**METEORITE RECOVERY USING AN AUTONOMOUS DRONE AND MACHINE LEARNING.**

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**Introduction:** Determining the composition of asteroids is critical to planetary defense because composition is directly related to an asteroid's potential threat and response to various deflection techniques. Apart from costly sample return missions, one of the few methods of determining asteroid composition is linking freshly fallen meteorites to specific asteroid families. This is possible only if the fireball trajectory is measured, allowing a computation of the pre-impact orbit of the meteoroid before it broke apart during atmospheric entry [1].

The semi-major axis, combined with the cosmic-ray exposure age measured from the recovered meteorites, points to the source resonance from which the meteorite type is delivered. The inclination of the orbit tends to be similar to that of the source region asteroid family. If a statistically sufficient sample of orbits can be measured, then it is possible to identify the source family from this information.

Until now, various fireball networks have recorded approximately 800 trajectories of meteoroids significant enough to have dropped meteorites on the ground, of which only 29 cases (3%) resulted in meteorite recovery [1]. Combined with the fireball trajectory, the use of Doppler weather radar signatures has helped locate the strewn field of meteorites. Meteorites are found in the strewn field through a physical survey, taking ~100 man-hours to locate one meteorite fragment. In order to increase the recovery yield meteorite falls, we need a better way to search for freshly fallen meteorites.

As part of NASA's 2016 Frontier Development Lab, a research accelerator in partnership with the SETI Institute, NVIDIA and Autodesk, we studied whether machine learning could be used in conjunction with an autonomous drone to detect meteorites in the field. Here, we outline a method using a commercial drone to survey the terrain and machine learning techniques to recognize meteorites in the images.

**Autonomous Data Collection:** We used a 3DR Solo quadcopter drone mounted with a GoPro HD camera for autonomous data collection. The quadcopter drone can fly on an autonomous grid search pattern at ~2 meters altitude, sufficient to survey an area of likely meteorite fragments. An example survey image is shown in Fig. 1, with the image divided into subsections that can be fed into an image classifier for meteorite detection.

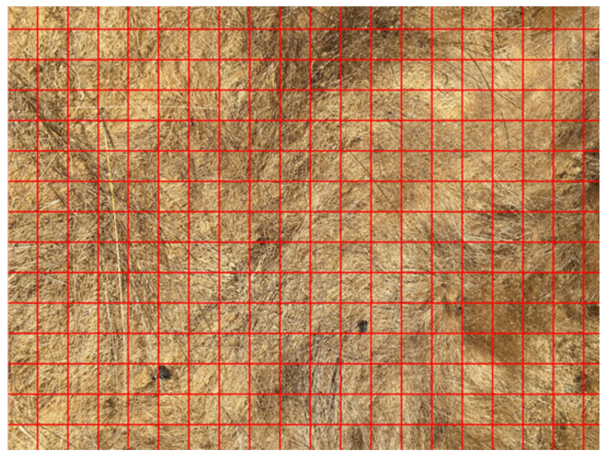

Figure 1. Sample drone image taken from ~2 meters altitude with two meteorite fragments on grassy terrain. The image is divided into subsections for classification.

**Machine Learning Algorithm:** Each of the patches outlined in Fig. 1 can be fed into an image classifier to determine the likelihood that a patch contains a meteorite. For image classification, we use a convolutional neural network that is trained to recognize meteorite fragments in a variety of terrains. The image classifier is implemented using the Caffe [2], Keras [3], and Theano [4], software packages.

Our image classifier is pre-trained using a dataset of roughly 15 million images called ImageNet [5] and highly accurate convolutional neural network architectures (e.g., GoogLeNet [6] and AlexNet [7]) designed to train on such large datasets. We pre-trained the network using an existing architecture (such as GoogLeNet), and initialized our parameters to be those which were the result of training on ImageNet. We subsequently train the network with a low learning rate on our set of training images.

The image classifier first trains itself on a dataset of positive and negative images (Fig. 2). Because the accuracy of the classifier is highly dependent on the number of training images, we assembled a database of ~600 positive meteorite image patches; 320 from photographing 8 meteorites in our possession on various local terrains, and 280 from cropping meteorite photos found on the internet. In order to increase the types of meteorite fragments in our training set, we also photo-shopped 35 meteorite fragments found online onto realistic terrain backgrounds. Our set of positive patches was augmented by rotations, reflections, and changes to resolution, brightness, and saturation. Because our positive patches were cropped from larger images (so the meteorite was 1/9th of the patch area), we were able to create a set of negative patches by cropping sections of the same images that did not contain meteorite fragments.

Figure 2. Sample positive (left) and negative (right) images used to train the image classifier.

**Results and Field Test:** To test the system we visited Creston, California, the site of a meteorite fall on October 24, 2015. Although our hardware/software was not yet mature enough for a full test, we were able to place meteorites in the field and survey them with the drone, obtaining test data to access the performance of our software pipeline in identifying meteorites at the location of an actual meteorite fall.

The results of locating the placed meteorites in the field had varying degrees of success. In the grassy terrain of Fig. 3(a), two of two meteorites were correctly identified and there were two false positives out of 17,000 classified patches. In the rocky terrain of Fig. 3(b), two of two meteorites were again correctly identified, but there were 174 incorrectly labeled patches out of 17,000. While the classification scheme we implemented performs well on certain images, on other images it produces many false positives.

**Conclusions and Future Work:** We demonstrated it is possible to identify meteorites in the field using machine learning to classify patches in images acquired by an autonomous drone. We were able to identify meteorites correctly, even with accompanying false positives, on terrain and meteorites we did not use as part of our training data set. The implementation can be improved in three areas: (1) reducing the false positives in our classification scheme, (2) decreasing processing time for each image, and (3) improving the hardware for more optimal automated searches.

Our field test shows that the use of an automated drone has the potential to be move efficient than a human at locating a meteorite in the field. With updated software and hardware, the system could prove a valuable tool for increasing the number of meteorite fragments found from fresh falls. By continuing to improve the system, it may be possible to increase the number of meteorite fragments found that can be associated with imaged fireball trajectories, increasing our understanding of the composition of Earth impactors and their parent asteroid bodies.

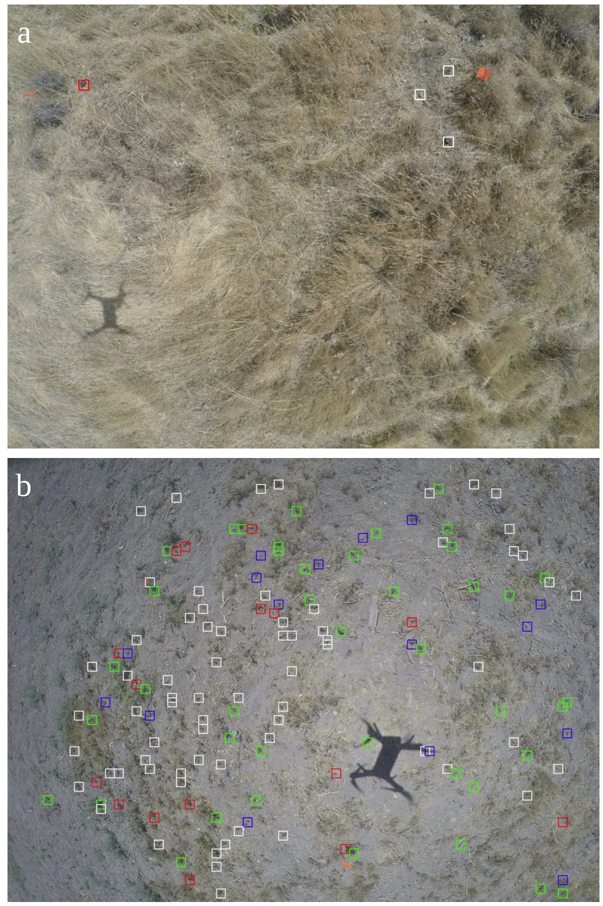


Figure 3. Field test images with accurate (a) and inaccurate (b) classifications. Boxes surround patches that were classified as having a meteorite, with the color denoting the accuracy of the classifier (red=high).

**References:** [1] Jenniskens P. (2013) *Proceedings of the Meteoroids 2013 Conference* 57–68. [2] Jia Y. et al. (2014) *ACM International Conference on Multimedia*, 675–678. [3] Chollet F. (2015) *GitHub Repository*. [4] Theano Development Team (2016) *arXiv e-prints*. [5] Deng J. D. J. et al. (2009) *IEEE Conf. Comput. Vis. Pattern Recognit*., 2–9. [6] Szegedy C. et al. (2015) *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 1–9. [7] Krizhevsky A. et al. (2012) *Adv. Neural Inf. Process. Syst. 25*, 1–9.