Key Engineering Materials
ISSN: 1662-9795, Vol. 685, pp 262-266
doi:10.4028/www.scientific.net/KEM.685.262

Submitted: 2015-10-08
Accepted: 2015-10-14

# Classification of the Signatures for Doppler Radar from the Standpoint of Active Perception Theory

V.E. Gai[1, a], A.M. Bogdan[2]

[1] Nizhny Novgorod State Technical University, 12B, 47 Kazanskoe shosse, 603087, Nizhniy Novgorod, Russian Federation

[2] Tomsk Polytechnic University, 30 Lenin ave., Tomsk, 634050, Russian Federation

[a]vasiliy.gai@gmail.com

**Keywords**: automatic target recognition, active perception theory, digital signal processing.

**Abstract**. This article describes the signals classification method when signals recording by land-based Doppler radar from different sources. It also presents various systems attributes defined within the active perception theory, which can be used to describe the signals. The results of computational experiments are presented.

## Introduction

The security of a location and its perimeter is ensured by different means: video/audio surveillance, security sensors, etc. In order to improve the security of the perimeter from trespassing the radar station can be used; radar station has a low sensitivity to weather conditions unlike optical and IR surveillance. The primary objective for perimeter radar is detection and classification of moving targets [1]. In typical radar systems, target acquisition is automatic while target classification requires operator. Classification of targets by signatures from the radar can be used for air / vehicle traffic control for military and peaceful purposes, etc. The objective of any recognition system is to get the more accurate interpretation of a target.

Signature recognition system of radar signals can be represented as a pattern recognition system.

The task of pattern recognition is one of the actual problems of theoretical computer science. The process of pattern recognition from the system analysis standpoint can be divided into three stages: 1) formation of the original description, 2) system characteristics location, 3) decision procedure [2].

There are problems associated with the use of existing methods of pattern recognition [2]:

1) the problem of forming the initial description, due to the fact that the existing models and detection methods are adapted to a particular class of applications and require prior knowledge of the analyzed signals properties;

2) system of signatures drawing problem is attributed to the choice of a finite set of signatures, ensuring the uniqueness of the classification solution at the stage of recognition and meeting the requirements of necessity and sufficiency;

3) the problem of decision-making under conditions of prior uncertainty.

The theory of active perception offers a solution to these problems [2].

Let's consider the techniques used at various stages for purposes of radar signals recognition:

1) signal pre-processing stage usually consists of filtering a signal. Considering that the recognition problem is solved in the conditions of a priori uncertainty, the selection of an appropriate filter is difficult;

2) to create a definition of input signal the signatures are calculated: Fourier spectrum coefficients, cepstral coefficient, mel frequency cepstral coefficients, linear predictive coding, wavelet spectrum coefficients, etc. [1, 3], Gaussian mixture or hidden Markov model can be used for data modelling;

3) neural network, support vector machines, nearest-neighbor method, Bayesian classifier, maximum likelihood [4, 5] are used at the stage of classification in recognition systems.

**Implementation of TAV recognition system**

**Signal pre-processing.** From the theory of active perception the signal pre-processing consists in performing the integration (Fig.1). At this stage of processing the test signal is divided into segments, each segment undergoes $Q$-transformation:

$$g(i) = Q[\ h_i\ ],\ g_i = \sum_{k=1}^{L} h_i(k),$$

where $i = \overline{1,N}$, $N$ is a number of samples in the signal $g$, $\mathbf{h} = \{h_i\}$, $\mathbf{h}$ is a set of calculated segments $f$, $L$ is a number of samples in the segment. Therefore the signal $g$ goes to the next stage of signatures calculating.

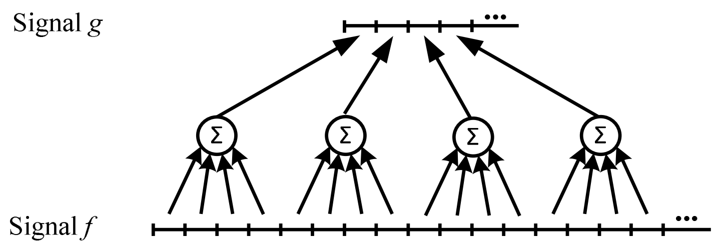


Figure 1. Signal preprocessing

**Formation of the feature description.** Let's consider the method proposed to create feature signal $g$ description:

1) signal $g$ readouts are divided into many segments $\mathbf{g} = \{g_k\}$, 16 samples with an offset to $S$ samples;

2) $U$-transformation ($U$-transformation is base in the active perception theory) is applied to each segment $g_k$, as a result spectral representation of each segment is created: $u_k = U\ [\ g_k\ ]$, $\mathbf{u} = \{u_k\ \}$, where $U$ – calculation operator $U$-transformation;

3) according to the calculated spectral representation $u_k$ the description of the segment $g_k$ is formed by one or more structures within the algebra of groups. There are the following groups in the algebra structure that can be used to create descriptions:

a) operators ($V$, 15 elements of 16 are of interest, given the fact that each element can take 0 and 1, feature space on operators basis includes 30 elements);

b) complete groups ($P_{ni}$), there are complete groups for multiplication ($P_{nim}$, 140 elements), and complete groups for addition ($P_{nia}$, 140 elements);

c) closed groups ($P_{si}$, 840 elements), closed sets ($P_{ci}$,840 elements). It is acceptable to use combinations of these structures. Calculation method of $U$-transformation, as well as complete and closed groups (and bodies) is given in [2]:

$\mathbf{V} = GV\ [\mathbf{u}]$, $\mathbf{P_{nia}} = GP_{nia}[\mathbf{u, V}]$, $\mathbf{P_{nim}} = GP_{nim}[\mathbf{u, V}]$, $\mathbf{P_{si}} = GP_{si}[\mathbf{u, V, P_{nia}, P_{nim}}]$,

$\mathbf{P_{ci}} = GP_{ci}[\mathbf{u, V, P_{nia}, P_{nim}}]$,

where $GV$ – calculation operator of operators, $GP_{nia}$ – calculation operator of full groups for addition, $GP_{nim}$– calculation operator of full groups for multiplication, $GP_{si}$ – calculation operator of closed groups, $GP_{ci}$– calculation operator of closed set,$\mathbf{V} = \{v_k\}$ – signal calculated operators range set, $\mathbf{P_{nia}}= \{P_{nia,\,k}\}$ – closed groups range set for multiplication, $\mathbf{P_{nim}}= \{P_{nim,\,k}\}$ – closed groups range set for multiplication, $\mathbf{P_{si}}= \{P_{si,\ k}\}$ – closed groups range set, $\mathbf{P_{ci}}= \{P_{ci,\ k}\}$ – closed set range, $k = \overline{1,N}$;

4) data merge from different segments of analyzed signal, structures elements histogram used in the description of the segment is calculated (see Figure 2):

$h_V= H\ [\ \mathbf{V}, \Gamma\ ]$, $h_{nia}= H\ [\ \mathbf{P_{nia}}, \Gamma\ ]$, $h_{nim}=H\ [\ \mathbf{P_{nim}}, \Gamma\ ]$,$h_{si}= H\ [\ \mathbf{P_{si}}, \Gamma\ ]$,$h_{ci}= H\ [\ \mathbf{P_{ci}}, \Gamma\ ]$,

$h_{niam}= H\ [\mathbf{P_{nia}},\mathbf{P_{nim}}, \Gamma\ ]$, $h_{sci}= H\ [\mathbf{P_{si}},\mathbf{P_{ci}}, \Gamma\ ]$,

where $h_V$ – operator histogram, $h_{nia}$ – histogram of full groups for addition, $h_{nim}$ – histogram of full groups for multiplication, $h_{si}$ – histogram of closed groups, $h_{ci}$– histogram of closed sets, $h_{niam}$–

histogram of full groups for addition and multiplication, $H$ – calculation operator histogram of specified length, $\Gamma$ – histogram length:$1d$ – one-dimensional histogram, $2d$ – two-dimensional histogram, $3d$ – three-dimensional histogram. Two-dimensional histogram covers the possible emergence of group pairs in the description of one signal segment, three-dimensional histogram covers triples. After the histogram formation you can normalize it by amplitude to the section [0; 1]:

$h' = NORM\,[\,h\,]$,

where $NORM$ – normalization operator of the histogram.

Thus, the histogram is used to combine the results of calculations of several segments, i.e. it allows you to get the general idea of the signal.

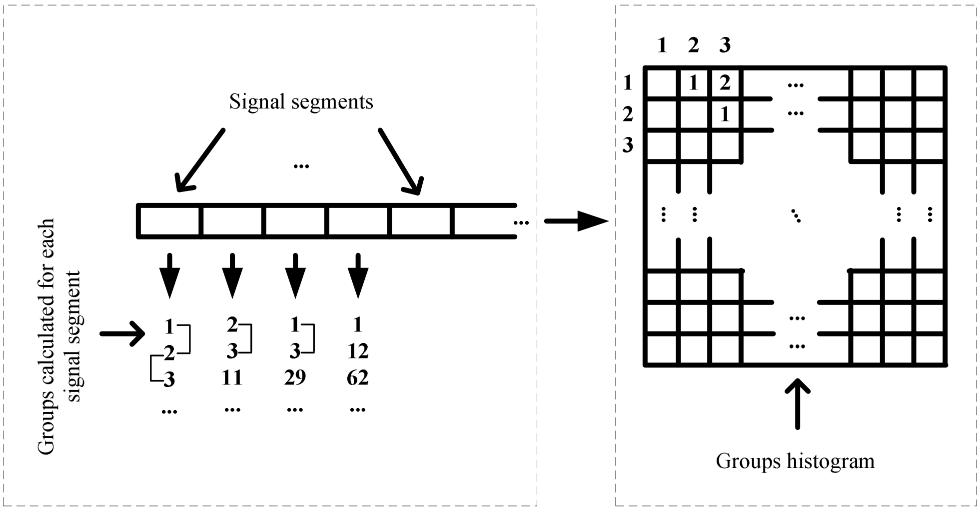


Figure 2. Two-dimensional histogram formation

**Decision-making.** Classification stage can be implemented using several classifiers. The current paper uses metric classification method $k$ nearest neighbor and support vector machines. The optimal parameter value $k$ can be measured by leave-one-out (LOO) cross-validation. This paper has two different ways for multiclass classification to translate the task to binary: One-versus-All and One-vs-One.

## Computational experiment

**Description of the database.** Computational experiment is based on radar signal database described in [6]. The sensor that is used to generate data – land-based pulse Doppler radar, operating at Ku band at a frequency of 16.8 GHz. The radar settings: average power 5 MW, pulse duration – 15 μs, average distribution by length – 150 m, distribution by height – 7.5°, azimuth – 5°.

**Known methods test results.** In this paper [1] the method of classification of radar signals based on the short-term Fourier transform. Reduction the data amount is carried out by key component analysis method, classification is based on the support vectors, testing was performed using the cross-validation. In the current work the classification of 5 classes is targeted (Table 1): 1) walking man; 2) running man; 3) crawling man; 4) walking group; 5) running group.

Table 1 Classification accuracy based on Fourier transform

| The number of component | PCA | Folded-PCA | Segmented-PCA |
|---|---|---|---|
| 10 | 10 85.54 ± 4.44 | 88.37 ± 3.49 | 89.70 ± 3.17 |
| 20 | 20 86.99 ± 5.46 | 88.61 ± 4.90 | 87.29 ± 5.00 |
| 30 | 30 87.17 ± 5.30 | 86.63 ± 4.59 | 86.45 ± 4.87 |
| 40 | 40 87.23 ± 4.79 | 86.39 ± 5.49 | 87.05 ± 5.14 |
| 50 | 50 86.69 ± 5.55 | 87.23 ± 5.42 | 87.35 ± 5.25 |

In [26] to describe radar signal pseudo Zernike moments of different orders were used. As in the previous work only 5 classes are classified (see Table 2). Classifier – SVM.

Table 2 Classification accuracy based on pseudo Zernike moments

| | | The order of pseudo Zernike moments | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Time (in seconds) | 4 | 62.8 | 81.8 | 88.8 | 93.5 | 95.2 | 95.3 | 95.3 | 95.7 | 95.9 | 95.8 |
| | 2 | 59.7 | 82.4 | 87.4 | 90.8 | 91.8 | 93.3 | 94.6 | 94.8 | 95.7 | 95.8 |
| | 1 | 57.6 | 80.4 | 82.7 | 85.7 | 86.8 | 88.4 | 90.6 | 91 | 90.8 | 90.8 |
| | 0.5 | 54.3 | 75.9 | 79.9 | 80.9 | 81.7 | 83.1 | 86.2 | 86.2 | 85.7 | 86.1 |

**The test results of the proposed method.** Numerical experiment was cross-validated. In the available data objects of one class occurs more frequently than the objects of another class thus during the division the learning / test sets were stratified: each of the four classes data is equally represented in test and training set.
The tables below use the following notation: 1*d* – one-dimensional histogram, 2*d* – two-dimensional histogram, 3*d* – three-dimensional histogram.

**SVM classifier.** Tables 3-4 show the results classification accuracy evaluation on SVM.

Table 3 Classification accuracy, One-vs-All

| | | 1*d* | | | 2*d* | | | 3*d* |
|---|---|---|---|---|---|---|---|---|
| | $L$ / $S$ | $h_{nia}$ | $h_{nim}$ | $h_{si}$ | $h_V$ | $h_{nia}$ | $h_{nim}$ | $h_V$ |
| With normalization | 4 / 2 | 0.94 | 0.96 | 0.95 | 0.92 | 0.95 | 0.96 | 0.96 |
| | 4 / 4 | 0.91 | 0.91 | 0.95 | 0.90 | 0.95 | 0.96 | 0.94 |
| | 4 / 8 | 0.89 | 0.90 | 0.92 | 0.89 | 0.92 | 0.93 | 0.92 |
| Without normalization | 4 / 2 | 0.92 | 0.93 | 0.95 | 0.75 | 0.96 | 0.97 | 0.94 |
| | 4 / 4 | 0.90 | 0.89 | 0.94 | 0.72 | 0.93 | 0.96 | 0.93 |
| | 4 / 8 | 0.86 | 0.86 | 0.91 | 0.73 | 0.92 | 0.93 | 0.91 |

Table 4 Classification accuracy, One-vs-One

| | | 1*d* | | | 2*d* | | | 3*d* |
|---|---|---|---|---|---|---|---|---|
| | $L$ / $S$ | $h_{nia}$ | $h_{nim}$ | $h_{si}$ | $h_V$ | $h_{nia}$ | $h_{nim}$ | $h_V$ |
| With normalization | 4 / 2 | 0.92 | 0.94 | 0.95 | 0.92 | 0.95 | 0.96 | 0.94 |
| | 4 / 4 | 0.90 | 0.92 | 0.96 | 0.89 | 0.94 | 0.95 | 0.93 |
| | 4 / 8 | 0.89 | 0.90 | 0.94 | 0.88 | 0.92 | 0.93 | 0.92 |
| Without normalization | 4 / 2 | 0.93 | 0.92 | 0.95 | 0.82 | 0.94 | 0.96 | 0.94 |
| | 4 / 4 | 0.91 | 0.93 | 0.94 | 0.76 | 0.93 | 0,96 | 0.93 |
| | 4 / 8 | 0.88 | 0.90 | 0.93 | 0.77 | 0.92 | 0.94 | 0.91 |

**KNN classifier.** The results of computational experiment on choosing the number of neighbors (*k* values) are shown in Table 5.

Table 5 Choosing the number of neighbours

| $k$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $L = 4$, $S = 4$, $h_V(2d)$ | 0.83 | 0.79 | 0.78 | 0.78 | 0.77 | 0.76 | 0.77 | 0.75 | 0.74 | 0.73 |
| $L = 1$, $S = 1$, $h'_{si}(1d)$ | 0.85 | 0.81 | 0.82 | 0.82 | 0.81 | 0.79 | 0.80 | 0.78 | 0.79 | 0.76 |

Table 6 show the results classification accuracy evaluation on *k* nearest neighbour.

Table 6 Classification accuracy, KNN classifier

| | | 1$d$ | | | 2$d$ | | | 3$d$ |
|---|---|---|---|---|---|---|---|---|
| | $L$ / $S$ | $h_{nia}$ | $h_{nim}$ | $h_{si}$ | $h_V$ | $h_{nia}$ | $h_{nim}$ | $h_V$ |
| With normalization | 4 / 2 | 0.89 | 0.88 | 0.90 | 0.86 | 0.91 | 0.89 | 0.89 |
| | 4 / 4 | 0.92 | 0.89 | 0.90 | 0.89 | 0.91 | 0.91 | 0.89 |
| | 4 / 8 | 0.91 | 0.89 | 0.91 | 0.89 | 0.91 | 0.90 | 0.90 |
| Without normalization | 4 / 2 | 0.91 | 0.91 | 0.92 | 0.90 | 0.92 | 0.92 | 0.90 |
| | 4 / 4 | 0.91 | 0.92 | 0.92 | 0.90 | 0.93 | 0.92 | 0.90 |
| | 4 / 8 | 0.90 | 0.91 | 0.93 | 0.90 | 0.92 | 0.92 | 0.91 |

The following conclusions can be drawn:
1) normalization of feature description of section [0; 1] improves the classification accuracy for the SVM and reduces the classification accuracy for $k$ nearest neighbor;
2) classifier SVM allows to achieve higher accuracy compared to $k$ nearest neighbor;
3) for the classification of $k$-nearest neighbors the best results are achieved with $k$ equal to 1;
4) for the SVM the best results are achieved with the One-vs-One multiclass classification approach;
5) two-dimensional histogram usage allows one to increase the classification accuracy;
6) for some signature systems there is no test data as it requires significant memory;
7) the acquired results of computational experiment confirm the effectiveness of the proposed signature systems.

## Conclusion

The paper considers the method of signatures calculation that enables to use the theory of active perception when calculating characteristics of regular signals. There are several variants of feature description. In the present work the results of computational experiment of testing the proposed signatures on radar signal database are shown. Comparing acquired results with known results allow concluding that using the proposed system of signatures one can get better results than present wide use classification approaches.

## References

[1] Zabalza J. et al., Novel folded-PCA for improved feature extraction and data reduction with hyperspectral imaging and SAR in remote sensing, ISPRS J. of Photogrammetry and Remote Sensing, 93 (2014) 112-122.
[2] Utrobin, V. A., Physical interpretation of the elements of image algebra, J. Advances in Physical Sciences 47 (2004) 1017-1032.
[3] Pallotta L. et al. Pseudo-Zernike moments based radar micro-Doppler classification, Radar Conference, 2014 0850-0854.
[4] M. Jahangir, K.M. Ponting, J.W. O'Loghlen, Robust Doppler classification technique based on Hidden Markov models, J. Proc.Radar Sonar Navig., 150 (2003) 33-36.
[5] I. Bilik, J. Tabrikian, A. Cohen, GMM-based target classification for ground surveillance Doppler radar, IEEE Trans. Aerospace and Electronic Systems, 42 (2006) 267-278.
[6] M. Andric, B. Bondzulic, B. Zrnic, Feature Extraction Related to Target Classification for a Radar Doppler Echoes, 18th Telecom. Forum, Belgrade, Serbia, November 23-25, 2010.