1 Aerial Coverage Optimization in Precision Agriculture 2 Management: A Musical Harmony Inspired Approach

3 João Valente*, Jaime Del Cerro, Antonio Barrientos, David Sanz

4 *CAR UPM-CSIC*
5 *Universidad Politécnica de Madrid*
6 *C/ Jose Gutierrez Abascal, 2*
7 *28006 Madrid, Spain*

8 Abstract

The coverage path planning (CPP) problem, is a problem belonging to a sub-field of motion planning where the goal is to compute a complete coverage trajectory from initial to final position, within the robot workspace subjected to a set of restrictions. This problem has a complexity NP-complete, and has no general solution. Moreover, there are very few studies addressing this problem applied to aerial vehicles. Previous studies point out that the variable of interest to be optimized is the number of turns. Thus, by minimizing the number of turns, it can be ensured that the mission time is likewise minimized. In this paper, an approach to optimize this cost variable is proposed. This approach uses a quite novel algorithm called Harmony Search (HS). HS is a meta-heuristic algorithm based on jazz musician's improvisation through a pleasant harmony. Finally, the results achieved with this technique are compared with the results obtained with the previous approach found in the literature.

9 *Keywords:* Mini Unmanned Aerial Vehicles, Quadrotor, Coverage Path

2 1. INTRODUCTION

3 Coverage path planning problem is the computation of a path that passes
4 through all the required points in the workspace from a starting point to a
5 final point. This problem has been mostly addressed to Unmanned Ground
6 Vehicles (UGV) applied in cleaning, farming, de-mining, etc.

7 The problem of covering a determinate area with an Unmanned Aerial
8 Vehicles (UAV) is directly related to the aforementioned problem. However,
9 the aerial coverage path planning (CPP) problem is subjected to harder
10 restrictions. Typically, UAV's have limited working cycles compared with
11 ground robots (i.e. the mission time has to be carefully optimized). Further-
12 more, they are not able to take off or land in random places (initial and final
13 positions are usually pre-defined).

14 Depending on the application, the problem restrictions can slightly change.
15 Herein, the problem of covering a wide area with an irregular shape is con-
16 sidered for mosaicking purpose. Mosaicking is the technique of mapping an
17 overall area by stitching a set of geo-referenced images acquired. In order
18 to achieve this objective with an UAV, the workspace is sampled by using a
19 regular grid (kind of Sukarev grid), where each cell corresponds to an image
20 sample. Then, a complete coverage trajectory must be generated ensuring
21 that no points are revisited, taking into account pre-defined take off and
22 landing positions, a required minimum number of turns. In this way, the

1 coverage time is minimized.

2 The study case presented is based on a vineyard parcel (see Figure 1),
3 since irregular shape fields are more challenging for addressing the related
4 problem. Mosaicking procedures can be applied in vineyards parcels for
5 weeding, frost monitoring, fruit maturity, as well as for measuring other
6 biophysical parameters of interest.

Figure 1: Vineyard parcel

7 The organization of the paper is as follows: After this brief introduction,
8 Section 2 reviews some related works. Section 3 introduces the HS algorithm
9 and shows how the CPP problem is addressed by employing this optimization
10 technique. Section 4 presents the results obtained and makes a comparison
11 with other techniques. Finally, Section 5 provides the concluding remarks of
12 this work.

13 2. PREVIOUS WORK

14 Coverage Path Planning is an extensively studied eld, and many tech-
15 niques and works are presented in the bibliography. Two main approaches

1 can be considered according to the execution of the algorithm: On-line and
2 Off-line planners.

3 On-line planning schemes are mostly reactive, providing the system with
4 much exibility and robustness. Furthermore, they require sensor information
5 as well as a more powerful CPU. The requirements have a direct impact
6 on power consumption, and also within the admissible ight time, which is a
7 critical constraint in aerial robotics. On the other hand, Off-line systems are
8 non-reactive to environmental changes but provide most efficient and suitable
9 plans. Furthermore, they require less on-board power consumption and the
10 CPU use, while - in most of the cases - they optimize the rate path/distance
11 covered. The effect of this factor is appreciated in the duration of the mission,
12 which appreciably decreases [1].

13 When multiple robots are used, a previous decomposition of the eld to
14 cover is required. Two approaches are commonly used: exact cell decomposi-
15 tions [2, 3] and approximate cell decomposition [4]. After this task, the path
16 for every vehicle to cover the area assigned is computed.

17 There are a few references concerning this planning. One of them is the
18 work presented by Maza and Ollero [3], where a team of aerial robots have
19 been used for inspection. After performing area assignation, the basic CPP
20 algorithm based back and forth pattern with the minimum number of turns is
21 executed for each robot. The solution proposed only considers convex areas
22 without obstacles. Moreover, such approach is mainly focused on the robot
23 assignment problem rather than the coverage path planning problem that is

1 solved by using basic algorithms in comparison with the proposed approach.

2 Another approach that reports a solution to the problem of area coverage
3 by using multiple UAVs applied to crop-dusting was presented by Moon
4 and Shim, [1]. Independently of the two algorithms presented in order to
5 perform the decomposition of the area, a procedure that selects points inside
6 the sampled set is employed to obtain a coverage trajectory. In the first case,
7 the resulting area coverage path is generated by using a spiral from outside
8 to inside, with no restrictions, which can be a problem in large areas if the
9 UAV runs out of fuel. The second case is based on a well-known exact cell
10 composition method that uses simple back and forth motions to cover the
11 areas. In any case, the provided results are only referred to simulations.

12 Li [2] also reports aerial CPP solutions, but the emphasis of the work is
13 focused on a recursive greedy algorithm applied in performing an exact cell
14 decomposition method, not on the coverage path-planning problem which is
15 solved by using back and forth motions. Additionally, the shortest coverage
16 path is determined through an undirected graph, in order to reduce the
17 number of turns. This work does not consider obstacles, and it is assumed
18 that the aerial vehicle just flies over convex polygonal areas. The proposed
19 method was only tested in simulations.

20 In previous work [5], an approach based on a wavefront planner with back-
21 tracking procedure was presented. Both heuristic and non-heuristic methods
22 were applied. A comparison of the result obtained with the novel approach
23 presented in this work, which employs a meta-heuristic algorithm, has been

1 provided at the end of the work.

2 **3. COVERAGE PATH PLANNING OPTIMIZATION**

3 *3.1. Problem Statement*

4 The area coverage problem oriented to mosaicking missions can be ab-
5 stractly described as follow: Given,

- 6 1. a convex or non convex shaped area $A \subset \mathbb{R}^2$ decomposed approximately
7 by a finite set of regular cells $C = \{c_1, .., c_n\}$ such that, $A \approx \bigcup_{c \in C} c$;
- 8 2. a coverage trajectory P with a finite set of continuous way-points p ,
9 which can be written as $P = \bigcup_{p \in P} p$. Where way-point correspond to
10 the centroid of a corresponding cell, and consequently a cell correspond
11 to an image sample, thus $dim(P) = dim(C)$;
- 12 3. a fleet of quad-rotors with attitude and position control, and capable of
13 way-point navigation. Each quad-rotor is characterized by a position
14 in $[X, Y, Z]$ and orientation¹ in $[\Theta, \Phi, \Psi]$.

15 The variable of interest to minimize is the number of turns performed in
16 P , which correspond to the number of rotations made by a quad-rotor around
17 the z-axis (yaw movements) as previously identified in [6]. The objective
18 function can be given as follow,

$$J = K_1 \times \sum_{i=1}^m \psi_k^{\{i\}} + K_2, \quad k \in \{135^\circ, 90^\circ, 45^\circ, 0^\circ\} \quad (1)$$

¹Roll, Pitch, Yaw

1 where,

$$\psi_{\pm 135^\circ} > \psi_{\pm 90^\circ} > \psi_{\pm 45^\circ} > \psi_{0^\circ}, \quad (2)$$

2 and K_i are weights such that,

$$K_2 > K_1, \quad K_{1,2} \in \Re \quad (3)$$

3 Finally, for each quad-rotor of the fleet an optimal trajectory can be
4 computed by $\min J(\mathbf{x})$, where $\mathbf{x} = [\psi]^T$.

5 3.2. *Harmony Search Algorithm*

6 The Coverage Path Planning problem has complexity NP-Complete. Soft
7 computing approaches (e.g., Metaheuristics), such as the Harmony Search
8 (HS) algorithm are typical and most convenient tools to address optimization
9 problems with this degree of complexity [7].

10 The approach proposed is based on the meta-heuristic algorithm denoted
11 by Harmony Search (HS). It is a population-based algorithm inspired in mu-
12 sician's improvisation process for a perfect musical harmony. The algorithm
13 has been introduced by Geem et al. [8] in 2001 and has already been applied
14 in several different engineering fields. Considering, some examples of the al-
15 gorithm usage for optimization can be found in [9, 10, 11]. Moreover, it has
16 been stated that this algorithm present advantages in comparison to other
17 meta-heuristic algorithms [12].

1 The algorithm can be abstractly described as follow: Imagine having a
2 group of Jazz musicians carrying different instrument. They start pitching
3 some notes in order to try to compose a new song. As they search for a
4 sequence of musical notes that give a good musical harmony, the harmonies
5 achieved up to the moment are kept in mind. If a new harmony sounds
6 better than a Harmony played before, then it is replaced by a new harmony.
7 From an optimization point of view, each player represents a variable and
8 each pitch, candidate value.

9 The main body of the algorithm is a Harmony Memory (HM) matrix
10 (defined in 4), where rows are candidate solutions vectors, and columns are
11 decision variables. The last column of the HM matrix is the cost function
12 value. The HM matrix is initialized by generating random candidate solu-
13 tions vectors.

14 The typical parameters from the HS algorithm are: Harmony Memory
15 Size (HMS), Harmony Memory Considering Rate (HMCR), and PAR (Pitch
16 Adjustment Rate). The HMS is the number of rows, or the number of candi-
17 date solutions considered. HMCR is the probability to choose a variable value
18 from the HM. Finally, a variable value is adjusted (switched by a neighbor-
19 ing value) with probability PAR. The uniform distribution $U(0, 1)$ is usually
20 employed [12].

$$HM = \begin{bmatrix} \mathbf{x}_1^{\{1\}} & \dots & \mathbf{x}_{\{N\}}^1 & \mathbf{J}(\mathbf{x}^{\{1\}}) \\ \vdots & \ddots & \vdots & \vdots \\ \mathbf{x}_{\{1\}}^{\text{HMS}} & \dots & \mathbf{x}_{\{N\}}^{\text{HMS}} & \mathbf{J}(\mathbf{x}^{\{\text{HMS}\}}) \end{bmatrix} \quad (4)$$

1 The algorithm can be synthesized in five steps: **Step 1**, Initialize HM;
2 **Step 2**, Improvise a new harmony vector $\mathbf{x}' = \{\mathbf{x}'_1, \dots, \mathbf{x}'_N\}$ from the HM
3 (with or without PAR) or by randomness. Improvisation means the gener-
4 ation of a new candidate solution vector. In other evolutionary algorithms
5 (e.g., Genetic algorithms (GA)) this step is addressed by the crossover oper-
6 ation; **Step 3**, Replace the new harmony by the worst in HM if better; **Step**
7 **4**, Check if stop criterion has been met (e.g. iterations, cost); if not, go to
8 **Step 2**, or else return the best solution.

9 3.3. Problem Solving with HS Algorithm

10 In order to address the aerial CPP problem with HS algorithm, the main
11 body of the optimization algorithm had to be adapted according to the for-
12 mulated problem in the previous subsection. In the following lines, the step-
13 by-step procedure of the algorithm is described.

14 As previously explained, HM is the main body of the HS algorithm. The
15 candidate solutions are herein stored, represented by N dimension vector,
16 which is made up of decision variables from the optimization problem. Each
17 decision variable is a real number that identifies the cell to be visited by the
18 aerial robot. This is a way-point coordinate, where a picture is going to be
19 taken, such that $X_i \in P$ with $i = 1, \dots, n$, where $n = \dim(P)$ (shown in Figure

1 2).

Figure 2: Decision variables mapped over the field.

2 Figure 3 shows how the variables are managed in the problem by consid-
3 ering HM with HMS=2. The depicted coverage trajectories are for example
4 the first two random Harmony vectors in the HM. The dotted lines are the
5 path transversed by the quad-rotors, which in both cases start from the cell
6 with index 1 to the cell with index 4.

$$\mathbf{x}^{\{1\}} = [1, 5, 9, 13, 15, 14, 10, 6, 2, 3, 7, 11, 12, 8, 4]$$

$$\mathbf{x}^{\{2\}} = [1, 5, 9, 13, 15, 14, 10, 11, 12, 8, 7, 6, 2, 3, 4]$$

Figure 3: Numerical example showing how the decision variables are managed to adapt HS algorithm to the problem.

7 *HM initialization*

8 The first step of the HS algorithm is the initialization of the HM. In
9 the first iteration the Harmony vectors (i.e. solutions) are usually generated

1 through a random process. As observed from the aerial CPP problem, the
2 time represents the main constraint of our problem, which causes other con-
3 straints to arise, such as the number of revisited places in the environment. It
4 is obvious that by reducing the number of revisited cells in the environment,
5 the path is also shortened, and consequently, its coverage time. In order to
6 solve the problem more challengingly and optimize the time as much as possi-
7 ble, the number of revisited points in the environment should be reduced. As
8 a result, HM with HMS permutation vectors with N elements must initially
9 be generated randomly.

10 An algorithm denoted Random Breath Coverage (RBC) has been used
11 for generating random Harmony vectors with permutation. RBC algorithm
12 is a hybrid algorithm that employs; two algorithms, Random search (RS) and
13 Breadth-first search (BFS). This algorithm provides a simple way to handle
14 the HM initialization (**Step 1**). The algorithm pseudo-code is depicted in
15 Algorithm 1.

Algorithm 1 Random Breath Coverage algorithm

```

1: Initialize  $FiFo = Start$ 
2: while  $S \neq \emptyset$  do
3:    $S \leftarrow BFS(FiFo)$ 
4:    $s \leftarrow random(S)$ 
5:    $FiFo \leftarrow FiFo + s$ 
6: end while
7: if  $dim(FiFo) = dim(C)$  then
8:    $P \leftarrow FiFo$ 
9: else
10:   $P \leftarrow \emptyset$ 
11: end if
12: Return  $P$ 

```

1 RBC algorithm expands all nodes from the unitary graph in a random
2 fashion from the starting position, which is equivalent to take-off deck within
3 the aerial robot workspace. Each node can or cannot have neighboring nodes
4 ², the set that contains all siblings is denoted by S , such that $S = \bigcup_{s \in S} s$ (see
5 Figure 4). The RBC algorithm finishes when $S = 0$. If the candidate vector
6 size is less than the number of decision variables, it means that the node
7 expansion has stopped without passing through all the nodes. Consequently,
8 that incomplete candidate vector is discarded.

Figure 4: Sibling set over the unitary graph. Each sibling is a nearest neighbor cell.

9 *New harmony vector improvisation*

10 An iterative process called improvisation starts after generating HM through
11 the method previously described. In order to ensure the permutation of the
12 Harmony vector, the new vector must be carefully obtained by slightly chang-
13 ing the mechanism of the conventional HS algorithm.

14 As in **Step 2**, each element of the new vector x' is either selected from the

²parent-child relationship

1 HM or the entire possible range of values. According to previously mentioned
 2 HMCR or 1-HMCR probability respectively. In the following paragraphs, the
 3 mechanism for each probability will be explained in detailed.

4 In the conventional HS algorithm a new x'_i value is randomly chosen with
 5 1-HMCR probability from the possible range of values. On the other hand,
 6 an x'_i value is typically chosen from the i th column of the HM with HMCR
 7 probability. In the present approach, the same reasoning is applied. However,
 8 the trajectory continuity must be ensured, which means that jumps over the
 9 cells are not allowed.

10 The problem can be solved as follows: a new x'_i value is randomly chosen
 11 with 1-HCMR probability from the set of the nearest neighbors of that deci-
 12 sion variable (i.e. all free cells adjacent to the cell addressed by the decision
 13 variable). If the new value is chosen from the entire possible range of values,
 14 the trajectory continuity is not ensured. Moreover, a random value from the
 15 i th column is selected according to the unvisited neighbor cells with HMCR
 16 probability. If there are no unvisited neighbor cells in that column, it chooses
 17 a random neighbor in the HM is chosen (see Eq. 5).

$$x'_i \leftarrow \begin{cases} x'_i \in \begin{cases} S_i \in X_i & \exists s \in X_i \\ S_i \in X & \nexists s \in X_i \end{cases} & w.p \text{ HMCR} \\ x'_i \in S_i & w.p \text{ 1-HMCR} \end{cases} \quad (5)$$

18 Besides the aforementioned occurrences, if the probability falls on HMCR,
 19 it has to be checked again that a new pitch adjusted (PAR) is required or a

1 new value from the decision variable remains unchanged (1-PAR).
2 In case the pitch is not adjusted, the new value of the Harmony vector
3 remains unchanged. Otherwise, some tuning must be done in this decision
4 variable. Usually, the adjustment relies on the displacement of K neighboring
5 values in the candidate set of values. In such case, the pitch adjustment is
6 the displacement of one neighbor within the neighborhood, by adding or
7 subtracting a unit in the admissible neighbors set (see Eq. 6).

$$x_i'' \leftarrow \begin{cases} x_i' \pm 1 & w.p \text{ PAR} \\ x_i' & w.p \text{ 1-PAR} \end{cases} \quad (6)$$

8 *HM update*

9 Every time that a new x_i' vector is created, the Harmony vector cost
10 is computed by using the cost function defined in Equation 1. If the cost
11 computed is better than the worst Harmony vector cost in the HM, the
12 new vector is then added to the HM, and consequently the Harmony vector
13 with the worst cost discarded from the HM matrix. If not, the HM remains
14 unchanged (**Step 3**).

15 *Stop criterion*

16 Similar to other optimization algorithms, the role of the stop criterion role
17 is to stop the optimization process when a determinate criterion is achieved.
18 After some iterations, the stop criterion can be set to reach a reasonable
19 number of turns, or even a determinate number of iterations. Since the goal

1 is to improve the results obtained with the wavefront planner with back-
2 tracking approach. After successfully obtaining less than one turn than in
3 the previous approach, the stop criterion was set to stop in 100 iterations.
4 It was experimentally proven that the best solution settles before that value.
5 The stop criterion was initially set to stop when the number of turns de-
6 creases a turn with regards to the previous approach presented in [5]. This
7 upper-bound iteration was obtained by trial and sufficient to optimize all
8 the aerial trajectories presented in the Section (**Step 4**). This can be better
9 understood in the Section 4 through Figure 8.

10 4. RESULTS

11 As previously mentioned, the case study presents a vineyard parcel lo-
12 cated in the southwest of Madrid, Spain (othophoto shown in Figure 5). Fur-
13 thermore, the results obtained in a previous approach have been compared
14 with the HS algorithm results.

Figure 5: Orthophoto of the vineyard parcel and landscape

1 In such manner, the results obtained by using the first approach are
2 shown in Figure 6. As observed, it is an area with irregular shape that is
3 divided into three quad-rotors through a negotiation-based approach. The
4 results obtained from this process determine that the first area assigned to
5 quad-rotor 1 can be sampled in 14 images (5-40); second area, assigned to
6 quad-rotor 2 can be sampled in 15 images (13-53); and finally, the third area
7 assigned to quad-rotor 3 can be sampled in 25 images (47-99).

Figure 6: Coverage trajectories obtained previously for three quad-rotors.

8 The workspace previously used in [5] was used in order to establish a com-
9 parision among the approaches aforementioned. Therefore, it was assumed
10 that the area negotiation and assignment are the same as in the previous
11 approach. The trajectories obtained with the HS algorithm are shown in
12 Figure 7. It can be observed that the number of planned images to be ac-
13 quired is equal in both workspaces, and that the take-off and landing positions
14 are maintained. The HS algorithm parameters employed in each area were

1 HMS=10, HMCR=0.9, PAR=0.3. The results presented were obtained with
2 the following number of iterations per area, respectively: Area 1, 28 itera-
3 tions, Area 2, 85 iterations, Area 3, 40 iterations. Figure 8 also depicts the
4 optimization of the trajectories iteration by iteration. It should be noticed
5 that the cost, means the average cost (i.e. turns) in the HM matrix.

Figure 7: Coverage trajectories obtained with the HS algorithm for three quad-rotors.

Figure 8: Optimization through iterations of the coverage trajectories.

6 A comparison with the results obtained in both approaches are shown
7 in Table 1. It can be observed that the number of turns obtained per tra-

1 jectory using HS algorithm are lower than the former apporach employing
 2 wave-front planner and backtracking procedure. Herein, the results consid-
 3 ering the number of turns and the computation time of the coverage paths
 4 are discussed. The number of turns per area has been improved, which can
 5 be better observed in the third area, where the number of turns was signif-
 6 icantly improved. For example, in the second area the number of turns was
 7 maintained. However, it can be easily noticed that the trajectory is already
 8 fully optimized and there is no change that a trajectory can be computed
 9 with less turns. Regarding, the computation time, it can be observed that
 10 slighty increased. However, on the one hand, this planning is off-line, and
 11 on other hand, the worst case required is 13s, which is an acceptable com-
 12 putation time considering the complexity of the problem, as enhanced in [6].
 13 Thus the computation time is useless to be considered as a drawback in this
 14 approach.

Table 1: Comparative between the former CPP approach, and the improved one, with the HS algorithm.

	Turns			Computation time[s]		
	Area 1	Area 2	Area 3	Area 1	Area 2	Area 3
Approach in [5]	9	8	20	0.15	0.02	0.02
HS algorithm approach	8	8	14	0.19	0.5	13

15 5. CONCLUSIONS

16 In this paper, a new approach to improve coverage trajectories was suc-
 17 cessfully employed. A novel algorithm denoted by Harmony Search was stud-

1 ied to be applied to the optimization of agricultural management tasks.

2 The results obtained with HS algorithm was compared with a former ap-
3 proach employing a wave-front planner with a backtracking procedure pre-
4 sented in [5]. The present approach showed better results in route optimiza-
5 tion compared with the former method. The key feature of this approach
6 is that it is able to reduce the number of turns of the coverage trajectories
7 significantly by holding the former start and goal positions set previously.
8 Although, the computation time is greater than in the previous approach, it
9 is an affordable cost, since the mission planner's aim is not to work on-line.

10 Moreover, the presented approach can be employed to plan aerial coverage
11 missions using any type of UAV, as well as in any agricultural field with
12 regular or irregular shape. Moreover, the mission completion time is reduced
13 by minimizing the number of turns, improving safety for the operator and
14 UAVs. In addition to this, and not less important, it optimize the usage of
15 resources and the economical cost involved in the mission.

16 This meta-heuristic algorithm is potentially a valuable method when em-
17 ployed in optimizing problems with high complexity. In such manner, the
18 present approach can be extended to other problems of PA practices where
19 autonomous robotic systems could be applied.

20 **6. ACKNOWLEDGMENTS**

21 This work has been supported by the Robotics and Cybernetics Research
22 Group at Technique University of Madrid (Spain), and funded under the

1 projects "ROTOS: Multi-Robot system for outdoor infrastructures protec-
2 tion", sponsored by Spain Ministry of Education and Science (DPI2010-
3 17998), and 'Robot Fleets for Highly Effective Agriculture and Forestry
4 Management', (RHEA) sponsored by the European Commission's Seventh
5 Framework Programme (NMP-CP-IP 245986-2 RHEA). The authors want
6 to thank all the project partners.

7 **References**

- 8 [1] S.-W. Moon, D. H.-C. Shim, Study on path planning algorithms for un-
9 manned agricultural helicopters in complex environment, International
10 Journal of Aeronautical and Space Sciences 10 (2) (2009) 1–11.
- 11 [2] Y. Li, H. Chen, M. J. Er, X. Wang, Coverage path planning for uavs
12 based on enhanced exact cellular decomposition method, Mechatronics
13 21 (5) (2011) 876–885.
- 14 [3] I. Maza, A. Ollero, Multiple uav cooperative searching operation us-
15 ing polygon area decomposition and efficient coverage algorithms, in:
16 R. Alami, R. Chatila, H. Asama (Eds.), Distributed Autonomous
17 Robotic Systems 6, Springer Japan, 2007, pp. 221–230.
- 18 [4] J. Valente, A. Barrientos, J. Del Cerro, C. Rossi, J. Colorado, D. Sanz,
19 M. Garzon, Multi-robot visual coverage path planning: Geometrical
20 metamorphosis of the workspace through raster graphics based ap-
21 proaches, in: B. Murgante, O. Gervasi, A. Iglesias, D. Taniar, B. Ap-

- 1 duhan (Eds.), Computational Science and Its Applications - ICCSA
2 2011, Vol. 6784 of Lecture Notes in Computer Science, Springer Berlin
3 / Heidelberg, 2011, pp. 58–73.
- 4 [5] A. Barrientos, J. Colorado, J. d. Cerro, A. Martinez, C. Rossi, D. Sanz,
5 J. Valente, Aerial remote sensing in agriculture: A practical approach to
6 area coverage and path planning for fleets of mini aerial robots, Journal
7 of Field Robotics 28 (5) (2011) 667–689.
- 8 [6] J. Valente, A. Barrientos, J. D. Cerro, Coverage path planning to sur-
9 vey large outdoor areas with aerial robots: A comprehensive analysis,
10 in: D. Chugo, S. Yokota (Eds.), Introduction to Modern Robotics II,
11 iConcept Press, Annerley, Australia, 2011, Ch. 5.
- 12 [7] T. Bäck, Evolutionary algorithms in theory and practice - evolution
13 strategies, evolutionary programming, genetic algorithms, Oxford Uni-
14 versity Press, 1996.
- 15 [8] Z. W. Geem, J. H. Kim, G. Loganathan, A new heuristic optimization
16 algorithm: Harmony search, SIMULATION 76 (2) (2001) 60–68.
- 17 [9] P. Tangpattanakul, P. Artrit, Minimum-time trajectory of robot ma-
18 nipulator using harmony search algorithm, in: Electrical Engineer-
19 ing/Electronics, Computer, Telecommunications and Information Tech-
20 nology, 2009. ECTI-CON 2009. 6th International Conference on, Vol. 01,
21 2009, pp. 354–357.

- 1 [10] H. Xu, Z. Zhang, D. Tan, X. Gao, G. Peng, S. Yu, Optimization of mo-
2 bile robot based on projection method and harmony search, in: Robotics
3 and Biomimetics, 2008. ROBIO 2008. IEEE International Conference
4 on, 2009, pp. 1653 –1658.
- 5 [11] E. Yazdi, A. T. Haghighat, Evolution of biped walking using neural
6 oscillators controller and harmony search algorithm optimizer, CoRR
7 abs/1006.4553.
- 8 [12] Z. W. Geem, Music-Inspired Harmony Search Algorithm: Theory and
9 Applications, 1st Edition, Springer Publishing Company, Incorporated,
10 2009.