Target Classification by Using Pattern Features Extracted from Bispectrum-Based Radar Doppler Signatures


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Abstract— In this paper, a novel bicepstrum-based approach is proposed for moving radar target classification. In our study, pattern features are extracted from short-time backscattering bispectrum estimates measured by using ground surveillance Doppler radar. Classifier performance is studied by Gaussian mixture model (GMM) and maximum likelihood (ML) making decision method. Our experimental results show that is quite feasible to recognize three classes of humans (single, two and three humans) moving in vegetation clutter environment by using proposed bispectrum-based strategy. Bispectrum-based features extraction provides additional insight into moving radar target classification that is superior to common utilizing energy-based features.

1. Introduction

The radar Doppler signature of a target is a time-varying frequency modulation contribution arisen in radar backscattering and caused by moving components of the target. In this report, we are focusing on solving classification problem concerning moving humans. Radar analysis of human motion by using Doppler frequency shift measurements has been under study in recent years [1]–[7]. Recognition, identification and classification human motion by using ground surveillance Doppler radar systems have a number of applications including security, military intelligence and battlefield purposes. One of the unique and effective pattern features in the sense of moving human classification used in automatic target recognition (ATR) system is the micro-Doppler (m-D) contributions containing in human radar signature. The time-varying trajectories of the different instantaneous m-D frequency shifts displayed in the time-frequency (TF) space are quite robust information features belonging to a human or group of humans. However, it should be stressed that problem of recognition single, two, three or more moving persons by using their radar signatures is the most difficult problem to be solved. Recently, the approaches exploiting the m-D radar signatures for moving human classification have been reported in literature [2], [5]. The most widespread approaches deal with quadratic (spectrogram-based) TF analysis of non-stationary and multi-component backscattered radar signals. Common drawback of the quadratic TF analysis is in impossibility of employing additional information about frequency-coupling and phase-coupling instantaneous frequencies containing in the radar signals backscattered by moving humans. Phase coupling containing in radar backscattering carries important information about unique target surface and properties. Extraction the latter pattern features could provide additional insight into moving radar target classification that looks to be superior comparing to common utilizing energy-based information features.

The objective of our report is study Doppler radar classifier performance operating by using novel features extracted from short-time bispectrum estimates measured by ground surveillance radar system in vegetation clutter environment.

In this work, we study three different moving human classes including a single human, two and three humans moving away or towards the radar.
2. Features Extraction and Target Classification Strategy

Bispectral estimation technique applied for the radar signals backscattered by moving humans is the basis of suggested approach for information features extraction in ATR system. The motivation for using bispectral estimation technique in ground surveillance radar signal processing arises from the following useful properties which bispectrum estimation possesses [8]. Bispectral estimation of chirp-like and multi-component radar backscattered signals allows extraction new information features which conventional techniques are simply unable to provide. These new information features are related to the phase coupling. The latter features can be extracted by bispectrum estimation, i.e. when coherent spectral components are in radar return, the coupled components contribute to the bispectrum estimate of a signal. On the other hand, the bispectrum tends to zero for a stationary zero-mean AWGN. It means that there are no phase coupled frequencies in a linear Gaussian process. The SNR can, in principle, be increased in the radar signatures by developing the algorithms which make use of these bispectrum properties. Therefore, bispectrum-based signal processing permits providing noise-robust features necessary for moving radar target classification in noise environment.

It has been demonstrated in our previous papers [6], [7] that the swinging legs and arms of a walking human are not independent mechanical sources provoking time-varying instantaneous frequencies in spectrum content, but they are related between each other via “common carrier” which is the translating and swaying human torso. It has been experimentally proved the evident presence of phase coupled harmonics containing in radar returns collected by ground surveillance radar [6]. Therefore, bispectrum-based extraction of these correlation dependences allows providing new features in radar target classification.

Signals received in ground surveillance radars are referred to non-stationary and polyharmonic audio signals collected and recorded in the wav-files. Because of this, we consider two bispectrum-based algorithms used for speech recognition [10], [11].

Integrated bispectrum (IB) is defined in [10] as

$$IB(\omega) = \frac{1}{K-\omega} \sum_{\omega_i=1}^{K-\omega} |B(\omega, \omega_i)|,$$

where \(\omega = 1, \ldots, (K - 1)\) are the normalized angular frequencies; \(|B(\omega_1, \omega_2)| = |X(\omega_1)| \cdot |X(\omega_2)| \cdot |X^*(\omega_1 + \omega_2)|\) is the signal magnitude bispectrum (bimagnitude); \(|X(\cdots)|\) are the sliding window short-time signal Fourier transforms (STFT); \(K\) is the width of sliding window used in STFT computation; * denotes complex conjugation.

Other algorithm for computation the averaged bispectrum estimate is considered in [10]. This algorithm deals with the averaging of the bimagnitude samples in bifrequency Domain along fixed Frequency Direction (DFB) \(f_3\) such as \(f_1 + f_2 = f_3\)

$$DFB(\omega) = \frac{1}{F} \sum_{f_2} |B(\omega - f_2, f_2)|^{1/3}.$$

The following bicepstral coefficients \(CIB\) and \(CDFB\) computed by using IB (1) and DFB (2) algorithms are used as pattern features for target classification

$$CIB[\omega] = |F^{-1}\{\log(IB[\omega])\}|,$$

$$CDFB[\omega] = |F^{-1}\{\log(DFB[\omega])\}|,$$

where \(F^{-1}\{\cdots\}\) is the indirect discrete Fourier transform.

From various numbers of existing now days approaches for radar target recognition and classification, maximum likelihood (ML) rule and Gaussian mixture model (GMM) are used in this paper to estimate bispectrum-based classifier performance. In our opinion, GMM is rather good strategy for unknown probability density function (pdf) approximation [11].

In general case, GMM [11] can be given as
\[ f(\mathbf{x}) = \sum_{m=1}^{M} \pi_m \phi(\mathbf{x}; \theta_m), \]  

(5)

where \( \pi_m \) is the mixture coefficients; \( \phi(\mathbf{x}; \theta_m) \) is the pdf of an arbitrary \( m \)-th component; \( \theta_m \) are the parameters of \( m \)-th component pdf; \( \mathbf{x} \) is the features vector.

The component pdf given by (5) of an arbitrary GMM component can be written as

\[ \phi(\mathbf{x}; \theta) = \frac{1}{(2\pi)^{D/2}|\mathbf{C}|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \overline{\mathbf{m}})^T \mathbf{C}^{-1}(\mathbf{x} - \overline{\mathbf{m}})\right), \]

(6)

where by \( \mathbf{C} \) the covariance matrix is denoted; \( \overline{\mathbf{m}} \) is the vector of the mean values.

Making decision rule based on the ML method is defined as follows:

\[ \hat{w} = \arg \max_{w=1, \ldots, \tilde{W}} f(\mathbf{x} | H_w), \]

(7)

where \( f(\mathbf{x} | H_w) \) is the pdf of feature vector \( \mathbf{x} \) referred to the classification hypothesis \( H_w \).

The \( K \)-fold cross-validation technique is applied to obtain more accuracy classification results. The most important benefit of \( K \)-fold cross-validation is that all signal radar records are used for both training and testing operations.

In order to compare performance of suggested bispectrum-based classifier with common power cepstrum-based classifier, the following power cepstrum coefficients \( C[\omega] \) have been considered

\[ C[\omega] = |F^{-1}\{\log(|X(\omega)|^2)\}|^2. \]

(8)

In order to rank the features according to their correlation referred to the class, the following conditional entropy \( H(\text{Class} | V) \) is used

\[ H(\text{Class} | V) = \sum_{j \in V} p_j * H(\text{Class} | V = j), \]

(9)

where \( p_j \) is the probability when \( V \) takes the state \( j \). The conditional entropy (9) indicates how much entropy is left if the state of feature \( V \) is known.

The information gain (IG) indicating the amount of additional information about class provided by feature \( V \), is given as:

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

(10)

3. Experimental Results and their Discussion

Vector features, which can be extracted by using bispectrum-based strategy described in previous Section II were collected by experimental measurement performed with ground surveillance Doppler homodyne, polarimetric and continuous wave radar.

The radar data referred to the listed below three pedestrian classes were collected. The following scenarios were studied in vegetation clutter and open space environment. 1) Single moving human: Human walking towards/away the radar with normal velocity of 3-5 km/h. 2) Group of moving persons: Two persons walking towards/away the radar with normal velocity of 3-5 km/h. 3) Group of moving persons: Three persons walking towards/away the radar with normal velocity of 3-5 km/h synchronously and asynchronously.

Ground surveillance radar system parameters are: wavelength – 8.8 mm, emitted radar power – 15 mW, receiving/transmitting antenna beam width in both \( E \) and \( H \) planes – 6°, level of side lobes in horn antenna pattern - 24 dB, cross-polarization level \( \leq -30 \) dB, receiver noise figure – 20.2 dB, two-channel 16 bit ADC, sampling rate in digital records – 8 KHz. Due to the SNR variations during the records depending on the time-varying target distance and direction of motion (away/towards the radar), averaged SNRs were estimated. Averaged SNR values are equal to 4 dB, 6 dB and 11 dB for single, two and three moving humans, respectively.
Each class contains 11 diverse experiments and above mentioned 11-fold cross-validation technique has been employed for target classification. It means that the features have been extracted from the measured data ten times for training data set and one time for testing data set during each experiment, i.e. 0.91 of the data collected are used as training data set, and the remaining 0.09 as the testing (validation) data set.

Examples of TF radar signatures of a single human moving in vegetation clutter environment are shown in Fig. 1. It is seen from Fig. 1 that AWGN is suppressed better in bicepstral-based radar signatures represented in Fig. 1(b) and 1(c) comparing to the spectrogram shown in Fig. 1(a).

Histograms of the second cepstral and bicepstral coefficients calculated for three considered target classes by using features (8) and (3) are demonstrated in Fig. 2. The histograms show that it is difficult to recognize single walking human from two or three persons by using just only this one feature. Both histograms in Fig. 2(a) and (b) referred to single walking human contain the intersection domains corresponding to the histograms obtained both for two and three persons. However, classes related to two and three walking persons are more separated in histograms plotted by using bicepstral coefficient (3).

Classifier performance can be gained by using the features having the lower inter-class similarity, i.e. when the same classifier but different feature vectors are used. In order to calculate inter-class similarity, Euclidean metric for sample cross-correlation function has been computed. Similarity measure $SM$ was calculated as:

$$SM(m) = \frac{1}{3m} \sum_{i=1}^{m} \sum_{k=2,3,1} \left| XCF(C_k(i,.), C_i(i,.)) \right|$$

where $m$ is the number of used cepstral or bicepstral coefficients; $XCF$ is the cross-correlation function; $k,l$ are the indexes belonging to three classes; $i$ is the cepstral/bicepstral coefficient number; $C_i(i,.)$ is the set of cepstral/bicepstral coefficient number $i$ belonging to the class $k$.

Dependencies of the selected similarity measures on number of the first cepstral/bicepstral coefficients are illustrated in Fig. 3. One can see the benefit produced by using bispectrum-based feature extraction (see the straight curve in Fig. 3) comparing to the power spectrum-
based technique (dashed curve in Fig. 3). This benefit can be assessed by comparison the values on the straight and dashed curves in Fig. 3. It is clearly seen that correlation values are smaller for bispectrum-based feature extraction technique. It means that the latter technique possesses better features orthogonality. Therefore, better classifier performance should be provided for bispectrum-based technique.

Ranked values of IG criterion estimated for different feature extraction techniques are illustrated in Table I. Values are computed with processing data length equals 512 samples. Conventional cepstrum based features (indicated as C) are listed only three times in top 20, in the same time bispectrum based features CIB and CDFB appear ten and seven times respectively. It means that bispectrum based features contain more information about training classes, however, IG criterion has one drawback – it assumes independence of features.

![Fig. 3. Inter-class similarity computed for feature vector (8) (dashed curve) and (4) (straight curve).](image)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Feature</th>
<th>IG value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CIB 1</td>
<td>0.64983</td>
</tr>
<tr>
<td>2</td>
<td>CDFB 1</td>
<td>0.64623</td>
</tr>
<tr>
<td>3</td>
<td>C 1</td>
<td>0.63466</td>
</tr>
<tr>
<td>4</td>
<td>CDFB 2</td>
<td>0.52238</td>
</tr>
<tr>
<td>5</td>
<td>CIB 2</td>
<td>0.50130</td>
</tr>
<tr>
<td>6</td>
<td>CIB 3</td>
<td>0.48975</td>
</tr>
<tr>
<td>7</td>
<td>CDFB 3</td>
<td>0.48864</td>
</tr>
<tr>
<td>8</td>
<td>CDFB 4</td>
<td>0.48408</td>
</tr>
<tr>
<td>9</td>
<td>C 2</td>
<td>0.48381</td>
</tr>
<tr>
<td>10</td>
<td>CDFB 5</td>
<td>0.48261</td>
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Table I. Features ranked by IG criterion.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Feature</th>
<th>IG value</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>CIB 4</td>
<td>0.48243</td>
</tr>
<tr>
<td>12</td>
<td>CIB 6</td>
<td>0.47186</td>
</tr>
<tr>
<td>14</td>
<td>C_3</td>
<td>0.46894</td>
</tr>
<tr>
<td>15</td>
<td>CDFB 6</td>
<td>0.46653</td>
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<tr>
<td>16</td>
<td>CIB 7</td>
<td>0.46295</td>
</tr>
<tr>
<td>17</td>
<td>CIB 8</td>
<td>0.46202</td>
</tr>
<tr>
<td>18</td>
<td>CDFB 7</td>
<td>0.46163</td>
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<tr>
<td>19</td>
<td>CIB 9</td>
<td>0.45798</td>
</tr>
<tr>
<td>20</td>
<td>CIB 10</td>
<td>0.45791</td>
</tr>
</tbody>
</table>

4. Classifier Performance Measurements

Processing data length has been selected to be 4096 samples (512 ms). This time interval corresponds to the period of human gait. Before making classification we should select two more parameters: the number of coefficients which will be used for classification and the order of GMM. The GMM order parameter was defined empirically; it is selected to be 4, it should be mentioned that this parameter doesn’t significantly affect classification results [7]. We have no rules how to select the number of features involved in classification therefore we use different values in range 5-40.

<table>
<thead>
<tr>
<th>Number of used features</th>
<th>5</th>
<th>10</th>
<th>20</th>
<th>40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDFB (4)</td>
<td>77.1 %</td>
<td>78.7 %</td>
<td>79.1 %</td>
<td>78.3 %</td>
</tr>
<tr>
<td>CIB (3)</td>
<td>74.7 %</td>
<td>76.9 %</td>
<td>75.3 %</td>
<td>71.0 %</td>
</tr>
<tr>
<td>C (8)</td>
<td>75.1 %</td>
<td>76.0 %</td>
<td>72.3 %</td>
<td>66.5 %</td>
</tr>
</tbody>
</table>

Table II. Classification rates

Probabilities of correct classification using different feature extraction methods and different number of features are listed in Table II. One can see the benefit of CDFB features, probability given by these features is higher by at least 2 percents at maximum. However, CDFB and CIB are extracted from the same bispectrum density but results are different, it can be explained by difference in efficiency of feature extraction procedures, it is also mentioned in [10]. It should be mentioned that CDFB reaches the highest value with 20 features; CIB and C reach with 10 features.
5. Conclusions

Bispectrum-based features extraction from Doppler radar returns to classify moving radar targets has been proposed. Data were collected by using ground surveillance Doppler radar for moving human subjects as single, two and three persons. Pattern features were extracted from integrated and averaged short-time bispectrum estimates of transient Doppler radar returns in the form of two kinds of bicepstral coefficients. Diverse scenarios have been considered and 11-fold cross-validation test has been employed for classification accuracy. Experimental results show that is quite feasible to recognize three classes of humans moving in vegetation clutter environment by using proposed bispectrum-based features extracted from Doppler radar backscattering. Bispectrum-based pattern features extraction from radar backscattering provides additional insight into moving radar target classification that is superior to common utilizing energy-based information features.

Obtained experimental results can give practical recommendations for development security and military ATR systems.

For more details look at the author’s web page: www.cs.tut.fi/~molchano/IRS2011, where one can download used database as well as Matlab files.

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References