Ground Moving Target Classification by Using DCT Coefficients Extracted from micro-Doppler Radar Signatures and Artificial Neuron Network

Pavlo Molchanov, Jaakko Astola, Karen Egiazarian  
Department of Signal Processing  
Tampere University of Technology  
Tampere, Finland  
pavlo.molchanov@tut.fi; jta@cs.tut.fi; karen@cs.tut.fi

Abstract— a novel approach to ground moving targets classification by using information features contained in micro-Doppler radar signatures is presented. Suggested approach is based on using discrete cosine transform (DCT) coefficients extracted from radar signature as a classification feature and multilayer perceptron (MLP) as a classifier. Proposed pattern classification algorithm was tested by utilizing experimental data measurements performed by ground surveillance Doppler radar system for four radar target classes as single moving human, groups of two and three moving persons and vegetation clutter. Suggested approach provides the probability of classification equal to 86%

Keywords- micro-Doppler radar signature, DCT coefficients, multilayer perceptron, probability of target

I. INTRODUCTION

Ground surveillance Doppler radars are widely used systems for detection, recognition and classification of moving objects in order to solve security tasks. It has been shown in [1] that performances of the systems using human-operator involvement for radar target recognition and classification are unsatisfactory. Moreover, target classification executed by skilled radar operators requires high expenses and huge human resources. One of the prospective ways to increase reliability of such radar systems and avoid human factor errors is to use automatic target recognition (ATR) system. Recently, some efforts have been undertaken in this field [1] – [5] and it has been demonstrated that radar operator could be successfully replaced by ATR system.

Non-stationary signal backscattered by ground moving target and observed at the radar output contains audio frequencies that correspond to Doppler frequency shifts caused by target motions along the radar line-of-sight (LOS). Recently, various number of target classification techniques have been developed by using information features contained in time-frequency distributions of those none-stationary and multi-component signals. The approaches described in [1], [5] are based on linear autoregressive model feature extraction technique. The approaches proposed in [6], [7] deal with the pattern features extracted from signal spectrogram, as well as the pattern features related directly to the backscattered signal parameters are used [8].

In this work we are focusing on the detection and classification of pedestrians walking in vegetation clutter environment. The micro-Doppler measurements permit to extract unique human motion characteristics [9] caused by contributions of many motion body parts provoked by human gaits. The micro-Doppler radar signature contains time-varying frequency modulation of the radar echo caused by moving components of a target. The micro-Doppler signatures are periodic and therefore spectrum analysis can be used to extract efficient features for object recognition. There are number of Doppler frequencies contained in backscattered signal embedded in radar clutter noise and this excess can lead to decreasing the ATR system performances. That is why efficient feature extraction in radar clutter environment and noise resistant signal processing techniques is required.

We will consider short distance between radar and object that can be explained as interest to throw-wall measurements capability [10] of micro-Doppler radar. Classification task of person’s number behind the wall seems to us very important in security applications.

The paper is organized in the following way. We start with a description of experimental radar data collection performed by a homodyne Doppler radar. The next Sections deal with classification features extraction and target classification strategy, description of suggested classification algorithm and analysis of the radar target classification results. The last Section contains some concluding remarks.

II. EXPERIMENTAL RADAR DATA COLLECTION

In this report, all experimental data used for solving radar target classification problem were collected in real-life conditions by using ground surveillance Doppler homodyne, continuous-wave, and polarimetric radar.

The technical characteristics of this radar system are listed below as follows:

- Wavelength 8.8 mm
- Emitted radar microwave power 15 mW
- Receiving-transmitting antenna beam width 6" in both $E$ and $H$ planes
- Level of side lobes in antenna pattern -24 dB
- Cross-polarization level $\leq$ -30 dB
- Receiver noise figure 20.2 dB
- Automated gain control system not used
Despite the radar is able operating in both vertical and horizontal polarizations, only horizontal one is considered in this report.

Radar measurements were performed for the following classes of targets: A single moving human: human walking towards/away from the radar; A group of moving persons: two or three persons walking towards/away from the radar; Radar clutter: open space, trees and bushes.

Sample rate of recorded data files was selected to be of 8000 Hz according to the possible moving pedestrian velocity. Total length of all audio signal records is equal approximately to 30 minutes.

III. FEATURES EXTRACTION AND TARGET CLASSIFICATION STRATEGY

Time-dependent instantaneous micro-Doppler frequency \(f_d(t)\) contained in multi-component radar signal backscattered by moving human can be considered as the following superposition of the contributions caused by multi-point scatterers of harmonic vibrations [6]:

\[
f_d(t) = \frac{2\pi}{\lambda} \sum_{i=1}^{l} [2v_i + 2D_i\omega_i \cos(\xi_i)\cos(\omega_i t + \varphi_i)],
\]

where \(l\) is the number of moving components involved in human gait; \(v_i\) is the radial velocity of the \(i\)-th component; \(D_i\) is the vibration magnitude of the \(i\)-th component; \(\omega_i\) and \(\varphi_i\) are the angular frequency and initial phase related to the \(i\)-th vibration scatterer, respectively; \(\xi_i\) is the angle measured between the vibration plane and the radar line of site; \(\lambda\) is the radar radiated wavelength.

Micro-Doppler signature plotted by projection of instantaneous frequency trajectories (1) into the time-frequency domain contains unique information about velocities of all radar target motion components. Therefore, evolutionary variations of the instantaneous micro-Doppler frequency \(f_d(t)\) (1) can serve as unique information feature related to the moving radar target under recognition and classification in the ATR systems operating in vegetation clutter environment.

In this report, we pay attention to the non-parametric spectrum estimation strategy that is able to suppress frequency dependent noise contributions and, hence, provide good classification results in real-life interference environment. It can be seen from equation (1) that observed echo-signal contains only cosine functions and it is real-valued oscillation. Because of this, DCT seems to be effectively used for micro-Doppler spectrum estimation. Moreover, DCT seems to be more effective in terms of energy compaction. Suggested signal processing operations used for feature extraction are listed below.

First, DCT should be applied to the micro-Doppler radar signature \(f_d(t)\) (1) as

\[
C(k) = h(k) \sum_{t=0}^{T-1} f_d(t) \cos \left[ \pi \left( t + \frac{1}{2} \right) \frac{k}{T} \right],
\]

where \(T\) is the length of observed radar signature; \(k \in [0, T-1]\);

\[
h(k) = \begin{cases} \frac{1}{\sqrt{T}} & \text{if } k = 0, \\ \frac{\sqrt{2}}{\sqrt{T}} & \text{elsewhere} \end{cases}
\]

As was mentioned above, input signal can contain frequency dependent noise. These interference frequency values are commonly higher than information ones. Noisy frequency contributions can be suppressed by the following procedure

\[
C_f(k) = C(k) \text{ if } k < 0.23 \times T,
\]

where \(C_f(k)\) is the truncated vector of the DCT coefficients of a length of \([0.23T];\) 0.23 is a constant value selected corresponding to the frequency of 900 Hz and it was defined by us empirically.

The last procedures, which should be performed in order to calculate feature vector \(G\) are given as

\[
G(n) = \sum_{k=0}^{N-1} h(k) \log_{10} C_f(k) \cos \left( \pi \left( n + \frac{1}{2} \right) \frac{k}{N} \right).
\]

It should be noted that the features extracted by the procedures (2) – (4) provide very important invariant property related to the radar target velocity.

Period of walking human gaits is equal approximately to 600 ms. In order to resolve Doppler frequency contributions corresponding to the human body micro-motions, processing data length should be significantly smaller than the period of human gaits. On the other hand, we will obtain lower frequency resolution with smaller processing data length. Therefore, optimization of parameter \(T\) contained in (2) – (4) must be taken into account.

After pattern feature extraction procedures (2) – (4) executed for each observed radar signature \(f_d(t)\), a vector of coefficients \(G\) is obtained. Now we should select optimal number of those coefficients which will be used for classification. On the one hand, if a small number of the coefficients will be selected than the information contained in other coefficients, worse classification performances will be obtained. On the other hand, the “curse of dimensionality” can arise if a large number of the coefficients have been selected. In order to reduce feature dimensionality, well-known principal component analysis (PCA) strategy [11] seems to be useful tool.

Unfortunately, preliminary study and tests with collected experimental radar data performed by us demonstrate that PCA makes resulting classification worse. Therefore, we propose to use a sorting procedure for DCT coefficients according to the information gain (IG) criterion in order to find the coefficients which contain more useful information for classifier. It has been demonstrated in [12] that this approach operates rather effectively with features and it helps to understand which feature contains larger amount of information.

Our strategy is based on the Shannon information theory. Entropy is an effective measure of variability in a random variable space. The entropy \(H\) of a feature \(V\) can be written as
\[
H(V) = - \sum_{j=\text{all of } V's \text{ states}} p_j \cdot \log_2(p_j),
\]

where \( p_j \) is the probability that feature \( V \) will take a state of \( j \).

Other information criterion is the conditional entropy \( H(\text{Class}|V) \) equal to

\[
H(\text{Class}|V) = \sum_{j=\text{all of } V's \text{ states}} p_j \cdot H(\text{Class}|V = j),
\]

where \( p_j \) is the probability that \( V \) takes a state \( j \). The conditional entropy (6) allows measuring how much entropy is left if one was known the state of feature \( V \).

The IG value indicates the amount of additional information about class provided by the feature \( V \), and it can be given as

\[
\text{IG(Class }| V) = H(\text{Class}) - H(\text{Class }| V).\tag{7}
\]

At the end of feature selection procedure we will choose fixed number of features according to the highest IG value in (7) and use them to classify an unknown target.

IV. SUGGESTED CLASSIFICATION ALGORITHM

The block-scheme of the proposed algorithm is represented in Fig. 1.

![Block-scheme of the proposed algorithm](image)

Data processing steps used in proposed target classification algorithm shown in Fig. 1 are listed below.

1) **Data preprocessing.**
   - An input is a database which contains micro-Doppler radar signatures. Data preprocessing means the partitioning input data into the number of segments executed for total processing data length.
   - **DCT.**
     - Coefficients of DCT are computed for each segment by using formula (2) and smoothing Hamming window.
   - **DCT coefficients preprocessing.**
     - Doppler spectrum contains, unfortunately, the interference frequencies which do not provoked by human gaits. In considered radar scenario, these interference frequencies are higher than 900 Hz. They are cut off in this data preprocessing block.
   - **Pattern feature calculation.**
     - The features are extracted from Doppler spectrum by using calculations performed according to the formulas (3) – (4). Now we have the features which are represented in the form of the DCT coefficients with high energy compaction.
   - **Feature selection.**

All extracted features are sorted according to the IG criterion (7). Number of coefficients is reduced to fixed predefined value. Ten coefficients are selected in this paper without loss of generality.

2) **Preprocessing features.**
   - Preprocessing block discards of 1 % of the highest and lowest values. In such a way we remove random interference outliers from the pattern feature set.

3) **Cross-validation.**
   - In order to obtain more accuracy classification results, \( K \)-fold cross-validation technique is applied as follows. Original samples are split into \( K \) subsamples of equal length, and then \( K-1 \) subsamples are used as a training set and one remaining subsample is used as a test set. The cross-validation process is repeated \( K-1 \) times (the folds), where each of the \( K \) subsamples is used as a test set. The \( K \) results from the folds are averaged to produce a single estimation.

4) **MLP.**
   - MLP is used as a classifier. To reduce statistical errors we repeat training procedure ten times and average MLP outputs over ten times (see the “Averaging of class conditional probabilities” block in Fig. 1).

5) **Integration of the probabilities.**
   - The idea is that more accuracy classification can be obtained by using not just current micro-Doppler signature realization, but also some amount contained in previous signatures. Normalized outputs are averaged over fixed number of realizations in the past before making decision. This number depends on practical application and technical limitations. If more realizations will be considered then more accuracy results will be obtained, but system will be less robust.

Since our strategy is based on the MLP approach, it is necessary to describe this approach in details. MLP is selected to be feed-forward back-propagation artificial neural network (ANN) with two hidden layers (ten neurons are contained in each hidden layer). Transfer function for them is selected to be the tan-sigmoid. Output layer contains four outputs with purelin transfer function. Mean squared error performance function is selected to estimate the ANN performance. ANN is generated by using standard Matlab functions.

First, ANN is trained by the following way. If the feature vector from class number one is an input then output node number one will have an output value “1”, and three other outputs will have the values “0”. Second, if the feature vector from class number one is an input then output node number two will have an output “1”, and others will have the output of “0”, etc. repeating for each studied class. We try to construct the ANN which possesses the probabilities belonging to the classes at the classifier output. When MLP will perform and all outputs will be computed, each output value will be divided onto the sum of all outputs, thereby we expect to obtain some similarity to class conditional probabilities at the MLP output.

Class corresponding to the input vector is defined by using maximum of the function. Constructing ANN we make it possible to use integration procedure.

In this report, ten DCT coefficients have been selected for solving radar target recognition and classification problem.
These first ten DCT coefficients provide highest information gain criterion and contain 25% of all features variability.

V. ANALYSIS OF THE RADAR TARGET CLASSIFICATION RESULTS

Database contains four classes: one, two, three moving persons, and vegetation clutter. Accumulating experimental data into the database was performed according to the following scenario. Initial position of the radar object was in a few meters from the radar. After that, person walked away from the radar for approximately 40 seconds, stayed for 2 seconds, turned around and came back, stayed for 2 seconds and repeat movement several times. Each examinee class contains 6 sets of experiments with walking away from the radar and 5 sets of experiments with walking towards the radar. As a result, each class contains 11 different sub-experiments. Therefore, 11-fold cross-validation is considered in this paper. It means that each sub-experiment will be used as testing set one time and ten times as part of training set.

Processing data length is selected to be of 128 ms that corresponds to 1024 digital signal samples contained in the records. Decision can be made every 128 ms or less frequently if integration procedure is applied. In such a way probabilities will be increased by using previous observations.

In this report, we assume that in the radar LOS at any time target could arise and our task is to answer the question. Does any target present in the LOS? If any then which of three target could arise and our task is to answer the question. Does any target present in the LOS? If any then which of three kind of ATR system if it will operate in real-life conditions. It has been demonstrated that proposed strategy provides probabilities of correct classification approximately equal to 86 percents for four-class test experimentally performed in the ATR system.

For more details look at author’s web page: http://www.cs.tut.fi/~molchanov/mrrs2011, where one can download used database as well as Matlab files.

ACKNOWLEDGMENT
Pavlo Molchanov is supported by the Graduate School in Electronics, Telecommunications and Automation, Finland, http://geta.tkk.fi/en.

REFERENCES


Analyzing the results in Table II, we can see that the worst probability of correct classification corresponds to class contained two humans; and it is equal to 81 percents.

VI. CONCLUSIONS

Novel approach based on ANN classifier has been proposed and studied in application to the ground moving target classification. DCT coefficients extracted from the micro-Doppler signatures are used as recognition and classification features. Performances of proposed classifier were tested with real data measured by using K-band Doppler ground surveillance radar. It has been demonstrated that proposed strategy provides probabilities of correct classification approximately equal to 86 percents for four-class test experimentally performed in the ATR system.

TABLE I. PROBABILITIES OF CORRECT CLASSIFICATION DEPENDING ON INTEGRATION TIME

<table>
<thead>
<tr>
<th>Integration time</th>
<th>2 s</th>
<th>1 s</th>
<th>512 ms</th>
<th>256 ms</th>
<th>128 ms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of correct classification</td>
<td>86%</td>
<td>81%</td>
<td>76%</td>
<td>70%</td>
<td>63%</td>
</tr>
</tbody>
</table>

The probabilities allow estimate what to expect from such kind of ATR system if it will operate in real-life conditions. It is seen from Table I that ATR system provides correct classification results with probability of 63 percents using only one realization every 128 milliseconds. With increasing of integration time (increasing number of previous realizations which will affect result) probability of correct classification tends to increasing, and reaches probability of 86% when integration time is equal to 2 seconds.

Let us consider confusion matrices which represent information about class classification probabilities. Table II represents results obtained with integration time equal to 2 seconds. One can see that now probabilities of false alarm as well as of target misclassification are decreased.

TABLE II. CONFUSION MATRIX, INTEGRATION TIME IS EQUAL TO 2 SECOND. VALUES ARE GIVEN IN PERCENTS.

<table>
<thead>
<tr>
<th></th>
<th>One human</th>
<th>Two humans</th>
<th>Three humans</th>
<th>Clutter</th>
</tr>
</thead>
<tbody>
<tr>
<td>One human</td>
<td>94.6</td>
<td>4.9</td>
<td>0.7</td>
<td>0.1</td>
</tr>
<tr>
<td>Two humans</td>
<td>7.6</td>
<td>86.7</td>
<td>4.8</td>
<td>0.9</td>
</tr>
<tr>
<td>Three humans</td>
<td>8.0</td>
<td>4.8</td>
<td>86.0</td>
<td>1.3</td>
</tr>
<tr>
<td>Clutter</td>
<td>5.6</td>
<td>12.2</td>
<td>3.4</td>
<td>78.8</td>
</tr>
</tbody>
</table>