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A Pattern Recognition System for the Automated Tracking and Classification of Meteors Using Digital Image Data

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Abstract. In this project, we aim to develop an efficient and reliable method to search through vast amounts of digital image data of the sky (at video rates of 30 fps) to identify meteors. We describe a pattern recognition system that accomplishes this goal in two steps. The first step keeps track of luminous objects that follow a straight path through a set of frames; multiple features become then available for each moving luminous object. During the second step, the system automatically labels the moving object as either a meteor or not (e.g., or satellite). The benefit of such a pattern recognition tool is twofold: 1) it obviates the process of searching through image data by eye, which is infeasible for producing a database with reliable statistics; 2) derived information can provide a better understanding of the mass distribution of meteors, which is crucial for determining the total mass flux incident into the upper atmosphere.

1. Introduction

There is broad and far reaching interest in studying meteor trail physics. For example, understanding the properties of the incoming meteoroid provides information about the interplanetary dust environment around Earth and how it has evolved during the evolution of the solar system. There are currently two main methods for this type of study: radars and imagers. The use of radars is more mature, but the techniques for deriving mass are not without limitations and assumptions about the radar scattering cross section of the plasma trail. The use of television imaging for meteor detection is relatively young, and has the main advantage of incurring fewer errors during mass calculations because of simpler and fewer assumptions than radar techniques. The main disadvantage is the tedious process of sorting through the television data; this has been a major drawback to setting up consistent, long term observations for detecting small meteors. Additionally, the large amount of data generated from an imager running at 30 or 60 frames per second (fps) can be around 15 GB per hour.

The goal of this study is to develop an algorithm to search through large volumes of television imaging data in order to identify and quantify meteors in an accurate and consistent manner. We describe a pattern recognition system for the automatic detection of meteors using image processing and classification. Our system will be tailored to the identification of meteors by exploiting the precise signature of these objects along several frames (e.g., trajectories are linear, few frames to cross the sky, trajectory displays a rectangular shape, etc.). Such singular behavior leaves patterns that can be quickly identified. The general mechanism for our proposed software tool can be divided into two main tasks: 1) removal of background and noise, and 2) meteor detection. We describe each of these tasks next.

2. Background and Noise Removal

Our current system receives as input a video capturing part of the night sky; videos are usually 8 minutes long and contain around 16,000 frames. Each frame is a pixel matrix of size 256×256. A pixel at coordinate (x, y) contains the value of gray intensity at that point in the sky.

For a new frame F_n, a first step is to remove some background noise by making all pixels binary-valued as follows. Let $V_{x,y} = I(x, y)$ be the value of gray intensity at entry (x, y) in the matrix. We assign a value of minimum intensity (black) if $V_{x,y} < \theta$, and a value of maximum intensity (white) if $V_{x,y} \geq \theta$ (we currently set θ empirically). This enables us to work with binary-valued pixels only, getting rid of faint sources, and highlighting sources bright enough for analysis. Figure 1 illustrates this operation.

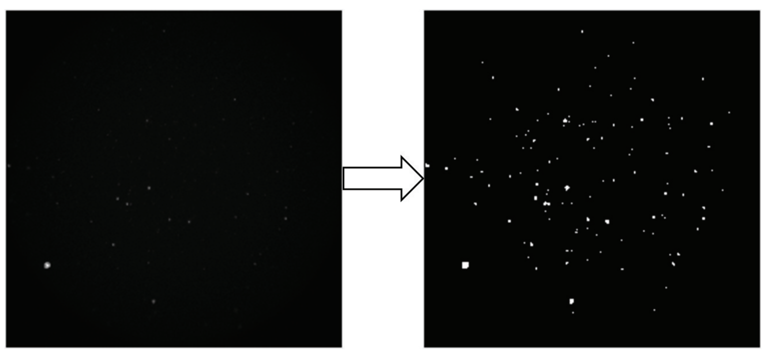

Figure 1. Our first step is to simplify the image to enable us to work with two values only, getting rid of tenuous sources, and highlighting bright sources.

The next step is to build an average background that we will use to subtract from our current frame F_n to eliminate all luminous objects that are static on the sky during a short time interval. To proceed, we create a queue Q of 50 frames that immediately precede current frame F_n. When we move to the next frame, the current frame will be added to the queue, while the last frame will be removed. In short, we keep a window of size 50 containing those frames that precede current frame F_n. Pixels in all frames in Q are averaged to produce a single average frame F_Q. This creates a background with no noise or fast moving objects. Figure 2 illustrates the process of averaging over several frames.

To remove noise corresponding to flickering stars, the average background image is dilated by one pixel (i.e., every white pixel is increased in size by making white its nearest neighbors). This increases the radius of all luminous objects by one pixel. The averaged background image F_Q is then subtracted from the current frame F_n. This has

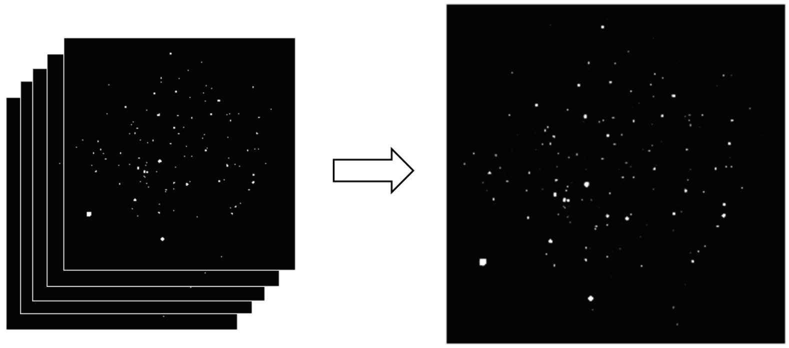

Figure 2. A queue of 50 frames previous to current frame F_n is used to produce a new image by averaging over all pixel values.

the effect of removing objects that appear in both F_n and F_Q (e.g., stars). Figure 3 shows an example of the effect of background removal. The last frame shows a few luminous objects corresponding to those that have just appeared in the sky.

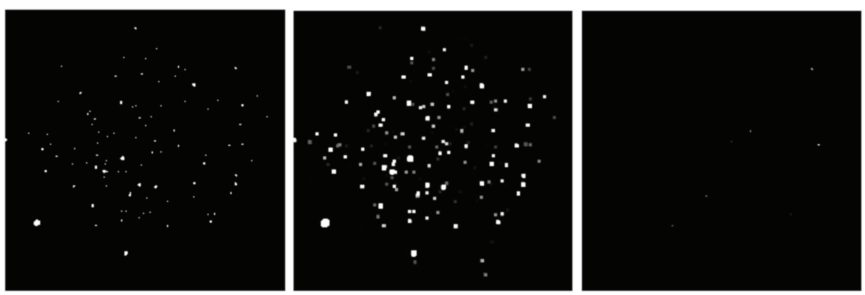

Figure 3. Left: Current frame F_n. Middle: Averaged background F_Q image after dilation. Right: The effect of subtracting F_Q from F_n.

3. Meteor Detection

We now explain how to identify meteors on an image where background has been already removed. We identify luminous structures using a technique known as blob detection (Treiber 2010). An 8-neighborhood algorithm is applied to each white pixel enlarging the size of the blob as long as white pixels remain connected. To eliminate faint sources, any blob with a size less than a minimum threshold ϑ is ignored (in our experiments we set $\vartheta = 3$). Our blob detection mechanism helps us extract several properties of the object under analysis, such as size, centroid, and shape. Due to the exposure of each frame, a particular signature of all meteors is that they will appear elongated; we thus eliminate all non-elongated blobs from the image using object properties. We infer that any object not eliminated by the previous step corresponds to a meteor. Figure 4 shows an example of the blob detection mechanism during meteor identification.

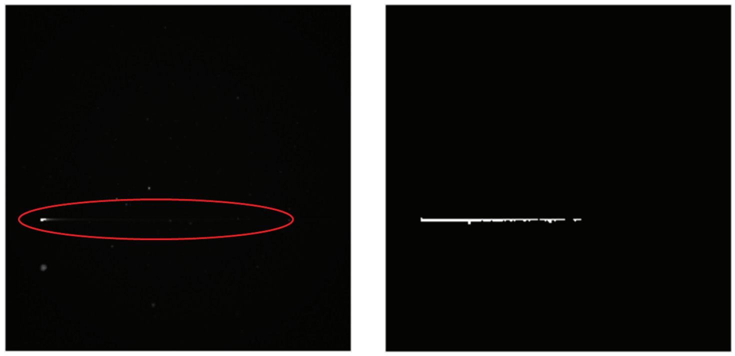

Figure 4. After applying the blob detection mechanism, it is possible to identify meteors by searching for long elongated bright signals.

4. Conclusions and Future Work

Our pattern recognition system provides a preliminary approach to meteor identification by isolating and extracting bright linear trajectories from video images. Many components of the system are amenable to refinement. For example, during the removal of background and noise, it is unclear what the correct value of θ is to transform the initial frame into a binary-valued frame. There is a possibility of eliminating faint sources corresponding to our target class (meteors). We plan to learn this value using machine learning techniques (Duda et al. 2001; Hastie et al. 2009). Our goal is to approximate the probability distribution of meteors and other luminous objects according to their brightness, which would enable us to predict the posterior probability of the class (meteor or other source) conditioned on brightness.

In addition, the background removal operation can be improved in several ways. The window size that is used to average over previous frames can be selected dynamically to increase computational efficiency (i.e., to decrease CPU time). The process of dilating luminous objects to avoid the effect of variability of the light source can also be adjusted to spread over a larger region. Such adjustments depend on the characteristics of the background during video recording, and can be optimized using a history of previous recordings.

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References

Duda, R., Hart, P., & Stork, D. 2001, Pattern Classification (New York, NY: Wiley-Interscience), 2nd ed.

Hastie, T., Tibshirani, R., & Friedman, J. 2009, The Elements of Statistical Learning: Data Mining, Inference and Prediction (Dordrecht: Springer), 2nd ed.

Treiber, M. 2010, An Introduction to Object Recognition (Dordrecht: Springer), 1st ed.