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An Efficient Approach for Ground Echoes Suppression Based on Textural Features and SVM

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Abstract: The use of the Support Vector Machine (SVM) technique for the clutter identification in the context of meteorological data is presented. The clutter is due to ground echoes and anomalous propagation. The SVM is combined with textural approach which is based on the Grey Level Co-occurrence Matrix (GLCM) that is the most used in the textural analysis image. An incoherent radar site is considered for this study. The results reveal that over than 91.1% of ground echoes are identified and 90.3% of precipitations are preserved. In addition 95.99% of anomalous propagations are removed. The use of our approach is lasts than 1mn for the treatment of each image. We can then filter the radar image in real time.

Keywords: *Precipitation echoes, ground echoes, anomalous propagation, textural parameters, support vector machine.*

1. Introduction

Meteorological radar data are considerably used to detect precipitations and to warn of impending severe weather in a certain region. However, these data are subject to many spurious echoes that reduce the radar's performance and cause several errors in the estimation of precipitation. These echoes can be due to the neighboring construction and mountain; they are observed at fixed positions and are named ground echoes. Other kind of disturbing echoes called Anomalous Propagation (APs) anaprops depending on the meteorological conditions and the state of the atmosphere appear at various distance from the radar. They vary in position, their suppression is difficult.

Several approaches were proposed to remove the undesirable echoes. The most used are the polarimetric and Doppler techniques (Rico-Ramirez et al; 2008) (Islam T et al; 2012) and when the radar is incoherent the clutter echoes are suppressed by comparing the statistical distribution of the ground echoes with those of the precipitation echoes. The texture was defined in (Haralick, R. M; 1979) and (Unser M; 1968) as a measure of spatial statistical distribution of gray levels. In (Haddad B et al; 2004), the ground echoes were eliminated by thresholding the textural parameters and in (Sadouki L et al; 2012) they were eliminated through textural-fuzzy system.

In this paper, we propose to combine the textural parameters and Support Vector Machines (SVM). The textural parameters characterize the data and the SVM allows separating optimally the ground echoes from the precipitation. The paper is then organized as follows. Section 2 gives the theoretical concepts. The system description is presented in 3 and the experimental results are presented in section 4. The last section gives a summary of the proposed method.

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2. Theoretical Concept

2.1. Textural Features

The texture of an image is defined by the first and the second order probability distribution function of gray levels. The most used methods for texture analysis are those based on joint probability of two pixels separated by a distance *d* according to an angle (θ) in a region R. The set obtained by all the joint probabilities forms a Grey Level Co-occurrence Matrix (GLCM) given by (Equation.1).

$$M_ct(a,b) = card\left\{(s,s+t) \in \frac{R^2}{A[s]} = a, A[s+t] = b\right\} \quad (1)$$

Where :

card (cardinal) is the number of elements;
a, b are the gray levels.
s is the coordinate (i,j) of the pixel.
t=(θ,d)=(Δx,Δy,d).

Eight computations of GLCM are possible from the eight directions (θ=0°,45°,90°,135°,180°,225°,270°,315°).
The textural parameters used are (Haralick, R. M; 1979):

$$mean = \frac{1}{K}\sum_{s\in R} A[s] \quad (2)$$

$$variance = \frac{1}{K}\sum_{s\in R}(A[s] - mean)^2 \quad (3)$$

$$energy = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} M_ct(a,b)^2 \quad (4)$$

$$entropy = 1 - \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} M_ct(a,b)\ln(M_ct(a,b))1_{M_{ct(a,b)}}}{(N_g)^2\ln(N_g)} \quad (5)$$

With: $\begin{cases} 1M_ct(a,b) = 1 \rightarrow if\ M_ct(a,b) \neq 0 \\ 1M_ct(a,b) = 0 \rightarrow otherwise \end{cases}$

$$contraste = \frac{1}{(N_g)^2(L-1)^2}\sum_{k=0}^{L-1} k^2 \sum_{|a-b|=k} M_ct(a,b) \quad (6)$$

$$local - homogeneity = \frac{1}{(N_g)^2}\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{M_ct(a,b)}{1+(a-b)^2} \quad (7)$$

$$correlation = \frac{1}{(N_g)^2\sigma_x\sigma_y}\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(a-\mu_x)(b-\mu_y)M_ct(a,b) \quad (8)$$

$$\text{with} \begin{cases} \mu_x = (\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} iM_ct(a,b))/(N_g)^2 \\ \mu_y = (\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} jM_ct(a,b))/(N_g)^2 \\ \sigma_x = (\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-\mu_x)^2 M_ct(a,b))/(N_g)^2 \\ \sigma_y = (\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(j-\mu_y)^2 M_ct(a,b))/(N_g)^2 \end{cases}$$

2.2. Bi-Class Support Vector Machine

The SVM is a learning method which has been used widely in many applications as for clutter identification in (Islam T et al; 2012). The SVM was introduced by Vapnik (Vapnik.V; 1995) to find an optimal hyper plane which separate linearly between two classes see (Figure.1).

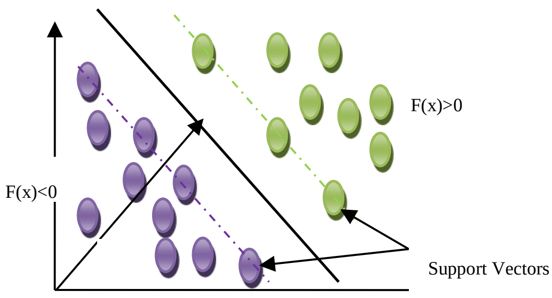


Figure 1. Data classification based on SVM

When the data are not linearly separable, a kernel function is used as a polynomial function or radial basis function (RBF) to build the hyper plane.
Let data sets $(x_1, y_1)\dots(x_n, y_n)$, $x_i \in R^m$, $y_i \in [1,-1]$ be training set, n is the number of training data and m is the size of the feature vector. The decision function is (Vapnik.V; 1995):

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i\, k(x, x_i) + b \quad (9)$$

Where α_i are Lagrange multipliers having values in the range $[0,C]$. C is regularization parameter which determines the compromise between the maximization of the margin and the minimization of the error of classification and b is the bias, a scalar computed by using any support vector.

3. System Description

3.1. Data preprocessing

The first step is to prepare the database which contains two classes, the first one includes only precipitation echoes and the second contains the ground echoes. The images of ground echoes have been collected in clear sky conditions. The images of precipitation echoes have been obtained by selecting rainfall cells from echoes cells, using the visual inspection and animation.

3.2. Feature generation

Features are generated from the two sets of samples where each pixel is the center of a window of 5x5. For each window, the seven parameters are calculated. These features are then used to generate the SVM model, which will allow us to separate the ground echoes from the precipitation.

3.3. Classification

The SVM is used to separate between two classes. However, the pixels are classified according the decision rule:

$$x \in \begin{cases} \boldsymbol{class(+1) \rightarrow if\ f(x) > 0} \\ \boldsymbol{class(-1) \rightarrow if\ f(x) < 0} \end{cases} \quad (10)$$

4. Experimental Result

4.1. Database description and evaluation criteria

The database used to evaluate our approach contains 10052 images from Bordeaux (France) in 1996. The images where collected with an incoherent-pulsed radar. These images were stored every five minutes following the CAPPI mode (Constant Altitude Plan Position Indicator), with a beam elevation angle of 1.5° for distances inferior to 50km and 0.4° above 50 km. They consist of 512x512 pixels and cover an area of 512x512 km^2. The number of levels encoding each pixel of these images is 16, see (Figure.2).

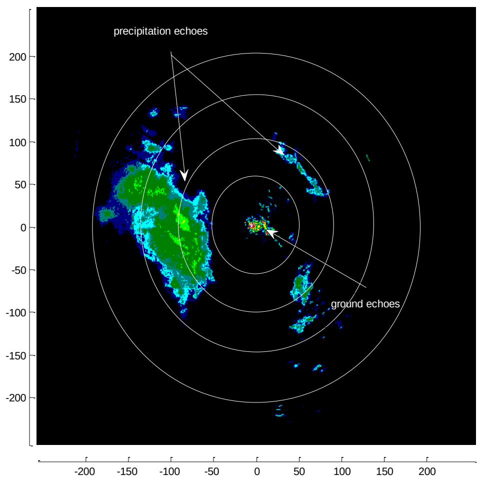


Figure 2. Radar image of the study sites (January, 5th 1996)

In order to evaluate the results, we calculate the rate of elimination of echoes (R_g or R_A) and the rate of preservation of precipitations (R_p). This rate is given by:

$$R = \frac{X_i}{N_i} \times 100 \quad (11)$$

Where:

X_i is the number of pixels classified to class i.

N_i is the number of pixels of classes i.

4.2. Model generation and results

The generation of the SVM requires two phases, training and testing phase. The training phase consists to find the optimal parameters: the kernel parameter $\boldsymbol{\gamma}$ and the regularization parameter C. The testing phase allows evaluating the robustness of the classification system (Guerbai Y et al ; 2012).

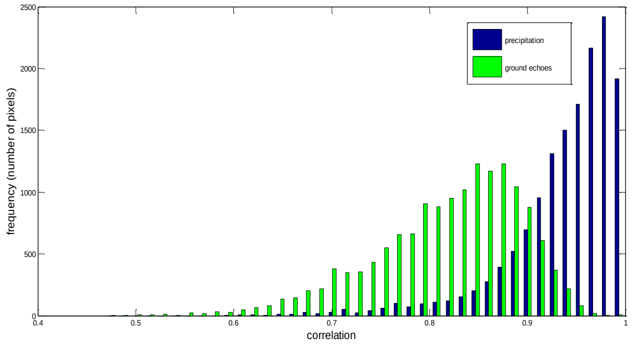
The kernel function used is the Radial Basis Function RBF given by:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \qquad (12)$$

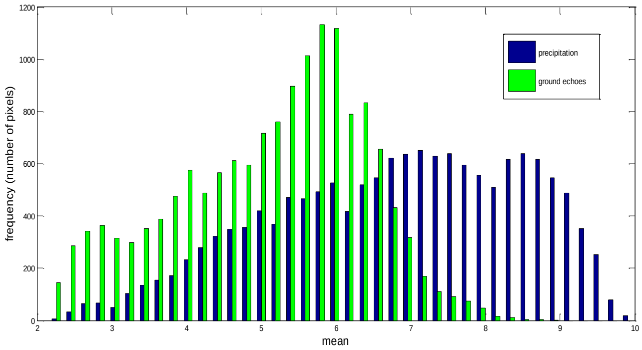
1) Ground echoes filtering:

The histograms of textural parameters are obtained for the both classes, all of them overlap. Fig 3 illustrates the correlation and the mean's histograms obtained for d=1 and θ=0° from an image taken on January, 5th.

The textural parameters are used as an input for the SVM in order to distinguish between the ground echoes and precipitation echoes. Two situations are considered, the first one is when we distinguish between the ground echoes from the precipitations as represented in Fig. 4a. In Fig.4b, the image is filtered, the percentage of elimination ground echoes is 94.15% and the percentage of preservation of precipitations is 85.66%.



(a)



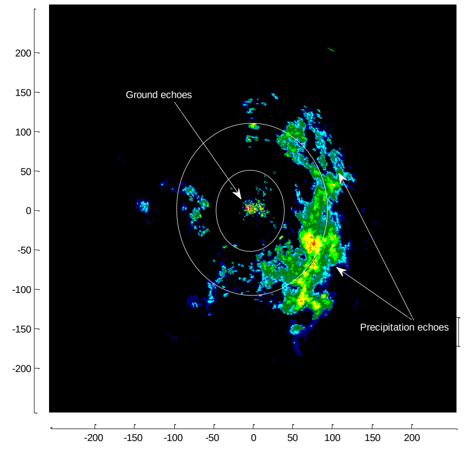
(b)

Figure 3. Histograms of textural parameters (a: correlation, b: mean) obtained from an image from Bordeaux sites

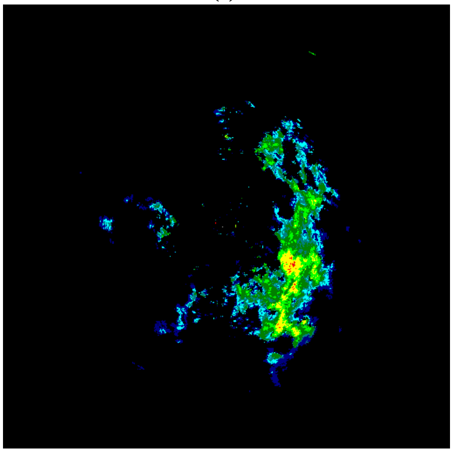
Table 1. Percentage of recognition of each class

Orientations	0°		45°		90°	
Rate	R_g	R_p	R_g	R_p	R_g	R_p
Percentage%	91.18	90.35	93.46	88.90	92.79	86.67

Table 1 gives the average rates obtained from the Bordeaux data base of 70 images, with θ=0°, 45°, 90°. For θ=45° we get the best R_g which reach 93.4% but R_p is lower compared to the other orientations.



(a)



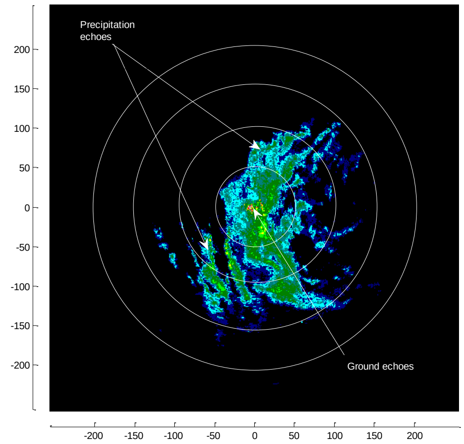
(b)

Figure 4. (a) Original and (b) filtred images from Bordeaux on January,5th 1996.

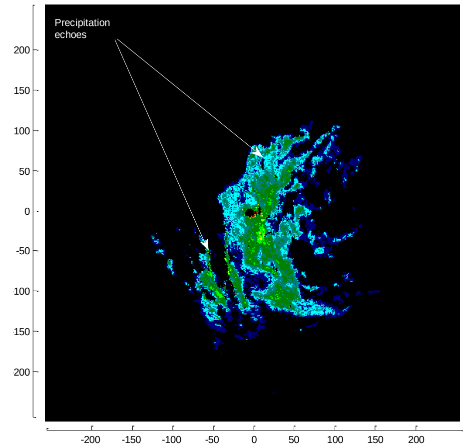
Now we consider when the precipitations cover the ground echoes as in Fig 4 which was taken in January 24th 1996. This case is more difficult for the treatment.

The estimation of the rejection rate of ground echoes and the preservation rate of precipitation is very difficult. We test several images from the data base; we observe that the majority of ground echoes are removed.

From the results we conclude that the combination of many textural parameters with the SVM gives good results. All the orientations give a rate of filtering around 90% but θ=0° give the best compromise between Rg and Rp.



(a)

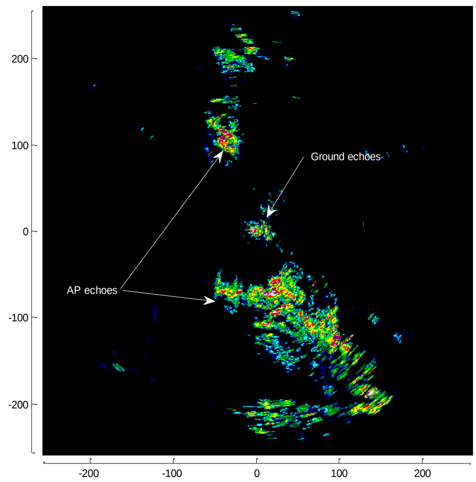


(b)

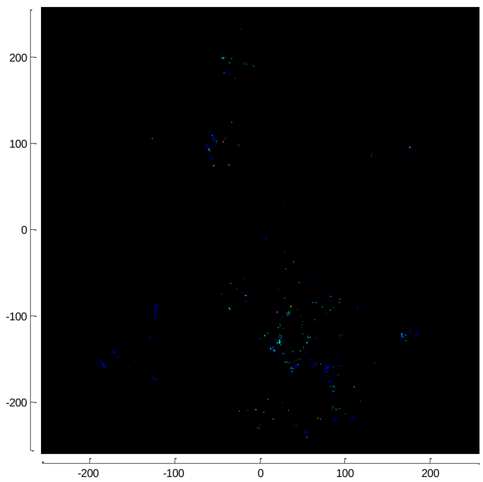
Figure 5. The case where precipitation echoes cover the clutter.(*a*) Original radar image of Bordeaux,(b) Filtered radar image of Bordeaux.

2) Anomalous propagation filtering:

The presence of APs in the radar images is the most complex situation since they depend on the atmospheric changes. These data are characterized by high reflectivity factors and inhomogeneous texture (see Figure. 5). The SVM parameter $\boldsymbol{\sigma}$ is equal to 10 for the all orientations. The table 2 gives the rates obtained for AP elimination.



(a)



(b)

Figure 6. image contaminated by ground and AP echoes, (*a*) Original image and (*b*) filtered image (for θ = 90°◦).

Table 2. Percentage of elimination of APs

Orientations	**0°**	**45°**	**90°**
Percentage	95.57	95.18	95.99

With this approach, APs are removed from the images with over than 95%, and the percentage reach 95.99% for the orientation θ=90°. Figure 5b. shows that all the APs are removed.

5. Conclusion

This paper presented an approach based on the combination of textural and SVM, applied to the filtering of meteorological images. It allows removing over than 91% of ground echoes and conserving over 90% of precipitation, which gives a mean rate of filtering about 90%. This method is effective for the elimination of APs, since the rate is about 95.9% for θ=90°. The use of our approach is lasts than 1mn for the treatment of each image. We can then filter the radar image in real time. These results are comparable with those of (Sadouki L et al; 2012).

In continuation of the present work, the next objectives consist to test out approach on other sites of different topography and climate.

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