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Vessel Identification Study for Non-Coherent High-Resolution Radar

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***Abstract*— This paper presents a vessel identification study based on vessel profile. The study was developed with real data obtained with high-resolution Continuous Wave Lineal Frequency Modulated (CW-LFM) radar. Cases studied in this work are vessels entering and leaving the harbor. Also, in this paper, a comparison between different classification techniques such as Neural Networks, Support Vector Machine and k-Nearest Neighbor is introduced. The differences between normalization methods are evaluated for each classification technique.**

Keywords—target identification; high-resolution radar

I. INTRODUCTION

Radar is a useful tool for security, allowing terrestrial, maritime and aerial moving target detection and tracking. Recently, the radar bandwidth has been increased to 2 GHz [1] allowing a greater target detection range resolution.

In the case of coast surveillance such as harbor traffic control or open sea fish-farm security, it is necessary not only to detect and track the target but also to identify it in order to present evidence before the court of any acts of sabotage, theft, etc. in private areas.

One way of carrying out vessel identification has been with two-dimensional images obtained from the Radar Doppler image. To apply Doppler to high-resolution radar presents the problem that the computational load increases with the radar resolution, reducing the ability of a real time application. Also for moving targets, Doppler spreading caused by migration through resolution cells usually arises [2].

To allow real time identification taking advantage of the higher radar resolution this paper proposes using one-dimensional target profile instead of Doppler image for target identification. We deal with the different profiles obtained due to vessel motion: pitch, roll, and yaw and the position angle with respect to the radar.

The paper is organized as follows. In Section II, first the K-Band High-Resolution Homodyne Continuous Wave Lineal Frequency Modulated (CWLFM) radar prototype is presented. Second, the database used for the experiment is detailed. Third, in section IV the problem is presented. Finally in Section V a comparison between different classification techniques is introduced. The differences between normalization methods are evaluated for each classification technique.

II. K-BAND CWLFM RADAR

The CWLFM radars are well known [3], however new technologies (e.g. those based on HBTS, HEMTs) allow more power in transmission and less noise in reception in the millimeter band. Working at higher frequencies makes the use of wider bandwidths possible, increasing the information about the target's presence, location and identity.

CWLFM systems utilize an active correlation process that consists of mixing the signal echoes with a replica of the transmitted signal, followed by a bank of filters. Mixing the received signal with the replica, distance information is converted to frequency domain, in such a way that each filter is equivalent to a distance cell. Fig. 1 shows the homodyne CWLFM radar prototype developed [4]. This prototype is a radar environments data capture system, with short medium range coverage (15 Km). Implementation requires a 400 Hz sweep control signal, 500 MHz bandwidth, and 14.5 GHz central frequency VCO. VCO output is multiplied by two, to meet a 1 GHz bandwidth (0.15 m range resolution). Once amplified, the signal is transmitted, and when a target is found the receiver antenna captures its echo. The received signal is mixed with the transmitted signal. This way the IF signal is obtained and then filtered and amplified. A data acquisition card in a PC captures the resulting IF signal. A non-coherent signal for a static spot target at a distance r_o from the radar is given by:

$$d_q(n) = A\cos\left[\frac{2\pi f_m r_0}{f_s \Delta r_o} n\right] + n_q(n) \tag{1}$$

where A is the received signal amplitude, f_m the modulation frequency, f_s the sampling frequency, $n_q(n)$ Gaussian noise, r_o the distance to the nearest point of the target reflector (Fig. 2) and Δr_o is the Radar resolution which depends on the radar VCO (Δf_m) bandwidth and light speed (c) and it is equal to:

$$\Delta r_o = \frac{c}{2\Delta f_m} \tag{2}$$

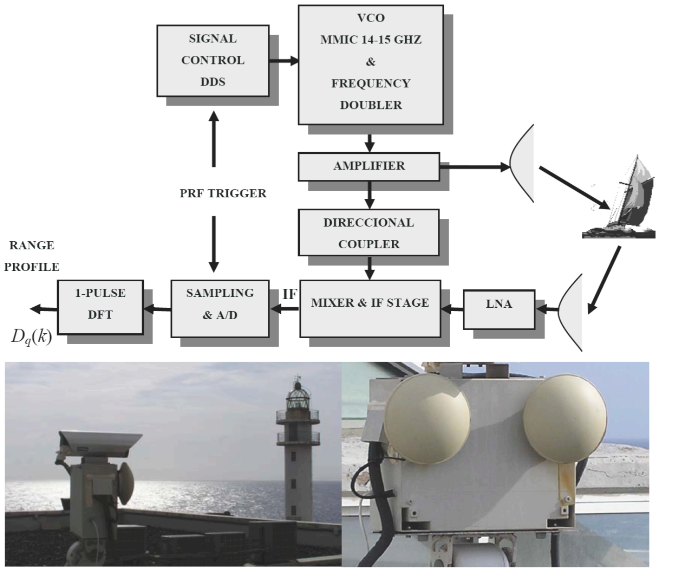

Fig.1. Block diagram and photos of the experimental Linear CWLFM radar system.

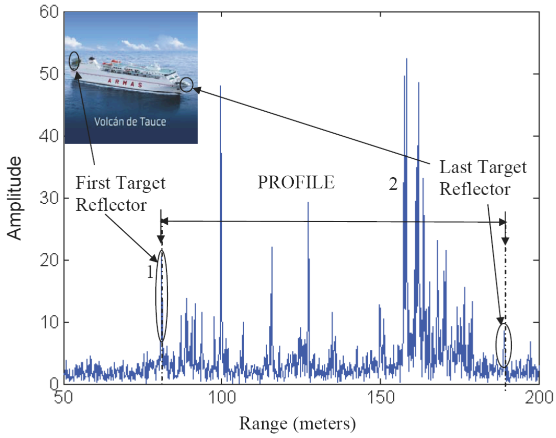

Fig 2. Range profile of real target (120 m length ferry) and target reflector example.

Finally, the digitalized IF signal (1) is Fourier transformed in order to obtain the range profile (Fig.2).

III. DATABASE ACQUISITION

For security applications of the radar, a real database is necessary in order to achieve vessel identification. With this in mind, the radar prototype presented in this paper allows us to obtain vessel profiles with a resolution up to 15 cm. The images in Fig. 2 and Fig. 3 have been obtained with the radar working just as explained in Section II. In the X axis the reflector distance to the radar is represented in meters and in the Y axis the amplitude (dB) is shown.

The real database contains 400 high-resolution radar profiles of seven different ships taken in different sea states (from 1 to 5), distances and position angles with respect to the radar. Fig. 3 shows the differences between two ferries. Fig. 4 shows the different photos of a ferry going out of the harbor. Fig. 5 shows some of the automatically aligned vessel profiles

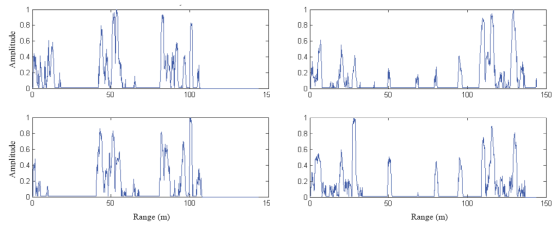

Fig 3. Profiles from ferries: "Volcán de Tejeda" (left) and "Volcán de Timanfaya" (right).

Fig.4. Ferry goes out of the harbor.

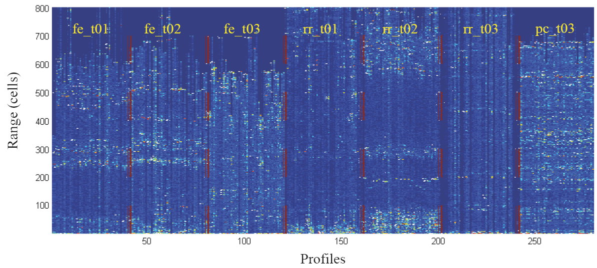

Fig.5. Profiles from different type of vessels.

used in this study. In this figure the nomenclature "fe" means ferry and "t01" means that is a type 1 ferry. Also "rr" means ro-ro and "pc" is container vessel. In this figure, the Y axis is the reflector distance to the radar in meters and in the X axis the different vessel profiles are shown.

IV. PROBLEM PRESENTATION

Once the profiles are automatically aligned, the problem is to select the best classification technique to get the best result. The automatic alignment method consists of selecting the first target peak detected, and using this point as the beginning of the profile. In order to select the most adequate classification technique for vessel identification, studies with Neural Networks (NN) [5], Support Vector Machine (SVM) [6] and k-Nearest Neighbor (KNN) [7] have been carried out.

As the received signals have different amplitude levels due to the varying distance of the radar from the target, amplitude normalization is necessary. The SNR vessel profile varies between 15 and 20 dB.

For each classification technique, three different normalization methods were used: maximum, energy and by limiting the signal level.

- Maximum normalization consists of dividing each profile amplitude level by the maximum level in each profile:

$$F_{\max} = \max\{x(n)\} \tag{3}$$

- Energy normalization is obtained by dividing the amplitude values by the profile energy value. This profile energy is given by:

$$F_{ener} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x(n)^2} \tag{4}$$

- The last method used was to limit all profile signals with a threshold and divided it by the same threshold.

V. RESULTS

In this section, first the results for the different identification and normalization techniques are presented. Second, the results for training SVM being first each vessel a class and second each vessel category a class. And finally, the experiment was to change the profile length used for training and test.

For each classifier-training phase, 40 random profiles of each vessel model were used. In the test phase 600 profiles were employed. The results for KNN, NN and SVM are shown in Table I, Table II and Table III respectively. These results were obtained after repeating the training and test process 100 times. The profiles were randomly selected each time.

Table I shows the KNN classification results for different normalization methods and without normalization. We can see the best results for energy normalization with 70.59% of mean recognition and an equal error rate (EER) of 0.81%.

In the NN study (Table II) the Matalb Toolbox was used for implementation. In this case the results are 20% better than for KNN. For NN the best results are with the maximum normalization method with a 91% mean recognition and an EER of 1.41%. Maximum normalization improved by 10 percentage points.

Table III shows the SVM results (SVMlight for Matlab Version 4.00 by Anton Schwaighofer). The best normalization results were for energy normalization with the KNN. Therefore, SVM is less affected by the normalization method than NN and KNN. The differences between normalization methods were lower than 2%. The mean recognition rate obtained by SVM was 91%, the same as NN, but the mean equal error rate was lower (0.95%) than for NN.

Table IV shows the confusion results for SVM with the energy normalization. We can see the greatest error rate was for twin ferries 1 and 2. However, we can see how the mean recognition rates are 84 % and 75 % respectively. This means that it is possible to identify the twin ferries by 400 profile range-sample (Fig. 6). For the other vessels the mean recognition rate is higher than 94.5%. For these reasons SVM is the classification method with best vessel identification results.

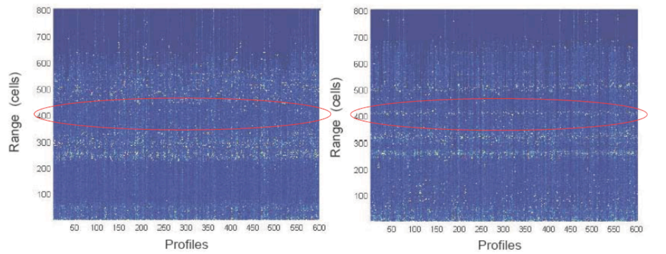

Fig. 6. Automatic profile alignment from twin ferries "Volcán de Tejeda" (left) and "Volcán de Tauce" (right).

TABLE I. THE KNN CLASSIFICATION RESULTS FOR DIFFERENT NORMALIZATION METHODS AND WITHOUT NORMALIZATION

	VESSEL TYPE							RECOGNITION RATE	
NORMALIZATION METHOD	fe_t01 (%)	fe_t02 (%)	fe_t03 (%)	rr_t01 (%)	rr_t02 (%)	rr_t03 (%)	pc_t03 (%)	Successes mean(%) /std	EER mean(%) /std
Amplitude	37.63	19.88	21.43	54.98	28.98	73.65	51.43	41.14/ 19.81	4.19/ 0.6
Energy	*53.44*	*39.14*	*79.41*	*72.06*	*66.45*	*90.83*	*92.80*	*70.59/ 3.98*	*0.81/ 0.38*
Limiter	18.00	12.50	85.85	1.54	6.09	38.92	60.14	31.86/ 2.41	0.84/ 0.53
Without normalization	16.82	11.53	84.20	1.29	4.78	36.27	56.57	30.2/ 2.36	0.6/ 0.4

TABLE II. THE NN CLASSIFICATION RESULTS FOR DIFFERENT NORMALIZATION METHODS.

	VESSEL TYPE							RECOGNITION RATE	
NORMALIZATION METHOD	fe_t01 (%)	fe_t02 (%)	fe_t03 (%)	rr_t01 (%)	rr_t02 (%)	rr_t03 (%)	pc_t03 (%)	Successes mean(%) /std	EER mean(%) /std
Amplitude	86.07	78.29	91.10	91.50	98.42	96.12	95.55	91/ 2.6	1.41/ 0.22
Energy	63.67	55.29	70.78	84.84	91.68	89.78	88.19	77.74/ 5.6	1.12/ 0.32
Limiter	79.11	66.06	94.71	89.26	96.39	94.95	96.47	88.14/ 2.91	0.96/ 0.16

TABLE III. THE SVM CLASSIFICATION RESULTS FOR DIFFERENT NORMALIZATION METHODS AND WITHOUT NORMALIZATION

	VESSEL TYPE							RECOGNITION RATE	
NORMALIZATION METHOD	fe_t01 (%)	fe_t02 (%)	fe_t03 (%)	rr_t01 (%)	rr_t02 (%)	rr_t03 (%)	pc_t03 (%)	Successes mean(%) /std	EER mean(%) /std
Amplitude	83	75.01	93.97	89.15	98.26	94.98	96.14	90.07/ 3.04	1.01/ 0.16
Energy	83.61	75.19	95.58	91.29	97.86	95.24	98	91/ 2.78	0.95/ 0.14
Limiter	82.49	71.38	95.22	89.66	97.52	94.78	97.11	89.73/ 2.89	1.03/ 0.16

Another experiment was vessel type classification. This means that the vessels are classified into three categories: ferry, container and ro-ro. Table V shows the results from the training process by vessels like in table III, and then the classification by vessel categories. We can see how the mean recognition rate increased to 97,6% and the equal error rate decreased to 0.57%. The experiment was then repeated but the training process was only done with the three categories. Table VI shows how the mean recognition rate decreased to 88,1% and the equal error rate increased to 10,51%. For this reason it is better to train SVM for each particular vessel independently.

TABLE IV. THE CONFUSION TABLE FOR SVM WITH THE ENERGY NORMALIZATION.

	fe_t01 (%)	fe_t02 (%)	fe_t03 (%)	rr_t01 (%)	rr_t02 (%)	rr_t03 (%)	pc_t03 (%)
fe_t01	83.61	10.56	0.97	4.5	0.2	1.9	0.8
fe_t02	13.24	75.19	8.92	0.8	0.4	1.5	1.2
fe_t03	0.98	4.53	95.58	0.008	0.003	0.04	1
rr_t01	0.99	1.05	0.003	91.29	3.08	0.01	0.4
rr_t02	0.09	0.1	0.3	1.39	97.86	1.39	0.002
rr_t03	0.07	0.48	1.7	0.74	0.49	95.24	0.14
pc_t03	0.81	1.2	0.02	0	0	0	98

The last experiment was to change the profile length used for training and testing. Table VII shows results using 600, 900 and 2000 profile samples. We can see that the best mean recognition rate is for longer profile length. But we can also see that for 600 sample length, the recognition rate only decreased by 4 percentage points and the equal error rate remained the same.

VI. CONCLUSION

With the aid of high-resolution radar and SVM classification technique, real vessel identification is possible.

For good identification it is necessary to select a normalization method suitable for each classification technique. From this study we can see that the SVM technique with energy normalization has the best results. Profile length is not an important factor in correct vessel identification. Also, it is possible to see that in the training process it is better to use one model for each vessel type than one model for each vessel.

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TABLE V. THE CONFUSION TABLE BY VESSEL CATEGORY TRAINING WITH VESSEL.

	Ferry (%)	Ro-ro (%)	Container (%)
Ferry	98	1.03	1.02
Ro-ro	0.53	97.1	0.17
Container	0.67	0	98

Mean recognition: ***97.6%***
EER: ***0.57%***

TABLE VI. CONFUSION TABLE BY VESSEL CATEGORY TRAINING WITH VESSEL CATEGORIES.

	Ferry (%)	Ro-ro (%)	Container (%)
Ferry	87.07	17.16	5.52
Ro-ro	18.44	80.76	12.89
Container	1.90	7.15	96.34

Mean recognition: ***88.1%***
EER: ***10.51%***

TABLE VII. RESULTS BY LENGTH.

	VESSEL TYPE							**RECOGNITION RATE**	
PROFILE LENGTH (CELLS)	**fe_t01 (%)**	**fe_t02 (%)**	**fe_t03 (%)**	**rr_t01 (%)**	**rr_t02 (%)**	**rr_t03 (%)**	**pc_t03 (%)**	**Successes** mean(%) /std	**EER** mean(%) /std
600	79.21	77.99	86.80	87.29	96.99	91.94	93.32	87.65/ 3.46	0.91/ 0.14
900	82.15	75.43	89.51	88.93	98.27	94.16	94.86	89.05/ 3.19	0.96/ 0.14
2000	83.62	75.19	95.58	91.29	97.86	95.24	98.00	91/ 2.78	0.95/ 0.14

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