INSTRUCTIONS TO AUTHORS FOR THE PREPARATION OF FULL MANUSCRIPT:

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ABSTRACT:

SE-Workbench-EO, also called CHORALE in France, is a comprehensive set of tools that aim at modelling a complex and dynamic environment and at physically rendering the 3D scene for a given EO/IR sensor. Main application is focused on parametric studies. SE-Workbench-EO helps users through simulation to assess the performance of a sensor with regard to several specific environments. One important application is missile homing with EO/IR seekers.
Recently, a new application in the field of Artificial Intelligence and especially Machine Learning is emerging. The operational challenge is to improve Image Processing thanks to modern devices based on Neuronal Networks. The first step consists in preparing datasets to train the Neuronal networks and to validate the training. Today, main datasets come from real images that have to be “labelled”. Synthetic images offer a key advantage to complete these datasets. The ultimate challenge is the physical realism of these synthetic images. SE-Workbench-EO seems to be a good candidate and a good starting point to take up the challenge.

The introduction shortly presents SE-Workbench-EO main features and objectives. The VV&A process will be detailed. Example of current application typically for parametric studies will be explained.

In the second part, we will discuss on the operational requirements for Defense application of Artificial Intelligence and more precisely for detection/navigation application using Image Processing.

In the third part, we will focus on synthetic images datasets for Machine Learning. Advantages of synthetic imagery will be detailed e.g. automatic labelling. Associated drawbacks and limitation will be discussed.

Then the main limitation and challenge is the lack of entropy (quantity of information, lack of details etc.) of synthetic images will be explicated, both from a geometrical point of view and from a radiometric (physical material) point of view. Concerning the geometrical part, we will insist on procedural micro vegetation, micro relief and associated animations (wind …). Concerning radiometry, we will insist on amount of physical material, and resolution of the distribution of material.

Then will give information on a new approach in SE-Workbench-EO tools called “material cover” and “ground cover”, that precisely bring a solution to enhance the image realism respectively for geometry and radiometry.

Finally, and before the conclusion, results will be shown.

The road map of this new orientation of SE-Workbench-EO will be presented as a conclusion.

1. SE-WORKBENCH-EO

1.1. Main feature & objectives

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1.2. Need for physical realism

Need for more geometrical details
Need for more radiometric details
Reach high level of image entropy

1.3. VV&A

Parametric studies based on simulation

2. ARTIFICIAL INTELLIGENCE

2.1. Defense context

Land, flying, marine systems
Detection, Identification, Navigation

2.2. New trends

Image Processing being replaced by AI

Machine Learning at a glance

Artificial Intelligence, Machine Learning and Deep Learning are very general expressions that refer in essence to the capability of a machine to imitate intelligent human behavior.
AI has been subject to several periods of advancement then stagnation, mainly constrained by lack of available data and computing power.
Actually, Machine Learning is a sub-category of AI that learns - by utilizing algorithms to parse data, learn from that data, and then apply what they've learned to make informed decisions (Ref.1 Zendesk).
Recently, Deep Learning has emerged as a subset of Machine Learning that rigorously mimics human brain.
Basically, the process associated to deep learning is divided in two phases:

- The machine (computer) is learning then a dedicated program is created
- The program is embedded in a system

We also say that the Training phase is followed by the Inference phase.
In this paper we focus on Deep Neurol Networks that manipulate images. The main objective of the system is to Detect and/or Navigate, using images, captured by sensors embedded on a carrier, for instance a UAV or a missile, in the Defense field.

The DNN is an aggregation of unitary neurons.
A neuron possesses several entries (X) and one output (Y). Parameters are scalars that weight each entry before summation. A dedicate activation function enables to validate or invalidate the output. The validation criterion is: the weighted summation is higher than a given threshold.
This is the simpler neuron structure called *perceptron*.

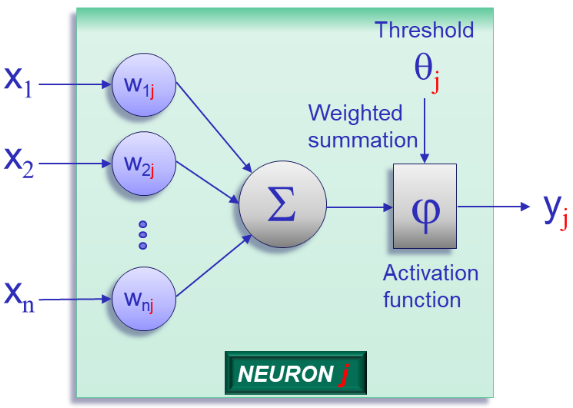


Figure 1. Neuronal (perceptron) structure

Then a generic network of "neurons" is constituted with several (Deep) layers. The DNN is born.

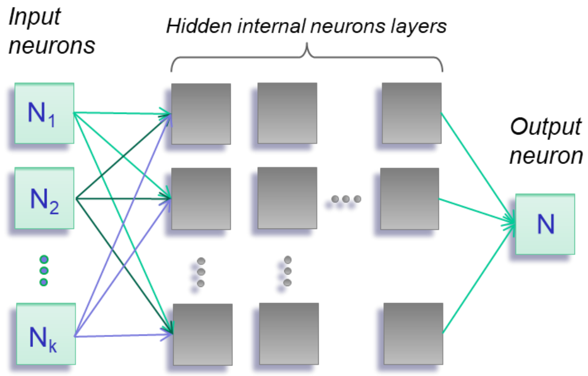


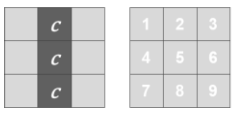
Figure 1. Full DNN network

Many images are collected. Some include the target, some not. Each image is enriched with a label. The simplest label is:" the target is present in the image" or "the target is not present in the image".

Thanks to the Training phase, all combinations are tried, using a lot of labelled (or tagged) images i.e., all the values of weights are assessed. At the end, the nicer combination that maximizes the output is kept, meaning the network is trained.

Simple example illustration

To give a practical example, let us take the case of the smallest perceptron using calibrated images of letters. To simplify, let us consider 3 x 3 pixels images (already filtered so that the letter is full screen, centered and not tilted). Besides, let us take the example of the detection of the "I" letter.



$W(1) = -1 \quad W(2) = 1 \quad W(3) = -1$
$W(4) = -1 \quad W(5) = 1 \quad W(6) = -1$
$W(7) = -1 \quad W(8) = 1 \quad W(9) = -1$

Figure 1. 9 entries and ideal weighting for "I" detection

The entry is a vector of 9 pixels either with a color value c, either with a 0 value. The simplest network is given by the following figure:

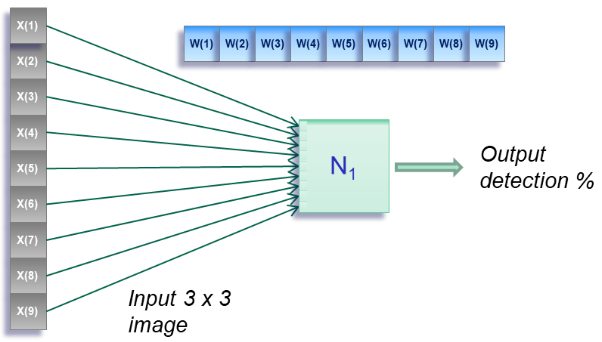


Figure 1. Simplest architecture: 1 layer of 1 neuron

The Output neuron structure is a simple weighted summation: $Y = \sum_{k=1}^{9} W(k)X(k)$
Once the network is trained, the values of the weights will be automatically identified. The higher the output is, the higher is the probability of a "I"

letter.

$$\begin{bmatrix} 0 & c & 0 \\ 0 & c & 0 \\ 0 & c & 0 \end{bmatrix} \qquad \begin{bmatrix} c & 0 & c \\ c & 0 & c \\ c & 0 & c \end{bmatrix} \qquad \begin{bmatrix} c & c & c \\ c & c & c \\ c & c & c \end{bmatrix}$$

$$Output = 3c \qquad Output = -6c \qquad Output = -3c$$

Figure 1. Example of outputs

A more complex network could be made of 2 layers of 3 neurons:

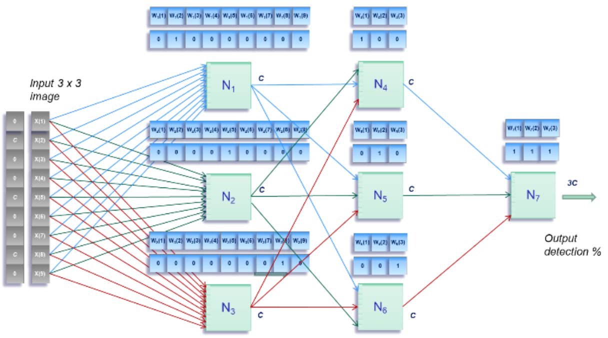


Figure 1. Architecture: 2 layers of 3 neurons

If the entry corresponds to "I" then the best score of 3*c* is obtained once the network is trained.

2.3. Neuronal Networks training

The main objective of the training phase is to design and train a model to perform a specific task with an acceptable level of accuracy.
It involves inputting sample data through the model and outputting a prediction, expressed as a percentage, that the model has accomplished its task. This cycle is repeated, adjusting the model weights by a forward and backward propagation till predictions meet the required accuracy.

Classical CNN
A Convolutional Neural Network is a dedicated class of NN dedicated to Image Processing oriented AI models.
An intuitive look at CNN is to see it as a collection of filters (Ref.2 Koul, Ganju, Kasam), for instance, a filter for enhancing image contrast or detecting edges using high-pass filters.
Lower-level layers of the CNN (that are closer to the input) are made of such filters. If we remember the previous simple example to detect a "I", the convolutive layer will enhance the input image contrast, will be responsible of the input image culling (that potentially contains a "I"), to make the "I" full screen, to make the convenient translations, rotations and scales. Actually, the convolutive layer performs a *classification* that eases the job of the layers after.

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GAN and advantage discrimination

A Generative Adversarial Network is a specific combination of 2 NN in order to improve the quality of detection, especially in the frame of imagery.
One NN is called the "Generator". The other one is called the "Discriminator". The generator's job is to generate synthetic images as realistic as possible and similar to the training data. The job of the Discriminator is to detect whether the image is real or fake. The Discriminator feeds back its output into the Generator to improve the cycle in case of fakes until the NN does not make any mistake. The more the Discirminator is sensitive, the more the images generated by the Generator are realistic.
The well-known *pix2pix* application uses GNAs for image conversion:

- Low resolution to higher resolution
- Black&White to colour
- Sketched to realistic.

GANs have been widely applied to generating realistic medical images. Another application is Arts and paintings for imitating famous artists. More recently, GANs have been used for "Deep fakes", for instance to mimic politicians.
GAN is the technics behind what is often called "Style Transfer" (for example for imitating Van Gogh painting style).
An interesting application concerns the mimicking of the Transfer Function of a sensor, typically an infrared sensor, especially if the characteristics of the sensor are not precisely known.
Nevertheless, if the sensor is known, we consider much more efficient to use synthetic images that are computed with a scientific model of sensor (SE-Workbench).
Anyway, GAN constitutes a very promising means to make synthetic images much more realistic in order to populate the training datasets.

Transfer learning
Transfer learning consists in reusing an existing AI system that has started to learn from a given dataset for a given class of object detection in order to apply it to extended classes of objects. In other words, it aims at removing only the last few layers of a given NN and reutilizing the generic layers. More simply, it is making new with old.
Transfer Learning is very important for industrial application, when the Training and Inference phases are very expensive. It enables to expand the application domain of an existing and pre-validated model.
But it is very important to understand that TL is not magic. Many PhDs in France and over the world investigate "impossible" TL such as transforming a NN trained for visible domain images into RADAR imagery or THERMAL imagery.
In that case, a much more efficient way, is to use synthetic images, based on a physical approach, to enrich the training datasets.

Frugal Learning
In Machine Learning domain, we distinguish Active

Learning and Incremental Learning. AL is used in cases where data are available but where labelling is quite expensive. By opposition, IL consists in continuously training the algorithm. IL is a "On Line" training when AL is a Off Line". Frugal Learning mainly concerns IL. FL is a means to overcome the lack of data and/or to overcome the cost of data. In simple words, FL is a specific ML declination with minimal resources.
Typically, in military domain, a complete database of targets is scarcely available, since confidential. In that case, FL becomes mandatory.
FL is aimed to build the most accurate possible models using the least amount of labelled image. The basic FL method consists in scoring then filtering the training datasets.
Synthetic images represent a nice opportunity for frugality. We can start with a huge amount of synthetic image and progressively simplify the dataset till the predictive accuracy of the NN remains good.
Thanks to synthetic images, it is possible:

- To compute all the possible combination of images (target position, orientation, scale, vicinity, movement…)
- To compute, for a given image, a set of Levels Of Detail of the image with several image quality.

Synthetic imagery is a good candidate for reducing image quantity, focus on quality and select the good images.

2.4. Neuronal Networks assessment

Make the NN explainable

Explainable AI is not a simple AI wherein the model only provides prediction. Explainable AI also accounts for the factors that caused to make a given prediction and reveals its areas of limitations. To make these models more explainable and interpretable, *heatmaps* come to the rescue. Heatmaps emphasises and shows a part of the image that leads to the prediction with higher intensity. For instance, it is interesting to know that datasets for recognizing helicopters are more sensitive to the wind screen than to the spinning blades.

Make the NN reliable

Explainable AI is a means to fight bias and to focus on good images (frugality). A classical tool to assess the robustness of the NN is the test of *occlusion sensitivity*. The idea is to mask a part of the image (e.g., using a small rectangle placed randomly over the image) and measure the prediction rank.
Besides, many research centres and SMEs have worked a lot on *formal validation* of AI, especially in France. Formal validation tools have been developed. These tools generate a dedicated heatmap that maps the formal validation ratio as a safeness percentage. A complementary method consists in introducing noise and tracing the curve robustness as a function of the noise power for several types of labelling.

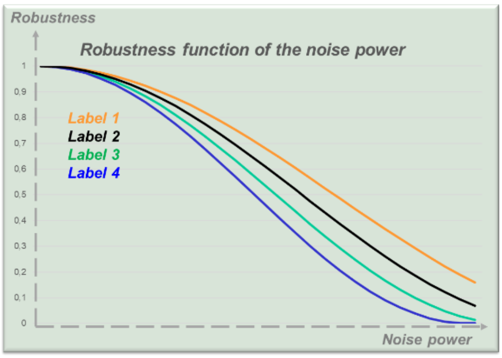

Figure 1. Robustness assessment

3. SYNTHETIC DATASETS FOR AI

In various domains, deep learning algorithms are exploited to process images data. Several applications are AI demanding:

- Earth observation from space
- Security surveillance (civilian safety)
- Guidance systems
- Vision based navigation systems (automotive, aviation, UAV, maritime and railway industries)
- Detection, Recognition and Identification (DRI) systems, in the defense industry

In these applications, and especially in the Defense domain, the access to relevant training database is not ensured. In the Defense field, the sensitivity of information leads to a noticeable scarcity of real learning data. The recent increase of sensor fusion systems merging visible, infrared and even radar images to enhance the detection capability makes things harder when comes the time to gather learning data covering all the sensors images of the same area at the same time.
The huge amount of image data available in world databases like COCO or ImageNet are most of the time in the visible domain only and cannot be considered as a solution for the critical Defense applications.

3.1. Why synthetic images

Dedicated approaches are currently investigated to tackle the lack of relevant real data. For instance, neural style transfer could help to create consistent infrared data as seen previously. But this becomes harder when considering Radar images (like Synthetic Aperture Radar) where there is no obvious correlation with an electro-optical image seen by a camera.
Frugal learning techniques are also investigated but still rely on the availability of some few real labelled data, which could be really challenging when addressing confidential areas or targets in the Defense domain.
Therefore, creating learning data, as we would expect the real ones to be, appears very attractive and anyway the only remaining solution.

3.2. Advantages of the synthetic approach

Lots of advantage is coming with synthetic approach for AI:

- **Automatic Labelling** (tagging)
  The following figure illustrates 2 basic labelling that are today available in SE-Workbench-EO, one gives every object type and apparent surface, the other gives the distance of the pixel to the sensor:

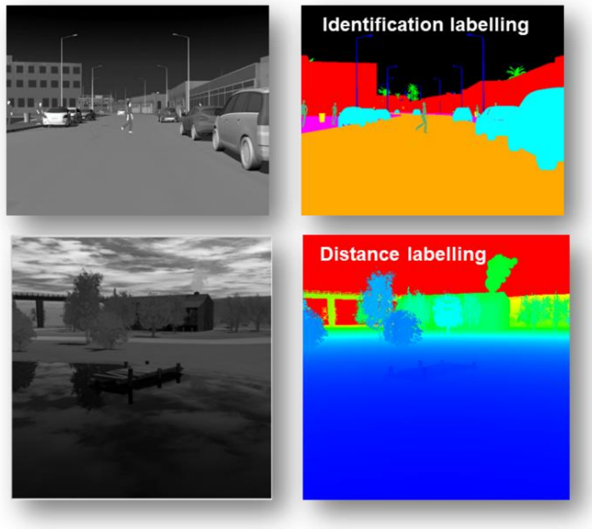

Figure 1. Meta Data associated to SE-WB images

  Many other automatic labels are on the road in SE-Workbench such as:
    - Behavior (altercation, weapon…)
    - Pixels radiometry
    - Masking
    - 2D/3D bounding boxes
    - Intermediate sensor output
- **Knowledge of the ground truth**: labelling is straightforward, no need of a skilled photo interpreter
- **Multi sensors capability**: same time, same position, same LOS for any waveband

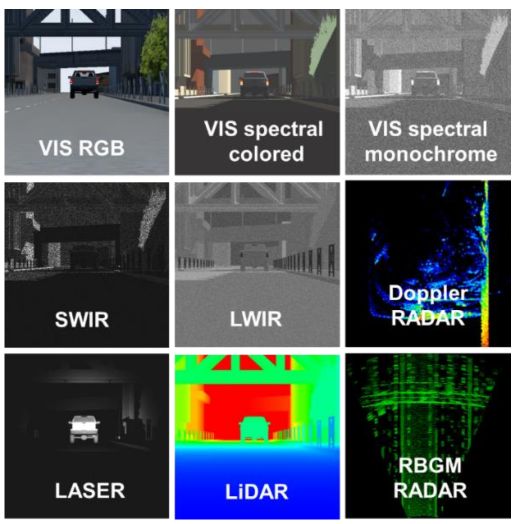

Figure 1. 9 consistent sensor simulation using SE-WB

- **Variability** and situation diversity: ability to consider any environment (background, weather, lightning conditions, clouds, targets, flares …)
- **Repeatability**: ability to carry out parametric studies
- **Big data capability**: No limit in the number of images.

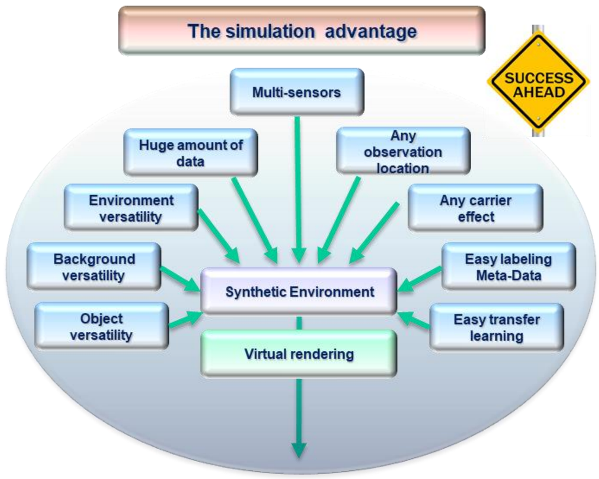

Figure 1. Main advantage of simulation for AI

3.3. Drawbacks of the real data sets

The three main problems due to real images training datasets are the following:

- The **lack of real usable images** especially for sensitive application (Defense) that is more and more demanding for sensors
- The **risk of coherency** of images in case of sensor fusion. It is almost impossible to find same scene/time/orientation real images from EO/IR and RF sensors
- The **cost of labelling** and the risk of errors and inconsistency.

Other drawbacks can be noted such as:

- **Overfitting**: due to limited size of training data sets to train an algorithm
- **Unbalanced training data sets**: lack of diversity
- **Observation locations**: difficult to find real images of the same scene from different viewing angle
- **Tagging quality**: tagging meta data in the images is limited
- **Repeatability**: impossible to change one parameter at a time in a real image
- **Transfer learning**: difficult to turn a dataset dedicated to one sensor into a dataset corresponding to another sensor. This is possible with SE-Workbench. The perfect image before sensor is archived and can be reused for several models of sensor.

3.4. The good balance

Actually, the main drawback of synthetic images is

the realism. The objective is not to train AI system for being embedded in a simulator. The objective is to use it in the real world. Of course, the advantage of real data is the realism.
As a matter of fact, the good approach is the middle one. Use as long as it is available the real images and use synthetic images as an add-on to complement real images.

3.5. Requirements for synthetic images

For last three years OKTAL-SE have computed a lot of datasets for many companies, research centres and state agencies, especially for defense aaplication (e.g., Man Machine Teaming project, in partnership with DASSAULT AVIATION, and THALES companies [*https://man-machine-teaming.com/oktal-se-magellium-et-le-projet-constitution-de-bases-de-donnees-de-scenes-synthetiques-eo-ir-rf/aeronautics and automotive*].
The lessons learned from these experiments is clear:

- The synthetic data have to be **realistic**, deep-learning algorithm wise
- The training process and the CNN configuration have to be **adapted to synthetic data**

3.6. Avoid traps with synthetic images

Good looking of synthetic images only, this is not sufficient for warranting the consistency with real world.
SE-Workbench has recently made significant progress for competing with reality.
Typically for targets representation:

Figure 1. VIS and IR SE-WB targets rendering

But also when integrated in the environment:

Figure 1. Influence of lightning and weather

And it is now possible to generate geo-specific images with SE-Workbench that can be indistinguishable from reality:

Figure 1. From reality to simulation

More and more visible cameras that are very useful for detection and navigation functions include short wave infrared capabilities. It is obvious considering mobile phones cameras that are able to take good pictures by night. Many VIS-SWIR cameras are now available on the market.
Infrared simulation implies to work in the spectral domain. SE-RAY-IR is the ray tracing kernel of SE-Workbench. SE-RAY-IR is a spectral ray-tracing. Every feature is spectral: the materials, the atmosphere, the detectors. SE-RAY-IR manages the combination of these spectral features with respect to the laws of Physics. SE-RAY-IR computes hyper spectral images (roughly 10 to 100 wavelengths in the sensor spectral band) before the sensor then SE-IR-SENSOR turns these photonic images into an after-sensor signal. So, infrared synthetic rendering implies to work in the spectral domain. Even for the visible band that is often extended by SWIR capabilities, it is also mandatory to work in the spectral domain.
Video games images are RGB images. A pixel is green because it has been "paint" in green colour.
Deducing its "colour" in the infrared domain is quite impossible. Considering SE-RAY-IR, a pixel is green because its reflection factor (BRDF) - that is defined from 0,2 micron to 16 microns - is particularly high around 0,54 micron i.e., the green wavelength.
In SE-Workbench, the sun and the sky dome emission are spectrally defined. The ambient light is modelled as a white light (slightly yellow) nearly constant over the visible spectrum. So, the green colour is due to the coupling of the solar spectrum and the "green" reflection factor.
As a consequence, RGB video rendering cannot be

seriously used for modelling large band sensors such as VIS-SWIR cameras. Spectral computation is not an option, it is necessary.
Another common mistake is to assess the quality of an image using human eyes. Actually, it is no use because for any application in the technological world, it is not a human being who sees but a Hardware device. Advanced Driver Assistance System is a good example in the automotive domain.
In the infrared domain, part of the quality of the image is due to its spectral content but also to the number of bits (resolution depth). A 16 bits image that provides 64 k grey levels is much more efficient for detection than a Black&White image limited to 8 bits (up to 10 bits in new GPUs) and coming from video game.
This is the reason why SE-RAY-IR computes radiances (W/m^2/sr/m) and not colours in floating point precision.
Synthetic images for AI have to respect at least:

- Computation in the spectral domain
- Computation in double precision
- Add-on of the Sensor Transfer Function

More conceptually we have to fight against:

- A common bias about realism perception:
  - Is the realism judging "human eyes" or "algorithm perception"?
- Physics and technology modelling is not an option:
  - It is vain to mimic reality and focus on cosmetic images, even in the visible domain, even if you have 2 eyes

4. SE-Workbench and AI

4.1. AI for SE-Workbench

Aim and DGA point of view

Source data cleaning & improvement
One important source of information that precedes the synthetic environment modelling is ortho-images. SE-Workbench includes the SE-AGETIM suit of 3D terrain modelling tools that automatically shape the terrain, profile infrastructures (roads, rivers…) and extrude superstructures (trees, buildings…). The real add-value of SE-AGETIM is the management of physical materials and the preparation of the scene for visible, infrared and radio frequency applications.
Ortho-images carry lots of useful information for terrain generation. For the terrain, most of the time, orthoimages are mapped onto the terrain tessellation. Nevertheless, there is a lot of artefacts. For instance, shadows. Shadows are not intrinsic. It is the job of the renderer to compute shadows (with a physical approach and depending on the ephemerid). So, we have to rub and erase them from the ortho-image. More generally all 3D objects, projected on the ortho-image have to be suppressed. For instance, in the case of a building, it is important to replace this 2D artefact information by a 3D object. In RGB approximation, it is not so critical. Of course, in IR (due to thermal computation) and in Radar (due to dihedron and trihedron effect), it is mandatory.
A special case is the ephemeral object. For instance, a car onto a highway will be simply erased. A car onto a parking will be replaced by a 3D instance.
AI is a perfect vehicle to perform this clever cleaning.

Figure 1. Example of ortho-image cleaning

Another important support from AI concerns the ortho-images improvement. The first need is to enhance the resolution of existing ortho-images adding "noise" and/or re-synthetise the image (GAN approach). The second one is the colour harmonization. It is a complex problem that is very hard to perform manually. Actually ortho-images are very depending on the acquisition sensor, on the cloud cover and on the date and country.

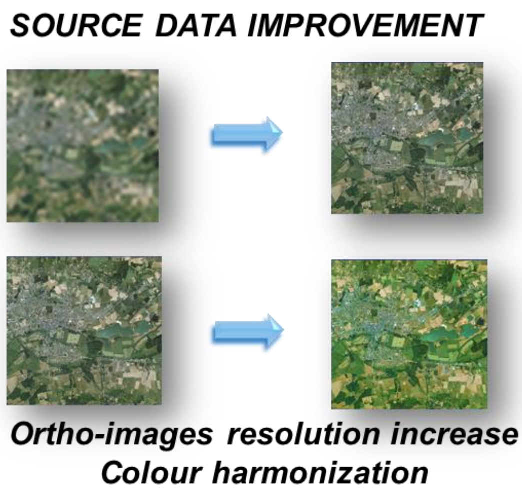

Figure 1. Example of ortho-image improvement

AI is also a perfect vehicle to perform this clever improvement.

Automatic physical classification

Classification consists in selecting the good physical material in a 3D synthetic environment. Today, SE-PHYSICAL-EDITOR is a manual tool, slightly assisted by some Image Processing

algorithms, that is used by graphists in order to assign the proper reference to the physical material database provided with SE-Workbench.
To do this human classification, all types of information are welcome. The main one is an image. The goal is to recognize what it is made of.
This operation is obviously made for AI and will be all the more efficient as the amount of data increases.

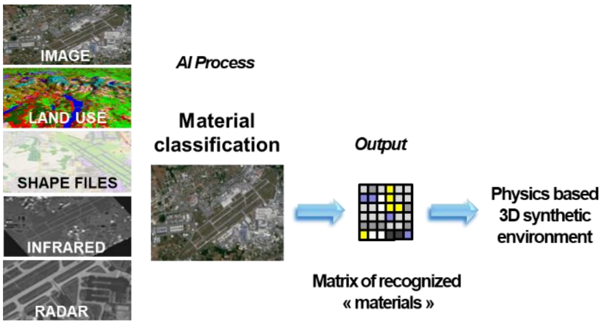

Figure 1. Using AI to automate and enhance physical materials classification

Aim and DGA point of view
Support to material classification

4.2. SE-Workbench for AI

The new trend for SE-Workbench is to provide synthetic datasets for NN training.

<u>Challenges to address</u>
The key challenge is the image entropy or variance. Entropy definition is based on statistical mathematics when variance concept is based on classical Image Processing.
The main risk with synthetic images is the lack of entropy. In practise, we can figure out the entropy concept using simple examples.
The first component is the geometric detail. Recent progress of computer graphics eludes this problem. Last decade, millions of polygons constituted a real challenge. Today, billions of polygons are reality. The second component is the lighting model. Thanks to ray-tracing techniques, shading, global illumination, ray marching in voxels and participant media provide nice solution. Then, Particles Systems for smokes, animatics for vehicles and skeleton animations of characters participates efficiently to realism. But the key feature is the entropy due to materials that are referenced through textures. A great amount of intrinsic physical materials is mandatory. Then complex combination of these materials within a texture conveys high variance level to the images.

<u>Material Cover & Ground Cover</u>
One recent improvement of SE-Workbench is **Material Cover**. To increase the texture resolution, the idea is to invent details inside a given texel (the texture element). Let us consider a 1024 x 1024 texture covering 1 km x 1 km. The texel size is then 1 m x 1m. In SE-Workbench, the texture does not contain a value but a reference to a physical material that contains lots of values. Each category of material is referenced in the 1024 x 1024 master texture. For instance, some texels reference earth, other gravels, other grass etc. The Material Cover idea is to replace the master texel by a second order new texture. For instance, the 1m x 1m texel of gravel is replaced by a 256 x 256 texture that represent an agrégation of asphalt and several varieties of stone. Then the resolution of the second order texel is 4 mm x 4 mm.

Figure 1. Material cover used to enhance detail of a 5mx5m ortho-image of an airport, rendered by SE-WB

Material Cover is a 2D super sampling. SE-Workbench allows a more complex 3D procedural enhancement, typically for grass or small vegetation, called **Ground Cover**.

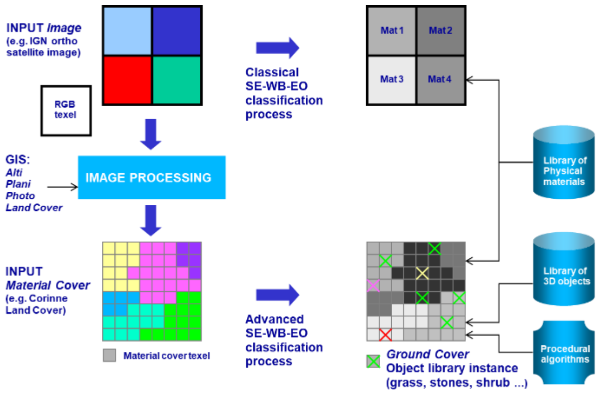

Figure 1. 3 ways to use texture in SE-WB: Classical classification, Material Cover & Ground Cover

Ground Cover is very efficient for increasing the entropy of synthetic images:

Figure 1. Ground Cover to figurate an assembly of grass and stones in SE-WB

Material cover & Ground cover
DGA results

Wang Tiling 2D & 3D

Another important improvement in SE-Workbench is the **Wang Tiling** algorithm. To remain simple, let us say that WT can transform a texture into a quasi-infinite set of similar textures, ensuring continuity between these textures, but without any repetition. WT protects against the "ravioli" self-repetition effect that does not exist in the real world of course.

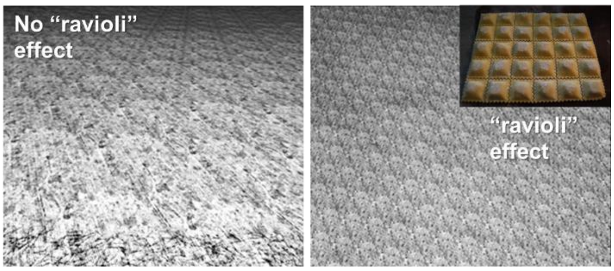

Figure 1. WT in the Left image: a means to fight against repetition and improve image variance

OKTAL-SE has generalized the WT algorithm to 3D, pushing the instantiation of similar 3D features but never self-repeated. It is a very efficient approach. First the modelling cost is very light since limited to a few templates. Then, no limit in details refinement since automatic. Finally, no room for error, neither for geometry nor for physical classification since the manual operations are reduced to a very limited set of templates.

Figure 1. Thousands of buildings for a dozen templates using WT 3D automatic generation

Figure 1. Millimetric details available for short range observation using WT 3D

Wang Tiling
DGA results

5. SE-WORKBENCH-EO ROAD MAP

Using physics-based sensor simulation software to generate synthetic datasets is a promising concept. However, some challenges have to be faced to turn this concept from a promising idea to an operational solution:

- A dedicated process, adapted to synthetic data, has to be developed for the training and the assessing phases of a CNN
- The quality of the generated data has to be improved (more Physics, more technology in the sensor modelling, more details in the 3D scenes…)
- More sensor modelling capability, in order to address fusion and take advantage of transfer learning and data frugality
- Tighten partnerships with partners for progressing (GAN, domain randomization, explanation, robustness, formal validation)

6. CONCLUSION

XX

7. REFERENCES

1. Zendesk - "A simple way to understand machine learning vs deep learning" (2017), https://www.zendesk.comSmith

2. Yann Le Cun - "When the machine learns" (2020), *Odile Jacob*

3. Koul, Ganju, Kasam - "Practical Deeo Learning for Cloud, Mobile & Edge" (2020), *O'REILLY*

4. Marc Fiammante - "History and uses of the newly published artificial images for neural networks patent" (2019), *LinkedIn*

5. Jonathan Tremblay - "Training Deep Networks with Synthetic Data: Bridging the Reality Gap by Domain Randomization" (2018)

8. GENERAL SPECIFICATIONS

The paper must be prepared in this two-column format and **must not be longer than** 12 printed pages including figures, tables and references, and the size of the electronic version must not exceed 10MB of memory.

9. PAGE LAYOUT

- Paper format: standard A4 (297x210 mm)
- Two-column format (8 cm each column)
- Margins: top 25 mm, left and right 20 mm, bottom 15 mm
- Fully justified

Font:
Text: Arial
Variable: *Arial italic*
Symbol: True Type Symbol font

Type Size:
Paper Id.: **10pt bold (1st page up-right corner)**
Paper title: **12 pt bold (TITLE)**
Author(s): **10 pt bold (Author)**
Affiliation(s): *10 pt italic (Affiliation)*
Normal text: 10 pt (regular text)
Captions: *10 pt italic (Figure…)*
Text in tables: 9 pt
Symbols: 10 pt ($\Omega \cong \phi$)
Sub/superscript: 7 pt (x^{y})
Page numbers: 10 pt (regular text)

10. HEADERS AND FOOTERS

Both the header and the footer should be left empty.

11. TITLE AND AUTHOR AFFILIATION

The paper title, author(s) name(s), affiliation, complete mailing address and email should be centred at the top of the first page using the fonts and type sizes indicated above. If there are several authors, the complete affiliation should be given for each of them using superscripts (1) in the authors (2) list to refer to them.

12. HEADINGS

This sheet has been typeset in accordance with the style to be followed for the headings. Use the decimal system in Arabic figures for the numbering of headings and subheadings. Major (or section) headings are to be in capitals and bold.

12.1. Subheadings

Subheadings or subsection headings are to be in lower case with initial capitals and bold font. They should be flush with the left-hand margin, on a separate line.

13. EQUATIONS

Equations are to be numbered consecutively throughout the paper. Each equation number must be unique. Equations should be centred, with the equation number in parentheses flush with the right-hand margin of the column. Leave a blank line before and after equations. Always refer to equations by number, as Eq. 1 or Eqs. 3-6, not as 'above' or 'below'.

Eq.1
$$T_s = \frac{T_b}{1+(\lambda T_b / \alpha)\ln\varepsilon}$$

14. FIGURES AND TABLES

Figures and tables can extend over <u>two columns</u> if required. Figure captions should be centred below the figures; table captions should be centred above the tables. Use full word 'Figure 1' or 'Table 1' in the caption. Use the abbreviation "Fig. 1" or "Tab. 1" in the text (even at the beginning of a sentence).

Figure 1. OPTRO2022

15. ABBREVIATIONS AND ACRONYMS

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Do not use abbreviations in the title unless they are unavoidable.

16. REFERENCES

Number citations consecutively in square brackets [1]. Refer simply to the reference number, as in [3]. Do not use 'Ref. [3]' or 'Reference [3]' except at the beginning of a sentence: 'Reference [3] was the first …'. The title of the book or of the journal should be in italic script.

Zendesk (2017)
A simple way to understand machine learning vs deep learning
https://www.zendesk.com

16.1. Sample References

1. Zendesk "A simple way to understand machine learning vs deep learning" (2017). https://www.zendesk.comSmith

2. Yann Le Cun "When the machine learns" (2020), *Odile Jacob*

3. Koul, Ganju, Kasam "Practical Deep Learning for Cloud, Mobile & Edge" (2020), *O'REILLY*

4. Marc Fiammante "History and uses of the newly published artificial images for neural networks patent" (2019), *LinkedIn*

5. Jonathan Tremblay “Training Deep Networks with Synthetic Data: Bridging the Reality Gap by Domain Randomization” (2018)

17. PDF PREPARATION

In order to allow reasonable quality printing, please avoid excessive compression when making your PDF file. Generally, image resolutions should be 600 dpi for monochrome, 300 dpi for greyscale and colour.
VERY IMPORTANT***:*** EMBED ALL FONTS and ensure that the PDF’s security setting is on ‘NO SECURITY’.

18. SUBMITTING THE PAPER

Papers must be delivered by **December 15th, 2021** at the latest, to be included in proceedings.

18.1. Paper identification

Each OPTRO2022 paper will be assigned a unique 3 digits number identifier: For example, ‘123'.
Letter of acceptance includes your personal paper identifier. All correspondence with the symposium organizers should include this identification number.
The filename must clearly identify the paper. Use the paper identifier number followed by underscore and the name of the main author (e.g. 123_SMITH.pdf). Use only capital letters.
DO NOT name your file “XXX.pdf”.

18.2. Papers are to be delivered by priority to the following login page:

www.3af-optro.com
Use personal login and password chosen when you created your online account.

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Only in case of difficulties in uploading your text your completed paper should be sent by email to the following address:

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