Fusion Fourier Descriptors from the E-M, K-Means and Fisher Algorithms for Radar Target Recognition

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Abstract—**The target recognition from Radar images was a crucial step in our research. This paper presents a process and an adopted approach for Automatic Target recognition using Inverse Synthetic Aperture Radar (ISAR) image. Indeed, the process adopted is composed of three steps. In the first step, we achieve the edge detection using of three techniques: Fisher, K-means and Expectation-Maximization (E-M). Each of these techniques is combined with Watersheds (WS) algorithm to obtain the closed target shape. In order to ensure that the shape descriptors must be accurate, compact and invariant to several geometrical transformations (translation, rotation, scale, etc.), we have used Fourier Descriptor computed on each obtained shape. To achieve a classification task in the last step, several techniques can be used to perform recognition tasks. We have used the nearest-neighbor classifier to retrieve a nearest known target for each unknown target in the test dataset.**

Finally, in order to validate our proposed approach a database of ISAR images reconstructed from anechoic chamber simulations will be used. The simulation results using Fisher, E-M and K-Means methods will be presented in the last section of this paper.

Keywords- ISAR image; Fisher; K-Means; E-M; Watersheds; Fourier descriptor; fusion; KNN classification

I. INTRODUCTION

Generally, the Automatic Target Recognition (ATR) includes four steps namely, data acquisition, data pre-processing, data representation and data classification for classification decision making [3] [15]. The principal goal is to identify and recognize a target from its echoes or its radar Images. However, extracting the target characteristics and then its signature from a radar echoes or radar image is the rather difficult task.

In this paper, we purpose an approach to compute radar signatures using ISAR images. The target signatures give us the acquire information about the target characteristics which we used to recognize target. In this step, the main difficulties are to make feature vectors from ISAR image which is able to guarantee scale and rotation invariance of image ISAR [15][2].

For target recognition, several studies exploit the theory and tools of artificial intelligence to develop sophistical algorithms for a decision making. In this work, we propose the one classification technique of ISAR images based on the classifier K-nearest neighbor (KNN).

The classification of the whole radar image (ex. ISAR) produces errors due to the large size of the ISAR image, variance in illumination, scale and orientation, etc. [15]. To solve these problems, several pre-processing techniques and image processing are studied and compared to provide answers to the problem in order to improve the correct classification rate.

The goal of these different approaches of feature vectors extraction is to compute target characteristics (shape) and then shape descriptors which are stored in database to classification step. We proposed in the first part of this paper the edge detection from ISAR images. Then, in the literature, several edge detectors methods are listed among which we can cite such as: Expectation-Maximization (E-M), K-means and Fisher, watersheds, Sobel, Canny, Perwitt, Snakes... In the second part of this work, the shape representation is necessary to compute the vector descriptors and to accomplish the classification task. It results from this, that the shape descriptors must be accurate, compact and invariant with a certain number of geometrical transformations (translation, rotation, scaling...). Other shape descriptors can be used in this step as curvature scale space descriptor (CCSD), Zernike moment descriptors (ZMD) and grid descriptors (GD), etc.. Finally, to achieve the targets recognition task, the K-Nearest Neighbor classifier will be used.

Many studies are interested in each phase of the classification process to present new techniques or to combine some already known tools. In our case, we highlight the impact of the fusion of the Fourier descriptor issued from three edge detection algorithms. In the next, section we detailed our proposed methods. In fact, our work is based on the combination of each segmented images obtained using the E-M algorithm, the K-means algorithm and the Fisher algorithm [7] with the watershed algorithm (WS) to compute the closed edge of target. Then Fourier descriptors are computed as shape descriptors. We also propose to fuse the obtained descriptors using the maximum operator, the minimum operator and the average operator to calculate new descriptors of the studied targets. At the end of this section, we present the algorithm K-Nearest Neighbors that we use as a classifier to evaluate our proposed methods.

In Section 3, we present the results and we discuss the impact of the merger of the descriptors, the number of neighbors used in the KNN algorithm and the ratio of the learning base on the performance of the target recognition process.

Finally, we conclude this paper by conclusion and perspectives.

II. THE PROPOSED METHOD

Our proposed method is based on the fusion of Fourier descriptors for the modeling of radar target shown in figure 1. In fact, we apply three types of algorithms clustering to the ISAR image namely, the Fisher algorithm, the Expectation-Maximization algorithm (E-M) and the k-means clustering. Then, the selected clusters of these techniques will be used in the watershed algorithm to calculate the target contour. Each contour allows us to model the target. Thus, we obtain three Fourier Descriptors of the sample of the ISAR image. Next, we combine these three descriptors to obtain the fused descriptor which we will use as an identifier for the target present in the image ISAR. Finally, we use the k-nearest neighbor algorithm (k-NN) to evaluate the performance of our descriptor compared to the descriptors issued from clustering algorithms the E-M, the K-Means and the Fisher.

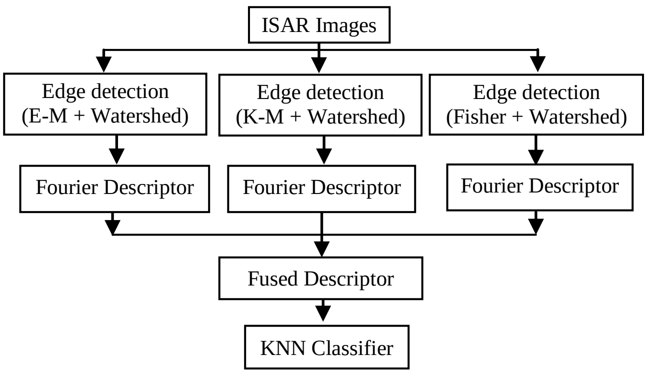


Figure 1. flowchart of the proposed method

A. *Extracted edge for radar Target recognition*

In the literature there are several segmentation techniques that are based on either the region approach or the contour approach. There are also other methods that combine several segmentation techniques. To define our target contour, we will use three segmentation algorithms namely Fisher, Expectation-Maximization (E-M) and K-means. Each of these algorithms provides us with a binary image separating the target from the background. Based on the binary image we can define the target contour. To overcome the problem of artifacts we resorted to the use of several morphological operators including the watershed algorithm to obtain a closed contour which allows us to identify our target easily.

1) Image segmentation by Fisher algorithm

The image segmentation Techniques are varied and differ mainly in the definition of thresholds separating different classes. In this context, Fisher [19] proposed a repartition method of individuals in a population characterized by a single variable [8]. Considering the image pixels as individuals characterized by their brightness, we can apply the Fisher algorithm for the grayscale images segmentation.

According to the Fisher algorithm, an optimal distribution is obtained by minimizing the total intra class variance W defined by the (1).

$$w = \sum t_i .\, v_i w = \sum t_i\, v_i \qquad (1)$$

Where t_i, m_i and v_i represent respectively the size, the average and the variance of a class $_{Ci}$.

$$t_i = \sum_{D_j} H(j), m_i = \sum_{D_j} \frac{j.H(j)}{t_i} et v_i = \sum_{D_j} \frac{(j-m_i)^2.H(j)}{t_i} \qquad (2)$$

With H a standardized histogram of the image and $D_j=[s_{i-1}\, s_i[$ the domain of grayscale associated with class C_i.

1) Image segmentation by K-means algorithme

K-means is an iterative algorithm that was defined by [11]. This technique is one of the simplest algorithms for image segmentation which classifies pixels based on their grayscale K classes. The main idea was to choose a random set of a priori fixed center and iteratively find the optimal partition. Each pixel is assigned to the class whose center is the nearest. After the assignment of all data, the mean of each group is recalculated. When resulting in a steady state (data groups do not change), the algorithm is stopped. The objective of the K-means algorithm is to minimize the maximum distance (in our approach we use the Euclidean distance) between each point and its nearest center [18] [17]:

$$J(X,V) = \frac{1}{2}\sum_{i=1}^{k}\sum_{x_j\in S_i} |x_j - \mu_i|^2 \qquad (3)$$

Where k is the number of cluster, S_i is the cluster i and μ_i is the its centroid (the average of the x_j points of the cluster S_i).

The main steps of this algorithm are [18] [6]:

- Random choice of the initial positions of the centroids of K classes
- (Re-) Assign objects to a class according to a criterion of minimizing distances
- Once all the objects are placed, recalculate K centroids

Repeat steps 2 and 3 until no movement is possible

3) Image segmentation by Expectation-Maximization (E-M) algorithme

The algorithm of the Expectation-Maximization (E-M) is an iterative algorithm widely used to search for parameter maximum likelihood [5].

In this algorithm, an input signal $E(x)$E is approximated by a sum of weighted Gaussian weights α:

$$\hat{E}(x) = \sum_{n=1}^{N} \alpha_n \, G(x, \mu_n, \sigma_n) \quad (4)$$

With $E(x)$: signal approximated of $\hat{E}(x)$ $\hat{E}(x)$ and N N the number of classes

μ_n μ_n : The average of class n , σ_n σ_n the variance of a class n

G : function of probability density of the Gaussian distribution.

Maximum likelihood is achieved by calculating a likelihood factor V(x, i) , specific to each pixel X and Gaussian I and which will allow, at each iteration to recalculate the parameters of Gaussian [5].

$$V(x, i) = \frac{\alpha_n . G(x, \mu_n, \sigma_n)}{\sum_{n=1}^{N} \alpha_n \, G(x, \mu_n, \sigma_n)} \quad (5)$$

The stopping criterion of the algorithm is either a maximum number of iterations to reduce the computation time, or an error inferior to ε between two successive approximations.

4) Algorithm watershed

A grayscale image could be seen as a topographic surface where the pixels coordinates are used to locate the pixel in the Cartesian space while its value represents the altitude of the geographic area. Relying on this specificity, the watershed operator aims to compute the limit separating two basin slopes [1] [4] [14] as illustrated in figure 2.

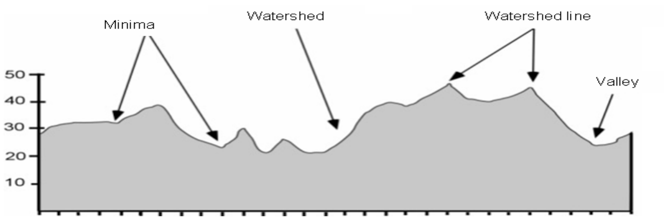


Figure 2. Principle of watershed line [4]

As known, the watershed (WS) is a morphological operator used to obtain closed edge from a binary image [10] and then it is generalized to be used as segmentation tool for grayscale images [16] [9].

B. Shape Modeling: Melting the Fourier descriptors

1) Fourier descriptor

The Fourier descriptor gives a frequency representation of the contour of the image extracted in the previous step [13]. In fact, we apply the discreet Fourier transform (DFT) to the extracted (represented in complex plane) edge of the ISAR image. The following equation describes the DFT:

$$F(n) = \frac{1}{N} \sum_{k=0}^{N-1} z(k) \, e^{-j.2.\pi.n.k/N} \quad (6)$$

These descriptions are the signature of the object extracted from the image. This signature is computed for a fixed number n of complex coordinates of the extracted contour. This yields to a descriptor formed by *n/2* coefficients.

Indeed, we have normalized the extracted contours to get the same size of the extracted contours and thus the same size of the signature used in the classification phase.

Moreover, the calculated Fourier descriptors must be invariant to geometric changes (translation, rotation and / or scaling) to increase the performance of the classifier [2].

The translation of descriptors is integrated in the first coefficient *F(0)*. To ensure translation invariance, we omit this first term of the Fourier descriptor.

On the other hand, the Fourier descriptors of $z'(k) = \alpha.\, z(k)$, where, α is the factor scale:

$$\begin{aligned} F'(n) &= \frac{1}{N} \sum_{k=0}^{N-1} z'(k) \, . \, e^{-j.2.\pi.n.k/N} \\ &= \frac{1}{N} \sum_{k=0}^{N-1} \alpha . \, z(k) \, . \, e^{-j.2.\pi.n.k/N} \quad (7) \\ &= \alpha . \, F(n) \end{aligned}$$

Therefore, to ensure the scaling invariance, we divide the Fourier descriptor by its first coefficient (*F (1)* in our case).

Finally, the rotation by an angel θ is obtained by multiplying the descriptors by the value $e^{i\theta}$. Thus, this transformation affects only the Fourier descriptor phase. Accordingly, we use the amplitudes of the Fourier descriptor coefficients only.

2) Melting the Fourier descriptors

The information fusion is to combine information from several sources. This process aims to improve the decision-making. In this work we suggest to fuse the each Fourier descriptors of edges obtained from algorithms of E-M, K-means and Fisher. To fuse these descriptors, we propose three mathematical operators namely minimum, maximum and mean. In the following equations we describe the three fusion descriptors :

$$DF_{min} = \min_{i=1,\dots L} (DF_{K-means}, DF_{E-M}, DF_{Fisher})(i) \quad (8)$$

$$DF_{mean} = \operatorname*{mean}_{i=1,\dots L} (DF_{K-means}, DF_{E-M}, DF_{Fisher})(i) \quad (9)$$

$$DF_{max} = \max_{i=1,\dots L} (DF_{K-means}, DF_{E-M}, DF_{Fisher})(i) \quad (10)$$

Where L is a size of Fourier descriptor, DF_{min}, DF_{mean}, DF_{max}, $DF_{E\text{-}M}$, $DF_{K\text{-}Means}$, DF_{Fisher} are Fourier descriptors of respectively fusion by minimum, fusion by mean, fusion by maximum, issue from E-M, K-Means and Fisher.

C. Classification by KNN

The method of K-Nearest Neighbor (K-NN) is one of classification techniques widely used in the artificial intelligence. This technique, known for its easy implementation and fast execution, adopts a supervised learning technique [3]. This classifier is very cited in the literature and known for its good performance. As its name indicates, this technique depends heavily on the index k given that the decision can be predicted on the basis of the distribution of the individual in the training set [12]. This algorithm is based on a learning database that consists of *N* pairs (input, output). To estimate the class of a new input *X*, the KNN algorithm takes into account the k inputs closest to *X* according to a predefined metric. Thus, *X* will be associated with the most represented class in the outputs of the *k* closest inputs to *X*.

The equation of this method is defined as follows:

$$y(d_i) = x\mathrm{argmax}_k \sum_{x_j \in kNN} y(x_j, c_k) \tag{11}$$

Where d_i is a factor test, x_j is one of the neighbors in the training set; $y(x_j, c_k) \in \{0,1\}$ indicates the degree to x_j of belonging to the class c_k

III. RESULTS AND DISCUSSION

To evaluate the efficiency of our proposed method we used an image database made up of 648 ISAR images representing 4 targets namely “Rafale”, “Harrier”, “Tornado” and “F117”. In fact, each target is represented by 162 images taken from different view angle. Each image is 256x256 pixels represented on grayscale level.

Figure 3, shows four samples from ISAR images database.

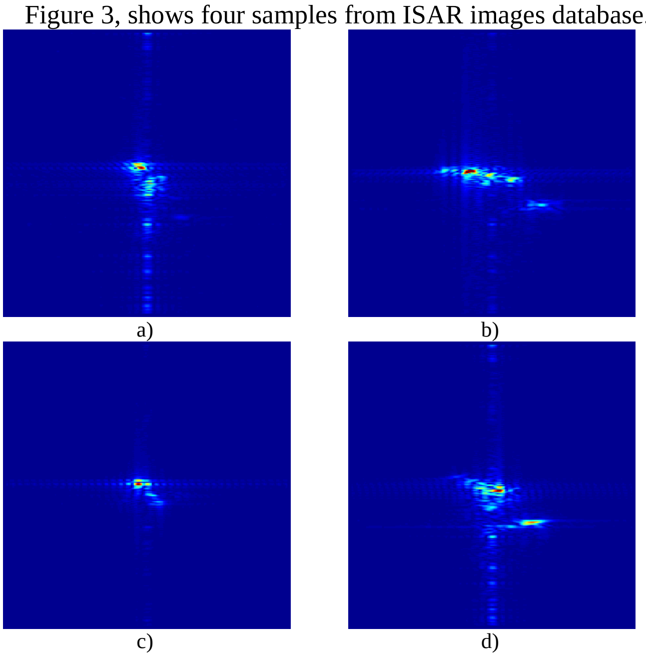


Figure 3. Example of ISAR images of a) F117 model, b) Harrier model, c) Rafale model and d) Tornado model

In figure 4, we illustrate the results of the superposition of different contours extracted from the original images. To differentiate these edges we colored respectively in blue, green and red the edges extracted by these algorithms the E-M, K-means and Fisher, combined with the WS algorithm. So,white magenta, cyan, yellow reflect the superposition of different predefined edges.

To compare the descriptors issued from different edges; these descriptors should have the same length. However, the length of the Fourier descriptor depends on the length of the edge of the target. Therefore, we should normalize the length of the extracted edges. In our study, we fixed the length of these edges at 80 points (*N*=80). Then, we applied the discrete Fourier transform on the coordinates (complex plane) obtained on each shape. The image is characterized by *N/2* Fourier descriptors. Finally, we could compress this Fourier descriptor by removing higher frequency coefficients. In our case, we compressed the descriptor Fourier to the half to obtain a final descriptor constituted by 20 coefficients.

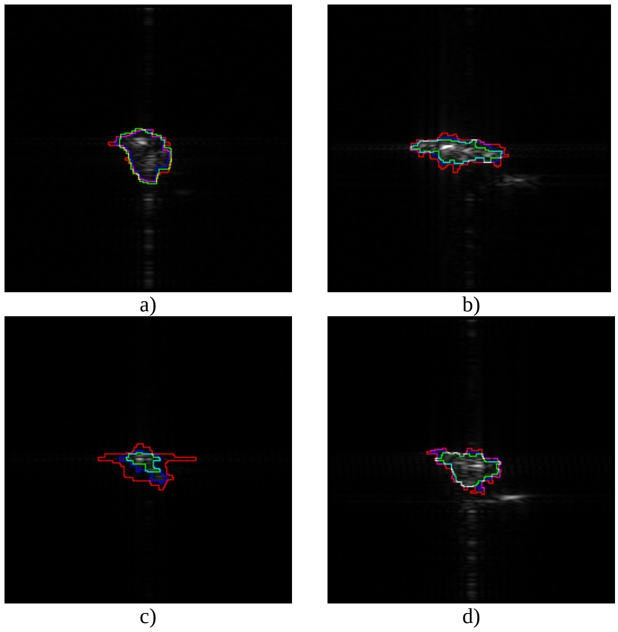
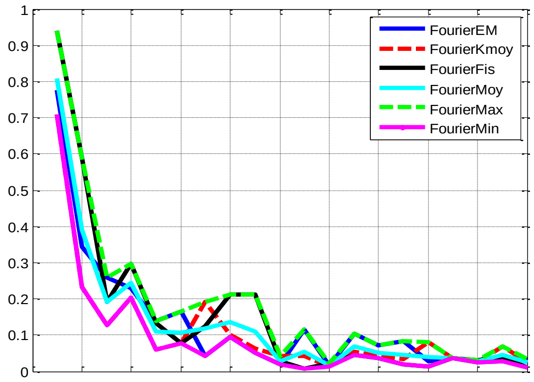


Figure 4. Edge extraction of a) F117 model, b) Harrier model, c) Rafale model and d) Tornado model

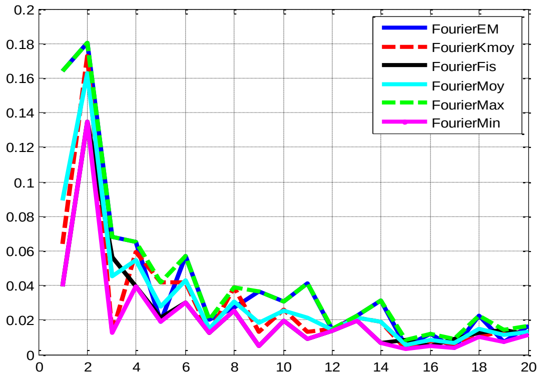
From the results shown in the figures above, we note that the Fourier descriptors from the 6 algorithms 4 targets ISAR images (Rafale, Harrier, Tornado and F117) have a very important similarity. At this level, it is difficult to distinguish the best descriptor to describe the shape of the target.

Therefore, a classification step is very required to evaluate our results in terms of recognition rate. To highlight the performance of each descriptor we choose the K-nearest neighbors (KNN) where we adopt the Euclidean distance as the similarity metric.

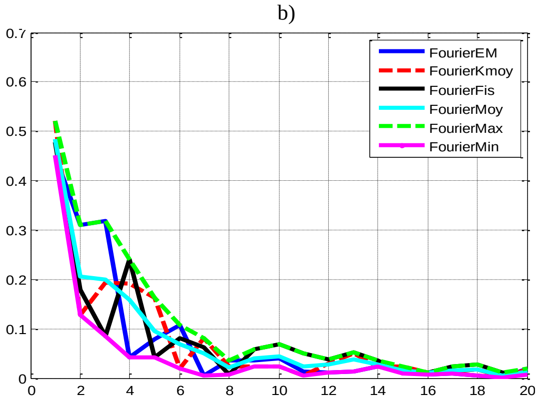
In the classification phase, the database is divided into two sub-bases (testing / learning) to evaluate the classification.



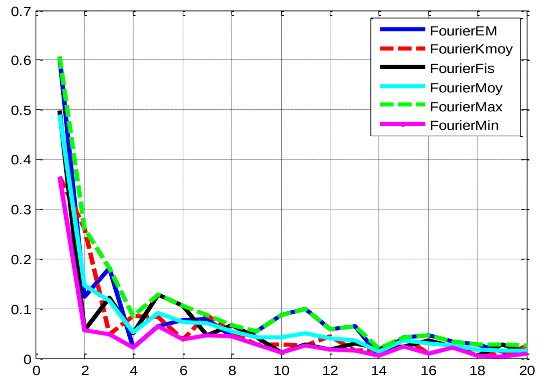
a)



b)



c)

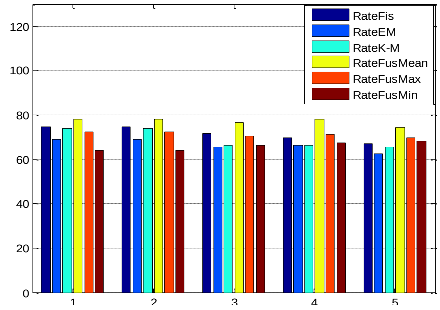


d)

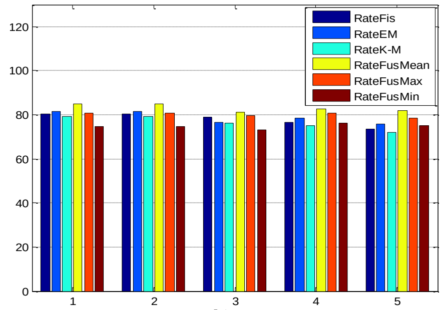
Figure 5. Fourier descriptors of a) F117 model, b) Harrier model, c) Rafale model and d) Tornado model

Figure 6, shows the performance of each method in terms of correct classification rate in function of the k neighbors adopted by the KNN classifier for different ratios (30%, 50% and 70%) used to form the learning basis.

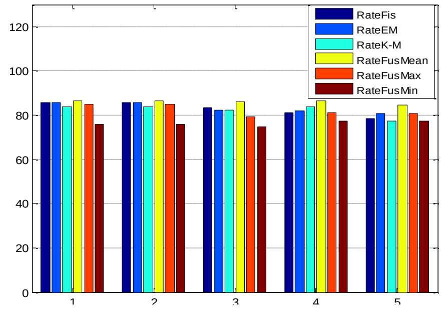
From the results shown in figure 6, it can be concluded that the application of individual descriptors from the three algorithms E-M, K-means and Fisher gives us a significant recognition rate. However, the fusion of descriptors affects the rate of the correct detection. In fact, the use of the maximum operator while computing the fusion descriptor turns to be nearly the best rate obtained by the individual descriptors. But, if we adopt the minimum operator to fuse descriptors, this seems ineffective to improve the recognition rate. Finally, it's clear that the fusion descriptor using the average operator ensures the best rate of target recognition.



a)



b)



c)

Figure 6. Rate correct classification by KNN for the learning base a) 30%, b) 50% and c) 70%

IV. CONCLUSION

In this work, we have presented our approach to achieve the target recognition based on ISAR images. The process adopted is made up of three steps. In the first step, the ISAR image segmentation for edge detection has been presented using three techniques: Fisher, K-mean and Expectation-maximization methods. Afterwards, we apply on the segmented image the watersheds algorithm to extract the closed edge of target available in ISAR image. In the second step of our approach, the edge representation to make edge descriptors is proposed using Fourier descriptors. Then, in order to get a satisfactory rate of correct recognition and complete our features vector, the fusion of the Fourier descriptors issued from the three edges extracted by the previous segmentation techniques is proposed using three mathematical operators namely, minimum, maximum and average. Finally and in the last step of our approach, the K-nearest neighbors classifier to highlight the impact of our new descriptors is implemented. In this order, the ratio of the learning base and the k parameter adopted in the KNN classifier in the process of recognition of targets from ISAR images are tested. The obtained results prove that adopting the fusion descriptor based on the average operator improves the rate of the correct classification in the ISAR target recognition process.

As future works, we could think to try other techniques of edge detection, shape descriptors and classifiers schemes. Then, information fusion could be used during each of the phases of the recognition process.

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