Subsurface targets detection using Faster R-CNN for Unmanned Aerial Vehicle Magnetic Survey

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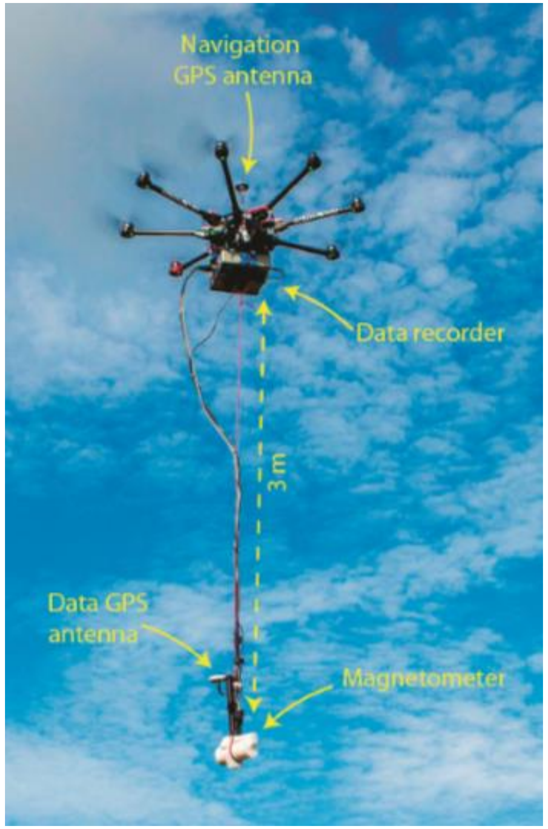
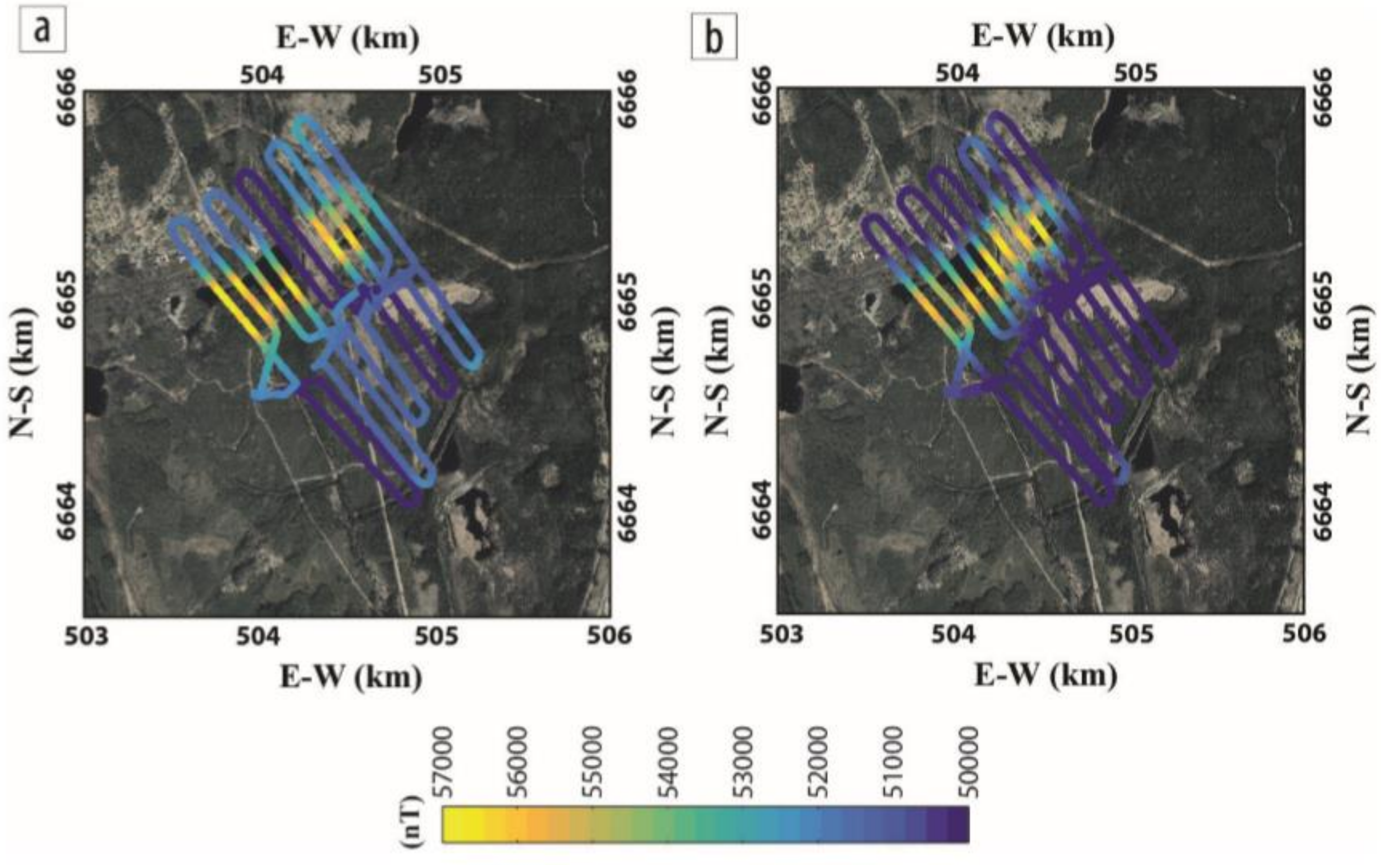
- The traditional handheld magnetic survey can acquire high-density magnetic data, but it is time-consuming, labor-intensive, and limited by the terrain.

- The fixed-wing airplane-based magnetic survey can realize fast and wide-range measurement, but the spatial resolution of magnetic is low and only suitable for the detection of large targets.

- Unmanned Aerial Vehicle (UAV) system provides an excellent platform in achieving low-cost, low-altitude, long-range, fast magnetic field monitoring, compared with the terrestrial, manned aircraft, and satellite magnetic survey, which opens a brand-new era in using UAV-borne magnetic survey.





- Our work focus on the remote detection of near-surface targets, like Unexploded Ordnance (UXO) ,using the UAV magnetic measurement system. The UAV magnetic survey shows significant advantages in the magnetic spatial resolution, work efficiency and experimental safety. However, UAV-borne magnetic survey is facing a lot of tough challenges due to its limited load capacity, short battery life, interference field generated by the drone, uncertainty of the position of the magnetic sensors, and so on.

- To date, considerable progress has been made in the integration and testing of the UAV-magnetometer system. However, the research on the processing and interpretation of UAV magnetic data is quite rare and challenging because of the low quality of magnetic data and the lack of interpretation methods for the UAV-based magnetic survey.

1.UAV-MAGNETOMETER SYSTEM

- A novel UAV magnetic measurement system is developed for the detection of near-surface targets. The UAV-Magnetometer system consists of two magnetometers, radar altimeter, differential GPS, data recording module and power module, as shown in Figure 1.

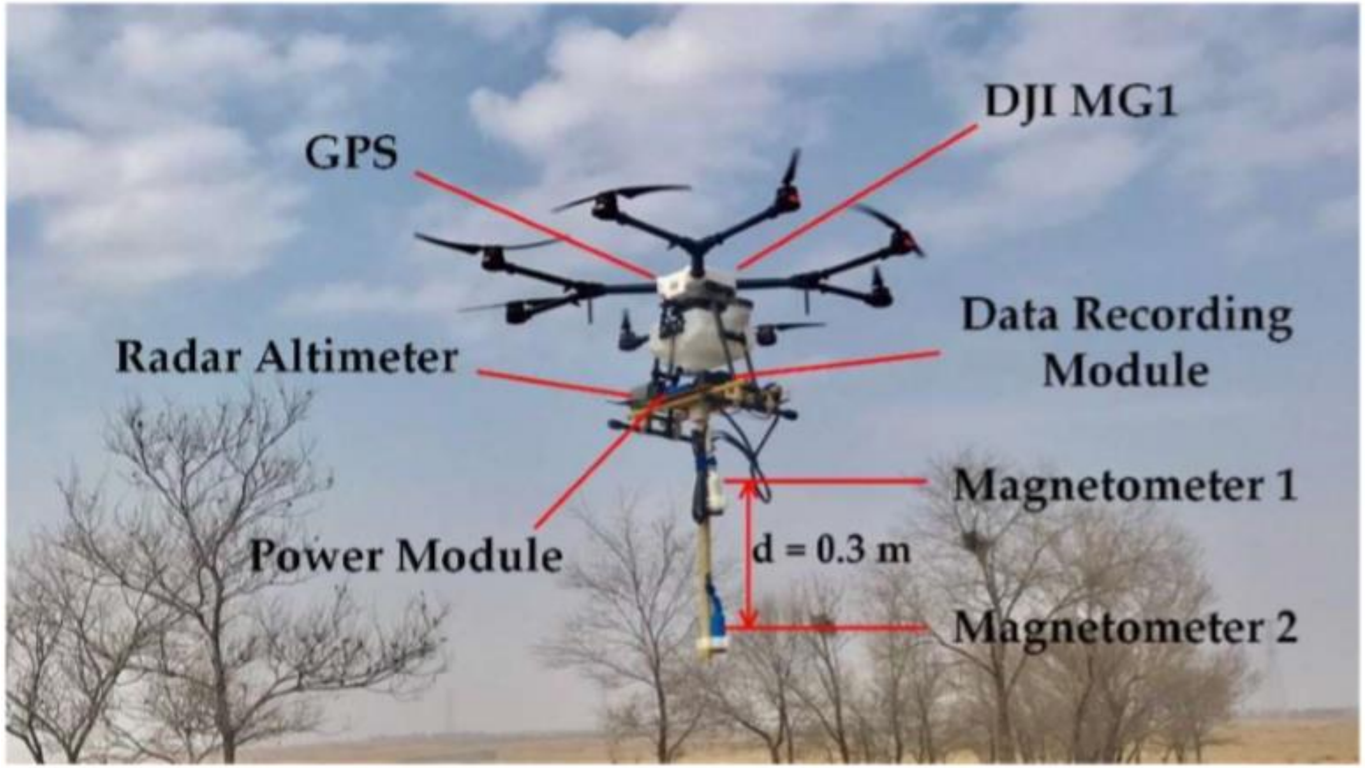


Figure 1. The Unmanned Aerial Vehicle (UAV)-magnetometer system. The top magnetic sensor is labelled as magnetometer 1 and the bottom magnetic sensor is labelled as magnetometer 2.

- The flight platform is the eight-rotor DJI MG1 unmanned aerial vehicle. Two Cs optically pumped magnetometers are mounted on the center of drone by a vertical boom, the vertical distance between two sensors is 0.3 m. The Cs optically pumped magnetometer is a lightweight, small-sized CAS-L3 designed for the drones by the Aerospace Information Research Institute, Chinese Academy of Sciences, China.

- The operating range of CAS-L3 is 15,000nT to 105,000nT and the noise sensitivity is 0.6 pTrms√Hz⁄@1 Hz in the shielded room. The radar altimeter is RD2412R, manufactured by SZ DJI Technology Co., Ltd., China. It measures the height of the drone above the ground ensuring that the UAV can actively avoid obstacles and fly safely in the complex terrain. Differential GPS T300, produced by Shanghai Sinan Satellite Navigation Technology Co., Ltd., is used to acquire the location of UAV, positioning accuracy is on the order of cm.

- Magnetic field data and position information are synchronized by the pps (pulse per second) signal. The custom-designed data recording module is constructed and fixed on the bottom of the UAV system. All modules have been installed reasonably to ensure the stability and balance of the UAV-magnetometer system; the entire payload weighs 4.37 kg meeting the requirement of the maximum load (13.7 kg).

Figure 2. The UAV-magnetometer system. Notice that the boom is half-fixed.

2. WORKFLOW FOR UAV-BORNE MAGNETIC SURVEY

- Applied to the near-surface targets detection, the workflow of the UAV magnetic survey is divided into three stages, the first one is data collection, including the preparation of test area, the setting of flight path and drone; the second phase is data processing, involved some signal processing methods to obtain high quality magnetic field data, the final stage is data interpretation, achieving the automatic detection and position estimation of buried targets. The complete workflow is listed in Figure 3.

- The mission planning is the preliminary task of the magnetic survey, comprising the setting of test area, profiles, and the drone. For the planning of the test site, the region of interest, topography, vegetation, weather and other factors need to be evaluated carefully. For the planning of the profile, the flight direction, length, and spacing should be considered. In addition, the working mode of UAV should be selected, such as manual or automatic flight, flying speed, above ground level (AGL), battery life. In short, the perfect mission planning lays the foundation for the UAV magnetic survey, ensuring that the drone can fly normally and collect the magnetic data.

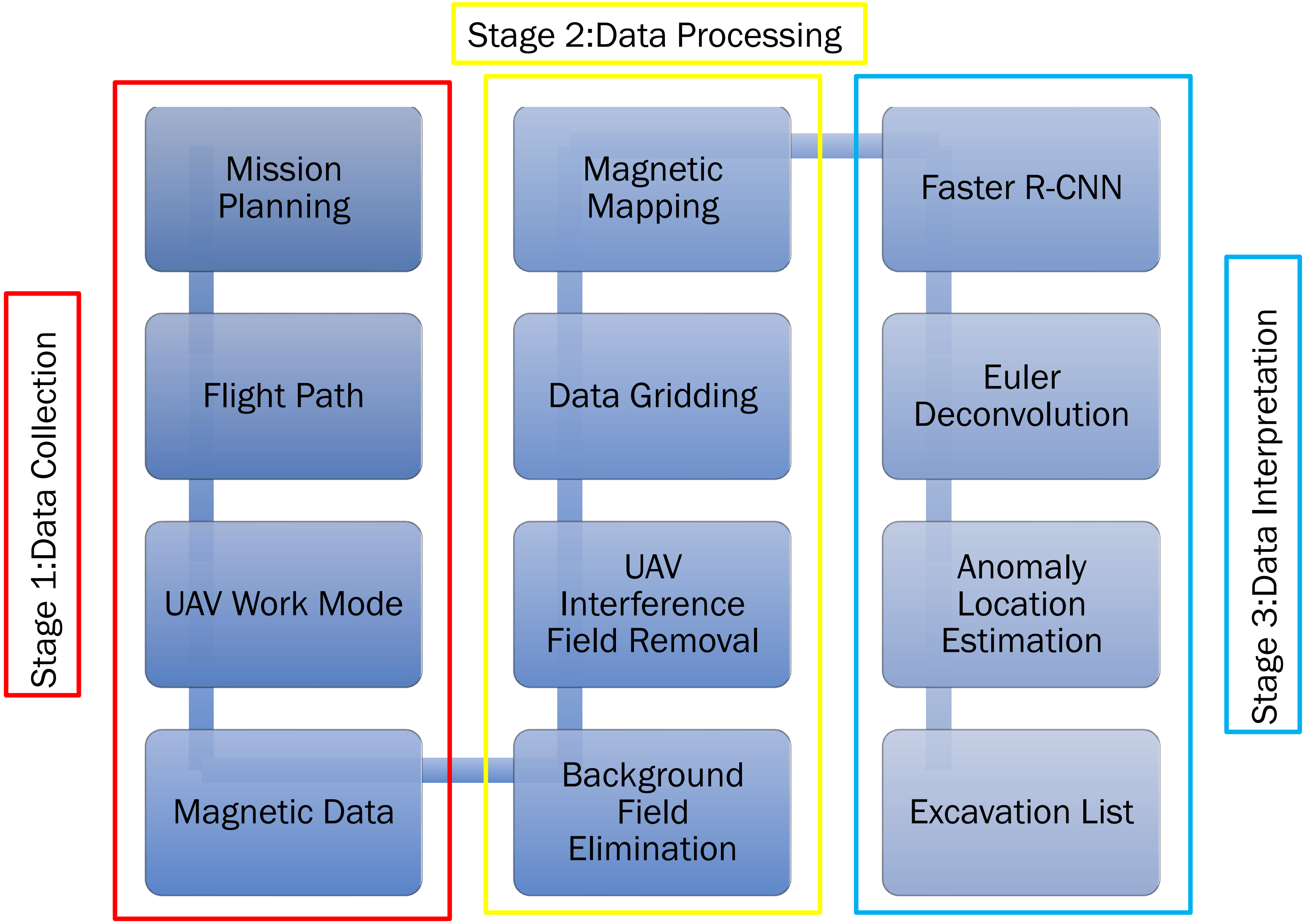


Figure 3. The workflow for UAV magnetic survey.

The purpose of data processing is to reduce the noise signal, extract magnetic anomaly signal, improve the signal-to-noise ratio (SNR). This stage contains the following actions intended for different functions:

- Background field elimination: The background field consists of the local geomagnetic field and the magnetic field produced by the ambient sources, like power grid, traffic, buildings. We are concerned with the magnetic anomaly signal from the underground objects, so the background field should firstly be removed.
- UAV interference field removal: Unlike the interference field from the external environment, UAV interference field is an inherent noise signal from system, which is related to the attitude of the drone. Herein, we propose a calibration method based on the signal correlation to separate the magnetic anomaly signal from the total field signal.
- Data gridding: It is customary to perform data gridding, which is to compute the magnetic field of regular grid nodes from the irregularly distributed sampling points by interpolation. Thus, a two-dimensional contour magnetic map is produced to reflect the abnormal distribution of the entire test area.

The aim of the magnetic data interpretation is to estimate the location of underground targets based on the spatial magnetic field data. The input data is the gridded magnetic data and a magnetic contour map (RGB image) of the test area, the Euler deconvolution based on Faster R-CNN method is developed to determine the 3D location of the targets.

3. UAV INTERFERENCE FIELD REMOVAL

- The interference field generated by the UAV platform is in the same frequency band as the anomaly field we are interested in, so it cannot be suppressed by the filter. A two-channel linear time-invariant (LTI) model is established based on the configuration of UAV-magnetometer system, as illustrated in Figure 4.

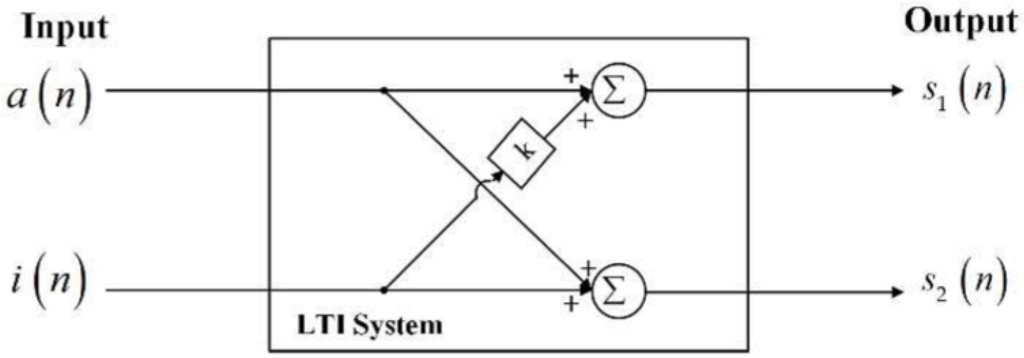


Figure 4. The signal model for the UAV-magnetometer system.

- All signal is sampled at the sampling rate of f_s, n indicates the sampling points, the input of LTI $a(n)$ denotes the magnetic anomaly field, $i(n)$ denotes the UAV interference signal, the outputs of LTI $s_1(n)$ and $s_2(n)$ are the measured total field signals by the magnetometer 1 and 2, respectively. The magnetometer 1 is closer to the interference sources than magnetometer 2;therefore, the interference field measured by magnetometer 1 is k times the interference field measured by magnetometer 2. The signal model is expressed as follows:

$$s_1(n) = a(n) + k * i(n)$$
$$s_2(n) = a(n) + i(n)$$

- The differential signal between two sensors $d(n)$ is:

$$d(n) = (k-1) * i(n)$$

- The interference signal is uncorrelated with the magnetic anomaly signal, so the outputs of correlating $d(n)$ with $s_1(n)$ and $s_2(n)$ are:

$$r_1 = \sum_{i=1}^{N} s_1(n)d(n) = k(k-1)\sum_{i=1}^{N} i^2(n)$$
$$r_2 = \sum_{i=1}^{N} s_2(n)d(n) = (k-1)\sum_{i=1}^{N} i^2(n)$$

- Consequently, the transfer function of k is estimated as:

$$k = \frac{r_1}{r_2}$$

- the magnetic anomaly field and the interference field are separated from the total signal:

$$i(n) = \frac{d(n)}{k-1} = \frac{s_1(n) - s_2(n)}{k-1}$$
$$a(n) = s_2(n) - i(n) = \frac{k * s_2(n) - s_1(n)}{k-1}$$

- The results after removing the UAV interference field are illustrated in Figure 5, The magnetic anomaly field and UAV interference field is superimposed and the UAV interference field from the magnetometer 1 even masks the anomaly signal completely. After the compensation, the magnetic anomaly signal and the interference field are separated from the total field, the extracted anomaly field indicates two potential targets, which is in accord with the actual scene.

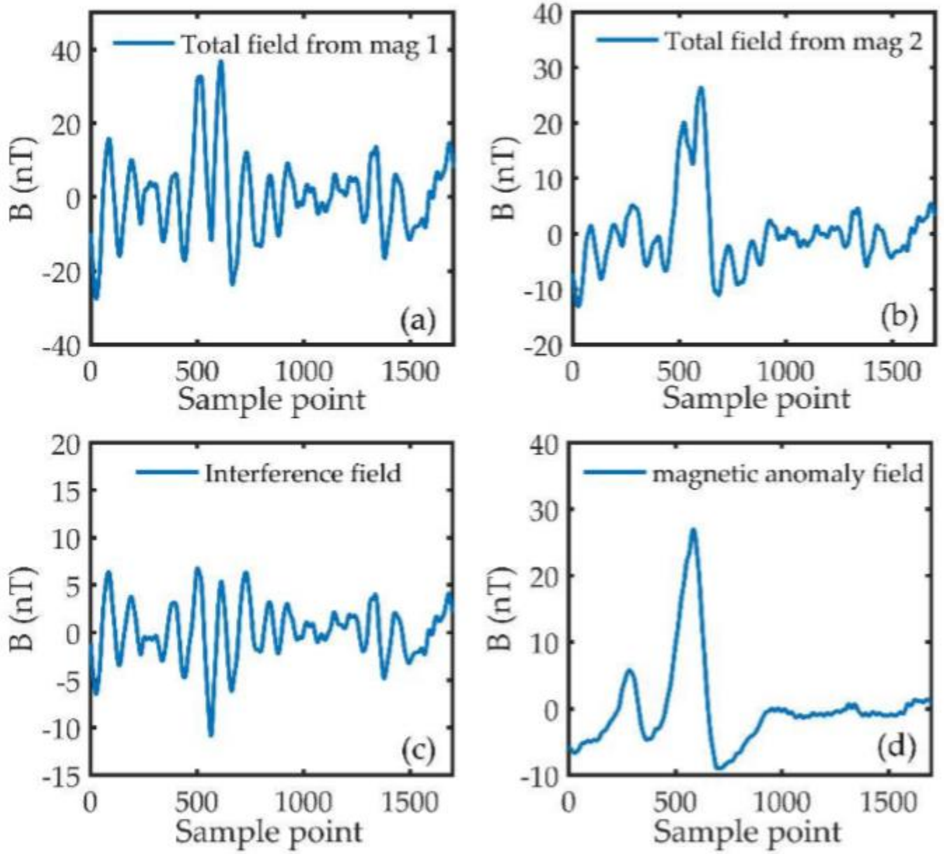


Figure 5. The removal of the UAV interference field. (a) The outputs of magnetometer 1; (b) The outputs of magnetometer 2; (c) The separated UAV interference field; (d) The separated magnetic anomaly field.

4. FASTER R-CNN

- R-CNN (Regions with CNN features) is a recently introduced deep learning based object detection and classification method. R-CNN’s have proved highly effective in detecting and classifying objects in natural images. There are many implementations of the R-CNN algorithm available on the web in TensorFlow, PyTorch and other machine learning libraries. For more detailed information about R-CNN’s, we refer to [*] and [**].

- A R-CNN uses neural networks to solve two main problems: 1.Identify promising regions (Region of Interest – ROI) in an input image that are likely to contain foreground objects; 2.Compute the object class probability distribution of each ROI – i.e., compute the probability that the ROI contains an object of a certain class. The user can then select the object class with the highest probability as the classification result.

- R-CNNs consist of three main types of networks: 1.Head; 2.Region Proposal Network (RPN); 3.Classification Network. R-CNNs use the first few layers of a pre-trained network such as ResNet 50 to identify promising features from an input image. The convolutional feature maps produced by the head network are then passed through the RPN which uses a series of convolutional and fully connected layers to produce promising ROIs that are likely to contain a foreground object. These promising ROIs are then used to crop out corresponding regions from the feature maps produced by the head network. This is called “Crop Pooling”. The regions produced by crop pooling are then passed through a classification network which learns to classify the object contained in each ROI.

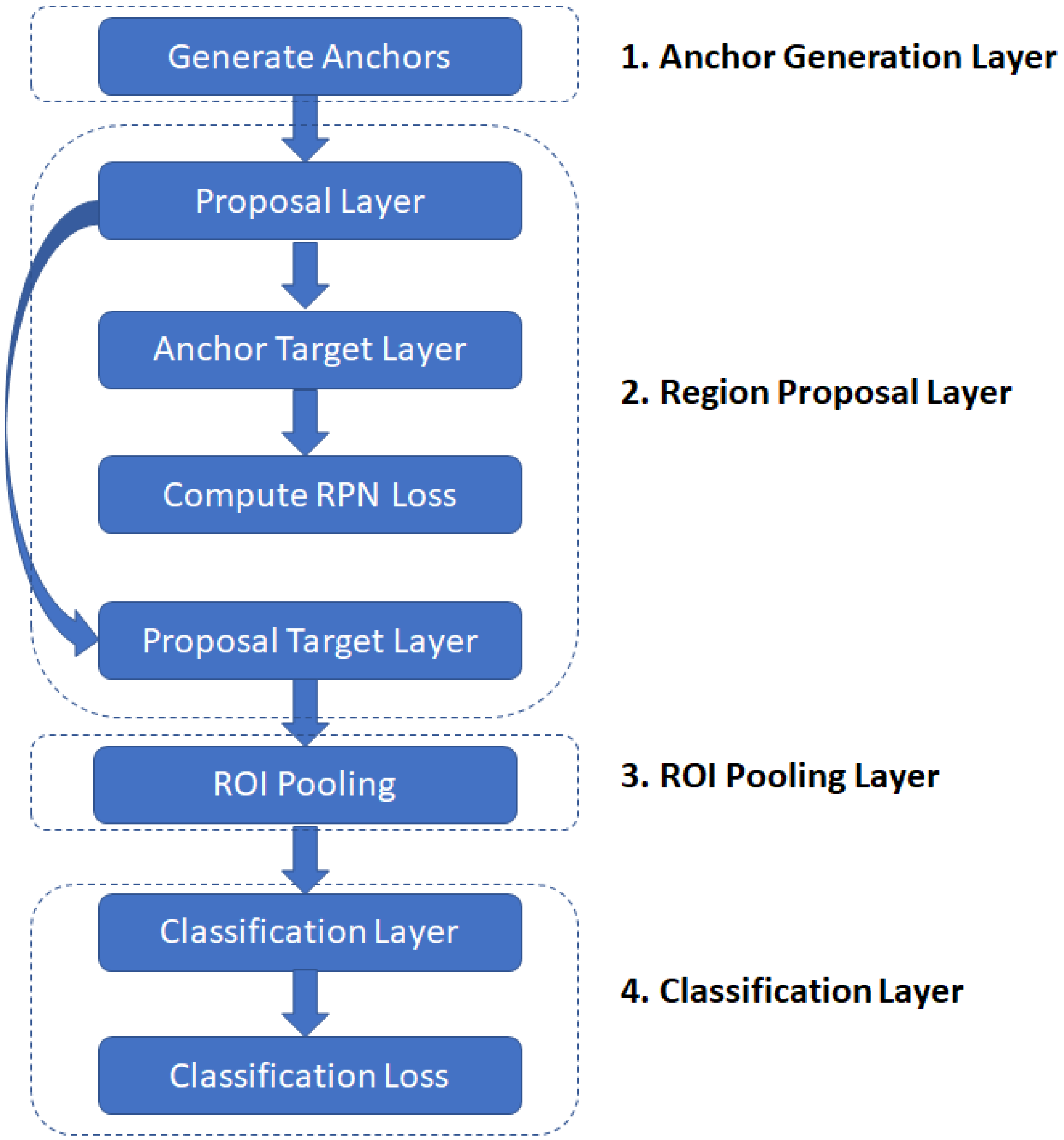


Figure 6. The software implementation of R-CNN

In the software implementation, R-CNN execution is broken down into several layers, as shown in Figure 6. A layer encapsulates a sequence of logical steps that can involve running data through one of the neural networks and other steps such as comparing overlap between bounding boxes, performing non-maxima suppression etc.

- Here, the input image is the magnetic contour map of the survey area. Unlike the generic object detection, Faster R-CNN is used to detect the anomalous field generated from ferrous targets. The ferrous target is approximately a magnetic dipole, when the distance between sensor and target is more than three times the maximum size of target. The anomaly field produced by a magnetic dipole is the bipolar anomalous field with positive and negative anomalies typically. Consequently, the targets to be tested which have a bipolar anomalous field will be labelled as Targets.

- The key points for applying Faster R-CNN to the magnetic survey are as follows: 1)Dataset: All samples in the dataset are in picture format. The dataset contains 740 2D magnetic contour maps, divided into 85% training set, 15% test data set. The changing number, size, position, depth, azimuth, declination, remanence of the targets and background fields make the magnetic maps different. The training set contains 629 images with 2840 instances of labeled anomalies, the test set contains 111 images with 520 labeled anomalies. Figure 7 shows some examples of the dataset. 2)Detection: our Faster R-CNN object detection network is composed of a feature extraction network followed by two subnetworks, the feature extraction network we use is a pre-trained CNN called ResNet-50, the initial learning rate is set to be 0.001 and the mini-batch-size is set to be 2. Finally, the output for predicted bounding box contains 6 values(top, left, bottom, right, score, class). 3)Evaluation: The trained Faster R-CNN yields a mAP of 85.42%, and the mAP is 80.68% for the test sets, indicating the reliable detection performance for the target anomaly.

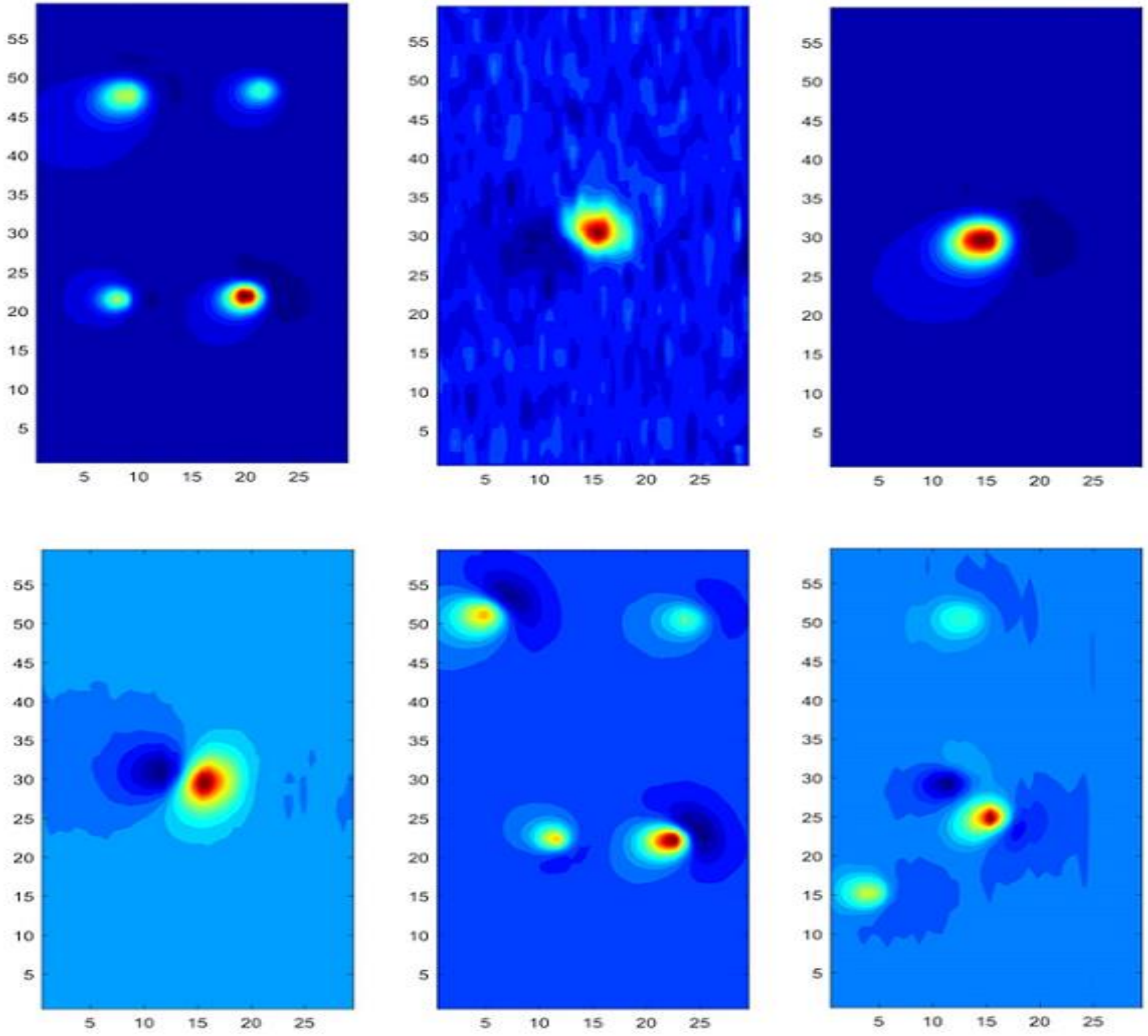
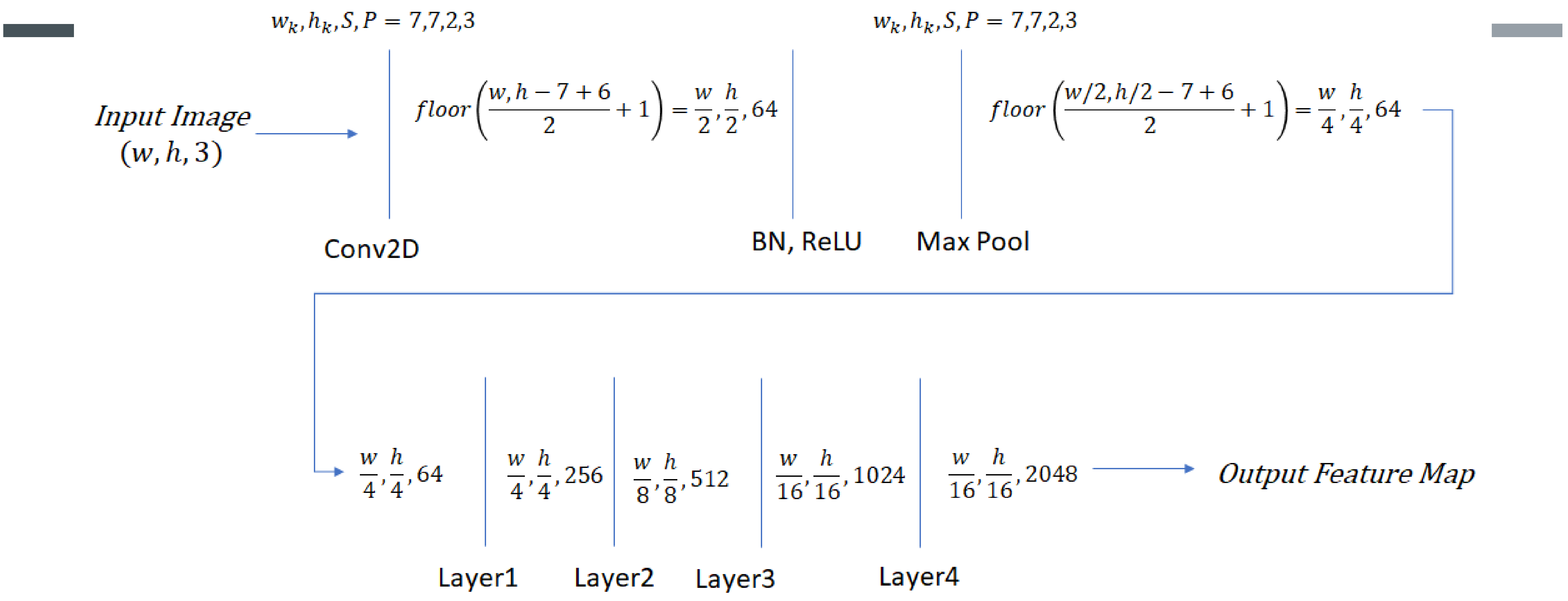


Figure 7. Partial samples in the dataset of Faster R-CNN. Each image is a 2D magnetic contour map, the unit of magnetic field in all figures is nano Tesla.



For a conv2d layer with filter parameters
(windows size, stride length, padding)
w_k, h_k, S, P, if input dimension $= w, h$,
output dimension $= \frac{(w,h)-(w_k,h_k)+2P}{S} + 1$

Figure 8. ResNet-50 Network Architecture

5. UAV-BORNE MAGNETIC SURVEY

- We have tested the UAV-magnetometer system and carried out the field experiments for the detection of near-surface targets in Hebei, China, in October 2019. The complete workflow proposed in this paper has been performed. A 28 m×33 m rectangular area was selected as the survey area, five ferrous objects with different diameters and heights were pre-buried into the test area. The programmed flight profiles run along the south-north direction, length is 62 m, spacing is 0.5 m. On a clear day, the UAV-magnetometer system was set to fly automatically as the planned profiles with AGL 2 m, the flying speed was set to 2 m/s. Figure 9 shows the flight path of the drone, the actual spacing between adjacent profiles is 0.3–0.7 m, limited by the effect of wind and the positioning accuracy of UAV. The WGS-84 coordinate was transformed into the local cartesian coordinate system along the north, east and down, the origin was the starting point of the flight. The effective profiles above the region of interest has been obtained after cutting off the undesired flight and curved data (Figure 9).

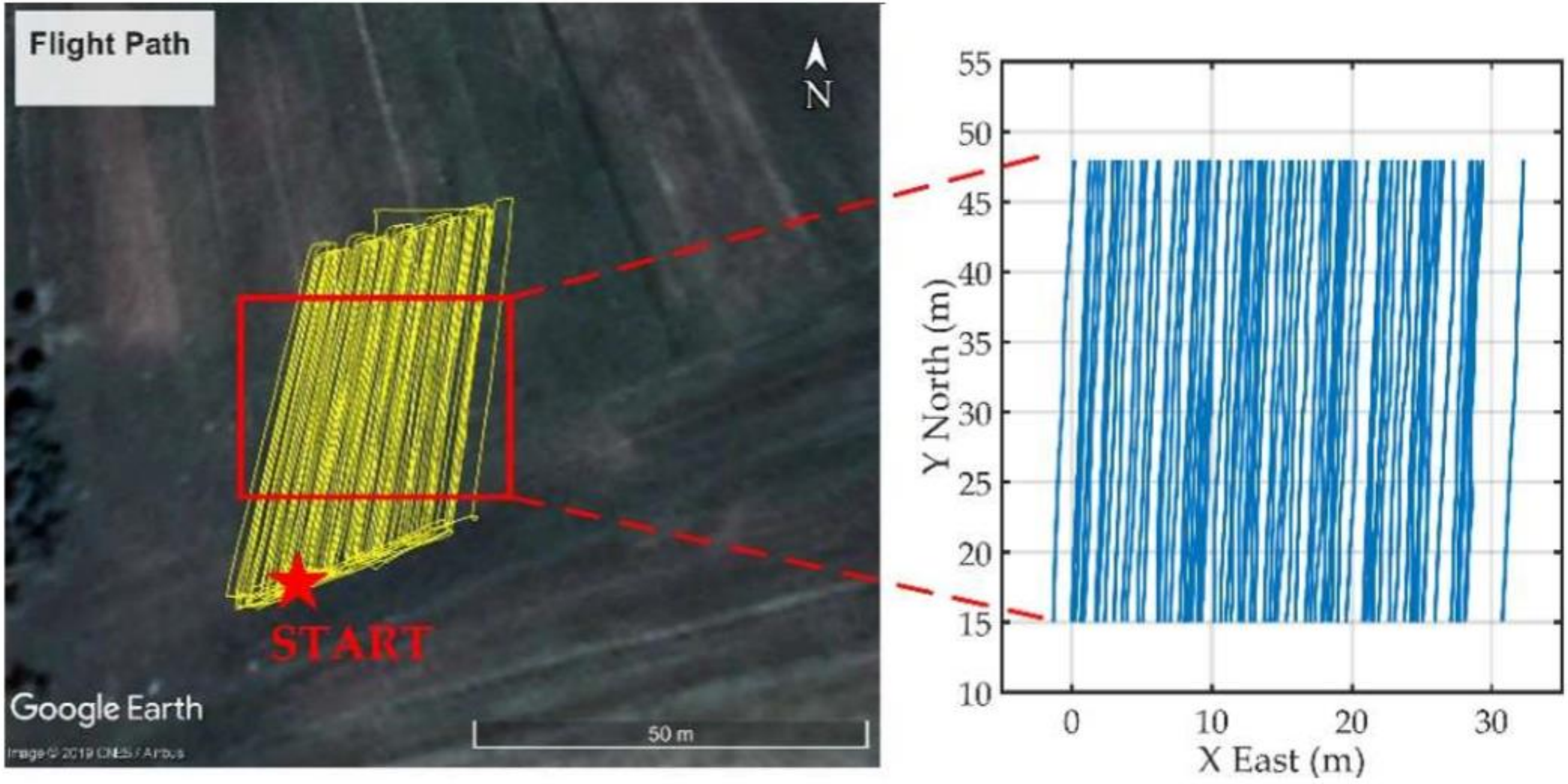


Figure 9. The planning of test site and flight path, multiple parallel profiles along the south-north direction cover the test area. The “START” is the starting point of the drone in the experiment and the trimmed profiles in the local coordinate are given on the right.

- Because of the COVID-19, the results of Faster R-CNN and our field experiment were left in my laboratory in Beijing, China and I can’t provide the detailed information about our work, what a pity!

- In our previous work which was shown above, the interpretation result is the location of subsurface targets, the characteristics of the target itself cannot be obtained. The future work is to identify the magnetic moment, size, and shape of the objects, achieving the classification of targets, like the discrimination between UXO and clutter.

References	
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