Meteorix — A new processing chain for real-time detection and tracking of meteors from space

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In the framework of the Universitary CubeSat project Meteorix of Sorbonne University, this article describes a processing chain for meteor detection from space. Unlike ground detection using stationary cameras with a still background, detection aboard a nano-satellite needs to deal with a camera in motion and a moving background. The main parts of this chain are an estimation of the apparent movement and the computation of angular statistics. The first results show a detection probability close to 96% on the whole set of Chiba videos from the PERC (Planetary Exploration Research Center) Meteor Project.

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1 Introduction

Meteorix (Rambaux et al., 2019) is the first Universitary CubeSat mission from Sorbonne University and its University Space Center. This mission has three main objectives. The main one is the detection and the characterisation of meteors and space debris in order to estimate the flux of these bodies entering in the atmosphere. The second is an educational goal to involve students in a space mission during all its phases. The third is a technological goal to demonstrate the feasibility of a real-time computer vision application on board a nano-satellite with strong constraints in terms of power consumption and execution time.

Space detection allows to go beyond meteorological constraints that ground detection has and offers a wide sky coverage. In 2016, Chiba University led an ISS mission named *ISS Meteor* in which a high resolution camera was filming toward Earth (Arai et al., 2014). They showed the feasibility of space observation of meteors but the recognition step was performed by human operators on Earth (Arai et al., 2018).

This proceeding covers the technological goal of the mission and it describes a new processing chain for meteor detection suited for space detection. Another proceeding (Rambaux et al., 2021) describes the optical part of the payload and its advancement.

2 State of the Art

Up to now, several detection techniques have been developed for ground detection by using a stationary camera, computer and processing chain.

In 2005, a review of processing chains (Molau & Gural, 2005) describes the different common steps of them and the image processing techniques used. Processing chains seem generally include at least three steps:

(i) A pre-processing step that mainly consists in keeping only the moving objects using a background subtraction technique (frame differencing, mean or median filter).

(ii) A classification step to know if there is a meteor in the frame. After a threshold, regions of interest are created from the brightest remaining pixels. Techniques exploiting spatial and/or temporal correlation are used to determine if a region is a meteor. The most popular techniques are the Hough transform, the template matching and the temporal tracking.

(iii) An extraction step to save each frame of a meteor as a sequence.

Some others steps can be included for analysis (orbit calculation, photometry...) but this goes beyond the scope of the meteor detection.

Four chains are described, including MetRec (Molau, 1999) and MeteorScan (Gural, 1997) which are very popular and still used nowadays, sometimes as a component of a new processing chain.

In 2009, (Gural & Šegon, 2009) propose a new processing chain in which the pre-processing step consists of merging 256 frames into a color bitmap image taking advantage of the fact that meteors are brighter than background to reconstruct the meteor trail. The blue channel is used to store values of the brightest pixels of images. The red and green channels are used to store the number of the image containing this bright pixel. That allows to keep the temporal dimension of the event. Then the classification is done by MeteorScan. An improved frames compression technique is used in the RPi Meteor Station (Vida et al., 2016) which is a processing chain designed for low cost embedded systems like Raspberry Pi.

The Fireball Recovery and InterPlanetary Observation Network (FRIPON) (Colas et al., 2020) comes with its own processing chain (Audureau et al., 2014), based on a classic background detection where successive frames are subtracted to keep only the moving pixels and on a tracking step.

Since few years, processing chains using neural networks have emerged. In (Galindo & Lorena, 2018), authors compare several convolutional neural networks (CNN) pre-trained with a huge dataset (ImageNet or

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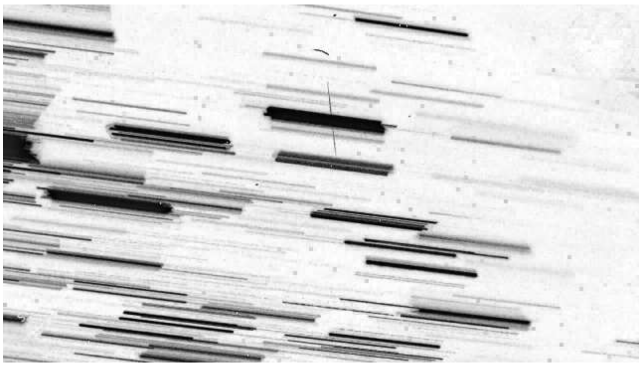

Figure 1 – Example of 256 frames compressed in one from RPi Meteor Station. Where are the 2 meteors? Each line can be the trace of a city (public lighting), a bright cloud or of a meteor.

Fashion-MNIST) in order to train with a small dataset of meteor images. The best configuration is composed of 18 layers and gives a detection probability of 96%. However, these experiments were done with a GPU Nvidia Quadro P4000 which cannot be embedded within a nano-satellite: its average TDP[a] is 105 Watt.

In 2020, another CNN was proposed (Cecil & Campbell-Brown, 2020) for the Canadian network CAMO in order to automate the classification step currently partially performed by a human operator. The network has been trained with the entire images to be used as a complete detector (therefor a one step processing chain). However, the number of false positives was too high. The solution was to add a pre-detection step as input of the network using the same image processing techniques (addition of several frames, Hough transforms). This processing chain has a detection probability of 99.8% and can reach a frame rate of 21 fps with a CPU Intel i7 6850k. Unfortunately, this CPU cannot be embedded within a nano-satellite, its average TDP is 140 Watt.

In the end, the image processing techniques discussed above are suitable when the camera is stationary where the only movements come from celestial objects and clouds. This is not the case for our nano-satellite. Indeed, its movement (7.2 km/s) must be taken into account in addition to that of Earth (460 m/s) making these techniques unsuitable because all points move between two frames. This is especially the case for the frame differencing algorithm or fusions of multiple frames (as shown in Figure 1).

Moreover, neural networks are mainly used as a component of the processing chain and require a preprocessing step using the same image processing techniques as the others. The hardware used for inference is also more powerful than that of a nano-satellite and they are not compatible with the energy constraints of a such embedded system.

For these reasons, we propose a new processing chain adapted for space detection that can be optimized to run in low-power system and using an optical flow estimation.

[a]Thermal Design Power

3 Processing Chain

The proposed chain is divided into seven steps.

The first step is an optical flow estimation. It is an estimation of the apparent movement between two images for each pixel (in pixels by frame). The Horn & Schunck algorithm (Horn & Schunck, 1981) in a pyramidal version (Meinhardt-Llopis et al., 2013) is well suited for the embedded constraints. Indeed, the algorithm is iterative in order to improve the accuracy. The pyramidal side allows estimation of wider movements.

The second step is a threshold on the speed – set to 2.5 px/frame – giving a binary mask of the fastest pixels. This threshold has been set after a manual analysis of video sequences of meteors (PERC, 2016) of ISS Meteor mission. In this mission they showed the feasibility of a space observation of meteors but the recognition step was done by human on Earth. Meteors movements are faster than Earth movement so this step allows to keep only the fastest pixels. Some others fast events can also remain after this step and will be eliminate later. Finally, two morphological operators (opening and closing) are applied on the binary mask in order to remove lonely pixels and to regroup nearby clusters of pixels.

The third step is a Connected Component Labeling (CCL) (Lacassagne & Zavidovique, 2009) that regroups connected pixels together into a region and provides then a unique label.

The fourth step is a Connected Component Analysis (CCA) (Cabaret & Lacassagne, 2014) that computes some features for each region such as its surface, or its average speed $\bar{v}$, the average angle $\bar{\alpha}$ and its standard deviation σ_α. The last two features are computed using formulas adapted for circular data (Fisher, 1993):

$$C = \sum_{i=1}^{n} cos(\alpha_i) \tag{1}$$

$$S = \sum_{i=1}^{n} sin(\alpha_i) \tag{2}$$

$$R_1 = \sqrt{C^2 + S^2} \tag{3}$$

$$\bar{\alpha} = atan_2\left(\frac{C}{n}, \frac{S}{n}\right) \tag{4}$$

$$\sigma_\alpha = \sqrt{-2 \times \ln \frac{R_1}{n}} \tag{5}$$

with n the number of pixels of the connected component, and i the i-th pixel of the connected component (and α_i its angle).

The fifth step is a classification by the angular standard deviation. The connected components represent the fastest objects of the scene like meteors, space debris and lightnings and it is necessary to differentiate them to keep only the first ones. The angular standard deviation is a good metric to do that. In fact, a meteor has a rectilinear path that means all its pixels have the same direction, inducing a low angular standard deviation. By contrast, the apparent movement of a lightening is a circular wave, its pixels go in all directions, inducing a high angular standard deviation. This step gives a list of supposed meteors.

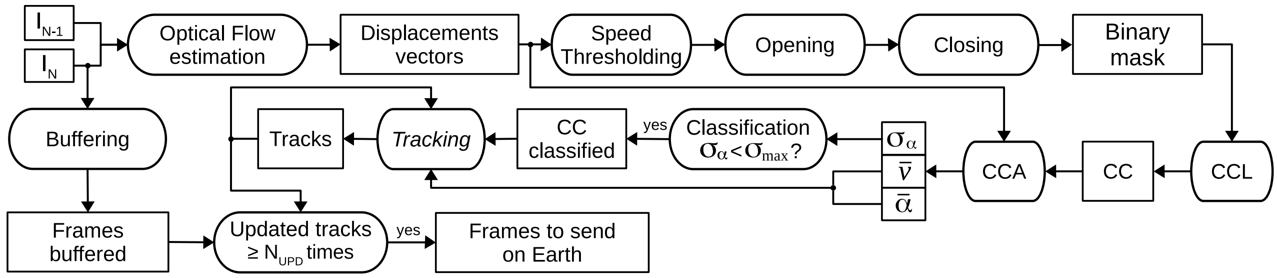

Figure 2 – CC = Connected Components, CCL = Connected Components Labeling, CCA = Connected Components Analysis, $\bar{v}$ = average speed, $\bar{\alpha}$ = mean angle, σ_α = angular standard deviation, $\sigma_{max} = 30\,\text{deg}$, $N_{MAJ} = 3$

The sixth step is a temporal tracking. This step has two goals. Firstly, the temporal dimension allows to confirm if a supposed meteor is a true meteor and not a false positive. For that, a same supposed meteor detected at least three times is considered as a true meteor. Secondly, to group the meteor images in a sequence.

The last step consists of sending meteors sequences on Earth. For meteor shower, the detection is limited to 20 meteors per day. In this case, the satellite will send the data of the first and last frame of the sequence with the regions of interest containing meteors. For sporadic meteor, we plan one meteor per day and all frames of it will be send.

A first port of these algorithms have been done on the CPU of Nvidia Jetson boards to estimate the processing time and the power consumption. For example, the best configuration of Horn & Schunck on Nvidia Jetson TX2 board consumes 22 ns/px and 133 nJ/px (Petreto et al., 2018). The latest CPUs should further improve these metrics.

4 Validation bench

A validation bench has been developed to qualify the proposed processing chain. For that, 150 videos from the ISS Meteor experiment were analyzed in which 50 meteors were found. A *ground truth* was built for each meteor, containing the date and the coordinates for appearance (x_0, y_0, t_0) and disappearance (x_1, y_1, t_1). These information allow the calculation of the meteor's path.

Each sequence containing at least one meteor is tested with the bench. A detection is considered as valid if there is a supposed meteor progressing on the ground truth trajectory and in the right direction. Finally, three scores are given.

(i) A binary score indicating if the meteor has been detected on at least 3 frames or not.

(ii) A ratio of the number of frames labelled as containing a meteor compared to the expected numbers of frames containing a meteor from the ground truth.

(iii) And the number of false positives in the sequence.

5 Results

For this first version 48 meteors of 50 are detected, which gives a detection probability of 96%. Moreover, 70% of images containing a meteor are labelled as such. The 30% remaining may come from human approximation in the ground truths (e.g. the time frame number of the beginning of the detection and/or the end of detection) or meteor undetected with or without extrapolation.

As a reminder, the camera is considered in motion pointing towards the Earth, not stationary on Earth pointing towards the sky and the processing chain has to deal with different types of scenes (see Figure 3) increasing the difficulty and so, requiring more complex algorithms. For this reason, these results can not be directly compare to those of the state of the art.

6 Conclusion

In this work, a new processing chain for meteor detection is proposed. It is designed to work on space observations in order to be embedded on the nano-satellite of the Meteorix mission. A validation bench was developed to qualify the processing chain with a dataset of meteors observed from space. The first results give a detection probability close to 96%.

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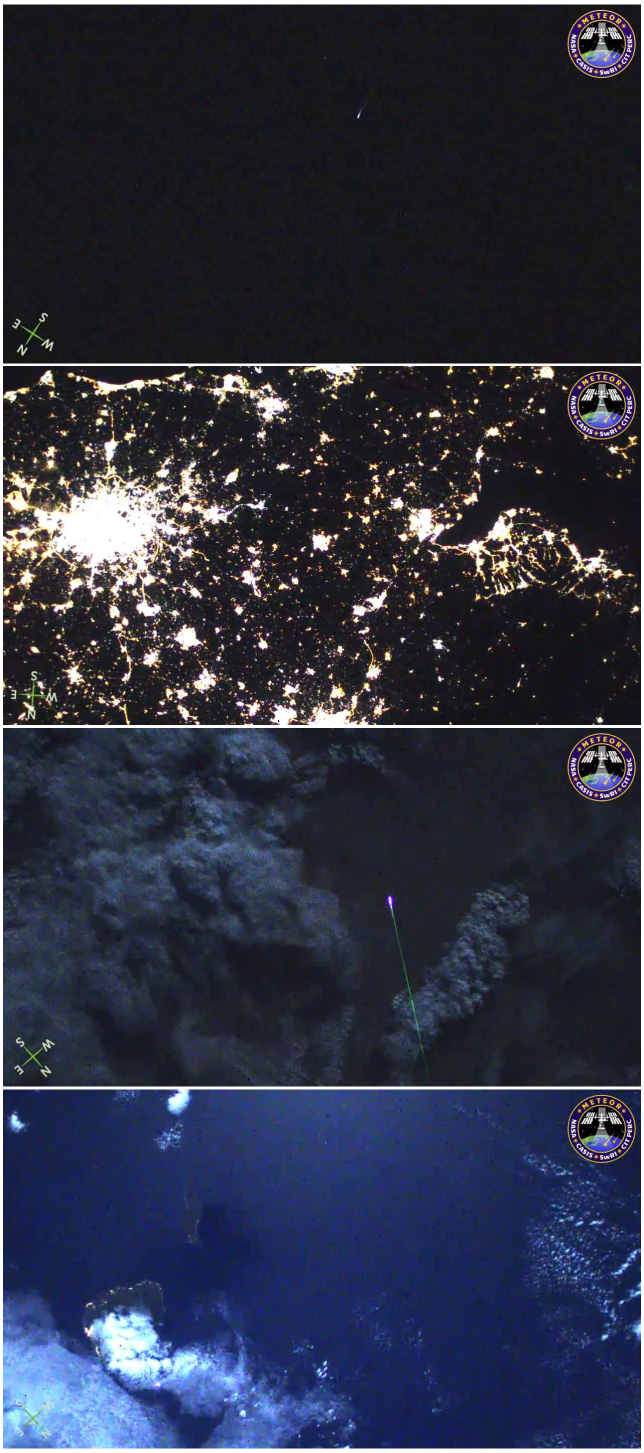

Figure 3 – The scene filmed by the camera can vary, from complete darkness to a cloudy or moonlit scene. Each picture contains a meteor (from Chiba sequences).

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