Xailient

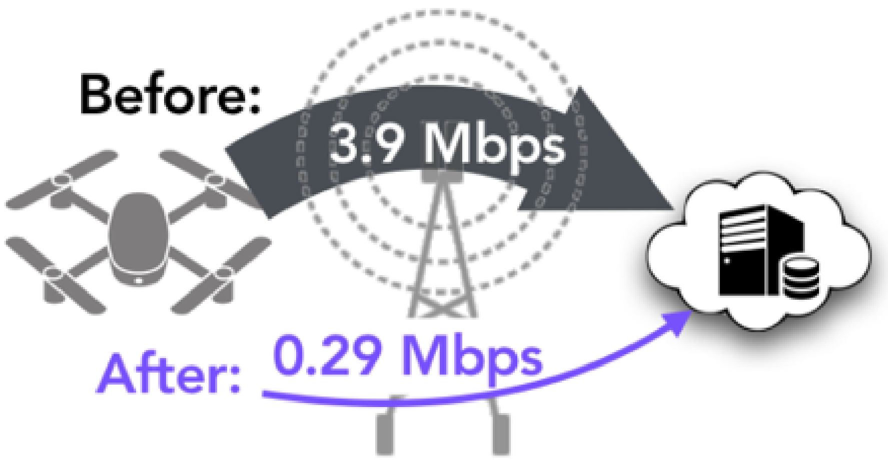
Case Study

Xailient Dramatically Reduces Drone Data-Usage by 94%

Synopsis

Drones are an important tool in spotting danger from a safe distance.

Xailient helps drones work faster and see better by optimizing drone's use of bandwidth.



Key Outcomes

✓ **Xailient cuts drone data-usage by 94%**

Problem Statement

Wireless networks are often congested, and high-fidelity video from drones can get interrupted or can squeeze out other critical traffic.

Every Xailient customer is different. A surveillance drone camera capturing 30 frames-per second at 4k resolution will use bandwidth at an average of 45 Mbps per second. In an operational environment, this level of data consumption can burden networks that are also serving other mission-critical purposes. When using commercial telecommunication networks, each hour of flight would incur significant data charges.

Industrial and consumer drones often use lower resolutions and transmit over traditional mobile networks. Even hobby drones leveraging traditional 4G networks can easily use 3 Gb of data per hour of drone flight, incurring $30 in data charges or more.

Video Resolution	Approx Bit Rate (Mbps)		1 Hour GB used	Cost per 1 Hour Flight
	24-30fps	60fps		
4k	45	68	20.25	$ 202.50
1440/2k	16	24	7.2	$ 72.00
1080p	8	12	3.6	$ 36.00
720p	5	7.5	2.25	$ 22.50

Activity

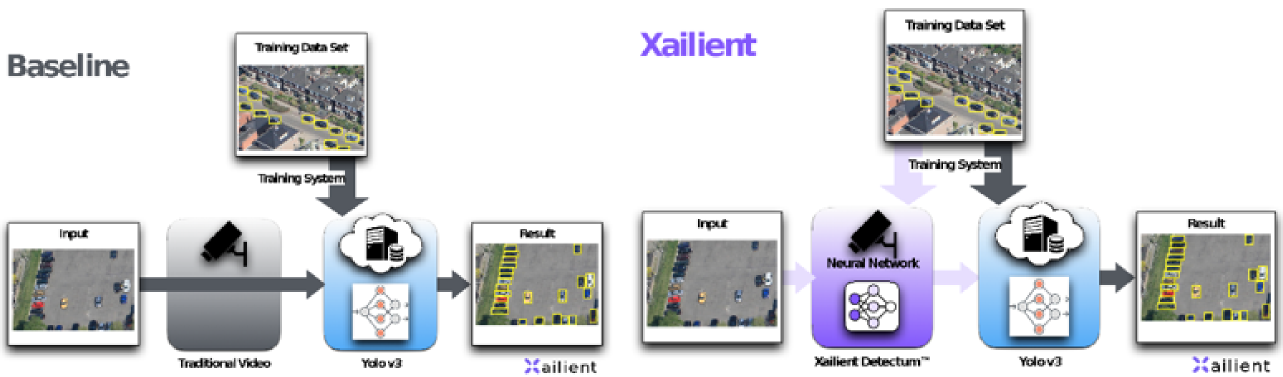
Yolo3 Model

We trained a Yolo3 model and Xailient Detectum Neural Network to detect cars and trucks from an overhead drone. The Yolo3 model was tested in isolation, and then in combination with the Detectum using the same input dataset. The Yolo 3 model was run in Google Cloud Platform and the Detectum on a Raspberry Pi 3.

Using open-source training datasets, Xailient trained a Yolo3 object detection neural network using traditional methods. This neural network provided the baseline performance of a traditional drone-AI deployment.

	Training Images	Training Instances
Total Annotated Dataset	14,013	29,040
Training Data	11,911	24,690
Testing Data	2,102	4,350

The baseline Yolo model was run on Google Cloud Platform and fed pre-annotated test data as input to establish a control dataset of accuracy and performance. The baseline model had an accuracy of 92% mean average precision (mAP).

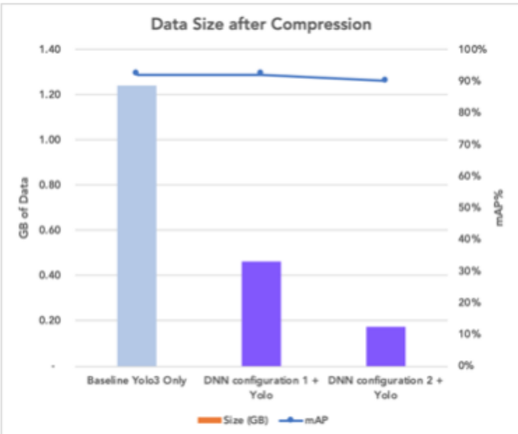


Xailient Detectum Impact

The Detectum Neural Net (DNN) was trained using the same data as the Yolo3 model. The same input test data was then run through the Xailient software before being fed into the Yolo3 baseline model. The function of the Detectum is to **identify objects of interest** (cars or trucks) and to **compress the image background** or skip entirely images with no objects of interest. A major benefit is to avoid transmitting data through the wireless network that has no value in object detection tasks. By dropping and compressing images, the Xailient software **reduced the total data transmitted**.

Two versions of the Detectum were tested. In the first, conservative thresholds were used to ensure no change in accuracy as compared to the control.

A second version of the Detectum used a more aggressive set of configurations.



Testing Data	mAP	Size (GB)	Compression Savings
Baseline Yolo3 Only	92%	1.24	
DNN configuration 1 + Yolo	92%	0.46	63%
DNN configuration 2 + Yolo	90%	0.18	86%

The images used in the test data were all different, with no data in common. The test data is not sequential frames from a related video. This is important because videos encoded with the mpeg standards (for example H.264) provide frame-overframe compression that can achieve significant data savings as compared to the sequence of still images that make up the frames.

Real-World Video Test

To see the impact of the Detectum on a video, the Xailient configuration was then run on “in the wild” videos of overhead drone footage.

Results

Xailient software **reduced data usage by 94%** on a characteristic 1080p “in the wild” test video of a drone following a vehicle.

A second version of the Detectum used a more aggressive set of configurations. In this result, the MAP reduced from 92% to 90%, and the data reduction progressed from 63% savings to **86%** (a further reduction of almost 2/3rds).

In the Real-World Video Test, benefits in total size and in transmitted bit rate were achieved over-and-above the compression achieved with mpeg.

Next Steps

The Detectum Neural Networks work best when trained to the specific purpose for which they are deployed. Training data and configuration parameters can all be adjusted to fit to purpose. The results obtained in this pilot project, while dramatic, are **just a starting place** in how Xailient can help drone operators.

Xailient is recruiting beta customers to test the Detectum, provide feedback about deployment environments, and further explore how the efficiency gains of Xailient software can benefit them.

Discussion

Since the Detectum Neural Net transmits objects of interest in full resolution, the exact savings depend on multiple factors, including the density of objects in the input. For example, a small car on a desert road has a high "background" ratio, as compared with a crowded highway. Similarly, a search and rescue or surveillance pass of empty desert will have a high "empty frames" ratio. Each of these would have different ultimate bitrates, but by using the Detectum, **Xailient customers can ensure they are not transmitting useless bytes.**

		Input Video			Xailient		Savings	
	Detectum	resolution/ framerate	Original Size (MB)	Average Bitrate (Mbps)	Size (MB)	Average Bitrate (Mbps)	Size	Bitrate
Crowded Highway	Config 1	316x600, 25fps	6.656	0.962	1.056	0.149	**84.13%**	**84.51%**
Rural Road	Config 2	1080x1920, 25fps	6.475	3.917	0.374	0.299	**94.22%**	**92.37%**

Ultimately, in the real-world video test of a 1080p Drone footage, Xailient achieved a **94% reduction in data usage; a 20:1 efficiency improvement.**