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Development of Multiresolution Hierarchical Trees to Non-cooperative Target Recognition

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***Abstract*—In this paper, problem of efficient representation of large database of target radar cross section is investigated in order to minimize memory requirements and recognition search time, using a tree structured hierarchical wavelet representation. Synthetic RCS of large aircrafts, in the HF-VHF bands, are used as experimental data. Hierarchical trees are built using wavelet multiresolution representation and K-means clustering algorithm. Criteria used to define these hierarchical trees are described and the obtained performances are presented.**

***Keywords*-radar, target recognition, wavelet, clustering.**

I. INTRODUCTION

Requirements for future air defence radar systems are detection, localization, but also identification of aircrafts. With the increasing resolution of modern radar systems, it is theoretically possible to store much information, according to aspect, elevation, pulse width, etc., of a complex target and to use them in the field of target recognition.

Advantage of the increasing resolution of radar systems is the opportunity to have more details characteristic of a specific target. Disadvantage is that these detailed characteristics require more and more computer memory to be stored, computer resources and increase the search computational time to NCTR (Non-Cooperative Target Recognition). It is therefore important to develop efficient methods to decrease the size of high resolution data of radar targets. One way to compress these data is to use tree structured representation using clustering algorithm coupled with a multiresolution wavelet representation to decrease the data size and the number of RCS signature [1].

In this paper, we investigate the problem of efficient representation of large database of radar range profiles in order to minimize memory requirements and recognition search time, using a tree structured hierarchical wavelet representation.

II. DESCRIPTION OF SYNTHETIC RCS DATABASE

The synthetic RCS database has been developed during the MOSAR project [2] [3] with the support of the French Ministry of Defence (DGA).

To be able to use a small computer like a PC, the simulation of RCS has been made with the free Numerical Electromagnetic Code NEC2 which is based on the Method of Moments (MoM). In this case, the aircraft structure is considered as a Perfect Electric Conducting (PEC) body. An example of wiregrid model is presented at Fig. 1.

The synthetic database is constituted of eight mid-range airplanes: Airbus A320, BAe 146-200, Boeing 727-200, 737-200, 737-300, 747-200, 757-200 and Fokker 100. For each aircraft, RCS has been determined as a function of angle aspect and polarization, in a frequency band between 20 to 100 MHz, with a frequency step of 1 MHz. Then, the range profile is estimated using an inverse Fourier transform from the frequency response. The synthetic database is finally constituted of around 300 000 range profiles. Figure 2 shows an example of estimated range profile.

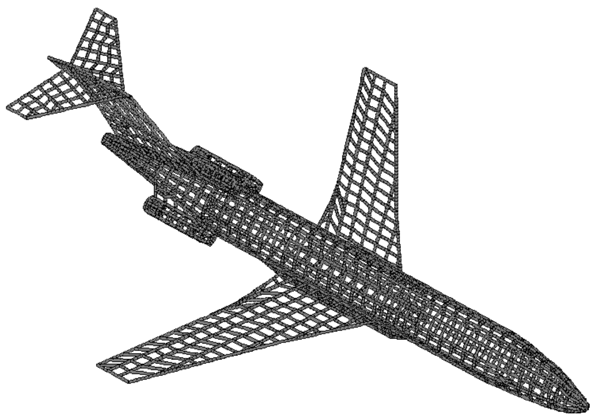

Figure 1. Example of modeling aircraft using a wiregrid model – Boeing 727-200.

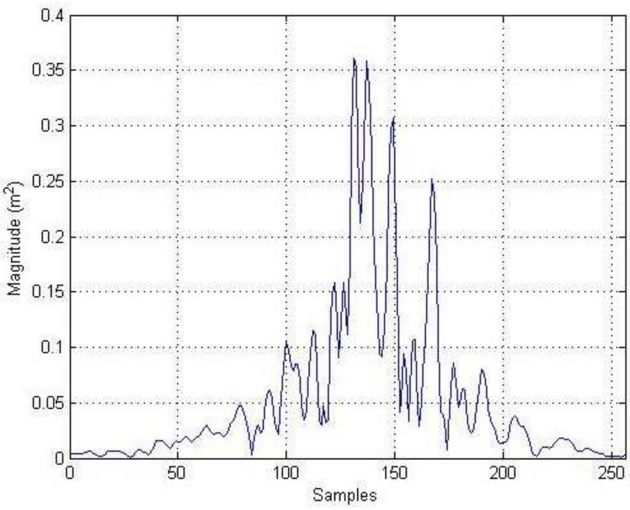

Figure 2. Example of estimated range profile – Boeing 727-200 – HH Polarisation – Frequency band: 20 – 100 MHz.

III. APPLICATION OF TREE STRUCTURED HIERARCHICAL WAVELET REPRESENTATION TO DATABASE COMPRESSION

A. Introduction

Wavelet transforms and clustering algorithms have been found useful in a variety of applications. Wavelets provide the analyst with an approximation of the signal and a detail of the signal as well. Clustering deals with finding a structure in a collection of unlabeled data. But each of them has its own limitations [4]. Application of wavelets representation to NCTR application gives a low decrease of recognition search time but with a low degradation of probability of false identification. At the opposite, use of clustering algorithms gives a very low decrease of recognition search time but with an important degradation of probability of false identification.

A way to improve these techniques is to merge them in a multiresolution hierarchical tree [5]. For a complete description of wavelet analysis and clustering algorithms, the reader should refer to [6–8]. A brief summary of how the wavelets and clustering were used is presented here.

B. Multiresolution wavelet representation of RCS database

The Discrete Wavelet Transform (DWT) of finite sequences analyzes a signal S by decomposing it into approximation A_i and detail D_i parts by a quadrature filter system [6], where i is the decomposition level. The approximation and detail parts are respectively obtained by a low-pass filter and a high-pass filter. At each level, the filtering process is followed by a decimation by *2* that decreases the data size. Fig.3 presents an example of range profile and its wavelet decomposition computed in four levels.

Then, the approximations and details at each level are pre-processed from the original signal and placed in the training data set.

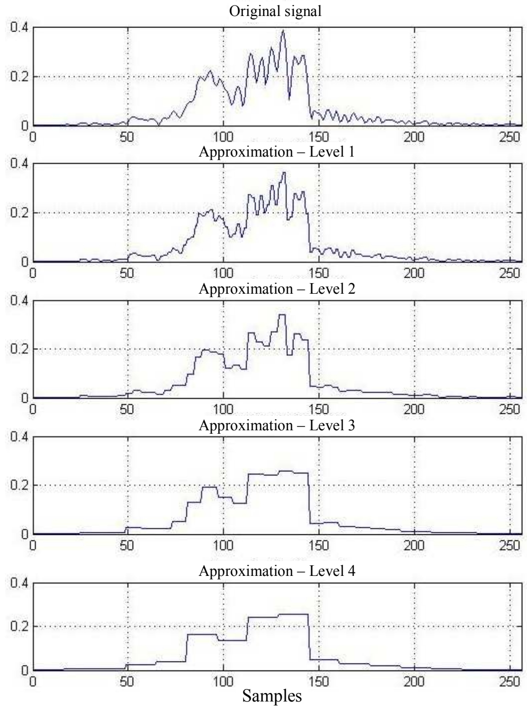

Figure 3. Example of range profile and its wavelet transform computed in four levels using the Haar wavelet.

Another work [4] has shown that there is no statistically significant difference in performance of the classifier when different wavelets are chosen. Thus, in the next sections, results obtained with the Haar wavelet are only presented.

C. Unsupervised clustering of RCS database

Clustering is the classification of objects according to similarities among them, and organizing of data in groups. Two types of clustering methods can be defined:

- Hard clustering techniques where data are set into C specified number of mutually exclusive subsets.
- Fuzzy clustering techniques where data can be assigned to several clusters simultaneously, with different degrees of membership.

For a complete description of these unsupervised clustering algorithms, the reader should refer to [7] [8].

Previous results [4] have shown that better performances are obtained with a hard clustering algorithm, like K-means, in NCTR applications. Thus, in the next sections, only results obtained with the K-means hard partitioning method are presented.

The K-means hard partitioning method is simple and popular [8]. From an $N \times n$ dimensional data set, K-means algorithm allocates each data point x_k to one of C clusters to minimize the following objective function:

$$J = \sum_{i=1}^{C} \sum_{k \in A_i} \left\| x_k - c_i \right\|^2 \tag{1}$$

Where A_i is a set of objects (data points) in the i^{th} cluster and c_i is the mean for those points over the cluster i.

Thus, c_i are called the cluster centres (centroids) and are defined as:

$$c_i = \frac{\sum_{k=1}^{N_i} x_k}{N_i}, x_k \in A_i \tag{2}$$

IV. TREE STRUCTURE DESIGN

In the case of a clustering algorithm applied to NCTR, best efficiencies are obtained for an optimum number of clusters [4]. For multiresolution hierarchical tree, problem is quite different. Number of clusters must be large to have a decrease of computational time, but probability of false classification must not be degraded. The clusters number on each decomposition level must be defined as a function of the distortion on the entire population of data vectors [1]. This distortion can be determined using a mean squared distance metric and is computed using the finest representation of the data vectors. It is defined as:

$$d_{(jc,0)} = \frac{n_c}{M} . \sum_{i=1}^{n_c} \left\| C_{(jc,0)} - S_i^0 \right\|^2 \tag{3}$$

Where j is the decomposition level, n_c, the number of data vectors in the cluster c, $C_{(jc,0)}$, the centroid of the cluster re-sampled at the finest resolution (*0*), S_i^0, the data vector number i at the resolution *0*, and M, the total number of the data vectors.

Then, to design the tree, processing steps are the following: Step *1*: loading of the complete target database, Step *2*: wavelet decomposition of the target database on different levels, Step *3*: computation of the clustering database on the lowest (coarsest) decomposition level using the $d_{(jc,0)}$ criterion, Step *4*: computation of the clustering database using the next finer resolution based on the previous subpartition and the $d_{(jc,0)}$ distortion criterion, Repeat step *4* until the decomposition level *0* corresponding to the finest resolution (original signals).

Once tree is built, a pruning is realised by inspecting the contents of the different clusters. To evaluate the consistence of the hierarchical tree, the total distortion *TD* and the entropy of the final partition *E* can be determined as a function of the number of clusters.

V. Performance Estimation Method

To test the efficiency of database compression using a multiresolution hierarchical tree, many criteria can be used:

- Probability of false classification (*Pfc*) as a function of Signal to Noise Ratio (*SNR*).
- Minimum *SNR* to obtain a *Pfc* smaller than *1 %*.
- Search computational time (*Sct*) for a fixed *SNR*.

The nearest neighbour algorithm using the Euclidean distance is used to recognize the target. It is a simple algorithm and is useful to use it to test the efficiency of the database compression.

In computing, to estimate the "Search computational Time" (*Sct*), a standard parameter is the number of MFLOPs. It's an acronym meaning "Million FLoating point OPerations".

With this parameter, it is very easy to make a comparison between the efficiencies of the different processing algorithms.

VI. Application of Multiresolution Hierarchical Tree to Target Recognition

Different multiresolution hierarchical trees have been designed from different beginning decomposition levels (*1* to *4*). An example of tree built from the decomposition level *4*, and using the Haar wavelet and the K-means hard partitioning algorithm, is shown at Fig. 4. This tree has 21 final clusters, an average distortion of *0.56* and a partition entropy of *2.9*. In this figure, the clusters are designated by a notation $C_{j,k}$, where k is the cluster number at resolution j. The number in each circle defines the percentage of data in the cluster.

Fig. 5 presents an estimation of *Pfc* as a function *SNR* for different multiresolution hierarchical trees designed from different beginning decomposition levels (*1* to *4*). A degradation of the *Pfc* can be observed as a function of the beginning approximation level.

Fig. 6 and 7 show the variation of minimum *SNR* to obtain a *Pfc* smaller than *1 %*, and the search computational time *Sct* for a fixed *SNR* as a function of the beginning decomposition level used to design the multiresolution hierarchical tree. We observe a degradation of the minimum *SNR* to have a *Pfc* < *1 %* of *8 dB*, but the *Sct* is divided by a factor of *13*.

Thus, multiresolution hierarchical trees are a solution to compress high resolution data of radar targets. But, other methods exist like the use of wavelet decomposition or the unsupervised data clustering [4] [9]. It must be interesting to compare these techniques as a function of the probability of false classification and the computational time of search.

Fig. 6 and 7 present the comparison between the minimum *SNR* to obtain a *Pfc* smaller than *1 %*, and the search computational time *Sct* for a fixed *SNR* as a function of the decomposition level for these different techniques (multiresolution hierarchical tree, K-means clustering algorithm, Haar wavelet decomposition).

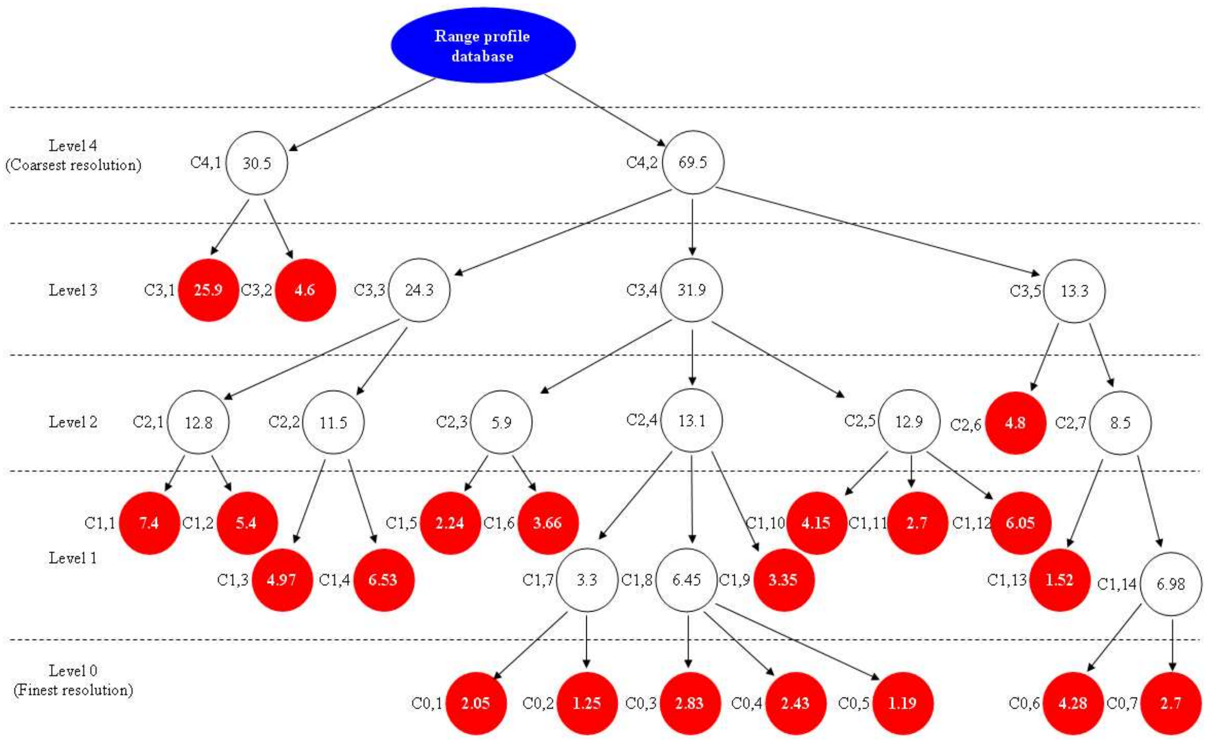

Figure 4. Example of multiresolution hierarchical tree built from the level decomposition 4, using the Haar wavelet and the K-means clustering algorithm.

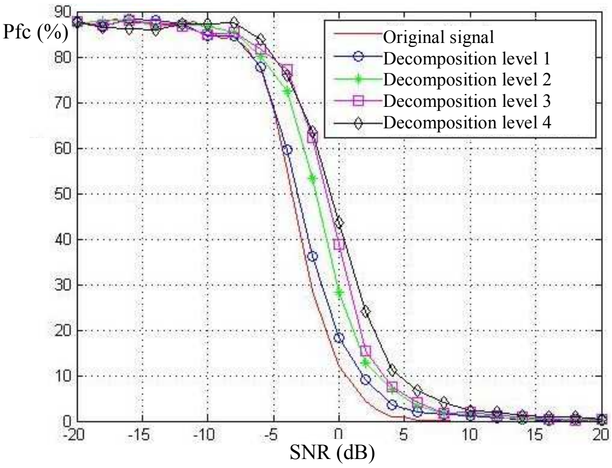

Figure 5. Probability of false classification *Pfc* as a function *SNR* for the original set and the multiresolution hierarchical trees designed from different beginning decomposition levels *4* to *1*, using a Haar wavelet and the K-means algorithm.

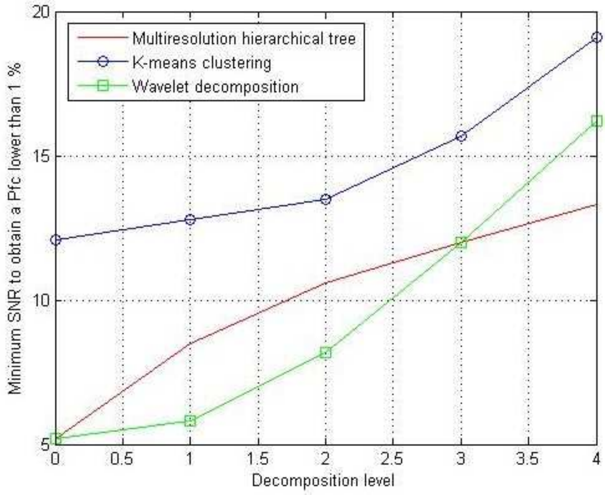

Figure 6. Minimum *SNR* to obtain a *Pfc* smaller than *1 %* as a function of decomposition level for the multiresolution hierarchical trees, K-means algorithm ($C = 50$), and the Haar wavelet decomposition.

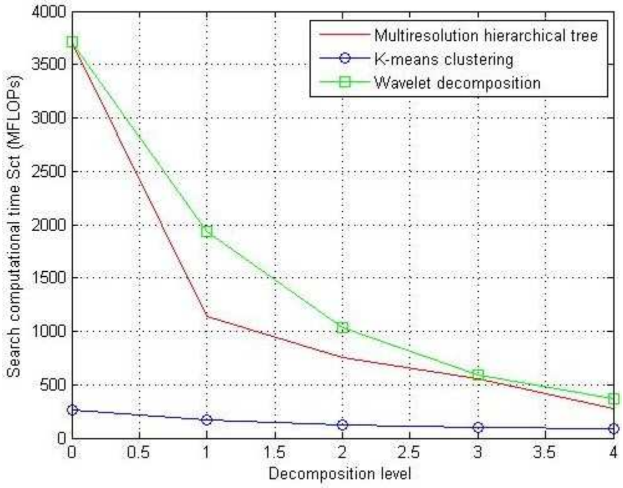

Figure 7. Search computational time *Sct* as a function of decomposition level for the multiresolution hierarchical trees, the K-means algorithm ($C = 50$), and the Haar wavelet decomposition.

The lowest *Sct* is obtained for the clustering algorithm but with the most important degradation of the minimum *SNR* to obtain a *Pfc* smaller than *1 %*.

Use of the approximation signals of wavelet decomposition to NCTR application makes it possible to obtain the weakest *SNR* to obtain a *Pfc* smaller than *1 %*, in particular for the first decomposition levels (*1* and *2*). Use of multiresolution hierarchical trees, designed from the coarser decomposition levels (*3* and *4*) is a good compromise between the data clustering and the wavelet decomposition, because a better performance is obtained for the minimum *SNR* to obtain a *Pfc* smaller than *1 %*, with a similar search computational time.

VII. Comments and Conclusion

The objective of this paper is to evaluate the efficiency of a tree structured hierarchical wavelet representation to minimize the computational search time to NCTR association. The hierarchical designing method based on the use of approximation signals of the wavelet decomposition coupled with the K-means unsupervised clustering algorithm, is described. A criterion is presented to determine the cluster number on each level of the tree with a hierarchical dependence. For a hierarchical tree designed from the decomposition level *4*, *Sct* is divided by a factor of *13*, with a degradation of the minimum *SNR* to have a *Pfc* < *1 %* of *8 dB*. Comparison with other database compression methods (wavelet decomposition, hard clustering) shows that the multiresolution hierarchical trees are a good compromise as a function of *Sct* and *Pfc*, if their design have been made from the upper (coarser) decomposition levels.

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