Semantic modeling and reconstruction of drones' trajectories

Andreas Soularidis[1] and Konstantinos Kotis[1][0000-0001-7838-9691]

[1] i-Lab, Dept. of Cultural Technology and Communication, University of the Aegean, Mytilene, 83100 Greece
cti21008@ct.aegean.gr, kotis@aegean.gr

Abstract. Research on semantic trajectories' modeling, analytics, and visualization has been conducted for a wide range of application domains. In contrast to raw trajectories, semantically annotated trajectories provide meaningful and contextual information to movement data. Unmanned Aerial Vehicles (UAVs), also known as drones, are becoming more and more widely used in modern battlefields as well as in search and rescue (SAR) operations. Semantic trajectories can effectively model the movement of swarms of drones towards enabling decision makers/commanders to acquire meaningful and rich contextual information about Points of Interest (PoI) and Regions of Interest (RoI) that will eventually support simulations and predictions of high-level critical events in the real field of operations. The goal of this paper is to present our position related to the semantic trajectories of swarms of drones, towards proposing methods for extending MovingPandas, a widely used open-source trajectory analytics and visualization tool. Such an extension is focused on the semantic modeling of drone trajectories that are automatically reconstructed from geo-tagged data, such as photographs taken during a flight mission of a swarm of UAVs, where its flight plan or real-time movement data have been either lost or corrupted, or there is a need for semantic trajectory cross-validation.

Keywords: Semantic trajectory, UAV, Geo-tagging, MovingPandas.

1 Introduction

A swarm of drones is a group of unmanned aerial vehicles that fly in collaboration to complete a specific mission. Depending on the type of swarm, single-layered (each drone is leading) or multi-layered (multiple leaders at different levels), different communication and interoperation strategies are feasible between units (drones), given that interoperability issues at different levels (network, syntactic, semantic, organizational) are already facilitated.

Effective semantic modeling and analysis of trajectories of swarms of drones enable the decision makers/commanders to acquire meaningful and enriched information about the current situation in the field of operations, supporting, eventually, tool-based automated or semi-automated simulations for making predictions of high-level critical events e.g., rescue or no-rescue due to the severity of weather condition at specific region of interest and time-window.

A *semantic trajectory of swarm of drones* is a synthesis of *semantic trajectories* [1] of multiple units moving (flying) in a specified formation, sharing common origin-destination points, having a common mission, enriched with *semantic annotations* at different levels of detail, having one or more complementary segmentations, where each segmentation consists of a list of annotated episodes. A *drone trajectory* is a sequence of points (*trace*) that specify the position of the *moving entity* in space and time. A *segment* is a part of the trajectory that contains a list of *episodes*. Each episode has a starting and ending timestamp, the segmentation criterion (annotation type) and the episode annotation. For example, an annotation type can be the “weather conditions” and an episode annotation can be “a storm”, “heavy rain”, “extremely high waves”, etc.

Swarms of drones are becoming widely used in modern battlefields as well as in search and rescue (SAR) operations [2][3]. To create the semantic trajectory of a swarm of drones, raw movement data collected from each unit is necessary. However, unpredicted threats (e.g., unit malfunction, hacking, weather condition) and known vulnerabilities of drones (e.g., operation conditions) can be the cause of incorrect, invalid, or missing movement data. To solve this problem, there is need to introduce methods for reconstructing the semantic trajectories using other data available during a mission, and cross-validate them against the movement data generated ones. In our work we propose to utilize the geo-tagged photos taken by drones’ carrying equipment during a mission, since they provide suitable meta-data for semantic trajectory reconstruction.

The aim of our work is a) to design and implement an ontology-based framework for the semantic modeling of trajectories of swarms of drones, reconstructed by geo-tagged photos, b) the development of a method for constructing semantic trajectories from geo-tagged photos. Although related research work exists in both directions, currently there isn’t any free and open-source integrated development environment available for supporting both tasks. The goal of our work is to do so by implementing both as extensions of the open-source and widely-used free environment for spatiotemporal trajectory analytics and visualization, namely MovingPandas [4]. Moreover, we plan to evaluate the implemented tasks with real data of drone flights that we are continuously collecting from our drones, as well as from open data. Last but not least, we plan to reuse datAcron ontology [5] in the semantic annotation task of the proposed framework, extending it were necessary, delivering a new UAV-specific ontological model.

The structure of this paper is as follows: Section 2 presents the state-of-the-art in related topics, and section 3 briefly introduces the proposed approach.

2 Related Work

Grasier proposes a general-purpose Python library for the analysis and visualization of trajectory data called MovingPandas [4]. In MovingPandas the trajectory is the core object, and modelled as time-ordered series of geometries, stored as GeoDataFrame and integrated with coordinate reference system information. A trajectory object in MovingPandas can represent its data either as point-based, or as line-based, while the analysis process and the visualization are executed in two-dimensional space. The proposed library can be used as a stand-alone Python script, as well as within the desktop GIS application QGIS as a plugin called Trajetools.

In the work of Cai et al. [6], the focus is on extracting Semantic Trajectory Patterns from geo-tagged data. They propose a semantic trajectory pattern mining framework, from geo-tagged data taken from social media, to create raw geographic trajectories. These raw trajectories are enriched with contextual semantic annotations, using a RoI as stop to illustrate a place of interest. The algorithm returns basic and multidimensional semantic trajectory patterns.

Santipatakis et al. [5] propose the datAcron ontology for representing semantic trajectories at varying levels of spatiotemporal analysis. Mobility analysis tasks are based on a wealth of disparate and heterogeneous sources of information that need to be integrated. The proposed ontology, as a generic conceptual framework, tackles this challenging problem. The experimental results (Air Traffic Management domain) demonstrate that the proposed ontology supports the representation of trajectories at multiple, interlinked levels of analysis.

3 Proposed Approach

As already stated, the goal of our work is to design and implement both a) a method for the semantic modeling of trajectories of swarms of drones, and b) a method for the reconstruction of semantic trajectories from geo-tagged photos, as extensions of the open-source and widely used free environment for trajectory analytics and visualization, namely the MovingPandas.

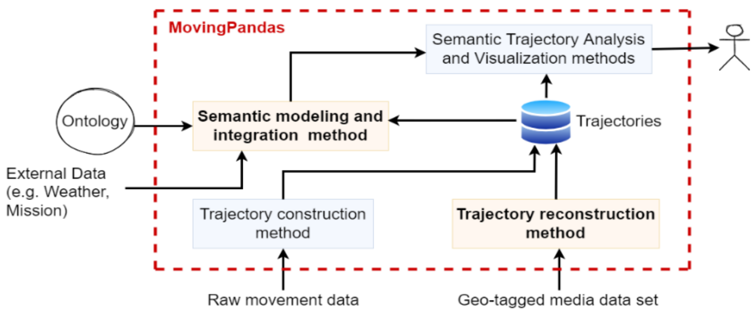

Fig. 1. High-level architectural design of the proposed approach (new methods appear in bold)

Towards this direction we propose a combination of approaches, ontologies, tools and methods for reconstructing and semantically annotating trajectories. Particularly, we propose the extension of MovingPandas with a trajectory reconstruction method using the suitable metadata of geo-tagged images (timestamp: date/time taken, GPS data: latitude, longitude, altitude) taken by drones during flights, along with the semantic modeling of trajectories of swarms of drones reusing the datAcron ontology within a new drone-related ontology (for modeling knowledge related to swarms of drones, their flights and missions, their recordings, etc.) which is currently under development in our laboratory. Figure 1 depicts the high-level architectural design of the proposed methods integrated in MovingPandas. The ontological approach ensures a high-level formalism for the representation of a semantic trajectory, as various heterogenous data such as altitude, sensor (attached to drones or gathered from terrestrial IoT platforms), and weather data (gathered from open Web services), along with mission (who, why, and what) and geographic data (e.g., shape files of documenting/recording areas), etc., are used for the enrichment of raw trajectories. Figure 2 depicts the high-level design of the core semantics of the proposed ontology. At this stage, a first draft version (1.0.0) of the semantic model (namely, Onto4drone) has been developed and it is available in OWL[1]. It is directly based on the datAcron ontology, and indirectly on the DUL, SKOS, SOSA/SSN, SF, GML, and GeoSparql ontologies. The model was developed following the HCOME collaborative engineering methodology, supported by Protégé 5.5 (for personal space model engineering), and WebProtégé (for shared space model engineering). In addition, Google docs and Meet have been used for further collaborative engineering tasks.

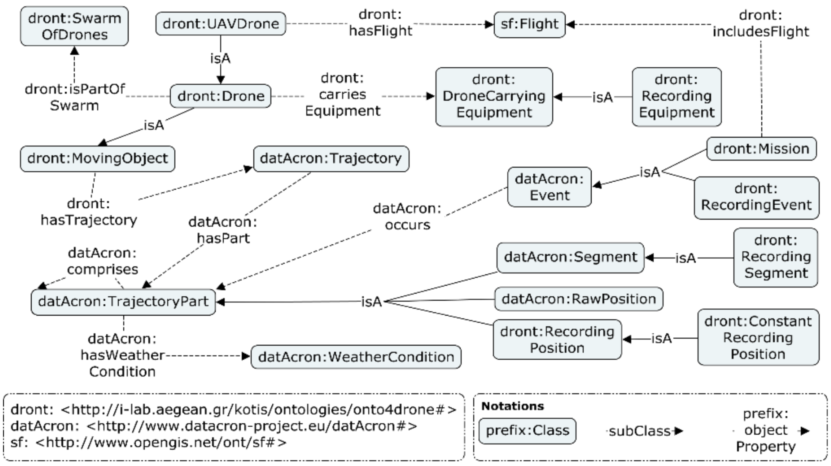

Fig. 2. Basic concepts and relations of the Onto4drone ontology.

The basic concepts and semantic relations of the model which were implemented in the Onto4drone ontology are briefly presented in Figure 2 in the form of a concept map. This version of Onto4drone includes classes, object properties, and data properties based on the motivated use case of a documentation flight with a mission to record a SAR event related to a sinking ship during a storm. A representative restriction that a RecordingEvent (e.g., a SAR event) occurs in at least one RecordingPosition or in a RecordingSegment. Additionally, a number of individuals have been added in order to evaluate the engineered model in different scenarios.

Beyond the development of the ontological model, current implementation of the proposed approach includes the following:

[1] https://github.com/KotisK/onto4drone

- The extraction of the metadata (timestamp: date/time, latitude, longitude, altitude) from geo-tagged images taken by drone during flight (several inhouse and open datasets from different types of drones have been already tested).
- The reconstruction of drone's raw trajectory using the extracted metadata, and their visualization in MovingPandas.
- The enrichment of drones' trajectories with the injection of additional data (currently missing from MovingPandas' representation capabilities) such as altitude, weather data, geographic data.

4 Conclusion

Managing data of drones' flights/missions are becoming more and more popular in a wide range of applications. To be able to derive meaningful and rich information from drones' movement in the field of operation, it is necessary to semantically enrich them with relevant heterogeneous data/information. In addition, it is necessary to find alternative ways of constructing their semantic trajectories. Towards this direction, we propose the development of a free and open-source semantic trajectory reconstruction module, along with a semantic modeling and integration module for the contextual enrichment of trajectories within MovingPandas.

References

1. Parent, Christine, Nikos Pelekis, Yannis Theodoridis, Zhixian Yan, Stefano Spaccapietra, Chiara Renso, Gennady Andrienko, et al. 2013. Semantic trajectories modeling and analysis. *ACM Computing Surveys* 45: 1–32. https://doi.org/10.1145/2501654.2501656.
2. Cook, Kendra L.B. 2007. The silent force multiplier: The history and role of UAVs in warfare. *IEEE Aerospace Conference Proceedings*. https://doi.org/10.1109/AERO.2007.352737.
3. Burridge, Brian. 2003. UAVs and the dawn of post-modern warfare: A perspective on recent operations. *The RUSI Journal* 148. Routledge: 18–23. https://doi.org/10.1080/03071840308446924.
4. Graser, Anita. 2019. MovingPandas: Efficient structures for movement data in Python. *GI_Forum* 7: 54–68. https://doi.org/10.1553/GISCIENCE2019_01_S54.
5. Vouros, George A., Georgios M. Santipantakis, Christos Doulkeridis, Akrivi Vlachou, Gennady Andrienko, Natalia Andrienko, Georg Fuchs, Jose Manuel Cordero Garcia, and Miguel Garcia Martinez. 2019. The datAcron Ontology for the Specification of Semantic Trajectories: Specification of Semantic Trajectories for Data Transformations Supporting Visual Analytics. *Journal on Data Semantics* 8: 235–262. https://doi.org/10.1007/s13740-019-00108-0.
6. Cai, Guochen, Kyungmi Lee, and Ickjai Lee. 2018. Mining Semantic Trajectory Patterns from Geo-Tagged Data. *Journal of Computer Science and Technology* 33: 849–862. https://doi.org/10.1007/s11390-018-1860-1.