Non-deterministic Operation Profiles Based on Multi-Layer Interest Landscapes for Autonomous Robotic Teams

Florian Segor, Igor Tchouchenkov, Aleksej Buller, Matthias Kollmann
IAS - Department of Interoperability and Assistance Systems
Fraunhofer IOSB
Karlsruhe, Germany
e-mail: {florian.segor, igor.tchouchenkov, aleksej.buller, matthias.kollmann}@iosb.fraunhofer.de

***Abstract*—Distributed deployment of cooperating unmanned vehicles is increasingly becoming a key element for expanding the range of operations in many domains. The Management by Objective Demonstrators is used to investigate procedures and potential solutions for a holistic approach to generate cooperating vehicle teams based on global planning paired with local reactive autonomy of individual vehicles. The implemented procedures deducing local autonomy from global planning are presented. Based on this, the use of operation profiles for aerial reconnaissance, which are intended to enable cooperative team behavior with respect to the global mission, are analyzed. The operation profiles are compared to traditional methods and their advantages and disadvantages are highlighted.**

Keywords-swarming; mission planning; reactive autonomy; reconaissance.

I. INTRODUCTION

Available autonomy within modern robotic systems is constantly increasing, opening up new fields of application and possible scenarios for corresponding systems. Autonomous Systems (AS) will be more and more considered critical for various types of missions in the future. As much as these increasing demands may drive AS development, many acute issues remain to be solved addressing individual solutions and specific operation requirements.

Our vision is to evoke an intelligent, effective and efficient cooperating behavior by creating autonomous responsiveness of individual robots to the individual situation while considering the overall mission objective, the actions of assigned team members, as well as the environment and its potential dynamic change. The concept of local responsiveness based on global planning is providing this autonomous decision-making capability to individual vehicles organized in a team. In the work presented here, the basic approach to achieve this system autonomy as a part of the flexible control chain of the Management by Objective Demonstrator [1] is described. The performance of this solution is discussed in the context of a specific application scenario - the coordinated deployment of multiple AS operating in a team to fulfill aerial reconnaissance.

The Management by Objective Demonstrator (MOD) is designed as a multi-layered flexible stacked architecture, integrating a modular, adjustable control chain of planning, monitoring, and evaluation algorithm. This is used to prepare and schedule collective actions at the global team level with respect to the mission objective, allocate resources, and provide the (physical or simulated) asset a framework for coordinated actions following the task-oriented Operation Profiles (OP) herein discussed. In this holistic approach, the OPs are used to create local behavior of the AS (also referred to as Reactive Artificial Intelligence (RAI)). These profiles provide the single team members the capability to autonomously decide and operate in their dedicated environment, while the global planning process assures that the mission target is fully contained by the cooperative assets.

In comparison with traditional planning and operating alternatives for aerial reconnaissance, the advantages and disadvantages of the proposed non-deterministic movement profiles for autonomous operation are discussed and the possible applications are analyzed.

The paper is structured as follows: After a brief overview of the state of the art in Section II, the concept of the Management by Objective Demonstrator is described in Section III. The structure of the multi-layer interest landscapes as well as their concrete application are considered in Section IV, and the simulated results are discussed in Section V. The paper is closed with a final discussion in Section VI.

II. STATE OF THE ART

Research and development in the environment of the parallel application of several, possibly heterogeneous sensor carriers, are a fast-growing field in different research areas [2]-[4].

Tan et al. [5] address the problem of navigating multiple individual vehicles in a swarm with respect to an anticipated environmental model. In order to navigate the vehicles, an Artificial Potential Field (APF) is generated that maps the obstacles and destinations of each vehicle as a mathematical function of attraction and repulsion. Each vehicle uses this information to find its way through obstacles to its destinations. This is a widely used approach (e.g., see [6][7] or [8]) that leads to good results if the environmental model is sufficiently precise in correctly representing the goals of the individual Unmanned Surface Vehicle (USV) or team members and real-world objects. As a promising approach, we have investigated APF solutions, but our findings indicated that, whilst providing inherent advantages regarding the determination of speed and course, pure APF introduces some significant shortcomings related to the movement decisions of an AS in complex situations (e.g., singularities).

Copyright (c) IARIA, 2023. ISBN: 978-1-68558-089-6

Alfeo et al. [9] propose to encode the waste management infrastructure into a map by using artificial pheromones and organize the waste disposal process by mimicking the biological models of stigmergy-based foraging. While the described approach is extremely relevant for the self-organization of a swarm, it bases it movement decisions on the fixed and reduced possibilities provided by the underlaying model of the existing streets. While this is perfectly sufficient for the waste disposal in urban area, it is not sufficient to organize a team of AS in a less-structured area, e.g., an open field.

In [10], the authors describe a multi vehicle approach using an artificial pheromone approach, that seems to be promising. Based on the different objectives of a task, diffusing and bleeding (fading out and fading in) pheromones are used to guide the assets to scan the positions with increased uncertainty of a designated target cell for potential threatening persons or vehicles. In contrast, the solution presented here operates on geographical coordinates and not with an artificial division of the real world into cells. Additionally, we calculate with a significantly larger movement variance (currently 360 possibilities in two dimensions). Other aspects such as task assignment, which is also discussed in [11], are components of the higher Artificial Intelligence (AI) in the MbO Demonstrator that are not considered in detail in this paper.

The proposed OPs for aerial reconnaissance are considering two basic approaches: the linear OP and the non-deterministic OP. The search patterns used in the linear approach are basically discussed in [12] and [13]. In [14], two basic search patterns, a linear approach as well as a tube approach are also studied in different embodiments for cooperative use. It is interesting to note here that the vehicles reconnoiter the identical area in parallel and no local separation by assigning sub-areas is proposed. However, the coordination effort seems to be significantly higher in this case, since the planned trajectories are in close proximity to each other. Correspondingly, a higher effort must be expended to enable secure operation. The same applies to the tube approach. Similarly, Choi et al. are creating a path following a spiral pattern [15]. While this circular approach can be well performed by the afterwards described interest landscape, it follows a clear and predictive behavior and is, therefore, not further investigated in this context. Fricke et al. are also proposing a distributed deterministic spiral search algorithm mainly as benchmark for non-deterministic solutions [16]. While this approach seems to show good results, it suffers from the fact that the search needs to be started in the center of the search area, which is a very specific situation not suitable for a generic solution.

III. MANAGEMENT BY OBJECTIVE DEMONSTRATOR CONCEPT

Autonomous Systems operating in a team to cooperatively solve a common problem is challenging from a technical perspective as well as from an organizational one. A multitude of solutions, technologies and strategies that solve specific aspects of autonomous UxV operation do exist. But it certainly requires a holistic approach considering the challenges to enable the efficient, effective and flexible operational use of such a Systems of Systems (SOS) in a real-world application. We addressed this problem by introducing the Management by Objective (MbO) concept [1]. MbO is not primarily focusing on the autonomy of the system, but on the question how a single operator can be meaningfully involved in the team's actions [17] [18]. Direct monitoring of individual vehicles is inefficient, as it usually exceeds the capacity of the operator, especially in high workload situations spread over a varying number of independent vehicles (see, e.g.: [19] [20]). Therefore, the MbO approach is not focusing on vehicle control, but on tuning the results or mission products (see Figure 1). The interaction between the operator and the assets take place via the adaption of the global mission tasks or finetuning of the mission product requirements.

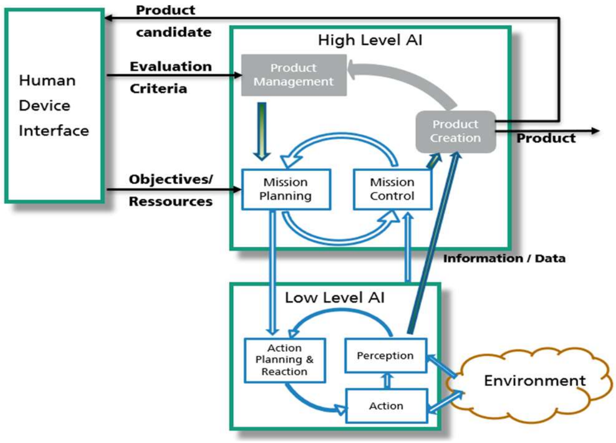

Figure 1. Management by Objective control cycles for AS as used in the MOD.

The concept can be decomposed into three main aspects: Mission Management, Product Creation and Asset Autonomy (see also Figure 1). The Mission Management, as part of the high-level AI, is fully responsible for planning and control of the cooperative actions. It is monitoring and analyzing the progress of the mission with respect to the defined parameters and objectives and is providing and manipulating the data basis of the low-level AI (reactive AI as part of the Asset Autonomy) for controlling the physical asset. The Product Creation within the high-level AI is responsible for processing collected data and provides aggregated products to the operator for evaluation. At the same time, the extracted information from the products is used as feedback to the Mission Management. The operator intervenes in the mission by adjusting the planning specifications based on the information retrieved.

Three different configurations of the MOD have been evaluated in different physical system configurations. Within the full centralized configuration, the high-level AI is a unique centralized instance accompanied by a number of also centralized Low Level AI Instances that only transfer control commands via dedicated wireless links to the interlinked assets. In the second configuration, the low-level AI is hosted on board the asset assuming the physical assets provide appropriate capacities. The third tested configuration is the full distributed approach, where the higher and the lower AI are hosted within the assets and each asset is capable of creating mission data for itself as well as for all team members.

Converting a task into a cooperative mission, based on given OPs, is a central component of the high-level AI. It is important to understand how the cooperative mission plan is translated into information measurable by the asset, in order to act autonomously. To solve this the MOD is using OPs as described in Section IV to transform the abstract mission specification into measurable representations, that can be interpreted by any low-level AI.

To create these representations, we propose to use a Multi-Layer Artificial Interest Landscape (ML-AIL) (similar to [21] [22]). The single layers of the ML-AIL are representing a specific object context or dimension, separating different types of information instead of a single merged source. Hence, we separate targets, obstacles, team members, etc. into the individual layers of the interest field and treat them according to their associated sensing algorithms. The output of the corresponding stack of sensing algorithms is fused into a control decision (see Figure 2). This approach increases the computational workload linearly to the used number of layers, but also allows to create differentiated decisions regarding the divergent mappings of the surroundings of the AS. The behavior can be optimally tuned, considering cooperative mobile objects (team members), static and mobile obstacles, mission targets (static and dynamic), as well as the physical characteristics of the asset.

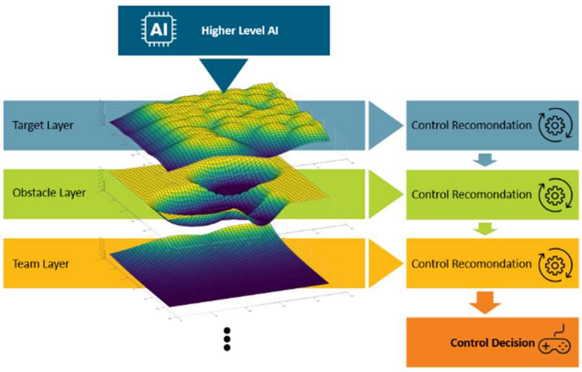

Figure 2. Multi-Layer Artificial Force Field Concept.

The current MoB is operating on three different AIL layers with the capability to add additional layers as needed:

The Target Layer is mimicking the biology inspired foraging process (e.g., see [8][9][23]). At the initial stage of a task-to-mission conversion the higher AI creates a collection of target features with appropriate parameterization, based on the mission requirements and the mission-specific chosen behavior patterns for the team and the team members. In the case of the herein discussed systematic area reconnaissance mission, the result is a set of uniformly distributed features with similar interaction behavior; in case of a non-deterministic approach the resulting features are randomly distributed with deviating interaction behavior. Defined sub-goals, a priori knowledge, mission requirements or the specified treatment of certain known objects or regions (e.g., bridges, buildings or streets that should be monitored more intensively) can be translated into accordingly adapted features, that represent the significantly higher interest in these regions. The AS is able to recognize the increased importance of these objects when analyzing the Target Layer of the ML-AIL and transfer this sensing results into corresponding target-based action recommendations. The basic behavior is not changed, but the specified areas receive increased attention. Scanning the areas is prioritized and happens on a more frequent basis (see also Section IV).

The Obstacle Layer represents the known environmental information and is translated into an AIL by the higher AI algorithms when composing the mission. Based on a real-world model, objects relevant for the mission area are extracted, translated into features of negative interest (leading to an avoiding behavior) and stored in the AIL. Objects that are detected during the mission, for example prior unknown obstacles, are dynamically integrated into this AIL and synchronized between the team members.

The Cooperative Layer is closely related to the obstacle layer and is used to store cooperative obstacles and team relevant information, as well as their history. The individual AS constructs an individual image of the current state of the team using the status information received from the other team members, e.g., to inject marker based stigmergy comparable to the concepts using an artificial pheromone trail. At the same time, it can also be used to correlate specific mission data. For example, a target may be specifically assigned to an AS, but if this target is covered and processed by another AS, the team layer information can be used to indirectly manipulate the target layer of the original assigned AS.

The individual layers use a geographic coordinate system and are described by a collection of data points called features. Each feature has inherent information, about the interaction between the layers, as well as between the layer and the AS, to be performed at layer update, based on the current situation.

As representatives of real-world objects, like obstacles or team members and virtual action or interest points, the content in the individual layers of the AIL are composed of pheromone-like interest features with an inherent information set. This contains the type (e.g., obstacle, target, POI, no-go, track, etc.), position and spatial extent, as well as the behavior during interaction with any AS.

Based on the type of the features the significance of the measured value is determined, e.g., the boundaries of a feature of type “no-go” should not be violated while the boundaries of a feature of type “obstacle” must not be violated.

Decision of the AS is based on the sensing of these features. We distinguish between an attracting and repelling influence leading to avoiding or a searching behavior. In combination with the effect on the perception (the strength of the measurement taking the distance between AS and the feature), these values are used for the sensing within the single layers. Further important parameters used to modify the interaction are the dynamic degradability (the impact on the strength of the feature under influence of an AS, e.g., if mimicking the foraging process the maximum measurable strength of a visited feature is decreased), the recovery procedure (if an who fast a once depleted feature can recover and to what maximum strength), the range of perceptibility (the distance in which the AS is still capable to sense the Feature) or the affiliation (a feature to AS mapping, providing the possibility to assign specific features to specific assets).

For the translation of the AIL into movements of the AS, we use a temporal projection of the current geographical position P to potential future positions P'_j based on the current speed $\vec{v}$ of the AS (see Figure 3). Depending on the precision necessary to operate the physical asset in the given environment the granularity of P'_j can be adapted. The MOD currently calculates with a scheme consisting of 360 anticipated future geographical positions, one position per full degree ($j = 360$). For each P'_j a State S_j is calculated based on the measured influence ($\overrightarrow{F_r}$ and $\overrightarrow{F_a}$) of a subset $M_{sub} = \{T_{sub}, W_{sub}, C_{sub}\}$ of the surrounding objects in the associated AIL Layer (Target T, World W, Cooperative C) filtered by the sliding window only considering relevant objects in range of the original position P.

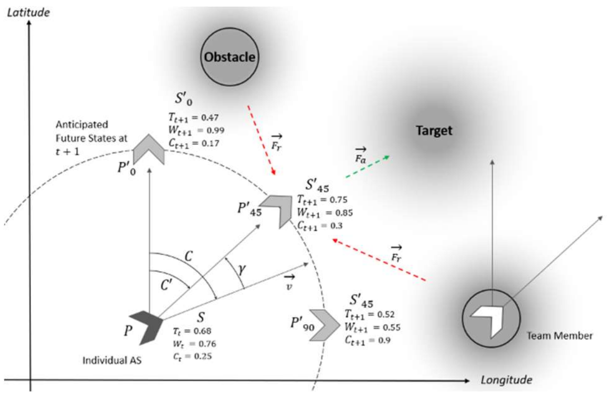

Figure 3. Sensing and decision making based on the ML-AIL for local reactive autonomy.

As impact calculation of each feature upon S_j different approaches have been implemented and evaluated (1) and (2).

$$\frac{F}{{d_f}^2 + \sigma} \qquad (1)$$

F is the current maximum value of the feature to be measured, d_f corresponds to the distance and σ is the slope coefficient that describes the fuzziness or expansion of the feature. A higher σ increases the distance and strength of the measurement of the feature.

Alternatively, the harmonic oscillation approach was tested, where a full computation of the P'_j values is not necessary. Based on the observation that each feature-specific value in S_j given by (1) behaves computably for all other P'_j based on a shifted harmonic oscillation function (2), regarding the given maximum measurement of the corresponding feature.

$$u * \sin(\omega j + \varphi) \qquad (2)$$

Here $u = \frac{F}{2}$ translates the function to oscillate between the maximum measurable F, ω identifies the constant angular velocity and $\varphi = -\frac{\pi}{2} - S_a$ is the phase shift, where S_a corresponds to j of the maximum measurement identical with the vector indicating the direction of the feature.

Single feature measurements are not summed up, so that strong features superimpose weaker one's or the ones that are further away. If, nevertheless, features are measurable above the baseline of the dominant feature, the harmonic oscillations are sequence wise composed. In both approaches, the output of T_{sub}, W_{sub} and C_{sub} is fused afterwards and the result is an anticipated best future state used by the low-level AI to identify the current intension C', as well as the angle offset γ. Based on this intension, the asset specific short-range navigation path is identified and translated into control commands.

IV. CREATING TEAM BASED MULTI-LAYER AIL FOR RECONNAISSANCE MISSIONS

The distributed multi-layer AIL approach for mission conversion in a coordinated team allows to create a specific mission environment for each AS. A central question is how to design the main target layer of the AIL via the translation of the mission aspects into corresponding features and how these features should be parameterized, so that the AS can fulfill its task in the mission context.

In this context, several scenarios were investigated and evaluated for suitability with different feature distributions. Where possible, traditional methods were used as benchmarks. The results are compared in Section V.

A. Area Reconnaissance

A basic task, in which a team approach is valuable to increase efficiency, is reconnaissance for mapping and clearance of large areas with a parallel and coordinated deployment of several reconnaissance vehicles. This scenario requires, that the entire area defined in the mission (target area) must be inspected completely.

In traditional approaches, a pre-planned trajectory for a single (or multiple) vehicle(s) is created to ensure complete coverage (see Figure 4).

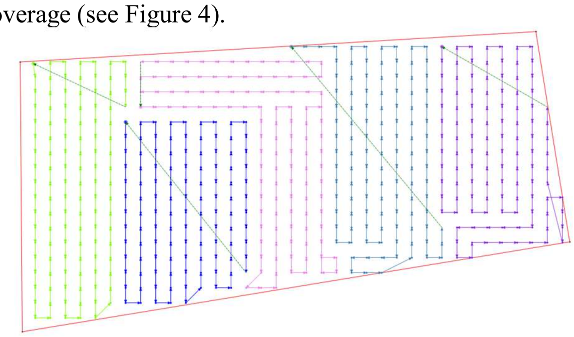

Figure 4. Pre-calculated Flightpath for five AS.

When using the ML-AIL in the MbO Demonstrator, preplanning is not intended. The AS acts autonomously and makes decisions based on the interpretation of the individual ML-AIL.

Following the classical reconnaissance approach, we use a linear feature distribution oriented horizontally (see Figure 5), vertically or along the main orientation of the target area. The special arrangement of the paths is defined by the resolution of the desired footprint, taking a potential overlap into account.

Figure 5. Linear Feature Distribution for 8 AS.

In order to allow evenly spaced tracks with a minimum of course adjustments, the features are compacted in the direction of the main axis. Without condensing the features in the ML-AFF in the direction of the main axis, the AS do not recognize the axis of operation when they are converted into local control commands. Accordingly, the decisions would lead to movements with significantly less focus, which creates disadvantages in terms of endurance and mission time.

B. Area Reconnaissance based on Chaotic Profiles

Regardless of the generation of the reconnaissance patterns, linear behaviors suffer from some drawbacks. In non-cooperative scenarios, when the searched object does not intent to be localized, or the objects to be searched are placed unfavorably with respect to the individual areas to be searched, a linear behavior may be disadvantageous. Chances to avoid detection are significantly higher when the movement pattern of the searchers are predictable since it is easy to anticipate which areas will be checked next.

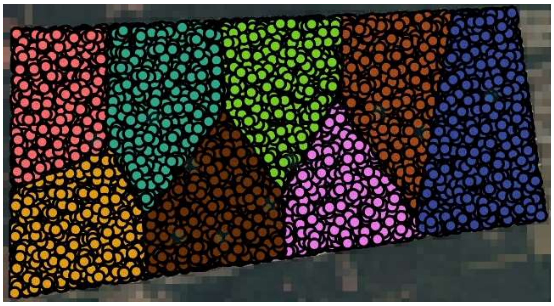

Figure 6. Chaotic Feature Distribution for 8 AS.

At the same time, large, contiguous areas remain unobserved for a long period. For this form of reconnaissance and surveillance missions, we introduced a chaotic, non-deterministic operational profile. For this purpose, the features for the operation area are not ordered linearly, but placed randomly and more densely (see Figure 6). At the same time, the features are generated with divergent properties in terms of their temporal existence and life cycle, resulting in a high fluctuation in the target layer of the ML-AIL. This fluctuation allows the AS to move unpredictably and individually in the operation area, regardless of the prior made movement decisions. In a short-term aspect this behavior leads to a more well-distributed coverage of the area, as the targets are not sequentially organized (all parts of the mission region are potentially visited next) and the feature distribution can attract the AS to search in a non-deterministic manor. However, this unpredictable behavior is bought by the drawback that a complete monitoring of the whole area, where all regions are reliable searched, is not guaranteed.

C. Object Search based on Chaotic Profiles

In contrast to the complete static area reconnaissance, where ideally every location is scanned only once by the sensor of the AS, the search for target objects in an area does not need to fulfill these requirements. In this case the mission target is to localize the searched objects as fast as possible. In case of static searched objects, the preconditions are close to the ones for the area reconnaissance. If targets are considered mobile, the complete coverage of the area cannot guarantee a detection rate of 100%, since a searched object may well pass undetected from a region not yet visited into a region already finally processed (active evasion) during the search phase.

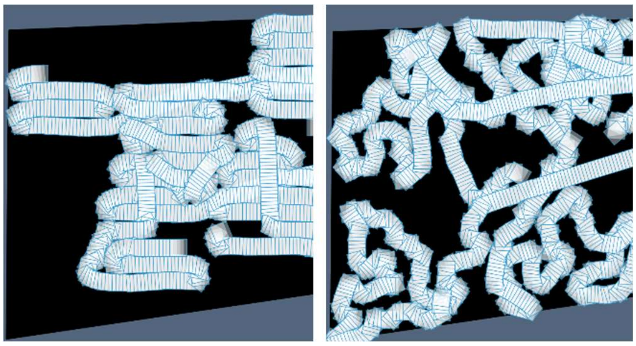

Figure 7. Left: linear reconnaissance of eight AS after 15 Minutes, right: chaotic reconnaissance of eight AS after 15 Minutes.

In this case, the proposed chaotic non-deterministic OP (see Figure 7, right side) provides some advantages over the deterministic one (see Figure 7, left side): First, the non-deterministic behavior of the AS does not allow the searched object to predict the operations of the searchers and, thus, makes it significantly more difficult to evade detection. Secondly, a scanned area is not excluded from further operations, so that even if the detection is successfully avoided, hiding in already scanned areas is not permanently promising.

D. Area Reconnaissance with Mission Focus

To fully exploit the strengths of a non-linear, chaotic search approach, mission planning should consider a priori information and co-translate it into feature data for the ML-AIL. In this scenario we assume that the entire mission area, as marked in the yellow rectangle (see Figure 9), is of importance. The probability that the searched objects are

Copyright (c) IARIA, 2023. ISBN: 978-1-68558-089-6

located on or close by the red marked areas (building, road, or forest edge) is assumed to be significantly higher than in the rest of the area.

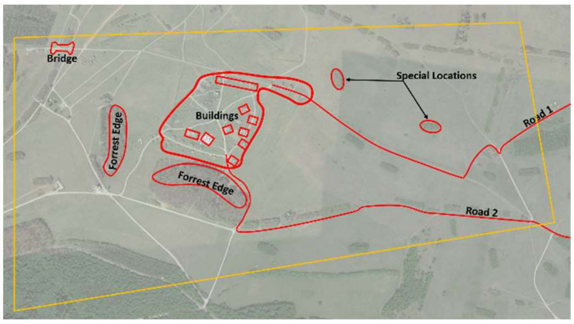

Figure 8. Mission area with high priority regions.

To have these areas searched preferably, mission planning must mark them as prioritized targets. The entire mission area is flooded with random distributed target features of variable expression, as in the basic chaotic approach. At the same time, features are placed in said regions that have a higher attraction and thus, will be preferably investigated. The chaotic, non-deterministic mission profile is preserved, while prioritizing appropriate objects and regions.

Figure 9. Chaotic Reconnaissance with high priority regions (eight AS after 15 Minutes).

Figure 9 shows that the cooperating AS are scanning the area according to the chaotic behavior profile. However, especially at the beginning of the mission, a variance can be recognized with respect to the regions marked with increased importance. The individual assets operate in their subareas with a primary focus on the prioritized regions.

V. Results

To analyze efficiency and effectiveness of the proposed chaotic OPs in comparison with traditional approaches, a series of simulations were conducted and analyzed.

The simulation is conducted in a fixed mission area with a total size of 2.03 square kilometer, defined as the main target area (see also Figure 9). In order to increase the measurability and to simplify the evaluation procedure, a reduced sensor footprint is assumed, corresponding to a ground resolution of 60x60 meters. The position angles of the sensor carrier are not considered and thus, have no effect on the simulated footprint, except for direction changes. The footprint is steadily aligned in nadir. The team consists of homogeneous virtual AS, moving at a maximum speed of approximately 20 km/h and reaching a maximum rotation rate to the vehicle's rotation axis of 28 deg/s. Tests were performed with several simulated vehicles, while the main test series was limited to missions with 5 and 8 vehicles. To complement the measurements of the Reconnaissance Factor (RF) (percentage of overall scanned area), objects were randomly placed in the target area to be found in mission. A hidden object is considered found if it is inside the simulated sensor footprint. The mission duration is defined by the timespan necessary for the assets to conclude the preplanned linear operation path, but is extended to follow the development over time for the other OPs.

All four described methods were tested and compared:

1. Linear search with deterministic pre-planned paths.
2. Autonomous linear search with quasi deterministic search behavior
3. Aerial reconnaissance with non-deterministic motion profiles
4. Multi Target search with non-deterministic motion profiles and prioritized areas.

The analysis shows, that linear methods achieve satisfactory results in terms of the Reconnaissance Factor (RF) (see Figures 11-14). The meander-shaped motion profiles allow a continuous scanning of the entire area, where only few areas are left out. As outcome, the linear methods achieve a stable RF of more than 90% to the end of the mission with the selected movement pattern. This is valid for teams of five vehicles as well as for eight assets and can be qualified increased close to 100% using a higher overlap and full utilization of the area with a small extension in mission duration. Compared to the preplanned linear approach, the procedure degrades slightly when operating autonomously. This can be explained by the absent pre-mission optimization and the associated potential lengthened route traveled in case of a non-optimized area entry as well as transversal movements via already scanned areas, especially at the end of the mission in case of remaining isolated sub-areas.

Both, the chaotic and the multi-target chaotic procedures, can perform comparable, especially at the beginning of the mission. Significant performance losses manifests during the second half of the mission. This can be expected, since by design, the chaotic profiles do not exclude areas that have already been scanned from further processing. Thus, these areas are potentially scanned several times, while the trajectories are not aligned for minimal footprint overlap. In consequence, the profiles cannot compete with the linear optimized ones. The RF ranges from 60% to 80% at the end of the mission, depending on the mission type but reaches up to 90% in the simulation context with the appropriate time addition.

It can be observed, that increasing the number of assets in linear procedures, allows a continuous increase in performance, which in turn results in a reduction of the mission duration. However, it is most interesting to note that

Copyright (c) IARIA, 2023. ISBN: 978-1-68558-089-6

the chaotic procedures seem to benefit more from increasing the number of team members. In particular, the degradation of performance in the second half of the mission is significantly reduced by the use of eight assets compared to the mission with five assets, resulting in a final RF of more than 80% (compare Figure 10 and Figure 11).

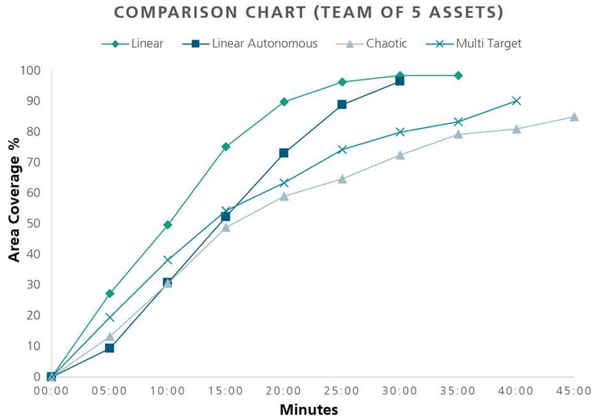

Figure 10. Comparison of mission performance for five AS.

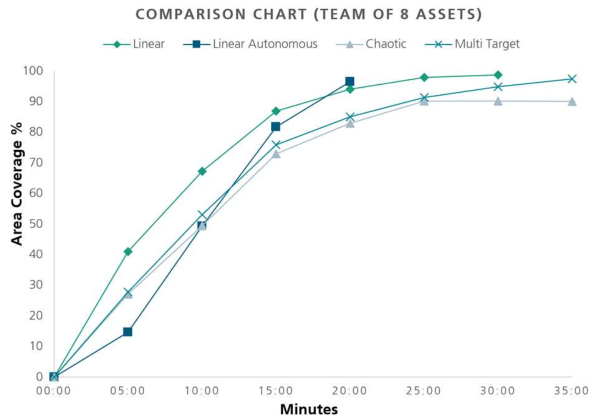

Figure 11. Comparison of mission performance for eight AS.

Analyzing the performance of the profiles regarding the detection of local static objects, the linear methods show merits to a limited extent. Especially at the beginning of the mission, the chaotic methods are at least on par or demonstrate significantly better results. During the second half of the mission, linear methods can catch up and compensate the weak start, while all methods tend to stagnate to the mission end (see Figure 12 and Figure 13).

The initial difficulties of the linear methods can be explained by the applied search patterns. Whether logically planned or linearly autonomously searched, the AS always start at a corner or edge of a region and work their way forward in a clearly structured manner. If targets are not present at the edges of the area the linear approach may take longer to achieve success. The chaotic procedures cover the area more evenly / widely distributed and thus, can show faster results in the first halve. In particular, the multi target method has an advantage over the purely random or linear methods, as the regions with an expected higher density of targets are prioritized.

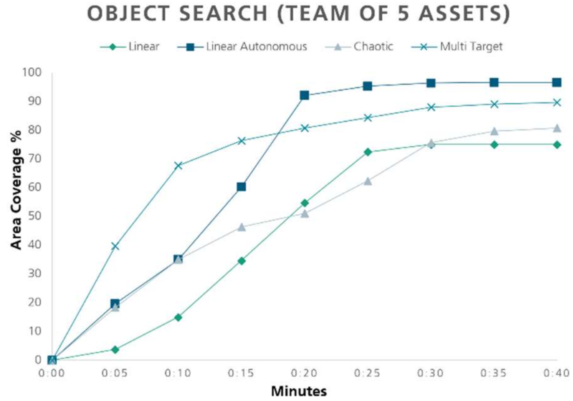

Figure 12. Comparison of object detection for five AS.

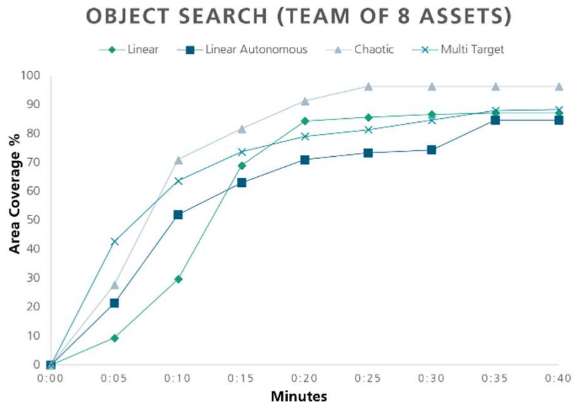

Figure 13. Comparison of Object Detection for Eight AS.

In the second half of the mission, this advantage is partially lost, which can also be explained by the multiple searched areas and the non-footprint-optimized path. As a result, significantly less area is observed (see also Figure 12 and Figure 13), which makes it more difficult for the search method to find the last targets.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have presented and investigated several methods for team-based area reconnaissance. We have described how these methods are implemented in our MbO demonstrator to allow a team of vehicles (simulated or real) to cooperatively work on a joint mission.

Encoding a Multi-Layered AIL via varying feature deployment in the lower AI layer of the MbO demonstrator, based on the planning data provided by the higher AI control cycles, have been described and how the ML-AIL is used to generate action recommendations and consolidated decisions to control the physical vehicle. Since the translation of a mission objective into feature distribution is the essential step to enable efficient and effective mission delivery by multiple vehicles, we simulated procedures for cooperative area reconnaissance and search for hidden objects in teams of vehicles in the MbO demonstrator. This showed that, as expected, the proposed chaotic procedures perform less optimal in terms of RF compared to preplanned linear or autonomous linear procedures. At the same time, however, they offer advantages in terms of hidden object search, whilst the benefits of apparently chaotic movement profiles with regard to the unpredictability of the movement is not measurable in this context. Nevertheless, we expect a significantly improved search performance, especially in the case of non-cooperative evasive targets. As result the advantages of non-deterministic methods prevail the disadvantages in comparison to linear methods in applications that require an unpredictable behavior.

At the same time, the experiments have shown potential for future improvement of the non-deterministic methods. Especially, if the higher AI is qualified via advanced planning algorithms to provide an improved feature distribution and parameterization in the context of mission objectives and environmental data, we expect a performance increase that further reduces the deviation to the linear profiles. Increased cross-correlation of layers of the ML-AFF in the lower AI cycle, especially to account for sensor footprint and team behavior are additional promising candidates for further development and performance enhancement.

References

[1] F. Segor, I. Tchouchenkov, A. Buller, M. Kollmann, and W. Müller, “Controlling swarm complexity: a management by objective approach,” Open Architecture/Open Business Model Net-Centric Systems and Defense Transformation, vol. 11015, pp. 211-220, 2019.

[2] M. Schranz, M. Umlauft, M. Sende and W. Elmenreich, “Swarm Robotic Behaviors and Current Applications,” Front. Robot. AI vol. 7, pp. 36, 2020, doi: 10.3389/frobt.2020.00036.2020.

[3] J. Barca and Y. Sekercioglu, “Swarm robotics reviewed,” Robotica, vol. 31, pp. 345-359, 2013, doi:10.1017/S026357471200032X.

[4] R. Arnold, K. Carey, B. Abruzzo and C. Korpela, "What is A Robot Swarm: A Definition for Swarming Robotics," 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, NY, USA, 2019, pp. 0074-0081, doi: 10.1109/UEMCON47517.2019.8993024.

[5] G. Tan, J. Zhuang, J. Zou, L. Wan and Z. Sun, “Artificial potential field-based swarm finding of the unmanned surface vehicles in the dynamic ocean environment,” International Journal of Advanced Robotic Systems, vol. 17, no. 3, 2020.

[6] F. Bounini, D. Gingras, H. Pollart, and D. Gruyer, “Modified artificial potential field method for online path planning applications,” 2017 IEEE Intelligent Vehicles Symposium IV, pp. 180-185, 2017, doi:10.1109/IVS.2017.7995717.

[7] H. Lyu and Y. Yin, “COLREGS-Constrained Real-time Path Planning for Autonomous Ships Using Modified Artificial Potential Fields,” The Journal of Navigation, 72, pp. 588-608, 2018, doi:10.1017/S0373463318000796.

[8] P. Lin, W. Y. Choi, J. H. Yang, and C. C. Chung, “Waypoint Tracking for Collision Avoidance Using Artificial Potential Field, ” Proceedings of the 39th Chinese Control Conference, pp. 5455-5460, 2020.

[9] A. L. Alfeo et al., "Urban Swarms: A new approach for autonomous waste management," 2019 International Conference on Robotics and Automation (ICRA), pp. 4233-4240, 2019, doi: 10.1109/ICRA.2019.8794020.

[10] J. A. Sauter and K. Bixler, "Design of unmanned swarm tactics for an urban mission," Proc. SPIE 11021, Unmanned Systems Technology XXI, vol. 110210, pp. 124-139, May 2019, doi: 10.1117/12.2518116.

[11] W. Liu, X. Zheng, and Z. Deng, „Dynamic collision avoidance for cooperative fixed-wing UAV swarm based on normalized artificial potential field optimization,” J. Cent. South Univ. 28, 3159–3172, 2021, https://doi.org/10.1007/s11771-021-4840-5.

[12] F. Segor, A. Bürkle, M. Kollmann, and R. Schönbein, “Instantaneous Autonomous Aerial Reconnaissance for Civil Applications - A UAV based approach to support security and rescue forces,” 6th International Conference on Systems ICONS, pp. 72-76, 2011.

[13] E. Santamaria, F. Segor, and I. Tchouchenkov, “Rapid aerial mapping with multiple heterogeneous unmanned vehicles,” ISCRAM, vol. 6, pp. 592–596, 2013.

[14] R. R. Hashemi, L. Jin, G. T. Anderson, E. Wilson and M. R. Clark, "A comparison of search patterns for cooperative robots operating in remote environment," Proceedings International Conference on Information Technology: Coding and Computing, Las Vegas, NV, USA, 2001, pp. 668-672, doi: 10.1109/ITCC.2001.918874.

[15] Y.-H. Choi, T.-K. Lee, S.-H. Baek, and S.-Y. Oh, “Online complete coverage path planning for mobile robots based on linked spiral paths using constrained inverse distance transform,” IEEE/RSJ International Conference on Intelligent Robots and Systems, 2009. IROS 2009, pp. 5788 -5793.

[16] G. M. Fricke, J. P. Hecker, A. D. Griego, L. T. Tran and M. E. Moses, “A distributed deterministic spiral search algorithm for swarms,” 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, Korea (S), 2016, pp. 4430-4436, doi: 10.1109/IROS.2016.7759652.

[17] M. L. Cummings, S. Bruni, S. Mercier and P. J. Mitchell, “Automation Architecture for Single Operator, Multiple UAV Command and Control,” Technical Report, Massachusetts Institute of Technology: Cambridge, MA, USA, 2007.

[18] L-F. Bluhm, C. Lassen, L. Keiser, and J. Hasbach, “Swarm View: Situation Awareness of Swarms in Battle Management Systems,” STO-MP-SCI-341, 2021.

[19] M. L. Cummings and P. J. Mitchell, "Predicting Controller Capacity in Supervisory Control of Multiple UAVs," in IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 38, no. 2, pp. 451-460, March 2008, doi: 10.1109/TSMCA.2007.914757.

[20] B. Mekdeci, and M. L. Cummings, “Modeling Multiple Human Operators in the Supervisory Control of Heterogeneous Unmanned Vehicles,” A. f. Machinery, Proceedings of the 9th Workshop on Performance Metrics for Intelligent Systems, (S. 1-8). Gaithersburg, Maryland, 2009, doi:10.1145/1865909.1865911.

[21] C. R. Tinoco and G. M. B. Oliveira, "Heterogeneous Teams of Robots using a Coordinating Model for Surveillance Task based on Cellular Automata and Repulsive Pheromone," 2019 IEEE Congress on Evolutionary Computation (CEC), 2019, pp. 747-754, doi: 10.1109/CEC.2019.8790266.

[22] J. T. Ebert, M. Gauci, and R. Nagpal, “Multi-Feature Collective Decision Making in Robot Swarms,” In Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems (AAMAS '18). International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1711–1719, 2018.

[23] G. Wang et al., “Emergent Field-Driven Robot Swarm States,” Phys Rev Lett. 2021 vol. 126, no. 10, pp. 108002.