Stack-CNN algorithm: a new approach for the detection of space objects

A. Montanaro[a,2,*], T. Ebisuzaki[b], M. Bertaina[a,1,*]

[a]*Dipartimento di Fisica, Università degli studi di Torino - 10125 Torino, Italy*
[b]*Computational Astrophyiscs Laboratory, RIKEN - 351-0198 Wakoshi, Japan*

Abstract

We present here a new trigger algorithm based on a stacking procedure combined with convolutional neural network that could be applied for any object moving linearly or with a known trajectory in the field of view of a telescope. This includes the detection of high velocity fragmentation debris in orbit. A possible implementation is on an orbiting Space Debris (SD) remediation system. The algorithm has been initially developed as offline system for Mini-EUSO, on the International Space Station. We evaluated the performance of the algorithm on simulated data and compared with those obtained by means of a more conventional trigger algorithm. Results indicate that this method would allow to recognise signals with ∼1% Signal over Background Ratio (SBR) on poissonian random fluctuations with a negligible fake trigger rate. Such promising results lead us to not only consider this technique as online trigger system, but also as offline method for searching moving signals and their characteristics (like speed and direction). More generally any kind of telescope (from ground and from space) like those used for space debris, meteors monitoring, cosmic ray science could benefit from this automatized technique. The content of the current article is part of the recent Italian patent proposal submitted by the authors (patent application number: 102021000009845).

Keywords: convolutional neural network; space debris; trigger algorithm

*Corresponding author, now at Politecnico di Torino, Torino, Italy
[1]marioedoardo.bertaina@unito.it
[2]antonio.montanaro@polito.it

1. Introduction

STACK-CNN stands for STACKing method plus Convolutional Neural Network. It is a completely new detection system that combines two existing algorithms in a peculiar way. The Stacking Method (SM) was first proposed by Yanagisawa (1) for SD detection and independently developed as part of the trigger system for JEM-EUSO (2).

It produces a stacked image, that is a sum-image made by overlapping many frames shifted by one or more pixels according to the speed and the (opposite) direction that an object (or a particle) can have in the Field of View (FoV) of a telescope. Since all the possible motion parameters are not known a priori, the SM produces a lot of combinations and distinguishing the right ones from the wrong ones requires some decision algorithms. If in the past such algorithms exploited the SBR enhancement for recognition of a right combination (leading however not so high performances), today we can exploit the most advanced algorithms for image recognition, Convolutional Neural Networks (CNNs). CNN is one of the most famous and used NNs. It finds application especially in computer vision: image classification, video analysis, anomaly detection, drug discovery and so on. Since its inception, physicists discovered its utility in astronomy, like for classification of galaxies. Today, whenever there are images or video, like those recorded by telescopes, CNN, and more in general Machine Learning (ML), can give a fundamental contribution to their study. Nowadays applied CNNs come from Le Cun proposal, LeNet-5 (3), which was first applied to hand written digits classification. In the last years, notable improvements concerning new optimizers in the learning phase (like Adadelta(4) used in this work) have been introduced, and the automatization of training (advanced backpropagation and available hardware accellerators) on open source platforms has made ML accessible for different scientists. A CNN of this kind is considered in the STACK-CNN algorithm with suitable adaptations (see CNN description in subsection 5.2).

In this paper we consider one of some possible applications for STACK-CNN, SD detection, keeping in mind a possible implementation on board of new remediation systems.

We have chosen this because SD have become a serious problem in the last years and many space agencies are trying to figure out new tracking systems assembled with new instruments to de-orbit or capture as much as possible SD.

Among these, a remediation system comprised of a super-wide field-of-view telescope (EUSO) and a novel high-efficiency fibre-based laser system (CAN) can become a feasible solution (5).

Such system could benefit from the STACK-CNN as trigger system because it is fast, simple to implement and can be mounted on Field Programmable Gate Unit (FPGA).

As a first step in this direction, the Mini-EUSO detector (6) on board the ISS could be used to make a proof of principle of the detection strategy and possibly tracking of SD. For this, STACK-CNN is totally adapted for Mini-EUSO images, giving proof of its ability and encourage to explore its power also as offline detection technique in the whole Mini-EUSO dataset. It is compared to a standard trigger system developed in the framework of cosmic ray science and adapted for SD.

The paper is structured in the following way. Section 2 explains what SD are and what risks they can cause. Section 3 describes the observational principle of space debris of the employed system detailing the Mini-EUSO configuration. Section 4 describes the simulation approach developed to test the trigger performance and the conventional method. Section 5 describes the Stack-CNN method. Section 6 presents the results compared to the conventional trigger. A discussion of the results and the conclusions are reported in Section 7.

2. Space Debris

Over the last 60 years, since man began to explore space, several thousand tons of satellites and missiles have been launched and there are about 18,000 objects in orbit; 1100 of them (6%) are still in operation, while the remaining (94%) can be classified as Space Debris (SD) (ESA), which are mainly derelict satellites, parts of rockets and space vehicles, no longer in use, and that remain in orbit around the Earth. These objects travel at high speeds, of the order of 7 - 9 km/s near the Low Earth Orbit, and can collide with spacecrafts such as the ISS or other manned or unmanned spacecrafts, damaging them and in turn producing new debris. The great majority of these objects are not catalogued and, even if they were catalogued, usually tracking data are not precise enough. Moreover, most of them are cm-sized, that makes their detection even more difficult.

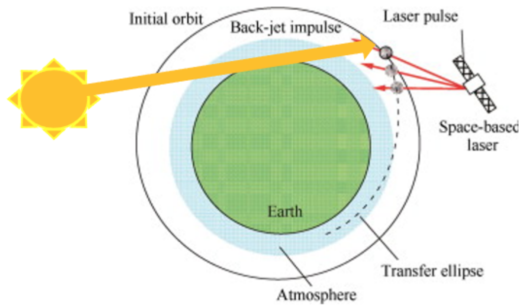

Figure 1: Conceptual figure for the SD detection by a Mini-EUSO-like telescope. It detects the reflected light of SD illuminated by the Sun. Size of objects is not in proportion.

3. Observation principle of space debris and the Mini-EUSO application

SD itself do not emit light but an instrument can detect the reflected light from the SD illuminated by a laser or by the Sun or by the Moon light (see figure 1). In such a way, SD can be detected as tracks crossing the Field of View (FoV) of the detector, enabling to identify and track the SD. In case of Mini-EUSO this approach could be tested in two different ways: a) at sunrise or sunset when the earth is still in umbra while the high atmosphere is already illuminated by the Sun; b) with the ISS turned by 90° or 180°, and the Sun shines from the back to avoid direct sunlight as it happens in case a) if the instrument is not properly shielded.

Mini-EUSO (Multiwavelength Imaging New Instrument for the Extreme Universe Space Observatory or "UV atmosphere" in the Russian Space Program) is a telescope operating in the UV range (290 - 430 nm) with a square field of view of ∼44° and a ground resolution of ∼6 km (6). Mini-EUSO was brought to the ISS by the uncrewed Soyuz MS-14, on August 22, 2019 and installed for the first time on the nadir-facing UV transparent window in the Russian Zvezda module of ISS on October 7. Since then, it has been taking data periodically, with installations occurring every couple of weeks on average. The instrument is expected to operate for at least three years. The scientific objectives of Mini-EUSO include among others the study of the exposure for the space-based observation of ultra-high energy cosmic rays, the UV mapping of the Earth, the detection of meteors and space debris, the observation of Transient Luminous Events and bio-luminescence, as well

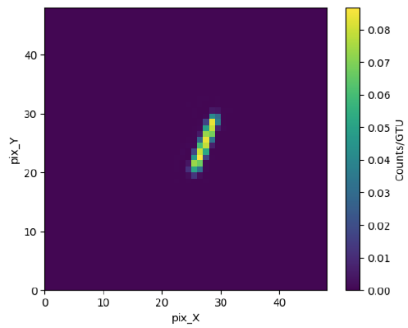

Figure 2: Example of a simulated SD track using ESAF software.

as the search for strange quark matter. Examples of the various phenomena observed in the first months of operations can be found in (8). The optical system consists of two Fresnel lenses with a diameter of 25 cm. The focal surface, or Photon Detector Module (PDM), consists of 36 MultiAnode Photomultipliers (MAPMTs) tubes, 64 pixels each from Hamamatsu, capable of single photon detection. Readout is handled by ASICs in frames of 2.5 μs. Single photon discrimination is 5 ns. Data are then processed by a Zynq based FPGA board which implements a multiple level triggering, allowing the measurement of triggered UV transients for 128 frames at time scales of both 2.5 μs and 320 μs. An untriggered acquisition mode with 40 ms frames (this is defined as 1 Gate Time Unit, GTU in the following) performs continuous data taking (9). This is the acquisition mode considered for the detection of SD.

4. Simulation studies and standard trigger results

In order to study the performance of Mini-EUSO detector in recognizing the presence of SD in the FoV at sunset or sunrise by means of the Stack-CNN algorithm we used the EUSO Simulation and Analysis Framework (ESAF) (10). ESAF is an end-to-end simulation of the phenomenon from the light emission at the source, the propagation through the environment, to the simulation of the detector response and its reconstruction algorithms.

The Mini-EUSO configuration in ESAF is implemented and it includes the simulation of a light track from a SD. Figure 2 shows an example of the expected light signal on the PDM of Mini-EUSO.

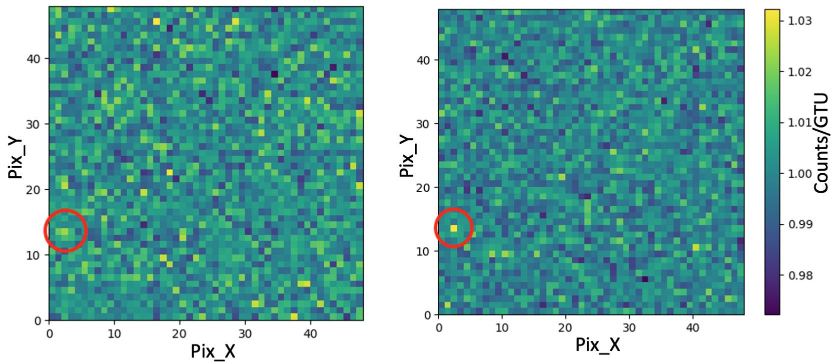

Figure 3: Example of a simulated SD moving from one GTU to another in Poissonian background condition. The scale refers to both images.

The simulations with ESAF allowed also to develop the detection strategy, by testing different trigger algorithms. Hence, our proposed method is compared to a standard technique used for Mini-EUSO data (11). In such approach, 25 'virtual' Elementary Cells (ECs) are defined and the trigger scans the entire PDM and looks for an excess in neighboring pixels, which is lasting 5 consecutive GTUs. One EC consists of 4 MAPMTs. Neighbouring ECs are overlapping each other by 2 PMTs vertically or horizontally, or by 1 PMT diagonally. With a threshold on pixel counts, which is 3σ above the average background in the pixel (μ_{pix}), $\mu_{pix} + 3\times\sigma_{bkg}$, the fake trigger rate becomes low enough (order of 10^{-5} - 10^{-6} Hz). More details can be found in (11).

Despite the good performancse of this technique, we challenged the possibility to push further the detection, going below $3\times\sigma_{bkg}$ threshold, by introducing the STACK-CNN. The simulated background follows the Poisson statistics (as good approximation for real background). An example of faint SD can be seen in figure 3.

5. The STACK-CNN trigger algorithm

5.1. Stacking Method

Let's consider a SD that has a fixed speed $|\overrightarrow{v}|$ and direction θ. For semplicity the debris has only an horizontal velocity ($v_z = 0$) and starts at position (x_0,y_0,h), where h = 0 km means on the ground. At h the size of one pixel l_p is calculated knowing the altitude of the detector (400 km) and the size of one pixel l_g on the ground (∼6 km). Naming α the aperture angle of one pixel:

$$l_p = (400 - h) \times tan(\alpha) = \frac{400 - h}{400} \times l_g \tag{1}$$

the detector stores $n+1$ packages starting from GTU t_0, where SD is detected for the first time, until GTU t_n where SD is visible for the last time. Naming $I(t_i)$ the 48×48 image at GTU t_i and Δt the time difference between two GTUs the stacking consists of two iterative steps: a Shift and an Add. The image $I(t_1)$ is shifted of dx along x-axis and dy along y-axis according to SD motion but in opposite direction:

$$\begin{aligned} dx &= |\overrightarrow{v}| \times \Delta t \times cos(-\theta) \\ dy &= |\overrightarrow{v}| \times \Delta t \times sin(-\theta) \end{aligned} \tag{2}$$

Assuming SD starts in the center of a pixel, if dx (dy) is smaller than $l_p/2$, then the matrix is not rolled (meaning that the debris moves within the space projected by the pixel), otherwise it is rolled by one or two pixels depending on whether dx (dy) is bigger then $l_p/2$ or $l_p/2 + l_p$. Once $I(t_1)$ is rolled, it is added to $I(t_0)$ to form a summed image ΣI_1. The procedure is iteratively applied for all the considered n frames. After the last step the value of ΣI_n in a pixel (x,y) follows this formula:

$$\Sigma I_n(x, y) = \Sigma_{k=0,n} I(x + k \cdot dx, y + k \cdot dy, t_k) \tag{3}$$

ΣI_n is the stacked image and is more advantageous than a single image because the Signal / Noise Ratio (SNR) is increased by $\sqrt{n}$ factor due to the random Poissonian fluctuations and coherent signal. The specific parameters of a SD are not known a priori and stacking method has to produce all possible combinations; there will be one or more that match SD motion and the rest will be wrong. Once the right combination is found, SM gives speed, direction and the starting pixel position of SD according to the chosen reference frame. This is an important aspect, because the reference frame fixes an height and a corresponding pixel size that lead to a particular horizontal speed. The number of combinations is a significant aspect too. All possible combinations could lead to an huge amount of images. For this reason a CNN is used to help recognizing the right combinations.

5.2. Convolutional Neural Network

The type of CNN considered for this algorithm is a *shallow*-CNN, that means a CNN as simple as possible and with few parameters. The reasons

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 48, 48, 10)	170
max_pooling2d_3 (MaxPooling2	(None, 24, 24, 10)	0
conv2d_5 (Conv2D)	(None, 24, 24, 5)	805
max_pooling2d_4 (MaxPooling2	(None, 12, 12, 5)	0
conv2d_6 (Conv2D)	(None, 12, 12, 1)	81
flatten_2 (Flatten)	(None, 144)	0
dense_4 (Dense)	(None, 72)	10440
dense_5 (Dense)	(None, 72)	5256
dense_6 (Dense)	(None, 1)	73

Total params: 16,825

Figure 4: CNN architecture for Stacking Method. The first column shows the layer type, the second the corresponding output and the third one the associated weights parameters.

are two. The first one is that we would like to develop a system that could be mounted on board of new telescopes through FPGA. It's obvious that a huge network with milions of parameters would be difficult to adapt to this system. The second one is that a CNN with few parameters can learn very well features associated to stacked images, and so deep architectures are not necessary. The CNN considered for this purpose has only 16,825 parameters. Figure 4 shows the layers structure (first column) and the number of parameters associated to each layer (third column). From this it is clear that convolutional layers get involved with few parameters and the greatest part of parameters is associated to Fully Connected layers. Although more performing CNN can be computed, it turns out that this very simple network is very effective for our purpose.

The final output of the network is one unit: it is a value between 0 and 1, where 0 means wrong combination and 1 right combination. This architecture was found after several attempts, keeping always in mind different theoretical aspects: the simplicity of the images that have to be learnt, using few max-pooling to avoid information loss and few filters for elementary shapes in the images.

A dataset for CNN study includes three subsets:

- Train: It is the biggest one and has all the images that statistically cover the phase space. Through this, the network updates its weights minimizing a loss function.

Radius	Pixel Position	Speed Range	Direction Range	Height
cm	pixel (X,Y)	km/s	deg	km
1	(12 - 34 , 12 - 34)	5 - 12	0° - 360°	370

Table 1: Space Debris Parameters simulated with ESAF.

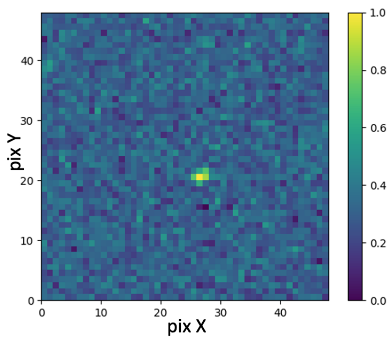

Figure 5: Right combination coming from SM over 12 frames.

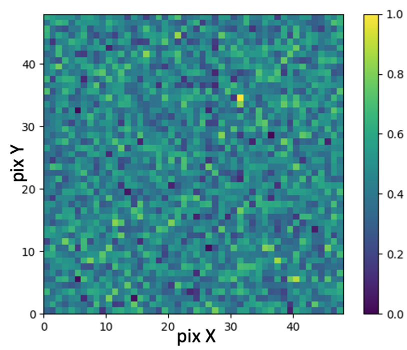

Figure 6: Background Combination coming from SM over 12 frames.

- Validation: Usually it is a percentage of the training dataset that is not used for training but for validating the performance of the network and seeing if there are some overfitting or loss of generalization.

- Test: It includes a lot of images never seen before and it is used for determining the final accuracy and error of the network.

A set of 80 debris simulated with ESAF with the parameters indicated in table 1 is used as a training set. The background level is set to 1 count pix^{-1} GTU^{-1} (where 1 GTU is a data sampling of 40 ms) which is a typical value for the background measured by Mini-EUSO on oceans, due to the UV nightglow and absence of Moon light see(8). Images are shifted in θ direction through steps of 15°, from 0° to 360°, and with a step of 2 km/s for speed starting from 5 km/s until 11 km/s. This leads to 4 combinations of speed and 24 combinations of directions, for a total of 96 combinations. For 80 SD, in total there are 7680 combinations. A couple of them are shown in figures 4-5.

The images are transformed in grey scale values (i.e. values between 0 and 1) through the following formula:

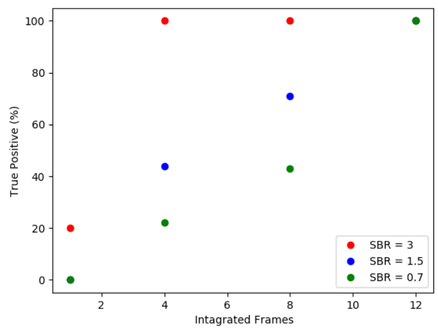

Figure 7: TPR for CNN trained with different SBRs and different stacked images.

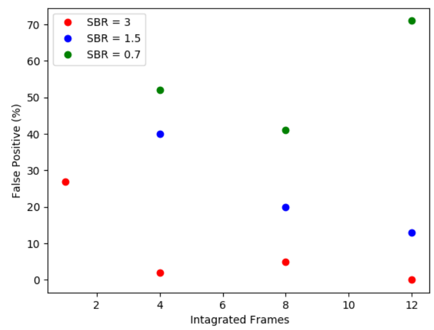

Figure 8: FPR for CNN trained with different SBRs and different stacked images.

$$GV = \frac{PV - mV}{MV - mV} \tag{4}$$

where PV indicates the pixel value and mV and MV the minimum and maximum value recorded by the pixel, respectively. The training dataset consists of about 500 stacked images, one half with right combinations and the other with background ones. The 3% of this set is passed to the validation dataset. All the training process, weights updating and model evaluation is done exploiting the high-level API Keras, running on platform Tensor- Flow. These Python programs are executed on the interactive enviroment Google Colab notebook (Google Colab). The few parameters allow to train CNN in short time and without implementation of hardware accellerators.

We select the best CNN to assemble to SM, training the same architecture but with a dataset made by different Signal over Background Ratio (SBR), 3%, 1.5% and 0.7%. The network is even trained over different stacked images with 0, 4, 8 and 12 integrated GTUs.

After training, CNN is tested over 30 SD never seen before and 30 background images as well. A True Positive Rate (TPR) and a False Positive Rate (FPR) is defined and calculated over the different configurations (figures 6-7).

A 100% TPR was reached with 4 stacked images with 3% SBR while 12 stacked images were necessary for the other two SBR levels. However, with 12 stacked images only the 3% SBR had a FPR of 0 while for the other two it was much higher (13% and 70% for 1.5% and 0.7% SBRs, respectively).

This preliminary test shows that the network trained over 0.7% and 1.5% SBRs certainly does not provide acceptable results (because it is not able to extract clear informations from faint debris). It should be kept in mind that the final solution should have a rate of FPs of the order of 1 per hour to avoid, for example, unnecessary shooting of the CAN laser when being part of a full-remediation system. To investigate more deeply the performance of the network with 3% SBR condition, 4.8×10^4 background images were created with Poissonian fluctuations around the same average background level. This corresponds to a 33 minutes equivalent time for Mini-EUSO. All of them are splitted in 4000 packages each one with 12 GTUs. SM acts on these, creating $96 \times 4000 = 3.84\times10^5$ combinations. After running the CNN it turned out that even with a threhsold of 0.99 for a positive results (i.e. for good combination the CNN output must be bigger than 0.99), a FPR of 0.25% is obtained, which corresponds to 1 event every $\sim$3.3 minutes and it is still not acceptable.

Looking more carefully at these fake events, it turned out that they really hold some brighter pixel that deceives the network leading to a wrong prediction. This also means that SM creates, in the space of all possible combinations, some stacked images that are overlays of positive fluctuations; the more combinations are performed, the greater is the risk to get false positives. The best solution is to exploit the difference between a SD and a fake background combination, which is the fact that SD has a steady coeherent movement for long time. When SM finds a right combination, it gives the speed and direction associated to that combination. If SD moves through the focal surface for long time, it stands for more than 12 GTUs. For this reason, starting from the two parameters it is possible to repeat the stacking operation once more but this time for many more GTUs. Moreover, it is possible to produce more correct combinations according to a fine tuning around the selected speed and direction. Such operation can enhance an optimized combination making more contrast between spot and background. On the contrary, for a false positive, repeating SM for many GTUs allows to kill the fake event. After producing these new stacked images, it is the task of CNN to recognize if these are again right combinations. The CNN is the same as in the first level of the algorithm, because it has to perform the same task, therefore, it is not useful re-training a new network. As last condition characterizing the whole system, if CNN has recognized a right combination in both first and second trigger levels these two selected images must have an overlapping maximum in a neighborhood of at maximum two pixels. All

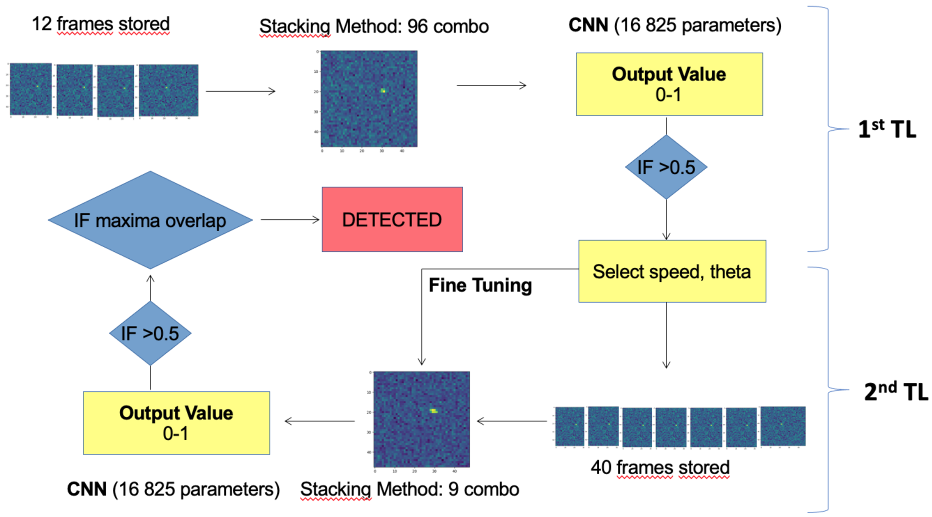

Figure 9: The STACK-CNN trigger system.

this system is called STACK-CNN and it is summarized in Figure 9. It is the last version of STACK-CNN and its robustness is proven over different tests as explained in the next section.

6. Results of the Stacking-CNN algorithm

First of all, the whole STACK-CNN is tested on pure background level for FPR evaluation: 1.08×10^5 Poissonian events (with mean 1 count pix^{-1} GTU^{-1}) are simulated. This means a total of 1 h and 13 min equivalent acquisition time. This time is organized in packages of 40 GTUs for a total of 2700 packages. Each package is passed through STACK-CNN that automatically generates 96 combinations in the first trigger level. Here the CNN performs a first threshold, that is it outputs for each combination a value between 0 and 1, and if one is bigger than 0.5 then the event is passed to the second trigger level where other 9 combinations are produced (shifting and adding 40 frames) according to a fine tuning around its speed and direction. CNN searches again for a good combination; if this is the case then the last test checks if the two maxima are overlapped in the same pixel positions (in a neighborood of two pixels). Figure 10 shows two clear examples on how STACK-CNN avoids false positives.

Though two spots are visible in the two triggered combinations at the first trigger level (top images), when the second stacking occurs starting

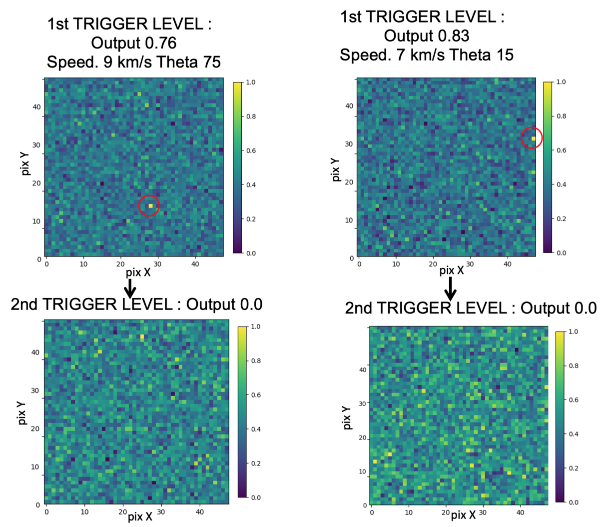

Figure 10: Two examples showing how STACK-CNN manages false positives. If in the top images two spots are visible and correctly found by CNN with the first triggering level, after stacking over 40 GTUs these disappear and CNN classifies them as background.

from the selected parameters, the resulting images (bottom images) do not have anymore such spots and so the CNN classifies them as background. The final result is that no background event gives rise to a false positive in 1 hour and 13 minutes of integrated time.

As a second test the performance of STACK-CNN is verified on debris of different size and distance, and compared with the performance of the standard trigger system. The SD reflectivity is set at 50% for a more realistic scenario.

Figure 11 shows two examples with SD. Compared to the background cases shown before, after applying the second level trigger, the spots become brighter (about a factor of $\sqrt{40}$ with respect to the signal in a single image) and they are located in the same portion of the FoV. Therefore, the SD is correctly classified as a true positive. The results of the comparison with the standard trigger are presented in Figure 12.

Red points show the detection limit for the standard method, instead blue points show detection limit for STACK-CNN, both tested over the same dataset produced with ESAF. The improvement of STACK-CNN is clear at all distances, preserving a TPR = 100%. The STACK-CNN can reach maximum distances showed by green points, accepting a TPR = 50%. In

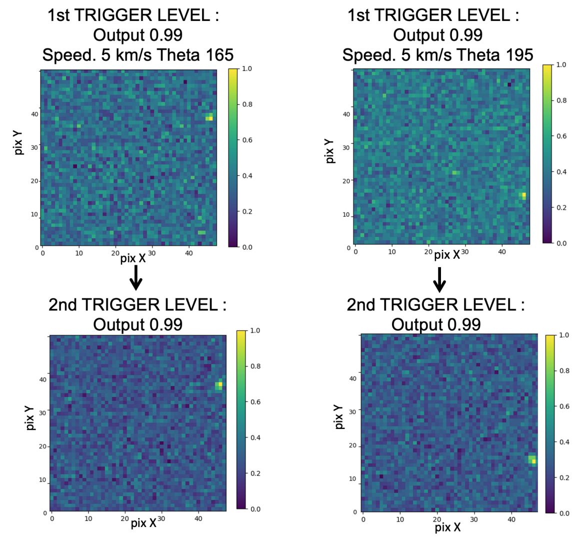

Figure 11: Two examples showing how STACK-CNN manages SD candidates. If in the top images two spots are visible and correctly found by CNN with the first triggering level, after stacking over 40 GTUs these spots are brighter and CNN correctly classifies them as SD.

terms of SNR this means that the STACK-CNN is able to detect signals up to SNR = 1.3 against SNR = 4 for the standard method. This means that even if CNN is trained over SD with SNR = 4, it is able to find fainter debris up to SNR = 1.3 thanks to this peculiar combination of the two methods.

Stack-CNN should be able to detect real SD around this value. This result is reassuring and even indicating that if the ISS will be turned by 90° or 180° Mini-EUSO should be able to detect SD in GEO orbit within acceptable distances and sizes.

7. Discussion and conclusions

A new trigger algorithm based on a stacking procedure combined with convolutional neural network that could be applied for any kind of light-sources moving linearly (or with a known trajectory) has been presented. Its application on the detection of high velocity fragmentation debris in orbit is shown as first adaptation. A possible future implementation is on an orbiting debris remediation system comprised of a super-wide field-of-view telescope like EUSO and a novel high-efficiency fibre-based CAN laser system. The

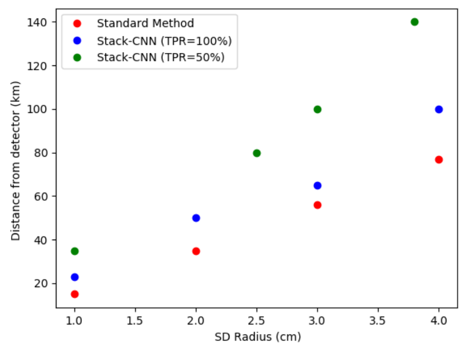

Figure 12: Comparison between the detection limit for STACK-CNN and standard method.

algorithm has been developed based on an initial proof of concept stage of this system which is the Mini-EUSO detector on the ISS. By means of a simulation code of space debris we evaluated the performance of the algorithm and compared with the results obtained by means of a more conventional trigger algorithm. Results indicate that this method would allow to recognise signals with ∼1% SBR on poissonian random fluctuations with a negligible fake trigger rate. This has been done assuming the average background level seen by Mini-EUSO on the ISS and pointing nadir. Most probably the typical background level pointing towards the zenith would be lower by at least a factor of two, increasing its sensitivity.

The next step would be to test it either from ground or with space-based observatories pointing towards the zenith to mimic more realistic conditions.

In parallel, the flexibility of this approach allows to test this logic directly on Mini-EUSO data to search for SD, meteors and other point-like sources which have a speed comparable to the one this algorithm has been trained for. Moreover, by simply re-adapting the speed range of STACK-CNN it could also be applied to cosmic ray science as an offline scanning algorithm. Other practical applications about events not related to physics could be considered too.

The "light" CNN involved and the computational speed of the whole STACK-CNN allow the system to be mounted on board of future telescopes (such as for SD removal) inside FPGA. Indeed, the last objective will be seeing STACK-CNN that autonomously triggers and classifies events, taking a step forward for the artificial intelligence of space systems.

8. Acknowledgments

The authors would like to thank the Mini-EUSO collaboration for the fruitful discussions, and Francesco Fenu for his support about ESAF simulations and Hiroko Miyamoto for the comparison with the standard approach to detect SD in Mini-EUSO.

[1] Detection of Small GEO Debris by Use of the Stacking Method, Transactions of the Japan Society for Aeronautical and Space Sciences 51(589): 61-70.

[2] M. Bertaina et al., The trigger system of the JEM-EUSO project, Proc. 30th Int. Cosmic Ray Conf. (Merida), (2007).

[3] Y. Lecun, L. Bottou, Y. Bengio and P. Haffner, "Gradient-based learning applied to document recognition," in Proceedings of the IEEE, vol. 86, no. 11, pp. 2278-2324, Nov. 1998, doi: 10.1109/5.726791.

[4] Zeiler, Matthew. (2012). ADADELTA: An adaptive learning rate method. 1212.

[5] T. Ebisuzaki et al. 2015, Demonstration designs for the remediation of space debris from the International Space Station, Acta Astronautica, 112 (2015) 102 - 113.

[6] F. Capel *et al*, Mini-EUSO: A high resolution detector for the study of terrestrial and cosmic UV emission from the International Space Station, Advances in Space Research, 62 (2018) 2954 - 2965.

[ESA] https://www.esa.int/Our_Activities/Space_Safety/Space_Debris

[8] S. Bacholle et al., ?Mini-EUSO Mission to Study Earth UV Emissions on board the ISS?, The Astrophysical Journal Supplement Series, Vol. 253, pag. 36 (2021), https://doi.org/10.3847/1538-4365/abd93d https://arxiv.org/abs/2010.01937

[9] A. Belov *et al*, The integration and testing of the Mini-EUSO multi-level trigger system, Advances in Space Research, 62 (2018) 2966 - 2976.

[10] C. Berat et al. (2010), Full simulation of space-based extensive air showers detectors with ESAF. Astropart. Phys. 33 (4), 221247.

[11] H. Miyamoto et al., Proc. 36th Int. Cosmic Ray Conf. (Madison), PoS(ICRC2019) 253 (2019).

[Google Colab] https://colab.research.google.com/notebooks/intro.ipynb