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Research Article

Real-Time Traffic Incident Detection Using Dynamic Time Warping Algorithm

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Abstract

In recent years transportation system has become a crucial infrastructure for transferring people and goods from one point to another. However, its reliability can be decreased by major events such as recurring and non-recurring traffic congestion. Therefore, monitoring the performance of transportation systems play an important role in any transportation operation and planning strategy. This study utilized the historical and real-time traffic data collected through the INRIX XD monitoring platform. In this article, we used the mean of the aggregated 1-minute speed data as the microscopic indicator of interest and the 75th percentile of normal travel speed as the threshold to trigger data collection. Also, this endeavor proposes a moving window approach to detect the incident. After implementing the triggering algorithm, the DTW algorithm is applied to the data collected in each window to combine the collected time series (i.e. query) and an appropriate reference time series. Along with existing DTW concepts, this study uses a rolling window approach to collect the real-time data. This was proposed in contrast to the existing fixed-window method, which tends to collect data over a longer period of time, potentially resulting in a greater mean time to detection. Moreover, a new technique on the DTW outputs is implemented for traffic incident detection, using the area under the warping path as a measure to detect an incident. Finally, the proposed algorithm reports a sensor experiencing a congestion when at least three of their six windows have ratios greater than 77 percent and have one ratio greater than 65 percent. If such conditions are met within the first four windows, the algorithm stops collecting and analyzing data for the following two windows and reports the incident, otherwise it moves on to the last window.

Keywords: Dynamic Time Warping (DTW); Traffic Incident Detection; INRIX; Rolling Window

Introduction

Improving traffic safety and operations have long been areas of focus among researchers and engineers. Traffic incidents, particularly traffic crashes, are of great interest due to the huge costs that traffic injuries and fatalities impose to the society. According to the United States Department of Transportation, traffic incidents are the main cause for more than half of traffic congestions that occur along US highways [1]. Such traffic delays are attributed to nonrecurring incidents including but not limited to traffic crashes, construction events, and adverse weather conditions. These incidents may also result in other consequences like secondary crashes and delays in the emergency medical services that can cause further complications and impose additional costs. Consequently, monitoring the transportation network and being able to detect and report anomalies in real time are of great importance in the realm of traffic management. As a result, in-time detection and elimination of traffic incidents can play a significant role on how well a network operates. Recently, machine learning algorithms have extensively been studied and deployed to detect traffic incidents and to mitigate the impacts they can have on transportation networks.

This study utilizes two months -November and December 2016- of probe data along approximately 107 miles of Interstate-80 and Interstate-380 in Cedar Rapids/Iowa City area in state of Iowa and employs machine learning algorithms to identify traffic incidents. This study focuses on Dynamic Time Warping (DTW) algorithm to detect such traffic anomalies. The objectives of the study presented herein are as follows: (1) apply the DTW algorithm to identify the shortest (optimal) warping path; (2) detect traffic incidents using the DTW outputs; (3) and ultimately, deploy the process to detect incidents in real-time.

Literaure Review

Traffic incident management (TIM) and trying to identify appropriate processes to detect network anomalies on transportation systems have become of a significant interest to researchers in recent years. Given the importance of such identifications, researchers have directed considerable effort to examine various algorithms and to improve detection processes. In general, traffic incident detection techniques are based on either spatial measurements (i.e. implementing image processing techniques on video traffic data) or measurements on points/links (i.e. automatic incident detection (AID)) [2]. Point-based measurement techniques including inductive loop detectors and microwave radar have frequently been used to collect traffic data; however, collecting data using links such as vehicles and smartphones have become more common in recent years.

Back in the date researchers tried to develop mechanisms to detect incidents by comparing the measures from inductive loops across different locations, or between different times at one single location [3-5]. While these studies simply focused on using occupation information, some others included additional traffic attributes such as volume in their efforts to obtain more reliable strategies [6-9]. One concern that arises when performing such analyses is the occurrence of false alarms. Consequently, a number of studies eliminated such high-frequency noises by averaging short adjacent measurements. Recently, several studies tried to determine the best variable to be used for traffic incident detection [10,13]. These studies reported the mean speed, and standard deviation in speed followed by headway and flow rates to best indicate traffic conditions.

In recent years, substantial efforts have been made to develop and identify appropriate algorithms to detect traffic abnormal conditions. Such algorithms were invented based on specific principles, assumptions, and conditions. Consequently, they can be deployed on trained roadway data under given implementation methods. Collectively, such algorithms can be grouped into either macroscopic or microscopic with the majority being macroscopic.

Automatic incident detection techniques employs various methods some examples of which are pattern recognition (e.g. California algorithm), statistical analysis, catastrophe theory (e.g. McMaster algorithm), time-series models (e.g. ARIMA), and machine learning algorithms. The statistical techniques are based on the assumption that certain predictable patterns can be attributed to time-series traffic data resulting in the ability to detect anomalies by implementing mathematical techniques and calculate the deviation from the normal condition at any given time period [16]. Machine learning algorithms, on the other hand, are utilized to improve efficiency by using machines as the decision maker to apply algorithmic processes and determine the state of existing traffic (e.g. Bayesian, Fuzzy Logic, support vector machine classifications, and artificial neural network) [17-24].

Dynamic Time Warping (DTW) algorithm which is used in this study is a data mining and time-series classification technique that leverage concepts and methods from several different fields including statistics, machine learning, and artificial intelligence to distinguish traffic incidents. DTW was used in a traffic incident detection endeavor by Hi-ri-o-toppa., *et al*. According to this study, DTW was reported a detection rate of 90-percent with a five minute and forty seconds mean time to detection [10]. However, one concern that arises with respect to this study is that only sixteen incidents occurred during the six-month study period which may result in reporting illusive numbers due to the high tendency of the algorithm to overfitting. This method is based on aligning two independent time-series that are similar but locally or timely different. These series are then compared in a non-linear framework. This analysis framework is used in the study presented herein, and is furtherly explained and discussed in the Methods section.

Along with existing DTW concepts, this study employs new techniques in data collection and decision-making steps to improve the existing processes. This study utilizes a rolling window approach to collect the real-time data. This was proposed in contrast to the existing fixed-window method which tend to capture data over a longer period, potentially resulting in larger mean-time-to-detection. Also, this study detect a traffic incidents through implementing a new technique on the DTW outputs. While previous studies mainly focused on the warping path and its configuration to detect an incident, this study deploys the area under the warping path as a measure to capture an incident.

Figure 1: Location of the select XD segments.

Data

This study utilized the historical and real-time traffic data collected through the INRIX XD monitoring platform. Real-time traffic data including speeds, travel times, as well as location information are provided by the INRIX which is currently regarded as the largest crowd-sourced traffic data. With the help of today's technologies including connected vehicles and smartphones, INRIX leverages great amount of historical and real-time data which can be analyzed and investigated to improve transportation networks performance. In this study two month worth of data –November and December, 2016- were extracted for approximately 107 miles of Iowa primary network along I-380 and I-80 near Cedar Rapids/Iowa City area. A total of 150 XD segments were identified along the select stretch of the network which is also spatially shown in figure 1. For each of the XD segments, the speed, as well as the corresponding date and time of traverse were provided. In addition, the incident database for the entire state of Iowa which is maintained by the Iowa Department of Transportation was available. The incident report dataset included information as to the date and time when the incident was received and cleared, as well as location information. This dataset was explored in combination with the INRIX database to identify candidate location-incident combinations for further investigation.

Candidate locations were identified for three major scenarios: 1) Nonrecurring congestion; 2) Recurring congestion; 3) Non-congestion or normal condition. Recurring congestion is regarded as the congestion caused by the routine traffic in a normal environment which is somehow expected, whereas nonrecurring congestion is unexpected and is most likely caused by an incident. Nonrecurring congestion may emerge as a result of a variety of factors like lane blocking crashes or disabled vehicles, work zone lane closures, and adverse weather conditions. Consequently, the candidate locations for nonrecurring congestion (i.e. incident locations) were identified based on two criteria: (1) the mean of 1-minute aggregated speed data for that location must drop below 75^{th} percentile for a significant period of time, and (2) a matching incident must be reported close enough to the time during which the drop was observed. In addition, locations were selected as candidates for recurring congestion if significant drop in the mean of 1-minute aggregated speed data (i.e. below 75^{th} percentile) was reported for similar times of day and/or days of week. Ultimately, non-incident locations were the ones where neither of these happened in their 5-mile buffer along the select roadway.

Methodology

The purpose of this study was to apply the Dynamic Time Warping (DTW) algorithm to the microscopic traffic data to detect traffic incidents. The DTW algorithm, which was first proposed by Brendt., *et al*. in 1994, evaluates the similarities between patterns of different time-series in a non-linear environment to detect incidents [25]. The first chart in figure 2 demonstrates how the distance between two time-series is calculated using the traditional Euclidian method (a), whereas the other two (b and c) illustrates the proposed DTW algorithm which is aimed at twisting the time axis in order to achieve much precise distance measurements between the two time-series.

The DTW framework requires two sets of time-series X and Y which are of m and n elements respectively:

Figure 2: Measurements between two time series using Euclidian and DTW algorithms [26].

$$X = x_1, x_2, \ldots, x_m \quad \text{-------------- (1)}$$

$$Y = y_1, y_2, \ldots, y_n \quad \text{-----------(2)}$$

Subsequently, a matrix with m-by-n dimensions is produced each element of which is the Euclidean distance between the two points:

$$m_{ij} = d(x_i, y_j) = (x_i - y_j)^2 \quad \text{------------------- (3)}$$

Figure 3 shows the constructed matrix and the optimal warping path which indicates the distance measures between each combination from time-series X and Y respectively. This shortest path, W, is comprised of adjacent matrix elements where:

$$W = w_1, w_2, \ldots, w_k \text{---------------(4)}$$

$$\max(m, n) \leq K \leq m + n - 1 \text{----------------(5)}$$

The DTW algorithm is based on three distinct assumptions:

Boundary Conditions: The optimal path starts and ends on opposite corners:

$$w_1 = (1,1)\,,\, w_k = (m, n) \quad \text{----------------- (6)}$$

Continuity Condition: The optimal path is comprised of adjacent matrix elements, meaning that there must not be any gaps along the path:

$$\text{if } w_{k=}(i, j) \text{and } w_{k-1} = (i', j') \text{---------------(7)}$$

$$\text{then } i - i' \leq 1 \text{ and } j - j' \leq 1 \text{----------------(8)}$$

Monotonicity: The path elements must be monotonically positioned with respect to time which prevents the cells to overlap one another:

$$\text{if } w_{k=}(i, j) \text{and } w_{k-1} = (i', j') \quad \text{--------------(9)}$$

$$\text{then } i - i' \geq 0 \text{ and } j - j' \geq 0 \quad \text{-----------------(10)}$$

Figure 3: Shortest or optimal warping path illustration example [26].

Given these constraints one can come up with a multitude of warping paths; however, the DTW algorithm is aimed at identifying the optimal path which satisfies the following equation:

$$\text{Shortest or Optimal Warping Path} - W(X, Y) = \min\{(\sum_{k=1}^{K} w_k / K)\} \text{-----------(11)}$$

One concern that arises in the context of this study is the fact that real-world traffic data are associated with some issues like missing values, as well as high-frequency noises. Consequently, the initial step was to smooth the data, overcome the existing inconsistencies, and eliminate the outliers to prepare a robust dataset to be examined for incident detection. After eliminating the data issues, the triggering algorithm should determine when the real-time data must start to be collected and furtherly examined. Several studies indicated that storing and analyzing real-time data for incident detection purposes are futile and in most cases not feasible due to processor limitations [10,27]. These constraints warranted developing a triggering algorithm which determines when the data must be stored as inputs for further analyses by DTW.

In recent years some of these constraints have been relaxed through parallel processing and the fact that real-time data can be captured, stored, and analyzed using multiple processors. While such techniques have eased the data processing endeavors, performing computational and analytical tasks in most efficient ways is still a goal to researchers.

Triggering algorithm – moving window

This study used the mean of 1-minute aggregated speed data as the microscopic indicator to be examined and the 75th percentile of normal travel speed as the threshold to trigger capturing data. Also, this endeavor proposes a moving window approach to detect the incident. As soon as the mean speed drops below the 75th percentile, the data are accumulated 15 minutes backward. Consequently, the window is moved forward with a step of δ which can be customized as necessary (Figure 4). Following the implementation of the triggering algorithm, the DTW algorithm is applied to the data captured in each window for the combination of the captured time-series (i.e. query) and a proper reference time-series. It should be also noted that the data is captured and analyzed through a rolling window approach with each window being deleted after each step.

Figure 4: Triggering algorithm demonstration.

Incident detection approach

Following applying the DTW algorithm to the data, a framework is required to actually detect an incident. Figure 5 demonstrates the optimal warping path and the corresponding cost matrix for an incident (left) and a non-incident (right) case. Previous studies used different approaches that can collectively be grouped as either empirical or artificial methods [26,28]. While empirical approaches use portions of data as training datasets, artificial methods employ mathematical techniques to cluster time-series data based on pattern similarities [29].

While prior research utilized measures such as the pattern or the slope of the optimal path as the incident detection indicator

Figure 5: Sample incident and non-incident warping path.

[26], this study presents a new approach based on calculating the cumulative area under the warping path. As described in Equation 5, the minimum and maximum length of warping path for an m-by-n matrix are and resepectively. Consequently, the area below this path varies between and. Figure 6 presents these extreme conditions, where the area is equal to (left chart), and where it reaches its minimum possible value –zero- (right chart).

Figure 6: Maximum and minimum possible area under warping path.

In order to ensure that the proposed techniques are capable of properly detecting the incidents, 61 different scenarios were synthetically generated and examined. Such scenarios were selected through an extensive investigation of the historical traffic data, in addition to the research team's suggested situations which were believed to challenge the proposed processes to the extent possible. Moreover, these select time-series were examined using multiple reference series to capture different combinations of query and reference pairs. These data were extensively investigated to set a robust threshold for the ratio of the area under the warping path over the maximum area possible for incident detection purposes. While this ratio clearly varies between zero and one, incidents are associated with much larger ratios. Ultimately, the threshold was identified and set for subsequent steps.

Results

As described in the previous section, synthetic data were examined to set the threshold for the decision-making algorithm. Due to the space constraint, just a few examples of such data are presented here. The first example demonstrates a situation when the operating speed drops below the threshold, and continues at a nearly consistent speed close to the threshold (Figure 7). This query is plotted over a straight horizontal line as the reference. Figure 8 presents the warping path associated with each of the six rolling windows.

Figure 7: Example 1 - Continuing speed close to the threshold.

Figure 8: Example 1 - DTW Outputs.

The second example corresponds to a situation where there is an abrupt decrease in the operating speed. This query was also examined in combination with multiple references. The one presented in figure 10 demonstrates the results of the select time-series versus a reference which also has a decreasing trend.

Figure 9: Example 2 - Abrupt Decrease in Operating Speed.

Figure 10: Example 2 - DTW Outputs.

Ultimately, the last example shown in figure 11 presents a condition where the query has a decending trend that drops below the designated threshold. In this case, the reference is also descending but it does stay in the over-threshold zone. The DTW outputs over the six rolling windows are also provided in figure 12.

Figure 11: Example 3 - Operating Speed with Descending Trend.

Figure 12: Example 3 - DTW Outputs.

Ultimately, considering all the 61 conditions generated synthetically, the decision-making threshold was set. The algorithm reports a sensor experiencing an incident when at least three out of the six windows have ratios over 77 percent, and have a ratio over 65 percent. If such conditions are satisfied within the first four windows, the algorithm stops collecting and analyzing data for the subsequent two windows and report the incident, otherwise it keeps moving towards the last window in case the conditions are met considering all six windows.

As explained previously, the DTW algorithm requires two time-series as the query and the reference to be compared for incident detection purposes. As explained in the Methodology section, incidents are associated with larger areas under the warping path, whereas the opposite is true for incident-free locations. As an example, a 15-minutes moving window with a step (δ) of 3 minutes was selected for the random location presented in figure 13 through figure 15. Figure 13 shows the two-way plots between the refrence time-series (i.e red dashed line) and the query time-series for windows one through five. These plots demonstrate how the time axis is warped to reach the optimal path presented in the subsequent figure. Figure 14 includes the reference time-series on the vertical axis, as well as the query time-series on the horizontal axis. Ultimately, the warping path is plotted during each timing window for subsequent area calculations. Figure 15 is density plot indicating the cumulative cost landscape with the warping path overimposed. It provides similar information in addition to the cost values with green being associated with lowest cost, and orange being assoicated with the highest cost.

Figure 13: Two-way plots for the sample moving windows.

Figure 14: Three-way plots for the sample moving windows.

Figure 15: Density plots for the sample moving window.

Following to obtaining the optimal warping path for each time window, the area associated with each plot was calculated and compared to the designated threshold to determine whether or not an incident occurred. Table 1 provides the calculated areas for the moving time windows of the example presented in figure 13-figure 15.

Time Window	Area Under Warping Path	Ratio
1	176	0.90
2	194	0.99
3	176	0.90
4	185.5	0.95
Maximum Possible Area	196	-

Table 1: Calculated areas for incident determination.

The areas associated with each of the windows were all found to be significantly large compared to the threshold with which they were compared. Consequently, the proposed algorithm distinguished this case as an incident.

Future work includes developing an algorithm which applies the steps presented in this study to the real-world data. In addition to the original DTW algorithm, its other variants like the dDTW (i.e derivative DTW), wDTW (i.e. weighted DTW), and shapeDTW will be investigated for potential improvements. Subsequently, the detection rate and the false alarm rate, as well as the mean-time-to-detection can be reported. Also, the data would be examined in a multivariate framework where each sensor would not only be compared with its own historical data, but also with that of other sensors in close vicinity to capture any potential shift or movement in captured congestion as compared to the historical data.

Conclusion

In the past years, traffic congestion has become a significant problem in urban areas. People in the United States travel billions of additional hours and use billions of additional gallons of fuel each year due to traffic congestion. Therefore, monitoring the performance of the transportation system plays an important role in any transportation operation and planning strategy. This study utilized the historical and real-time traffic data collected through the INRIX XD monitoring platform.

In this article, we used the mean of the aggregated 1-minute speed data as the microscopic indicator of interest and the 75th percentile of normal cruising speed as the threshold to trigger data collection. Also, this endeavor proposes a moving window approach to detect the incident. After implementing the triggering algorithm, the DTW algorithm is applied to the data collected in each window to combine the collected time series (i.e. query) and an appropriate reference time series.

In addition to existing DTW concepts, this study uses new data collection and decision-making techniques to improve existing processes. This study uses a rolling window approach to collect the real-time data. This was proposed in contrast to the existing fixed-window method, which tends to collect data over a longer period of time, potentially resulting in a greater mean time to detection. In addition, this study detects traffic accidents by implementing a new technique on the DTW outputs, using the area under the warping path as a measure to detect an incident.

Ultimately, the algorithm reports a sensor experiencing a congestion when at least three of their six windows have ratios greater than 77 percent and have one ratio greater than 65 percent. If such conditions are met within the first four windows, the algorithm stops collecting and analyzing data for the following two windows and reports the incident, otherwise it moves on to the last window if the conditions are met considering all six windows.

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