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Radar Target Classification Technologies

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1. Introduction

Apart from object detection, plot extraction and tracking, automatical classification is becoming one of the challenges of modern sensor systems.

In civil applications for example, different classification techniques are used for air traffic control (ATC) purposes. The primary purposes of air traffic control systems are collision prevention, the organization and control of the air traffic; furthermore it should provide information as well as other support for pilots. In most cases the general traffic situation is well known (aircraft, flight number, flight road, flight departure and destination, etc.), but the exact prediction of natural processes (weather, bird migration, wind mill rotation activities, insect migration, etc.) still remains rather difficult. For this reason the demanded expectations are stable feature extraction methods and classification technologies.

In meteorological applications, weather radars use backscattered echo signals to locate precipitation, calculate its motion, estimate its type (rain, snow, wind, hail, etc.) and forecast its future position and intensity. For this purpose modern weather radars are mostly pulse-Doppler radars. These are able to detect the motion of rain droplets as well as to estimate the intensity of precipitation. The structure of storms and severe weather can be derived from these data. In order to improve the efficiency of new weather radar product families, strong feature extraction and classification algorithms are required.

In the automotive industry, due to higher safety measure requirements in road traffic, the adaptive cruise control (ACC) is becoming unavoidable. These systems often use a radar setup to slow the vehicle down when approaching another vehicle or other obstacles and accelerate again to the present speed as soon as traffic allows it. ACC technology is widely considered as a key component for future generation's smart cars, as a form of artificial intelligence that can be used as a driving aid. For that reason robust signal feature extraction and classification methods are required.

For airborne applications, two kind of radars can be integrated in air platforms, in order to support the navigation and missions. The first category encompasses primary radars, the second category secondary radars. Civil airborne primary radar systems support the pilot by providing actual information like position or weather. Civil secondary surveillance radars (SSR) are radar systems supporting air traffic control (ATC). These systems do not only detect and measure the position of aircraft but also request additional information from the aircraft itself such as its identity or altitude. While primary radar systems measure only the range and bearing of targets based on reflected radio signals, SSRs rely on radar transponders aboard aircrafts. These transponders reply to interrogation signals by

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transmitting responding signals containing specific encoded information. The SSR technology is based on the military "identification, friend or foe" (IFF) technology, which was developed during World War II. These two systems are still compatible today. Nowadays monopulse secondary surveillance radars (MSSR) represent a improved version of SSR. For military applications radars are used in fighter aircraft for finding enemy aircraft and controlling air-to-air missiles, rockets, and guns. It is used in bombers to find surface targets, fixed or moving, and to navigate and avoid obstacles. It is used in large aircraft as an airborne warning and control system, searching the skies over great distances for enemy aircraft, tracking them, and controlling interceptors. It also is used to search the seas for surface vessels or surfaced submarines. Furthermore special space technology is used in commercial as well as non-commercial spaceflight activities. For such purposes spaceborne radar systems are often used in spacecraft, in order to locate patterns of activity. Such critical applications need robust preprocessing, feature extraction, pattern classification, fusion and recognition methods. The knowledge of the target class has significant influence on the identification, threat evaluation and weapon assignment process of large systems. Especially, considering new types of threats in Anti Asymmetric Warfare the knowledge of a target class is of significant importance. The target class can also be used to optimize track and resource management of today's agile sensor systems.

This chapter consists of the following sections (cf. Fig. 1): 1. the data acquisition section part, 2. introduction to methods of signal preprocessing, 3. introduction to methods of feature extraction, 4. basics of classification and sub-classification methods, 5. introduction to fusion methods, 6. recognition, typing or identification basics, 7. some experimental results, 8. some product examples of modern radar systems and finally 9. a brief conclusion.

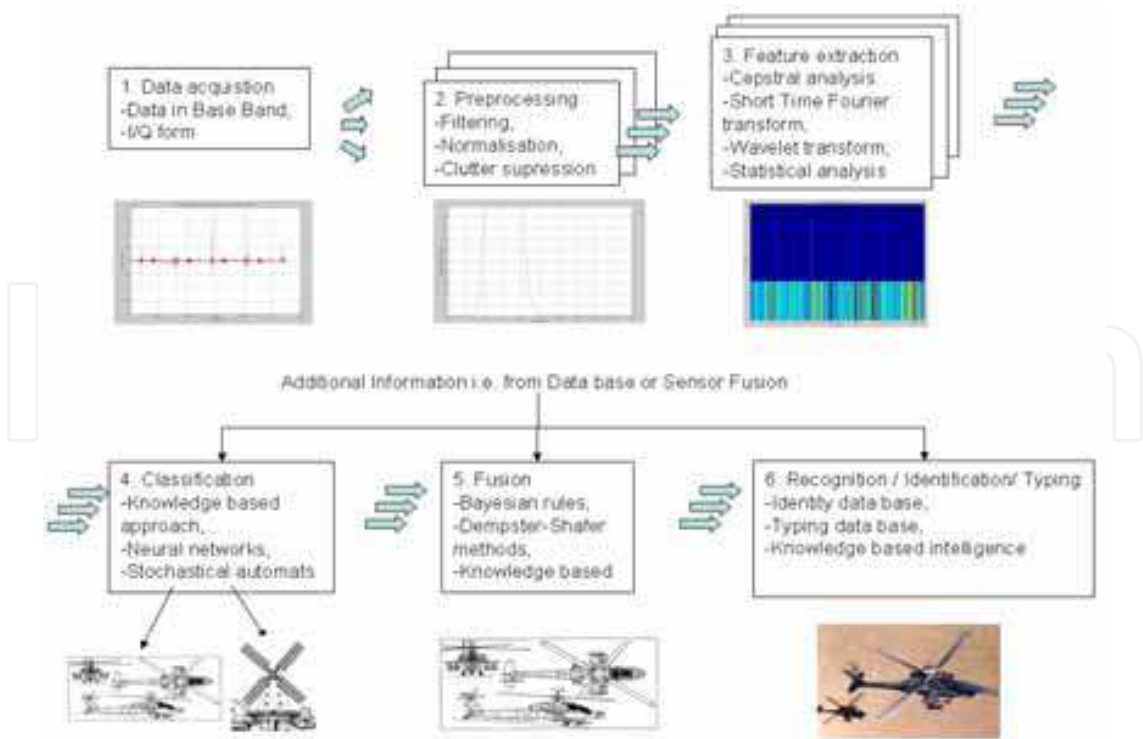


Fig. 1. Simplified structure of a modern radar classification function chain

2. Data acquisition

For the data acquisition part an active or passive radar frontend can be used. Either a primary or a secondary radar is usually taken into consideration. This radar uses self- or friendly generated waveform to reconstruct information from the environment with different objects or targets. The data acquisition part usually provides backscattered radar echo signal in I- and Q-form in the baseband.

For following chapter parts, we will assume that a backscattered radar echo signal is given. A simplified data acquisition chain can be resumed as following:

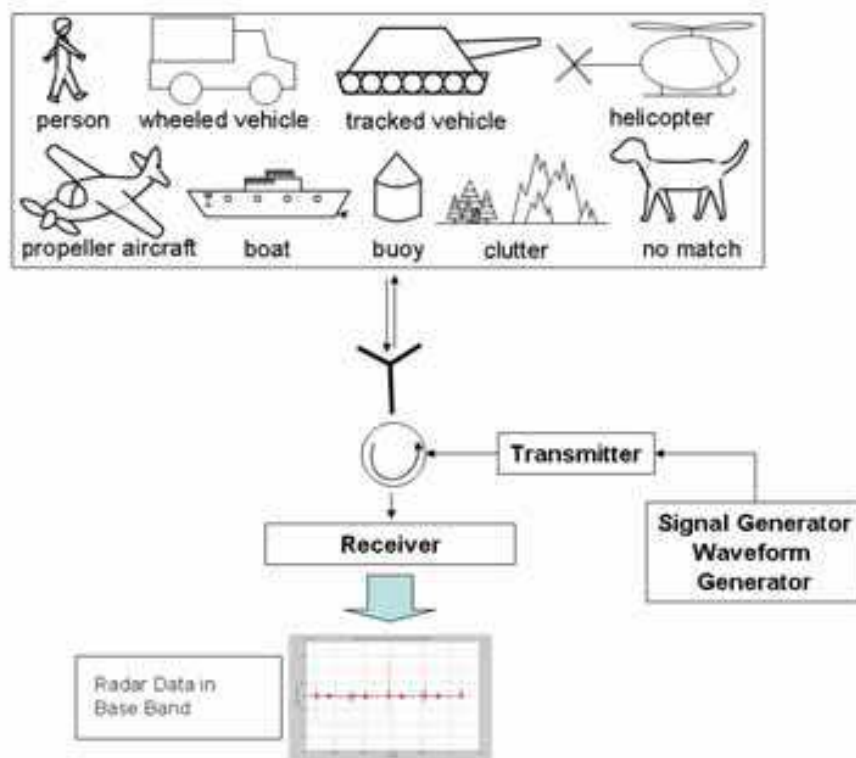


Fig. 2. Simplified diagram of a radar data acquisition process

3. Methods of signal preprocessing

The aim of signal preprocessing in modern radar classification function chains is to prepare and condition the acquired signal in order to simplify the feature extraction and later classification or recognition of the required patterns.

Generally the following three steps are indispensable:

1. Filtering and noise suppression;
2. Clutter suppression;
3. Normalisation

Filtering and noise suppression consists of all processes in the classification chain that are required to eliminate deterministical and well-known noise effects. For this purpose finite impulse response filters (FIR) as well as infinite impulse response filters (IIR) can be used. The filter design requires a good understanding of the defined radar, environment and target scenario. The following filter types are commonly used for suppressing noise in low, high, bandpass or stopband form (Stimson, 1998; Kouemou et al., 1996; Kouemou, 2000; Kammeyer & Kroschel, 2002):

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$$X_h(t, \omega) = \int_{-\infty}^{\infty} x(\tau) \cdot \bar{h}(\tau - t) \cdot e^{-i\omega\tau} d\tau \quad (1)$$

where h is a windowing function (Kouemou, 2000; Kammeyer & Kroschel, 2002; Kroschel, 2004). In Fig. 5 an example of a short-time Fourier transform of a time signal can be seen.

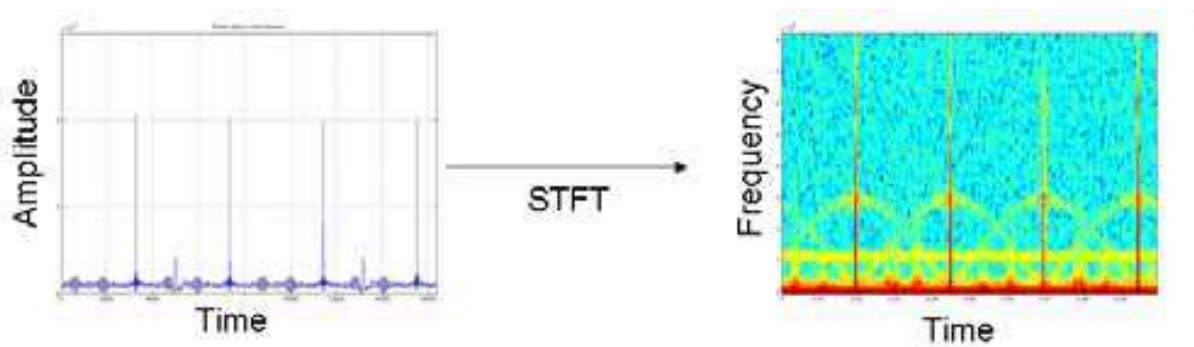


Fig. 5. Example of a short-time Fourier transform

4.2 Cepstral-analysis

The feature extraction process can also use a spectral-based technique similar to those which are used in speech processing, namely the Melscale Frequency Cepstral Coefficients (MFCC). It is well-known that moving targets create a modulated radar return signal whose characteristics in spectrum can be used to distinguish between the classes. This process is based directly on the complex I/Q radar Doppler signals. Due to several moving parts with different velocities of a target, the radar return signal may cover the whole frequency band, depending on the pulse repetition frequency (PRF), from $-\text{PRF}/2$ to $\text{PRF}/2$. Hence no linear filter is applied in order to retain any important frequencies. The common MFCC process is adapted to complex radar signals. The radar return signal of several hundred milliseconds is framed using a half-overlapping Hamming window in order to create signal segments representing the short quasi-stationary parts of the Doppler signal. The following feature extraction process is done for every frame and each frame results in a feature vector (Kouemou, 2000; Kouemou & Opitz, 2007a; Kouemou & Opitz, 2007b):

1. Apply the Fast Fourier Transform (FFT) to the signal resulting in the spectrum $\mathcal{F}\{s(n)\}$, $n = 1, \dots, T$, where T is the number of samples.
2. Calculate the power spectrum

$$\mathcal{P}_f\{s(n)\} = \mathcal{F}\{s(n)\} \cdot \mathcal{F}_f\{s(n)\}^* \quad (2)$$

3. Mirror the power spectrum at zero frequency and add the negative frequencies ($n = 1, \dots, T/2$) to the positive ones ($n = T/2 + 1, \dots, T$) to get a positive spectrum $\tilde{\mathcal{P}}_f\{s(n)\}$ of half the length as the sum of amplitudes of negative and positive frequencies, i.e. for $n = 1, \dots, T/2$:

$$\tilde{\mathcal{P}}_f\{s(n)\} = \mathcal{P}_f\{s(T/2 + n)\} + \mathcal{P}_f\{s(T/2 - n)\} \quad (3)$$

4. Apply a k channel mel filter bank to $\tilde{\mathcal{P}}_f\{s(n)\}$ of triangular shaped filters by multiplying with the transfer function $H_i(n)$ of the i th filter to get the filter bank results $Y(i)$. The number of channels is adapted to operator's capabilities.
5. Calculate the logarithm $\log(Y(i))$
6. Decorrelate the result with the Discrete Cosine Transform (DCT) to get the so called mel cepstrum
7. Take only the first m of the k coefficients of the mel cepstrum result
8. The feature vector can be extended adding dynamic features by using the first and second derivative of the coefficients with respect to time
9. The zero coefficient is replaced by a logarithmic loudness measure

$$c_0 = 10 \log \left(\sum_{n=1}^{T/2} \tilde{\mathcal{P}}_f\{s(n)\} \right) \quad (4)$$

The mel filter bank in step 4 is based on half-overlapping triangular filters placed on the whole frequency band of the signal. The lower edge of the first filter may be placed on a frequency greater than zero in order to filter out any dominant ground clutter.

As a result from the method above we achieve a sequence of MFCC feature vectors which represent the radar Doppler signal.

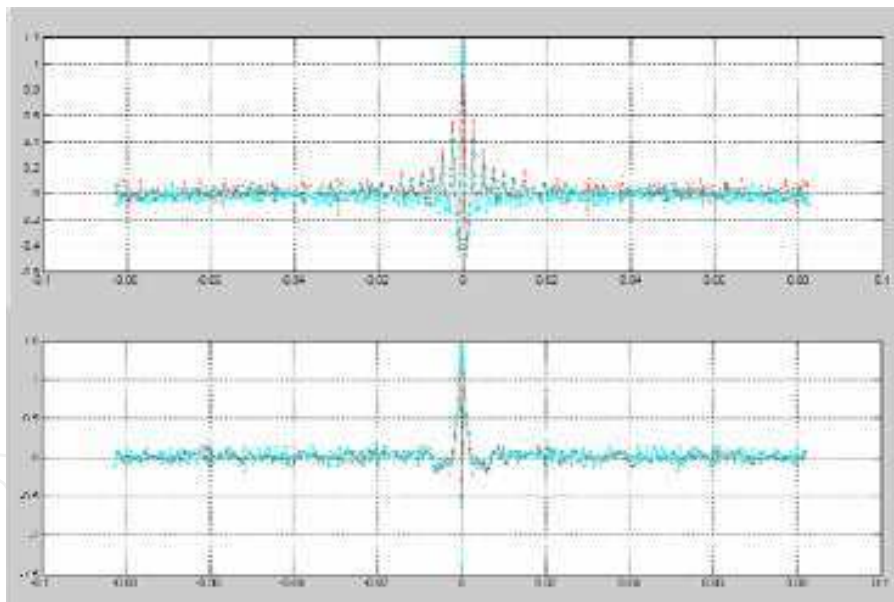


Fig. 6. Example of extracted cepstral based feature vectors of person (bottom), and tracked vehicle (top)

4.3 Wavelet-transform

The Wavelet transform W of a radar echo signal f (cf. Fig. 7) is basically defined by the following equations with normalisation factor a and time shift factor b :

$$W\{f\}(a,b) = \int |a|^{-1/2} f(t) \psi\left(\frac{t-b}{a}\right) dt \quad (5)$$

$$W_{m,n}\{f\} = \int a_0^{-m/2} f(t) \psi(a_0^{-m} t - nb_0) dt \quad (6)$$

where in both cases we assume that the "Mother Wavelet" ψ satisfies the condition

$$\int \psi dt = 0 \quad (7)$$

By restricting a and b to discrete values one can obtain formula (6) from (5): in this case $a = a_0^m$, $b = nb_0 a_0^m$ with $m, n \in \mathbb{Z}$, $a_0 > 1$, $b_0 > 0$ fixed.

The most popular Wavelets are: the Daubechies (Daubechies, 1992), Meyer, Mallat (Mallat, 1999), Coiflet, Symlet, Biorthogonal, Morlet and the Mexican Hat.

The Wavelet based feature extraction methodology that was developed for this study is decomposed in five main steps (Kouemou, & Opitz, 2005; Kouemou & Opitz, 2008b):

1. Design of the Wavelet type
2. Definition of the Wavelet observation window as subfunction of time on target
3. Definition of the Wavelet scaling function
4. Definition of the Wavelet dependency function to the radar operating pulse repetition frequency
5. Definition of the statistic adaptation model by combining the Wavelet extracted feature to the Discrete Hidden Markov Model

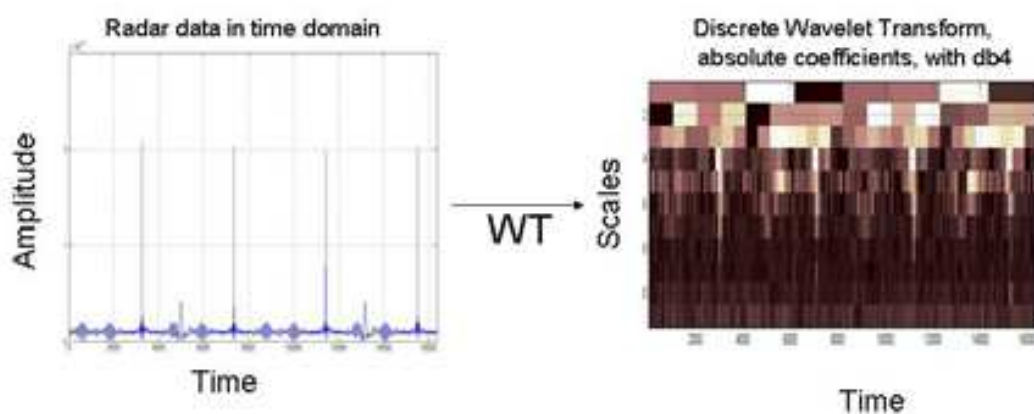


Fig. 7. Example of Wavelet extracted feature from a given air target using a Pulse-Doppler radar

4.4 Fuzzy-logic

The calculation by using the fuzzy logic module works slightly different. For this approach physical parameters, for example the velocity, the acceleration, the RCS, etc., of the target have to be measured. We need supporting points h_n to set up the fuzzy membership functions. Those membership functions have to reflect physical limits stored in knowledge data base (Kouemou et al., 2008; Kouemou et al., 2009; Kouemou & Opitz, 2008a).

For each class, membership functions are set up and membership values m depending on the supporting points are calculated as follows:

$$m(i, j) = \begin{cases} 1 & \text{if } w \leq h_1 \\ \frac{-1}{h_2 - h_1} (w - h_1) + 1 & \text{if } h_1 \leq w \leq h_2 \\ 0 & \text{else} \end{cases} \quad (8)$$

where w is the measured value for the considered physical attribute. With those membership values, the elements of a matrix \tilde{P} , containing probabilities for each parameter and each considered target class, are:

$$\tilde{P}_{i,j} = \frac{m(i,j)}{\sum_{k=1}^N m(i,k)} \tag{9}$$

An example membership function is illustrated in Fig. 8, where in the upper picture the membership function for a knowledge-based module, a special case of the fuzzy-logic approach, is shown, while in the lower picture the membership function for a trapezoidal fuzzy logic module can be seen.

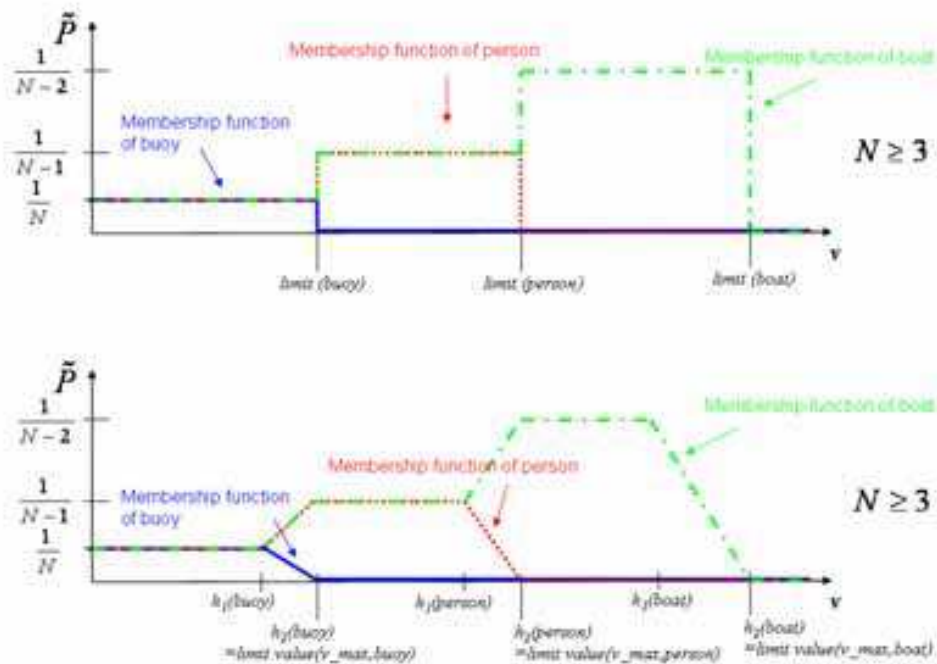


Fig. 8. Example of membership functions of target classes 'buoy', 'person' and 'boat' for knowledge-based and fuzzy logic module

The next step in order to receive the result vector is the introduction of a so called weighting matrix W . The weighting matrix contains elements $\omega_{i,j}$, with $i=1...M$ and $j=1...N$. The weighting matrix represents the influence of the single physical values i on the classification result for a given target class j .

The elements of W depend on several conditions, like available measurement data of radar, quality of knowledge database and terrain character, environmental or weather conditions. Further feature extraction methods also considered in modern radar target classification are different types of autoregressive filters, auto- and crosscorrelation functional analysis as well as linear and non-linear prediction-codeanalysis (Kammeyer & Kroschel, 2002; Kroschel, 2004).

Further applications use the properties of the Karhunen-Loewe transform as well as moments of higher order (Gardner, 1980; Gardner, 1987; Gardener, 1988; Gardner & Spooner, 1988; Fang, 1988; Fang, 1991).

5. Classification technologies

In this section two main philosophies for classification and subclassification will be presented. The first philosophy consists of a learning process. The second philosophy consists of knowledge based evidence. The different kind of classification and subclassification methods in most modern radar systems can be divided into deterministical methods, stochastical methods and neural methods. The deterministical methods in this section are essentially based on the handling of logical operators and knowledge based intelligence. The stochastical methods described in this section are based on finite stochastical automats. The finite stochastical automats which will be presented are usually based on different variants of learning Hidden Markov Models. Furthermore the neural methods illustrate the capability of solving pattern recognition problems in modern radar systems by using different kind of artificial neural networks. For specific classification or subclassification challenges in modern radar applications hybrid classifiers can also be recommended. These classifiers use – depending on the situation – learnable or non-learnable algorithms. The learnable algorithms can be designed using supervised or unsupervised learn concepts.

5.1 Classical knowledge based approach

For calculation with the classical knowledge-based approach, we need known limits for the considered physical values applying to the considered target classes. For example, the knowledge database needs to hold maximum velocities for persons as well as for tracked vehicles and all others. With the limit interval L from the knowledge database and the measured value v , we can calculate the elements of matrix \tilde{P} :

$$\tilde{P}_{i,j} = \begin{cases} \frac{1}{Q} & \text{if } v \in L \\ 0 & \text{else} \end{cases} \quad \forall i, j \quad (10)$$

Q represents the number of classes for which the measured value v is within the limits of the interval L . Therefore, the summing up of all $1/Q$ terms always has to yield 1.

Three technologies for radar target classification will be described in this section. One based on a classical knowledge based approach, one based on neural networks and the other based on stochastic automats.

5.2 Neural networks

Many different families of artificial neural networks are state-of-the-art in modern radar classification and identification issues. They can be divided into statical and dynamical networks (Rosenblatt, 1962) on one side, and into self-organising (Kohonen, 1982; Kohonen, 1984; Kohonen, 2001) and supervised learnable networks on the other side (Zell, 1994).

In this section the time delay neural networks (TDDN) as an example for dynamical feed-forward networks will be briefly introduced.

The time delay neural networks (TDNN) were developed by Waibel and Lang for classifying phonemes of speech in 1987. They belong to the class of forward networks and were firstly used in the speech recognition. Nowadays the classical architecture of TDNN was extended with special techniques for radar classification purposes. Classically, these networks consist of an input layer, an output layer and one or more hidden layers (cf. Fig.

9). The hidden layers lie between the input and the output layer. The number of hidden layers has to be determined depending on the application.

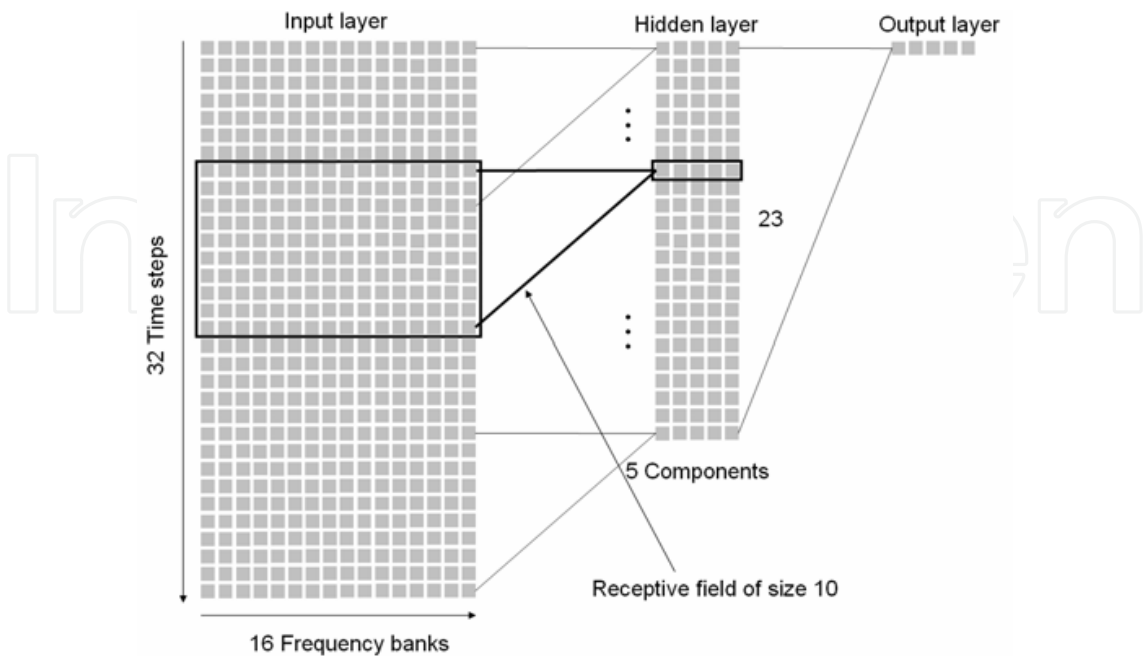


Fig. 9. Exemplary structure of a time delay neural network

Every layer is described by a matrix. The columns of the input layer represent the created frequency bank of the recorded Radar Doppler signals. The rows describe the time delay of the input pattern. A layer consisting of 32 rows denotes that an incoming information will be included in the calculation for 32 time units. The layers are divided into varying long time steps Δt according to the application.

The connection between the layers depends on the size of the so called receptive field. A receptive field means that a row of the subsequent layer is only connected to a defined number of rows of the preceding layer. For instance a receptive field of size 10 means that 10 rows of the first layer are each connected to a row of the subsequent layer. Thus a row of the subsequent layer can only see a short time period of the preceding layer.

Of course the neurons of a layer can be connected to every neuron of the preceding layer. Thus the recognition and training time of the networks would increase significantly. By the use of a receptive field of size r the number of connections can be reduced. Without this factor the combination of a layer of size 32×16 with a subsequent layer with 23×5 neurons would require 58,880 connections ($32 \cdot 16 \cdot 23 \cdot 5 = 58,880$). For $r=10$ a row of the hidden layer sees only a temporal sequence over ten rows of the input layer. This reduces the number of connections significantly (instead of 58,880 only $10 \cdot 16 \cdot 23 \cdot 5 = 18,400$). Thereby the length of the subsequent layer is determined by the receptive size of the previous layer:

$$l = d - r + 1$$

(11)

- whereas the parameters are the following:
- l is the length of the subsequent layer
 - d is the number of time pattern frames
 - r is the size of the receptive field

The number of components (of columns) of the hidden layers is chosen according to the application. The more components exist, the more precise the recognition will be. However, the higher the number of components and the longer the layers are, the longer the recognition and training time will be.

The characteristic of this network lies in the recognition of features in time varying patterns at different positions and of different lengths. Their architecture permits to recognise the components of time varying patterns, in spite of time shift.

5.3 Stochastic automats

One of the most important family of classifiers nowadays in modern radar applications consists of finite stochastic automats. They are most the time derived from extended Bayesian networks. One of the most successfully integrated stochastic automats in technical radar systems applications are Markov-based learnable models and networks. In this section a brief introduction will be made exemplary by taking the Hidden Markov Model (HMM) (Kouemou, 2000; Kouemou & Opitz, 2007a; Kouemou & Opitz, 2007b; Kouemou & Opitz, 2008a; Kouemou & Opitz, 2008b, Rabiner, 1989). Some experimental results of classification problems using HMMs will be shown in the experimental section.

A HMM consists mainly of five parts:

1. The N states $S = \{S_1, \dots, S_N\}$;
2. M observation symbols per state $V = \{v_1, \dots, v_M\}$;
3. State transition probability distribution $A = \{a_{ij}\}$, where a_{ij} is the probability that the state at time $t+1$ is S_j , given the state at time t was S_i ;
4. Observation symbol probability distribution in each state $B = \{b_j(k)\}$, where $b_j(k)$ is the probability that symbol v_k is emitted in state S_j ;
5. Initial state distribution $\pi = \{\pi_i\}$, where π_i is the probability that the model is in state S_i at time $t = 0$.

Mainly three different types of HMM exist in literature: the HMM with discrete outputs (DHMM), HMM with continuous output probability densities (CHMM) and the trade-off between both, the semi-continuous HMM (SCHMM).

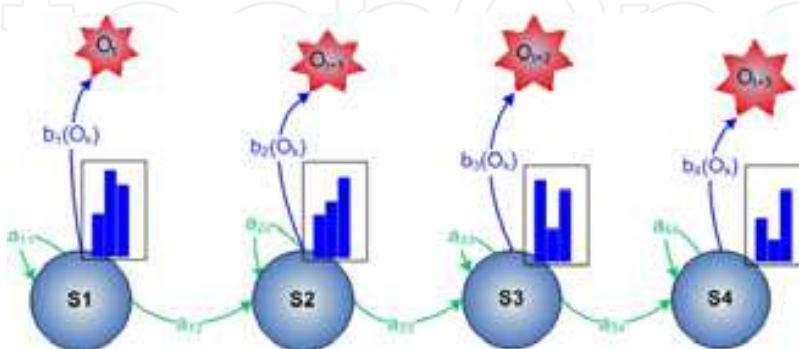


Fig. 10. Example of an HMM

Further methods for automatic target classification applied in modern radar systems are based on alternative methods such as classical learning Bayesian networks (Bayes, 1763; Kouemou, 2000; Pearl, 1986; Pearl & Russell, 2003) as well as polynomial classifiers

(Schürmann, 1977), learning support vector machines (Ferris & Munson, 2002; Burges, 1998; Drucker, 1997) or evolutionary algorithm (Bäck, 1996; Bäck et al., 1997; Goldberg, 1989).

6. Classifier fusion technologies

Different techniques and strategies can be used in order to fuse information from different sensor systems. For example beside the Doppler information can also information of a radar tracking system be used for classification. From the information of a tracking system physical parameters such as velocity, acceleration, etc. of the target can be estimated (Kalman, 1960; Bar-Shalom, 1989; Blackman & Popoli, 1999). The introduced data fusion techniques can also be integrated in a stand-alone sensor system in order to produce a robust classification and recognition result. For this purpose three technologies will be presented in order to solve the given problems:

Bayesian networks based method, Dempster-Shafer rules based fusion methods and finally classical rule based methods.

6.1 Bayesian rules

For the application of Bayes' Theorem (Bayes, 1763) we assume that the considered physical parameters are stochastically independent. This requirement has to be verified. This can be done by considering the correlation between the physical values. If the correlation is nearby zero, the assumption can be held up.

The probabilities $P(j|I)$, i.e. the probabilities of the classes $j \in J$ under the condition of certain measured physical values, are searched.

From the classification one gets a matrix P whose items can be interpreted as conditional probabilities $P(i|j)$. The individual probabilities P_{ij} shall be combined for all j to one probability p_j of the class j .

The stochastically independence of the physical values is assumed, as mentioned before. If the classes are additionally independent, the following equation holds:

$$P(I|j) = P(i_1|j) \cdot P(i_2|j) \cdot \dots \cdot P(i_M|j) \quad (12)$$

To simplify the calculation this assumption is also done.

Furthermore let all classes have the same a priori probability:

$$P(j) = \frac{1}{N} \quad \forall j \in J \quad (13)$$

The $j \in J$ generate a complete event system, i.e. $J = j_1 \cup j_2 \cup \dots \cup j_N$ with $j_k \cap j_l = \emptyset$ for $k \neq l$. This yields:

$$\begin{aligned} P(j|I) &= \frac{P(I|j) \cdot P(j)}{P(I)} = \frac{P(I|j) \cdot P(j)}{\sum_{k=1}^N P(I|k) P(k)} = \frac{P(I|j)}{\sum_{k=1}^N P(I|k)} \\ &\approx \frac{P(i_1|j) \cdot P(i_2|j) \cdot \dots \cdot P(i_M|j)}{\sum_{k=1}^N P(i_1|k) \cdot P(i_2|k) \cdot \dots \cdot P(i_M|k)} = \frac{\prod_{\nu=1}^M P(i_\nu|j)}{\sum_{k=1}^N \prod_{l=1}^M P(i_l|k)} \end{aligned} \quad (14)$$

This proceeding can be done inside a trackbased classification considering two or more physical parameters. But it can be also used to fuse different classifiers to get a combined classification (Kouemou et al., 2008; Kouemou & Opitz, 2008a).

6.2 Dempster-Shafer method

The Dempster-Shafer theory of evidence is a generalization of Bayes' theorem. It is based on the universal set $P(J)$ of the set of all considered target classes J .

$$P(J) = \{ \emptyset, \{person\}, \{tracked\ vehicle\}, \{helicopter\}, \dots, \\ \{person, tracked\ vehicle\}, \{helicopter, propeller\ aircraft\}, \dots \\ \{person, wheeled\ vehicle, tracked\ vehicle, helicopter, \\ propeller\ aircraft, no\ match\} \} \quad (15)$$

For this approach 'No match' denotes the set of all considered target classes and all objects which can not be allocated to one of the defined classes. In the Bayesian approach 'No match' denotes only all objects not allocated to one of the classes is therefore strictly separated from the other classes.

Compared to the Bayesian approach the target class 'no match' is not strictly separated from the other classes when using Dempster-Shafer. Evidences are used instead of probabilities. So there is an opportunity to deal with uncertain information and illustrate ignorance explicitly (Dempster, 1968; Shafer, 1976; Shafer, 1990; Shafer & Pearl, 1990).

The task is to combine the results coming from Doppler sound classification and from trackbased classification. The elements of the vectors are considered to be evidences E .

The evidences are combined using Dempster's rule of combination:

$$E_l(j) \oplus E_{l+1}(j) = \frac{1}{1 - k_l} \cdot \sum_{Y \cap Z = j} E_l(Y) \cdot E_{l+1}(Z) \quad (16)$$

$$k_l = \sum_{Y \cap Z = \emptyset} E_l(Y) \cdot E_{l+1}(Z) \quad \text{with } Y, Z \in J \quad (17)$$

The factor k expresses the conflict between the propositions, $k=1$ stands for totally contradictory propositions. The result of this combination is the combined vector p , whose elements are also evidences. Using these evidences, degrees of belief and plausibility can be calculated:

$$bel(A) = \sum_{B: B \subseteq A} E(B) \quad (18)$$

$$pl(A) = \sum_{B: B \cap A \neq \emptyset} E(B) \quad (19)$$

In doing so, the degree of belief shows how well the evidences support the proposition. On the other side, the degree of plausibility shows how well the negation of one proposition is supported. With $bel(A)$ being a lower bound for the probability of proposition A and $pl(A)$ being an upper bound, one gets a limited interval for the probability of A .

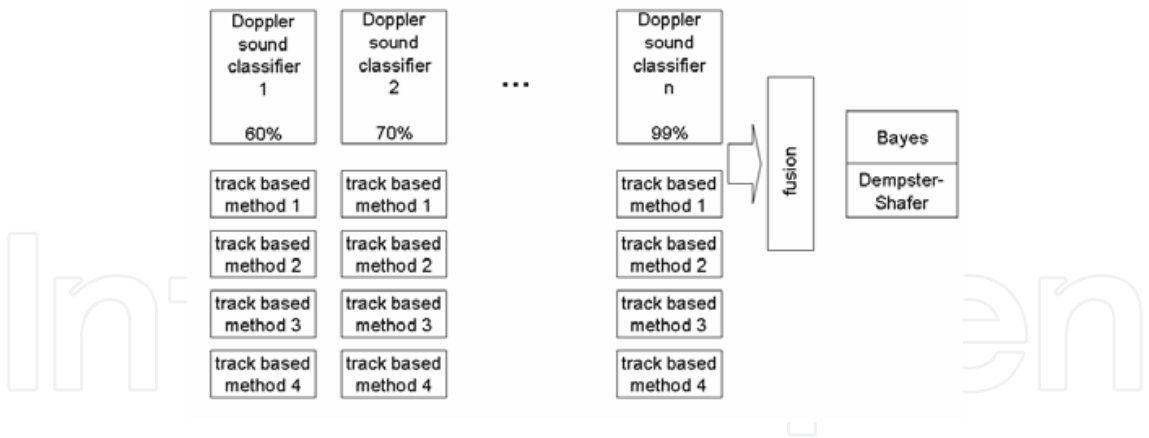


Fig. 11. Possible combinations of classifiers

As several HMMs are available for classification purposes as well as different methods to apply the track based classifier, a comparison of possible combinations is necessary. In Fig. 11 possible combinations are shown. In the track based classification, the evaluation of the target dynamics can either be performed in a classical knowledge-based way or by applying fuzzy logic, while the combination of the single membership values can be either done by applying Bayesian or Dempster-Shafer rules. These methods can be combined resulting in four different ways to use the track based classifier (Kouemou et al., 2008; Kouemou et. al, 2009).

6.3 Classical rule based approach

For this approach first two vectors p_1 and p_2 , each containing probabilities for the several target classes, are considered. These vectors can be derived from each of the methods mentioned in the previous section. So the vectors are:

$$p_1 = [p_{1,1} \ p_{1,2} \ \cdots \ p_{1,N}] \tag{20}$$

$$p_2 = [p_{2,1} \ p_{2,2} \ \cdots \ p_{2,N}] \tag{21}$$

Both vectors shall be fused to one result vector using a rule based approach. This can be exemplary done with the following rule:

$$i = \arg \max(p_1) \\ p := \begin{cases} p_1, & \text{if } p_{2,i} \neq 0 \\ [0 \ 0 \ \cdots \ 0 \ 1], & \text{if } p_{2,i} = 0 \end{cases} \tag{22}$$

The second case is also called rejection, i.e. the classifier makes no decision due to lack of information or contradictory results of the stand-alone classifiers.

7. Object recognition

In modern radar systems, recorded data as well as recorded intelligence information can be used together with the classifier output or data fusion output information in order to exactly recognize, identify or type an object. This process is depicted in Fig. 12. The recognition can be done for example with an identity data base, with a typing data base or with knowledge based intelligence (Kouemou & Opitz, 2005; Schürmann, 1996).

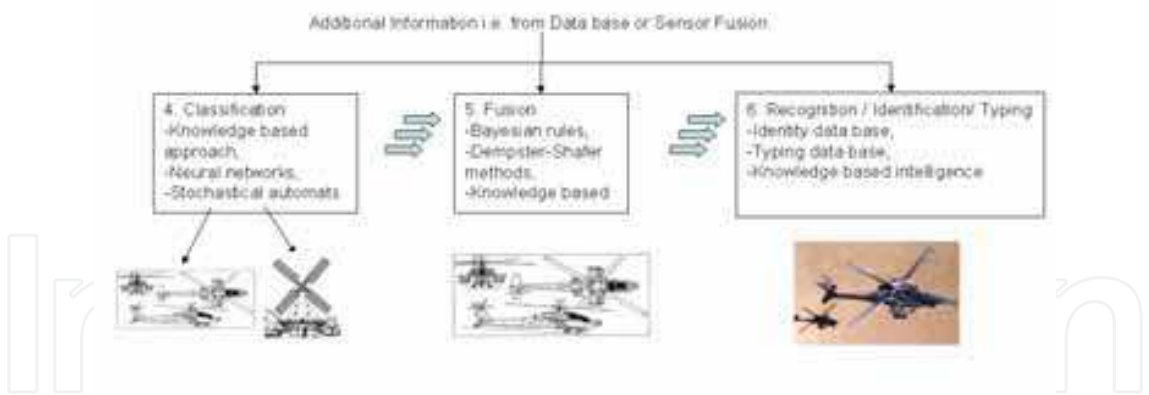


Fig. 12. Simplified illustration of an object recognition process

8. Some experimental results

In this section some classification results, where the introduced technologies were successfully tested, are presented. Due to company restrictions only results based on simulated data are presented.

8.1 Exemplary training algorithm

The following Fig. 13 illustrates a typical functional flow-chart of a supervised training procedure. This can be used for example to train a rapid backpropagation algorithm for an artificial network classification process. Similar structures can be used for the training of stochastic automats or support vector machines (Ferris & Munson, 2002; Burges, 1998; Drucker et al, 1997).

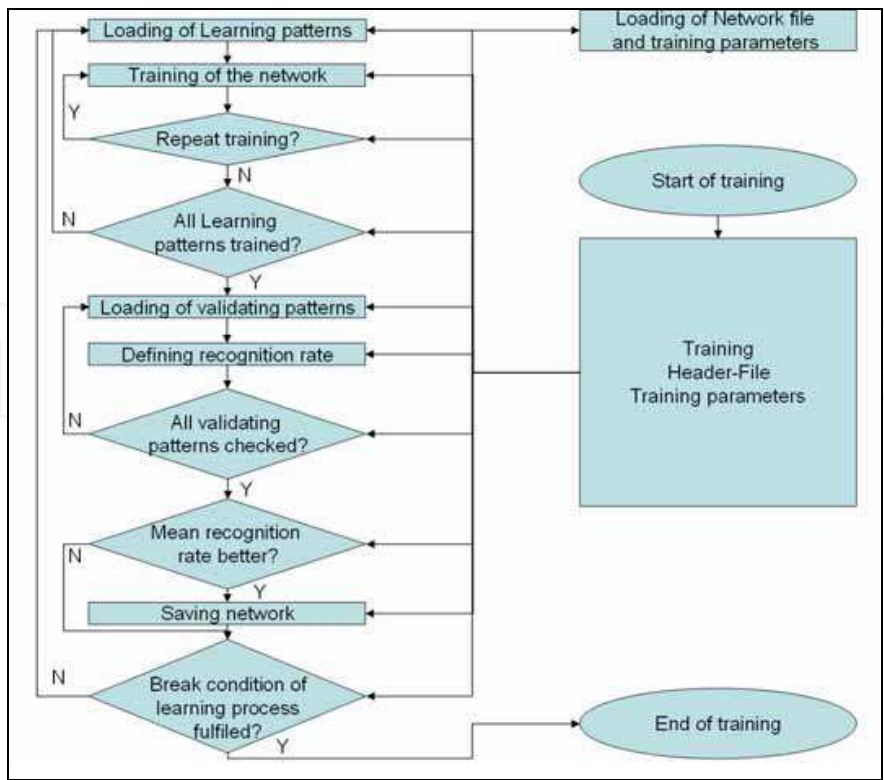


Fig. 13. Simplified illustration of an exemplary training proceeding

8.2 Exemplary identification results based on Hidden Markov Model and neural network technology

The following results were obtained by simulating a naval based radar target identification scenario using special neural network algorithms. It was presented at the International Radar Symposium in Berlin, Germany, 2005. Fig. 14 shows the two helicopters to be identified. A typical feature extraction process necessary as pre-classification step for the neural network is shown in Fig. 15. An exemplary confusion matrix of the classifier result is shown in Fig. 16.



Fig. 14. Typical helicopter identification example, on the left side a Bell Jet Ranger 206 B and on the right side a Bell UH1D

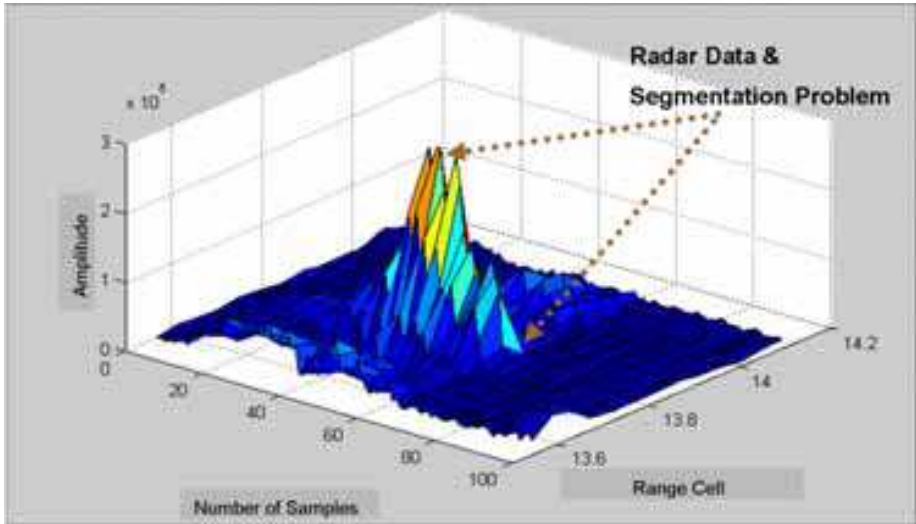


Fig. 15. Typical feature extraction process necessary as pre-classification step for the neural network of a simulated Bell jet helicopter.

	Bell UH 1D	Jet Ranger	No Match
Bell UH 1D	93,25	1,62	5,13
Jet Ranger	2,45	90,24	7,31

	Bell UH 1D	Jet Ranger	No Match
Bell UH 1D	94,75	0,93	4,32
Jet Ranger	1,75	91,21	7,04

Fig. 16. Two exemplary identification confusion matrix results using neural network on the left side and a Hidden Markov Model on the right side

8.3 Exemplary classifier results based on a hybrid system with a stochastic automaton and Dempster-Shafer method

An Exemplary structure of the simplified hybrid classifier operating with a knowledge based fusion technique. It was presented at the IEEE Radar 2008 in Adelaide, Australia.

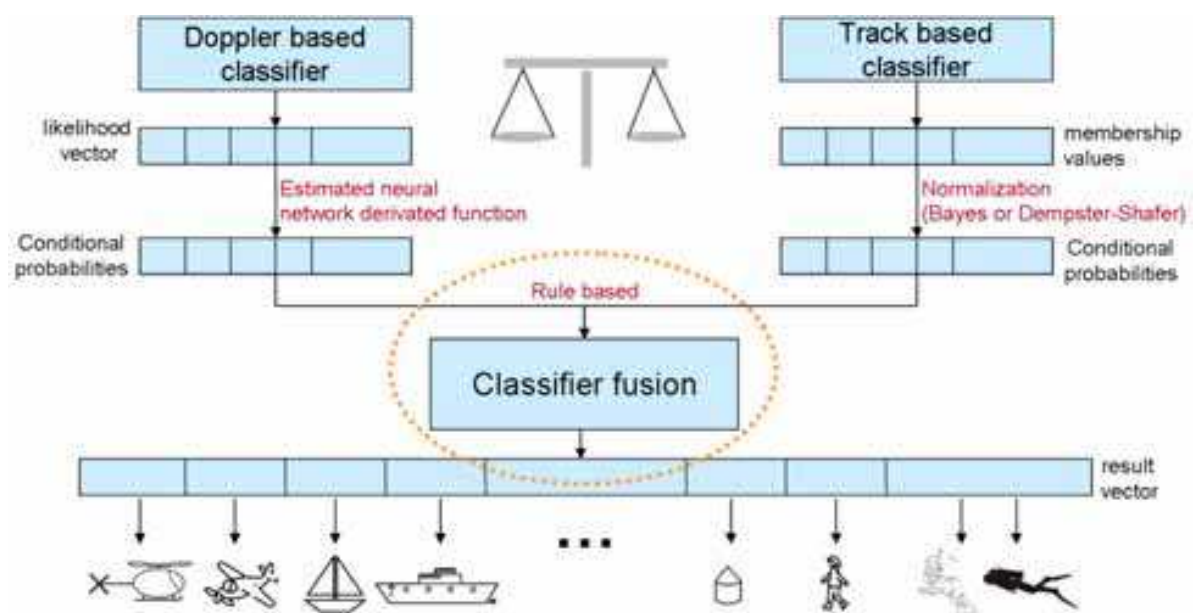


Fig. 17. Simplified structure of fusion process using Dempster-Shafer and knowledge based rules.

labeled as	person	100	0	0	0	0	0	0	0
	wheeled vehicle	0	87	12	0	0	0	0	1
	tracked vehicle	0	26	74	0	0	0	0	0
	helicopter	0	0	0	89	0	0	0	11
	propeller aircraft	0	0	0	8	92	0	0	0
	buoy	0	0	0	0	0	84	16	0
	boat	0	0	0	0	0	0	100	0
	no match	31	0	0	11	0	0	0	58
	rejection	0	0	0	0	0	0	0	0
		recognized as							
		person	wheeled vehicle	tracked vehicle	helicopter	propeller aircraft	buoy	boat	no match

Fig. 18. Typical confusion matrix of a classifier fusion obtained after simulating a testing process as described in the scheme above (Fig. 17)

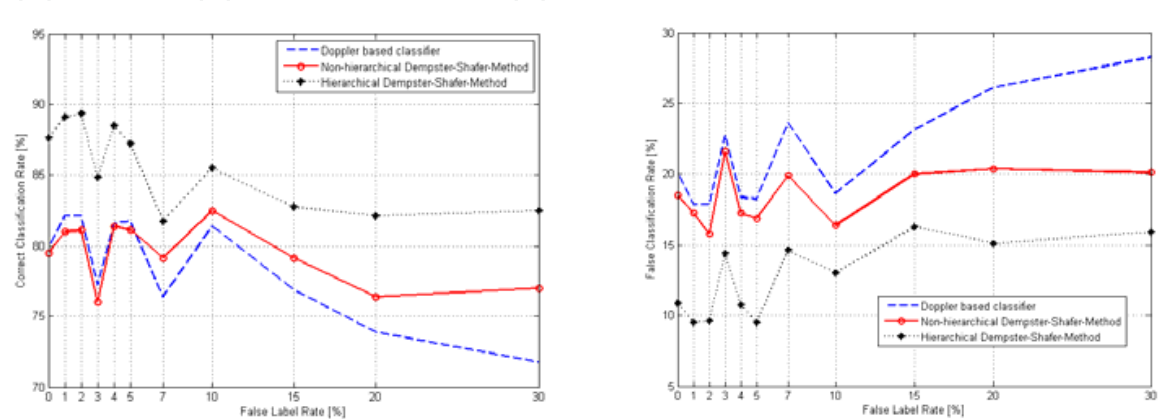


Fig. 19. Typical improvement obtained after fusing a stand-alone trained Doppler classifier with two Dempster-Shafer techniques.

9. Some application examples with modern radar systems

9.1 Example of an airport surveillance radar system (ASR-E)

ASR-E is the latest generation of a modern approach control radar for civil, military and dual use airports. ASR-E provides most advanced technologies. It uses a fully solid state S-band Primary Radar with outstanding, reliable detection performance and a monopulse Secondary Radar covering civil, military and Mode S interrogation modes. It is used for example by the German Air Force.



Fig. 20. Airport Surveillance System (Photo courtesy of EADS)

9.2 Example of a naval surveillance radar system (TRS-3D)

The TRS-3D is a multimode surface and air surveillance and target acquisition radar, designed for complex littoral environment with excellent clutter performance to detect small fast flying threats.

The TRS-3D is used for the automated detection, track initiation and tracking of all types of air and sea targets.

- Automatic detection and track initiation for air and sea targets
- Very low antenna weight
- Proven AAW weapon engagement support
- Gunfire control for sea targets (no FCR required)
- Helicopter automatic detection & classification
- Helicopter approach control
- Data correlation with integrated IFF interrogator
- Low risk integration with many CMS systems

The TRS-3D is used by various navies worldwide and has proven its operational performance from arctic to subtropical regions.

9.3 Example of a tactical radar ground surveillance system (TRGS)

The TRGS is a high performance ground surveillance radar system for the automatic detection, identification and classification of ground targets, sea targets and low flying air targets.

It is a vehicle integrated system with multi-sensor configuration. The electronically scanning antenna is one of the advanced technologies used in this system. One of the key features is the particularly high target location accuracy.



Fig. 21. TRS-3D on the Finnish guided missile boat "Hamina" (Photo courtesy of EADS)



Fig. 22. TRGS on the armoured vehicle "DINGO2" (Photo courtesy of EADS)

9.4 Example of an airborne radar integrated in a modern combat helicopter (Tiger)

The Tiger HAP is an air-to-air combat and fire support medium-weight (6 tonnes) helicopter fitted with 2 MTR 390 engines. It is daytime and night combat capable and is operable in NBC environments. Three basic parameters were taken into account right from the start of the development phase: low (visual, radar and infrared) detectability, which provides excellent survivability on the battlefield, maximum efficiency of the weapons and the associated fire control systems without heavier workload for the crew, and an optimized logistic concept offering minimum possession costs. The integrated airborne high-PRF radar fulfils all requirements needed in a critical combat environment.

9.5 Example of a spaceborne radar integrated in a satellite system (TerraSAR-X, TanDEM-X)

TanDEM-X ('TerraSAR-X add-on for Digital Elevation Measurement') is a radar observation satellite, which, together with the almost identical TerraSAR-X radar satellite, will form a high-precision radar interferometer system.



Fig. 23. Tiger HAP (Photo courtesy of EADS Eurocopter)

With this TerraSAR-X/TanDEM-X tandem formation, generating images similar to stereoscopic pictures, it will be possible to measure all the Earth’s land surface (150 million square kilometres) within a period of less than three years. For a 12m grid (street width), surface height information can then be determined with an accuracy of under two meters. One goal is the production of a global Digital Elevation Model of unprecedented accuracy. As for TerraSAR-X, the TanDEM-X project will be carried out under a Public-Private Partnership between Astrium and the German Space Agency DLR. TanDEM-X is due for launch in 2009, and is designed to operate for five years. Use of the data for scientific applications will be the responsibility of the DLR's Microwaves and Radar Institute. Commercial marketing of the data will be managed by Infoterra GmbH, a wholly-owned subsidiary of Astrium.

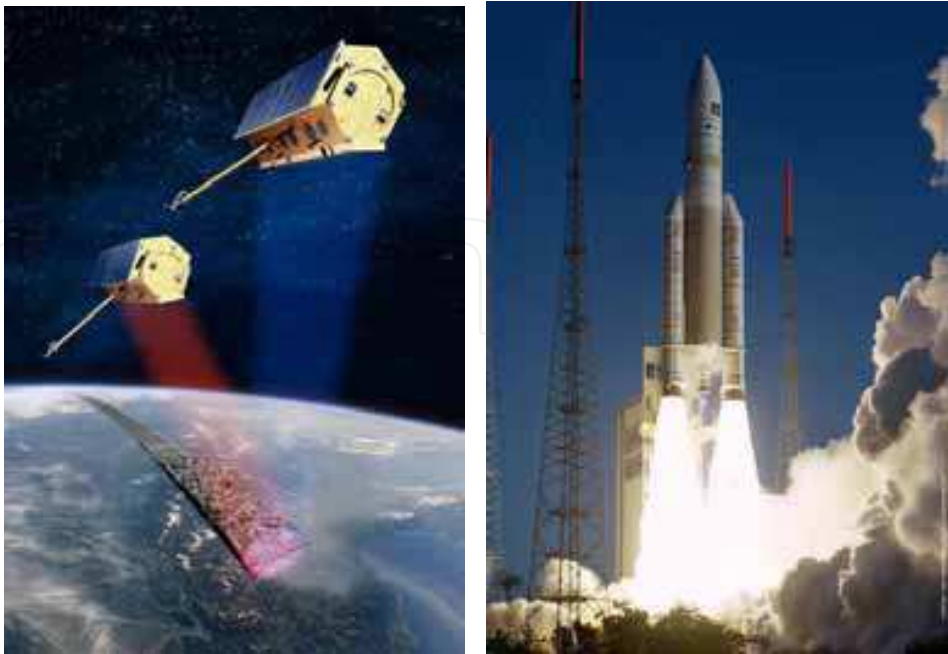


Fig. 24. TanDEM-X in space (left illustration) and an Ariane 5 at launch (right photo) (Photo courtesy of EADS Astrium)

10. Conclusion

In this chapter basics of radar target classification technologies were introduced. A classification technology was presented, that decomposes a pattern recognition module of any modern radar system in the following components:

Data acquisition part, signal preprocessing and feature extraction part, classification and subclassification part, data and information fusion part and finally object recognition or identification or typing part.

For the data acquisition part an active or passive radar frontend can be used, that uses self- or friendly generated waveforms to reconstruct information from the environment with different objects or targets. The data acquisition part usually provides such backscattered radar echo signal in I- and Q-form in the baseband.

For the signal preprocessing part some basic techniques were described in order to filter and normalise the sampled signal. It was mentioned that some measures must be taken into consideration in order to respect the basics of information theory.

For the feature extraction part several basic techniques can be used. It was also mentioned that one of the most successful philosophies in designing modern radar systems for classification purpose is the best handling of the feature extraction. This philosophy consists of best understanding of the physical behaviour of a radar system in its environment. Based on this understanding characteristic feature must then be mathematically described depending on the given requirements. For this purpose the following basic methods were presented as central components of the feature extraction process: Short-Time-Fourier transform, cepstral analysis, wavelet transform and Fuzzy-logic.

For the classification and subclassification part two main philosophies were presented. The first philosophy consists of learning processes. The second philosophy consists of knowledge based evidence. The different kind of classification and subclassification methods in the most modern radar systems can be divided into deterministical methods, stochastic methods and neural methods. The deterministical methods introduced in this section were essentially based on the handling of logical operators and knowledge based intelligence. The stochastic methods described in this section were based on finite stochastic automats. The finite stochastic automats presented in this section were based on different variants of learning Hidden Markov Models. Furthermore the neural methods presented in this section illustrate the capability of solving pattern recognition problems in modern radar systems by using different kinds of artificial neural networks. It was also shown that for specific classification or subclassification challenges in modern radar applications hybrid classifiers can also be recommended. This classifier uses depending on the situation learnable or non-learnable algorithms. The learnable algorithms can be designed using supervised or unsupervised learn concepts.

For the data and information fusion part it was pointed out that different techniques and strategies can be used in order to fuse information from different sensor systems. It was also shown that the introduced data fusion techniques can also be integrated in a stand-alone sensor system in order to produce a robust classification and recognition result. For this purpose three technologies were presented in order to solve the given problems:

Bayesian networks based method, Dempster-Shafer rules based fusion methods and finally classical rule based methods.

For the object recognition, identification or typing part it was mentioned that in modern radar systems, recorded data as well as recorded intelligence information can additionally

be used together with the classifier output or data fusion output information in order to exactly recognize, identify or type an object.

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