Hybrid Mobility Model with Pheromones for UAV detection task

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***Abstract*—Over the last years, the activities related to unmanned aerial vehicle have seen an exponential growth in several application domains. In that context, a great interest has been devoted to search and tracking scenarios, which require the development of novel UAV mobility management solutions. Recent works on mobility models have shown that bio-inspired algorithms such as ant colonies, have a real potential to tackle complex scenarios. Nevertheless, most of these algorithms are either modified path planning algorithms or dynamical algorithms with no a priori knowledge. This paper proposes H3MP, a hybrid model based on Markov chains and pheromones to take advantage of both static and dynamic methods. Markov chains are evolved to generate a global behavior guiding UAVs to promising areas while pheromones allow local and dynamical mobility management thanks to information sharing between UAVs via stigmergy. Experimental results demonstrate the ability of H3MP to rapidly detect and keep watch on targets compared to random and pheromone based models.**

I. INTRODUCTION

According to the definition provided by the Joint Capability Group on Unmanned Aerial Vehicles [1], a UAV is *"A reusable aircraft designed to operate without an on-board pilot. It does not carry passengers and can be either remotely piloted or preprogrammed to fly autonomously."*. Often referred to as to drones by the public, UAVs have proven during the last years their utility in many civilian application cases. This is explained by their ability to go to places unreachable by humans (e.g volcanic activities monitoring) as well as their flexibility in terms of payload (e.g. camera, infrared sensors, GPS). Among the wide range of possible missions, UAVs are very often employed to keep watch, search and track. One must also distinguish *remote-controlled* and *autonomous* UAVs. The former still requires human decisions while the latter relies on artificial intelligence (AI).Recently, autonomous UAVs have become one hot topic. Many works focused on obstacle avoidance and intelligent path planning without any human intervention.

In this work, we consider a patrol-surveillance scenario which objective is to maximize targets detection. For such needs, we propose H3MM, a Hybrid Evolvable Markov Mobility Model for a fleet of UAVs based on Markov chains and indirect cooperation, i.e. stigmergy. The environment is first partitioned in several zones after the passage of a high-altitude and fixed-wing UAV. Then a Markov chain is generated from this geographical decomposition. Each zone represents a state of the chain and transitions can only occur between neighboring zones. Each UAV implements this Markov chain except that the transition probabilities may vary from one UAV to another. Then, UAVs follow their own transition probabilities to explore each zone. The union of all transition probabilities implemented by the fleet of UAVs may be assimilated to a set of possible strategies (solutions) to perform patrols. In order to improve this set, an evolutionary algorithm, in this work a genetic algorithm (GA), is be employed. This evolution could be easily performed by a high-level UAV or the base station. Transition probabilities leading to the best detection patrol are the most rewarded. Since the environment is dynamic and may change rapidly, it is required to implement an evolutionary algorithm taking into account these modifications. For this purpose, a local procedure is added to the evolution to tackle this problem. When targets are encountered, transitions are reinforced using direct communications between UAVs. If a change occurs suddenly, the information is directly propagated and a bad strategy may become efficient without dead time. This first part permit to discover the best patrol zone and can be considered as the highest level of the proposed mobility model. Inside a patrol zone, the adopted mobility model is based on stigmergy, i.e pheromones.

The remainder of this paper is organized as follows. The next section deals with related work on the topic. Section 3 describes in details the different mobility models while section 4 explains how the H3MP model is conceived as a hybrid from the models seen in section 3. The experimental setup and numerical results are introduced in section 5 and 6 respectively. Finally, we conclude and propose some future perspectives in section 7.

II. RELATED WORK

Unmanned Aerial Vehicles (UAVs) are aircraft having the ability to fly without an on-board pilot. Their utilization has seen an exponential growth over the recent years and many models of UAVs have been designed to answer various situations. In [2], small UAVs are deployed to monitor urban highway traffic. Geologic activities can also be surveyed with the aid of UAVs. For instance in [3], remotely piloted helicopters were equipped with a system for sampling and analyzing gas inside volcanic plumes. Fire detection also belongs to the range of possible missions assigned to UAVs. In [4], the authors present a collaborative system of UAVs composed of several aerial vehicles and a central station for forest fire fighting. Finally, some works have been dedicated to maritime rescue using UAVs and USVs (Unmanned Surface Vessel). In [5], a Bayesian Network is used as decision model to take into account uncertain factors. UAVs have also the advantage to go and explore dangerous zones for human beings. In [6] and [7], the authors employed UAVs for radio-detection purposes in radioactive zones. Concerning categorization, metrics have been developed to classify UAVs such as Mean Takeoff Weight (MTOW) or Operational Altitude. However it is very difficult to keep a definitive and up-to-date model since the UAV market is still growing at a fast pace. A lot of engineering and research topics (e.g. UAV control [8], UAV sensor [9]) have been investigated which continuously contribute to improve UAVs' application domains.

Nowadays, two main kinds of UAVs can be distinguished: remote controlled and autonomous UAVs. While the former is widely used today, the latter is certainly the most promising in terms of research and applications. Autonomous UAVs allow faster and longer missions since they do not rely on human control. They require developing decision-making model [10] which relies on artificial intelligence such as pattern recognition[11] or path planning[12]. Among these models, mobility models play an important role. There exist not only path planning but also intelligent motion algorithms based on collaboration between UAVs. In order to inject intelligence and self-governance to UAVs mobility, many researchers rely on bio-inspired algorithms such as Ant colony [13], Particle Swarm [14] or Bee algorithms [15] which mimic the behavior of social species in nature. For more details, the reader can refer to [16].

In this work, we focus on bio-inspired mobility models designed to explore and detect a maximum number of targets. Some existing works extend the basic concept of ant pheromones to different kinds, such as attractive and repulsive ones. This approach has been successfully used in [17] and [18]. Optimal deployment[19] has been tackled using particle swarm optimization (PSO) and bacterial foraging algorithm (BFA). These algorithms can be refereed to as swarm algorithms. In this case, communication is of major importance as defined in [20] where network clusters are formed to provide stability and reliable communications.

We here propose to classify these mobility models based on two types of approaches: *tactical* and *strategic*. The strategic approach relies on path planning [21] and a global identification of the actions to achieve a goal. In the tactical approach, online algorithms [22] are developed to take uncertainties or a dynamic environment into account. The contribution in this paper, i.e. H3MP, is a combination of such two types of mobility models with opposite characteristics. While the Markov model is well-suited for general and global patrol, the pheromone-based mobility model has already proven its efficiency for tracking purposes. However, it remains inefficient until the first pheromones are dropped on the map which may take very long time for large environments. Indeed, most of the models presented in the literature adopted a random procedure when no pheromones are present. We argue that it is possible to improve the time to the first detection by using the Markov model since UAVs are forced to change zones. Once targets are detected, zones with high detection probabilities are more often explored and the pheromone mechanism becomes more efficient. As a consequence, the proposed H3MP model combines the advantages of both strategic and tactical approaches.

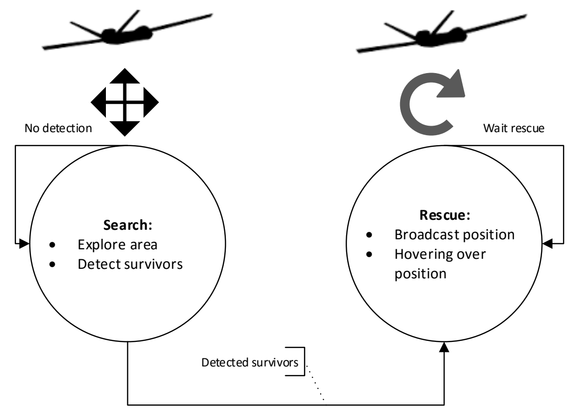

Fig. 1. Search & rescue UAV in maritime context

III. UAV MODEL AND MOBILITY MODEL APPROACH

A. UAV model description

In H3MP, UAVs and targets are modeled as agents which are able to sense the environment and act upon it. An efficient way to implement agents is to model them as finite-state machines (FSM) which can be mathematically formulated as a quintuple $(\Sigma, S, s_0, \delta, F)$. Σ is the set of percepts, S a finite set of states, s_0 the initial state and δ the state-transition function $\delta : S \times \Sigma \to S$ in the deterministic case or $\delta : S \times \Sigma \to P(S)$ in the non-deterministic case. Depending on the input received from the environment and the current state, an agent performs some specific tasks. Let us take the example of a search and rescue UAV (see Figure 1) launched by a cost guard ship during sea rescue. This UAV could be represented literally as two states:

- The search state aims at covering a wide area to find some survivors as fast as possible;
- The rescue state occurring after detection which continuously broadcasts the position of the detected survivors while hovering over the detection zone.

To each state corresponds one particular task/mission which is the building blocks of the agent. In the case of an autonomous and intelligent agent, we could imagine that states are updated by the agent itself based on the acquired knowledge. A large number of missions can be modeled with FSM. This is the first reason explaining our choice. The second one is that it allows us to compare fairly different algorithms by having a clear stopping condition, i.e. the maximum number of state-transitions. It ensures that the same number of steps has been respected even though algorithms are very different.

In the related work section, we defined two different groups of approaches: the tactical and the strategic ones. While a tactical approach relies on *local procedures*, a strategic approach tries to determine *globally* the best set of actions to achieve a goal. Both approaches have complementary strengths and weaknesses. A tactic approach involves short and ad-hoc actions defined at specific moments to respond to some events. A strategic approach requires to create plans and anticipate some events. Using a military metaphor, we could say that you make tactical choices to "win a battle" while you make strategic choices to "win the war". Both constitute an inseparable unity. To win a war, you have to win battles while winning battles does not imply that your are winning the war. This is the reason why it seems obvious to combine both. The next section will explain our choice in terms of local procedure (tactic) while the next one will explain how adding a global procedure can enhance a UAV task. These methods are defined to improve target detection in the context of fire starts, search & rescue missions and many other situations involving detection purposes.

B. Tactical mobility: communication based on pheromone tracks

Communication is particularly important when considering a fleet of UAVs. The tactical mobility model presented here relies on the concept of *stigmergy*. It is a bio-inspired communication concept used by social insects through the modification of the environment, e.g., by leaving pheromone tracks. In this work, a virtual map is shared by the operational base (central entity). Each UAV connected to this base is able to drop and retrieve some information (virtual pheromones) on the map. When the connection is lost with the group, a UAV uses a local copy of the map. Once the connection is restored, the UAV reconnects and updates the virtual map. The advantage of such a mechanism is that UAVs may be autonomous or semi-autonomous since the map is owned by a central entity. Either the map is only updated with the information provided by UAVs or the central entity may influence them as well to patrol some area by modifying the virtual map. This second possibility has not been tested yet and will be tested in future work. This indirect cooperation approach has been implemented based on a dual-pheromone mechanism as proposed in [18]. Attractive pheromones are dropped on nodes where targets are detected while repulsive ones rely on node visitation, to favor the exploration of the least frequently visited nodes. It means that the attractiveness of a node can be compensated by a large number of visits. Contrary to [18], we keep the random proportional transition rule introduced by the authors of Ant Systems [23]:

$$p_m^k = \begin{cases} \frac{\pi_m^\alpha(t).\eta_m^\beta(t)}{\sum\limits_{p \in J_j^k} \pi_p^\alpha(t).\eta_p^\beta(t)}, & \text{if m} \in J_j^k \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where m is a destination node, p_m^k is the probability for a UAV k to go to node m, J_j^k is the set of all nodes belonging to the destination zone j,$\pi_m^\alpha(t)$ is the attractive pheromone intensity at iteration t on node m while $\eta_m^\beta(t)$ is the repulsive pheromone intensity on this same node at t. Repulsive pheromones just represent the inverse of the number of times each node has been visited. In the remainder of this paper, we consider $\alpha = \beta = 1$. Further investigations will be done in the future to find a trade-off between these two parameters. Without any tracks, UAVs take random decisions which may lead to bad behaviors. This is clearly the main drawback of such indirect approaches and the reason why we propose to hybridize it with the second mobility model introduced in the next section.

C. Strategic Mobility: patrol rules based on Markov chains

In order to cope with the weaknesses of the pheromone-based model, an evolvable Markov model is designed. First, the UAV navigation mesh is partitioned into several zones (or clusters). A standard clustering algorithm such as K-means or DBSCAN can be used for this purpose. The number of zones is a parameter which should not be too large or too small. The first reason is that a large number of zones will be difficult to explore exhaustively while a too small number of zones will have a negative effect on the exploration since UAVs will change zones very frequently without deeply exploring them. Finding a trade-off for this parameter is necessary. Knowing the size of the considered map in this work and based on previous experiments, we here considered 10 zones. We also use the K-means algorithm in order to have zones with approximately the same size. This is one of the specificity of K-means which tends to generate round and equal clusters (here zones). This partitioning could be realized by the passage of high-altitude UAVs or using satellite imagery. We recall that Markov chains are generally represented as a sequence of random variables X_k where the probability of moving from one state to another only depends on the present state. Each Markov chain can be modeled as a matrix $\mathcal{P}$ with $P_{ij} = \mathcal{P}r(X_{k+1} = i | X_k = j)$. In this model, each state represents exactly one zone. Moving to another zone can be modeled with the use of transition probabilities. It means that P_{ij} is the probability to move to zone i knowing that the present zone is j. Therefore, the structure of the Markov chain is automatically deduced from the clustered navigation mesh, as illustrated in Figure 2. Two non-adjacent zones i and j have $P_{ij} = P_{ji} = 0$. For instance, in Figure 2 it means that a UAV cannot take the decision to go directly from zone 1 to zone 10.

By adjusting transition probabilities, UAVs can be driven to patrol more frequently some specific zones. We considered transitions as strategies and evolved them using genetic algorithms. The strength of this Markov mobility model is that UAVs leave unpromising zone more often. UAVs are not wasting their time by doing random search in zones where no pheromones tracks are present. Therefore their search becomes more efficient.

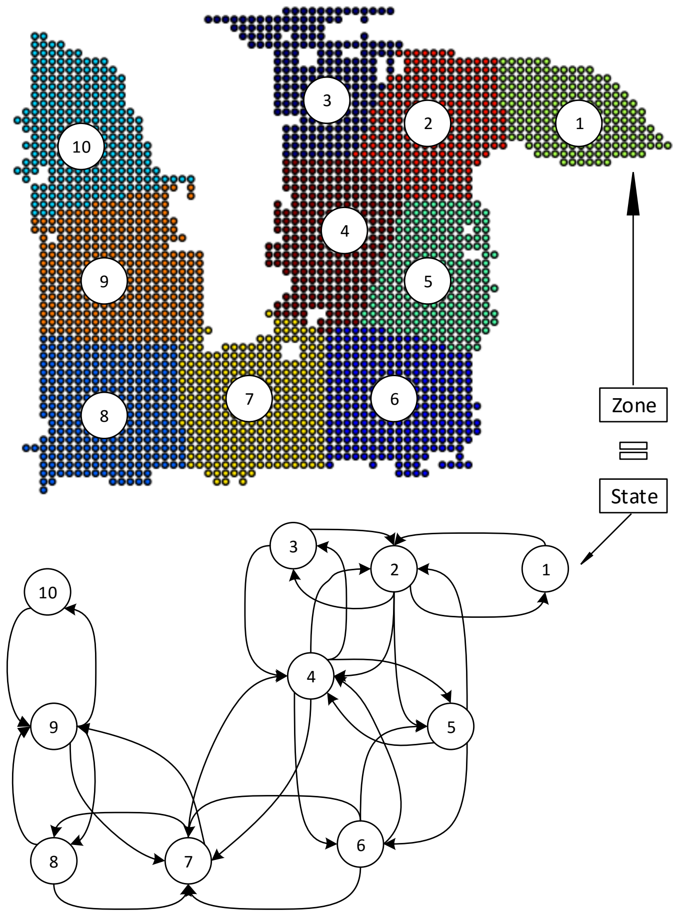

Fig. 2. 10 zones obtained after clustering the UAV map (top) and the corresponding Markov Chain (down)

IV. H3MP - Hybrid Markov Mobility Model with Pheromones

In the previous sections, the tactical and strategic mobility models have been briefly described. By combining them together, we propose H3MP, a hybrid model taking advantage of a dynamic mechanism brought by the pheromone-model as well as a strategic mechanism consisting in finding the best transition probabilities to globally adjust the patrol. As aforementioned, targets and UAVs are FSM. Targets are only composed of a single state with a loop. At each iteration, a target chooses a random position and moves to it. Concerning UAVs, the model is composed of two states: *the Destination state* (see Algorithm 1) and *the Move state* (see Algorithm 2). In the *the Destination state*, a UAV selects a destination based on the transitions probabilities while *the Move state* corresponds to the local search based on pheromones.

At each iteration and until it reaches its destination, a UAV updates the shared pheromones tracks and reinforces the transition probabilities between zones according to the observed number of detections. We recall that this direct reinforcement (previously mentioned in section I) is performed to avoid dead times and accelerate the generation of good strategies when changes occur. Once these two tasks are done, it retrieves the next destination node and moves to its direction.

Algorithm 1 ComputeDestination state

```
proc Destination(uav):
{Select next destination according to the mobility model and
 the best tracks}
newZone ← uav.MarkovMobility.nextZone(uav.currentZone)
nodes ← getNavigationPoints(newZone)
probabilities=
for n in nodes do
    p ← getProbabilities(getAttractivePheromones(),
    getRepulsivePheromones(),
    alpha = 1,beta=1)
    probabilities.add(p)
end for
newDestination ← rouletteWheelSelection(probabilities)
uav.path ← computeRoute(destination, uav.position)
return  state Move
```

Algorithm 2 Move state

```
proc Move(uav):
{Select next point from the computed path}
newPoint ← uav.path.pop()
uav.moveTo(newPoint)
{Update tracks as well as the mobility model}
updatePheromones(uav)
if len(uav.path) == 0 then
    return  state Destination
else
    return  state Move
end if
```

The evolution of the transition probabilities or strategies permits UAVs to execute a stochastic patrol. In order to generate the best patrol, transition probabilities are evolved using a generational genetic algorithm (see Figure 3) [24]. A random population of probability vectors, referred to as individuals in Algorithm 4 (line 2), is first generated according to the Markov chain obtained after discretizing the environment. In order to evaluate these probability vectors using the evaluation function described in Algorithm 4, each UAV is assigned one vector and performs p iterations. This evaluation function relies on a simulation. Since UAVs are modeled as FSMs, one iteration represents one FSM state-transition. For each UAV, the number of detected targets after p iterations represents the fitness value of its probability vector. Then evolutionary operators (line 6 to 7) are applied and the population is replaced by the generated offspring (line 9). This step constitutes a single generation. The total number of generations is the stopping criterion.

Concerning the evolutionary operators, we consider a modified version of the BLX-0 crossover to generate two offspring. Let x and y be two chromosomes selected to mate. $x_i(y_i)$ is an allele of x(y) occurring at position i. $0 \leq x_i \leq 1$, $0 \leq y_i \leq 1$ $\forall i\{1,...,N\}$ with N the chromosome length. Two offspring z^1 and z^2 are generated from x and y according to the following formulas:

1) $\forall\ i\ z_i^1 = \max(x_i, y_i) \times \mathcal{U}(0,1)$
2) $\forall\ i\ z_i^2 = \mathcal{U}(0,1) \times (1 - \min(x_i, y_i)) + min(x_i, y_i)$

Algorithm 3 Pseudo-code of a the GA

```
proc Evolve(genga,targets,quad-copters)
Initialisation(genga.pop);
Evaluation(offspring,target,quad-copters);
for i in 1 To Ngen do
    parents ← Tournament(genga.pop,2);
    offspring ← Recombination(genga.Pc,parents);
    offspring ← Mutation(genga.Pm,offspring);
    Evaluation(offspring,target,quad-copters);
    genga.pop←offspring;
end for
end procEvolve
```

Algorithm 4 Evaluation function

```
proc evaluation(individuals,targets,uavs)
for i in len(uavs) do
    uavs[i].ptransitions ← individuals[i]
end for
Agents ← Union(targets,uavs);
for i in 1 To p do
    for agent in Agents do
        agent.executeStateTransition();
    end for
end for
for i in len(uavs) do
    individuals[i].fitness ← uavs[i].nbDetection
end for
end proc evaluation
```

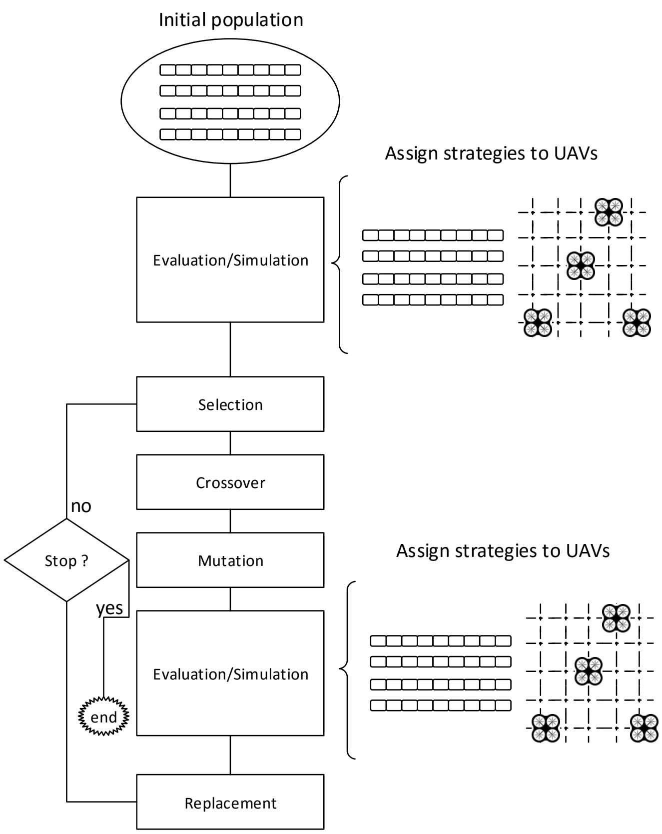

Fig. 3. Genetic algorithm: workflow

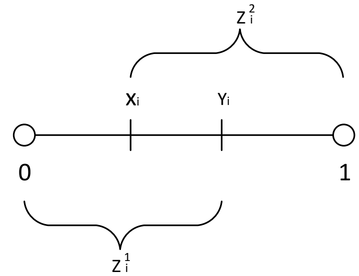

Fig. 4. Allele generation for offspring from parents alleles

For instance (see Figure 4) if $\max(x_i, y_i) = y_i$, then $z_i^1 \in [0, y_i]$ and $z_i^2 \in [x_i, 1]$. Mutation is performed given the mutation probability p_m, the mutation operator modified a chromosome x using the formula: $x_i \leftarrow 1 - x_i$ if $\mathcal{U}(0,1) \leq p_m \ \forall i\{1, ..., N\}$. Finally in a Markov chain, all transitions probabilities going out of a state have to sum to 1. A repair procedure has been added to ensure that transition probabilities going out each state sums to 1. This is basically a normalisation procedure dividing each allele x_i by $\sum_i x_i$ which guaranties that the individual is then valid.

V. Experimental setup

A. Scenario

In this work, we consider a patrol scenario involving more targets than UAVs such that the trivial strategy consisting in assigning UAVs to targets once they have been detected is inefficient. This is motivated by real application cases, where the number of targets is not known a priori. The considered UAVs are quad-copters. The environment is a 3D map, illustrated in Figure 5, designed by the authors of the 3D game engine described in [25]. This map has been selected to increase the environment complexity. Its topology has interesting properties since it is made of two main areas separated by a hill. A small corridor links these areas. As aforementioned, targets and quad-copters will move based on discretized versions of the environment. A target navigation mesh has been first generated by computing all points on the ground satisfying static collision constraints. Contrary to targets, the quad-copter navigation mesh is generated given the flying altitude and collisions are tested as well (e.g. collision with the hill). By applying this abstraction, we avoid computing static collisions during simulations reducing the computation cost. Collisions between UAVs may be simply avoided by changing the altitude of the two UAVs having collision course. Another approach could be to share trajectories between UAVs through the virtual map to avoid any collision courses. We selected the first one which does not require extra implementation. Indeed, it exists large number of works in the literature focusing on collision avoidance and control theory which are not the purpose of this paper.

B. Settings

In order to compare and evaluate our H3MP model, referred to as *H3MP* (Hybrid Markov Mobility Model with

Fig. 5. The environment: a 3D map

Pheromones), we considered two other mobility models: a random-based and a standard pheromone-based. In the random mobility model, later named *Random*, quad-copters select uniformly at random a new destination node in their neighborhood. They basically have the same mobility model as the target. They do not have a priori knowledge or the ability to communicate. This random mobility model is just a basic reference to show that H3MP has a better behavior than the random one. The real comparison is performed with the pheromone-based model, referred to as *Pheromone*. It is inspired by the works presented in [17] and [18]. Both models use an online-based approach but the authors in [18] added attractive pheromones for tracking scenarios. Both works focused on fixed-wing UAVs while we here consider quad-copters. They also use a continuous environment while we have a discrete one. Table I describes the parameters used for the simulation. For the sake of comparison, statistics on the number of detections are recorded at each round. A round is obtained when quad-copters and targets have each performed 100 iterations, i.e. 100 state-transitions. 100 rounds in total are performed for all mobility models. Once a round has been completed, information about target detection and area coverage are retrieved. Once again, targets are moving using a random mobility model comparable to the one implemented for the random-based mobility model of UAVs. One could say that a random behavior for targets seems unrealistic. Nevertheless in this work, we just want to compare two mobility models without focusing on a particular mission. Furthermore a random behavior for target should be even more difficult than predictable trajectories. In any case, further investigations will be performed using game theory to provide some adversarial behavior to targets. All mobility models have been implemented in Python. Experiments were performed on a High Performance Computing platform. Each run was completed on a single core of an Intel Xeon E3-1284L v3 @ 1,8 GHz, 32Gb of RAM server, which was dedicated to this task.

VI. Numerical results

Figure 6 represents the average number of detections for each mobility model while Figure 7 depicts the minimum

TABLE I
PARAMETERS USED FOR THE EXPERIMENTS

	H3MP	Pheromone	Random
Iterations[3]	100	100	100
Rounds	100	100	100
Total iterations	10e4	10e4	10e4
Independent runs	30	30	30
Selection	BT^1	$\times$	$\times$
Crossover probability: pc	0.8	$\times$	$\times$
Mutation probability: pm	$\frac{1}{\#variables}$	$\times$	$\times$
Pheromones update	local	local	$\times$
Pheromones type	$A+R^2$	$A+R$	$\times$
Pheromones evaporation[3]	10%	10%	$\times$
Detection range[4]	5	5	5
Number of targets	20	20	20
Number of quad-copters	10	10	10

1: Binary Tournament; 2: Attractive + Repulsive; 3: Each round; 4: Maximal distance to detect targets

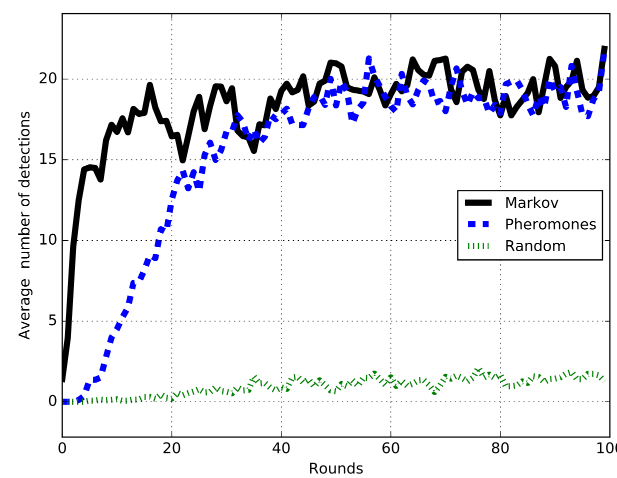

Fig. 6. Average number of detections

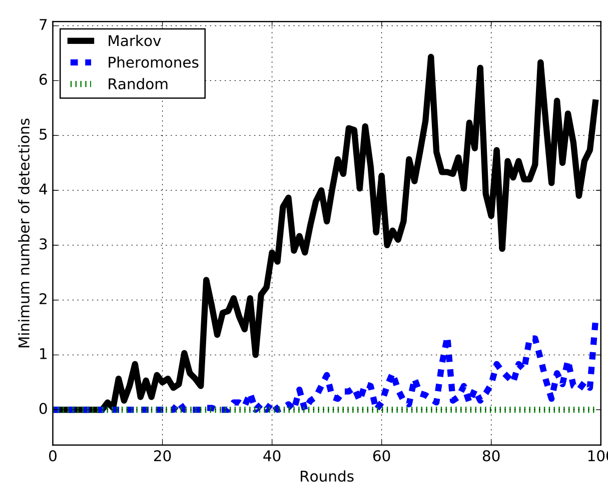

Fig. 7. Minimum number of detections

TABLE II
P-VALUE FOR PAIRWISE COMPARISON BETWEEN THE MOBILITY MODEL PERFORMANCE

	Rounds				
Pairwise comparisons	**1**	**25**	**50**	**75**	**100**
H3MP vs. Pheromone (Average)	*1e-3*	*5.7e-2*	*5.4e-1*	*3e-2*	*9.4e-1*
H3MP vs. Pheromone (Minimum)	*1.0*	*4.9e2*	*1.1e-4*	*1.24e-7*	*3.05e-6*
H3MP vs. Random (Average)	*1.0e-2*	*3.49e-11*	*1.33e-11*	*1.33e-11*	*6.47e-11*
H3MP vs. Random (Minimum)	*1.0*	*4.9e-2*	*4.59e-6*	*1.38e-8*	*1.63e-7*
Pheromone vs.Random (Average)	*1.0*	*6.78e-11*	*1.47e-11*	*1.33e-11*	*5.11e-11*
Pheromone vs. Random (Minimum)	*1.0*	*1.0*	*2.7e-1*	*2.7e-1*	*1.9e-1*

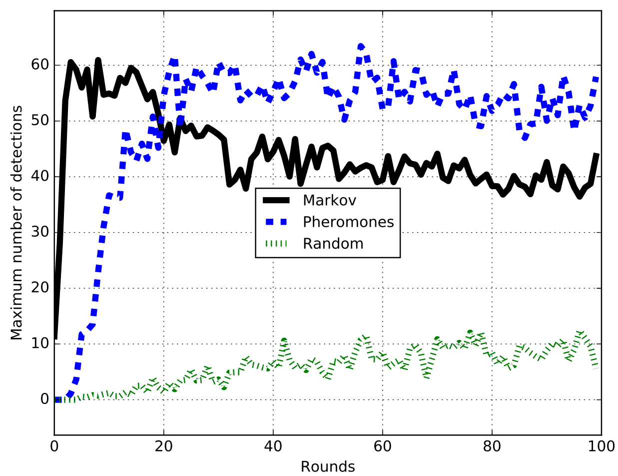

Fig. 8. Maximum number of detections

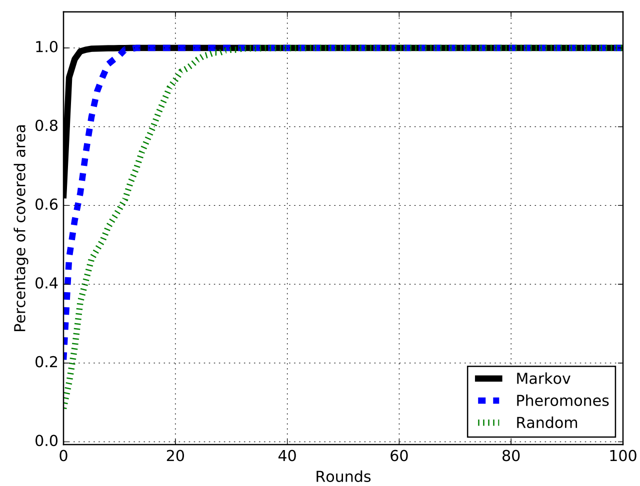

Fig. 9. Percentage of covered area

number of detections. Each experiment has been repeated 30 times (see Table I) to achieve a sufficient statistical confidence since all models are stochastic. Using Wilcoxon rank sum test, all mobility models' results have been statistically compared for different rounds (see Table II). As planned, the random model detects targets with difficulty and constitutes the baseline. On the contrary, one can observe that H3MP is able to detect targets sooner than the other models. This is due to the partitioning of the geographical search space. Indeed contrary to the other models, hybrid Markov-based quad-copters have to leave a zone once they arrive and are thus able to explore the environment faster. After 20 rounds, the difference between the pheromone-based and the Markov-based model decreases, and according to Table II the average number of detections is not statistically different anymore. Figure 7 depicts the minimum number of detection for the three mobility models. One can see that this number is larger for H3MP while it remains very low for the other two approaches. Table II shows that the minimum number of detection is statistically higher than for the other two models. On the contrary, it can be observed that the maximum number of detection (Figure 8) is the highest for the pheromone model. H3MP ensures that each quad-copter detects as fast as possible targets. They cannot loop inside a zone of the map and thus discover more targets. Pheromone-based quad-copters may suffer from a lack of tracks forcing them to move randomly during the first step. This is the reason why it is not so different as our reference, i.e. the random mobility model. Once pheromone-based quadcopters detect targets, the number of detection increases making the pheromone-based model better for the maximum number of detection (see Figure 8) but worst for the minimum number of detection. This could be explained by the fact that pheromone-based quadcopters are certainly better for tracking but do not guarantee an overall good performance for all cooperative UAVs. In fact, the cooperation is basically poor since some UAVs do not benefit from the information provided by the others if they are not able to catch the tracks. With smaller zones as implemented in H3MP, pheromones tracks are more efficient. On large maps, it is difficult to find the best evaporation parameter and some zones may lose all the information dropped by one UAV. This drawback does not appear with H3MP since UAVs also have a global patrol forcing them to change zone. Concerning the coverage of all the area, Figure 9 illustrates the percentage of covered area over all rounds. The area is covered faster with H3MP quad-copters than pheromone-based or random-based quad-copters.

VII. Conclusion and perspectives

In this work, we proposed H3MP, a hybrid approach based on a Markov mobility model and pheromone tracks to enhance the target surveillance-patrol abilities of UAVs flying in swarms. This hybrid approach has been studied to counterbalance some drawbacks of local procedure based on pheromones. H3MP is generated from a preceding partitioning of the environment which could be performed by a fixed-wing UAV flying at high altitude. Transition probabilities are then improved using a standard genetic algorithm to find the best stochastic patrol according to the location of detected targets. Simulations involving the detection of randomly moving targets by quad-copters have been designed and implemented to evaluate the potential of the proposed mobility model. Its performance was compared to two other mobility models, pheromone-based and random-based. Numerical results have demonstrated that H3MP ensures a maximal utilization of each quad-copter while the pheromone model tends to have some big detection gap. Future works will be devoted to study a bi-level (Stackelberg game) version of this hybrid Markov mobility model where clusters (zones) may change based on a dynamic cooperation between quad-copters and high-altitude UAVs.

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