Implementation of Runway Detection Systems using Machine Learning

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1 Context

This internship proposal lies within the currently very active research field aiming at implementing Machine Learning techniques to increase autonomy level and reliability of autonomous aerial vehicles, in accordance with the EASA roadmaps[1] [1]. Recent advances in vision sensors and hardware computing performances, together with improved learning algorithms, make vision-based solutions a real asset to improve guidance, navigation and control architectures for autonomous flights. In particular, during landing, considered by far the most critical phase, vision-based solutions are proven to be extremely useful for enriching data fusion algorithms and consequently drone absolute/relative positioning calculations [2]. However, image processing techniques employed until now for runway detection are mostly based on low level feature extraction and/or pre-knowledge of the landing site geographic

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[1]`https://www.easa.europa.eu/downloads/109668/en`

data [3, 4]. For all these reasons, this proposal focuses on the implementation and evaluation of Machine Learning techniques for runway detection on aerial images.

2 Research Objectives

Vision-based runway detection can have significant application in advanced landing systems for fixed-wing commercial or military aircraft, and unmanned flying drones. The detection of runways in aerial images is a hard task due to the high variety of contextual information, image patterns, and imaging conditions (i.e. camera exposure, weather conditions, observation angles). In addition, the topological similarity to other existing entities and contexts (for example highways, rivers and coast lines) complexifies remarkably the feature identification process.

Another issue concerning Computer Vision for aerospace applications is the quality of the training dataset. Almost all remote sensing image datasets have limitations, in terms of size, representation of some classes or diversity of scenes and contexts.

Different methodologies have been investigated to tackle the problem of runway detection and are described in [5]. The majority of the proposed early solutions in literature relies on handcrafted approaches and/or shallow trainable convolutional neural network (CNNs). However, more recent advances confirm that deep convolutional neural networks (DCNNs) are best suited for this type of problems and generally outperform the previous one. Different architectures for DCNNs exist and are worth of investigation for the runway detection problem [5].

On these bases, the objectives of this research internship are as follows:

- implementation of a reliable generator of aerial images for training and validation of Computer Vision algorithms;
- design of a vision-based algorithm for region of interest (ROI) extraction and runway detection;
- evaluation of the achieved detection performance.

3 Project Description

To achieve the proposed objectives, the main issues are the generation of the labeled images, and the evaluation of the performances of different classifier structures. A

general overview of the architecture to be implemented is given in Figure 1.

The study will be carried out as follows:

- literature review on Machine Learning and Computer Vision techniques (classification [6], segmentation [7], detection and localization [8]), transfer learning [9] and the runway detection problem;
- generation of a first dataset and preliminary DCNNs training using a classical Deep Learning library like Pytorch [10];
- propose a method to automatically generate consistent synthetic images and programmatically label them;
- propose a classifier architecture, or a method based on pre-trained networks[2], able to identifies ROIs and extract runways from images.

Good knowledge in Probability-Statistics and Matlab/Python programming.

[2] `https://pytorch.org/hub/hustvl_yolop/`

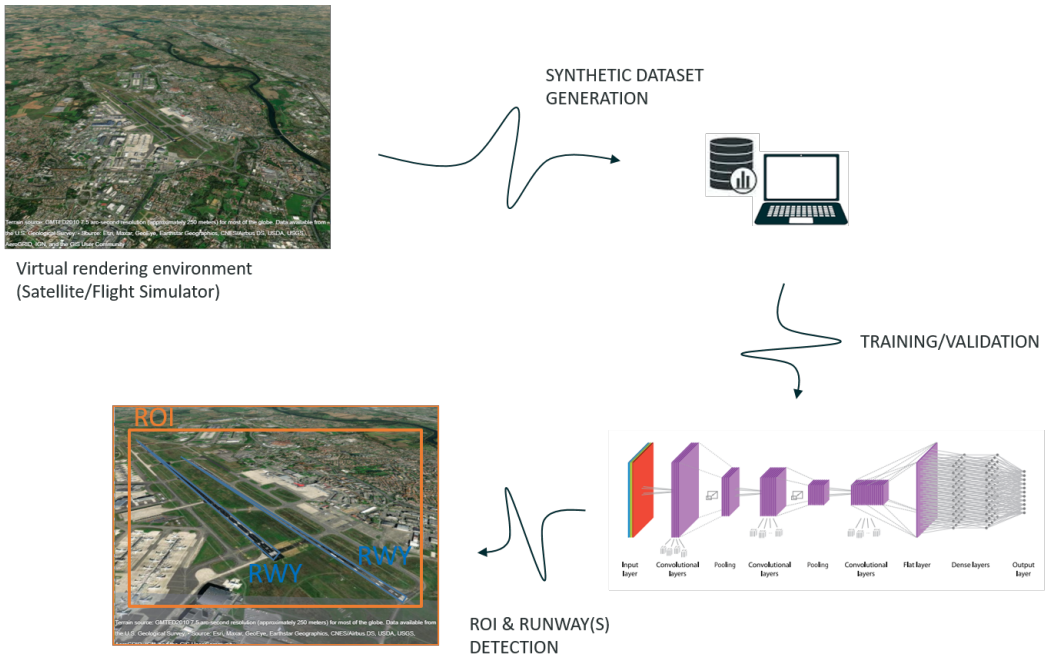

Figure 1: General architecture of the runway detection system to be implemented.

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