Towards a Social-media Driven Multi-Drone Tasking platform

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Abstract— We present a framework for utilising social-media for tasking drone swarms in search and rescue missions. As elaborated in this work, social-media are a source of timely and valuable information regarding the occurrence, the evolution, and the damage produced in disasters. Exploiting this source of knowledge can be very valuable in planning search and rescue missions and identifying tasks to be conducted. In this work a novel multi-drone search and rescue framework is developed that considers social-media signals in the creation of search tasks. The key design challenges of implementing the proposed framework are discussed and a simulated scenario based on a real-life Twitter data set is presented as a means of providing evidence of the effectiveness of the proposed framework.

Index terms—Multi-agent systems, constraint programming, emergency response, UAS swarms, social sensing

I. INTRODUCTION

Emerging Information and Communication Technologies (ICTs) including robotic systems (e.g., Unmanned Aerial System (UAS)) and social-media platforms (e.g., Twitter) provide novel, safer and better ways of gathering information on emergency events and assisting first responders in their operations. UASs; which include an Unmanned Aerial Vehicle (UAV), a ground-based controller, and a system of communications between the two, had instrumental roles in emergency response missions to date, including firefighting incidents [1], flooding or hurricane monitoring [2], [3], and have been aiding first responders by providing situational awareness, relief, detecting survivors and conducting rescue operations [4], [5], [6]. It is evident that UAVs have an advantage over conventional manned aerial inspection approaches, due to their low cost of deployment, their smaller size and greater flexibility in their navigation. In addition, UAVs allow operators to remain safely on the ground without being exposed to potential dangers during an emergency scenario.

The rapid advances in UAV payloads and data processing technologies have greatly improved the capacity of U to assist first responders in a more substantial way. However, even with their increasing capabilities, commercial off-the-shelf UAVs (that are mostly used by first responder teams) have limited autonomy and thus naively searching over large areas can be very inefficient and unproductive [7]. Importantly, UAVs currently utilised in emergency response missions rely on the operator insights to point guide them to specific locations [7] without taking into consideration information coming in from the affected population. Hence, by exploring complementary sources of information can provide valuable insights regarding the whereabouts and urgency of events and make better use of the UAV assets.

Social-media provide a unique opportunity to gain fast and valuable information for the occurrence and evolution of an event. This is achieved by the spontaneous and voluntary participation of users. Social-media users can be considered as “social sensors”, who provide “social signals”: information about situations, facts related to the users and their social environment. Social signals have already been utilised for gathering updated information about emerging situations of danger, such as detecting earthquakes [8], seismic events [9] and to support emergency planning, risk and damage assessment in the cases of forest fires. Nevertheless, exploiting social signals is challenging, due to their inherent inconsistencies and their noisy nature. Hence, carefully considerations need to be made when using these social signals in search and rescue planning.

Let us consider as an example the case of Hurricane Harvey, that made landfall in Texas and Louisiana in August 2017, causing catastrophic flooding. Fig. 4 presents two tweets posed during Hurricane Harvey. Both tweets provide information about the criticality of the event, how many people were in danger and their location. The first tweet asks for help due to flooding, while the second one reports a missing person. Both tweets include visual clues to emphasise on the urgency of events and help in their resolution. Leveraging these tweets to guide search and rescue efforts has the potential to expedite situational awareness over the affected area and purposefully task assets to the specific needs.

Our aim is to design a multi-drone tasking platform that relies on social-media signals to dynamically task search efforts over the affected area. To realise such a platform multiple challenges need to be addressed. Firstly, the inconsistent and noisy nature of social-media signals, poses challenges in their reliable use. Secondly, designing a multi-drone tasking algorithm based on social-media signals poses challenges related to the dynamic nature of retasking as new
The proposed framework extends our existing framework (detailed in [10] and [11]) to integrate data provided in social-media platforms regarding relevant events and aggregates processed information to conclude on specific tasks. Using these tasks, the proposed framework employs a robust (re)tasking algorithm taking into account the physical limitations of the available drone swarm (including availability and capacity of the UAVs), their distances from the identified locations and their battery availability to guide the drones over the desired locations. Over time, the system recalculates and reallocates the tasks to the UAVs by leveraging the new knowledge shared on social-media platforms.

The rest of the paper is organised as follows. Section II presents related work, while Section III presents the proposed framework and elaborates on the social-media content processing and the multi-agent tasking algorithms. For the multi-agent tasking problem that arise, we first formulate the mathematical programming model to demonstrate the complexity of the underlying problem and then suggest heuristic approximations for solving the problem in real time. Section IV provides evidence of the applicability and reliability of the framework. Specifically, we provide simulations for the performance of the social-media processing and experimental results of the framework using a dataset of Tweets collected during the Hurricane Sandy dataset. Finally, Section V provides concluding remarks and future venues of research.

II. BACKGROUND AND RELATED WORK
A. Social sensing for Emergency Response

Twitter has shown its prominence, among the available social-media platform, as an useful information layer for emergency response systems [12], [13], [14]. Twitter has proved to be a valuable communication channel for high emergency events such as the Great East Japan Earthquake [15] and more recently the Hurricane Irma in 2017 between others [16]. Twitter was recently used to determine the severity of disasters and particularly flooding [17], [18]. In particular, Kankanamge et al. [17], identified highly impacted disaster areas as perceived by the local communities. They provided evidence that (a) Twitter is a promising approach to reflect citizen knowledge; (b) tweets could be used to identify the fluctuations of disaster severity over time; (c) The spatial analysis of tweets validates the applicability of geo-located messages to demarcate highly impacted disaster zones. Indeed, Earle et al. [19] and Avvenuti et al. [8] used Twitter as a source of information for detecting earthquakes, with remarkable results. Twitter was also been utilised to develop early warning systems [20], [21], online interactive maps of the affected areas using machine learning classification [22], and filters for inundation mapping using the photos accompanying tweets [23]. Related research leveraged social-media to enhance situational awareness using conventional Natural Language Processing (NLP) approaches such as keyword-based filtering, as well as more sophisticated approaches including machine learning. Sakaki et al. [24] focused on the detection of earthquake events based the analysis of linguistic features, such as the number of target-event words. Imran et al. [25] presented a methodology exploiting Tweets content to gain situational awareness while Yin et al. [26] attempted to discover important topics in tweets using a burst-detection module. More recently, Habdank et al. [27], focused on analysing the content of tweets and categorising them according to their emergency types. For example, for an emergency situation on critical infrastructures they would inspect if a tweet contains words related to infrastructures (e.g., roads). Moreover, the extracted sentiment of tweets was utilised to gain situational awareness [28] and estimate the critically of events as in [29].

These studies provide valuable models for detecting different aspects of emergency events leveraging social signals. However, less attention is paid a) to the relevance and informativeness assessment of Twitter messages with an emergency event an b) the extraction of information that can be beneficial in UAV-assisted emergency response. Such information include the address of the event, and the classification of the Tweet in a task that can be allocated to a UAV. Most importantly, these solutions solely rely on the social-media data that tend to be noisy and unreliable. In contrast, utilising social signals in a drone sensing system has the potential to overcome reliability and shortcomings of social sensing. Inspired by the works mentioned above, we propose a methodology for exploiting the information offered in tweets with the goal of deriving tasks for UAVs and optimising multi-drone tasking.

B. Multi-agent tasking utilising social-media

State-of-the-art research on multi-agent systems for emergency response applications focus on operational decision on specific tasks [30], [6], [31], while only limited work has looked into using social sensing to optimise multi-agent systems. Cervone et al. [32] leverage on data harvested from Twitter for tasking the collection of remote-sensing imagery via satellites during emergencies. They then undertake a damage assessment through the fusion of satellite images and images collected by social-media. We argue that using satellite data can be costly and UAVs may offer an alternative, faster approach, when possible, for undertaking rapid situation assessment.

More closely related to our proposed work is the approach recently investigated in [33], [34], where the authors present a reinforcement learning-based drone dispatching mechanism that dynamically determines the appropriate number of drones to dispatch and propose a Bottom-up Game-Theoretic task allocation. In their approach, the multi-agent system utilises social sensing to narrow down on the scope of sensing to conserve drone resources. However, the content of the tweets is not exploited towards the effectiveness of the framework, neither to avoid propagating the noise and unreliability of social sensing into the system. Firstly, they do not calculate the relevance of the tweet with the emergency before considering it, which can result in false alarms. Secondly, they ignore the valuable information included in
the tweets, which can potentially increase the efficiency of multi-drone tasking such as the address, or identifying the type of event (e.g., monitoring, urgent supplies delivery). Thirdly, they do not consider a varying capabilities swarm nor the different types of events.

Efficient and effective UAV task allocation should consider and adapt to the dynamic environment UAVs are tasked to operate, the timeliness of social-media, the inconsistent reliability of social signals, the varying capabilities of each of the UAVs in a heterogeneous swarm and their different attributes such as flyability, and resource availability. We argue that fully leveraging social sensing can importantly optimise multi-drone tasking algorithms in terms of a) conserving UAV batteries by narrowing down the scope of monitoring and b) allocating task to UAVs to according to their capabilities and payload.

The main contribution of this work is the development of an unified framework that encompasses the above previously mentioned challenges, by taking into account a) the uncertainty of the environment and the constraints posed by this uncertainty, b) the limitations and constrains posed by off-the-shelf hardware (including UAVs and mobile computing units) and c) the challenges of leveraging social signals. In addition to the novel mathematical modelling, we also implement the proposed framework and we evaluate the impact of introducing social sensing using a real dataset. The proposed framework is developed as an integration the prototype multi-drone platform that we have previously detailed in [11].

III. SOCIAL-MEDIA DRIVEN MULTI-UAV TASKING FRAMEWORK

In this work we propose a social-media driven multi-drone framework. As illustrated in Fig. 2 the framework listens to tweets referencing specific events as hashtags (e.g., “sandy’’). The content of the tweet is then processed using Natural Language Processing (NLP) techniques. In particular, we use text processing to remove stop words, we calculate the relevance of the tweet for a particular event, we extract the location from the text (if present) and the type of the task (e.g., search for missing person). Each tweet is then clustered to a task according to its geographical location, the semantics of the tweet and the time it was created. Upon the tasks definition, we calculate the urgency of each task and implement a UAV tasking algorithm to allocate each task to a UAV.

In a nutshell, the objective of the proposed social-media driven multi-drone system is to a) process and aggregate tweets to define geo-located tasks and b) to schedule and route multiple UAVs considering the following:

- a UAV must have the payload necessary of executing a particular task,
- the total flight time of a UAV does not exceed the maximum flight time of the UAV,
- the total duration of the mission is minimised.

In addition, each task has the following characteristics:

- Has a type (e.g. delivery, missing person)
- Consists of a location defined by latitude and longitude.
- Has an urgency based on a semantic value, the number of social data in that location, and the time since the posting of the social signal.
- Requires the UAV to stay over each location for a particular duration of time. We define this requirement as the demand of the task.

Moreover, each UAV has the following characteristics:

- It has a defined maximum flight time.
- It has a battery consumption per minute ratio.
- Should take-off and land at the depot.
- Travels at a constant predefined speed.
- Can undertake specific types of tasks.

A. Defining Tasks based on social sensing

The multi-drone tasking algorithm accepts a set of tasks which consist of a location, a type, an urgency and a demand. This set of tasks is derived by leveraging social sensing, and in particular knowledge shared on Twitter.

1) Data processing and semantic analysis: As emphasized above, although valuable information is offered by social sensing, data from social-media platforms suffer from inconsistency and varying quality in the sensing data. The data shared in social networking sites often contain noise which makes their processing challenging. In this study, we adapt text mining techniques to the specific application domain. Hence, the social sensing data is processed in the following four steps:

- Text pre-processing: We undertake the conventional Natural Language Processing (NLP) approach of pre-processing the tweets by removing stop words, emoticons and words with three or less letters. We do so using the Natural Language Toolkit (NLT) library [35].

Fig. 2. The Social-media driven multi-UAV framework
Relatedness calculation ($\rho$): To identify if the tweet is relevant to the event under focus, we investigate the semantic similarity $\rho$ of the previously processed text of the tweet with the name and type of the event. This is achieved by utilising WordNet [36]: a large lexical database of nouns, verbs, adjectives and adverbs grouped into sets of cognitive synonyms to compute similarity between short texts [37], and the semantic similarity measure described in [38], effectively utilised in [39], [40].

Location extraction: Then, we attempt to extract if the tweet refers to a physical location. This is required since some shared tweets report information regarding events happening in different locations. To do so we follow the approach in [41] to detect which part of the text refers to an address. The approach has a reported high performance in identifying the street and address in a short text (79.85% in recall and 93% in precision [41]). Then, we query that text to the Google Maps Places API [42] to receive a specific location defined by a latitude and a longitude. This location can then used to define a particular task.

Type of task extraction: UAVs of different capabilities can be assigned different tasks in an emergency response mission. For example, searching for people demands a with a high definition optical camera on the UAV, while for the delivery of a first aid kit requires a delivery mechanism attached on the UAV. To identify the type of task we measure the relatedness of the content of the text of the tweet with the task, in other words we inspect if the tweet refers in any of a predefined set of tasks. To do so, we use a) a simple bag-of-words check, b) we measure semantic relevance to the words defining the task using WordNet [36], and c) we apply Named Entity Recognition (NER) [43] using the TagMe semantic annotator [44] to check if any of the topics match the words describing the task. An example is shown in fig. 3. If we cannot match the signal to one of the tasks using any of the three approaches, then, the task is set to monitoring as a default.

Fig. 3. Identifying the type of task using TagMe [44]

2) Clustering social sensing data to tasks: For defining the tasks we exploit the geographical location, the semantics of the tweet and the time it was created. We firstly define a set of tasks by leveraging social signals we can formulate our problem as follows. Given a set of $Z$ social signals $z_{ij}$ = \{1, 2, ..., $Z$\} the problem that arises is how to aggregate them into $Q$ groups, $g_{ij}$ = \{1, 2, ..., $Q$\}, which will be used as the tasks the UAVs must execute. To address this problem we consider the k-means clustering algorithm. The objective function $J$ is based on the distance between a social signal $z$ in group $q$ and the location of the corresponding cluster centroid $c_j$, can be defined as follows:

$$J = \sum_{j=1}^{Q} \sum_{i=1}^{Z} \left| z_{ij} - c_j \right|^2$$

(1)

To cluster the tweets using k-means we consider the geographical distance between the location associated with each tweet. Secondly, we derive the task $t$ by selecting between the social signals included in each cluster, the one that has a combination of the highest semantic value and the latest time created. If all the social signals in a cluster have the same value and time created, then the task is defined as the centroid of the cluster, that is the middle between all the points of the cluster. Thirdly, we calculate the urgency of the task $t$, using the number of tweets included in the cluster, their semantic value, and the time that has passed since the time of creation of the centroid. The urgency $p^t$, $t \in T$ of a task is computed as:

$$p_t = p_t \ast g_t \ast h_t$$

(2)

where $p$ is the aggregated relatedness of social signals in the cluster, calculated as described above, $g$ is calculated as the number of social signals in the cluster, over the maximum number of social signals at all defined clusters, and $h$ the time value decay rate, $h = e^{-k/\epsilon}$, where $\epsilon$ is a tuning parameter.

The introduction of a time value decay is based on the fact that latest tweets are more important than previous tweets, and also agrees with the fact that social-media signals are found to be more reliable through the progression of the event. The clusters are then filtered based on a threshold on their urgency. Only clusters with urgency higher than 0.5 are considered.

It is important to note, that the system is always on and expects new tweets from in the area of interest. New tweets go through this prepossessing and clustering procedure and if they are not relevant to an already relevant task a new task is defined. As elaborated below, the tasking algorithm builds on the assumption that newer tweets are important than older tweets and adds a certain urgency parameter on the tasks created by newer tweets.

B. Mathematical programming formulation

The problem of scheduling and routing UAVs to undertake specific tasks in an area can be formulated as follows. Let $t \in T$ be set of tasks and $k \in K$ the set of UAV agents. The problem is how to allocate each task to each agent, and derive which routes should be followed by each agent in order to complete all the tasks in the most efficient way in terms of UAV resources. To address this problem we adapt the Vehicle Routing Problem (VRP) to the requirements of UAV scheduling and routing. In the VRP, the tasks are modelled as nodes with demands and the routes are computed as edges with cost representing the task requirements.

We mathematically define the problem as follows: Given $K$ UAVs, initially located at some source node $s$, closed walks shall be found to enable UAVs to visit the nodes in the network with some urgency $0 \leq p^t \leq 1$, $t \in T$, and some
demand \( b_t^i \), \( t \in \mathcal{T} \) while maintaining the smallest cost (i.e., consuming the least battery consumption). We approach this problem by considering the affected area as a fully connected weighted graph \( G \) where edge costs \( c_{ij} \) represent flight time required by a UAV to go through the edge \( i \mapsto j \). We solve the problem by deriving a linear integer program on \( G \) to generate the paths required for the available UAVs \( k \in \mathcal{K} \) to undertake the tasks \( t \in \mathcal{T} \) without exceeding flight time capacity of each UAV.

Let \( G = (\mathcal{N}, \mathcal{E}) \) as a quantized version of the target area where \( \mathcal{N} = \{1, 2, \ldots, N\} \) is the set of nodes (i.e., discrete location) and \( \mathcal{E} \) is the set of edges. A UAV spends cost \( c_{ij} \geq 0 \) in flight time to travel through edge \( (i, j) \in \mathcal{E} \), and possibly a different cost \( c_{i_j} \) to travel through edge \( (j, i) \in \mathcal{A} \). All UAVs are initially located at the source node \( s \in \mathcal{N} \) (i.e., the depot) and have initial flight time availability is \( B(k), k \in \mathcal{K}, k = \{1, \ldots, K\} \). The aim is to find a route for each \( k \) that starts at the source node \( s \) visits some other nodes in \( N \) to undertake tasks with a calculated task demand \( b_t^i \leq 0, i \in \mathcal{N}, t \in \mathcal{T} \) and returns back to \( s \) within its total flight time availability. The recharging of agents is facilitated by assuming that the source node \( s \) has a finite resupply capability which allows agents to recharge their batteries. This is modelled on a graph by assuming an edge \( s \mapsto s \) with cost \( c_{ss} > 0 \) and a positive supply \( b_s^t > 0 \). The waiting of UAV agents required for their batteries to replenish is modelled by the cost \( c_{ss} > 0 \), while the positively supply \( b_s > 0 \) gained for their waiting increases their capacity (i.e., their flight time) to traverse the rest of their defined routes. The objective \((P1)\) of the following linear integer problem is to minimise the total flight time cost under the autonomy of each agent, the demands set and the urgency set by the set of tasks.

\[
(P1) \min \sum_{k=1}^{K} \sum_{(i,j)\in\mathcal{E}} c_{ij}^k x_{ij}^k
\]

subject to

\[
\sum_{t=1}^{T} \sum_{(i,j)\in\mathcal{E}} c_{ij}^k x_{ij}^k \leq B(k) + \sum_{k=1}^{K} b_{i}^k \sum_{(i,j)\in\mathcal{E}} x_{ij}^k \forall \ k \in \mathcal{K} \quad (4)
\]

\[
\sum_{k=1}^{K} \sum_{(i,j)\in\mathcal{E}} x_{ij}^k \geq \begin{cases} 0, & \sum_{t=1}^{T} p_i^t b_{i}^k = 0 \\ 1, & \sum_{t=1}^{T} p_i^t b_{i}^k > \alpha, \forall i \in \mathcal{N} \end{cases} \quad \forall k \in \mathcal{K} \quad (5)
\]

\[
\sum_{j: (i,j)\in\mathcal{E}} x_{ij}^k - \sum_{j: (j,i)\in\mathcal{E}} x_{ji}^k = 0 \forall \ k \in \mathcal{K}, t \in \mathcal{T}, i \in \mathcal{N} \quad (6)
\]

\[
\sum_{i: (i,j)\in\mathcal{E}} x_{ij}^k \geq 1 \forall \ k \in \mathcal{K} \quad (7)
\]

\[
M \sum_{(i,j)\in\mathcal{A}(Q)} x_{ij}^k \geq \sum_{(i,j)\in\mathcal{A}(Q)} x_{ij}^k \forall \ Q \subset N, \ Q \neq 0, k \in \mathcal{K} \quad (8)
\]

\[
0 \leq x_{ij}^k \leq p_i^t, x_{ij}^k \in \mathbb{Z} \quad (9)
\]

In \((P1)\), the integer variable \( x_{ij}^k \) indicates the route for UAV \( k \) and denotes the number of times that agent \( k \) crosses edge \( (i, j) \). The objective function defined in \((3)\) takes into account the urgency of each task with goal to minimise the total flight time cost, that is the time required by all agents to complete their routes. The constraints at \((4)\) are being use to warrant that all the computed paths respect the flight time limitations of each UAV according to its available capacity \( B(k) \). The constraints at \((5)\) make sure that nodes with non-zero task demand and non-zero urgency \( p^t \) are indeed visited by at least a single agent when \( \sum_{t} p_i^t b_{i}^k \) is above a threshold \( \alpha \). The conservation of flow constraints at each node \( i \) are given in constraint \((6)\). For ensuring a closed cycle for the computed route for each UAV, in other words to make sure that each agent leaves from \( s \) and returns to \( s \) the equations \((7)\) and \((8)\) are used. The constraint in \((8)\) enables agents to visit a previously visited node, and has been defined based on the basic subtour elimination achieved using the Miller-Tucker-Zemlin (MTZ) constraints.

To find an allocation where nodes are visited exactly once, that is a minimum-cost Hamiltonian tour, we implement the MTZ subtour elimination constraints. These constraints also eliminate all disconnected subtours, except a cycle that is formed with \( s \) included, as presented in \((8)\). This is achieved, by defining two sets; \( Q \subset N \), and \( \delta'(Q) \) with \( Q \subset N \) as the set of edges with one end in any subset \( Q \subset N \), and \( \delta'(Q)t \) those with both ends in \( Q \). The right part of the constraint represents the total flow in \( Q \) with respect to UAV \( k \) and its left part demonstrates the total flow in and out of \( Q \). The existence of a flow in \( Q \) with respect to \( k \), makes the right part as positive and therefore forces the left part to be positive, and therefore a flow in \( Q \) is connected to nodes outside of \( Q \). This constraint is used to eliminate any disconnected flow cycles except flow cycles that lead to the source node.

If solved optimally, \((P1)\) can produce the alternative routes to cover all the tasks with a minimum cost. However, the exponential number of constraints used in eq. \((8)\), \((P1)\), make this computationally hard to solve in practice. For this reason, in the next section we present an alternative heuristic solution which aims to solve the objectives of \((P1)\) efficiently and capable of constructing and updating routes in real-time.

\section*{C. Social-Media driven Multi-Drone Tasking Algorithm}

The Social-media driven multi-drone tasking (SM+MDT) algorithm proposed in this paper, extends the multi-drone tasking algorithm presented in [10] by leveraging social-media to define and prioritise tasks. In particular, SM+MDT considers: a) the urgency of each of the tasks, b) demand of each of the tasks, and c) the capacity (in terms of flight time) of each UAV to complete that task.

The suggested algorithm considers input the number of UAVs, the number of tasks, the maximum total mission time, the location of the depot, the speed of the UAV, and the recharging time required to replenish battery levels by some amount. As presented in Alg. 1, each UAV \( k \) has a flight time capacity (associate with its battery level) \( B(k) \), and each task has a urgency \( u_t, t \in \mathcal{T} \) and a demand \( b_t^i, t \in \mathcal{T} \) at location \( i \in \mathcal{N} \) from a set of locations that must be visited, an order number, and an indicator demonstrating if the task can be undertaken by multiple UAVs simultaneously. To solve this problem we use Constraint Programming (CP) and in particular we used the library offered by the Operation Research tools (OR-tools) algorithmic toolkit [45]. As a strategy for finding solutions we use the Path Cheapest arc.
that is a greedy algorithm that starts from the source node and connects it to the node with the cheapest route segment, proved effective in previous work [10]. The generated route is further extended by iterating on the last node added to the route.

Note that to accommodate for the social-media driven multi-drone tasking, we extend the standard VRP heuristic approach using additional constraints to accommodate the restricted capacity of each drone, and the dynamic demand and urgency of each task. We further explicitly demonstrate the applicability of the defined constraints, in an example the case of collaboratively monitoring an area by a fleet of agents. Note that in our experiment, the number of nodes in \( N \) representing the field is governed by the number of tasks defined after the pre-processing, filtering and classification of tweets into tasks.

Algorithm 1 Social-media driven Multi-drone Tasking

Require: \( G(\mathcal{N}, \mathcal{E}), B(k), p_i^t, b_i^t, c_{ij}^k, \forall k, i, j \)
1: if \( \sum_{i,j} b_i^j > \sum_k B(k) \) then return;
2: else
3: \( \text{start}_{\text{fn}} \leftarrow \text{sameStartFinish} = \text{True} \)
4: \( \text{model}_{\text{parameters}} \leftarrow \text{default parameters} \)
5: \( \text{parameters} \leftarrow \text{default search parameters} \)
6: \( \text{parameters.set.first_solution_strategy}() \)
7: \( \text{parameters.time.limit} \leftarrow \text{time.limit} \)
8: \( \text{routing.setCost} \leftarrow \text{dist}_{\text{fn}} \)
9: \( \text{routing.addDimension} \leftarrow \text{total time} & \text{flight time} \forall k \)
10: \( \text{routing.addDimension} \leftarrow \text{task urgency} & \forall N \)
11: \( \text{timeDimension.setUpperbound forVehicle} \leftarrow b_i^j \)
12: \( \text{routing} \leftarrow \text{CP}(G(\mathcal{N}, \mathcal{E}), B(k), p_i^t, b_i^t, c_{ij}^k, \text{parameters}) \)
13: \( \text{assignment} \leftarrow \text{routing.solveWithParameters}() \)
14: return assignment;

IV. EMPIRICAL EVALUATION

A. Methodology

We carried out an evaluation of the proposed framework across a real-world disaster response case study: the Hurricane Sandy occurred in 2012. The performance of the proposed framework was compared against a representative baseline and a variation of the algorithm, and evaluated in terms of UAV-resources efficiency.

B. Dataset

To evaluate our framework, we use a real-world dataset using Tweeter data feeds posted during the Sandy Hurricane: that is, tweets posted on Twitter during the period from October 22, 2012 (the day Sandy was formed) till November 2, 2012 (the day Sandy dissipated) in the area of the Northeastern United States. To collect the dataset, we used the first 2 million rows of the public dataset released by [46], which contains a list of IDs of around 6 million geotagged tweets. Using the Tweets IDs, we crawled all the necessary information of the Twitter posts (i.e., timestamp, geo-location, tweet message and user ID) with the Twitter Streaming API [47].

From the collected dataset, we removed Tweets without a geo-location (i.e., do not have an associated latitude and longitude), and tweets that do not contain the word “sandy”. The resulting dataset includes 8,266 timestamped, geo-location marked tweets. The statistics of the dataset are summarised in Table 1. To provide some insight regarding the text included in the tweets, we present a word-cloud comparison in Fig. 4.

In the word-cloud presented the size of words depends on the frequency of each word in the dataset. A preprocessing stage of removing stopwords has been undertaken before producing this word-cloud.

C. Compared Baselines

1) Multi-Drone Tasking: The first baseline used is the multi-drone tasking algorithm, which this work aims to optimise. The algorithm [10] takes into account the availability and capacity of the UAVs, their distances from the identified locations and allocates tasks and guide the drones to the desired locations. The locations are evenly distributed in the area of focused and are calculated based on the Field-Of-View of the drones.

2) Social-media driven Multi-Drone Tasking: Along with the multi-drone tasking algorithm we include a simplified approaches of the proposed framework as a baseline. We generate the baseline of Social-media Multi-Drone Tasking algorithm “SM+MDT” by only considering the distances of shared tweets from the drones using only the relevance pre-processing. Including this baseline allows us to understand how the absence of semantic and relevance analysis and clustering of tweets into formulated tasks, and is indicative of related work. Next, we incorporate the introduction of relevance analysis and clustering of tweets to generate the Clustered social-media driven Multi-Drone Tasking “CSM+MDT”. Doing so, we assess how the absence of a threshold in the definition of new tasks for the UAVs impacts their performance.
The proposed algorithms and framework were evaluated using tweets from the Hurricane Sandy real world dataset. This dataset includes tweets from all over the USA. For the purposes of this experiment, and to imitate how emergency response teams would tackle an emergency we restrict our experiment on to a specific area.

To evaluate the applicability of the framework we select a particular area of focus. For this experiment we use the tweets transmitted in the area bounded by longitude 40.5 to 41.5 and latitude -75.5 to -74.5 which total to 155 tweets.

Fig. 5 demonstrates the task definition approach. On the top left graph we present the conventional approach of monitoring a field using UA Vs, that is using the Field of View (FOV) of the camera of the UA Vs to calculate the distance between the locations for monitoring the complete field. On the bottom left graph, we cluster the FOV points to reduce the monitoring time. However, this is calculated without any additional knowledge and can result into neglecting important locations. On the top right graph we can see the location of the Tweets transmitted in our area of interest - the colours indicate how these Tweets can be clustered based on their geographical location. The bottom right graph demonstrates the centroids of the clusters produced after the clustering of the tweets. These locations (centroids) have been produces based on the social signals and we assume that they indicate the location of reported emergency events.

Fig. 6 demonstrates allocation for searching the specified area with and without social sensing. With no indication of where help is needed, what time of help is needed and the urgency of it, emergency services must scan the whole area. In such scenario, a Multi Drone Tasking algorithm (MDT) [10] would first calculate the points of interest (set of locations) based on the field of view of the drones, and then allocate these points to the drones according to their battery level.

By introducing social sensing and defining specific tasks from the tweets we can significantly narrow down the area of focus and achieve more effective task definition and allocation. As shown in Fig. 6, the tweets in the area are classified into six tasks with specific reasoning.

Fig. 7. Tasks defined by leveraging Tweets

We achieve narrowing down the area of focus by the definition of specific tasks using In Fig. 7 we can observe that by introducing a threshold to the definition on tasks, based on their relevance with the event, their semantic value and their occurrence time, we can further narrow down the scope and be more effective in using UAV resources. Fig. 8 confirms that this has an important effect in minimising the flight time of the UAVs and provides evidence of the energy efficiency of the CSM+MDT approach presented in this article, over the conventional MDT approach and the SM+MDT which considers only the geographic location of the social signals.

V. CONCLUSIONS AND FUTURE WORK

This paper investigated how valuable information shared in social media can be incorporated in a multi-drone tasking algorithm for emergency response. The work presented extends our previous investigation in developing multi-drone tasking platform. [10] with a framework for the automatic definition of tasks, their type and urgency, based on the social-media signals. The investigation presented in this paper provides evidence that social-media signals can result in effectiveness in terms of UAV resources conservation in search and resource missions. At the same time, the automatic translation of social-media signals to emergency
The presented framework achieves to handle affects of noise contained in tweets to the definition of emergency response tasks by utilising NLP techniques. Specifically, it implements text pre-processing, relatedness calculation, location extraction and type of task extraction. However, the presented framework is limited in terms of considering the validity of the tweets (e.g., tweets that contain fake incident reports). The exploitation of tweets can be further improved by utilising the photos associated with them as a two-step validation of the reliability of social-media. In addition, the novel, latest published, approaches for the automatic labelling of tweets [48], [49], [50], [51], such as the one proposed by Alrashdi et al. [49] using distant supervision and the approach by Roy et al. for the classification and summarising of informative tweets [50], shall be evaluated, compared to the current methodology.

We acknowledge that although the framework has been evaluated on a real dataset, using a static known dataset is prone to over-fitting. Future work will exploit the effectiveness and accuracy of the presented system should be evaluated across other datasets of real time messages from live feeds.

A real-life evaluation of the proposed framework and the developed platform outside the lab shall be undertaken to provide evidence of the effectiveness of the framework and shed lights to more challenges and conversations. Finally, the multi-drone tasking algorithm presented in this work can be extended by introducing more variables related to the dynamic operating environments of emergency response such as weather conditions [52].

The multi-drone tasking algorithm as well as all modules for social sensing have been implemented in Python.

All code and Tweet IDs used in this study are publicly available at https://github.com/mariankh1/TweetDrone.

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