Radar Classifier for Small Manned Air Targets

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***Abstract* — The ALFA project aims at timely detection, tracking, classification, and intent assessment of LSS targets. The system relies on a heterogeneous sensor suite, including radar. The objective of the radar component is sector surveillance including target classification. Since the revisit time needs to be short, classification must be done with very short time-on-target. Based on measurements, three suitable features for classification of two relevant target classes, i.e., small aircraft and helicopters, have been developed. These features exploit the targets' micro-Doppler characteristics and their evolution over time. Best classification performance is obtained by using a combination of these features and by considering the variation of the features' distributions depending on the signal-to-noise ratio.**

***Keywords* — micro-Doppler, range-Doppler, classification, radar.**

I. Introduction

Around the Strait of Gibraltar the African and European continents come very close together; the distance varies from only 14 km to 44 km. This short distance is easily and quickly traversed by small boats or aircraft and even drones, which may be exploited to smuggle drugs from Morocco to the mainland of Europe through the south coast of Portugal or Spain. The current sensor systems for border control focus on monitoring the sea and the airspace above. These systems have difficulty tracking small air targets crossing the coastline and flying further inland due to sensor limitations, terrain features or buildings. In turn this makes it difficult to timely intercept such aircraft might they exhibit suspect behaviour. The Advanced Low Flying Aircraft Detection and Tracking (ALFA) project has been initiated to address this capability gap.

ALFA is a three-year European Horizon 2020 project, which was initiated in 2017. The final objective of the ALFA system is timely detection, tracking and classification of Low, Small and Slow (LSS) air targets in support of existing surveillance systems for border control [1]. The focus is on the following classes of LSS targets: small (manned) aircraft and helicopters, hang gliders, and drones. The ALFA system should furthermore assess the intent of suspect air targets and timely provide a prediction of the landing or dropping zone, such that law enforcement can intercept the illicit transport. The ALFA system is developed for maritime border surveillance, but it is based on a heterogeneous sensor suite and should be suitable for other missions such as event protection or the security of critical infrastructure.

The ALFA system is built around an open architecture infrastructure, see Fig. 1. This infrastructure connects the ALFA prediction core, sensor stations, external surveillance systems, (gap-filling) mobile sensors, and end-user displays. The ALFA sensors form a heterogeneous set including radar, electro-optical, and RF emitter localization components. The information collected by the various sensors is combined in the ALFA core, which performs the target classification and intent assessment and provides the landing site prediction.

In this paper the focus is on the radar component of the ALFA system. The radar component needs to detect, track and classify the relevant low-flying targets. Since the targets are manoeuvrable it is important to maintain short revisit times. Consequently, the targets must be classified while using the standard (scanning) surveillance waveform. Thus relevant target features must be found that can indeed be extracted using very short time-on-target. Target features suitable to classify drones and discriminate them from birds have already been presented in [2]. In addition to that study, here features are discussed suitable for the classification of manned helicopters and manned fixed-wing aircraft.

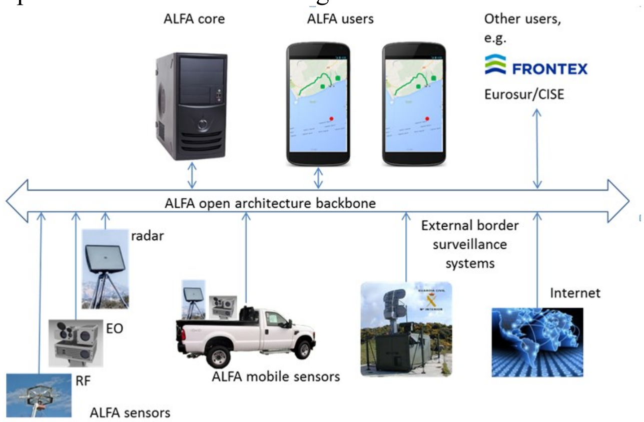

Fig. 1. The high-level ALFA system architecture [1].

To find and evaluate potential features, measurements of the two target classes (i.e., helicopter and fixed-wing aircraft) have been performed. The measurements and some promising features are discussed in Section II. Subsequently, in Section III, the radar classification chain is explained. The classification results are evaluated in Section IV. Finally, conclusions are provided in Section V.

II. TARGET FEATURES DEVELOPMENT

A. Measurement Campaign

Measurements of a manned helicopter and fixed-wing aircraft have been performed early 2018 at the seashore in The Netherlands. The helicopter and aircraft flew different tracks along the coastline offering a relevant radar sea clutter environment. Measurements have been conducted for incoming and outgoing flights, under diverse aspect angles, altitudes, and ranges. They are therefore representative for a large number of operational situations. The targets were a Hughes 300C helicopter and a Cessna 150 small fixed-wing aircraft. The helicopter has a three-bladed main rotor of 8.2 m diameter and a rotation rate of about 470 RPM. The fixed-wing aircraft has a wingspan of around 10 m. Its propeller diameter is about 180 cm and its rotation rate is comprised between 2200 and 2400 RPM.

The measurements were done with the SQUIRE radar developed by Thales Nederland. SQUIRE is a Frequency Modulated Continuous Wave (FMCW) radar [3]. During the measurements, typical radar surveillance waveform settings were used. The SQUIRE radar scanned the sector to survey in azimuth. The scanning speed and radar waveforms have been optimized to maintain good tracking capabilities over successive scans. This means that a short time-on-target is available to perform classification. Target tracks and the related radar video data were saved for further processing.

Fig. 2. Photo of the SQUIRE radar at the beach and inserted photos of the measured targets during the ALFA measurement campaign.

B. Range-Doppler Representation

In FMCW radars, range is determined by measuring changes in beat frequency. Such changes can also occur due to moving targets [4]. The ambiguity in the interpretation of the cause of the changes in beat frequency is referred to as range-Doppler coupling. A consequence is that the responses of target parts moving at velocities higher than the unambiguous velocity appear in different range cells than the response of the target fuselage as observed in Fig. 3.

In Fig. 3, the target fuselage position (range) is indicated by the black dashed line. Away from this dashed line, the micro-Doppler signals due to the rotating blades can be observed [5]. The micro-Doppler characteristics differ for the two types of targets considered. In order to develop the radar classification chain, target features should be found that exploit these differences. Potential features are discussed in the following subsections.

C. Maximum Observable micro-Doppler Speed

On the left of the dashed line in Fig. 3 (left), strong micro-Doppler signals are present in an extended area. The signals represent the flash of one approaching helicopter blade. The blade tip velocity is around 200 ms^{-1}. Since the applied radar waveform has an unambiguous velocity of around 25 ms^{-1}, the blade signal is expected to be present in more range cells. On the right side of the dashed line, in Fig. 3 (right), the reflection of an outgoing rotating blade of the aircraft is observable. During the measurement, the blades were rotating at about 2350 RPM. The tip velocity was thus around 230 ms^{-1}. Applying the same reasoning as above, the micro-Doppler signal should be present in about the same number of range cells as for the helicopter. However, this is not the case: the propeller blade is a pitched blade whose reflection weakens with the distance to the blade centre. In addition, due to the blade pitch, one of the sides of the blades will reflect much more than the other. For an approaching aircraft at low elevation with a clockwise rotating blade, the outgoing blade presents a larger surface than the approaching blade.

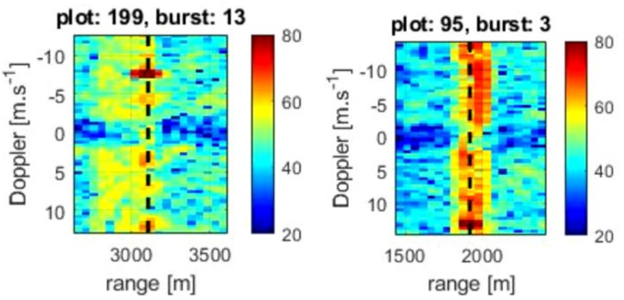

Fig. 3. Range-Doppler representation of a helicopter measurement (left) and a fixed-wing aircraft measurement (right). The colour scale is in dB.

D. Burst-to-Burst micro-Doppler Spectrum Uniformity

The signal amplitude from the blades of a fixed-wing aircraft in a range-Doppler representation should remain roughly constant, as long as the aspect angle does not vary too much. Consequently, the micro-Doppler characteristics of a fixed-wing aircraft should be fairly constant from burst-to-burst.

For the helicopter, the situation is different: an incoming rotating blade will give a flash at ranges shorter than the range of the helicopter fuselage response, whereas the flash of outgoing rotating blades will be seen at longer ranges. The flashes of an incoming blade occur every 45 ms for a rotating speed of 470 RPM and a three-bladed rotor. Due to the blade flashes, the helicopter micro-Doppler characteristics will vary from burst-to-burst.

E. Micro-Doppler Spectrum Periodicity

Another interesting difference is the presence of periodicity in a single range cell, i.e., along the Doppler dimension, in the range-Doppler representation of the fixed-wing aircraft measurement. This spectrum periodicity (due to modulation peaks) is related to the frequency of the blade flashes, which in turn depends on the angular velocity of the rotor or propeller [2]. The propeller of the fixed-wing aircraft rotates much faster that the helicopter's rotor. Therefore, the modulation lines start appearing only for the aircraft.

These differences in micro-Doppler characteristics can be exploited to determine if an air target belongs to the helicopter class or the fixed-wing aircraft class. The radar classification chain developed for the ALFA project uses these discriminative features to label the targets. The classification chain is introduced in the next section.

III. Radar Classification Chain

The development of a classifier generally undergoes a training and a testing stage. After these stages, the operational classifier can be specified. In this section, the different components within the classification chain are explained.

A. *Classification Chain for Training and Testing*

The block diagram of the radar classification chain for training and testing is provided in Fig. 4. As mentioned above, the feature extraction and classification are based on single radar bursts of about 30 ms each. Several hundreds of measurements (bursts) of the helicopter and the fixed-wing aircraft have been gathered and they have been split between a training set and a testing set.

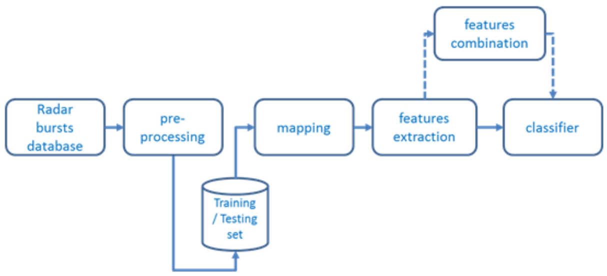

Fig. 4. The radar component's training/testing classification chain.

The preprocessing stage of the radar classification chain is used mainly to filter the land and the sea clutter returns present in the coastal environment. In the mapping stage the time-sampled radar signals are transformed to the range-Doppler domain, as presented in Fig. 3. In the feature extraction stage, discriminative target features are investigated. In the ALFA radar classification chain, the three micro-Doppler features as discussed in Section II have been implemented: the maximum observed micro-Doppler speed, the micro-Doppler spectrum uniformity from burst-to-burst and of the micro-Doppler spectrum periodicity.

Finally, a class label must be assigned to each measured target, based on the extracted features values. Because of its popularity and simplicity, a (recursive) Naïve Bayesian classifier is used for the radar classification chain. The recursive Bayesian classifier is given by:

$$p(c/Z_k) = \frac{p(z_k/c)\cdot p(c/Z_{k-1})}{p(z_k/Z_{k-1})} \quad (1)$$

where $p(c/Z_k)$ is the posterior probability on the target class $c \in \{1, \ldots, C\}$ with C the total number of target classes, given all features $Z_k = \{z_k, z_{k-1}, \ldots z_1\}$ processed so far, $p(z_k/c)$ is the conditional likelihood on the current feature z_k, and $p(z_k/Z_{k-1})$ is the total likelihood of the current features given all previous ones. Finally, $p(c/Z_0)$ is the prior probability on each class. The training set is used to estimate the parameters describing the conditional class-dependent probability densities of the extracted features, which are assumed to be Gaussian densities. Possible statistical dependencies between the features are ignored. This knowledge is used during the testing and operational stages to determine to which class a measured target most likely belongs, i.e., the target class with highest posterior probability.

By using multiple features, the classifier robustness can be improved. Therefore, a feature combination stage is added to the radar classification chain. When the feature values become available, the likelihoods for all classes are computed. Considering multiple (assumed) independent features leads to a situation for which not only performance improvement can be expected but also more confidence can be gained in the classifier outcome.

B. *Operational Classification Chain*

The radar classification chain can be applied to any target in track. At each track update, new measurements become available. This additional information can serve as new evidence to update the target classification output. The operational classifier chain presented in Fig. 5 makes use of the pre-processing, mapping and feature extraction blocks developed during the training and testing stages. In order to improve the stability of the classification output, the feature values are filtered scan-after-scan using a low pass filter. Then, the features are combined. Finally, the recursive Naïve Bayesian classifier can determine to which class the detected target belongs.

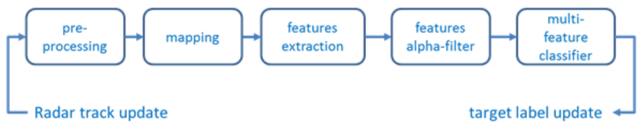

Fig. 5. The radar component's training/testing classification chain.

C. *Features' Dependency on SNR*

The features values depend on the available micro-Doppler signal-to-noise ratio (SNR). By considering this dependency in the features values distribution model the performance may be improved with respect to the situation where a mean distribution over the entire training set (thus independent of SNR) would be used.

Fig. 6 provides histograms of the micro-Doppler spectrum periodicity feature for the manned helicopter and the manned fixed-wing aircraft classes, for different SNR values. This histograms represent the occurrence of feature values over the entire training set. The distributions originating from helicopters and fixed-wing aircraft appear to have different means at large SNR which is an indication that this feature is able to discriminate between targets belonging to the two classes. However, a large overlap between the two distributions exists at lower SNR, indicating that misclassification can be expected.

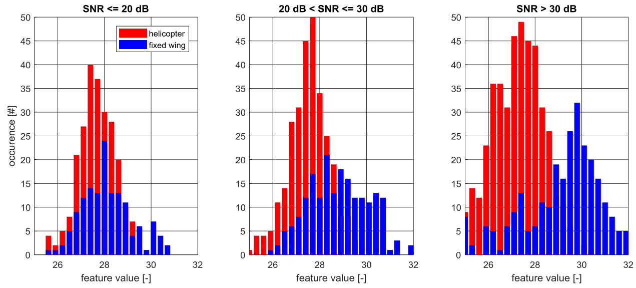

Fig. 6. Histogram for the micro-Doppler spectrum periodicity feature plotted for different SNR, left: SNR ≤ 20 dB, middle: 20 < SNR ≤ 30 dB, and right: SNR > 30 dB.

IV. Classification Results

In this section, the classification results, at the end of the training and testing stages, are presented. These results are obtained considering individual bursts. It is important to note that an additional performance gain will be achieved when the classifier will be used with its operational settings:

- The features values are filtered over time to improve the consistency of the classifier outcome;
- The classification label is achieved using an iterative Naïve Bayesian classifier therewith combining the outcome of multiple bursts.

The single-burst classification results are presented in the form of confusion matrices. The probability of correct classification Pcc is also computed. In Fig. 7, the performance achieved with a classifier that does not take the features' SNR dependency into account is compared to the one achieved with a classifier that considers this dependency. The feature considered is the maximum observable micro-Doppler speed. The benefit of including the SNR dependency is clearly seen for this feature as a classification performance gain of nearly 10% is achieved.

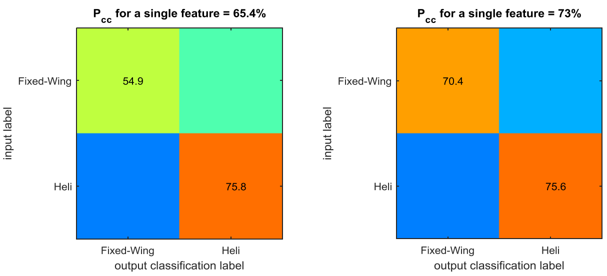

Fig. 7. Confusion matrices for single bursts for the maximum observable micro-Doppler speed feature for a classifier that does not take SNR into account (left panel) and a classifier with SNR dependency included (right panel).

In Fig. 8, the classification performance including the SNR dependency achieved with a single feature, the micro-Doppler spectrum periodicity, is compared to the performance achieved when using all three designed micro-Doppler features. Nearly 4% in classification performance is gained by combining the three micro-Doppler features.

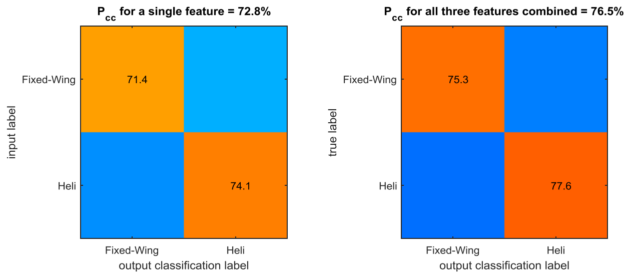

Fig. 8. Confusion matrices for single bursts achieved with one single feature (left panel) and with the micro-Doppler features combined (right panel).

V. Conclusions

ALFA is a H2020 project with the objective of bridging the current capability gap of operational border surveillance systems regarding detection, tracking and classification of LSS air targets. The radar component of the ALFA system is used for sector surveillance including the classification of targets that are in track. To uphold short revisit times, only a short time-on-target is available for classification. Based on measurements, three suitable features have been developed: the maximum observed micro-Doppler speed, the micro-Doppler spectrum evolution over time and the periodicity of the micro-Doppler spectrum. These features can be extracted using only short time-on-target and they can be used to discriminate between two relevant target classes, i.e., small helicopters and aircraft.

The classification performance for single bursts is assessed. It is noted that an additional performance gain will be achieved when the classifier will be used with its operational settings. It is shown that best classification performance is obtained by combining features. In addition, the classification performance can be improved by considering the variation of the features' distributions as function of SNR.

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References

[1] R. van Heijster, J. van der Velde, and G. Vella, "ALFA H2020 project: SafeShore-ALFA common dissemination," in Proc. 1st ALFA Workshop, 2018. [Online]. Available: https://alfa-h2020.eu/downloads/ALFA-Technical-Presentation.pdf (accessed Jan. 7, 2019).

[2] R.I.A. Harmanny, J.J.M. de Wit, and G. Prémel-Cabic, "Radar micro-Doppler feature extraction using the spectrogram and cepstrogram," in Proc. EuRAD, 2014, p. 165-168.

[3] SQUIRE radar description, 2018. [Online]. Available: https://www.thalesgroup.com/en/squire-ground-surveillance-radar (accessed Dec. 14, 2018).

[4] A.G. Stove, "Linear FMCW Radar Techniques," IEE Proceedings F - Radar and Signal Processing, vol. 139, no. 5, pp. 343-350, Oct. 1992.

[5] J.J.M. de Wit, Ph. v. Dorp, and A.G. Huizing, "Classification of air targets based on range-Doppler diagrams," in Proc. EuRAD, 2016, p. 89-92.