Dynamic Plume Tracking Utilizing Symbiotic Heterogeneous Remote Sensing Platforms

Iakovos T. Michailidis[1 [0000−0001−7295−8806]], Athanasios Ch. Kapoutsis[1 [0000−0002−1688−036X]], Elias B. Kosmatopoulos[1 [0000−0002−3735−4238]], and Yiannis Boutalis[1 [0000−0003−3717−3565]]

Electrical and Computer Engineering Dpt. (ECE) of the Democritus University of Thrace (D.U.TH.), Kimmeria Campus, 67100, Xanthi, Greece
imichai@ee.duth.gr, akapouts@ee.duth.gr, kosmatop@ee.duth.gr, ybout@ee.duth.gr

Abstract. The current study focuses on the problem of continuously tracking a dynamically evolving CH_4 plume utilizing a mutually built consensus by heterogeneous sensing platforms: mobile and static sensors. Identifying the major complexities and emergent dynamics (leakage source, intensity, time) of such problem, a distributed, multi-agent, optimization algorithm was developed and evaluated in an indoor continuous plume-tracking application (where reaction time is critical due to the limited volume available for air saturation by the CH_4 dispersion). The high-fidelity ANSYS Fluent suite realistic simulation environment was used to acquire the gas diffusion evolution through time. The analysis of the simulation results indicated that the proposed algorithm was capable of continuously readapting the mobile sensing platforms formation according to the density and the dispersed volume plume; combining additive information from the static sensors. Moreover, a scalability analysis with respect to the number of mobile platforms revealed the flexibility of the proposed algorithm to different numbers of available assets.

Keywords: Swarm Intelligence · Symbiotic Remote Sensing · Multi-Agent System · Dynamic Plume Tracking · ANSYS Fluent Testbed

1 INTRODUCTION

Recent research results related to robotized applications have been introduced in literature [4,21]. Low production costs, high agility, high parts-reliability, low operational costs, lightness and deployment ease, long range operation, large variety of sensory add-ons and chassis customization; have rendered unmanned tele-operated platforms into a quite appealing solution for even more complicated missions.

Severely hazardous accidents or terrorist attacks; caused by unnoticed flammable toxic or epidemiological contagious plume dispersion are more than often reported in industry [27,6] where mid-, or even short-, term exposure may cause permanent respiratory or cardio-vascular issues. More specifically, on the 6th of January 2005, a 54,915 kg chlorine release was caused after a rail-accident in Graniteville, South Carolina, USA where 500 workers cohort revealed significant reductions in lung function immediately after the incident while 9 fatalities were also reported [9]. On the 28th of June 2004, a pre-dawn train collision and derailment just outside of San Antonio, TX, USA released 60 tons of chlorine in less than three minutes. Due to poor situation overview, all of the first responding units arrived were almost entirely killed, the Union Pacific train engineer, 23 civilians, and 6 emergency responders were treated for respiratory distress as well. The environmental cleanup costs were estimated at 150,000$ [7].

Things become way more dangerous when indoor leaks are dispersed; usually in industrial hangars, warehouses or production plants. In an indoor plant, a gas plume is limited to consume the fixed volume of the building, thus the concentration of the leaked gas may rapidly increase where, given sufficient time, even the smallest of leaks can exceed the LEL (explosive) or TLV (toxic) levels; leading to nonrecoverable fatalities [16].

Reaction time is the most critical indicator for a successful emergency situation management. Unmanned Vehicles (UxVs) can offer emergent reaction capabilities with minimal on-site human interception; properties which are considered critical especially during highly-unlikely events when effective situation management and reaction time can significantly minimize human lives risk [35,28].

However, UxVs may not always be appropriate to constantly maintain a highly-elaborate situation overview and awareness. As the remote sensory platform increases its complexity and operational diversity, the demand for more computational power and energy reserves increases as well, rendering autonomous UxVs still inappropriate for patrolling and long-term missions in general [8,29]. Lightness is still an issue for multipurpose remote sensing platforms intended for long-range/long-term missions, significantly limiting their extensibility and operational effectiveness.

For this reason, significant work has been undertaken recently towards the development of low-power, high-performance sensor networks, developed for long-term, uninterrupted and reliable operation. Hyperspectral analysis of mobile visual sensors or satellite images have been proposed in literature; suffering from low point accuracy during early dispersion stages and high computational costs (usually adopting highly elaborate methodologies such as deep CNNs) [19,5].

Existing static networked sensory elements - which may be limited to cover the same specified area/range of interest - are considered ideal for constant long term low-cost monitoring [33,11]. Therefore, specific dispersion monitoring cases are addressed with static UV sensors [30], mounted IR sensors [25] or low-cost customized sensor networks [1]. UxVs are usually utilized complementary and synthetically to static area sensors; when needed. Since both monolithic approaches have advantages and disadvantages, several studies focus on the symbiosis of the two heterogeneous types of remote sensing (mobile and static) [10,34]. On the same matter, the current study focuses on a gas plume tracking simulative application where static and remote sensing platforms are called to form a symbiotic network of heterogeneous yet collaborative elements where both are exploited according to their particular operational advantages.

2 CONTRIBUTION AND LITERATURE ANALYSIS

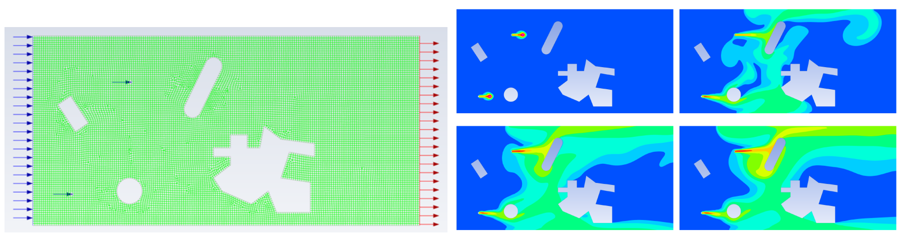
As the reaction time is the most critical aspect in emergency cases, the objective of the current study is to test and analyze the behavior of symbiotic static and mobile (autonomous ground and/or aerial or even handheld) sensing platforms to quickly detect, locate and track leaking incidents. The static sensors are responsible for collecting concentration measurements from their area-of-interest (AoI). The chemical sensors are strategically positioned so as to detect as soon as possible any potential leak. Moreover, mobile platforms are called to effectively deploy in order to mutually locate its source and levels of spread at the minimum possible time.

Several literature studies have already been proposed that consider centralized optimization and coordination topologies [31,13]. Centralization allows for a more elaborate situation consensus exploiting every observable state variable at one single node. However, as the scale of the problem (number of sensing elements) increases, centralized approaches severely suffer from communication and computational intensity. This translates to significantly higher communication (for transmitting of sensory readings from every corner of the network to a central node) and computational (for processing larger amounts of aggregated data) demand. Multi-agent studies have been also proposed in literature, mimicking biologically-inspired algorithms employing open-loop control and proprietary mission planning [32,20]. Proven efficient enough, this kind of solutions is based on random search principles which may lead to poor convergence rates and sub-optimal solutions [26,2]. This study proposes a systematic approach for the time-efficient coordination of autonomous mobile sensory platforms when measurements from static sensors are also available as well. Ultimately the swarm is responsible to self-deploy its assets in order to mutually build an extended situation consensus with minimum intra-communication requirements. Initially, the problem of dynamically tracking a continuous evolving plume is transformed to an optimization setup. To appropriately tackle the transformed optimization problem, a distributed approach tailored to the problem at hand is developed. The developed approach is based on a recently proposed optimization methodology for multi-agent system with a priori non-computable objective functions [14,18]. The approach belongs to the family of Local4Global Cognitive Adaptive Optimization (L4GCAO) algorithms [17] which has already been successfully evaluated in several simulative [24,22] and real-life tests [23,12].

3 SIMULATIVE ENVIRONMENT

The test case focuses on an emulated indoor gas leak where static gas sensors are already strategically positioned and are constantly monitoring a large indoor industrial plant, consisted by large indoor obstacles, while aerial mobile sensory platforms are called to complement the gas plume tracking task as well as to locate the leakage source as quickly as possible.

More specifically, the high fidelity ANSYS Fluent CFD suite [3] was used to emulate the dispersion of methane CH_4 inside a cluttered environment. The interior space was designed to be a rectangle area of $92 \times 42m^2$ with both convex and non-convex, non-traversable obstacles as depicted in figure 1(a). For the space discretization, a standard linear model, specialized for computational fluid dynamics, with a default element size of $5.1m$ is employed (green grid). A constant airflow with a velocity $1m/s$, turbulent intensity of 10% and hydraylic diameter of $0.44m$ was also applied on the left side of the environment (blue arrows). The environment's outlet was on the right-hand side and is depicted with red arrows. The methane was dispersed inside the environment from two sources, as indicated by the blue arrows inside the grid.



(a) (b)

Fig. 1: CH_4 simulative instance. (a) Space geometry along with inlets and outlets, blue and red arrows respectively; (b) Evolution of CH_4 dispersion over time.

4 PROBLEM FORMULATION AND PROPOSED METHODOLOGY

4.1 Problem Constraints

Based on the aforementioned description of the modeled problem, we consider that both static and mobile sensing assets are fully operational and seamlessly interconnected i.e., all assets are within communication range with a central station which is only responsible to collect the local performance observations and calculate the overall consensus at each cycle. In order to render the evaluation more realistic, specific operational constraints were imposed in the behavior of the system, as follows:

– The formulation of the problem considers a continuous state space which reflects the position of every movable sensing asset. The state transition (position change) is limited only by the imposed operational constraints of

the UxVs i.e., each mobile asset has a maximum movement step in every cycle. This limitation imposes linear constraints on the control variables.
- As already discussed in Section 3 above, the environment involves large obstacles that do not allow UxVs to pass through (or over for AUVs) that represent industrial machines and infrastructure (see Figure 1(a)). To this matter, all UxVs are simulated with safety mechanisms based on sonar proximity sensors and are able to avoid collision with the obstacles as well as with each other during the execution of the mission. This dynamic will impose strongly non-linear constraints on the positioning decisions (state variables).
- Moreover, the sensing radius and profile of both static and mobile assets is modeled to sense a sub-part of the environment; more specifically, a circular area of interest (AoI) centered by the current position of each UxV's location. The sensing profile represents the decaying measurement reliability as the distance from the sensor increases by considering a truncated 3-D Gaussian distribution centered at the sensor location. The non-linear measurements-reliability profile emulates the behavior of "electronic-noses" i.e., relates the sensitivity/accuracy of the measurement with the distance from that sensing point. Note that the proposed algorithm is agnostic to the analytic sensor models. As shown in subsection 4.3, the sensor models are considered as unknown implicit dynamics of the system.
- At this point it must be highlighted that the specified operational constraints were directly implemented in the simulation dynamics of the system instead of the distributed optimization algorithm performance index as penalty functions. Therefore, feasible solutions were directly generated complying a priori with the default system dynamics and imposed limitations without requiring feasibility check.

Finally, as already discussed the objective of the current application is to detect and track the diffused gas volume emphasizing on the convergence rate and the overall plume-volume coverage maintained as the incident evolves. Equivalently, based on the available observations of the system, the accumulated concentration of gas that is measured by all sensing assets at every timestep is considered as the optimization goal to maximize. Note that when the concentration of a single point in the environment is within the AoI by more than one sensing assets, only the most reliable (the measurement from the closest sensor) is considered for the calculation of the total accumulated one. Conceptually, at each simulation timestep, by maximizing this objective, the swarm is "forced" to utilize wisely its overall sensors' capabilities, spreading the team members over the whole mass of gas, while aggregating in areas of high intensity.

4.2 Problem Formulation

Based on the aforementioned rationale, the problem of dynamically choosing the values for a set of decision variables $u(k) = \Delta x(k)$, where $u(k)$ represents the UxVs' augmented positions $x(k)$ change, where k represents the simulation timestep, can be equivalently formulated as follows:

$$\begin{aligned} max : \mathit{\Pi}(y(x(k))) \\ s.t. : C(u(k), x(k)) \leq 0 \end{aligned} \tag{1}$$

where $y(k)$ is the augmented vector of the gas concentration measurements both from static and mobile assets; $\mathit{\Pi}()$ is the performance criterion function value at the $k-th$ timestep i.e., the observed accumulated concentration of dispersed gas at the current timestep; $C()$ represents the appropriately reformulated set of operational constraints as described above.

Evidently, as the dispersion phenomenon evolves the optimal formation that maximizes the monitored gas plume volume varies through time. As a result, the maximum of $\mathit{\Pi}(y(x(k)))$ is also evolving according to the dispersion model and the stochastic/unknown environment characteristics (e.g. wind direction, source intensity, type of gas, environment shape/structure). Therefore traditional gradient-based optimization is not appropriate for the aforementioned problem since the performance criterion function is not analytically available.

4.3 Proposed Intelligence Methodology

The proposed methodology attempts to effectively address the distribution of the optimization problem allowing seamless scaling up with minimized communication requirements. The problem is being mutually solved by equivalent locally-driven problems through a paralleled operation of a virtual network of cooperative agents which are self-orchestrated based on the accumulated performance results by a single common overarching central node. The swarm intelligence of agent is linked to each remote sensing (AUV) platform based, however; on a mutually built consensus of the external environment by all sensing elements (both remote and static).

The distributed algorithm has been theoretically established in [14] based on a thoroughly evaluated approach [17] and has already been successfully tested in a relevant simulative, comparative case study in [15] where the environmental situation awareness is driven solely by the mobile remote sensing platforms' observations. However, this is the first study that the proposed algorithm is being considered for coordinated dynamic plume tracking applications that utilize information originated both by static and mobile sensory platforms.

The proposed distributed plume detecting, locating and tracking algorithm capable of coordinating the positioning of $N \in \mathbb{N}$ UxVs on-the-fly, aiming at optimizing the objective function Eq. (1) based on a mutually built consensus from $M > N \in \mathbb{N}$ assets, can be described as follows:

- Initialize — Choose a positive time-smoothly-decaying function $\alpha(k)$ and initialize $0 < \alpha(0) \leq 1$.
- Step 1 — At the end of every timestep k, collect the corresponding measurements $y(x(k))$ from every sensing asset, referring to their AoI.

- Step 2 — A central node responsible accumulates the performance index $\Pi(y(x(k))$ based on each (static and mobile) of the M sensing platform's visibility / measurements and calculates $\Delta_i(k) = \Pi(y(x(k))) - \Pi(y(\Delta x_i(k)))$ only for the moveable mobile $i-th$ assets; where $\Delta x_i(k) = [x_1(k), \ldots, x_i(k-1), \ldots, x_N(k)]$
- Step 3 — The contribution $\Delta_i(k)$ from each robot to the overall performance is sent back to each agent to construct a linear-in-the-parameters (LIP) estimator to approximate $\tilde{J}_i(k) \approx J_i(k) = J_i(k-1) + \Delta_i(k)$
- Step 4 — Generate $R \in \mathbb{N}$ random feasible (within feasible displacement normalized radius $\alpha(k)$ from the current position $x_i(k)$) control decisions $u_i^r(k)$ for every moveable asset.
- Step 5 — The next position for every moveable sensing asset is determined by proactively validating the randomly generated corresponding control decisions $u_i^r(k)$ (see Step 4) on the constructed distributed LIP estimators (see Step 3); selecting the one that is expected to maximize the overall performance $u_i^*(k) = argmax \left\{ \tilde{J}_i(k) \right\}$.
- Step 6 — If overall $J_i(k)$ performance convergence is achieved then STOP otherwise GO TO Step 1.

Due to space limitations, the interested reader is referred to [14,17] for more background details.

5 EVALUATION OF RESULTS

5.1 Performance Analysis

To examine the effectiveness and efficiency of the plume tracking algorithm, as described in the previous section, a team of $N = 8$ UAVs is deployed in the simulation set-up of section 3. Along with the team of UAVs, 3 stationary sensors have been placed on the perimeter of the obstacle volumes. As long as the static sensor readings contribute to the mutual perception of the region; consequently the algorithm is responsible to readapt the formation of the UAV swarm to unmonitored areas, accordingly.

Figure 2 depicts the swarm configurations for such a simulation instance. The intensity of CH_4 is illustrated with a contour representation, the values of which are denoted in the colorbar on the left-hand side of the figure. Figure 2(a) illustrates the initial deployment of the UAVs (cyan rhombuses) along with their sensing capabilities (fading cyan region around each UAV). Also, the position of the static sensors along with their field of coverage is illustrated in red tones. For this first timestamp, almost the whole terrain is considered CH_4-free. Sub-figures 2(b),(c) and (d) demonstrate the changes in swarm formation with respect to the evolution of the CH_4 dispersion for 33%, 66% and 100% of the experiment's progress, respectively. Figure 2(e) depicts the evolution of the objective function (1) during the experiment.

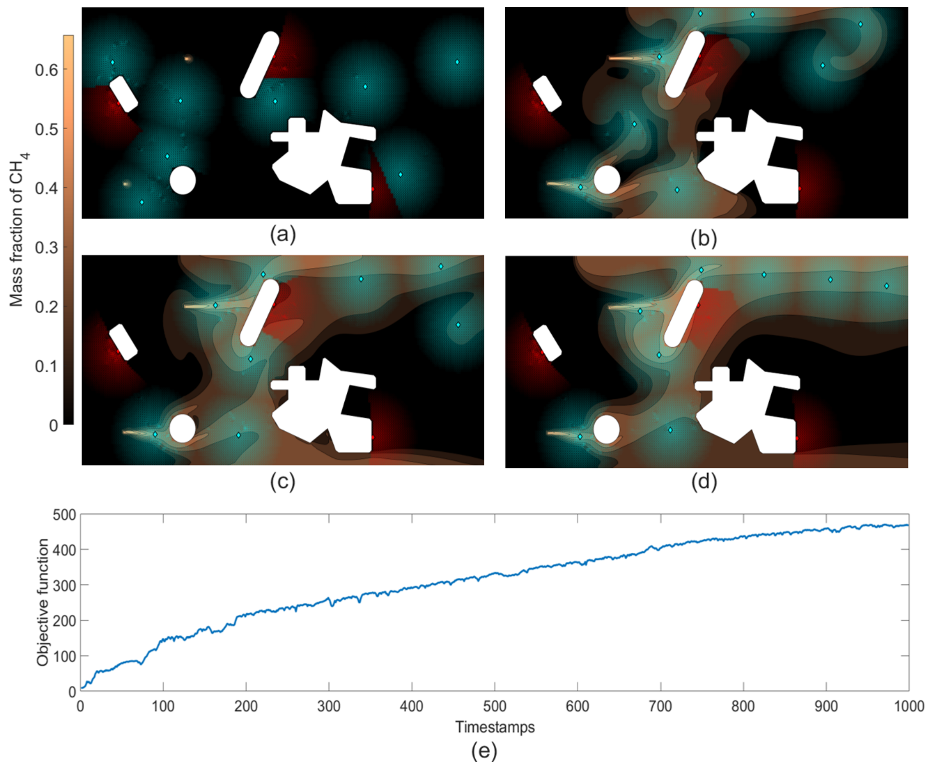


Fig. 2: Experiment with 8 UAVs (cyan areas) and 3 static sensors (red areas). (a) Initial random deployment the UAVs and static sensors locations. (b),(c) and (d) denote to the formation of the UAVs with respect to the CH_4 dispersion at 33.3%, 66.7% and 100% of the experiment, respectively. (e) Evolution of the objective function over the experiment's horizon

Figures 2(b)-(d) demonstrate that the formation of the UAVs is deployed to critical positions that maximize the cumulative coverage (consensus) of the CH_4 plume density. In addition, the deployed formation (i.e., position) of the mobile assets achieved to constantly adapt to the static sensors coverage; reasonably leading to tracking positions over unmonitored AoI that did not additively overlap with others. Thus, although the intensity of CH_4 around the static sensor, in the north of the terrain, is relatively high, no UAV is assigned to be close to that region, as there is a constant flow of information regarding this sub-area. Another important feature is revealed by the study of the objective function (see Figure 2(e)) where despite the fact that the nature of the problem at hand is time-variant (1), having a different optimal configuration per timestamp, the proposed plume tracking algorithm is capable of following these changes without any significant peaks and valleys in the objective function value.

5.2 Scalability Analysis

The experimental analysis is concluded by performing a series of experiments for swarms with different team members. More specifically, 6 different swarm configurations were deployed with 4, 6, 8, 10, 12, and 14 UAVs. 100 experimental instances with randomly chosen initial UAVs' positions were generated for each different size of UAV-team. For all investigated setups the number (3) and location of static sensors remained the same, as depicted in Figure 2. Table 1 reports the average objective function score along with the corresponding standard deviation. Apart from the final value of (1), $\sum_{k=1}^{T_{max}} \Pi(y(x(k)))$ is also reported to evaluate the overall performance during the experiment. The results

Table 1: System's performance for varying number of UAVs

# UAVs	Final $\Pi(\cdot)$	Cumulative $\Pi(\cdot)$
4	305.53 ± 16.18	202028.08 ± 8814.86
6	396.87 ± 6.75	259214.70 ± 9513.94
8	464.02 ± 5.27	307607.19 ± 8495.18
10	526.59 ± 5.77	348339.71 ± 8150.65
12	583.71 ± 6.36	387004.46 ± 7530.05
14	632.56 ± 5.27	419231.78 ± 5396.50

indicate that the proposed, plume-tracking algorithm is capable of exploiting the additional UAVs. This can be extracted from the substantial increases in the perception scores, as the number of UAVs is growing. The last remark is devoted to the evolution of the deviation around the average scores. Although an increase in the number of UAVs leads to higher average values for both scores, the deviation around these values is shrinking. The causality behind this trend is that the effect of the initial deployment of UAVs is reduced with the increase in the number of (randomly initiated) UAVs. This can be better understood by focusing on the average final values for 4 and 6 UAVs, respectively. Although the average value for 6 UAVs is increased by 91.34 ($\approx 30\%$ increase), the deviation is reduced from 10.6% of the average value for 4 UAVs to 3.4% of the average value for 6 UAVs.

6 CONCLUSIONS

The current study focuses on the evaluation of a novel approach that tackles the problem of continuously tracking a dynamically evolving CH_4 plume, utilizing a symbiotic team of heterogeneous sensing platforms: mobile (i.e., UAVs) and static sensors. The proposed approach is responsible for the continuous adaptation of the mobile platforms formation in order to maximize the plume volume and density that is being monitored by all sensing assets, at a constant basis.

Initially, 8 mobile and 3 static sensory platforms were considered. Figures 2(b)-(d) demonstrate that the proposed approach was capable of defining the formation of the moveable assets (i.e., UAVs) in a real-time manner as the plume volume was increasing and diffusing dynamically in order to constantly maximize the cumulative coverage (consensus) of the monitored CH_4 plume density. The position of the static sensors is also adopted inside the overall design of the UAVs formation.

Finally, the results of the scalability analysis indicate that the proposed, plume-tracking algorithm is capable of effectively exploiting the additional UAVs. Table 1 quantifies the increasing trend of the cumulative performance function which also reflects to the plume-monitoring accuracy as well as the reaction time of the overall tracking system.

ACKNOWLEDGMENTS

This research is carried out / funded in the context of the project "Development and evaluation of an optimal decision-making algorithm for cooperative autonomous vehicles" (MIS 5050057) under the call for proposals "Researchers' support with an emphasis on young researchers- 2nd Cycle" (EDULLL 103). The project is co-financed by Greece and the European Union (European Social Fund- ESF) by the Operational Programme Human Resources Development, Education and Lifelong Learning 2014-2020.

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