Honeybees as an Intelligent based Approach for 3D Reconstruction

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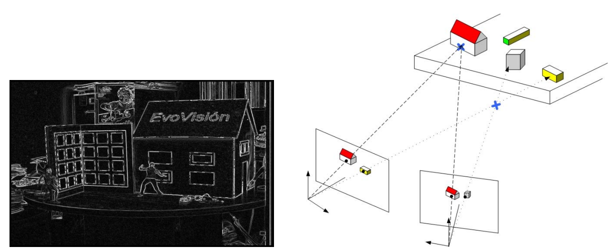
1 Introduction

This work is about the communication system used by honeybees with the idea of designing a new intelligent approach for 3D reconstruction. A new framework is proposed to allow the communication between 3D points in order to achieve an improved quasi-dense reconstruction. This method could be used reliably in further visual computing tasks because the obtained reconstruction emerges as a by product of an algorithmic intelligent process. 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. This work is inspired by the work of Louchet and his colleagues [8, 1, 9] 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. One of the drawbacks of this approach was the lack of a 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 [2, 4, 12]. 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

Today, most scientists in the honeybee behavioral community agree that the communication system of the bees is a language regarding insect capacities [2]. 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 nest-mates 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 discovered resource.



a) b)

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.

These ideas could be used to implement a new algo-

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rithm based on the activities that are founded in the honeybee search process: exploration, recruitment and harvest. The search process is inherently parallel and thus the algorithm that we are currently proposing could be further enhanced. The honeybee pass from an inactivity state to the exploration state in which the “scouts” travel considerable distances to investigate potential resources, 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 stage is accomplished 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

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 allows the computation of the 3D scene. The kind of reconstruction that is obtained is related to the amount of knowledge applied and this has derived into the calibrated and uncalibrated approaches. 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 has 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 [7] 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 [11]. 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 proper care is not taken. To eliminate those errors it is necessary to apply the best possible algorithm in the calculation of the projection matrix [10]. The problem in this work is posed as a search process in which the 3D points are searched using the direct 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 onto a couple of 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 is used to decide if both image points represent the same 3D point, see figure 1.

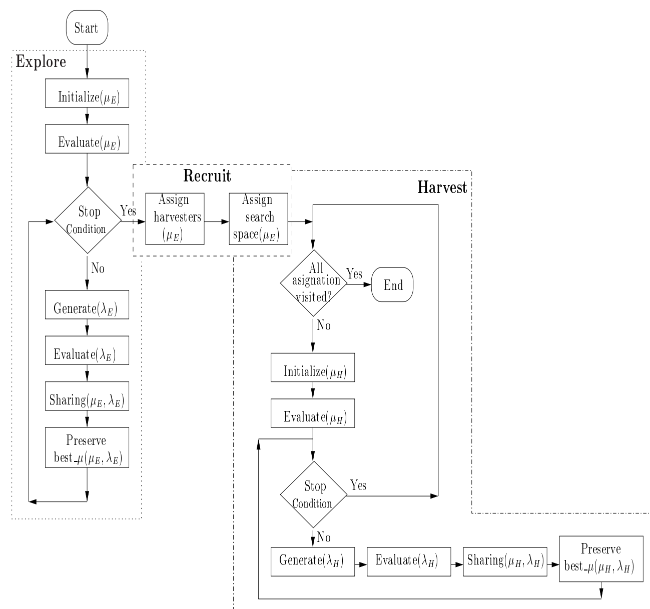


Figure 2. Flow chart describing the honeybee search algorithm.

In this work we have developed an algorithm based on the three main stages that were previously identified in the honeybee search behavior, see figure 2. Two evolutionary algorithms are used in the exploration and harvest stages. We decide to apply an evolutionary algorithm similar to evolution strategies $(\mu+\lambda)$ in which mutation and crossover are applied as the main search operators. These algorithms use a step called sharing in order to balance the distribution of the explorers in the Euclidean world. 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 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. We repeat this process 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 stereo pair (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

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

In order to have an evaluation about the depth in which the points are located. Now, we can proceed to reduce the search space with the following relationship:

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

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 as the one used in the exploration stage but with two cycles. The first cycle is dedicated to visit each place that was selected by the explorers. In this way, the foragers that have been assigned to each explorer start 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 its 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 [6]. Also, the size of the search space is obviously smaller with respect to the exploration stage where the whole space is considered. 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.

The honeybees are recombined, coordinate by coordinate, using the SBX crossover operator [3]. 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:

$$\begin{array}{l} C_1 = 0.5[(1+\beta)P_1 + (1-\beta)P_2] \\ C_2 = 0.5[(1-\beta)P_1 + (1+\beta)P_2] \end{array}$$

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

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:

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

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

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 [5]

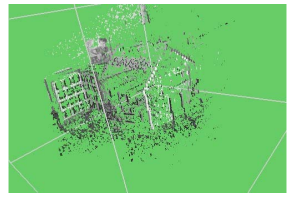
$$Sh(d_{i,j}) = \begin{cases} 1 - \frac{d_{(i,j)}}{\sigma_{share}} & \text{, if } d_{i,j} \le \sigma_{share} \\ 0 & otherwise \end{cases}$$

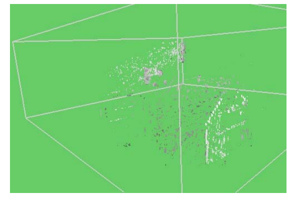
where $d_{(i,j)}$ is the distance between the individuals i and j. σ_{share} is the threshold that controls the ratio of sharing. The above function is applied to each individual to obtain a niche count as follows: $n_i = \sum_{j=1}^{N} Sh(d_{i,j})$. Then the shared fitness function is calculated with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

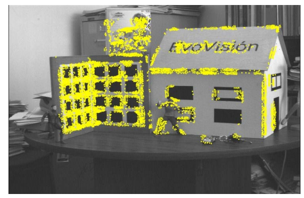
4 Results and Conclusion

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 the stereo pair called evovisión. The images of Figure 3 were captured with a Pulnix digital camera TM-9701d with a C-mount Fujinon lens HF16A-2M1, of focal length $f = 16mm$. We now describe the parameters that we have used in each stage of the algorithm. The exploration stage in Figure 3e, 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 for 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.

In this work we have presented a novel bioinspired evolutionary algorithm based on the honeybee search behavior. The advantage of using the honeybee search algorithm is the robustness against outliers. We can appreciate in the *VRML* images of Figure 3 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. This algorithm searches the 3D space through a coordinate and intelligent process that removes significantly the outliers that were normally produced in the work of Louchet, as well as in regular triangulation, see Figure 3. Also, we can appreciate from the results that the number of 3D points necessary to obtain 3D information is minimal compared with triangulation based approaches. Moreover, This work opens the avenue towards new intelligent reconstruction that we are planning to use as a sonar in a mobile robot.

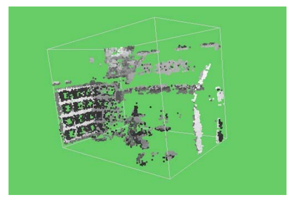

a) 60000 points.


b) 12000 points.



c) Bees projected on the left image.

d) Right image.


e) 16000 bees.

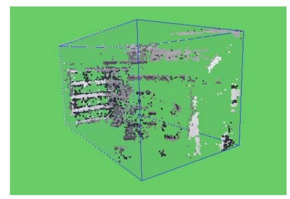

f) 8000 bees.

Figure 3. 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.

Acknowledgments

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