ABSTRACT

Detecting and identifying objects in satellite images is a very challenging task: objects of interest are often very small and features can be difficult to recognize even using very high resolution imagery. For most applications, this translates into a trade-off between recall and precision. We present here a dedicated method to detect and identify aircraft, combining two very different convolutional neural networks (CNNs): a segmentation model, based on a modified U-net architecture [1], and a detection model, based on the RetinaNet architecture [2]. The results we present show that this combination outperforms significantly each unitary model, reducing drastically the false negative rate.

Index Terms— CNNs, deep learning, segmentation, identification, aircraft, satellite images

1. INTRODUCTION

The last decade has seen a huge increase of available high resolution satellite images, which are used more and more for surveillance tasks. When monitoring military sites, it is necessary to automatically detect and identify objects of interest to derive trends. In this domain, aircraft recognition is of particular interest: each aircraft model has its own role, and a variation in the number of a specific type of aircraft at a given location can be a highly relevant insight. This recognition task needs to be reliable to allow the automation of site analysis – in particular to derive alerts corresponding to unusual events. Robustness to noise, shadows, illumination or ground texture variation is challenging to obtain but mandatory for real-life applications (see Fig. [1]).

Nowadays, CNNs are considered as one of the best techniques to analyse image content and are the most widely used ML technique in computer vision applications. They have recently produced the state-of-the-art results for image recognition, segmentation and detection related tasks [3]. A typical CNN architecture is generally composed of alternate layers of convolution and pooling (encoder) followed by a decoder that can comprise one or more fully connected layers (classification), a set of transpose convolutions (segmentation) or some classification and regression branches (object detection). The arrangement of the CNN components plays a fundamental role in designing new architectures and thus in achieving higher performances [4].

For segmentation tasks, the U-net architecture has been widely used since its creation by [1]. This architecture allows a better reconstruction in the decoder by using skip connections from the encoder (Fig. [2]). Various improvements have been made in the literature considering each CNN components [4], but the global architecture of the U-net is still one of the state-of-the-art architecture for the segmentation task.

For detection tasks, two main categories have been developed in the literature. The most well-known uses a two-stages, proposal-driven mechanism: the first stage generates a sparse set of candidate object locations and the second stage classifies each candidate location either as one of the foreground classes or as background using a CNN. One of the most used two-stages model is the Faster-RCNN [5], which has been considered as the state-of-the-art detector by achieving top accuracy on the challenging COCO benchmark. However, in the last few years, one-stage detectors, such as the Feature Pyramid Network (FPN) [6], have matched the accuracy of the most complex two-stages detectors on the COCO benchmark. In [2], authors have identified that since one-stage detectors are applied over a regular, dense sampling of object locations, scales, and aspect ratios, then class imbalance during training is the main obstacle impeding them from achieving state-of-the-art accuracy. They thus proposed a new loss function that eliminates this barrier (the focal loss) while integrating improvements such as the FPN [6] in their model...
known as the RetinaNet [2].

In this paper, we are looking for a dedicated and robust approach to address the aircraft detection and identification problems, that can be easily adapted to multiple applications. We propose a hybrid solution based on different CNNs strategies: a segmentation model based on the U-Net architecture [1] for a better detection rate and an object detection model based on the RetinaNet [2], a fast one-stage detector, for identifying and improving the precision. Section 2 details this concurrent approach while Section 3 presents results obtained on high-resolution satellite images.

2. CONCURRENT SEGMENTATION AND OBJECT DETECTION APPROACH

In this section, we present the choices made in designing each model considering the aircraft recognition problem, and how they interact together. These choices are based on simple observations: (i) changing the paradigm of training modifies the way features are learnt/extracted inside the model, (ii) segmentation models are really efficient but suffer from bad separation and identification of objects, (iii) in high-resolution images from satellites, aircraft are of limited size. We also based our choices on the latest developments in the field.

2.1. Segmentation CNN

Our segmentation model is based on the U-net architecture, illustrated in Fig. 2 (original architecture).

![Fig. 2. Original U-Net architecture (from [1]).](image)

For our concurrent approach, the objective of this model is: (i) to detect aircraft (without identification), (ii) to have a very high recall (in particular for the location even if the delineation is of low quality), (iii) to be robust to difficult cases (like occultation, shadow or noise). For that purpose, the U-net architecture has been updated:

- convolutional layers have been replaced by identity mapping (IM) blocks, as proposed by [7]. It has been proven that this choice eases the training and the efficiency of deep networks;
- maxpool layers have been replaced by convolutional layers with a stride of 2 (we reduce the spatial information while increasing the number of feature maps);
- the depth and the width of the network have been set accordingly to the application: spatial information is only reduced twice (while doubling filters), the encoding is composed of 36 IM blocks and the decoding of 8 IM blocks (resp. 72 and 16 conv. layers).

Skip connections of the U-net are used for a better reconstruction of the prediction map.

2.2. Object detection CNN

Our object detector is based on the RetinaNet architecture, illustrated by the Fig. 3.

![Fig. 3. Original RetinaNet architecture (from [2]).](image)

For our concurrent approach, the objective of this model is: (i) to split the detected objects and (ii) to correctly identify the objects. For that purpose, the RetinaNet architecture has been carefully set:

- one level has been added in the feature pyramid network [6] for a finest detection level (small objects);
- the backbone of the RetinaNet model to extract features is a ResNet101;
- a non maximal suppression (NMS) algorithm is used to remove duplicated results.

The focal loss proposed by [2] is used to address the foreground-background class imbalance encountered during the training.

2.3. Concurrent approach

The training strategy of each model is different. Features of the segmentation model are learnt on the aircraft objects, the model is then good at localizing objects but is not designed for separating or recognizing them. Features of the object detection model are learnt on the finest aircraft identification (see Section 3.1), the model is then good at separating and recognizing aircrafts but has a very low precision but a high recall. The idea of our concurrent approach is to use these complementary properties to improve detections. The process of the system is sequential and can be summarized by the following steps.
1. Apply the segmentation model on the unknown image to extract the prediction value for each pixel. This is the localization step.

2. Apply the object detector for each positive area of the localization step. This process can be iterative, considering how shift-invariant the object detection model is, by repeating: (i) apply the detection model, (ii) remove the detected objects from the segmentation map.

3. (optional) Study the remaining positive areas of the prediction map to increase the recall: add objects to the detected list considering size or distance to the detected aircraft.

These steps allow the definition of several operating modes considering the intrinsic qualities of the models: parameters definition can yield a system dedicated to high recall, to high precision or balanced.

3. EXPERIMENTAL RESULTS

3.1. Data information

Our method has been applied to the aircraft recognition problem. Our datasets have three levels of aircraft identification: the first level is the type of the object (‘aircraft’), the second level represents the function of the aircraft (‘bomber’, ‘civilian’, ‘combat’, ‘drone’, ‘special’ and ‘transport’) and the third level is the aircraft identification. This last level is currently composed of 61 classes (for example ‘F-16’ Fighting Falcon is a third level of type ‘combat’ and Tupolev ‘Tu-95’ a third level of type ‘bomber’). Fig. 4 shows an example of the ground truth at level 3.

![Fig. 4. Example of the ground truth at level 3.](image)

Train and test datasets have been created using images from different satellites (resolution 30-50 cm). Train tiles are of size 512 pixels, with an overlap of 128 to improve shift invariance. The test dataset is composed of 30 satellite images at unknown locations (not seen during the training). Details of the datasets are given in Table 1.

| Datasets     | N img | N obj | N tiles | Area  |
|--------------|-------|-------|---------|-------|
| Train - Seg  | 9,984 | 122,479 | 105,206 | 51,166 |
| Train - Obj  | 10,179 | 128,422 | 361,843 | 49,905 |
| Test         | 30    | 689   | -       | 403   |

Table 1. Dataset information. Areas are in km².

3.2. Method parameterization

The segmentation model has been trained using a weighted categorical cross-entropy loss:

\[ wCE(y, \hat{y}) = -\sum_{i=1}^{C} \alpha_i y_i \log \hat{y}_i \]  

(1)

where \( \hat{y} \) is the prediction, \( y \) the ground truth, \( C \) the number of classes and \( \alpha \) the median frequency balancing weights. These weights allow to balance the class distribution (compensate the high number of background pixels). ADAM optimizer has been used with an initial learning rate of 0.001 (this one is decreased on plateau considering the validation loss).

The object detector has been trained using the focal loss for the classification and the smooth L1 loss for the regression. We slightly increased the weighting of the classification compared to the regression (with a factor of 1.5) and used the ADAM optimizer with an initial learning rate of 0.0004. The NMS threshold has been set to 0.35 (aircraft have a low overlap rate).

For both trainings, various data augmentations have been used to increase model generalization: geometric transformations (flip, rotate) and radiometric transformations (grayscale, histogram equalization and normalization). For both models, different operating modes can be set by modifying two parameters: the prediction threshold and the minimum size. We empirically defined several modes, to balance recall and precision.

3.3. Quantitative and qualitative results

On our test dataset, we evaluated: (i) the segmentation model alone (an overlap of 50% is required to be considered as a detected aircraft), (ii) the object detection alone and (iii) our concurrent approach. Table 2 shows the detection results for each case, with two different modes: one balanced between recall and precision and one with a better recall. As expected, we can observe that our concurrent method allows to significantly increase the detection results compared to the segmentation model or the detection model alone: errors of each model are corrected by the other one to obtain better results (the false positives produced by the two models are not the same). This is illustrated in Fig. 5: we can observe that false positives obtained with the object detection model are removed by our method.

On the same test dataset, we evaluated the identification of well-detected aircraft. The identification rate for the level 2 is...
Table 2. Quantitative results of the aircraft detection on the test dataset (R: recall, P: precision).

|                | Balanced mode | Recall mode |
|----------------|---------------|-------------|
|                | R  | P  | R  | P  |
| Segmentation   | 0.91| 0.78| 0.95| 0.5 |
| Object detection| 0.87| 0.75| 0.95| 0.37 |
| Our approach   | 0.95| 0.88| 0.96| 0.84 |

Fig. 5. Visual comparisons of ground truth (light green), the segmentation result (pink), the object detection model (orange dotted lines) and our method (light blue).

0.91 and for the level 3 is 0.80. Some errors happen because of the definition of some level 3 labels: regrouping different aircraft in the same class (for example small-aircraft) can lead to confusion with combat aircraft. This can be seen in Fig. 6: the misclassified aircraft in the top image should have been assigned the small-aircraft label.

4. CONCLUSION AND PERSPECTIVES

In this work, we developed a concurrent method combining two CNNs: a segmentation model and a detection model. We have shown that this combination allows to significantly improve aircraft detection results (very low false detection rate and high rate of good identification). In the future, we plan on: (i) refining our level 3 dataset in order to avoid some identification confusions and (ii) designing an all-in-one model integrating level 1 and level 3 features in the same architecture.

5. REFERENCES

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