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Closed-Loop Satellite Planning and Scheduling for Low-Latency Data Collection

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Abstract

We demonstrate a closed-loop geospatial intelligence Tasking, Collection, Processing, Exploitation, and Dissemination (TCPED) pipeline that provides data and data analyses using commercial satellite imagery. Automated analyses drive automated re-tasking by Auria optimized collection planning software to shorten the timeline from the receipt of data with detectable events that would warrant follow-up data collection to the delivery of that follow-up data. This capability is enabled by the Cloud-based Automated Satellite Tactical TCPED (CASTT) software platform that leverages the proliferation of earth-observing satellites and the maturation of the commercial satellite imagery market. We connect these data sources with image analysis algorithms for object detection/pattern-of-life monitoring and state-of-the-art tasking algorithms, also taking advantage of the growth of available tools for AI/ML imagery analysis.

We implement an automated closed-loop pipeline that, based on high-level user-specified missions, continuously and autonomously tasks satellites for data collection, analyzes it, and then issues follow-up collection tasks to the satellites based on the analyses while disseminating data and analyses directly to end users. This results in lower latency and more relevant data and data products delivered straight to users and enables the effective monitoring of larger areas through the use of intelligent automation. In contrast, the current manually intensive satellite imagery intelligence process is time consuming, laborious, and slow. Automation and optimization results in more timely information, better use of highly constrained resources, and more relevant and insightful intelligence.

The tasking component is performed by Auria software for optimized collection planning and brokers data collection ordering from several different commercial satellite operators. We study the impact of using this optimized collection planning/brokering by using the planning and scheduling software to examine the latency from data request to task uplink to data collection to data downlink and delivery. In a representative scenario, we demonstrate how optimized brokering from a virtual constellation of 7 satellite operators improves median (worst) latency by 39% (80%) relative to the next-best single satellite operator.

We also demonstrate this process using real data and real automated commercial connections with satellite operators for a sample mission concerning a port monitored for pattern of life in ship behavior. In the sample mission, the high-level mission is pattern-of-life monitoring for detected ships of different classes for the sample mission. CASTT connects to automated target recognition software to detect ships of different classes in collected imagery. It determines pattern-of-life from historical data which it compares to incoming data. If there is a departure from the typical pattern of life – for example, a missing naval vessel – it orders the appropriate follow-up tasking – e.g., tasks data collection for other ports at which the vessel is known to frequent.

Keywords: TCPED Pipeline, GEOINT, Automated Planning and Scheduling, Collection Planning, Artificial Intelligence, Machine Learning

1. Introduction

The proliferation of remote sensing satellites [1] with different and diverse phenomenology, timing, and pricing options presents opportunities to provide a larger volume of more timely data in support of several application domains [2-5]. At the same time, the increased availability of Artificial Intelligence (AI) and Machine Learning (ML) tools for imagery makes the automated analysis of remote sensing data [6-9] more accessible. This means that the data generated by satellites is no longer just "a pile of pixels" [10] but these tools can perform the "extraction of meaningful information" [11]. Moreover, the availability of APIs with commercial satellite operators for tasking [12] makes it possible to task satellites as triggered by automated analyses for more timely follow-up data. Creative uses of this data and analysis have appeared frequently as they have been more accessible. Satellite data was used for a crowdsourced search for lost hikers from satellite imagery [13].

In this paper, we demonstrate an automated platform that leverages these opportunities for closed-loop Tasking, Collection, Processing, Exploitation, and Dissemination (TCPED). The Cloud-based Automated Satellite Tactical TCPED (CASTT) software implements a TCPED pipeline that provides data and data analyses using commercial satellite imagery [20]. It leverages the proliferation of earth-observing satellites and the maturation of the commercial satellite imagery market and connects them with AI/ML analysis algorithms. The pipeline uses high-level user-specified missions to determine which tasks and reactive actions to take. It continuously and autonomously tasks collection, analysis, and follow-up collection while disseminating data and analyses directly to end users.

This lowers latency for analysts and enables the effective monitoring of larger areas through the use of intelligent automation. It uses the aforementioned opportunities to improve the current manually intensive satellite imagery intelligence process. Automation and optimization results in more timely information, better use of highly constrained resources, and better intelligence.

CASTT is a collaborative commercial market solution. It uses remote sensing constellation options for better data coverage and quality with different phenomenologies, provides analytics options to support diverse missions with multi-image sequential processing for better intelligence, and has an easy to plug-and-play interface to facilitate new connections with satellite data providers and algorithm providers, preventing vendor lock. CASTT automates collection operations by implementing automated tipping and cueing from several sources and automated collection tasking. This enables near real-time tracking and custody maintenance using reactive follow-up tasking with tactical response times (up to a limit determined by satellite orbital geometry and ground station locations). Finally, it has a configurable level of autonomy, meaning that analysts can remain in or on the loop.

We demonstrate this process using real data and real automated commercial connections with satellite operators for a sample mission concerning a port monitored for pattern of life in ship behavior. In the sample mission, the high-level mission is pattern of life monitoring for detected ships of different classes for the sample mission. CASTT connects to automated target recognition software to detect ships of different classes in collected imagery. It determines pattern-of-life from historical data which it compares to incoming data. If there is a departure from the typical pattern of life -- for example, a missing aircraft carrier -- it orders the appropriate follow-up tasking -- e.g., tasks data collection for other ports.

2. CASTT Solution

In this section, we describe the implementation of the CASTT solution. CASTT is a holistic mission planning and collection management solution that delivers tactical timescale data and finished intelligence leveraging multiple internal and external analysis tools.

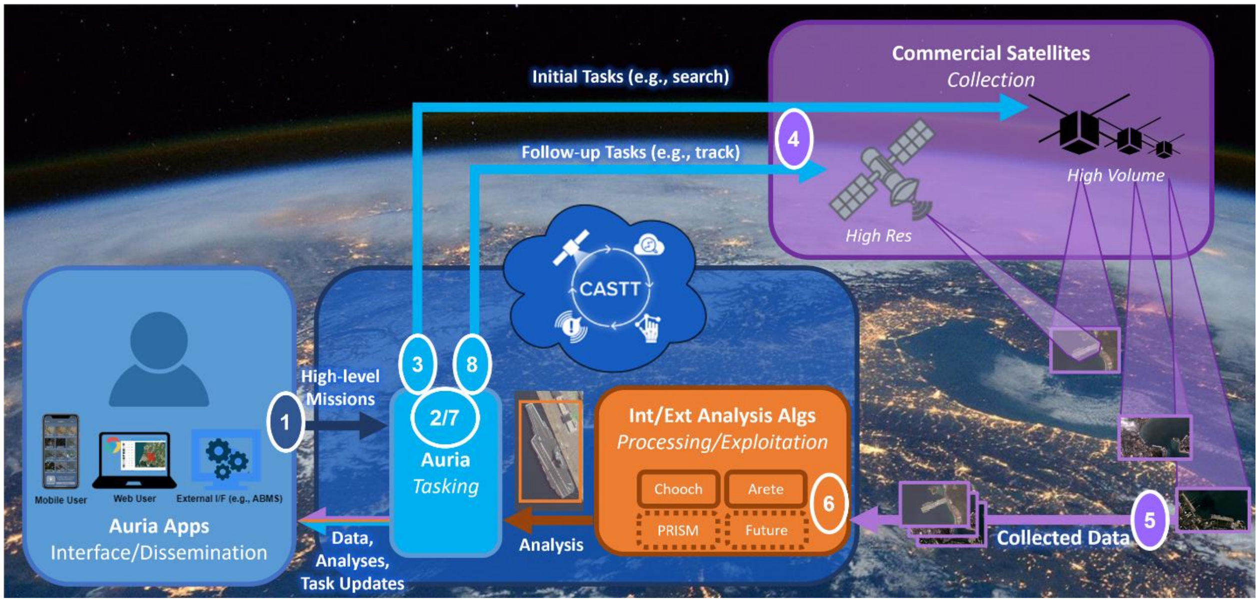

Figure 1: CASTT System Concept of Operations.

2.1 CASTT CONOPS and the TCPED Pipeline

CASTT orchestrates the TCPED pipeline by creating and managing the execution of several 'work items'. Work items correspond to steps in the TCPED process; however, this formalism is not mandatory and CASTT can be configured to manage different work items with different interpretations. The work items are created by previous work items and the logic governing their creation is inherited from a 'high-level mission'. The logic depends on the dependency graph of previous work items as well as the results of data collection and analysis work items that have been completed. CASTT leverages Auria's SpyMeSat to interface with satellite operators and Auria's Collection Planning and Analysis Workstation (CPAW) to perform the collection planning needed to broker between the satellite operators.

A sample concept of operations (CONOPS) is outlined below and illustrated in Fig. 1.

1. Rather than individual tasks, users configure high-level missions (e.g., search-detect-track)

2/8a. CASTT creates tasking work items (e.g., search collection orders) based on high-level missions

3. CASTT uses CPAW to broker between satellite operators, considering several collection options and choosing which to purchase; it completes the tasking work items and creates collection work items to purchase the chosen collections

4. CASTT uses SpyMeSat to issue collection orders to satellite operators

5. Imagery is received via S3 bucket, completing the collection work items and creating processing work items

6. Imagery is passed to processing algorithms (e.g., to detect vehicles), completing processing work items and creating exploitation work items (e.g., to estimate vehicle heading and speed)

7. CASTT completes the exploitation work items, based on the high-level mission configuration and the results of analyses, issues follow-up orders (e.g., track) that will be used to create new tasking work items.

8. CASTT creates and executes dissemination work items which transmit data, analysis results, and updates on tasking/work item creation to users in accordance with user settings and preferences.

The same process is illustrated in the context of the TCPED process in Fig. 2. From a software architecture perspective,

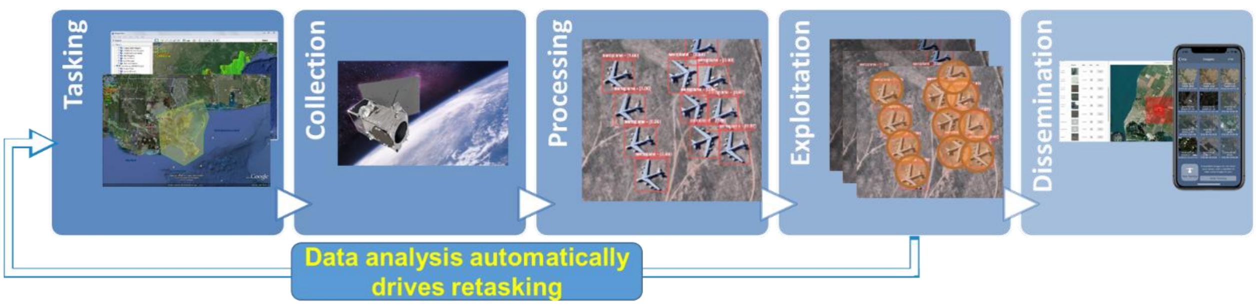

Figure 2: CASTT System and the TCPED pipeline.

2.2 CASTT Software Architecture

The software architecture is illustrated in Fig. 3.

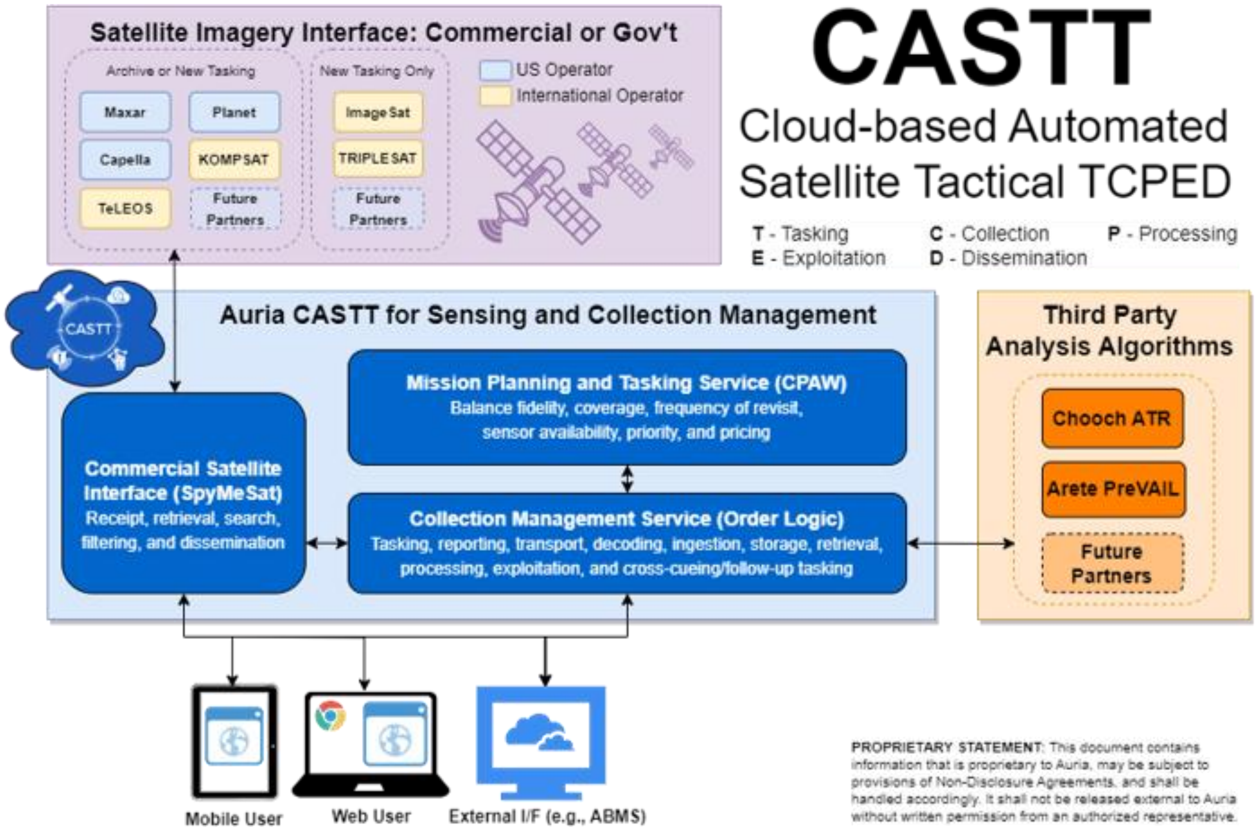

Figure 3: CASTT System Architecture.

2.2.1 Interface With Satellite Operators -- SpyMeSat

CASTT uses SpyMeSat to interface with satellite operators. Currently, those operators are:

- Archive and New Tasking:
  - Maxar
  - Planet
  - Capella
  - KOMPSAT
  - Teleos
- New Tasking Only:
  - Imagesat
  - TripleSat.

However, additional operators are easy to integrate since all connections are done via an API.

CASTT uses SpyMeSat to retrieve collection opportunity information from operators and to place specific tasking orders. This is done via a completely automated interface with no humans in the loop on the CASTT/SpyMeSat side. The specific latency of data collection depends on the responsiveness of the satellite operator.

2.2.2 Optimized Collection Planning -- CPAW

CASTT leverages CPAW for optimized mission planning and tasking. It uses CPAW to optimize collection tasking in order to select specific collection orders to place among all options from all the satellite operators available to SpyMeSat. CASTT weighs collection tasking options in terms of expected value of information, cost, etc. and requirements on resolution, etc. and decides which collection tasks to purchase from satellites.

CPAW targets the NP hard constellation collection planning problem [14, 15]. It is a Commercial-Off-The-Shelf (COTS) collection planning software primarily used for earth-imaging satellites [16] that is deployed for Maxar, Landsat 8/9 [17-19], the MUSES platform on the International Space Station, and other satellite operators. The brokering performed for CASTT is an existing CPAW capability that builds on its automated planning algorithms targeting a multi-factor configurable Figure-of-Merit, including cloud forecasts and other factors. CPAW generates validated, deconflicted, and optimized plans for imagery collection, calibration, housekeeping, and all associated maneuvers. This planning can target single satellite or large constellations jointly planning for the collection of several point or area targets including high fidelity spacecraft modeling for EO/IR/Multispectral/etc. and mission constraints (contact scheduling, etc.).

2.2.3 Algorithm Brokering

CASTT uses an API to interact with cloud-hosted analysis algorithms. Currently, CASTT uses Chooch (https://www.chooch.com/) for vehicle detection and Auria internal tools for pattern of life determination.

Chooch automatic target recognition (ATR) classification returns metadata such as true/false positive/negative rates, cloud cover percentage, misclassification probabilities, etc., for Bayesian beliefs updates about vehicle presence in monitored Areas of Interest (AOIs). The pattern of life algorithm uses multi-image analysis examining behavior over time with unsupervised AI/ML clustering to establish typical vehicle locations. It leverages image metadata along with data products (i.e., vehicle detections, detection class, confidence level, location, and size) from the Chooch ATR for Bayesian beliefs updates about vehicle presence in monitored Areas of Interest (AOIs). Additional algorithms are easy to connect via API; Arete's PreVAIL tool (https://arete.com/what-we-do/space/) was integrated as an alternative analysis option.

2.2.4 Reactive Tasking

Reactive tasking services connect to CASTT via API just as processing/exploitation do. Optimized reactive tasking is chosen maximize value of information from new collects by scoring and selecting potential collects based on expected reduction in uncertainty. Currently, the reactive tasking is issued by the pattern of life component based on whether expected behavior is identified in collected data. If a vehicle is found as expected, a follow-up collection will be issued at a 'nominal' cadence. If a vehicle is not identified in the image where it was expected, a follow-up collection will be issued at an area of interest that has been *a priori* identified as another probable location for the vehicle to reside.

3. Latency Analysis

5.1 Theoretical Latency

CASTT accelerates follow-up data gathering after detected event. The CASTT pipeline without Collection -- Tasking, Processing with Chooch ATR, Exploitation with Auria POL, Dissemination -- takes <5 seconds. The actual collection latency depends on the level of satellite operator support. With appropriate contracts, latency could be reduced up to a point determined by satellite orbits and ground station/target locations. We use CPAW to study achievable latency determined by uplink-collection-downlink timing using SpyMeSat virtual constellation.

To perform this study, we use the constellations available to SpyMeSat (listed in Sec. 2.2.1) using ephemerides from space-track.org. We use ground stations from a well known satellite commercial ground station operator. We model all satellites with the same sensor and capabilities for ease of interpretation; however, this is not necessary with the system.

We consider monitoring of the sample AOI over a week. We aggregate the latency from request time to data receipt considering a request on the AOI for every hour in the study period. To do this, we first consider the soonest you could uplink a command to any given satellite, the soonest collection opportunity for the satellite over the AOI after the command uplink, and the soonest downlink opportunity for the satellite after the collection opportunity. This determines the latency for a given satellite for a given request.

The latency for a given satellite operator for that request is the minimum latency over its satellites. We also consider 'virtual constellations' obtained by brokering over different sets of satellite operators. The virtual constellation latency is the minimum latency over its component satellite operator's latencies.

We considered two virtual constellations: one with all 7 SpyMeSat satellite operators available and one with only the US providers in SpyMeSat. To avoid attaching formal numbers to the informal analysis in this paper (since real sensor capabilities are not modeled, etc.) we anonymize the satellite operators, ground station provider, AOI, and period of interest. The latencies for the satellite operators and virtual constellations are listed in Tabs. 1 and 2 and illustrated in Fig. 4.

The median/average latency was 85/99 minutes with full virtual constellation and 97/114 minutes with only US operators. The full virtual (full US virtual) constellation improved latency by 39/36% (31/25%) on median/average relative to the best individual operator. Moreover, the best individual operator's worst latency was 5 times higher than virtual constellation's.

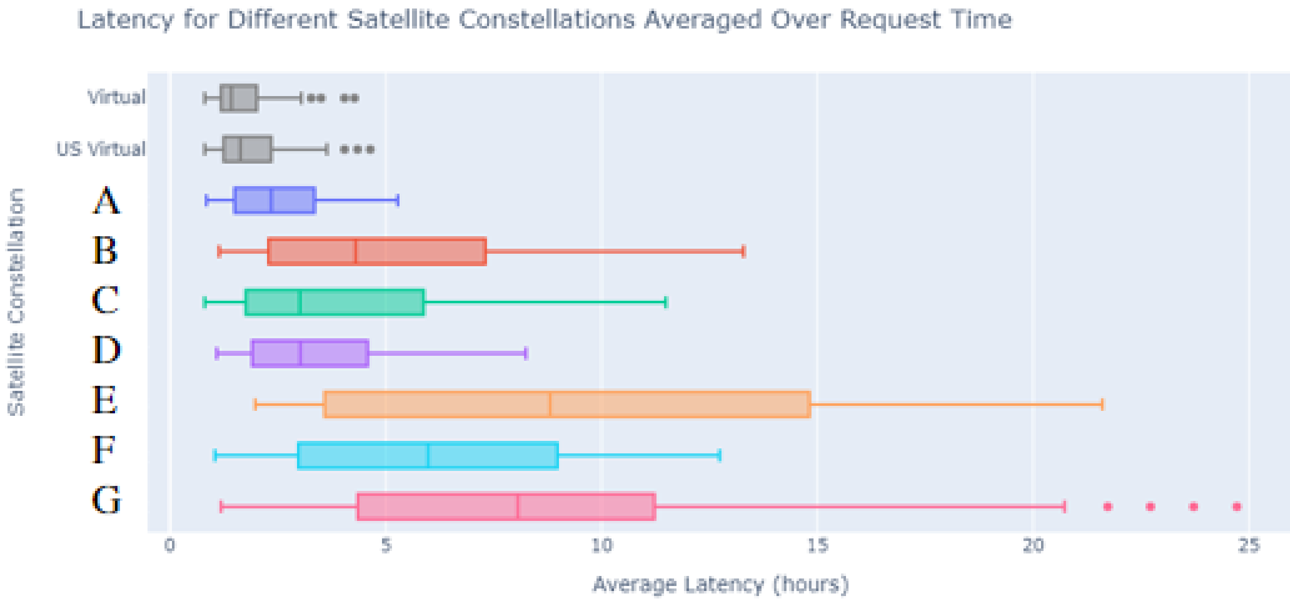

Figure 4: Latency for Commerciasl Satellite Operators and Virtual Constellations.

Table 1: Latency for SpyMeSat Virtual Constellation.

Operator	*Median Latency (min)*	*Average Latency (min)*	*Worst Latency vs US Virtual Constellation (%)*
US Virtual	97	114	0
A	141	151	394
B	258	299	1409
C	180	240	716
D	181	203	577
E	529	583	2123
F	359	365	1236
G	484	516	2704

Table 2: Latency for SpyMeSat US Virtual Constellation.

Operator	*Median Latency (min)*	*Average Latency (min)*	*Worst Latency vs US Virtual Constellation (%)*
US Virtual	97	114	0
A	141	151	394

B	258	299	1409
C	180	240	716

5.2 Actual Latency

We performed an additional study in which we used queried Operator A for available tasking every hour. We considered a time period of collections over two weeks on three target AOIs. Clearly, the data generated by this approach will only be accurate up to the query interval. This gave us data on the achievable real latency on short timescales with real provider support. This was motivated that sometimes, close to the tasking window, the opportunity is no longer available to task. This study quantified the magnitude and prevalence of this effect.

Table 3: Statistics on Lowest Request-to-Collection Latencies.

TARGET AOI	**TARGET 1**	**TARGET 2**	**TARGET 3**
MINIMUM LOWEST LATENCY (H)	6.91	7.65	6.91
MEDIAN LOWEST LATENCY (H)	34.22	47.57	32.04
MAXIMUM LOWEST LATENCY (H)	84.04	145.29	79.04

Note however, that this study measured the request-to-collection latency, as opposed to the need-to-data-delivery latency studied in the prequel. The need-to-data latency is the sum of the need-to-request latency, the request-to-collection latency, the data collection itself, and the collection-to-data-delivery latency.

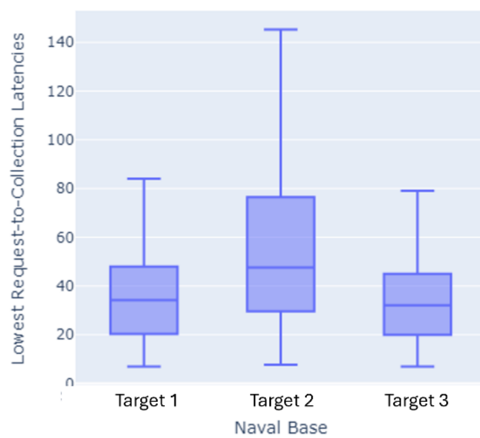

Figure 5: Minimum Request-to-Collection Latency in Hours from Requests to Operator A Collection Time.

Figure 6: CASTT Demonstration Mission. From top to bottom: 1) Initial collect reveals no ship where one was previously expected, 2) Follow-up collection on a different port detects the ship and 3) Ship detections from follow-up collection are compared with POL for that port determined from historical data on that location.

For each collection, there were several available times at which we could task Operator A. We term the minimum of these the 'lowest request-to-collection' latency. The lowest available request-to-collection tasking over all collection opportunities on each target location was 7-8 hours, with the median at 35 or 47 hours, depending on the target area. A table of some relevant statistics is shown in Table 3and a box-and-whisker plot is shown in Figure 5.

4. Demonstration

In this section, we demonstrate a demonstration scenario performed by CASTT using real satellite collections and a fully automated CONOPS. The only manual step is shown in Fig. 6 wherein the high-level mission is configured. The mission is to monitor an AOI (anonymized for privacy) for a vehicle and to search for it if it is not in the AOI as expected.

The high-level mission prompts the creation of an initial collection order. This is passed to Chooch ATR which returns the detections. The pattern of life module identifies that something is off-nominal -- the expected ship is not detected -- so it issues a reactive task to collect on another location associated with the vehicle. We note that the figures have been anonymized for privacy to not reveal the AOIs or time period.

5. Conclusions

CASTT is an integrated platform for closed-loop remote sensing. It issues collection orders, analyzes the results, tasks new orders according to the analyses and a configured high-level mission, and disseminates all data, analyses, and tasking updates to users. Each element of the TCPED process it implements can use internal or external tools connected via flexible and robust APIs.

We performed a study showing that this system results in a much lower theoretical fastest latency for follow-up imagery collection. We also demonstrated the CASTT process for real custody maintenance of a maritime vessel.

Relative to the state-of-the-art, CASTT is differentiated by several key features:

- Operational Heritage: its component products have been deployed for >20 years
- Multi-Satellite Vendor Data: it gathers data from several constellations using existing commercial interfaces
- AI/Optimization: it easily integrates, chooses, swaps out, etc. analysis algorithms from several providers
- Lower Latency: by performing multi-provider brokering and automated retasking, it accelerates timelines
- Multi-Image Analysis: performing long-reaching examinations allows it to provide better context
- Lack of Vendor Lock: its API connections make connections with new partners easy
- Flexibility and Configurability: the software architecture adapts and scales quickly for new missions
- Time to Market: it can be rapidly deployed and refined.

Several directions for future work have been identified. These include tailoring for specific mission(s), integration of additional data providers/algorithms, expanded toolset for latency analysis, expanded Pattern of Life algorithms, and edge deployment.

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