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SVM Classifier for Meteorological Radar Images

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***Abstract*— This paper proposed an efficient approach, for weather Radar image classification and filtering, which is based on the combination of the textural analysis and support vector machine (SVM). Since the images are formed by two kinds of echoes, precipitations (rainfalls) and ground echoes (clutter), caused by earth's surface, thus, our purpose is to preserve precipitations and eliminate ground echoes from radar images recorded by weather radar of Setif. The filtering method consists of extracting features using gray level co-occurrence matrix (GLCM) for each type of echo. In order to identify data formed by the elements of the useful textural parameters, a Support Vector Machine classifiers were used with different forms of kernel function. The achieved result for the mean rate of correct recognition of echoes is about 94.77%.**

***Keywords*— SVM, Image, Radar, Precipitations, Ground echoes.**

I. Introduction

Precipitation or rainfall has great influence on the conditions of human activities and on the Earth's natural environment in general. For this reason, observation of precipitation is an important field in meteorological science and operational meteorology. The weather radar is the most widely used sensor for obtaining observations of precipitation in the atmosphere. Forecasters have to manage the increasing data volume, notably from Numerical Weather Prediction models; meteorological satellites, radars and other observation systems such as radiometers wind speed, and humidity detectors etc. Weather Radar is the most important tool used in meteorology; however a lot of work was performed in order to acquire clear images and consequently, we may have correct previsions. Different techniques were used in order to eliminate noises caused by many effects and affect the weather radar images, such as Doppler filtering [1], or dual polarization filtering [2]-[3]. In order to classify the Doppler radar echoes types, fuzzy logic technique were applied [4] or to identify non-precipitating echoes in radar scans [5]-[6]-[7], Furthermore, [8] used the neuro-fuzzy approach to eliminate noise in Doppler radar signals. In [9], they used an Adaptive Neuro-Fuzzy inference system (ANFIS) for echoes classification in images recorded by non coherent pulsed radar.

Support Vector Machine (SVM) represents an efficient approach, which is used for classification, regression analysis and forecasting [10], besides SVM were used for rainy areas detection and convective cells' delineation using MSG satellite images. [11] In this study we explore the possibility of echoes classification by means of textural parameters, extracted from radar images recorded in Sétif (Algeria) region, and SVM approach. It's worth noting that the texture analysis can be performed using different ways such as the Wavelet approach or even the Fourier approach. However, texture analysis, defined by Haralick, which is related to the way in which the human visual system perceives the texture [12], is widely used in image segmentation or even in classification.

II. Method

We implement in this paper an algorithm which combines the textural features, based on the method of grey-level co-occurrence matrices (GLCM), and Support Vector Machine (SVM) with various kernel functions, such as linear, polynomial, quadratic, Multi Layer Perception (MLP) and Radial Basis kernels. The input variables for our SVM system are the best textural parameters in terms of effectiveness (in distinguishing between precipitation echoes and clutter).

A. Datasets

Database used in this paper consists of images taken during the period of 1997-2001 by Sétif radar which is positioned at latitude of 36°11'N, a longitude of 5°25' E and an altitude of 1700 m above the sea level. It records every fifteen minutes an image of 512×512 pixels using the PPI (Plan Position Indicator) presentation, with a resolution of 1 km per pixel.

As shown in the image of Fig. 1, the images recorded in this site using the C-band meteorological radar, use a palette of sixteen colors. We find in those images a lot of ground echoes coming from the earth's surface. These echoes are, in particular, due to the fact that Sétif region is a part of the Algerian highlands and its Radar is surrounded by several ground obstacles. The nearest ground echoes are produced largely by the industrial area. Beyond the horizon, the ground obstacles produce several ground echoes in the radar images. For example, to the southwest, 60 km away from the radar, there are the mountains of Djurdjura, which reach an altitude of 2300 m. In the same direction, 40 km away from the radar, we find the mountains of Bibans with a height of 1417 m. To

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the northeast, at a shorter distance (about 30 km away from the radar), are located the mountains of Babors, which reach an altitude of 2004 m.

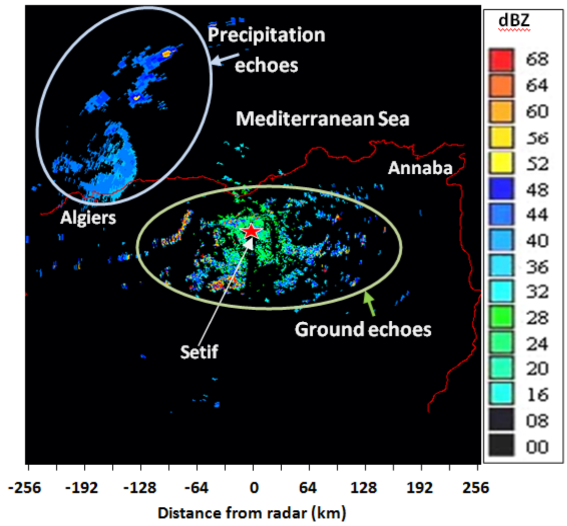

Fig. 1 Radar images of Sétif.

B. Co-occurrence Matrices' approach

The grey-level co-occurrence matrices are among the most frequently used statistical methods in the field of the texture analysis of the radar and the satellite images [13]. The gray-level Co-occurrence matrix of an image is obtained by estimating the joint conditional density of probability functions of second-order P (i, j / d, θ), the latter represents the transition probability of a pixel of gray level "i" to a pixel of gray level "j". This transition is controlled by: the distance "d" between the two pixels and the orientation "θ"which is defined by the angle between the direction of transition and the image scanning direction.

The orientation "θ" can be determined also with Cartesian coordinates (Δx, displacement in the horizontal direction and Δy, displacement in the vertical direction)

The elements P (i, j) denoted Pij of the Co-occurrence matrix represent the frequency of occurrence of the pair of gray levels (i, j) in the processing window "W" of T1×T2 size, according to a relationship represented by the pair (Δx, Δy). They are defined as follows:

$$P(i, j / \Delta x, \Delta y) = \text{Card}\{(m, n), (m+\Delta x, n+\Delta y)\ \Delta\ W / I(m, n) = i \text{ and } I(m+\Delta x, n+\Delta y) = j\} \quad (1)$$

Where Card, is the cardinal or the number of elements, and I (m, n) and I (m+Δx, n+Δy) represent respectively the intensities of pixels "i" and "j" located at (m,n) and (m+Δx, n+Δy) in the window "W".

The elements of the direction matrix Cij (θ, d) are written:

$$C_{ij}(\theta, d) = P(i, j / \Delta x, \Delta y) / r \quad (2)$$

Where "r" is the normalization parameter which is equal to: (T1-|Δx|) × (T2-|Δy|).

There are eight Co-occurrence matrices C (θ, d) for different directions (θ = 0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°).

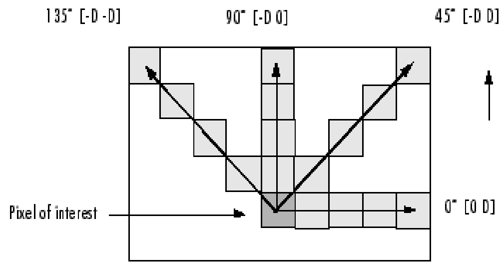

Fig. 2 Directions of co-occurrence matrix.

We can calculate, using the Co-occurrence matrix, a set of statistical properties (i.e. Mean, Variance, Inertia, Local homogeneity, Energy, Correlation, Entropy, Cluster shade, and Cluster prominence), which allow us to reveal the particular characteristics of image texture.

The parameters are shown in Table 1 are calculated by considering a sliding window on an image containing Ng grayscales.

TABLE I
STATISTICAL PROPERTIES

Mean	$\mu_x = \sum_{i=0}^{N_g-1} i \sum_{j=0}^{N_g-1} C_{ij} \qquad \mu_y = \sum_{j=0}^{N_g-1} j \sum_{i=0}^{N_g-1} C_{ij}$
Variance	$\sigma_x^2 = \sum_{i=0}^{N_g-1} (i-\mu_x)^2 \sum_{j=0}^{N_g-1} C_{ij}$ $\sigma_y^2 = \sum_{j=0}^{N_g-1} (j-\mu_y)^2 \sum_{i=0}^{N_g-1} C_{ij}$
Inertia	$I = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-j)^2 C_{ij}$
Local homogeneity	$LH = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \left[1/\left(1+(i-j)^2\right)\right].C_{ij}$
Energy	$E = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} C_{ij}^2$
Correlation	$COR = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \left[(i-\mu_x).(j-\mu_y)/(\sigma_x.\sigma_y)\right].C_{ij}$
Entropy	$ENT = -\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} P_{ij}.\log C_{ij}$
Cluster shade	$CS = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i+j-\mu_x-\mu_y)^3.C_{ij}$

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Cluster prominence	$CP = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \left(i + j - \mu_x - \mu_y\right)^4 . C_{ij}$

In this paper, we will use one direction θ =0° and one distance d=1, which correspond to the Cartesian coordinates (Δx=0, Δy=1).

Using Grey-Level Co-occurrence Matrices, and by taking samples from the two classes, we determine the maximum and the minimum values for each parameter described before, in order to identify a notable difference.

C. Support vector machine

Support vector machine is a machine learning method that is widely used for data classification. The algorithm was invented by Vladimir VAPNIK in the late seventies. SVM's have been applied in many fields such as handwritten digit recognition, object recognition, speaker identification, face detection in images and text categorizatio.

Although SVM is considered easier to use and efficient in some applications than Artificial Neural Networks (ANN), or Adaptive Neuro-Fuzzy Inference System (ANFIS). However, users who are not familiar with SVM often get unsatisfactory results at first. But SVM's classifier constructs a "best" separating hyperplane (the maximal margin plane) in a high-dimensional feature space which is defined by nonlinear transformations from the original feature variables.

The SVM analyzed two kinds of data, i.e. linearly and nonlinearly separable data [14].

The advantage of SVM is that they can make use of certain kernels in order to transform the problem, such that we can apply linear classification techniques to non-linear data. Applying the kernel equation arranges the data instances in such a way within the multi dimensional space, that there is a hyper-plane that separates data instances of one kind from those of another. The optimal hyper-plane classifier of a SVM is unique.

The kernel equations may be any function that transforms the linearly non-separable data in one domain into another domain where the instances become linearly separable. Kernel equations may be :

1) Multilayer Perceptron Kernel: The Multilayer Perceptron (MLP) Kernel is also known as the Sigmoid Kernel and as the Hyperbolic Tangent kernel. The Sigmoid Kernel comes from the Neural Networks field, where the bipolar sigmoid function is often used as an activation function for artificial neurons.

2) Linear Kernel: The Linear kernel is the simplest kernel function. Kernel algorithms using a linear kernel are often equivalent to their non-kernel counterparts.

3) *Polynomial Kernel:* The Polynomial kernel is a non-stationary kernel. Polynomial kernels are well suited for problems where all the training data is normalized.

4) *Radial basis function kernel:* The Gaussian kernel is an example of radial basis function kernel.

5) *Rational Quadratic Kernel:* The Rational Quadratic kernel is less computationally intensive than the Gaussian kernel and can be used as an alternative when using the Gaussian becomes too expensive.

D. Data processing

Our analysis consists of choosing an image, where precipitation echoes are distinctly separated from the ground echoes (as shown in Fig. 3). After that, different steps are performed as follows:

- For the samples (yellow windows) of each type of echoes, we compute for each pixel, the different parameters described previously based on (GLCM), by using the surrounding pixels that construct a matrix of 5×5 pixels (or a sub-window of 5×5 pixels).
- We compute for all parameters and for each type of echo, the values of the different samples (with giving the minimum and the maximum values).
- We plot the parameters' histograms.
- Define the useful parameters from the histograms.
- Utilize the useful parameters as inputs to an SVM classifier, in order to classify the data into two kinds: precipitations that we want to keep and ground echoes that we want to remove.

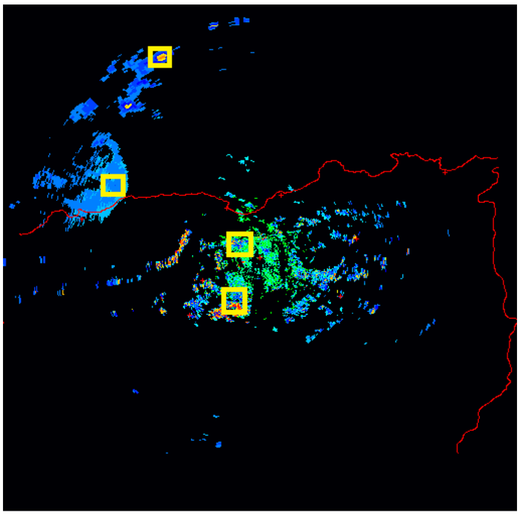

Fig. 3 Selection of samples for each type of echo (illustration).

It's worth noting that, the concurrence matrix of each sub-window consists of 15×15 elements; this is due to the number of colors used in this site.

III. Results

After calculating the nine parameters, we get the results of the maximum and the minimum values for each kind of echo. Those values are presented in the table II for the parameters Energy, Local homogeneity, contrast and correlation. We

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select only those parameters in order to illustrate positive and negative samples.

TABLE III
MINIMUM AND MAXIMUM VALUES OF 4 TEXTURAL PARAMETERS

Parameter	Precipitations		Ground Echoes	
	Min	**Max**	**Min**	**Max**
Energy	0.25	1	0.05	0.35
Local homogeneity	0.53	1	0.21	0.63
Contrast	0	112.5	5.05	53.4
Correlation	-0.37	0.68	-0.17	0.87

As we can see from Table II, Energy and Local homogeneity give the results the most uncorrelated. In addition, we remark that the others textural parameters we didn't get the required results due to the total overlapping between the results of the precipitations and those of the ground echoes (as illustration the results of the contrast and the correlation).

After calculating the parameters, for both parameters Energy and Local Homogeneity, we assign the value "1" for precipitations class and the value "0" for ground echoes class in order to use them in the SVM classifier as shown in the Fig. 4.

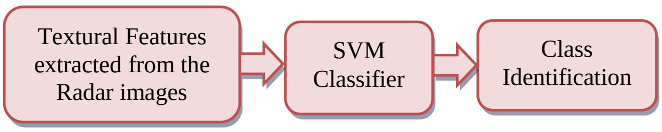

Fig. 4 SVM Classifier

The training database that corresponds to our two classes is composed of 970 samples, 500 for clutter and 470 for precipitations.

The output of the SVM classifier will be used later to find an appropriate approach, which will allow us to separate the ground echoes from the precipitation echoes in order to eliminate the undesirable echoes.

After classifying the data into two distinct classes using, various forms of kernel function

In order to find the best kernel for our problem, we applied our approach using the five kernel functions. For each case we gave the SVM plot of data (see Fig. 5, 6, 7, 8, 9).

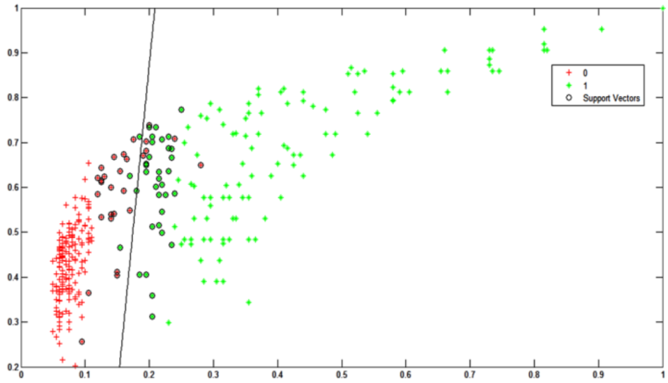

Fig. 5 SVM Linear kernel plot of data.

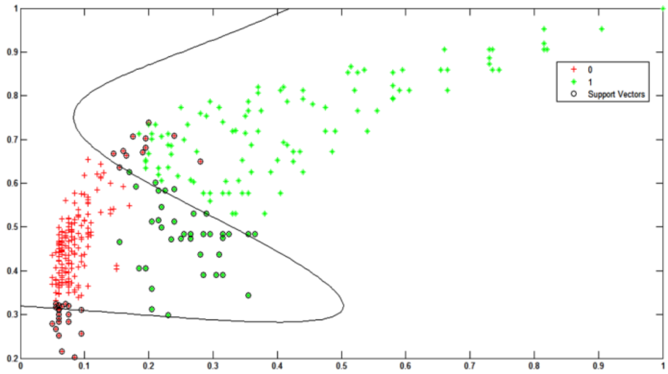

Fig. 6 SVM multilayer perceptron kernel plot of data.

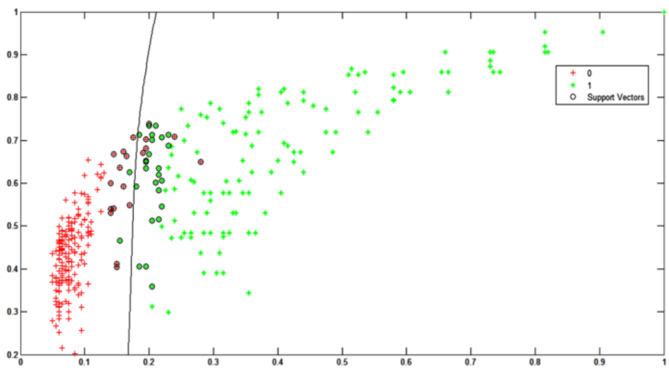

Fig. 7 SVM polynomial kernel plot of data.

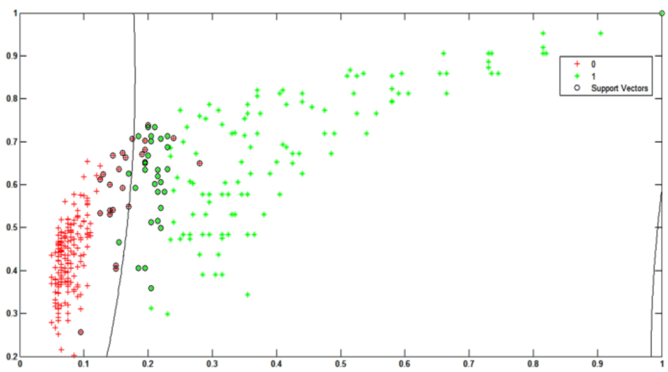

Fig. 8 SVM quadratic kernel plot of data.

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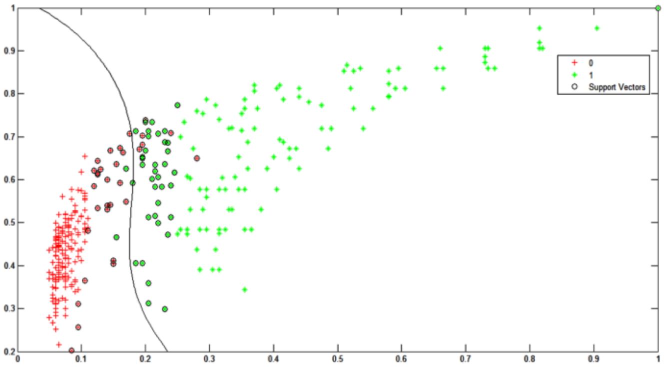

Fig. 9 SVM radial basis function kernel plot of data.

In order to eliminate the clutter, we used our approaches, to classify and filter our images. To do so, we performed the following process:
For each pixel in the image and using the surrounded pixels, we computed the textural parameters, after that, we applied them to the SVM classifier to get, as result, the appropriate class for that pixel.

In order to determine the rate of identification of the two classes, we calculated the mean rate of correct recognition for each image (denoted RM). This rate is calculated by the following expression:

$$RM = \left(\sum_{i=1}^{c} X_i / N\right) \times 100 \qquad (3)$$

Where:
c : Is the number of classes.
N : Is the total number of pixels.
Xi : Is the number of pixels correctly classified to the class i.

Table III gives the rate of recognition of each class and the total mean rate of the classified and filtered images using the five kernel functions.

TABLE IIIII
PERCENTAGE OF CORRECT RECOGNITION OF THE TWO CLASSES

Kernel function	Rate of correct recognition (%)		
	Precipitations	Ground echoes	Total Rate
Linear	89.52	98.40	94.10
Multilayer perceptron	91.34	93.36	92.38
Polynomial	90.39	98.50	94.57
Quadratic	91.26	98.07	94.77
Radial basis	90.50	98.63	94.69

We can clearly see through Table III, that the application of this approach gives a total mean rate of correct recognition of echoes to over 94.77% using the quadratic kernel. The best rate given for precipitations or rainfalls is recorded using multilayer perceptron kernel with 91.34%, whereas for the ground echoes, we found the value of 98.63% with the radial basis kernel function.
Using our SVM classifier with quadratic kernel, we can clearly see, through Fig. 10 and Fig. 11, that the ground echoes appearing on the considered Radar image of Sétif are completely eliminated, whereas the precipitations are almost totally preserved.

In order to compare our approach with the previous studies, Table IV collects the results of three methods. We can see that our approach improved the total rate of recognition and filtering quality.

TABLE IVV
COMPARISON WITH THE PREVIOUS STUDIES

Approach	Total rate of correct recognition (%)
Textural approach [15]	91.50
Fuzzy logic approach [7]	94.50
ANFIS approach [9]	93.52
SVM approach	94.77

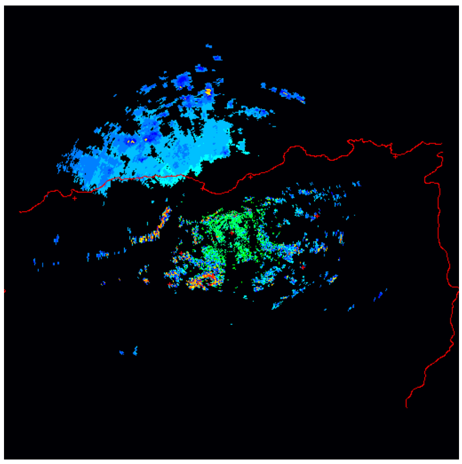

Fig. 10 Original image

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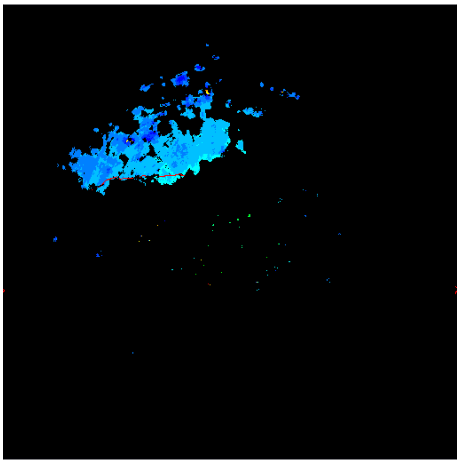

Fig. 11 Filtered image

IV. Conclusions

In this paper, we carried out the classification of Radar image echoes using the combination of gray level co-occurrence matrices (GLCM) and the support vector machine (SVM) classifier, in order to obtain a clear radar image and eliminate the noise caused by the earth surface which is the ground echoes.

Gray Level Co-occurrence Matrix is an algorithm based on feature extraction. We have applied it using the one directions ($\theta = 0°$) and we found that the parameters energy and local homogeneity are the most effective elements in echoes classification.

Support Vector Machine classifiers were used to identify data formed by the elements of the two textural parameters. We have used the different forms of kernel functions to classify and filter the radar images those functions are the linear kernel, Multilayer perceptron (MLP), Polynomial, Quadratic and Radial basis function kernel (RBF). And we have shown that the quadratic kernel gives the best result in term of mean rate of correct recognition. Whereas the multilayer perceptron kernel is well adapted for the identification of precipitations and the radial basis kernel function for the ground echoes or clutter. As a result of this study, we can say that the total mean rate of correct recognition of echoes is about 94.77%. Also increasing the number of samples or indeed the diversity in database, improve the filtering rate.

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