deployed to meet various colony needs such as: changed to monitor shifting environmental conditions, responsive to communication with hivemates, and switched on the basis of superior information from other dancers. Hence, these features suggest that the dance is a tool used by the bees, rather than a behavioral pattern rigidly emitted. When a honeybee discovers a rich patch, she returns and seeks out her hivemates in a specific location near the hive entrance called the “dance floor”.

Honeybees perform the dance on the vertical comb in the dark hive surrounded by numerous potential recruits. The dancer pauses for antennal contact with her followers in order to transfer some of the nectar she has harvest to them. The communicative nature of the dance is apparent in that dances are never performed without audience. While the dance is mostly used to indicate the location of flowers, it is also used for pollen, water when the hive is overheating, waxy materials when the comb needs repair, and the new living quarters when part of the colony must relocate. The angle that a bee flies during the flight to the resource, relative to the sun azimuth (the horizontal component of the direction toward the sun), is mirrored in the angle on the comb at which the waggle portion of the dance is performed. If the resource is to be found directly toward the sun, a bee will dance straight upward. If the resource is directly away

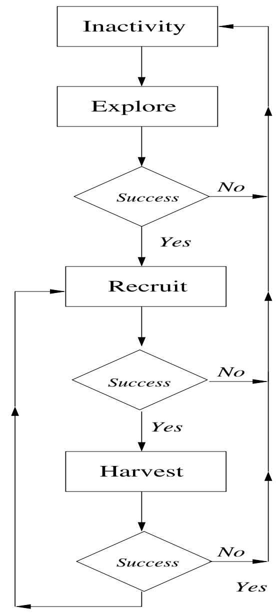


Figure 2: The honeybee search process is composed of three main activities: exploration, recruitment and harvest.

from the sun, the bee will dance straight downward. If the resource is at 45° to the right of the sun, then the dance is performed with the waggle run at 45° to the right of the vertical, and so forth. Honeybees make a transition from round dances for food near the nest to waggle dances at a greater distance. In fact the bees perform the round dance as the waggle dance being performed on the same spot first in one direction and then in the other. The bees trace out a figure-of-eight with its two loops more or less closely superimposed upon one another. In this way, the waggle dance is represented at its minimal measure of a single point.

These ideas can be represented as a flow diagram in order to develop an algorithm. Figure 2 shows the flow diagram of the search process employed by the honeybees. The honeybee algorithm that we are proposing is composed by three main activities: exploration, recruitment and harvest. We would like to point that this process is inherently parallel and the algorithm that we are currently using could be further enhanced. The honeybee pass from an inactivity state to the exploration stage in which the “scouts” travel considerable distances to investigate potential sources, and then return and dance to recruit foragers. The sharing of information about the location of sources such as: nectar, pollen, water, and propolis; makes it possible for a honeybee colony to serve as an information center. This communication system allows the reconnaissance of its many foragers, surveying a vast area around the nest, to be used in the discovery of the best sources. Once the exploration is started the recruitment and harvest stages are initialized, and the whole cycle is repeated indefinitely only changed by the current requirement of the hive.

5. THE HONEYBEE SEARCH ALGORITHM

In this section we give details about the algorithm that we are proposing to obtain information about the three-

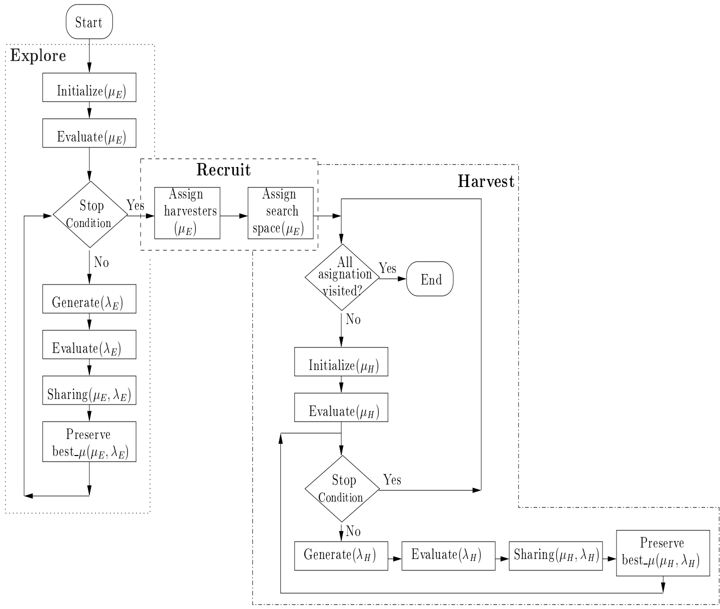


Figure 3: Flowchart describing the honeybee search algorithm.

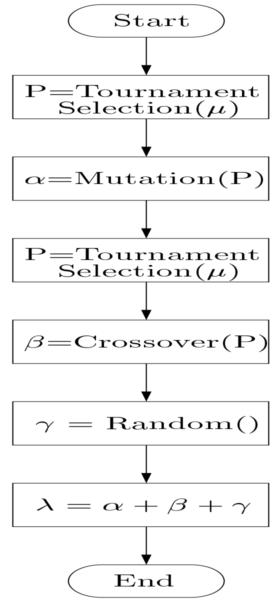


Figure 4: Flow diagram detailing the generation of a new population.

dimensional world. Normally, the reconstruction of the three-dimensional world is achieved using calibrated and uncalibrated approaches in which several geometric relationships between the scene and the images are computed from point correspondences. The projection matrix models the transformation from the scene to the image, and this could be thought as a direct approach. On the other hand, the transformation from the images to the scene is realized by a process known as triangulation and this could be imagined as an inverse approach. Obviously, to triangulate a 3D point, it is necessary to use two 2D points obtained from two images separated at least by a translation. We would like to state that errors on the calculation could produce misleading results. Therefore, it is necessary to apply the best possible algorithm in the calculation of the projection matrix using appropiate feature extraction techniques and bundle adjustment. The problem in this work is posed as a search process in which the 3D points are searched using the direct approach. In this way, it avoids the use of the epipolar geometry computation. This idea represents a straightforward approach in which a 3D point with coordinates (X, Y, Z) on the Euclidean world is projected into two 2D points with coordinates (x_l, y_l) for the left camera coordinate system and (x_r, y_r) for the right camera coordinate system. A measure of similarity is computed with the *Zero Normalized Cross-Correlation* (ZNCC) and the image gradient to decide if both image points represent the same 3D point. We apply an evolutionary algorithm similar to evolution strategies $(\mu + \lambda)$ in which mutation and crossover are applied as the main search operators.

In this work, we follow the approach proposed by Boumaza in which the new population is created independently by the addition of three different process, see Figure 4. This process is used by the exploration and harvest stages in the honeybee search algorithm, see Figure 3. The exploration stage starts creating a random population μ_E of 3D points called explorers, which are then transformed into a new population λ_E using the mutation, crossover and random steps. This stage attempts to simulate the natural process in which the bees explore asynchronously the space in search of the food source. The selection of the best explorers is made with a tournament selection after being evaluated together with the old population. We apply a sharing step in order to balance the distribution of the explorers in the Euclidean world. We repeat this stage until a given number of generations $n = 30$. Then, the recruitment stage is started. Each explorer recruits a number of foragers proportionally to its fitness function. The size of the search space is proportional to the distance between the pair of cameras (hive) and the current 3D point (explorer). Obviously the explorers that are closer to the hive should have a bigger search space, compared with the explorers that are farther away. We start with a fixed size $\zeta \in R^3$ to the nearest visited place near the hive. Then, as long as the bees are farther away from this initial bee; the search space starts to be reduced using as information the distance on the images in order to have an evaluation about the depth in which the points are located.

$$d_i = \sqrt{(x_l - x_r)^2 + (y_l - y_r)^2}.$$

Now, we can proceed to reduce the search space with the following relationship:

$$\begin{array}{c} f = 0.5 \times (1 - u) + u \ , \\ \zeta_i' = \zeta_i \times f \ . \end{array} \qquad (1)$$

Where $u = d_i / d_{max}$ represents the degree of desirability that a place holds according to its distance within the image. The value of f lies in the interval $[0.5, 1]$, where 0.5 is related to the highest distance, while 1 is related to the closest 3D point.

The next stage is to harvest the source patch for each explorer using a similar algorithm with two cycles. The first cycle is dedicated to visit each place that was selected by the explorer. In this way, the foragers that have been selected by the explorer start a new search process around the point where the explorer is located in order to exploit this location. This emulates the local and global stages in which the exploration and exploitation steps are achieved by the explorers and foragers respectively. As we can observe each group of foragers exploits sequentially all places. Note that the number of foragers that have been assigned to each explorer is variable according to the fitness function. It is possible that not all explorers have assigned foragers to harvest their place location. In order to know how many foragers are assigned to each explorer, we calculate the amount of foragers using the proportional fitness

$$p_i = fitness_i / \sum_{j=1}^{N} fitness_j \quad .$$

Thus, the number of foragers assigned to each explorer is computed using the following factor

$$r_i = p_i * \lambda \quad , \tag{2}$$

where λ is the total size of the population. The second cycle is similar to the exploration stage. Here, the fitness function computation uses besides the ZNCC, the homogeneity of the texture without gradient computation . The homogeneity is computed using the *Gray Level Coocurrence Matrix* because it has been proved reliable in image classification and segmentation for content based image retrieval [15]. Also, the size of the search space is obviously smaller with respect to the exploration stage where it is considered the whole space. However, the number of bees could be even bigger with respect to the exploration stage because the total number of foragers is bigger than the total number of explorers. In this work, we use 200 explorers and 2000 foragers. Next, we explain the main search operators.

5.1 Evolutionary Search Operators: Mutation, Crossover, and Sharing

The honeybees are recombined coordinate by coordinate using the SBX crossover operator [6]. The SBX operator emulates the working principle of the single point crossover operator on binary strings. From two parent solutions P_1 and P_2, it creates two children C_1 and C_2 as follows:

$$C_1 = 0.5[(1+\beta)P_1 + (1-\beta)P_2]$$
$$C_2 = 0.5[(1-\beta)P_1 + (1+\beta)P_2]$$

$$\text{with } \beta = \begin{cases} (2u)^{\frac{1}{\eta_x+1}} & \text{if } u < 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{\frac{1}{\eta_x+1}} & \text{otherwise.} \end{cases}$$

The spread factor β is dependent on a random variable $u \in [0,1]$ and on an user defined nonnegative value η_x that characterizes the distribution of the children in relation to their parents. Mutation is applied to each of the real variables using a polynomial distribution perturbation. The mutation operation modifies 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:

$$C = P + (P^{(UP)} - P^{(LOW)})\delta$$

$$\text{with } \delta = \begin{cases} (2u)^{\frac{1}{\eta_m+1}} - 1 & \text{if } u < 0.5 \\ 1 - [2(1-u)]^{\frac{1}{\eta_m+1}} & \text{otherwise .} \end{cases}$$

In order to save computational time we use a representation used for real-coded evolutionary operators. This consists in encapsulating both crossover and mutation into a single algebraic affine transformation. Since two real-coded variables Y_1 and Y_2 represent a point in the affine plane, an affine transformation of the form

$$X_1' = b_{11}X_1 + b_{12}X_2 + C_1$$
$$X_2' = b_{21}X_1 + b_{22}X_2 + C_2$$

is applied, where the coefficients are arbitrary real numbers, subject to $|b_{rs}| \neq 0$. This transformation can be extended to include the n variables contained in two different solutions. Accordingly, the generation of new solutions within the evolutionary algorithm can be stated as follows:

$$\begin{pmatrix} X'_{1_1} & Y'_{1_1} & Z'_{1_1} & \dots & Z'_{1_n} \\ X'_{2_1} & Y'_{2_1} & Z'_{2_1} & \dots & Z'_{2_n} \end{pmatrix} =$$
$$\left[\underbrace{\begin{matrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{matrix}}_{Crossover} \quad \underbrace{\begin{matrix} C_1 \\ C_2 \end{matrix}}_{Mutation} \right]_n \begin{pmatrix} X_{1_1} & Y_{1_1} & Z_{1_1} & \dots & Z_{1_n} \\ X_{2_1} & Y_{2_1} & Z_{2_1} & \dots & Z_{2_n} \\ 1 & 1 & 1 & \dots & 1 \end{pmatrix}$$

The advantages of this encapsulation are:

1. Standardized treatment of all transformations
2. Complex transformations are composed from simple transformations by means of matrix multiplication.
3. Simple inversion of the transformation by matrix inversion.
4. Extremely fast, hardware supported matrix operations in high-power graphic workstations.

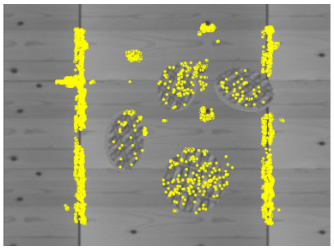
Finally, we applied a 3D sharing to the honeybees in order to balance the diversity of solutions. In the work of Louchet a 2D sharing was applied with the idea of simplifying the computation. However, this has the drawback of incorrectly penalizing those 3D points that projects into the same image location without being actually around the same 3D space. Thus, we decide to use the sharing proposed by Goldberg and Richardson [13]

$$Sh(d_{i,j}) = \begin{cases} 1 - \frac{d_{(i,j)}}{\sigma_{share}} & \text{, if } d_{i,j} \leq \sigma_{share} \\ 0 & otherwise \end{cases}$$

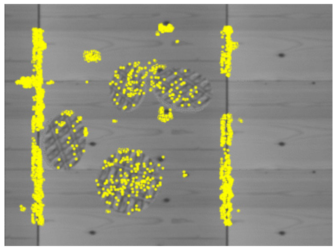
where $d_{(i,j)}$ is the distance between the individuals i and j. σ_{share} is the threshold that controls the ratio of sharing. The above function is applied to each individual to obtain a niche count as follows: $n_i = \sum_{j=1}^{N} Sh(d_{i,j})$. Then the shared fitness function is calculated with the following expression $fitness_i' = \frac{fitness_i}{n_i}$.

6. EXPERIMENTAL RESULTS AND CONCLUSIONS

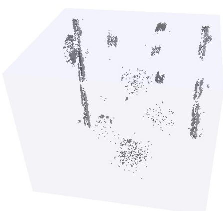
We have applied the honeybee search algorithm described in this paper on several pairs of images. Here for reason of space we show the results that we have obtained with two stereo pairs called coins and evovisión. The images of Figure 7 were captured with a Pulnix digital camera TM-9701d with a C-mount Fujinon lens HF16A-2M1, of focal length



a) *Left image.*



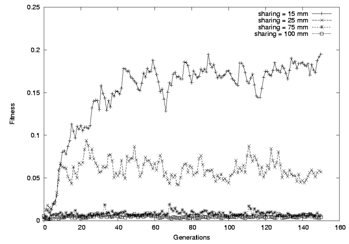
b) *Right image.*



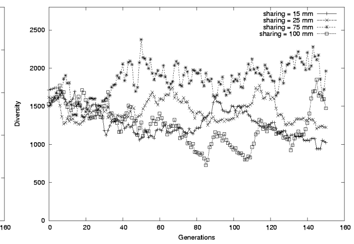
c) *Frontal view.*

d) *Aerial view.*

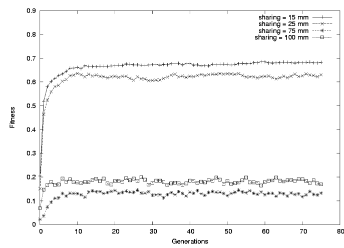
Figure 5: These images show the result of applying the honeybee search algorithm to the coins stereo pair. The first row presents six thousand artificial honeybees projected in the image pair, while the second row shows two snapshots of the 3D model.



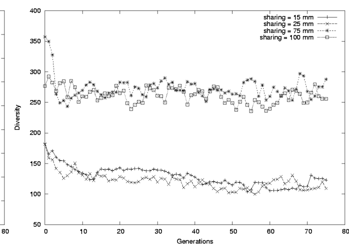
a) *Fitness for the explorers.*



b) *Diversity of the explorers.*



c) *Fitness for the foragers.*



d) *Diversity of the foragers.*

Figure 6: Comparison of the honeybee search algorithm using 4 different sharing coefficients. The comparison is made considering fitness value and the diversity.

$f = 16mm$. We describe now the parameters that we have used in each stage of the algorithm. The exploration stage in Figure 7e, uses a parent population $\mu_E = 4000$, and a child population $\lambda_E = 8000$. The child population is generated according to the following rates: mutation $\alpha_E = 0.6$, crossover $\beta_E = 0.1$, and random $\gamma_E = 0.3$. The harvest stage uses a parent population of $\mu_H = 16000$ and a child population $\lambda_H = 32000$. The rates are the same of the exploration stage. The parameters of the recruitment stage are automatically computed as we have explained in the document, see Equations 1 and 2. As we have commented during the paper, we decide to tune the algorithm parameters through experimentation. Figure 6 show 4 graphs plotted to illustrate the performance of the algorithm using several levels of sharing: $\sigma_{share} = \{15, 25, 75, 100\}$. The figure 6a shows that while we use a smaller σ_{share} the fitness value increase for the exploration stage. This is because a smaller σ_{share} could handle better the improvement of the explorers. However, the diversity is not necessarily affected because the range for the whole scene is very big considering this value, see Figure 6b. On the other hand, Figure 6c shows also that for a smaller σ_{share} the fitness is higher. However, the diversity starts to play a higher role. Figure 6d shows how the diversity decrease when a smaller σ_{share} is used. This kind of analysis helps to visualize the importance of choosing correctly the σ_{share}. Note also that the objects on both images are placed more or less at the same distance to the stereo rig. The parameters of the evolutionary operators of mutation and crossover are as follows: mutation $\eta_m = 25$ and crossover $\eta_x = 2$. Note that the last two parameters describe how the evolutionary operations are applied, while the rates of mutation and crossover specifies how many individuals are generated with those operations.

The advantage of using the honeybee search algorithm is the robustness against outliers. We can appreciate in the *VRML* images of Figure 7 that all 3D points are grouped coherently with the goal of reconstructing compact patches. This is due to the intelligent process described in this paper in which some artificial honeybees (explorers) guide the search process to obtain an improved sparse reconstruction. The explorers guide the foragers using texture and correlation information during the whole process. Similar to the natural process the goal is achieved using a communication system that we have adapted to the classical evolutionary algorithm. It is suitable to think that the honeybee search algorithm could be applied in other contexts.

Acknowledgments

This research was funded by UC MEXUS-CONACYT Collaborative Research Grant 2005; through the project "Intelligent Robots for the Exploration of Dynamic Environments". Second author supported by scholarship 0179377 from CONACyT. This research was also supported by the LAFMI project.

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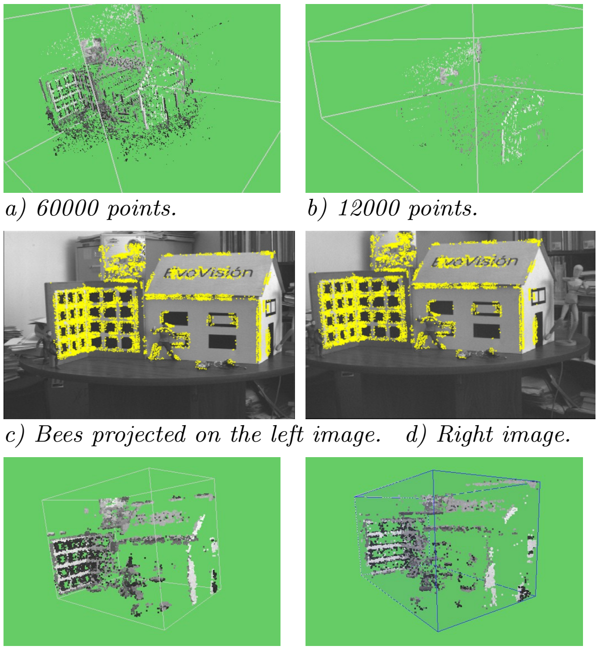

a) 60000 points. *b) 12000 points.*

c) Bees projected on the left image. *d) Right image.*

e) 16000 bees. *f) 8000 bees.*

Figure 7: These images show the results after applying the honeybee search algorithm to a real stereo pair. The first row shows the 3D reconstruction using the method of triangulation, while the third row shows our results.

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