The Honeybee Search Algorithm for Three-dimensional Reconstruction

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Abstract. This paper investigates the communication system of honeybees with the purpose of obtaining an intelligent approach for three-dimensional reconstruction. A new framework is proposed in which the 3D points communicate between them to achieve an improved sparse reconstruction which could be used reliable in further visual computing tasks. 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.

1 Introduction

Three-dimensional reconstruction has always been a fundamental research topic in computer vision and photogrammetry. Today the importance of image and vision computing task has gained relevance in the evolutionary computing community. This paper proposes a bioinspired approach to tackle the problem of sparse and quasi-dense reconstruction using as model the honeybee search behavior. This work is also inspired by the work of Louchet [12, 1, 13] 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 application of 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. For more about the Parisian approach we recommend [7] and [2]. One of the drawbacks of the approach of Louchet was the lack of a paradigm to provide those 3D points with intelligent capabilities. Indeed, a high number of outliers were produced with their technique. 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.

2 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 [3]. The honeybee dance language has been used by researchers to create machine vision systems [19, 20], as well as for robotics tasks [11]. All these works attempt to provide knowledge based on the study of the honeybee. 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 is more general field called swarm intelligence [5, 6]. However, our work is also strongly related to evolutionary computing as we will explain later. 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 [16, 18]. 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 began 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. Moreover, a question arise: if 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". She performs the dance on the vertical comb in the dark

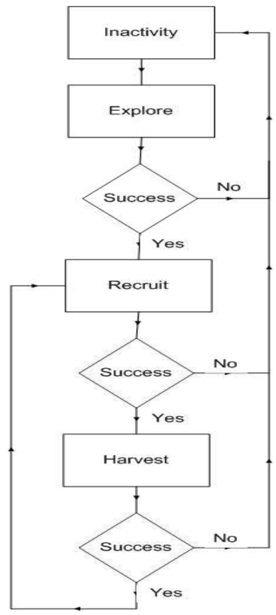

Fig. 1. The honey bee search process is composed of three main activities: exploration, recruitment and harvest.

hive surrounded by numerous potential recruits. The dancer pauses for antennal contact with her followers, and 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 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.

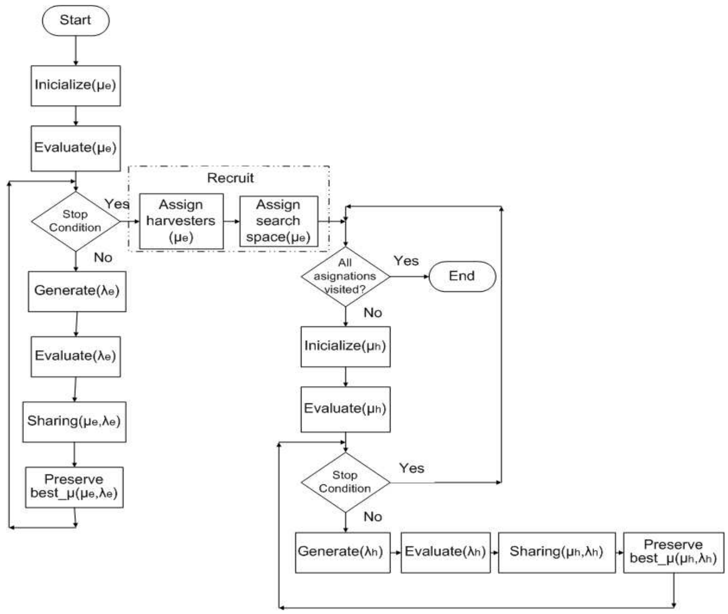

Fig. 2. Flow chart describing the honeybee search algorithm.

These ideas can be represented as a flow diagram in order to develop an algorithm. Figure 1 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.

3 The Honeybee Search Algorithm

In this section we give details about the algorithm that we are proposing to obtain information about the three-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 stay 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. 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 is avoid 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 3. This process is used by the exploration and harvest stages in the honeybee search algorithm, see Figure 2. 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 evaluate 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 the 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 ζ 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.

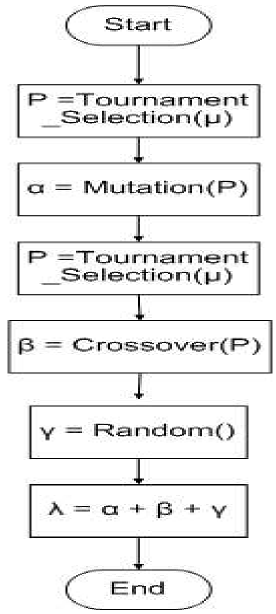

Fig. 3. Flow diagram detailing the generation of a new population.

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

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

$$\begin{aligned} f = 0.5 \times (1 - u) + 1 \times u \quad , \\ \zeta_i' = \zeta_i \times f \quad . \end{aligned} \tag{1}$$

Where u represents the degree of desirability that a place holds according to the distance d_i/d_{max}. 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 starts a new search process around the point where the explorer is located in order to exploit this location. Hence, 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 proportion of foragers being assigned to the explorers using the proportional fitness

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

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

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

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 [10]. 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 much bigger than the total number of explorers. Here, we use 200 explorers and 2000 foragers. Next we explain the main search operators.

3.1 Evolutionary Search Operators: Mutation, Crossover, and Sharing

The honeybees are recombined coordinate by coordinate using the SBX crossover operator [4]. 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:

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

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

A novel representation proposed in [14],[15] is used for the 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

$$\begin{aligned} X_1' &= b_{11}X_1 + b_{12}X_2 + C_1 \\ X_2' &= b_{21}X_1 + b_{22}X_2 + C_2 \end{aligned}$$

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:

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

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 [9]

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

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 $fitness'_i = \frac{fitness_i}{n_i}$.

4 Experimental Results and Conclusions

We have applied the honeybee search algorithm described in this paper on several pair of images. Here for reason of space we show only the results that we have obtained with two stereo pairs. Those images were captured with a Pulnix digital camera TM-9701d with a C-mount Fujinon lens HF16A-2M1, of focal length $f = 16mm$. We describe now the parameters that we have used in each stage of the algorithm. The exploration stage uses a parent population $\mu_E = 200$, and a child population $\lambda_E = 500$. 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 $\mu_H = 2000$ and a child population $\lambda_H = 4000$. 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. The sharing uses the following parameter $\sigma_{share} = 100mm$. Note 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 4 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.

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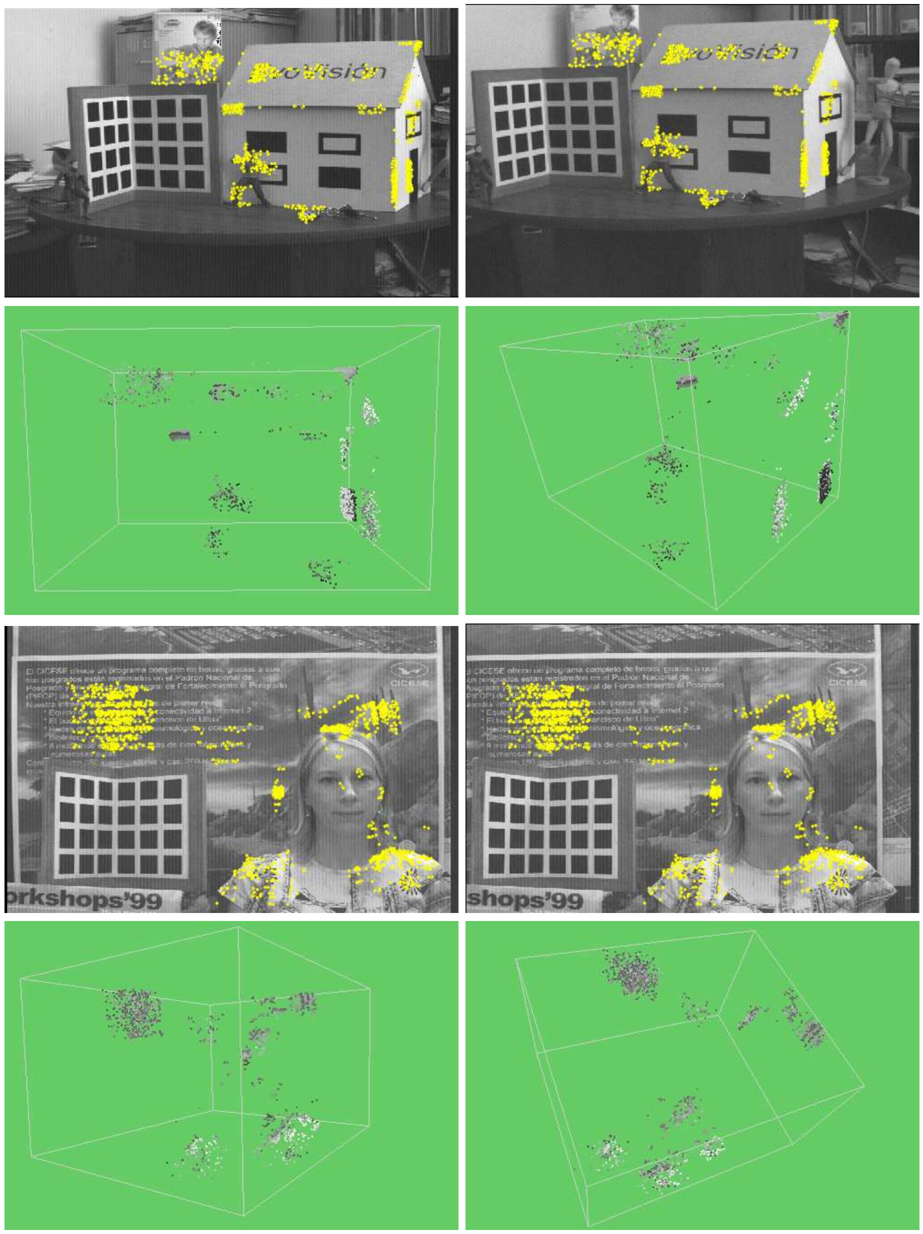

Fig. 4. These figures shows the results of applying the honeybee search algorithm. The first two images shows the first stereo pair with the projection of the artificial honeybees, while the second row shows the *VRML* to appreciate the spatial coherence. The third and fourth rows show the results with a real person.