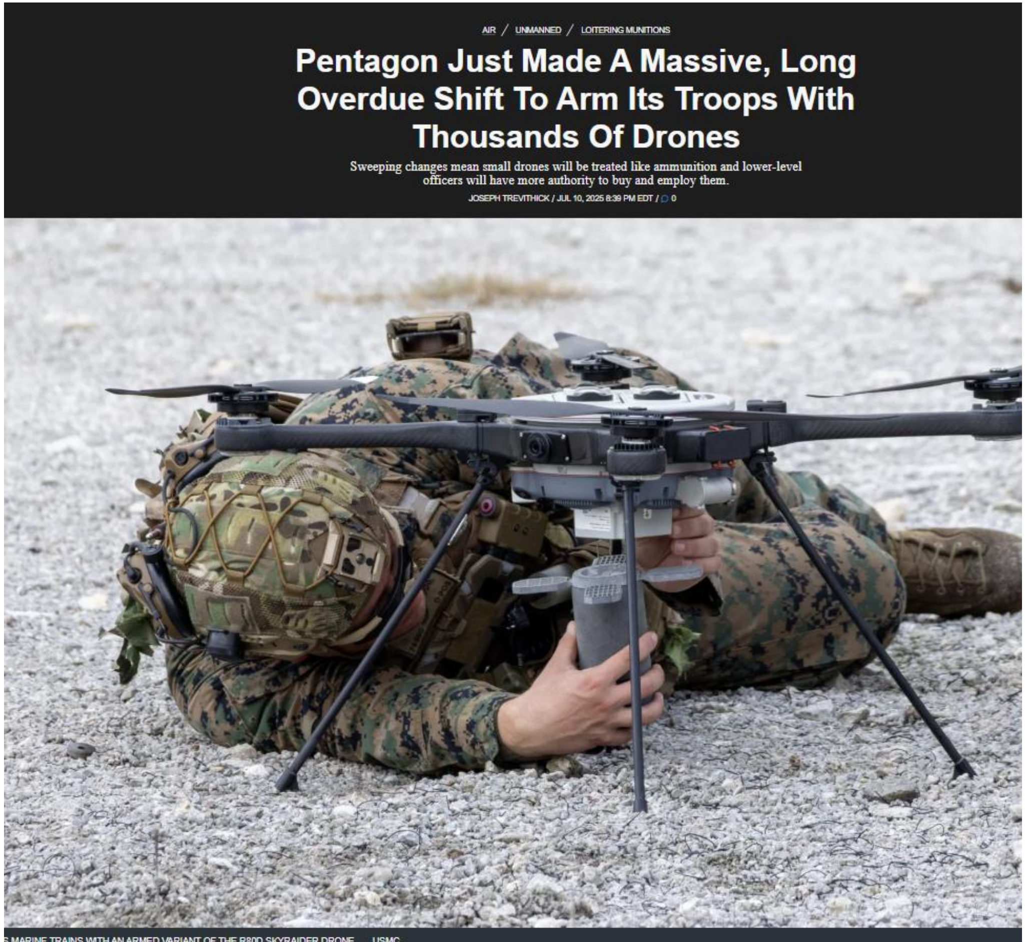
DRONE WARFARE

INTRODUCTION


AIR / UNMANNED / LOITERING MUNITIONS

Pentagon Just Made A Massive, Long Overdue Shift To Arm Its Troops With Thousands Of Drones

Sweeping changes mean small drones will be treated like ammunition and lower-level officers will have more authority to buy and employ them.

JOSEPH TREVITHICK / JUL 10, 2025 8:39 PM EDT / 0

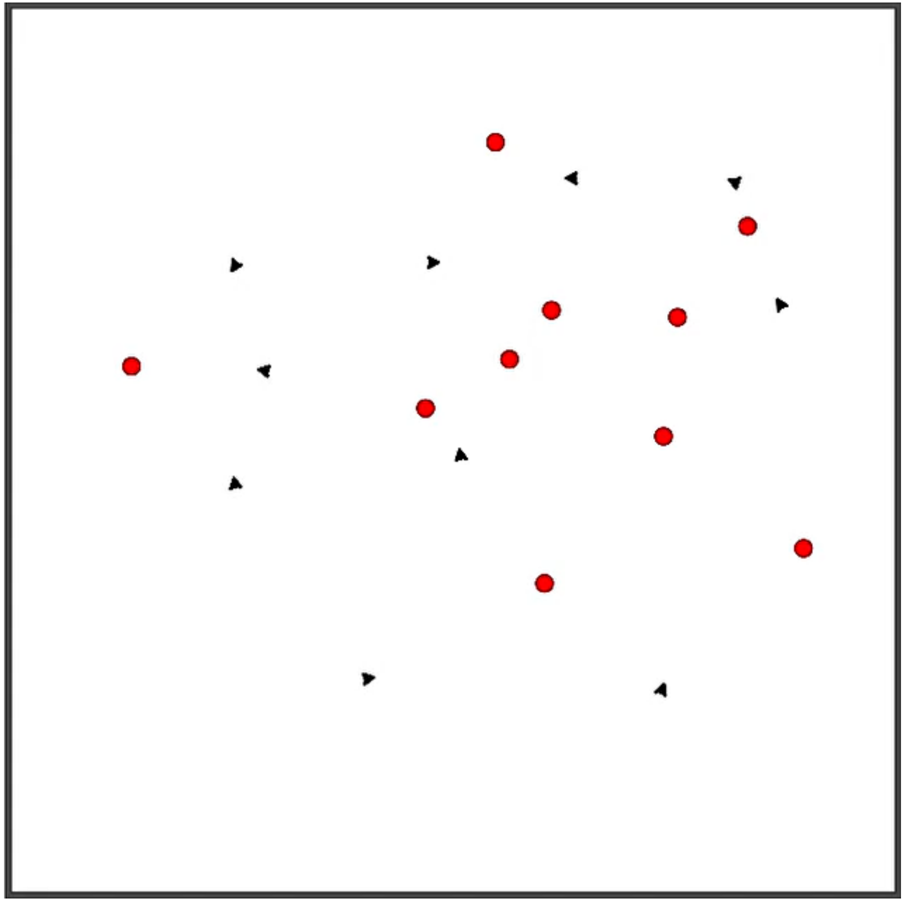
S MARINE TRAINS WITH AN ARMED VARIANT OF THE R80D SKYRAIDER DRONE. USMC

- A new paradigm.
- Warfare is no longer about who has more guns, but who has the smarter, more adaptive machines.

TARGETING ENEMY DRONES

AI²

- A group of drones targeting multiple enemy drones
- Drones are sharing a single NeuraBASE
- Drones are trained to chase targets and avoid friendly drones
- Learning is faster due to larger pool of information received from multiple drones

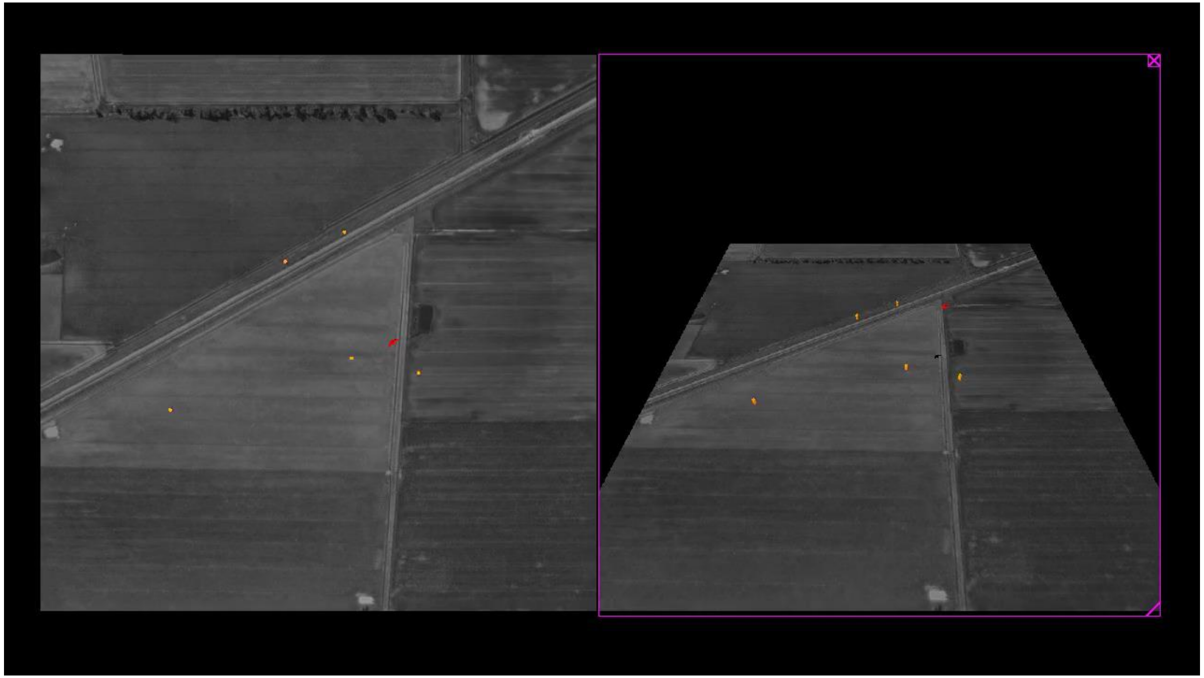


LETHAL AUTONOMOUS DRONE

US Army’s live-grenade drop from a drone in Grafenwoehr Training Area, Germany.

* https://www.twz.com/air/army-touting-grenade-dropping-drone-shows-just-how-alarmingly-behind-the-curve-it-still-is?utm_source=flipboard&utm_content=topic%2Ftechnology

LETHAL AUTONOMOUS DRONE



- Drone travels at 25 metres height and selects a target to track and destroy by dropping a grenade.
- When the drone is near the target, it will descend to 8 metres and release a grenade.

- Vision is used by the drone to identify targets.
- Once a target is selected, the position of the target is stored as sensory information.
- The positions of the target are captured at intervals, forming a sequence of positions.
- The sensory sequence is stored in NeuraBase as sensory neurons. This information is associated with motor actions (as motor neurons) to be taken to pursue the target. The correct motor actions are learnt through reinforcement learning.

GPS-DENIED NAVIGATION

INTRODUCTION

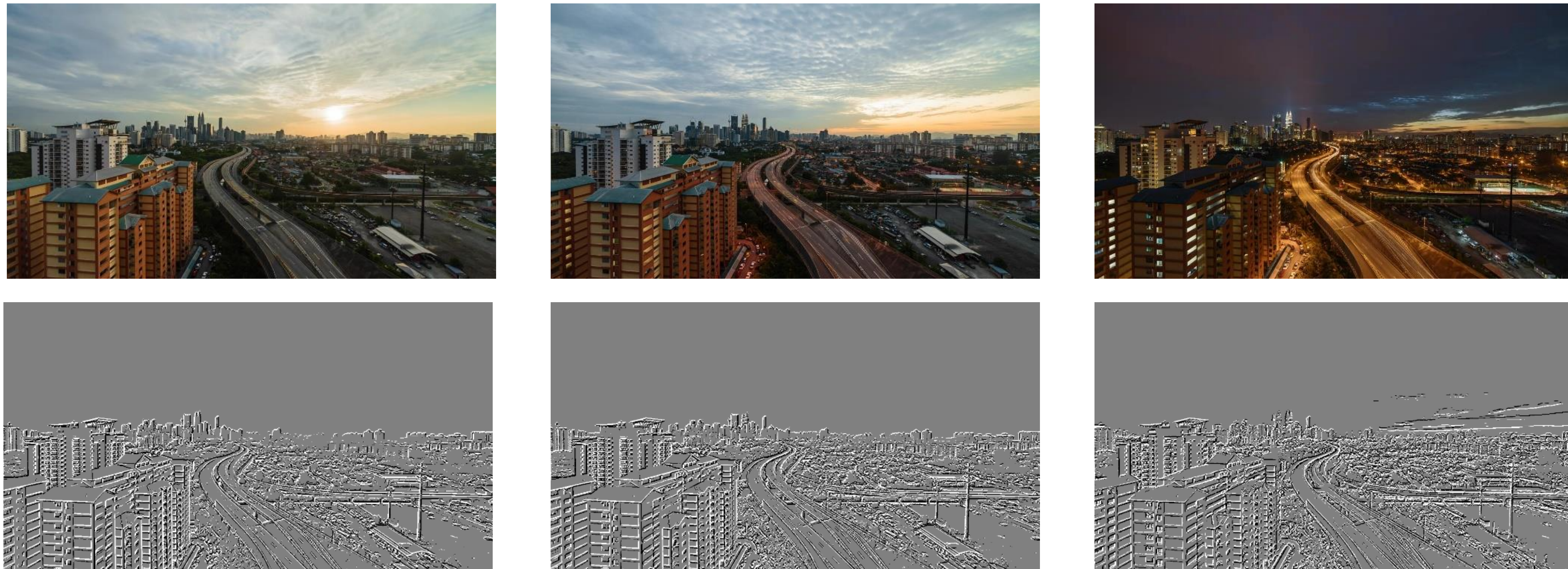
- Issues:
  - Spoofing: fake GPS signals are broadcasted.
  - Jamming: RF interference to intentionally “drown out” satellite signals and controller communication.
  - Interference of visual data transmission.

INTRODUCTION

AI²

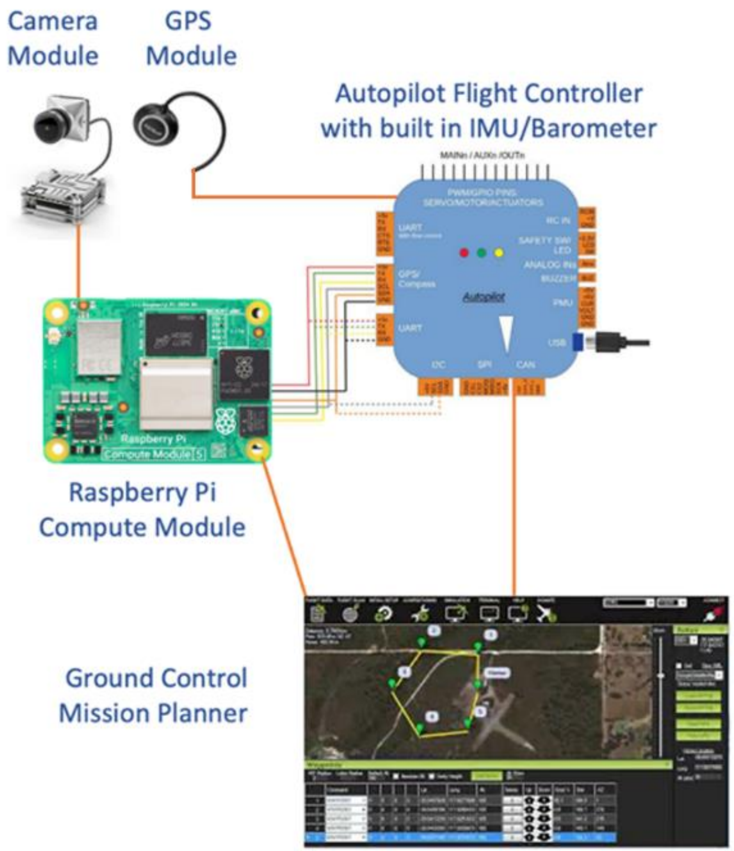
- Solutions:
  - Inertial navigation system (INS), by measuring acceleration, velocity and orientation using gyroscopes and accelerometers, or IMU. *Problem:* ***drift, errors that accumulate over time as the system loses accuracy****, needs correction algorithms.*
  - Simultaneous localization and mapping (SLAM) using LIDAR, by analysing visual cues from the environment. *Problem:* ***high compute and memory requirements, costly***.
  - Features-based localization. *Problem:* ***high data storage, sensitive to lighting conditions***.
  - Visual odometry: *Problem:* ***doesn't work on high altitude***.
  - AI-based features matching. *Problem:* ***requires careful training and tuning, costly.***

NEURAMATIX EDGE DETECTION – LIGHTING INVARIANCE



NEURAMATIX EDGE DETECTION – LIGHTING INVARIANCE

HARDWARE REQUIREMENTS



- Raspberry Pi (RP) Compute Module.
- RP interface with Autopilot Flight Controller (to provide computed GPS coordinates) & Camera Module (downward facing).
- Ground Control Station (GCS) with Mission Planner software loaded on laptop for setting flight strategies and mission objectives.
- GCS interface with onboard Autopilot Flight Controller to load mission.
- GCS interface with RP module via SD card to load image database (salient maps).

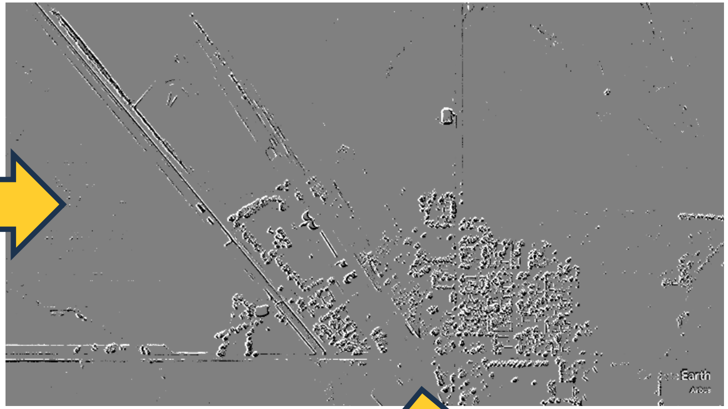
IMAGES TRANSFORMATION TO SALIENT MAPS

AI²

Image (1920x1080 pixels, 24 bits/pixel)

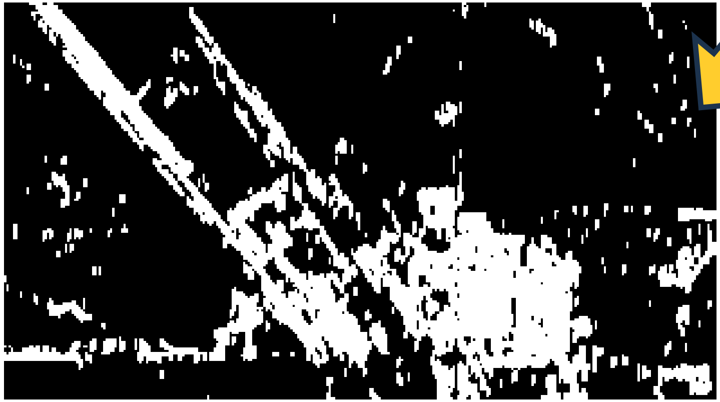
6M bytes

NeuraBase Edges (1915x1075pixels, 2 bits/pixel)



500K bytes

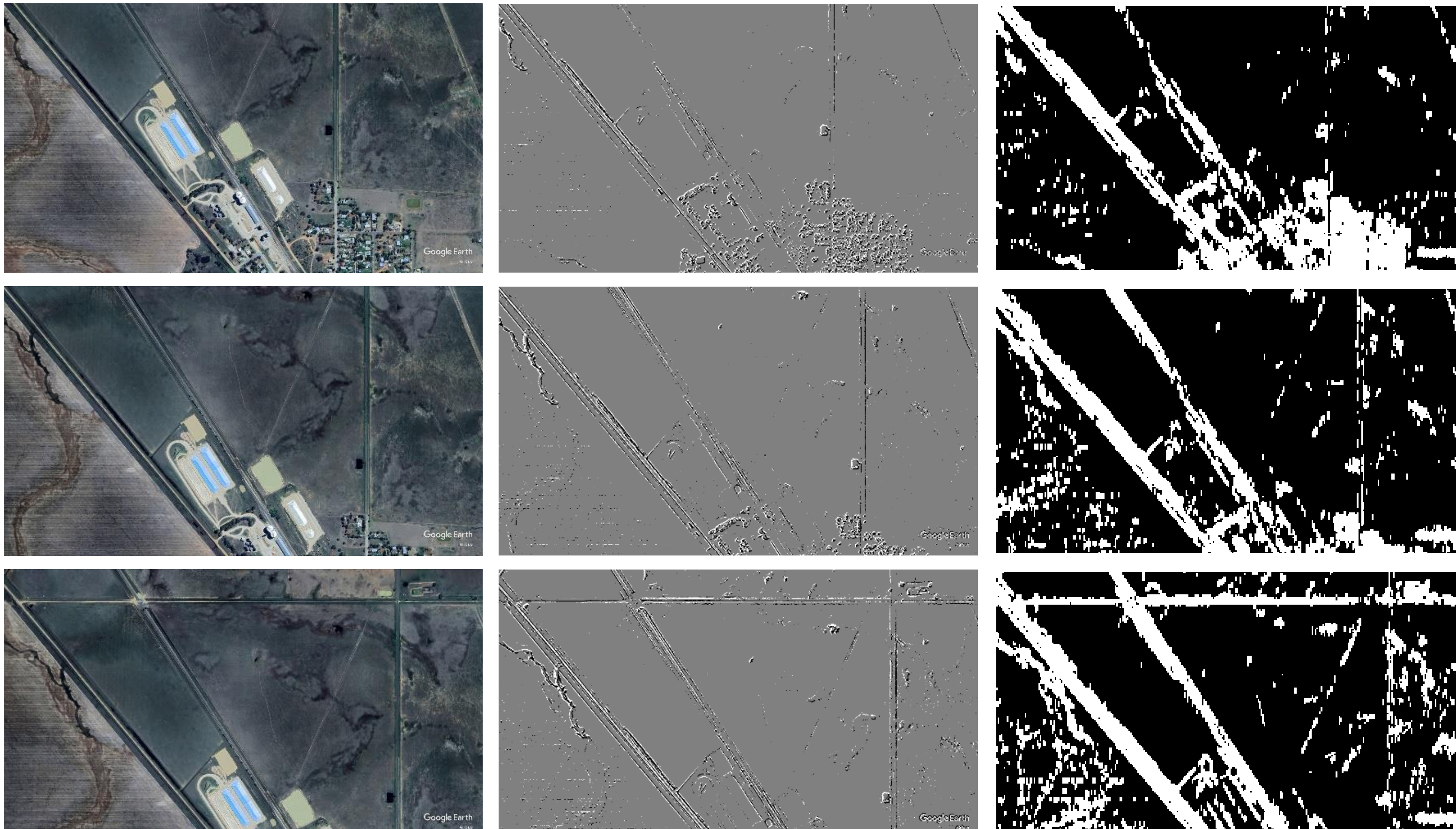
NeuraBase Salient Maps (316x176 pixels, 1 bit/pixel)



56K bytes (.png 3K bytes)

IMAGES TRANSFORMATION TO SALIENT MAPS

Image | **NeuraBase Edges** | **NeuraBase Salient Maps**

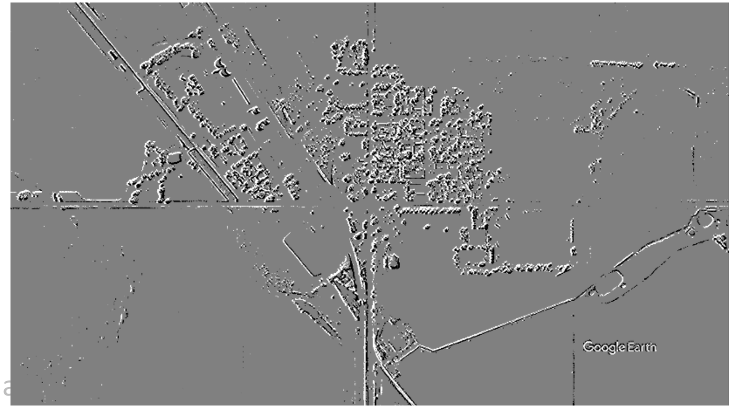


SALIENT MAP CHARACTERISTICS

AI²

Image (1920x1080 pixels)

NeuraBase Edges (1915x1075 pixels)



Salient Map Size 1 (.png 1 kB)

Salient Map Size 2 (.png 2 kB)

Salient Map Size 3 (.png 3 kB)

Salient Map Size 4 (.png 5 kB)

SALIENT MAP CHARACTERISTICS

AI²

- Larger salient maps have a smaller distance-per-pixel and can store more salient features.

Salient map size	Width	Height	Area size (pixel²)	Distance/pixel (metres)	20000 salient maps storage size (MB)
1	116	64	7424	15.05	14.1
2	236	131	30916	7.53	33.2
3	316	176	55616	5.65	49.7
4	475	265	125875	3.76	86.0

EXAMPLE

Original (1920x1080 pixels, 6M bytes)

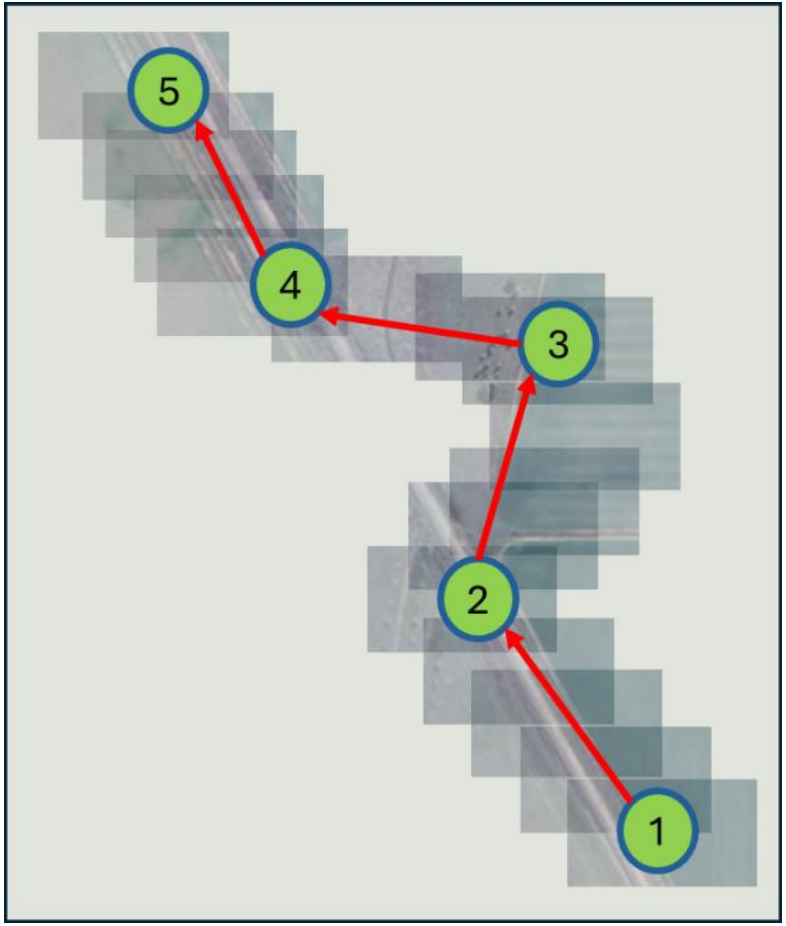
NeuraBase Edges (1915x1075, 500K bytes)

Salient Maps (316x176 pixels, 56K bytes)

Mitiamo to Pyramid Hill Flight Plan Salient Map

- Google Maps of a 20 kilometres flight path, at 3000 metre altitude.
- Converted to NeuraBase edges, which are then converted to salient maps.

PRE-FLIGHT PROCESS



- Relevant salient maps along the planned path to target, are selected from a database of maps covering the areas of interest. Path to fly on the maps are marked with waypoints.
- The flight path will result in overlapping images, so that the waypoints are joined continuously. This will reduce storage and processing time as only a small sequence of regions of interest are taken into consideration. Each image will contain the actual GPS location and elevation.
- The maps are uploaded to the drone.

IN-FLIGHT PROCESSING

- The drone's real-time salient maps are continuously searched in the neighbouring pre-loaded maps, to find the best match.
- The GPS location is computed with reference to the best matching neighbour, which is then fed into the drone's flight control system.
- Based on the location, the Autopilot can navigate the drone to stay on the desired flight path.

IN-FLIGHT PROCESSING PERFORMANCE

AI²

- Time required to compare a flight salient map with a single neighbouring map:

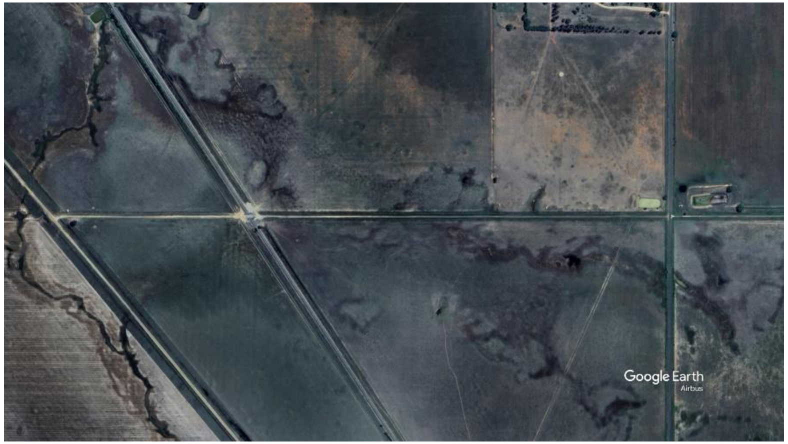
Salient map size	Computation time (msec)	Distance travelled during computation at 50 km/h (m)	Distance travelled during computation at 100 km/h (m)	Distance travelled during computation at 200 km/h (m)
1	3.71	0.05	0.10	0.21
2	22.78	0.32	0.63	1.27
3	54.91	0.76	1.53	3.05
4	155.73	2.16	4.33	8.65

* Program was run on an Intel Core i7-1070H CPU @ 2.60GHz.

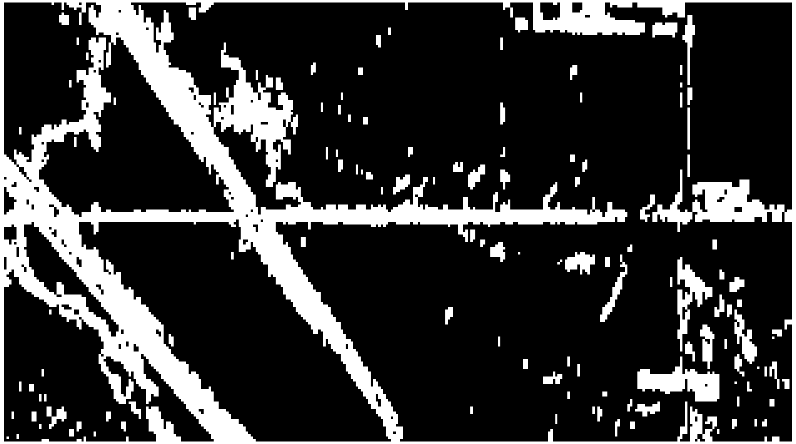
GPS LOCATION CALCULATION

AI²

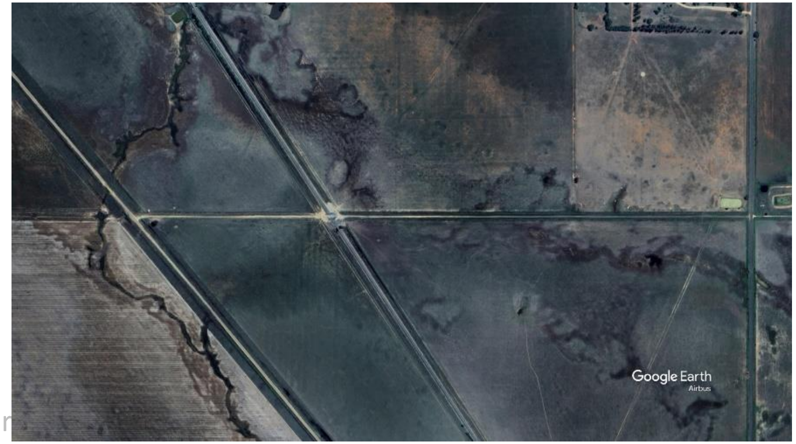
Flight Image 1



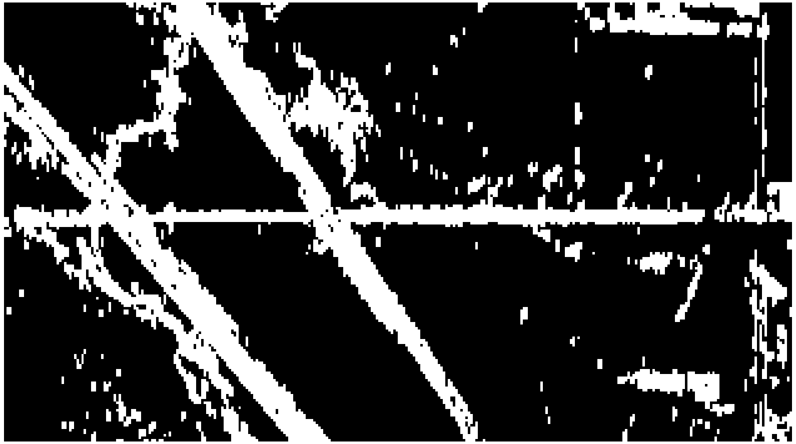
Salient Map of Flight Image 1



Best Matching Base Map

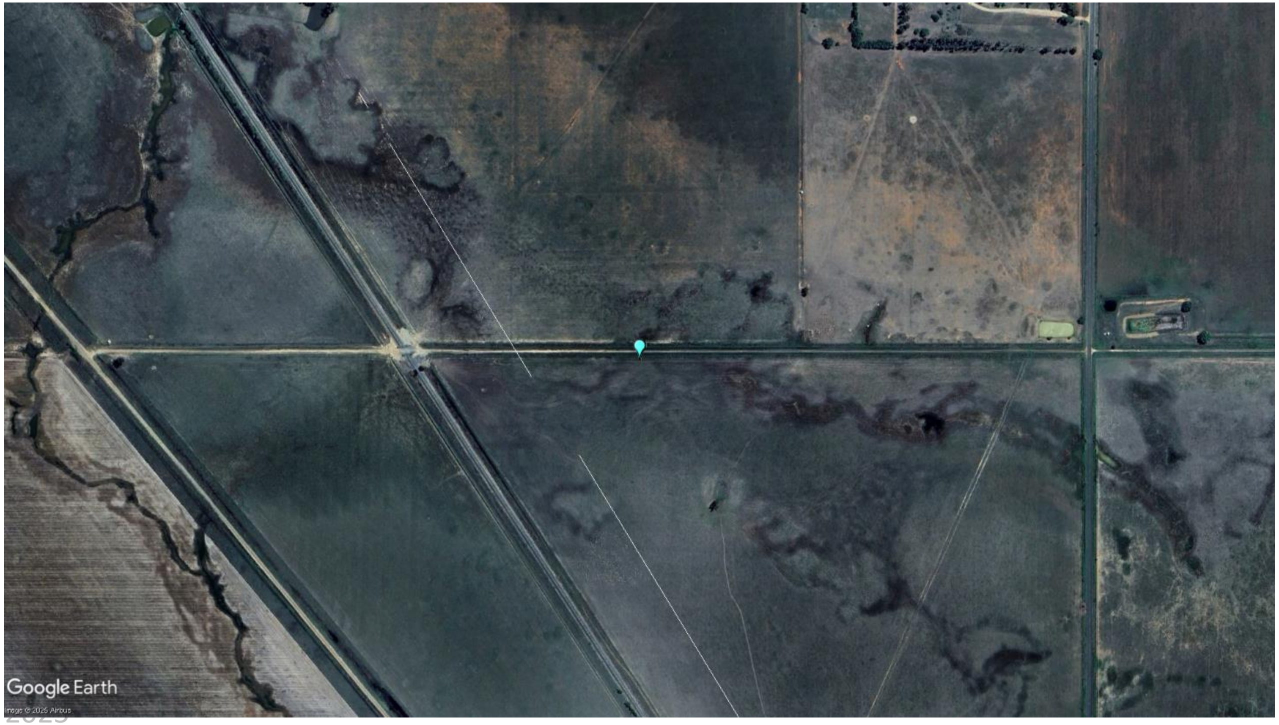


Salient Map of Best Matching Base Map



GPS LOCATION CALCULATION

- Computed GPS: S36° 11’ 56.94”, E144 ° 13’ 29.094” (blue icon)
- Actual GPS: S36° 11’ 56.94”, E144 ° 13’ 29.145” (green icon)
- Distance Error: 1.3 m (using salient map size 3)

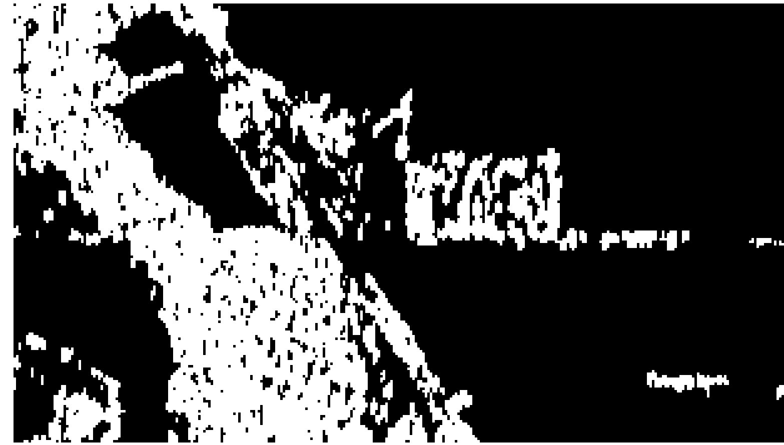


GPS LOCATION CALCULATION

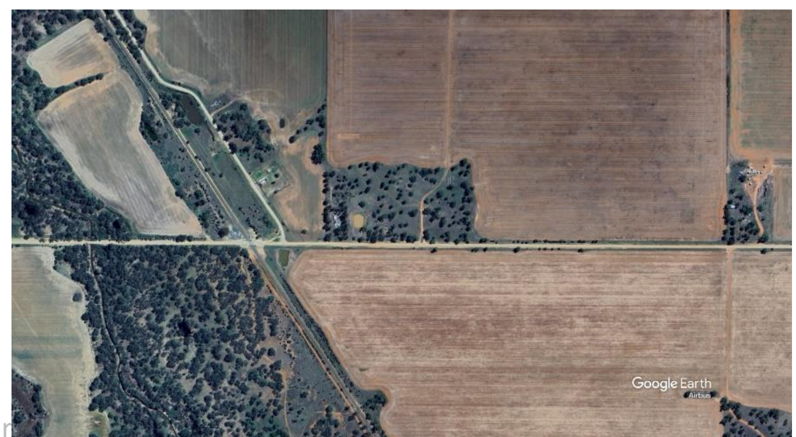
AI²

Flight Image 2

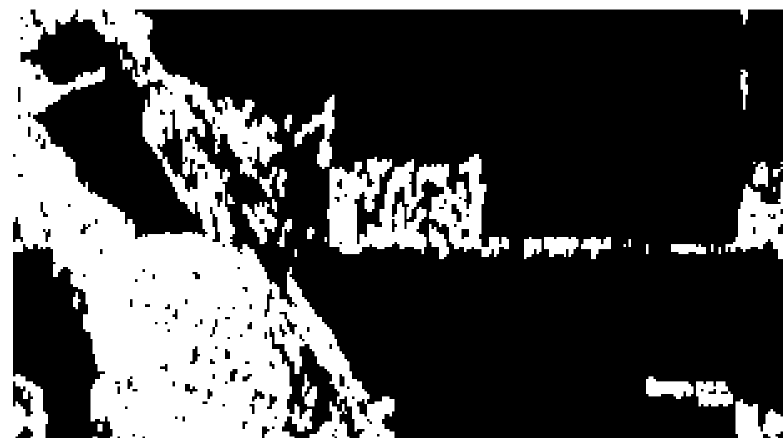
Salient Map of Flight Image 2



Best Matching Base Map



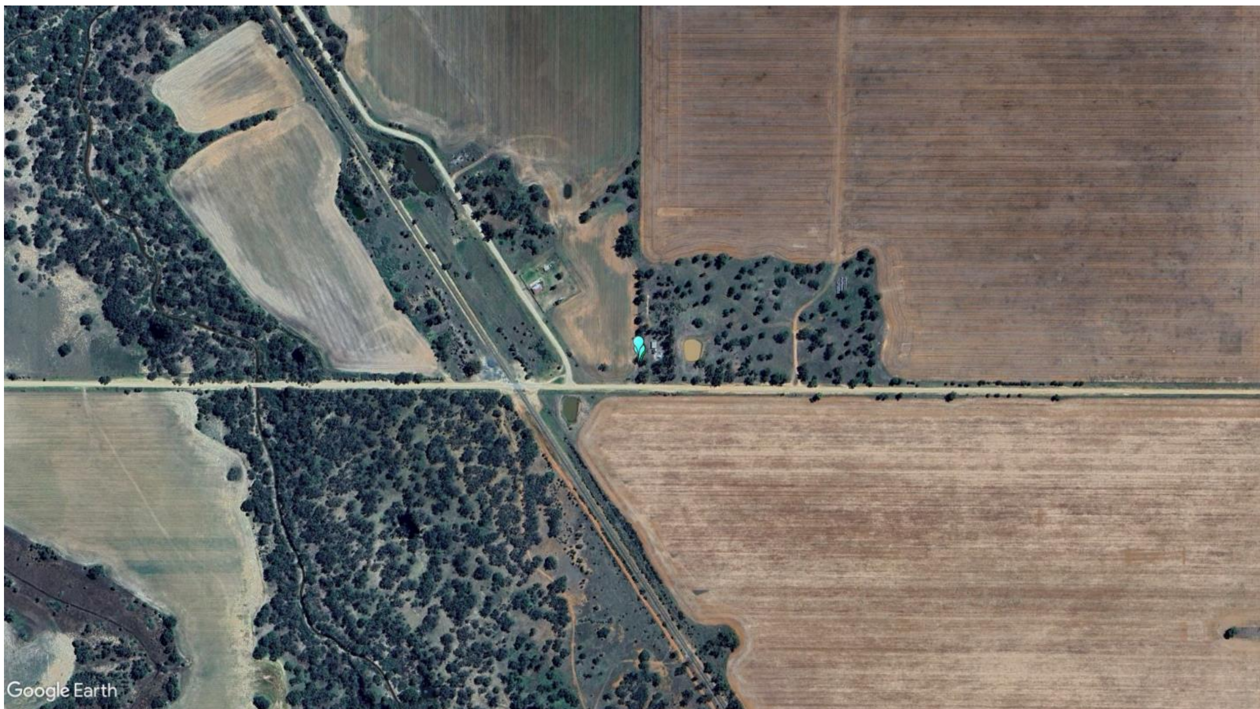
Salient Map of Best Matching Base Map



GPS LOCATION CALCULATION

AI²

- Computed GPS: S36° 9’ 18.42”, E144 ° 11’ 15.96” (blue icon)
- Actual GPS: S36° 9’ 18.48”, E144 ° 11’ 16.02” (green icon)
- Distance Error: 2.3 m (using salient map size 3)



400 SQUARE KM AREA TRANSFORMATION TO SALIENT MAPS

AI²

- Images were generated over a 400 square kilometre area.
- Image-overlap was 90%.
- Distance between adjacent maps vertically (North-South) was 102 metres.
- Distance between adjacent maps horizontally (East-West) was 181 metres.
- This resulted in 20000 images (35GB).
- These images were then converted to edges (2.5 GB).
- The edges were then converted to salient maps, using map size 3 (49.7 MB).
- Only the salient maps are required to be stored in the drone navigation system, **~49.7 megabytes storage per 400 square kilometre area**.

FLYING AT DIFFERENT ALTITUDES

AI²

Image at 1000 metres altitude (1920x1080 pixels)

Image is scaled to match image features at 3000 metres altitude (595x334 pixels)

Image at 3000 metres altitude (1920x1080 pixels)

At lower altitude, the image features are larger compared to the features of image at higher altitude. Therefore, the image needs to be scaled to match the features at higher altitude based on ground elevations.

FLYING AT DIFFERENT ALTITUDES

Scaled image (595x334 pixels) from image of 1000 metres altitude

Salient Map Size 3 (x5) of scaled image (95x51 pixels)

Salient map generated from the scaled image at lower altitude (1000 metres), in comparison to the salient map at 3000 metres altitude.

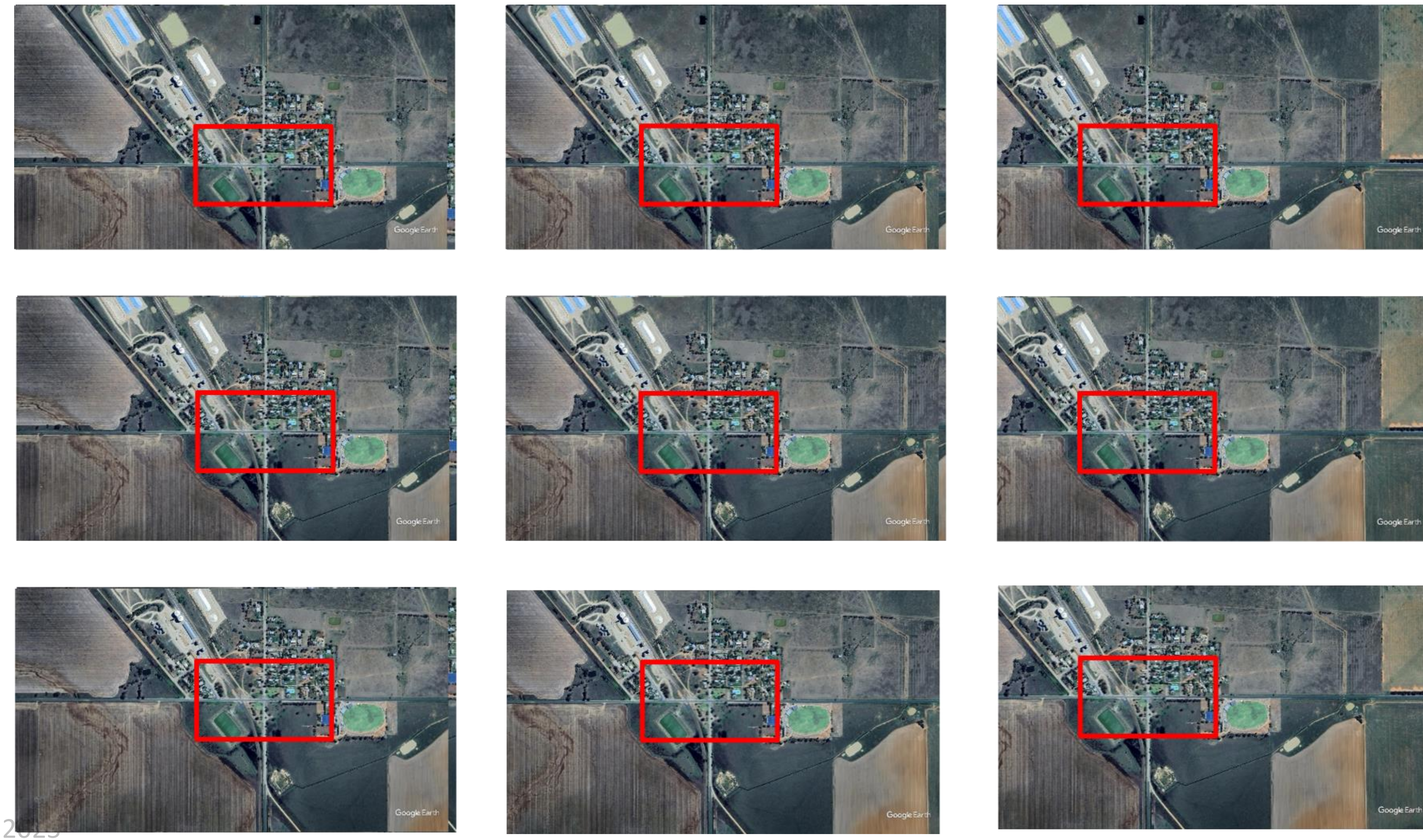
Image at 3000 metres altitude (1920x1080 pixels)

Salient Map Size 3 (x5) of image at 3000 metres altitude (316x176 pixels)

FLYING AT DIFFERENT ALTITUDES

Nine neighbouring matching maps from 400 square kilometre area to scaled flight image

Scaled flight image



HEADING ERRORS

AI²

- The images from the drone are required to be properly aligned with North before processing, using the drone's current heading, provided by its onboard sensor.
- However, the heading provided by sensor sometimes could be wrong, because of faulty sensor, or other factors. Therefore, mitigations (rotation correction) are required.
- Experiments with heading errors of between -5 to 5 degrees.

Heading Error (°)	Correction Angle(°)	Distance Error (m)	% of Saliency Matching
-5	5	3.30	86.00
-4.5	4	5.06	87.08
-4	4	1.50	90.00
-3.5	3	2.13	89.62
-3	3	3.19	89.23
-2.5	2	4.24	91.43
-2	2	3.14	92.16
-1.5	1	2.02	94.26
-1	1	2.47	95.85
-0.5	0	1.96	92.32
0	0	1.57	90.94
0.5	-1	1.56	94.60
1	-1	2.91	95.75
1.5	-2	0.57	95.28
2	-2	1.31	98.67
2.5	-2	2.18	93.05
3	-3	2.02	95.73
3.5	-4	1.56	92.42
4	-4	2.67	96.55
4.5	-5	2.23	92.88
5	-5	1.89	93.98

* Distance error is accurate within 1 pixel of salient map

CONCLUSION

AI²

Approach	Description	Processing speed	Data storage	Environment adaptability	Cost
Inertial navigation systems (INS)	Uses accelerometers and gyroscopes to track motion and orientation	Very fast (real-time)	Minimal (no map needed)	**Affected by drift problem**	$
Simultaneous localization and mapping (SLAM)	Builds map from sensor (LIDAR)	**Slow (heavy computation)**	**High (map storage, 3D model)**	Robust in static environment	$$$$
Feature-based localization	Matches onboard visual to preloaded maps	Variable, depends on matching algorithms, most use Jetson	**High**	**Sensitive to lighting conditions**	$$$
Visual odometry (optical flow)	Uses onboard camera	Moderate (image processing)	Moderate (image logs)	**Doesn't work at high altitude**	$$
AI-based systems	Combines multiple sensors and models, but **requires careful training and tuning**	Variable (depends on model), most use Jetson	Moderate to high	Highly adaptable	$$$
Neuramatix	Matches onboard visual to preloaded **salient maps**	Very fast (real-time)	Low	Highly adaptable	$

CONCLUSION

AI²

- These systems are commonly combined to balance trade-offs.
- However, combination of systems often results in higher cost.
- Examples:
  - Aurelia X6 Max: AI-driven INS [https://bavovna.ai/gps-denied-navigation/]
  - OMNInav: combining SLAM, AI and fusion of sensors (INS) [https://oksi.ai/omninav-gps-denied-navigation/]
  - Raptor: feature-based localization, using onboard camera, and 90 million-plus sq km of global 3D terrain data [https://www.maxar.com/press-releases/maxar-launches-raptor-a-first-of-its-kind-software-that-unlocks-next-gen-gps-resilience-for-autonomous-systems]