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Dynamic time warping under pointwise shape context

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ABSTRACT

Similarity measures are of fundamental importance in time series data mining. Dynamic Time Warping (DTW) is a quite popular measure because it handles time distortions well. However, DTW has an inherent shortcoming in that DTW can lead to pathological alignments between time series where a single point maps onto a large subsection of another time series. To overcome this problem, we propose a novel variant of DTW named SC-DTW. SC-DTW employs shape context, a rich local shape descriptor, to replace the raw observed values considered by conventional DTW. The main novelties of SC-DTW are (1) it deeply explores both the numerical nature and shape nature of time series; and (2) neighborhood information for each point is taken into account. SC-DTW can generate a more feature-to-feature alignment between time series and thus serves as a robust similarity measure. We test the performance of SC-DTW on UCR time series datasets using the one nearest neighbor (1NN) classifier. Compared with other well-established methods, SC-DTW provides better accuracy on 24 of 34 datasets.

1. Introduction

Time series exist ubiquitously in various fields [16,31,18,32,29,7]. Compared with static data, time series can fully capture the temporal evolution of a phenomenon. A fundamental task in time series analysis is quantitatively measuring the similarity between two time series [13,44,54]. Currently, mainstream similarity measures such as Euclidean distance and DTW [36] are both based on alignments between time series. The accuracy of an alignment-based similarity measure relies heavily on the quality of the alignment. There are two categories of alignments: time-rigid alignment and time-flexible alignment. Euclidean distance adopts time-rigid alignment where the time axes of two time series must be lined up strictly; thus, it is sensitive to time distortions. In contrast, DTW [36] allows time-flexible alignment; hence, it handles time distortions well. Because time distortions are quite common in time series datasets, DTW has become more widely used. Many applications have shown its superiority [32,4,35,17].

However, DTW has its inherent weaknesses. In a time series, the x-axis represents the observation time and the y-axis represents the observed value. DTW assumes that all variabilities in observed values are caused by time distortions even when no time distortion really exists [26]. As a result, DTW tends to explain all fluctuations in the y-axis by warping the x-axis, which leads to pathological results. Fig. 1 shows an example of a pathological alignment generated by DTW where a single point maps onto a large subsection of another time series. An ideal alignment should be feature-to-feature, for example, a local peak should always be aligned to the corresponding peak in another time series rather than a valley.

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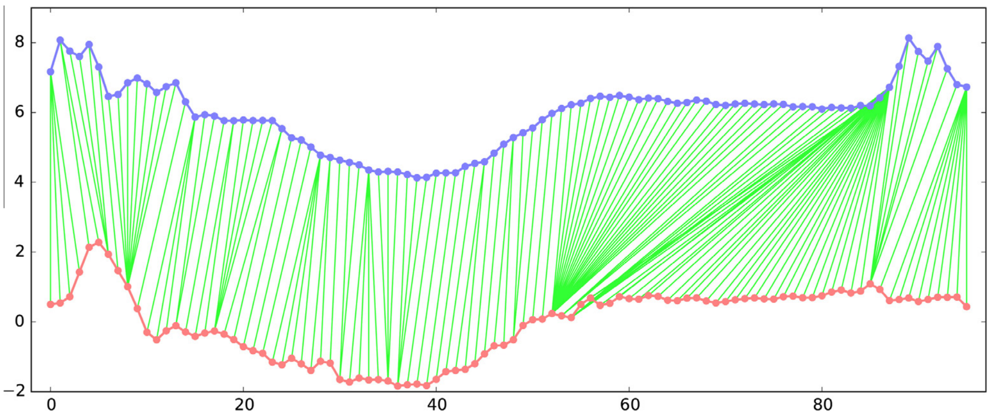

Fig. 1. A pathological alignment generated by classic DTW. Note that DTW failed to generate natural feature-to-feature alignment. Instead, a single point maps onto a large subsection of another time series. The two time series are the first and fourth records of the ECG200 dataset.

Researchers have long noticed the drawback of DTW and proposed many variants of DTW [26,46,22,34] (we will discuss them in Sections 2.1 and 2.2). However, most of them essentially set additional constraints on the alignment, but they do not improve the underlying mechanism of DTW. They cannot solve the pathological alignment problem thoroughly, and they have a common risk of missing the correct alignment.

The main cause of the pathological alignment is the feature DTW considers. DTW only considers the raw numerical value of each single point, ignoring its context or local shape feature. The optimal alignment sought by DTW means an alignment that minimizes the total cumulative cost where the cost is defined in terms of the feature DTW considers. Suppose two points inside two different time series have equal value, but one is a local peak and the other is a local valley, DTW tends to align them because the cost between the two points is zero. However, from a shape point of view, a local peak cannot be matched up with a local valley.

Because our objective is a peak-to-peak and valley-to-valley alignment, we decided to use the local shape feature directly to generate the alignment. Shape context [3,40] is a rich local shape descriptor famous for its effectiveness and robustness. It captures the distribution of all neighborhood points by counting the number of points located in each log-polar bin. In this paper, we propose a novel variant of DTW called SC-DTW that uses shape context to replace the raw values considered by the original DTW. Shape context compares local neighbor shapes, and thus it can generate more feature-to-feature alignments.

The basic steps of SC-DTW are as follows: (1) calculate the shape context of each point; (2) find the optimal alignment that minimizes the total shape context cost; and (3) calculate the cumulative distance by considering raw values. Note that we use shape context only to generate the alignment, and then we still adopt raw values to calculate the cumulative distance. The reason is that the cost between shape contexts is based on the chi-square test, so it is not a distance metric.

Time series have both a numerical nature and a shape nature. Classic DTW explores only the numerical nature of time series. The novelty of our proposed method is that we consider time series as both a 1-D array and a 2-D shape. Context information is also taken into account when calculating the cost between each pair of points, which would dilute the impact of distortions and outliers.

The boundary between time series and contour-based shapes is blurring. In this paper, SC-DTW treats time series more like shapes. However, just opposite to our idea, shapes can also be converted into pseudo time series using the centroid distance approach [24,49,50]. Then, researchers can use these 1-D time series to represent 2-D shapes directly [24,45] or to derive other features, for example, Fourier descriptors [23,50,1]. SC-DTW can cope with both real time series and these pseudo time series.

The one nearest neighbor (1NN) classifier is the most convincing method to test the accuracy of a similarity measure because 1NN has no parameter; thus, the classification accuracy depends only on the similarity measure itself. SC-DTW is tested by 1NN on 34 datasets of the UCR time series data mining archive [25], which contains carefully collected datasets from various domains, including pseudo time series converted from contour-based shapes.

The rest of this paper is organized as follows. Section 2 reviews the background of our proposed method in detail and discusses some related work. Section 3 details the SC-DTW algorithm. Section 4 shows the datasets used in our experiments and the experimental results. Finally, we draw a conclusion in Section 5.

2. Background and related work

2.1. Dynamic time warping (DTW)

Dynamic time warping (DTW) is one of the most popular and time-honored time series similarity measures [13,44,55]. Its superiority has been demonstrated in many applications [32,4,35,17]. Compared with Euclidean distance, DTW can