Stingray: Photometric Survey of the GEO Belt

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ABSTRACT

Stingray is a 15-camera optical array dedicated to a nightly photometric survey of the Geostationary Orbit (GEO) belt visible above Tucson, Arizona. The primary scientific goal of the Stingray system is to classify GEO and near-GEO satellites based on their photometric properties and is inspired by the COTSCam system developed at USNO by Dave Monet. This system is designed to be completely automated in both data collection and processing, with human oversight reserved for data product quality assurance and system maintenance. The 15 ASI 1600 MM Pro cameras are mated to Sigma 135 mm f/1.8 lenses and are controlled simultaneously by four separate computers. Each camera is fixed in position, and images a 7.6 by 5.8 degree portion of the GEO belt for a total of a 114 by 5.8 degree field of regard. The GAIA DR2 catalog is used for image astrometric plate solution and photometric calibration to GAIA G magnitudes. There are approximately 200 satellites on any given night that fall within the Stingray system's field of regard, and all those with a GAIA G magnitude brighter than approximately 15.5 are measured by the automated pipeline. This survey began its commissioning phase on November 16, 2021 and ran every clear night until June 16, 2022, when it was shut down for the local monsoon season.

1. INTRODUCTION

Physical characterization of artificial space objects enables their unique identification. Characterization techniques include photometric and spectroscopic studies that aim at understanding the behavior of light as it interacts with the object in question. Traditionally, photometric surveys of the GEO belt visible from a given location on the ground have used two modes of operation: 1) “hopscotch” through the satellites each night using a single telescope, only collecting a few observations of each satellite before moving on; or 2) staying fixed on one or a few satellites in the telescope field of view each night for the whole night. Skipping between satellites all night allows for a shorter “revisit time”, getting at least some data on most, if not all, desired satellites each night, however the data duration is short which makes characterization and behavior/change analysis difficult. On the other hand, observing one or a few satellites all night long allows for a longer duration of data making characterization more informative, however the longer “revisit time” between subsequent nights of observing the same satellite makes behavior/change analysis for much more than seasonal effects intractable. Having real-time data on each

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GEO satellite all night long, every night would be the most ideal scenario for space domain awareness (SDA) applications.

Machine Learning (ML) has been shown to be a very effective tool for satellite characterization ([5], [7], [8], [9], [10]), but one of the biggest limiting factors in the development of these algorithms for real-world use is the availability of high-quality training data. Having access to not just nightly, but real-time observations of every GEO satellite above a location on the ground opens the door for new types of periodic characterization analysis, focusing on instantaneous, short-term, and long-term effects that has never before been possible for GEOs en masse.

In this paper, we present details on the Stingray system, a 15-camera optical array located in Tucson, Arizona that is designed to collect data every clear night on all GEO satellites visible from its location. The details of the Stingray hardware setup are covered in Section 2. The automation and data management considerations for the large volume of expected data as well as the processing for this data are covered in Sections 3 and 4, followed by an initial look at some of the results from the 7-month commissioning and testing phase in Section 5.

2. HARDWARE

The Stingray system is comprised of 15 ZWO ASI1600MM Pro cameras, each mated to a Sigma 135 mm f/1.8 lens. All cameras are mechanically fixed in position, each staring at a different section of the GEO belt visible above Tucson, AZ. The Sigma lenses were selected after completing a trade study with 12 different lenses from three different manufacturers. Using a prototype system, the lenses were evaluated based on achieved image limiting magnitude, image flatness (edge distortion, or lack thereof), image sharpness, cost, FOV, focal ratio, and resolution. The Sigma 135 mm lens performed very well across the board, even outperforming more expensive lenses, and overall was a good design fit for our desired system. Using 600 nm as a central wavelength (halfway between our detector peak QE and GAIA G central wavelength), the 75 mm aperture of the Sigma 135 mm lens gives a theoretical resolving power of 2 arcseconds, which is roughly equivalent to our site's seeing, however the detector pixel pitch is 3.8 μm giving a pixel scale of 5.9 arcseconds per pixel. The limiting magnitude of the system was found to be just brighter than 16 GAIA G magnitude. Some relevant system details are given in Table 1.

Table 1. Relevant physical parameters for the Stingray system.

Name	Camera	Focal Length (mm)	Aperture (mm)	FOV (deg)	FOR (deg)	Pixel Scale ($\frac{arcsec}{pixel}$)
Stingray	ZWO ASI1600MM Pro x15	135	75	7.6 x 5.8	114 x 5.8	5.9

To control all 15 cameras simultaneously we use four separate Intel NUC computers, each connected to four cameras (one connected to only three), and a fifth Intel NUC to act as a master node. Since the entire system is automated, the master node is responsible for monitoring the weather in real time, opening and closing the roof when appropriate, and issuing start/stop/pause imaging commands to the four camera control nodes. Each of the camera control nodes, upon receipt of a command from the master node, performs the appropriate action with its four cameras. Image plate solution and photometric calibration can happen either in real-time on each camera control node, or in batch at the end of the night. As a precaution, real-time updates on weather, roof status, imaging sequence state, and data processing, as well as an end of the night summary of data collected and visual proof of roof closure (photo) are all sent from the master node using Slack for easy remote system monitoring.

3. DATA COLLECTION AND HANDLING

Since Stingray is a completely autonomous system, by default data is to be collected every night. The master node that handles the weather monitoring makes the decision on when/if to open the roof for imaging on a given night. Nominally, imaging is set to start every night when the sun is 12 deg below the local horizon, however if there are clouds overhead, or other adverse weather conditions, the master node will delay the start until the conditions clear. Similarly, if the conditions worsen at any point during the night, the master can pause imaging and close the roof if necessary to wait for the conditions to improve. In this way we can get some data even on less-than-optimal nights, while maintaining system safety, without having to have an operator manually monitoring the system all night every night.

During our commissioning and testing phase, Stingray collected over 350,000 images. Since we are still testing the system, both the raw images and the calibrated/plate solved images are saved comprising over 8 TB of data so far. To help limit the volume of data produced during testing, we have altered our imaging plan to a pair of images every 5 minutes using 2x2 binning. We collect a pair of images (one 20 second and one 2 second exposure) to help in our quality analysis of the system during our commissioning phase. The 2 second exposure image has sufficiently round PSFs from the stars in-frame to allow for a set of "control" images that can be used to validate data processing as well as check for any issues such as focus drift, poor calibration, etc.

Nominally, the imaging plan for our GEO survey is a pair of images every minute from all cameras, 1x1 binning. If we continue to save both the raw and calibrated/solved images, based on the average number of images collected per night so far, this means we will be generating roughly 1 TB of data per night. Though if we forgo collecting the 2 second exposure images every minute, and instead only collect them periodically throughout the night or not at all, we can reduce the data volume by up to half. In addition (or instead), we may revert to 2x2 binning and quarter the data volume. Moreover, if only the calibrated/solved data is saved, this further reduces the data volume by one third. Assuming an 80% duty cycle (290 clear nights a year in Tucson, AZ), this gives a range of 25 TB - 0.3 PB of data per year.

To-date, taking both 2 and 20 second exposures in pairs has proved very useful in understanding Stingray's nightly performance, and some preliminary testing has shown some advantages to using 2x2 binning besides just data volume reduction. Taking this into account, and assuming the same 80% duty this yields on average roughly 73 TB of data a year. Backups of this data are made nightly, and are kept on a local high-density storage system that is capable of hosting a year's worth of image data at a time.

4. DATA PROCESSING

Image nonuniformity corrections, plate solutions, and photometric calibrations can all be done either real-time as images are collected, or in batches at any later point. The desired data products from this survey are satellite metrics (angular position and brightness), and these can be extracted from the images also in real-time or in batch, though due to the stochastic nature of the automated satellite extraction process, it is often more robust when processing is done in even small batches as opposed to an image-by-image basis. Nonuniformity corrections are done with sets of calibration images collected once a month. This includes camera readout bias and dark frame subtraction as well as flat field division. Ideally, calibration images would be collected on a nightly basis, but the cameras do not have individual filter wheels so doing so requires manually changing the filter on each camera.

Image plate solution and photometric calibration are done using the GAIA DR2 catalog. Our photometric measurements are calibrated using in-frame solar type stars, chosen based on the criteria published in [1], and corrected to first order in GAIA G magnitude ([3], [4], [6]). Since each image is quite large (44 deg^2) and we expect to take an average of ten thousand images a night, using in situ network access to the GAIA DR2 catalog is not an option. As such, we have created our own custom local star catalog from GAIAA DR2 that is made of a strip of the sky centered on the GEO belt as seen from Tucson (-5 deg declination). This local catalog contains over 35 million stars and has information for stars as faint as 18 GAIA G magnitude.

Since Stingray's cameras are mechanically fixed and take 20 second exposures, star trails in the images are approximately 25 pixels long when binned 2x. While not pathologically long, these trails do have the potential to contaminate satellite observations. Special care has been taken to minimize this effect on the results at each step of the processing pipeline, including a final stochastic filtering step on the extracted satellite observations which is designed to reject observations believed to be contaminated by nearby stars in the image. As such, the total number of observations for each satellite will be reduced, but the astrometric and photometric quality of the observations will be more reliable.

Once the data for each object of interest in each of the images is extracted for the night, the observational data will be uploaded to VerSSA (the University of Arizona SSA cyberinfrastructure system) for further processing. The

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output format of the reduced satellite measurements is flexible, though nominally the measurements are 80 bytes per observation so only a few megabytes of data will need to be transferred each night. This can be adapted to accommodate a real-time or small batch stream of observations to VerSSA instead of an end-of-the-night accumulation, if closer to real-time analysis is desired.

5. COMMISSIONING PHASE RESULTS

We began collecting test data with Stingray on November 16, 2021, allowing the system to run every night and incorporating any changes to software or hardware as needed. Data was successfully collected for an average of just over 8 hours a night for 160 nights until June 16, 2022 when Stingray was temporarily shut down for the local monsoon season. As an example, let us consider the most recent night of data. Although the moon was approximately 98% full and there were some dispersed clouds early in the night, Stingray was still able to maintain an average photometric calibration error of 0.06 magnitudes across all catalog sources in all images that were successfully plate solved. Astrometric and photometric measurements were extracted for 117 GEO satellites, averaging 50 observations per satellite.

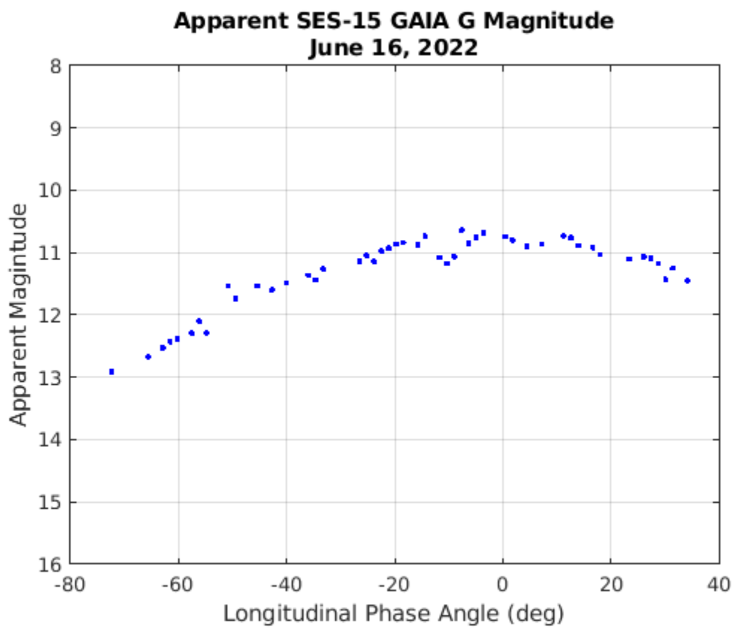

Fig. 1. Stingray observations of SES-15, taken on June 16, 2022 by the Stingray system.

Since SES-15 is part of the Wide Area Augmentation System (WAAS) used to help improve GPS, it has publicly available, accurate ephemeris that makes it a very useful calibration target. Comparing the ephemeris for SES-15 to our observations on June 16, we find that the average error in declination measurement is consistent with zero (8 thousandths of a pixel) with a standard deviation of approximately 0.1 pixels which is consistent with sub-pixel centroiding limits. The average error in right ascension is biased at 2 pixels with a standard deviation of approximately half a pixel. Given that SES-15 has a near-zero inclination (< 0.02 deg), the right ascension error can be considered analogous to a time error, which in this instance corresponds to a timing error of 1.6 seconds. Performing a similar analysis on GALAXY-30, another WAAS satellite which is seen from a different Stingray camera, but controlled by the same computer as the camera which took data of SES-15 shows a similar timing error of 1.2 seconds.

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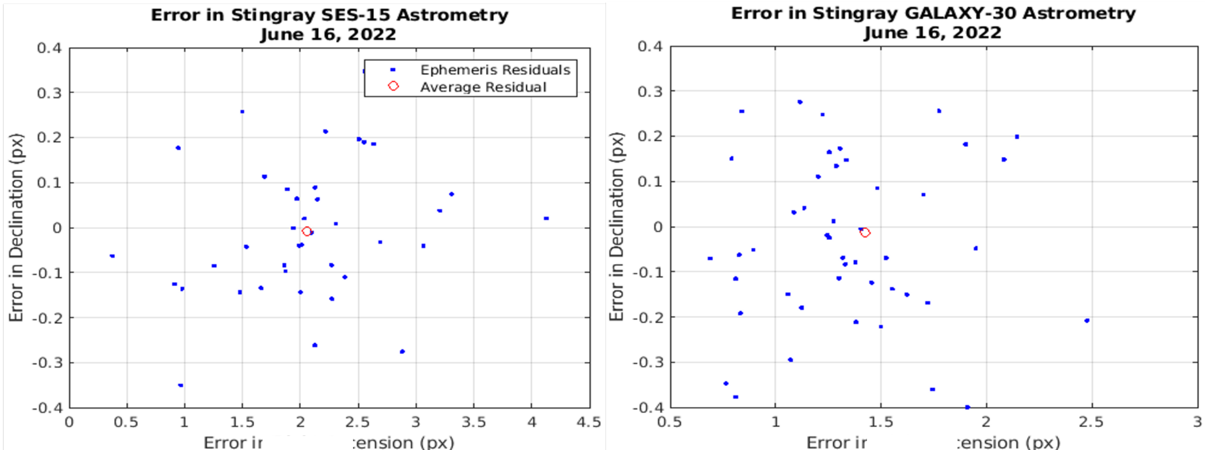

(a) (b)

Fig. 2. The astrometric residuals for Stingray observations of two WAAS satellites on June 16, 2022. Both sets of observations were taken using the same computer but two different cameras. Observations of SES-15 (Fig. 1a) and GALAXY-30 (Fig. 1b) each have an average declination error consistent with zero and standard deviations appropriate for subpixel centroid limits (~0.1 pixels). The error in right ascension is biased, and corresponds to an approximate time error of 1.3 seconds.

Time on each of the Stingray computers is controlled by a background process that syncs with a public NTP server every minute, while network latency and system clock drift may play a part in this error (likely at most a few tenths of a second), it is unlikely this is the sole cause of the error. There will also be some latency in the image capture, readout, and file creation process that is not reflected in the time information in the image header. This is something that merits further analysis and characterization so that it can be mitigated in future data.

6. ACKNOWLEDGMENTS

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