Connectivity Stability in Autonomous Multi-level UAV Swarms for Wide Area Monitoring

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ABSTRACT

Many different types of unmanned aerial vehicles (UAVs) have been developed to address a variety of applications ranging from searching and mapping to surveillance. However, for complex wide-area surveillance scenarios, where fleets of autonomous UAVs must be deployed to work collectively on a common goal, multiple types of UAVs should be incorporated forming a heterogeneous UAV system. Indeed, the interconnection of two levels of UAVs—one with high altitude fixed-wing UAVs and one with low altitude rotary-wing UAVs—can provide applicability for scenarios which cannot be addressed by either UAV type. This work considers a bi-level flying ad hoc networks (FANETs), in which each UAV is equipped with ad hoc communication capabilities, in which the higher level fixed-wing swarm serves mainly as a communication bridge for the lower level UAV fleets, which conduct precise information sensing. The interconnection of multiple UAV types poses a significant challenge, since each UAV level moves according to its own mobility pattern, which is constrained by the UAV physical properties. Another important challenge is to form network clusters at the lower level, whereby the intra-level links must provide a certain degree of stability to allow a reliable communication within the UAV system. This article proposes a novel mobility model for the low-level UAVs that combines a pheromone-based model with a multi-hop clustering algorithm. The pheromones permit to focus on the least explored areas with the goal to optimize the coverage while the multi-hop clustering algorithm aims at keeping a stable and connected network. The proposed model works online and is fully distributed. The connection stability is evaluated against different measurements such as stability coefficient and volatility. The performance of the proposed model is compared to other state-of-the-art contributions using simulations. Experimental results demonstrate the ability of the proposed mobility model to significantly improve the network stability while having a limited impact on the wide-area coverage.

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Keywords

UAV, mobility model, ACO, clustering

1. INTRODUCTION

Many unmanned aerial vehicles (UAVs) varying in technology, design, and size have been developed. Each UAV type aims to address requirements for the peculiarities of different applications such as searching, mapping and surveillance. Although possessing multiple unique characteristics, UAVs can mainly be classified in fixed-wing UAVs and rotary wing UAVs. Operating with low energy consumption, the overall design of a fixed-wing UAV allows significantly longer flights durations with increased velocity. Additionally, the payload for fixed-wing UAVs can be higher than for a rotary wing UAV, allowing to equip sophisticated sensors. Their design allows rotary UAVs to takeoff and land vertically as well as conducting precise manoeuvring making them the preferred choice for specific scenarios. In contrast to fixed-wing UAVs, rotary wing UAVs offer lower speed and have shorter flight ranges. Additionally, the sensor equipment payload is restricted and reduces tremendously the flight duration.

UAVs can contain built in sensors which enable them to form an inter-connected autonomous UAV swarm, or a so-called flying ad hoc networks (FANETs) [2]. FANETs are formed when multiple UAVs flying in a spatial proximity – within a mutual transmission range – spontaneously form network communication links. A FANET is able to function without fixed infrastructure and therefore adaptable to requirement changes such as flight pattern or flight trajectory. A FANET of UAVs extends the possibilities of a single drone in terms of mission duration, coverage, and quality of collected data. There is a tremendous potential for FANETs to be utilised in applications such as surveillance, search and rescue in disaster recovery, object localization, and environment mapping [8].

While most FANETs consists of one UAV type, heterogeneous FANETs, which combine the advantages of different UAV types, are less studied. The interconnection of two levels of UAVs, one with fixed-wing UAVs and one with rotary-wing UAVs, can provide applicability for scenarios which cannot be addressed by either UAV type.

This work considers higher-altitude fixed-wing UAVs with longer flights for wide-area coverage and which serves as a communication backbone network for lower-altitude rotary UAV swarms which allow precise manoeuvring for e.g. tracking, precise mapping, or high-precision surveillance. For example, if the higher-altitude UAVs detect an area of interest, these command a rotary-wing swarm to that area for surveillance. The rotary-wing swarm needs to self-organise in a cluster formation in order to maximize the coverage over the area, while remaining connected with the swarm leader.

Due to its role in maintaining the connectivity of the entire UAV system, the high-level mobility is less relevant in this paper. The focus is therefore put on the mobility management of the low-level UAV system in this paper. The efficiency of the UAV surveillance system decidedly relies on the deployment and foremost on the flight trajectories. Some flight planning approaches consider offline methods, i.e., they are planning trajectories in advance following a map. In scenarios with an incomplete knowledge about the environment, however, online centralized methods have been developed. These methods require a central decision-making and require more message exchanges. These methods have their limitation when spatial communication constraints apply, i.e., when UAVs are not in mutual communication range. Additionally, in a real-world scenario, it is important to act and react to unforeseen events for which offline or/and decentralised approaches are unsuitable. Therefore, in this paper the focus is on an online and decentralised approach, i.e., autonomous decision-making of the individual UAVs.

In this paper a complex wide-area surveillance scenario is considered, where a larger number of UAVs must be deployed to work collectively on a common goal. Specifically, wide-area surveillance or aerial monitoring of areas where occurrences need to be analysed close-by for a final conclusion in usually inaccessible areas. The described scenario poses several challenges: The interconnection of multiple UAV types in different level poses a significant challenge, since each UAV level moves according to its own mobility pattern, which is constrained by the UAV physical properties. In general, the inter-level connections provide some sort of stability in the short-term and in the long-term to allow a reliable communication within the UAV system to take place. Additionally, the rotary-wing UAV swarm follow a leader, which is called clusterhead. The leader makes autonomous decisions about its movement and the rest of the UAV swarm needs to follow.

If the UAVs mobility causes significant change in the network topology, the clusterhead will suffer in its quality to provide an efficient interconnection point. If these changes are detected a new clusterhead needs to be elected, which causes additional messages to be exchanged and can result in interruption of the communication of the UAV system. Therefore, clusterhead re-election or cluster reorganization should be avoided, in particular in cases where only few network attributes changed, e.g. one new neighbour.

The proposed approach is based on combining the ACO-based mobility model used in [12] with the KHOPCA clustering algorithm [7, 6] on the low-level UAV swarm to optimize surveillance capabilities such as coverage area and stability of the network-wide connectivity. The connection stability is evaluated against different stability measurements such as stability coefficient and volatility. The overall performance is compared to two other mobility models from the literature.

This paper is organized as follows. The next section introduces related work. Section 3 then presents and formalises the problem. The proposed cluster-based mobility model is described in detail in section 4. The different metrics to evaluate its performance for the surveillance scenario are introduced in section 5. The experimental setup used and the obtained results are then discussed Section 6 and and 7 respectively. Finally section 8 concludes the paper and provides some perspectives.

2. RELATED WORK

Different ways of controlling the mobility of UAVs swarms have been studied in the literature. The first proposed approaches compute the flight plan in a centralised fashion, like in [3], where evolutionary algorithms are used to optimise the UAVs trajectories. Most of existing techniques consider such centralised computations, either offline or online. Offline planning does not permit to adapt in case of unexpected technical issues or harsh weather conditions. Therefore online mission planning is highly desirable for surveillance missions as considered in this work. However, updating the whole fleet flight plan via a unique access point, e.g. satellite connection, also has drawbacks in terms of scalability, robustness or communication costs.

This work is thus interested in online and distributed approaches, where no central authority is in charge of the path planning. UAVs are autonomous entities equipped with wireless communication capabilities and have to self-organise to complete their mission. Each UAV is able to exchange information in a peer-to-peer fashion and to determine its flight plan solely based on its aggregated local knowledge. UAVs communication was already studied in various works, from the hardware level with digital beamforming antennas [13] to communication scheduling optimisation [9].

Some online and distributed approaches have been proposed, such as the dynamic agent-based simulation using swarm control for cooperative hunting from McCune *et al.* [14]. Other approaches rely on stigmergy, and more precisely Ant Colony Optimisation (ACO), in which UAVs are ants leaving pheromone trails. Sauter *et al.* demonstrated in [18] the effectiveness of digital pheromones for three types of scenarios: surveillance and patrol, target acquisition and tracking. Similarly, Kuiper *et al.* in [12] proposed a pheromone-based decentralised mobility model for coverage missions. Repulsive pheromones are used to indicate the already covered regions. Schleich *et al.* in [20] tackled the same problem with additional connectivity constraints. They considered 4 objectives: finding the fastest coverage, the largest coverage, the most uniform coverage and the connectivity maintenance. However these works only focused on single-level and homogeneous swarms.

UAVs are typically dedicated systems which are only able to achieve restricted area missions due to their embedded equipment. Using swarms of heterogeneous UAVs, i.e. equipped with different sensors, is therefore one hot topic in the field, where cooperation between UAVs has to be optimised to complete the mission [15].

Another open issue in FANETs is the network scalability problem. One possible solution is the usage of multi-level UAVs, i.e. swarms flying at different altitudes. However very few works have tackled this problem and only at the communication protocol level, referred to as hierarchical routing. Zang *et al.* in [21] aimed at maintaining stable clusters by using dictionary Trie prediction algorithm, while in [10] the clusters are precomputed and adapted in operation.

Maintaining stable structures is one important feature for an efficient communication in multi-level swarms. It was studied in the single-level swarm context by Schleich et al. in [19] proposed the CEDBBT broadcasting algorithm for FANETs that relies on a community detection algorithm.

Other works in the mobile ad hoc networks (MANETs) domain have considered the same issue. For instance a data gathering protocol relying on clustering was proposed for vehicular ad hoc networks (VANETs) in [4]. Another approach combined clustering and prediction for data dissemination, routing and visual tracking in VANETs [11]. Finally the stability of one-hop clusters in VANETs was evaluated in [1]. However these were not transposed to the FANET field.

To conclude, to the best of our knowledge, no existing work considered the mobility management of heterogeneous multi-level UAVs swarms.

3. SYSTEM MODEL

This section defines the system model of the bi-level UAV swarm under consideration and the formal notations used to describe it.

The flying ad hoc network proposed in this work consists of two levels; one with low-altitude rotary-wing UAV swarms and one with a high-altitude fixed-wing UAV swarm. Each UAV in the proposed system is equipped with ad hoc communication capabilities, in which the high-level UAVs provide a communication bridge for the low-level UAV fleets.

The UAV swarm communication network on each level is given by an undirected Euclidean graph $G = (V, E)$ for which $V \in \mathbb{R}^3$ is a set of UAV nodes. The set E of links of the graph G are defined as follows: For any pair $u, v \in V$ of nodes holds that $dist\,(u,v) \leq r \implies \{u, v\} \in E$ and $dist\,(u,v) > r \implies \{u, v\} \notin E$, where r is the communication range for each $v \in V$. For the sake of simplicity, it is assumed that r is equal for all UAV within the same level. This paper focuses on the low-level UAV swarm, and more precisely the structural and networking aspects within this swarm. Therefore, it is furthermore assumed for the communication range r_h of the high-level UAV swarm that r_h is sufficiently large so that full connectivity within the high-altitude level and connectivity from the high-altitude to the low-altitude swarm is guaranteed.

Each UAV node $v \in V$ has a neighbouring list $Neigh(v) \subset V$, which is the set of UAVs directly connected to UAV v, such that $\forall u \in Neigh(v)$, $d(v, u) \leq r$. The neighbouring list $Neigh(v)$ is created initially and is updated with frequency f. Besides being able to communicate with its direct neighbours (nodes in the neighbouring list $Neigh(v)$) designated nodes—clusterheads—are able to establish communications to designated nodes in the other level. The clusterhead UAV delivers data to the high-level fixed-wing UAV swarm.

Furthermore, it is assumed that the UAVs in each level move according to their own mobility patterns. Mobility must ensure an efficient coverage of the geographical zone but poses a significant challenge to the interconnection of different UAV types by creating instability in the network connectivity. For instance, communication links may fail or disappear from the local network, due to obstacle avoidance or energy-constraints.

This work proposes to tackle these two conflicting objectives by designing a distributed mobility model that combines a pheromone-based model for covering the area and clustering to enable reliable communication within the proposed UAV system.

4. CLUSTER-BASED MOBILITY MODEL

The proposed mobility model combines the pheromone-based approach from [12] with the KHOPCA clustering algorithm from Brust et al. [7]. Both components are presented in detail in this section, followed by the contribution of this work, the cluster-based mobility model.

4.1 Pheromone-based model

The pheromone-based model from Kuiper *et al.* exploits the concept of stigmergy, i.e. an indirect communication of UAVs implemented by repulsive pheromones spread in the environment. The geographical area is discretised in different cells that are characterised by a pheromone level. Each UAV then chooses its direction among three possibilities, front, left or right, with a probability inversely proportional to the amount of pheromones in these locations. These repulsive pheromones permit the UAVs to better explore the least visited places. In case no pheromones exist in any direction, a random direction is picked.

4.2 KHOPCA clustering algorithm

The k-hop clustering algorithm KHOPCA is a dynamic multi-hop clustering technique for mobile wireless and sensor networks [7]. KHOPCA creates trees of a maximum depth k, i.e., the maximum graph distance between the clusterhead (centre of a cluster) and the cluster border is k hops. The algorithm itself is based on the repetitive application of four simple rules in a distributed and localised fashion, that define the transition of each node's state. In the context of the multi-level UAV swarm, each clusterhead in the low-level UAV swarms represents an efficient communication end-point to the high-level UAV swarm. Therefore, a clusterhead is an appropriate choice to be selected as a communication bridge between the different swarm levels.

Although a multi-hop cluster is formed—i.e., there are UAVs which are connected to the clusterhead UAV only via intermediate UAVs—each cluster must have exactly one clusterhead. Additionally, each cluster UAV needs to own basic information about how to forward data to the clusterhead. Both requirements are delivered by the transition rules for the KHOPCA clustering algorithm regarding a UAV n, which are formalised below:

$$s(n) = \begin{cases} min\left(s\left(N\left(n\right)\right)\right) & \text{if } s\left(m\right) < s(n), \forall m \in N\left(n\right) \\ 0 & \text{if } s\left(m = k, \forall m \in N\left(n\right)\right) \\ s\left(n\right) + 1 & \text{if } s\left(n\right) \neq 0 \land s\left(n\right) < s\left(m\right), \forall m \in N\left(n\right) \\ s\left(n\right) + 1 & \text{if } s\left(n\right) = 0 \land \exists m \in N\left(n\right) \text{ with } s\left(m\right) = 0 \end{cases}$$

Applied to a UAV swarm, every UAV n is initially assigned the same state value s, which is a value between 0

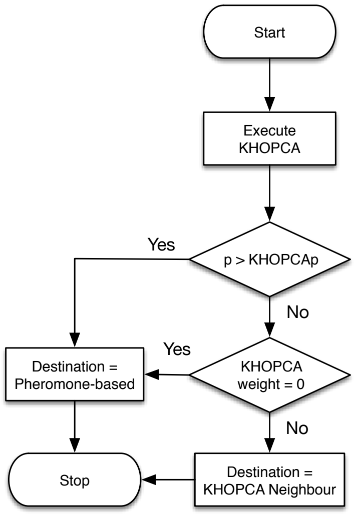

Figure 1: Flowchart of the KHOPCA-based mobility model

and k. Each time the UAV neighbouring discovery service is executed on a UAV n, UAVs in its communication range are detected. The neighbouring list N for n is updated, which in turn will be used to recalculate the state value s for each UAV. UAVs with state value 0 are the designated clusterhead UAVs.

The first rule creates an ordering between neighbouring nodes such that the maximum state value difference between two neighbouring nodes is 1. The second rule defines a clusterhead (value 0), when all of n neighbours have state value k. The third rule solves situations where the UAV n is considered as an intermediate node to the clusterhead, while, in fact, n does not point to any clusterhead. The last rule reorganises situations with directly connected clusterheads in one cluster.

As result of the function s, clusters will be created, which contain exactly one clusterhead each and which have a maximal graph distance k from the clusterhead to the most distant cluster member.

4.3 Our approach

The KHOPCA-based mobility model is executed locally on each node. It uses either the pheromone-based direction or a KHOPCA-based direction using the probability $KHOPCA_p$.

In a first step the KHOPCA algorithm is executed. If $p > KHOPCA_p$, or if the node is a clusterhead, i.e. its state value (or weight) is equal to 0, then the pheromone-based destination is used as in the original model. Otherwise, the destination is equal to the position of the one hop neighbour with the lowest KHOPCA weight. In case of tie, one destination among the possible ones is chosen randomly. The corresponding flowchart is presented in Figure 1.

5. METRICS

This section introduces the different metrics used to assess the performance of the proposed mobility models both in terms of coverage and UAV network connectivity. The quality of the surveillance area coverage is assessed by three metrics, the number of scanned cells, the exhaustivity and the faireness of the coverage. Three additional metrics are used to evaluate the network properties, i.e. the ability to maintain structures: connectivity, stability and volatility.

5.1 Exhaustivity of the coverage

The exhaustivity of the coverage indicates the percentage of the surveillance area that has never been scanned during a run [20]. It is formalized as follows:

$$ex = \frac{|\{c_{i,j} \in C,\ Scan(c_{i,j}, t_{max} = -1\}|}{NbCells} \quad (1)$$

with C the set of all cells in the simulation area, $c_{i,j}$ the cell in location i, j in the simulation grid. The function $Scan : C, T \to T$ be the function that returns the last time at which a cell has been scanned by a UAV in the time interval $[0, t \in T]$. Scan returns -1 if a cell has never been scanned yet. The parameter t_{max} is the simulation time end.

5.2 Fairness of the coverage

The fairness allows to measure if the cells are equally and regularly scanned by using the dispersion of the number of scans for all the cells of the simulation area [20]. It is computed as the standard deviation of the number of scans for all the cells:

$$fairness = \sqrt{\sum_{c \in C} \frac{(\overline{nbScan} - nbScan_c)^2}{|C|}} \quad (2)$$

with $nbScan : C \to N$ the function returning the number of times a given cell has been scanned.

5.3 Percentage of scanned cells

This metric indicates the percentage of the surveillance area that has been recently scanned by at least one UAV, i.e. that contains pheromones, at each iteration step:

$$scanned = \frac{|\{c_{i,j} \in C,\ 0 \leq t - Scan(c_{i,j}, t) < evap\}|}{NbCells} \quad (3)$$

with $evap$ the required time for complete pheromone evaporation.

5.4 Connectivity

A connected component of a graph is any maximal set of vertices which are pairwise connected by a path. The number of connected components provides information about how strongly disconnected a graph is. The optimal (and minimal) value for this metric is thus 1. Let $nbCC_t$ be the number of connected components at a time $t \in T$.

5.5 Stability

The UAVs mobility causes constant changes on the entire network topology. To discover how much the local neighbourhood of a node n changed, the stability coefficient metric is used [5]. The stability coefficient takes into account the neighbours of a node n at one point in time t_1 and compares it with the neighbours at a later point in time t_2. The number of lost neighbours $|(Neigh_{t_1}(n) \setminus Neigh_{t_2}(n))|$ and new neighbours $|(Neigh_{t_2}(n) \setminus Neigh_{t_1}(n))|$ is calculated and divided by the sum of the number of neighbours at t_1 and t_2. Thus, the stability coefficient of a node is defined as:

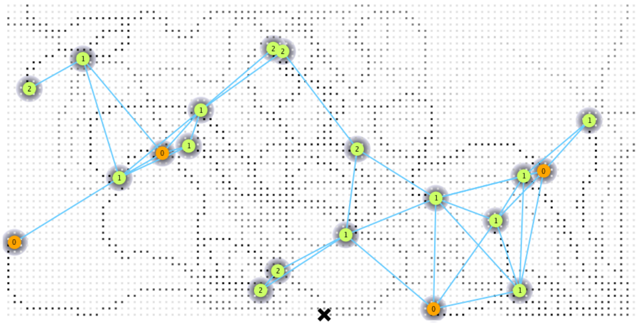

Figure 2: Simulation snapshot

$$stability = \frac{lostNeighbors + newNeighbors}{|Neigh_{t_1}(n)| + |Neigh_{t_2}(n)|} \quad (4)$$

For example, if a clusterhead is surrounded by a group of UAVs and they are moving together into the same direction, they might pass few additional UAV which temporarily connect to the clusterhead. Since they disappear from the neighbouring list after the swarm has passed, the stability coefficient will indicate only a low change in its value for the clusterhead.

5.6 Volatility

The volatility of an element, i.e. an edge in this work, is defined as the ratio of its number of appearances over its accumulated age [16]:

$$volatility(e) = \frac{appearances(e)}{accumulatedAge(e)} \quad (5)$$

The number of appearances of an edge is a counter incremented by one each time a link changes its state from non-existent to existent. Its optimum is a constant value of one, which means that all edges of the graph have only appeared once over the simulation period.

The accumulated age is defined as the sum of the time intervals the edge has existed during the simulation:

$$accumulatedAge(e) = \sum_{i=0}^{n} t_{presence_i} \quad (6)$$

Its optimum is equal to the total time of the simulation which means that this element has been active during the whole simulation period.

The optimum value of the volatility of an element tends to zero, which indicates that it has been active for a long period while appearing only few times. The volatility of a network is thus the sum of the volatility of all edges.

6. EXPERIMENTAL SETUP

This section first presents the parameters used for the simulations and then provides a short description of the third mobility model used for comparison, i.e. the random movement.

6.1 Simulation environment

The simulation environment is a custom-made simulator based on a the Graphstream dynamic graph library [17].

Parameter name	**Parameter value**
Simulation area	
L	2000
l	1000
L_{cell}	20
UAV Autopilot	
Speed	[0 .. 10]
Acceleration	[−1 .. 1]
Heading Change	[0 .. 0.2]
Decision Frequency	30
Wireless range	400
Experiments	
Mobility models	Rand., Pheromone, KHOPCA
KHOPCA probabilities	0.05, 0.1, 0.2
# of UAVs	[10, 20, 30, 40, 50]
# of runs per experiment	30

Table 1: Main simulation parameters

Both the networking and UAV physical models are therefore simplified, i.e. respectively considering idealistic communication conditions (no collision, interferences, unlimited bandwidth) and no realistic physical quadcopter model. However these already permit to provide a fast and sufficiently accurate evaluation of the different mobility models. The different parameters are presented in Table 1 and described following in detail. A snapshot of one simulation of the KHOPCA-based model with 20 UAVs is presented in Figure 2, in which the orange nodes are the clusterheads and the green nodes the cluster members with their respective state value s. Shaded cells represent the pheromone traces and lines represent the ad hoc communication links.

6.1.1 *The Area*

The simulated surveillance area is a rectangle with a long side L=2000 and a shorter side l=1000, discretised into square-shaped cells of side L_{cell}=20. The total grid is thus composed of 100 x 50 = 5000 cells. The smaller the cells the more precise the simulation but also the more computationally demanding.

6.1.2 *Autopilot*

The autopilot mimics a simple quad-copter UAV behaviour. It only requires the definition of a destination to operate, i.e. the heading of the aircraft is automatically set as well as its speed in the range [0,10]. The current destination is modified every 30 time-steps in order to reduce the computational cost as in [20]. In case the UAV is far from its destination, the autopilot instantly modifies the heading to align with it and then proceeds in a straight line. The main parameters related to the flight behaviour of the UAVs are shown in Table 1.

6.1.3 *Simulation parameters*

Each mobility model has been evaluated with five different UAV densities, i.e. 10, 20, 30, 40 and 50, with a wireless transmission range fixed at 400. Since all mobility models are stochastic, each experiment was repeated 30 times to obtain statistically significant results. All metrics results thus correspond to the average value obtained during the simulation, averaged over 30 runs.

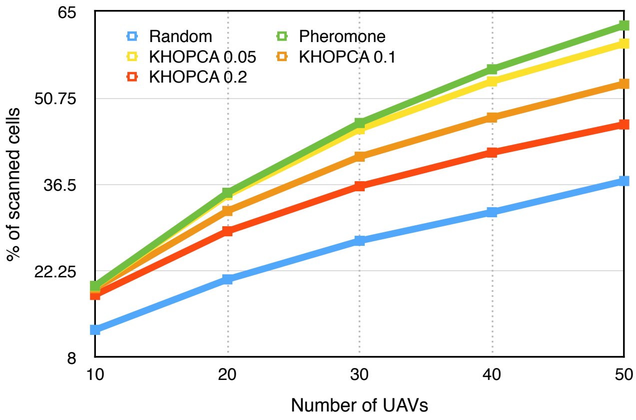

Figure 3: Percentage of scanned cells

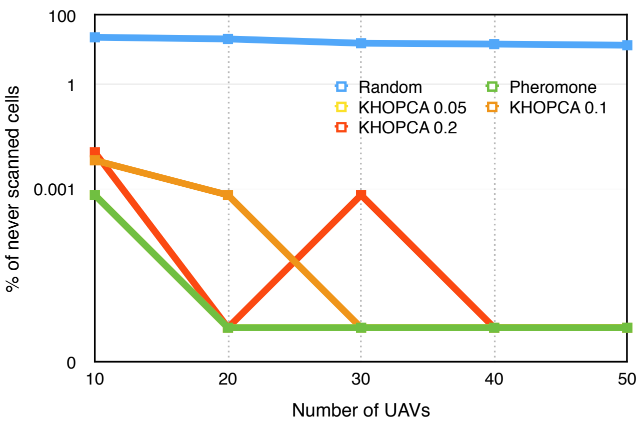

Figure 4: Exhaustivity of coverage

6.2 Compared mobility models

The performance of the KHOPCA-based mobility model is compared to two other models: the pheromone-based mobility model described in section 4.1 and the random mobility model briefly described below.

6.2.1 Random mobility model

The random mobility model chooses, at each decision step, a direction at random between three possibilities: front, left or right with probabilities 60%, 20% and 20% respectively as in [12]. The autopilot then computes a corresponding destination point that can be reached by the UAV.

7. EXPERIMENTAL RESULTS

This section presents the evaluation and comparison of the different mobility models using the metrics presented in section 5.

7.1 Percentage of scanned cells

This first analysis on the percentage of scanned cells outlines the poor performance of the random model for all network densities. This indicates that already visited cells are revisited by other UAVs. The probability of the KHOPCA-based model has some influence, a high probability inducing a lower percentage of scanned cells. This demonstrates the conflict between maximizing the stability of the network structure and maximizing the area coverage. However, the probability provides some control, since the probability of 0.05 performs best for KHOPCA and the worst is reached with a probability of 0.2. The pheromone-based model is the overall best, but the difference with KHOPCA 0.5 ranges only between 0.3% and 4.8% from the 10 to 50 UAVs.

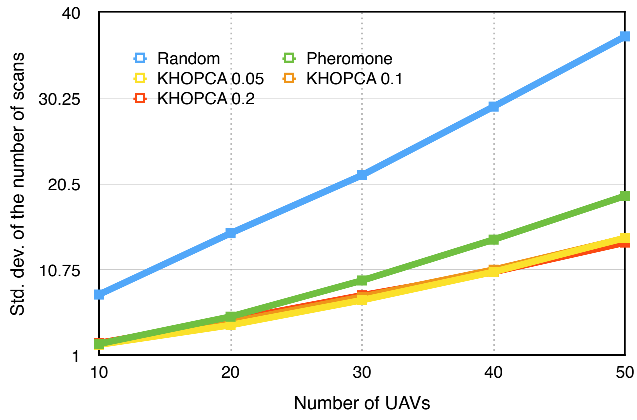

Figure 5: Fairness of coverage

7.2 Exhaustivity of the coverage

The percentage of never scanned cells is presented in Figure 4. It obviously appears that the random mobility model performs much worse that all other models. Indeed, with random movement the percentage of never scanned cells ranges between 23.5% and 13.9%, while other models are close to 0% for any other model, i.e. close to a complete scan of the surveillance area. The KHOPCA-based models have slightly worse results than the pheromone-based model, but this difference is almost negligible.

7.3 Fairness of the coverage

The fairness of the coverage is presented in Figure 5. Similarly, the random mobility model performs very poorly for all UAVs densities. The other mobility models perform similarly with 10 UAVS, but for higher densities the KHOPCA-based models provide a fairer exploration of the area. This indicates that the addition of the clustering algorithm to the pheromone-based model allows to more uniformly scan the area while maintaining a higher connectivity.

7.4 Connectivity

The number of connected components is illustrated in Figure 6. With 10 UAVs the KHOPCA-based mobility model with the highest probability provides the best result, i.e. it permits to maintain a high network connectivity in a sparse network. Between 20 and 40 UAVs, the random mobility model has the best result. The pheromone-based model that performs the worst with the sparse network obtains the best result in the densest case, i.e. 50 UAVs. It can also be noticed that for sparse to medium densities, the probability of the KHOPCA-based model allows to control the connectivity, a high probability ensuring a low number of connected components.

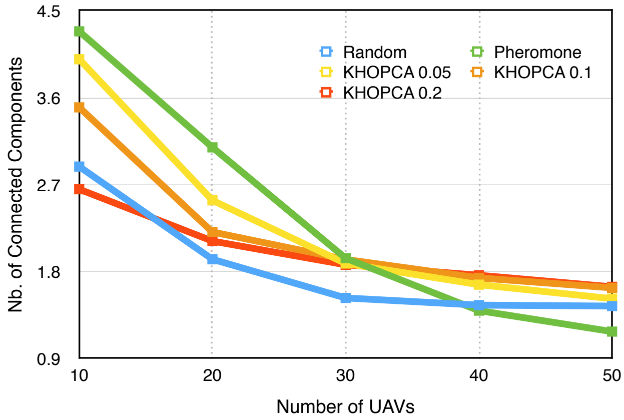

Figure 6: Number of connected components

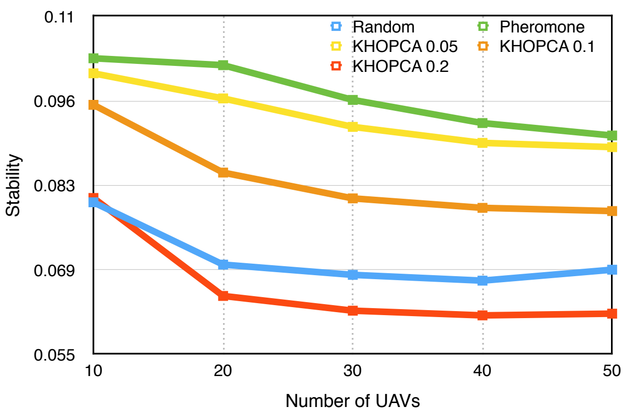

Figure 7: Stability

7.5 Stability

Figure 7 illustrates the stability results. Similarly, the the probability of the KHOPCA-based model permits to control the stability. A high probability ensures a better stability (i.e. a lower value). The addition of the clustering to the pheromone-based model allows to improve the stability in all cases. However, quite surprisingly, the random model performs pretty well, providing the second best results after the KHOPCA-based model with the highest probability.

7.6 Volatility

Regarding the volatility presented in Figure 8, it is also improved by the KHOPCA-based model compared to the pheromone-based model. This means that the connections between UAVs are preserved for longer times and also appear/disappear less often, which is a desirable property in a multi-level UAV swarm system. Finally, the KHOPCA-based model probability again allows to control this value, a high probability providing a low volatility.

7.7 Summary

This experimental validation has demonstrated the ability of the KHOPCA-based mobility model to efficiently handle the trade-off between maintaining a stable network structure and covering a large area. Indeed, the different metrics

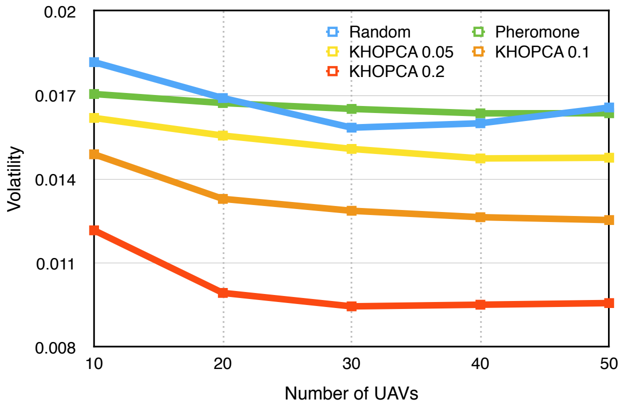

Figure 8: Volatility

outline that the high increase in the network stability negatively impacts the area coverage only to a limited extent, especially for low probabilities, and even positively for the fairness of coverage. Finally, the probability provides control on the mobility model focus, a high probability favouring the network connectivity.

8. CONCLUSIONS

This article proposed a novel mobility model for multi-level UAV swarms for area surveillance. In this preliminary work, the focus is put on the low-level UAV swarm, with a model that combines a state-of-the-art pheromone-based mobility model with the KHOPCA clustering algorithm. Each UAV chooses its destination with some probability between its one-hop neighbour with the highest cluster member value and the area with the least pheromone. With the objective of using the low-level swarm clusterheads as bridges to the high-level swarm, this mobility model aims at efficiently dealing with two conflicting objectives: keeping a stable UAV network structure while efficiently covering a wide geographical area. Its performance is evaluated using a set of quality metrics and compared to two other models from the literature. Experimental results demonstrated the ability of the KHOPCA-based model to greatly improve the network stability with a limited impact on the surveillance area coverage. Future work will extend the model to the higher-level swarm by considering its mobility management to ensure stable inter-level communications.

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