

Improving image recognition with synthetic images

Overfitting in image recognition is a frequent problem due to limited size of training data sets. Another training problem comes from unbalanced training data sets where a feature is over represented, such as sunny weather condition, or a given hours of day range lighting, different object colors. These problems expand exponentially if we talk about infrared or SAR images, such as the ones commonly used in drones, satellites, or video-surveillance image processing applications.

Let us do a simple math with a vehicle detection case, with usual classification :

9+1: 9

most popular vehicle colors
1 for all other colors.

10

different landscape:
city, coastal, mountain,
snowy, desert, tropical,
rocky, riverside, forest,
farm field

8

or more view angles

4 traffic conditions

7

lighting conditions under 3 latitudes,
12 hours sun light orientation plus
night street light, shade

3

spectral bands: Visible, Infrared (LWIR),
and SAR images

24

different models in the official classification as
described in Wikipedia https://en.wikipedia.org/wiki/Car_classification

6

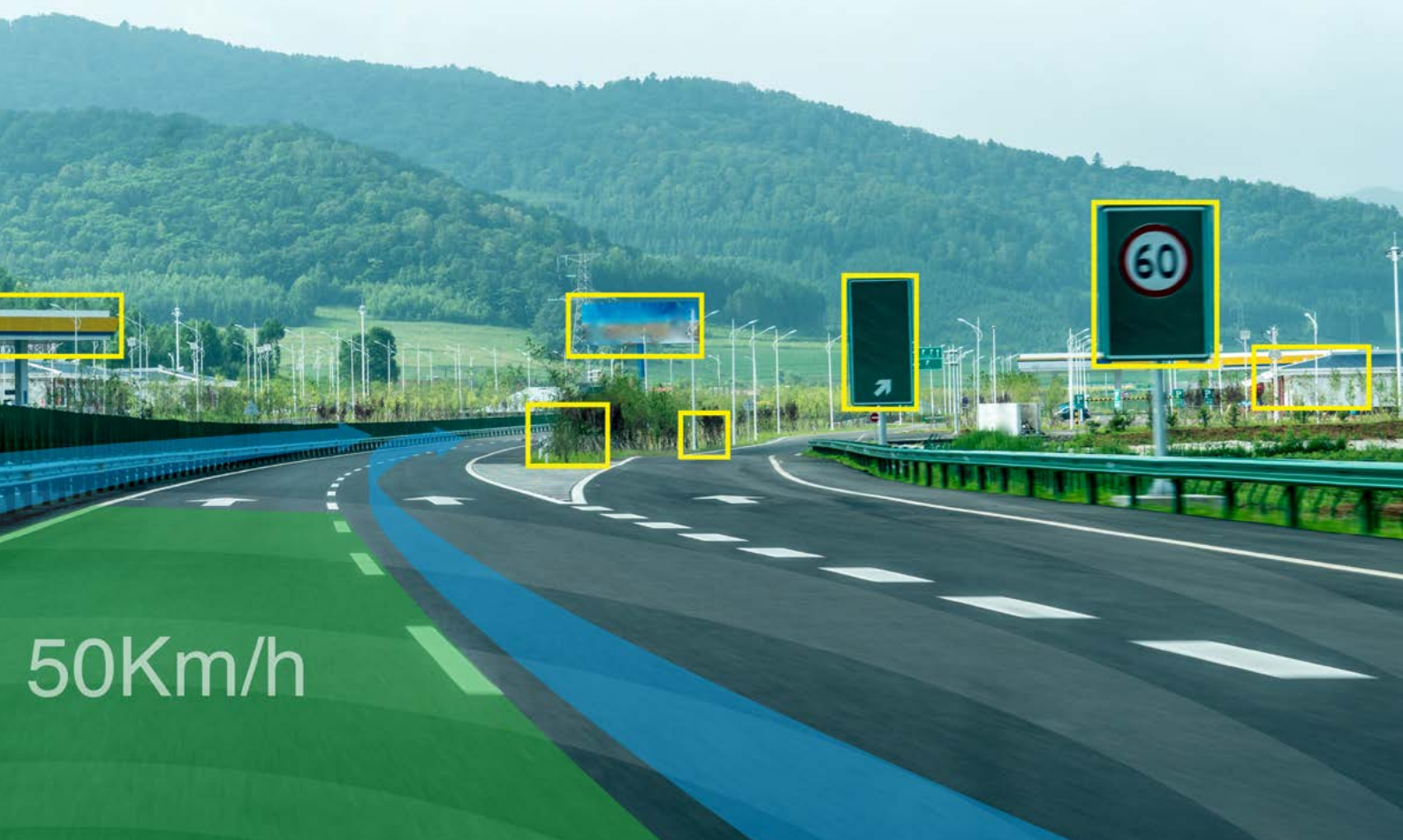
Weather conditions:
sunny, fog, rain, dust wind,
wind alone, snow

That gives us a minimum of 29 million combinations ($10 \times 24 \times 10 \times 7 \times 3 \times 6 \times 4 \times 8 \times 3$) in a balanced data set which is hardly obtainable by a manual selection.

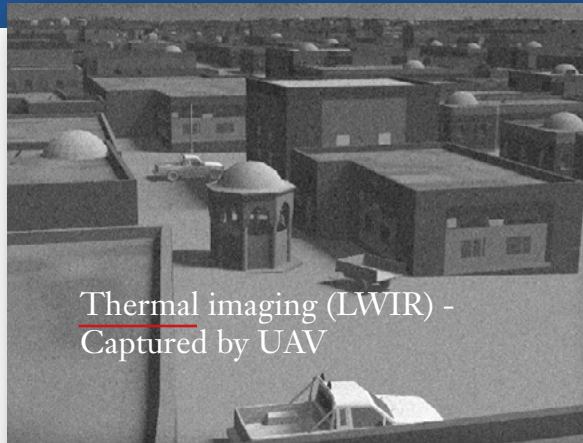
In a pilot project use-case the initial training set was far from being enough. Therefore, we partnered for that project with Oktal-SE who provided synthetic images that complemented the initial training and test sets.

Oktal-SE has a unique technology that uses large 3D region landscape, very close to real large areas around the world, then simulates any kind of motion through or above the landscape, using ray tracing spectral images close to physics to reconstruct either in batch or dynamically the view from that position in any of the mentioned spectral band (visible, infrared or radar).

In our case we travel virtually through the landscape and take snapshots. The material spectral response corresponding to the context, visible, infrared or radar is computed and create a close to real image.



Below is an example of synthetic images in the visible, infrared, and SAR domains, representing different car observation scenarios, from ground, drone, and satellite observation level (publicly releasable images courtesy of Oktal-SE) :



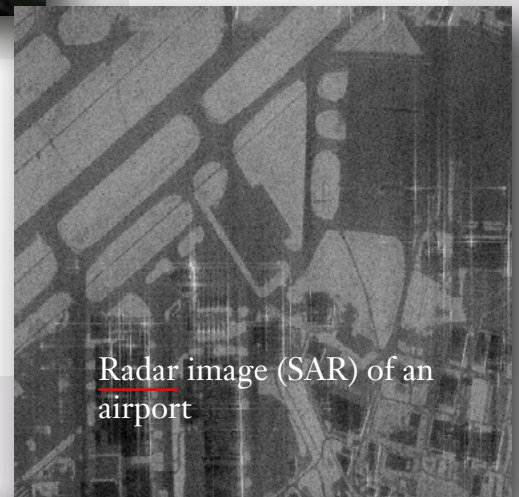
Thermal imaging (LWIR) -
Captured by UAV



Captured from car visible image



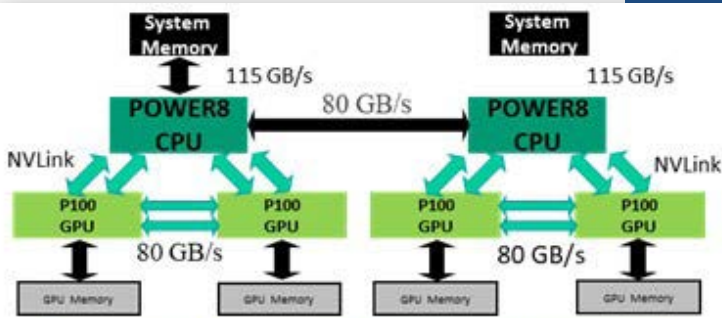
Captured from car visible image



Radar image (SAR) of an
airport



Night Vision Image (SWIR)
captured from an UAV

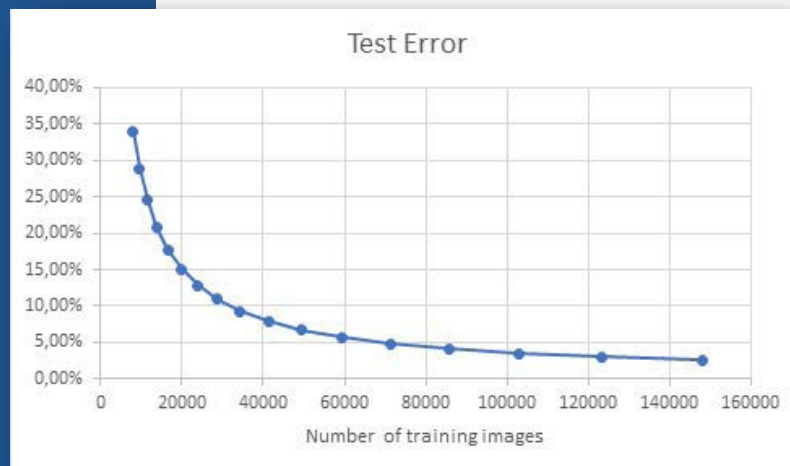


Compute	Pascal Architecture Highest Compute Performance NVLink GPU Interconnect for Maximum Scalability CoWoS HBM2 Unifying Compute & Memory in Single Package Page Migration Engine Simple Parallel Programming with Virtually Unlimited Memory Space
Memory	5.3 TF DP · 10.6 TF SP · 21.2 TF HP
Interconnect	HBM2: 720 GB/s · 16 GB
Programmability	NVLink + PCIe Gen3
Availability	Page Migration Engine Unified Memory Shipping in IBM Power Systems S822LC for HPC

All the varieties of conditions that I listed at the beginning of the article can be generated too.

In our project we did tests both with simple Convolutional Neural Networks and Deep Residual Neural Networks on PowerAI machines with a mix of real and synthetic images. IBM's PowerAI is at least twice as efficient as Tesla K80 GPU. It uses the PowerAI specific « NVLink » between CPUs and GPUs allowing a memory access to large data sets into the system memory. A clearly quicker exchange comes from the 2 NVLink connections between each GPU and CPU-GPU each at a minimum rate of 80 GB/s.

The training rate we achieve using Keras with the Tensorflow which is shipped with PowerAI is of 500 images per second, with Epochs between 40 seconds and 2 minutes depending on the neural network depth. Our implementation is multithreaded and multi GPU too. The consistent impressive improvement we got by introducing synthetic images is roughly reduction of 15% of errors for each addition of 20% synthetic image. Tests are run on a random mix of real and synthetic images different from training and cross validation sets.



Overall the approach is very promising, and given the speed provided by PowerAI, there is no blocking factor for training neural networks with gigantic sets resulting from a mix of real and balanced features synthetic images ensuring the best possible quality in training.

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