Target Classification in Sparse Sampling Acoustic Sensor Networks using DTWC Algorithm

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Abstract

To extract as much accurate information as possible, especially in the case of a sparse sampling acoustic sensor network, the approach of time series can be effective. However, both problems of local time shifting and spatial variations should be solved to apply the time series analysis. This paper proposes the DTWC (DTW-Cosine) algorithm, as a time series manner, to solve the two problems and proves the performance through several experiments. We also considered acoustic variations, which can occur, by using data set mixed with various effects as input. Our experimental results show that the target classification rate of our algorithm not only outperforms the other time-warped similarity measure algorithms but it also has a robust performance over various volumes in combination with a smoothing technique. Since this proposed algorithm produces such a satisfactory result with sparse sampling data, it allows us to classify objects with relatively low overhead.

1. Introduction

The problems of target classification using sparse sampled data are one of the key issues of Wireless Sensor Networks (WSN) applications since WSN consists of a large number of low-power and inexpensive sensor nodes. When sensor nodes sense and transfer data to a base station (BS), the network cost might increase dramatically as the hop count increases. Especially, in the case of acoustic data which is so complicated and variable, it needs more numerous and dense data to obtain sufficient information. This is a problem since acoustic sensors is one of the most frequently used and performs a central role in a target classification system of WSN. The bigger the WSN is, the less data should be basically transferred to increase the life span. It is because the mechanism of sensing frequently and transferring all of the data causes the nodes to be exhausted very fast. So, the mechanism of sparse sampling should be considered

Most of the researches [1,2] extracted features using the FFT and classified targets with some classification algorithms such as k-nearest neighbor (kNN), maximum likelihood (ML), support vector machine (SVM), etc. However, the FFT typically needs a high sampling rate and thus, a broader bandwidth network to transfer assuming a centralized processing scheme of WSN. To achieve a realistic acoustic WSN, the problem of how to get some meaningful information with sparse sampled data, which can not afford to serve any spectral information (see Figure 3), should be solved. Time series analysis could be an effective method for target classification with sparse sampling data when a specific pattern can be found in time-axis. Actually, the sounds of most WSN targets, tank engine, step, etc, have their own inherent patterns. A lot of research have been performed for this method, mainly to retrieve some patterns in a large database or to do data mining [5-7]. To classify targets with the manner of time series in acoustic WSNs, the local time shifting problem, named the problem of time warping matching, should be overcome as well. The DTW (Dynamic time warping), the LCS (Longest Common Subsequence) and the ED (Edit Distance) algorithms can be applied to solve the problem [6]. These algorithms or their variants are famous as well as frequently compared with each other in time series analysis [6, 7].

In this paper, we focus on target classification using a time series technique with several sound patterns of military targets in acoustic WSNs. The DTWC (DTW-Cosine) algorithm is proposed as a new technique to solve the problems of local time shifting and the problem of spatial variations caused by different distance between a target and a node. Our data set are also made by adding various acoustic effects to each original signal to emulate some distortion effects which can occur. Moreover, the performance is analyzed over various acoustic volumes, i.e. sound pressures, to consider the spatial variations.

The rest of this paper is organized as follows. Section 2 explains the DTWC algorithm, and the design of classification system using time series method is described briefly in Section 3. We empirically evaluate the performance of proposed algorithm in Section 4. Finally, Section 5 concludes our experiments and discussions for future works.

2. DTWC (DTW-Cosine) algorithm

As mentioned, two problems, local time shifting and spatial variations, should be solved to apply the time series manner to the classification system of WSN. The first problem arises when a sequence is shifted or has different lengths from the other. The other one is that all the signals from an object should be identified regardless of the strength of volume in a WSN.

The first problem is solved by a time warping algorithm such as DTW, LCS [8], or ED [9]. Among the above algorithms, The DTW algorithm is representatively used to find the warped path through a matrix of points representing possible time alignments between two patterns [3]. It is because the DTW produces a matched array much easier than the others without any scaling problem. Given two time sequences $X=(x_1,x_2,\ldots,x_m)$ and $Y=(y_1,y_2,\ldots,y_n)$, the DTW algorithm fills an m by n matrix representing the distances of best possible partial path using a recursive formula:

$$D(i,j) = d(i,j) + \min \begin{cases} D(i,j-1) \\ D(i-1,j) \\ D(i-1,j-1) \end{cases} \tag{1}$$

where $1 \leq i \leq m$, $1 \leq j \leq n$, $d(i,j)$ represents the distance between x_i and y_j. $D(1,1)$ is initialized to $d(1,1)$. The alignment that results in the minimum distance between the two sequences has value $D(m,n)$. The DTW distance between time series is the sum of distances of their corresponding elements.

Many variants of DTW have tried just to find a more optimally matched array so far. In this case, the DTW algorithm coalesces with the Cosine algorithm to solve the second problem caused by distance, which is named DTWC. The Cosine similarity treats the matched pairs as components of an N-dimensional vector, and the similarity is the cosine of the angle between these sequences. Let x' and y' be a matched array respectively. It ranges from +1 to -1. A correlation of +1 means that they have a perfectly positive linear relationship with each other. Inversely, a correlation of -1 also means a perfect negative linear relationship, and 0 means there is no linear relationship at all. This similarity is given by Eq 2.

$$C_{\cos ine}(x', y') = \frac{\frac{1}{N}\sum_{i=1}^{N} x'_i \times y'_i}{\| x' \| \times \| y' \|} \tag{2}$$

where $||x'||$ and $||y'||$ is the norm of x'_i and y'_i individually.

Both of the Euclidean algorithm and the Pearson algorithm can be also combined to the DTW algorithm to compute a similarity. They are called DTWE (DTW-Euclidean) and DTWP (DTW-Pearson) respectively. First, the Euclidean distance is just the sum of the squared distances of two vectors of observation. So, the less distance means the more similarity. The value of Euclidean similarity can be simply computed as Eq 3.

$$C_{Euclidean}(x', y') = \sqrt{\sum_{i=1}^{N} (x'_i - y'_i)^2} \tag{3}$$

The other Pearson similarity is a parametric measure of correlation and reflects the degree of linear relationship between two sequences that are on an interval or ratio scale [4]. The similarity is computed as Eq 4.

$$C_{pearson}(x', y') = \frac{\sum_{i=1}^{N} (x'_i - m_{x'})(y'_i - m_{y'})}{\sqrt{\left[\sum_{i=1}^{N} (x'_i - m_{x'})^2\right]\left[\sum_{i=1}^{N} (y'_i - m_{y'})^2\right]}} \tag{4}$$

where $m_{x'}$ is a mean value of x'_i and $m_{y'}$ is a mean value of y'_i respectively. It ranges from +1 to -1. A correlation of +1 means that they have a perfectly positive linear relationship with each other. Inversely, a correlation of -1 also means a perfect negative linear relationship and a correlation of 0 means there is no linear relationship as well.

To compare the Cosine algorithm with the other similarity measure algorithms, the Euclidean and the Pearson, in WSN applications, suppose that there are three signals collected on a BS in a WSN as them in Figure 1. y1 and y2 can happen when a moving object is varying in distance to sensor nodes over time, which means a similarity measure algorithm should identify them.

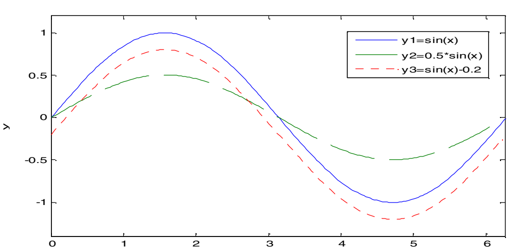

Figure 1. Three signals for comparison of similarity measurement

Referring to Table 1, the measures by the Euclidean algorithm represent distance values while the Cosine algorithm and the Pearson algorithm compute similarity. The Pearson and the Cosine similarity algorithms identify y1 and y2 while the Euclidean algorithm is unable to classify them well. On the other hand, y3 and the others may not be caused by the same object, which means they can be regarded as not exactly the same but similar. Table 1 shows that the Cosine similarity identifies minute differences while the Pearson similarity does not. An original signal should not be confused with the others to maintain the performance. That is why the former outperforms the latter and this will be further analyzed in Section. 4.3. Consequently, we can imagine that the Cosine similarity can represent the characteristics of signal in WSN better than the others.

Table 1. Distance/correlation measures of three algorithms

Algorithm	Euclidean	Pearson	Cosine
data1 ⇔ data2	2.8025	1.0000	1.0000
data2 ⇔ data3	1.5875	1.0000	0.9622
data3 ⇔ data1	3.2211	1.0000	0.9622

3. Design of classification system

The overall system architecture consists of preprocessing, making reference, and classification parts, but the part that each reference model is modified associated with the size of input signal is different with the general classification system.

When an input signal enters, it is scaled and smoothed to be against outliers and, each reference model is trimmed with the PAA algorithm in [10] associated with the number of the input data to compare with one another. It is because each input signal has its own length. The PAA algorithm uses the absolute values of an object's signal to reduce the variation and the computational complexity since the signal comprises dense positive and negative values which are piecewise mixed up with each other.

The PAA compresses or models a signal as follows; there is a reference of time series as $X = x_1, x_2, \ldots, x_n$. Let N be the size of the transformed time series we wish to work with ($1 \leq N \leq n$). For convenience, we assume that N is a factor of n. A time series X of length n is represented in N space by a vector $\overline{X} = \overline{x}_1, \ldots, \overline{x}_n$. The i[th] element of $\overline{X}$ is calculated by Eq. 5.

$$\overline{x_i} = \frac{N}{n} \sum_{j=\frac{n}{N}(i-1)+1}^{\frac{n}{N}i} x_j \qquad (5)$$

Simply stated, to reduce the data from n dimensions to N dimensions, the data is divided into N equi-sized "frames." Consequently, each contour of the reference model is modeled through the PAA algorithm to compare with the input signal.

4. Experiments and evaluations

We first describe our experimental setup briefly and the optimal accuracies of the ED and the LCS are compared to the performance of the DTW. We then show the effectiveness of the proposed algorithm through several experiments.

4.1. Experimental setup and data collection

Three types of military targets - airplane, tank and soldier - are classified as shown in Figure 2. Each target's signal has been recorded with PCM (Pulse code modulation) signed 16 bit mono and consists of several local frames and has its own pattern. The sound of a soldier is a step sound which is very periodic and the duration of local frame is very short while the sound of an airplane is a-periodic and has a long local frame. The tank makes the sound of a-periodic explosions against a background of the sound of engine and wheels, which has a monotonous energy. We added some effects and noise which produces some distortion to the signals, e.g. various Doppler effects, some hissing noises by size, echo, flanger, mechanize, pitch change, some volume transforming effects(fade in/out), and time warping. We made 31 test data per target and totally have 93 test data. Each file is sampled at 10 Hz 20 times and classified 1860 times against targets before obtaining the result.

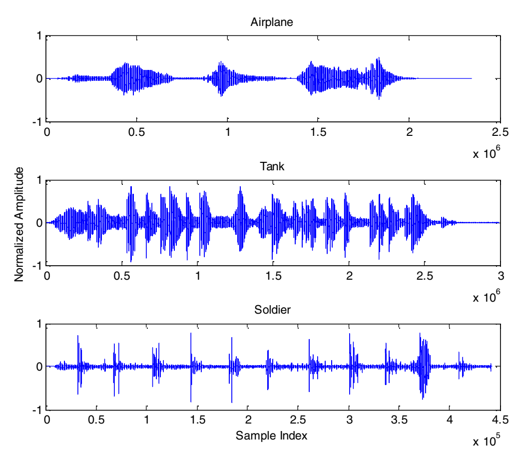

Figure 2. Original signals of military targets. Each of them is assumed to have its inherent patterns

Figure 3 shows the spectrogram of the used data which shows little frequency information is contained in the signal as a result of sparse sampling. Also, we found the accuracy rate of classification with spectral features converge into about 1 / N, where N is the number of candidates, below 100 Hz regardless of classifier.

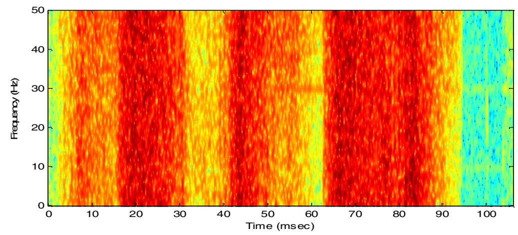

Figure 3. Spectrogram of airplane signal sampled at 100Hz with 80 points-STFT (Short-Time Fourier Transform)

4.2. Comparison of Time warping algorithms

Before comparing the effectiveness of three time warping algorithms, the ED, the LCS and the DTW, we experimented with the performance of the ED and the LCS with three levels of volume - low (-6.02dB), normal and double (6.02 dB). This is because the ED and the LCS should use a scaling threshold for time series data, which consist of numeric values, and compare with the DTW. We explored the performance by varying the value of the threshold from 0.02 to 0.2. As described in Table 2, the optimal threshold has a tendency to move following the level of volume. i.e., the threshold shifts to a smaller value in higher volume while it becomes larger in lower volume. Consequently, it is clear that the threshold cannot be easily established over volume. Table 2 also shows the comparison of the performance of the time warping algorithms. The DTW algorithm gives a similar performance with the ED and the LCS in normal and high volume and all of them have a poor performance in low volume. It means that an algorithm which can improve the performance, especially in the case of low volume, is needed. Fortunately, the DTW can easily produce a time-warped array which can be used by any similarity measure algorithm such as the Euclidean or the Cosine algorithm to improve the accuracy.

Table 2. Comparison of time warping algorithms

Volume level	ED		LCS		DTW
	δ	%	δ	%	
Double (6dB)	0.07	0.77	0.06	0.79	0.77
Normal (0dB)	0.08	0.71	0.08	0.72	0.71
Low (-6dB)	0.1	0.51	0.1	0.51	0.45

- δ : Threshold, % : Accuracy

4.3. Comparison of time warping similarity measure algorithms

We explore the DTW combined with all similarity measure algorithms as illustrated in Section. 2. We then prove that the DTWC algorithm improves the performance in the area of low volume very effectively and outperforms the other algorithms as depicted in Figure 4. Although the performance of the DTW and the DTWE algorithm shows a good performance from 3 to 9 dB, their performances are poor in lower volumes as well as have a tendency of degrading dramatically after 10 dB, which means they are largely dependent on the level of volume.

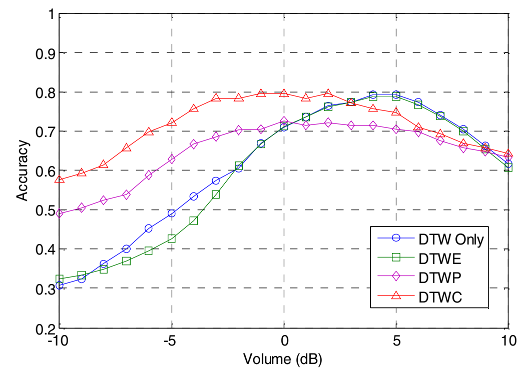

Figure 4. Comparison of time-warped similarity measure algorithms

On the other hand, the DTWP and the DTWC have saliently better accuracies in low volume and are comparatively less affected by volume. The former is inferior to the latter over volumes. It is inferable that these results are ascribed to the difference between the capabilities of each similarity measure algorithm on modeling signals in WSNs as described in Section. 2. Considering a range from -10 dB to 10 dB, the accuracy of DTW-only is 60.84%, DTWE is 59.57%, DTWP is 64.97% and DTWC algorithm is 71.4% on the average. However, all of them including the DTWC algorithm degrade accuracy in higher and lower volumes. This state can be healed a little by smoothing techniques, which will be described in the next sub-section.

4.4. Applying a smoothing technique to DTWC algorithm

Smoothing techniques are helpful in improving the accuracy through avoiding distortions caused by odd elements. It is widely used for eliminating environmental noise. We experimented with two kinds of smoothing methods, the Rectangular smoothing (RS) and the Gaussian smoothing (GS). Taken as a whole, the former is shown to have a similar performance with the latter within an allowable error range in Figure 5 except for the number of smoothing elements required. It also seems that the more the volume approaches both limits, the larger the difference the effect of smoothing makes. So, it turns out to be effective in improving the accuracy in both lower and higher volumes. However, the Rectangular smoothing with more than 3 elements can be said to be almost analogous in effectiveness. It is because the excessive number of smoothing elements mitigates the characteristics of each target signal. As depicted in Figure 5, the performance is improved in lower volumes by a maximum of about 12.74% and in higher volumes by about 9.19% when the number of the Rectangular smoothing elements is 3 (marked as RS3). We also explored this smoothing technique applied to the other algorithms and found that the curve of DTW and DTWE algorithms did not become flatter, which means they still had a bad accuracy in both lower and higher volumes, and the performance of DTWP was mostly inferior to DTWC as well.

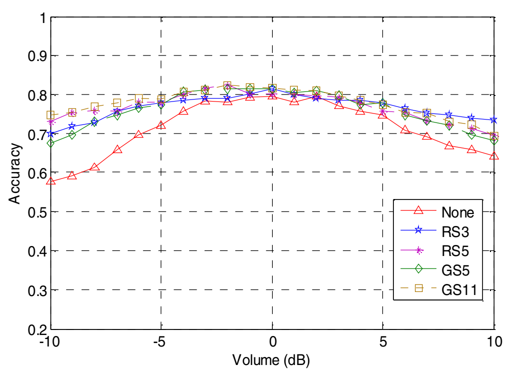

Figure 5. Comparison of the Rectangular smoothing and the Gaussian smoothing performances corresponding to the number of smoothing elements

Table 3 shows the confusion matrix of targets corresponding to volumes. The accuracies of tank and airplane outperform soldier by and large because the width of pillars of signal from the soldier are so narrow that they often can not be sampled while the interval between them are so large that even skipping sampling once can be critical to the performance. The influence of volume is also shown to depend on the sort of sound. i.e. monotonous signals such as a soldier or an airplane is affected negatively by strong volume while complicated and variable signals such as a tank is positively affected. It is because more monotonous signal is modeled relatively better in lower volumes than in higher volumes.

Table 3. Confusion matrix of DTWC algorithm with the smooth3 technique corresponding to volumes

Object \ Classified	Volume	Soldier	Tank	Airplane
Soldier	Half	0.60484	0.24355	0.15161
	Normal	0.58548	0.23710	0.17742
	Double	0.47258	0.35484	0.17258
Tank	Half	0.09677	0.75968	0.14355
	Normal	0.02742	0.93065	0.04193
	Double	0.00484	0.99032	0.00484
Airplane	Half	0.01613	0.03710	0.94677
	Normal	0.00806	0.06452	0.92742
	Double	0.00484	0.16452	0.83065

Finally, the DTWC algorithm with RS3 produces an accuracy of 77.04% in low volume, 81.45% in normal volume and 76.45% in double volume, which means the proposed algorithm improved the accuracies by 26.04% in the low volume (-6.02dB) compared to the ED and the LCS in Table2. Furthermore, it is obvious that the lower or the higher the volume, the better our algorithm performs compared to the other algorithms as shown in Figure 5.

5. Conclusion and future works

We proposed the DTWC algorithm as a time-warped algorithm and designed the comparing scheme of a WSN classification system using the PAA algorithm. The experimental results demonstrate that the proposed algorithm produces satisfactory accuracies over volumes compared to other algorithms such as the ED, the LCS, the DTW-only, etc. It is inferable that, even though the time series technique can be effective only when each target has its own patterns of time series, the method of time series analysis can not only be valuable in a sparse sampling WSN but can also work collaboratively with the method of frequency analysis. We believe that this is the first work to introduce the manner of time series analysis without analyzing frequency for target classification in a sparse sampling acoustic WSN. So, we can say with certainty that our work could be a baseline for the research of target classification, detection or tracking using the time series approach in the future.

Our future work will focus on applying physical features, the ZCR (Zero Crossing Rate), energy, etc, and multi-modal fusion to improve the accuracy since targets have different signatures from each other corresponding to multiple modalities, e.g. magnetic and seismic. The HMM (Hidden Markov Model) could also to it, the more sensor nodes, the better result could be expected by complementing each other.give us the capability to analyze more diverse, more general and longer signals. In addition

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