A wavelet-based feature set for recognizing pulse repetition interval modulation patterns

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Abstract: This paper presents a new feature set for the problem of recognizing pulse repetition interval (PRI) modulation patterns. The recognition is based upon the features extracted from the multiresolution decomposition of different types of PRI modulated sequences. Special emphasis is placed on the recognition of jittered and stagger type PRI sequences due to the fact that these types of PRI sequences appear predominantly in modern electronic warfare environments for some specific mission requirements and recognition of them are heavily based on histogram features. We test our method with a broad range of PRI modulation parameters. Simulation results show that the proposed feature set is highly robust and separate jittered, stagger and other modulation patterns very well. Especially for stagger type of PRI sequences wavelet-based features outperform conventional histogram-based features. Advantages of the proposed feature set along with its robustness criteria are analyzed in detail.
Key Words: Electronic warfare, Radar intercept systems, Pulse repetition interval modulation, Feature extraction, Wavelet transforms, Support vector machines.

1. Introduction

In dense signal environments where large number of (many) emitters can be active simultaneously, a radar intercept system receives an interleaved stream of pulses in natural time of arrival order. It is then the task of the intercept system to deinterleave this mixed pulse sequence and thus to identify the source emissions. For this identification task, various parameters such as pulse frequency (PF), pulse width (PW), pulse amplitude (PA), angle of arrival (AOA), and time of arrival (TOA) are measured and emission sources are classified accordingly. Among these pulse parameters, TOA is of considerable interest since it leads to a key derived parameter called Pulse Repetition Interval (PRI), which represents the difference of sequential TOAs of received pulses. Any emission source either intentionally or unintentionally varies (or modulates) this parameter for a specific mission requirement. Thus, it is important to recognize PRI modulations for identification of the emission source and its mission for possible counter measures. Additionally, some emitters may vary even PRI modulation type according to its mission. This makes estimation of PRI modulations more critical from operational point of view. As the subject is sensitive, and may require mostly classified data, it is not possible to see so many works toward resolving this problem.

In the literature, deinterleaving pulse trains has been in the focus of many researches in the past years [1-10]. Several studies were performed on estimation of PRI to construct
better deinterleaving algorithms. Cumulative Differences (C-DIF) and Sequential Differences (S-DIF) histogram techniques, techniques based on TOA matrix characteristics, and a transformation called PRI Transform leading to a kind of PRI spectrum were some amongst these algorithms that enabled new methodologies to estimate pulse repetition intervals of pulse sequences and thus to deinterleave them [7-10]. But, as the signal environments become more complex in electronic warfare due to evolving of technology, the need for not only estimating pulse repetition interval of radar pulses, but also recognizing the modulation patterns hidden inside them has become an inevitable task. So, in recent years, studies have been focused on this area and several methods have been proposed to recognize PRI modulation types [11-18]. In Noone [11], an N dimensional feature vector is deduced by using the second differences of the TOAs of a pulse train and PRI modulation types are classified via a neural network. In Rong, Jin, and Zhang [12], a two dimensional feature vector is formed by extracting frequency and shape features from this N dimensional vector which reduced the computation time greatly. In Ryoo, Song, and Kim [13] PRI modulation types are recognized based on the features extracted from the autocorrelation of the PRI sequences for each PRI modulation type. In this method, due to the sensitivity of the features against signal imperfections, compensation of missing pulses and the removal of spurious pulses must be performed as a preprocessing step. In Kauppi et al. [14] PRI modulation patterns are classified hierarchically. First, six modulation patterns are first grouped into three subpatterns by using a neural network classifier and then they are binary classified by using one-dimensional classifiers. Some proposed
features in this method are based on sequential difference (SDIF) histograms [8] and they need to be calculated for several orders due to unknown signal parameters.

In this study, we present new features based on the wavelet analysis of PRI modulation patterns to classify PRI modulation types. Features are extracted from multiresolution decomposition [19] of second difference of the TOAs signal by utilizing a discrete Haar wavelet. Experimental results show that the extracted features separate jitter, stagger and other modulation types very well and they are highly robust to real-world imperfections such as missing pulses, spurious pulses and TOA noise.

The rest of the paper is organized as follows: In Section 2, the basic PRI modulation types and their parameters are given. In Section 3, the proposed feature set and the method is described. Section 4 shows simulation results and discusses these results. Finally, Section 5 concludes this paper.

2. PRI Modulation

Let $F$ be a function describing the PRI modulation type:

$$x_n = y_{n+1} - y_n = F(n) \quad n = 1,2,\ldots, N-1$$  \hspace{1cm} (1)

where $y_n$ is the time of arrival (TOA) of the $n$th pulse received in a pulse sequence of length $N$ and $x_n$ is the difference of TOAs of two consecutive pulses.

In general, there are six common PRI modulation types: stable, jittered, stagger, dwell & switch, sliding and periodic. Each modulation type serves for a specific purpose, thus they represent some characteristics of emitters. Constant PRI means the peak variations in PRI values are less than about 1% of the mean PRI, whereas jittered PRI has large intentional
PRI variations up to about 30% of the mean PRI. Staggered PRI uses two or more PRIs selected in a fixed sequence. The sequence may contain more than one of the several intervals before it repeats. In dwell & switch PRI, the radar has bursts of pulses with several stable PRIs switched from one burst to the next. Sliding PRI is characterized by monotonically increasing or decreasing PRI followed by a rapid jump from one extreme value to the other. And finally, periodic PRI means that modulation is a nearly sinusoidal variation over a more limited range than sliding PRI. Common PRI modulation types and their parameterizations are presented in Table 1.

3. Methodology

It has been shown that multiresolution signal decomposition scheme proposed in [19] can be applied to PRI estimation in intercept receivers. In doing this, variation of wavelet coefficients are closely related with PRI modulation patterns obtained from the time sequences of interleaved pulses. Classical multiresolution concept based multichannel filter banks are adopted to PRI estimation in this work.

After detailed analysis of PRI modulation types via their wavelet decompositions, it was observed that local extrema of the wavelet coefficients of jittered type modulation patterns tend to have lower magnitudes compared to stagger type modulation patterns. This is due to the fact that in staggered sequences, PRI variation is done from pulse to pulse. The radar emitter staggers from one position to another abruptly. These abrupt changes are more likely to be reflected in magnitude to their detail coefficients in contrast to jittered sequences where PRI variation is within a predefined limited range. Also, the median of
the wavelet coefficients of other PRI modulation patterns (stable, dwell & switch, sliding, and periodic) tend to have lower values compared to jittered and stagger type modulation patterns. Smooth variations of those type patterns cause most of their detail coefficients tend to zero or to very low numbers in magnitude as compared to jittered and stagger type patterns. These observations gave us a chance to extract new features to distinguish between jittered, stagger and other PRI modulation types.

Radar intercept systems may encounter with a continuous stream of pulses accompanied by many imperfections, and they are required to work on a real-time basis. Since the Haar wavelet is computationally efficient and can be implemented in a transformation matrix form, it has been preferred in our study.

Feature analysis is performed on the second difference of TOAs by utilizing discrete Haar wavelet.

The Haar wavelet is defined as [20]:

$$\Psi(t) = \begin{cases} 
1, & 0 \leq t < \frac{1}{2} \\
-1, & \frac{1}{2} \leq t < 1 \\
0, & \text{elsewhere}
\end{cases} \quad (2)$$

and the whole set of basis functions is obtained by dilation and translation:

$$\psi_{m,n}(t) = 2^{-m/2} \Psi(2^{-m} t - n), \quad m, n \in \mathbb{Z}. \quad (3)$$

We call $m$ the scale factor, since $\psi_{m,n}(t)$ is of length $2^m$, while $n$ is called the shift factor, and the shift is scale dependent ($\psi_{m,n}(t)$ is shifted by $2^m n$). The normalization factor $2^{-m/2}$ makes $\psi_{m,n}(t)$ of unit norm.
The discrete case of the wavelet can be expressed as:

\[ g_{j,k}(n) = 2^{-j/2} g(2^{-j} n - k), \quad k, n \in \mathbb{Z}, \quad j \in \mathbb{N}. \quad (4) \]

where the wavelet filter \( g(n) \) plays the role of \( \psi(t) \).

The second difference of TOAs is defined by differentiating the modulation function \( F \) according to Noone [11]:

\[ z_n = x_{n+1} - x_n, \quad n = 1, 2, \ldots, N - 2 \quad (5) \]

where \( z_n \) is the second difference of the time of arrival of the \( n \)th pulse. Then the detail coefficients of the wavelet decomposition of \( z_n \) at scale \( 2^j \) can be expressed as:

\[ c_d(j, k) = \sum_n z_n g_{j,k}(n) \quad (6) \]

### 3.1. Analysis of Jittered and Stagger PRI Modulation Types

Two features are extracted from the wavelet decomposition of the vector of second differences \( z_n \) of length \( M \) as follows:

Let \( E_i \) be the square summable energy in the \( i \)th level or the \( i \)th subband of wavelet decomposition of \( z_n \) (d\(^2\)TOA), i.e,

\[ E_i = \sum_j \|c^i(j)\|^2 = \sum_j (c^i(j))^2, \quad j = 1, 2, \ldots, M/2^i \quad (7) \]

where \( c^i(j) \) denotes the \( j \)th detail coefficient of the \( i \)th level decomposition.

The first feature is defined as a vector of the energies in \( L \) levels:

\[ f_1 = [E_1 \ E_2 \ldots \ E_L] \quad (8) \]

where \( L \) is the effective number of decomposition levels which is analyzed in the next section.

The second feature is the magnitude of median of wavelet coefficients in the first subband:
\[ f_z = \text{abs} \left( \text{median} \left\{ c_j \right\} \right) \quad j = 1, 2, \ldots, M/2 \quad (9) \]

\( M \) is assumed to be a multiple of 2 which allows fast wavelet decomposition of the signal.

For classification task, we employ a cascaded form of a one dimensional binary classifier and a Support Vector Machine (SVM) classifier. SVM are from class of supervised learning algorithms that can be applied to classification or regression.

The SVM algorithm is based on the statistical learning theory developed by Vladimir Vapnik [21]. It was originally designed to solve two-class problems (binary classification), but can be easily extended to solve multi-class problems with combinations of binary classifiers. The goal of the algorithm is to determine the optimum hyperplane that separates two classes. More treatment of SVM theory is beyond the scope of this paper and can be found in [22]. For now, it should be pointed out that major advantages of SVM are that different learning machines can be constructed by utilizing different kernels and nonlinear classification problems can be solved by linear classifiers via mapping to higher dimensional spaces without explicitly modifying the kernels [23].

We first separate the jittered and stagger modulated patterns from others by using a binary classifier. Then, a SVM classifier is used to separate the jittered and stagger types. We use a linear kernel for evaluating the performance of our SVM classifier.

### 3.2. Analysis of Other PRI Modulation Types

The sample kurtosis of wavelet coefficients in the \( i \)th subband is given by:

\[
\text{Kurt} (c') = \frac{1}{M/2^i} \sum_{j=1}^{M/2^i} (c'_i(j) - \mu_{c'_i})^4 \quad \left( \frac{1}{M/2^i} \sum_{j=1}^{M/2^i} (c'_i(j) - \mu_{c'_i})^2 \right)^2 \quad (10)
\]
where \( c^i \) is the wavelet coefficients and \( \mu_{c^i} \) is the sample mean of the wavelet coefficients in the \( i^{th} \) subband, respectively.

Also, let the number of local extrema of wavelet coefficients in the first subband be symbolized as \( local\ extrema\ (c^1) \). Then the hybrid feature:

\[
f_j = [Kurt\ (c^1)\ Kurt\ (c^2)\ Kurt\ (c^3)\ localextre\ ma\ (c^1)]\ (11)
\]

is very efficient in separating dwell & switch, sliding and sinusoidal PRI modulation types. For the sake of illustration of the separating capability of proposed feature, three kurtosis components of this feature is depicted in the simulations section.

A generalized block diagram of the proposed method is presented in Figure 1.

### 4. Simulations

The data generation model proposed by Kauppi et al. [14] has a very high flexibility in modulation parameters and quite adequate for the generation of different PRI modulation sequences. The parameter limits used for data generation is given in Table 2. We train our SVM classifier for a scenario of an average missing and spurious pulses of 5%, TOA noise of 0.3% and with a very broad range of training data where limits are presented in Table 2.

We have created the test sequence from a broad range of PRI modulation parameters to test the separating capability of the feature set. Test sequence consists of six different type PRI sequences and their subsequences. Table 3 shows parameters of each PRI sequence. For each PRI sequence, subsequences are formed in such a way that they fully cover the limits of modulation parameters to ensure an unbiased sample space as possible and to see the robustness of the features against large variations of modulation parameters of PRI types.
For the sake of illustration of separating capability of the feature set, we simulated our
training data where parameter limits are presented in Table 2. The separating capabilities
of the proposed features are illustrated in Figure 2, Figure 3, and Figure 4, respectively.
Tests are performed for four distinct circumstances: in case of no imperfections, missing
pulses case, spurious pulses case and in case of TOA noise. For missing and spurious
pulses cases, tests are performed ten times and in case of TOA noise, the trials are
increased to 100 to reflect the statistics of noise as much as possible by varying pulse
repetition interval of PRI modulation types and the average recognition rate is calculated.
Computation results are obtained on a standard Pentium Dual Core 2 GHz PC with
MATLAB R2013a version.

The selection of L (the number of decomposition levels in the first feature) is crucial for
the separating capability of the feature for jittered and stagger modulated types. A
comparison about the results of Haar and Daubechies wavelets [24] for a typical scenario
of an average missing and spurious pulses of 5% and TOA noise of 0.3% is given in Table
4. It is observed that average recognition rates of jittered and stagger sequences are very
similar for both wavelets and the performance is greatly improved at two and three levels.

The average recognition rates of PRI modulation patterns are given in Table 5. It can be
inferred from the results that jittered and stagger PRI modulation types have high
recognition rates, usually around 95% except that recognition performance of jittered type
sequences decreases rapidly as the percentage of missing pulses increases. They are not
robust to missing pulses. This can be considered the only major shortcoming of the
proposed method. Also, other modulation types have average recognition rates of 85%,
except in the presence of TOA noise of 0.3% and 0.4%, which they are 81% and 70%
respectively. Even if they decrease gradually, they still show good performance at tolerable
TOA noise rates. One of the major advantages of the proposed features is that they are able
to separate stagger type modulation sequences with an accuracy of around 99%. Features
show great robustness to real world imperfections such as missing pulses, spurious pulses
and TOA noise. This property is further analyzed in the next subsections.

4.1. Comparison with histogram-based methods

In [14], jittered and stagger type PRI sequences are recognized by using histogram-based
features. The feature is extracted from higher order SDIF histograms and is defined as the
relative strength of a stable sum in the $d$th order SDIF-histogram.

The average recognition rates of jittered and stagger PRI modulation type sequences
against missing and spurious pulses are given in Figure 5 and Figure 6, respectively. It is
observed from Figure 4 that for jittered type sequences, histogram-based features perform
better than wavelet-based features. The average recognition rate of jittered sequences based
on histograms is above 80%, while this rate decreases to 60% for the extreme case of 15%
missing pulses when wavelet features are employed. For stagger type sequences, wavelet-
based features outperform histogram-based features.

In spurious pulses case (Figure 6), for both jittered and stagger type sequences wavelet-
based features perform better than histogram-based features. For jittered sequences, the
average recognition rates of both methods is above 85%, while for stagger sequences the
average recognition rate based on histograms decrease very quickly. This is due to that the
dynamic range of histogram-based feature proposed in [14] for stagger type sequences rapidly increases when the number of missing or spurious pulses increases.

Histogram-based features have also some bottlenecks. First, since the number of positions of a stagger type sequence is generally unknown due to the unknown signal parameters, the feature needs be calculated up to several orders [14]. Second, the relative tolerance defining constant time interval in histogram stabilization algorithm is a choice parameter which should be updated for dynamically varying signal environments.

A comparison about the runtimes of proposed and histogram method is presented in Table 6. With this comparison, a superior side of the proposed method has been observed. Since the number of positions in Stagger PRI is generally unknown, histogram based features are calculated according to the highest expected number of positions in Stagger PRI [14]. A general staggered PRI sequence can contain up to 64 positions as presented in Table 2. On the other hand, wavelet based features do not depend on the number of positions in Stagger PRI yielding much better run-time performances as seen from the Table 6.

4.2. Robustness criteria

One of the most important contributions of this work is that the wavelet features proposed is very robust for stagger type sequences and distinguish very well as shown in Table 5. Figure 7, Figure 8 and Figure 9 show the dynamic range of the energy feature for stagger sequences with number of positions 2 to 64 against increasing number of missing pulse, spurious pulse and TOA noise percentages, respectively. It is observed that the dynamic range of the energy feature against signal imperfections does not change
significantly and the calculated energy feature values vary between 10 and 25. It should be emphasized that energy feature values calculated for jittered sequences are low and this explains the high recognition performance of stagger type sequences in circumstances of missing and spurious pulses.

It is observed from Table 5 that both jittered and stagger type PRI sequences are highly robust to time of arrival (TOA) noise and have average recognition rates of about 98% even in the extreme case of 0.4% noise. This is due to the fact that the wavelet features are invariant to noise. This property is depicted in Figure 10 and Figure 11 for jittered and stagger sequences, respectively. For jittered sequence, jittered sequence with jitter deviation of 20% is modeled. For stagger sequence, a stagger sequence of 4 positions is modeled.

It can be inferred from the figures (Figure 10 and Figure 11) that for both jittered and stagger sequences, the dynamic range of the feature is nearly constant against increasing time of arrival uncertainty.

5. Conclusion

In this study, we developed a wavelet-based feature set to recognize PRI modulation patterns. Three wavelet features that span the full domain of common PRI modulation types were found to be distinctive to discriminate between jittered, stagger and other PRI modulation type sequences. The proposed features and classification method is very effective for, especially, emitters that vary PRI patterns continuously. Simulation results
show that the separating capability of the proposed features is pretty good and the method is encouraging for the problem of recognizing different PRI modulation patterns.

References


Figure 1. A generalized block diagram of the proposed method.
Figure 2. Demonstrating separating capability of the energy feature
Figure 3. Demonstrating separating capability of the median feature
**Figure 4.** Demonstrating separating capability of three kurtosis components of the 3rd feature

![Diagram showing kurtosis of wavelet coefficients across different subbands]
Figure 5. Average recognition rate of histogram and wavelet based features against missing pulses

Figure 6. Average recognition rate of histogram and wavelet-based features against spurious pulses
Figure 7. Robustness of energy feature against increasing missing pulses
Figure 8. Robustness of energy feature against increasing spurious pulses
Figure 9. Robustness of energy feature against increasing TOA noise
Figure 10. Variation of the energy feature calculated against increasing TOA noise for a jittered type PRI sequence.
Figure 11. Variation of the energy feature calculated against increasing TOA noise for a stagger type PRI sequence.
<table>
<thead>
<tr>
<th><strong>Constant</strong></th>
<th>( F(n) = c ), ( n = 2, \ldots, N - 1 )</th>
<th>( c ) : a constant real number.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stagger</strong></td>
<td>( F(i + kM) = F(i) ) ( i = 1, 2, \ldots, M ) ( k = 1, 2, \ldots, T )</td>
<td>( M ) : the number of positions in one period ( T ) : the number of periods in the pulse sequence. Total number of pulses in the pulse sequence is ( N = MT ).</td>
</tr>
<tr>
<td><strong>Dwell and Switch</strong></td>
<td>First stage: ( F(i) = F(1) ) ( i = 2, \ldots, N_0 ) Other stages: ( F(i) = F(1 + N_j) ) ( j = 0, 1, \ldots, M - 1 ) ( i = N_j + 2, \ldots, N_{j+1} )</td>
<td>( M ) : the number of stages in the pulse sequence ( N_i ) : the number of pulses in the ( i )th stage The total number of pulses in the pulse sequence is ( N = \sum_{k=0}^{M-1} N_k ).</td>
</tr>
<tr>
<td><strong>Jittered</strong></td>
<td>( F(n) = T + \epsilon_{\text{Gauss}} )</td>
<td>( T ) : the mean PRI ( \epsilon_{\text{Gauss}} ) : a random variable which has a Gaussian distribution with zero mean and ( \sigma ) standard deviation.</td>
</tr>
<tr>
<td><strong>Sliding</strong></td>
<td>( F(n) = \alpha (n - 1 \mod M) + \beta )</td>
<td>( M ) : the number of pulses in one slide period ( \beta ) : the minimum PRI (Min_pri) value ( \alpha = (\text{Max_pri} - \text{Min_pri}) / (M - 1) ), the slope of the modulation.</td>
</tr>
<tr>
<td><strong>Periodic</strong></td>
<td>( F(n) = T + A \sin(wn + \phi) )</td>
<td>( T ) : the mean PRI ( A ) : the modulation amplitude (generally up to 5% of mean PRI), ( w ) : the modulation frequency (generally between 20-50 pulses per period) ( \phi ) : the phase.</td>
</tr>
</tbody>
</table>

**Table 1.** Common PRI modulation types and their parameterizations
### Table 2. The parameter limits for synthetic data generation

<table>
<thead>
<tr>
<th>PRI Modulation Types</th>
<th>Parameters</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jittered</td>
<td>Jitter type</td>
<td>Gaussian, uniform</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>5% - 50%</td>
</tr>
<tr>
<td>Stagger</td>
<td>Number of positions</td>
<td>2 - 64</td>
</tr>
<tr>
<td>Dwell &amp; Switch</td>
<td>Number of bursts</td>
<td>2 - 64</td>
</tr>
<tr>
<td></td>
<td>Length of one burst</td>
<td>8 - 100</td>
</tr>
<tr>
<td>Sliding</td>
<td>Max-min ratio</td>
<td>2 - 20</td>
</tr>
<tr>
<td></td>
<td>Number of periods</td>
<td>1 - 20</td>
</tr>
<tr>
<td>Periodic</td>
<td>Amplitude deviation</td>
<td>4% - 50%</td>
</tr>
<tr>
<td></td>
<td>Number of periods</td>
<td>8 - 100</td>
</tr>
</tbody>
</table>

#### Imperfections
- Missing pulses: 0% - 15%
- Spurious pulses: 0% - 15%
- TOA uncertainty: 0% - 0.4%

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### Table 3. Test sequence

<table>
<thead>
<tr>
<th>PRI Sequence</th>
<th>Subsequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>10 subsequences.</td>
</tr>
<tr>
<td>Jittered</td>
<td>46 subsequences of standard deviations 5% to 50% and each subsequence has Gaussian and uniform distributions.</td>
</tr>
<tr>
<td>Stagger</td>
<td>63 subsequences of stagger positions 2 to 64.</td>
</tr>
<tr>
<td>Sliding</td>
<td>19 subsequences of max:min ratios 2 to 20 and each subsequence with periods 1,5,10,20.</td>
</tr>
<tr>
<td>Dwell-Switch</td>
<td>15 subsequences of number of bursts 2 to 16 and each subsequence with burst lengths 8,20, 50,100.</td>
</tr>
<tr>
<td>Periodic</td>
<td>47 subsequences of amplitude deviations 4% to 50% and each subsequence with periods 8, 20, 50, 100.</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>PRI Modulation Patterns</th>
<th>Average Recognition Rate of PRI Modulation Patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Haar wavelet</td>
</tr>
<tr>
<td></td>
<td>L=1</td>
</tr>
<tr>
<td>Jittered</td>
<td>72</td>
</tr>
<tr>
<td>Stagger</td>
<td>99</td>
</tr>
<tr>
<td>Computation time (ms)</td>
<td>1.904</td>
</tr>
</tbody>
</table>

**Table 4.** A comparison about the results of Haar and Daubechies wavelets (M=128).

<table>
<thead>
<tr>
<th>PRI Modulation Patterns</th>
<th>Average Recognition Rates of PRI Modulation Patterns (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No imperfections</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Jittered</td>
<td>99.35</td>
</tr>
<tr>
<td>Stagger</td>
<td>99.21</td>
</tr>
<tr>
<td>Others</td>
<td>100</td>
</tr>
</tbody>
</table>

**Table 5.** Classification Results (L = 3)
Table 6. A comparison about the runtime performance of proposed and histogram methods

<table>
<thead>
<tr>
<th>Number of stagger positions</th>
<th>2</th>
<th>4</th>
<th>8</th>
<th>16</th>
<th>32</th>
<th>64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed</td>
<td>2.886 (does not depend on stagger positions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>