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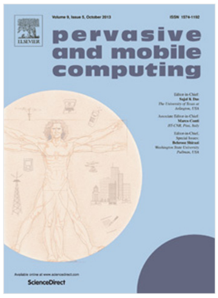

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A Smartphone Based Technique to Monitor Driving Behavior using DTW and Crowdsensing

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Abstract

Safety issues while driving in smart cities are considered to be top-notch priority in contrast to traveling. Today's fast paced society, often leads to accidents. In order to reduce the road accidents, one key area of research is monitoring the driving behavior of drivers. Understanding the driver behavior is an essential component in Intelligent Driver Assistance Systems. One of potential cause of traffic fatalities is aggressive driving behavior. However, drivers are not fully aware of their aggressive actions. So, in order to increase awareness and to promote driver safety, a novel system has been proposed. In this work, we focus on DTW based event detection technique, which have not been researched in motion sensors based time series data to a great extent. Our motivation is to improve the classification accuracy to detect sudden braking and aggressive driving behaviors using sensory data collected from smartphone. A very significant feature of DTW is to be able to automatically cope with time deformations and different speeds associated with time-dependent data which makes it suitable for our chosen application where data might get affected due to factors such as: high variability in road and vehicle conditions, heterogeneous smartphone sensors, etc. Our technique is novel as it uses fusion of sensors to enhance detection accuracy. The experimental results show that proposed algorithm outperforms

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the existing machine learning and threshold-based techniques with 100% detection rate of braking events and 97% & 86.67% detection rate of normal left & right turns and aggressive left & right turns respectively.

Keywords: DTW [1], Smartphone, GPS [2], Driving Behavior, ITS [3], Sensor Fusion.

1. Introduction

Transportation from one place to another following the shortest possible route and time has always been the necessity [1]. Therefore, the safety issues during traveling are often ignored [2]. This leads to accidents due to aggressive driving behaviors such as sudden lane change, overtaking and sudden braking. It has been researched that by monitoring the driver's driving behavior, the probability of dangerous or aggressive driving can be reduced [3]. There are some commercial products [4][5][6] available which can be mounted in-vehicle, and are equipped with various sensors like GPS, camera, accelerometer and so on and used for purposes such as tracking the taxi [7][8] routes and detecting driving behavior.

In ITS [9], the information related to the sensors is collected and sent to the central server for analysis. The information is further analyzed to find certain parameters like collisions, braking, congestion or traffic on the road and so on. Condition of vehicles and condition of roads are some of the other additional factors which can affect the driving behavior. Accidents due to road conditions have also been reported in the recent past [10, 11]. Hence, aggressive driving behavior can be distinguished from normal driving events, which occur while driving. Thus, it becomes imperative to detect these harsh events while driving and classify the aggressive behavior of a driver.

Nowadays high-end cars already have these sensors and warning systems

[1] Dynamic Time Warping
[2] Global Positioning System
[3] Intelligent Transportation Systems

in-built in a vehicle to assess the driving behavior [12]. In low end vehicles, driving monitoring systems can be embedded in-vehicle to record the driving behavior. These systems are usually not removable and hence cannot be used in other vehicles. In this paper, we investigate the use of smartphones as an alternative solution to embedded driving monitoring systems, as smartphones are easily available with all drivers. Smartphones are equipped with various multi-sensors on-board, through which data can be recorded. The recorded data can be analyzed to detect the driving behavior of the driver and can be classified them into aggressive and non-aggressive driving behaviors.

There are certain applications which can be installed on the smartphones to enable the use of in-built sensors such as accelerometer, gyroscope, magnetometer, GPS and so on [13]. The data from these sensors can be used to detect the human activity performed [14, 15]. Accelerometer sensor is widely used for longitudinal and lateral movements while GPS provides the location of the phone in terms of latitude and longitude. In the recent past, many researchers had used smartphone as a data collection tool for analyzing the driving behavior and road conditions [16] [17] [18] [19]. The smartphone can be mounted at a fixed position inside the vehicle to detect the driving events such as sudden acceleration, harsh braking, sudden left, right turns and so on. In this paper, we only focus on detecting braking events and lateral maneuvers experienced by the vehicle using accelerometer, gyroscope, GPS and gravity sensor of the smartphone using DTW (Dynamic Time Warping) algorithm.

Dynamic Time Warping (DTW) is an algorithm for comparing two given (time-dependent) sequences which may vary in speed, which has historically been applied to temporal sequences of video, audio, and graphics data, indeed any data which can be turned into a linear sequence can be analyzed with DTW. DTW has been used in well known application like automatic speech recognition, to cope with different speaking speeds [20]. Other applications include speaker recognition and on-line signature recognition [21] [22]. DTW computes similarities between two sequences of time series data and returns a distance value. The lower this value, the better the match, and a distance of zero means the sequences are identical. In order to classify an unknown time series sequence, it is compared with a number of different known template sequences. The above two steps give a value representing the similarity between one sample data set and one template (training) data set. Then these steps are compared for all of the sample/template data pairs. The pair that has the smallest "path sum value" indicates the detected event.

DTW has also been used in finding similarities in human walking patterns that is doing gait analysis [23], if one person was walking faster than the other, or if there were accelerations and decelerations during the course of an observation, DTW still able to detect similarity between the patterns.

1.1. The Problem

This paper focuses on the problem of analyzing driving behavior by detecting braking events and lateral maneuvers using efficient and low cost techniques. In recent past, the detection of driving behavior was done by detecting the events like sudden right turn, sudden left turn, sudden accelerate, sudden brake, U-turn and sudden U-turn etc. Many researchers have proposed different techniques for the detecting these events but most of them are based on fixed threshold values and machine learning techniques. The threshold values are dependent on type and condition of the vehicle, sensitivity of the sensor, and cannot accurately distinguish between an event and non-event caused by other factors thereby reducing accuracies when the same threshold values are used in different conditions. On the other hand, machine learning based techniques require intensive and continuous training to detect the events and hence do not work efficiently for such like applications. Our proposed technique does not use any specific equipment other than smartphones of the commuters to determine the reckless driving behavior.

1.2. Our Contribution

The main contribution of this paper is as follows:

1. Accelerometer, gyroscope, gravity sensor and GPS based sensory data has been collected by commuting on the roads of Chandigarh city. The data has been analyzed and patterns of events such as braking and lateral maneuvers have been extracted by conducting an empirical study.

2. DTW technique has been used to match patterns and find the similarity between different patterns. Instead of using fixed threshold based values, DTW method has been used to overcome the limitations of existing techniques (further explained in Appendix - I).

3. Filters has been applied on the raw accelerometer data to eliminate various noises such as vibrations of car and gravity component which got added in the accelerometer readings.

4. Fusion of sensors like gyroscope and gravity sensor has been done to acquire angular velocity w.r.t. direction.

5. A technique has been proposed to detect and identify the driving behavior event using sensory abilities of the smartphones. This information can be useful for school authorities and to commuters especially for senior citizens, patients and expecting women.

6. Extensive experiments have been conducted by collecting data from the sensors of the smartphones. The results show that our proposed method can identify the braking event as well as lateral maneuvers with enhanced accuracy when compared with the existing techniques.

Rest of the paper is organized as follows: Past work related to detection of reckless driving has been discussed in section 2. In section 3, the methodology used to carry out the work of detection of reckless driving has been discussed. In section 4, experimental design has been described where the techniques and smartphone sensors used have been elaborated. Data acquisition and pre-processing phases of raw data collected from sensors has been explained in section 5. The proposed system capable of detecting the braking events has been presented in section 6 along with the use of DTW and crowd-sensing techniques. Results are presented and discussed in section 7 where our proposed technique has been compared with the existing techniques. Conclusions and future directions stemming from our work have been presented in the last section.

2. Related Work

These days, smartphones are cost-effective and easily available in the market. These hand held devices are equipped with a variety of sensors through which various ITS related applications can be deployed. Mohan et al. [24] proposed a system where the smartphones were used to monitor road and traffic conditions such as potholes, bumps, braking and honking of the vehicle by using accelerometer and GPS sensors mounted on the vehicle. Similar approach is proposed in [25] where an application is installed on the smartphone which collects the data from multi-sensors to analyze the road conditions to classify road defects and braking events.

Dang et al. [16] had proposed a new system which can estimate the incident locations caused due to sudden braking. They performed their experiments when the vehicle stops and doesn't stops from a reference point, to evaluate the braking behavior of the vehicle (2 wheelers & 4-wheelers). The smartphone was installed in the vehicle to collect the data using the in-built sensors. GPS sensor was used to get location, speed and direction of the vehicle for the experiment where they compare the locations of collected data with the reference points.

Dai et al. [17] had proposed a system for detecting drunken drivers using smartphone sensors. They collected data from Unites States National Highway Traffic Safety Administration and analyzed that most of time the drunken driving goes un-noticed by the authorities. They categorized the drunk behavior by detecting two behavioral clues which are lane changing (drifting and swerving) and speed control (sudden acceleration and erratic braking). Authors had used pattern matching techniques to detect these events where they had achieved 0.49% of false negative in case of abnormal curvilinear movement and 2.39% of false positive in case of speed control problem (experimented on a very small dataset).

Eren et al. [18] had developed a system which can detect whether the driver's driving is either safe or risky using smartphone. They used accelerometer, gyroscope and magnetometer sensor to detect these events which are similar to [26]. They first eliminate the noise from the data collected using moving average filters and fed to DTW for event identification.

Johnson and Trivedi [26] had proposed an approach which can classify different driving styles by using smartphone sensors. In their approach, driving styles are categorized as normal, aggressive and very aggressive. The results from their work shows that the in-built sensors of the smartphone can provide good source of information for an accurate measure and classification of different driving styles. The proposed model utilizes DTW technique for detecting the events. Nearly 97% of aggressive events were correctly identified.

Bhoraskar et al. [27] proposed an approach to detect bumps and braking events using a smartphone. In their approach, smartphone was first virtually re-oriented to its original axes and then the analysis was done to categorize bump or brake using SVM [4] machine learning. The results of their work shows false positive rate of 2.7% and false negatives rate of 21.6% in case of braking. This paper had extended the work done by [24] and used SVM machine learning method instead of using threshold values to detect an event.

Saiprasert et al. [19] had proposed two algorithms which can detect the driving behavior events using a smartphone. The algorithms classify the events as aggressive and non-aggressive events based on the raw values of the accelerometer. Threshold and DTW techniques were used to classify the events where the pattern matching technique out-performs the rule-based algorithm in detecting the driving events in both lateral and longitudinal movements.

Fazeen et al. [25] had proposed a system which can detect the driving behavior, using a smartphone. The system in itself alerts the driver about

[4] Support Vector Machines

the dangerous vehicle maneuvers. However, the system also monitors the road surface conditions and shows the output on the map using markers.

White et al. [28] had developed a system named WreckWatch which detects the accidents using smartphone. An application was installed on the smartphone which interacts with the inbuilt sensors like accelerometer, gyroscope, magnetometer and GPS to detect the accidents. Data was recorded internally and later sent to the centralized server via GSM. The information pertaining to an accident can then be relayed to the civic authorities.

Table 1: Inference drawn from literature survey

Reference	**Detection Techniques**	**Sensors Used**	**Detection Purpose**	**Pitfalls**
Mohan [24]	Re-orientation, Pattern matching using threshold	Accelerometer, Microphone, GPS	Brakes, Honking, Bumps	Based on fixed threshold technique
Dai [17]	Re-orientation, Pattern matching using threshold	Accelerometer, Gyroscope	Lane changing and Speed control (Drunk Drivers)	• Dataset was small • Based on fixed threshold technique
Johnson [26]	DTW, End-point Detection	Accelerometer, Gyroscope, Magnetometer, GPS	Lateral and Longitudinal maneuvers	Non-aggressive Lane change is still indefinite
Eren [18]	DTW, End-point Detection, Bayesian Classifier	Accelerometer, Gyroscope, Magnetometer	Lateral and Longitudinal maneuvers	Unable to detect aggressive left and right turns
Fazeen [25]	Pattern recognition	Accelerometer, GPS	Lateral and Longitudinal maneuvers	Unable to detect aggressive left and right turns
White [28]	Threshold values	Accelerometer, Microphone, GPS	Accidents	Based on fixed threshold technique
Bhoraskar [27]	SVM Machine Learning	Accelerometer, Magnetometer, GPS	Bumps, Brakes	Dataset was small
Dang [16]	Pattern Matching	Accelerometer, GPS	Braking	• Dataset was small • Based on fixed threshold technique
Saiprasert [19]	Threshold values, DTW	Accelerometer, Magnetometer, GPS	Lateral and Longitudinal maneuvers	Unable to detect aggressive left and right turns

During the literature survey, it was observed that most of the research was done in the field of maneuver recognition and driving behavior classification. Existing systems could detect the maneuvers to classify the driving behavior of the driver. The normal driving style can be classified into various categories such as normal or aggressive, safe or risky, skilled or unskilled etc. Recommendations can be given to the driver to improve their driving accordingly. On the contrary, the driving behavior varies from person to person and also varies due to certain additional factors such as consumption of alcohol, drugs, emergency etc. In such situations, the automated driver monitoring system should raise an alert to the driver about their driving behavior and with their consent, their location can be notified to the civic authorities.

From Table 1, it is evident that the detection of braking events and lateral maneuvers are either based on threshold, machine learning and DTW techniques. In this paper, a novel method using sensor-fusion and DTW based on pattern matching technique has been proposed for detecting braking events and lateral maneuvers, which does not require extensive training as found in the methods proposed in existing research.

3. Methodology

Observing the limitations of existing work, present methodology introduces filters and DTW technique to detect braking events and lateral maneuvers to make the technique more accurate and efficient. Extensive experimentation has been carried out using smartphones placed inside the vehicle. The smartphones were aligned to the moving direction of the vehicle as shown in Figure 1. Data collected using sensors of the smartphones was sent to the central server for further analysis. Before the analysis, the smartphones were virtually re-oriented to its original axis (as explained in section 5.1). Filters were applied on the raw accelerometer data to eliminate various noises such as vibrations of vehicle and gravity component which got added in the accelerometer readings. Patterns were extracted based on ground truth collected from several events using accelerometer, gyroscope and gravity sensor data. These patterns for the events were called Template References. The template references for the two events: braking & lateral maneuvers and real time accelerometer, gyroscope and gravity sensor data collected using smartphones are the two inputs which are fed to DTW to find the closeness between the template reference and collected data. Based on the closeness measure, braking event and lateral maneuvers are detected and marked corresponding to the GPS locations. The output of DTW is then matched with locations marked against the ground truth to find the false positive and false negative rates.

4. Experimental Design

In order to investigate the accuracy and efficiency of detection of braking events and lateral maneuvers using our proposed method, experimental plan (Table 2) was designed and performed.

Table 2: Summary of Data Collection

	Parameters Considered
Location for Experimentation	Chandigarh City (located in Northern region of India)
Equipment used for Data Collection	Smartphone (Nexus 5)
OS platform of smartphone	Android 6.0.1, SDK [5] version 23
Sensors Used	Accelerometer, Gyroscope, Gravity and GPS
Actual sampling rate	200Hz
Vehicle(s) used	Motor-bike & Car
Mount Points	Backseat (Motor-bike) & Dashboard (Car)
Detection Purpose	Brakes & Lateral Maneuvers
Vehicle's speed considered for experimentation	20kmph and 30kmph
Techniques Used	Filters, Fusion of sensors and DTW (Dynamic Time Warping)

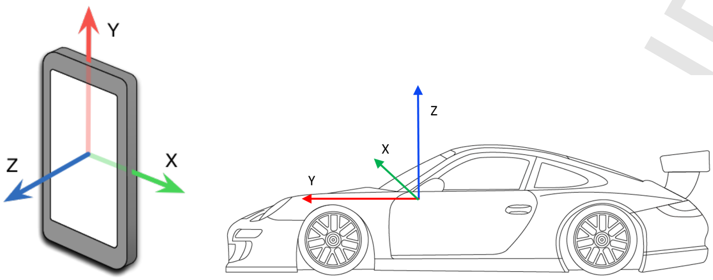
The summary of data collection parameters is illustrated in Table 2. The data has been collected by driving on the roads of Chandigarh city (located in the Northern region of India) with smartphones mounted in-vehicles. An android application has been developed and installed on the smartphone, that interacts with the in-built sensors, extract the values from the sensors and save

[5] Software Development Kit

into a local file. Sensors like accelerometer, gyroscope, gravity and GPS have been used and the actual sampling rate of accelerometer of 200Hz is considered. The sampling rate has been chosen based on efficiency & detection rates of events. The gravity sensor and gyroscope values were fused together for the detection of lateral maneuvers. While performing the experiments, the smartphone was mounted at the backseat of bike and on the dashboard of car, whose Y-axis was aligned with the direction of the vehicle. The speed of vehicle was chosen to be 20kmph and 30kmph. It has been observed that the events are more accurately detected at low speed, which is explained in the later section and also a single pattern is considered for detection at different speeds (implies the pattern is independent of different speeds). These patterns were fed as input to DTW technique to find the similar patterns in the data so collected.

5. Data acquisition and Pre-processing

The data was collected using inbuilt sensors like accelerometer, gyroscope, gravity sensor and GPS of the smartphone to detect the braking events and lateral maneuvers. The accelerometer sensor produces significant readings in the form of acceleration signals when the vehicle experience brakes. Gravity sensor and gyroscope data are fused together to detect the lateral maneuvers like sudden left turn, sudden right turn and lane change events maneuvers. An algorithm is developed to detect these events based on the analysis of the data collected from sensors. As shown in Figure 1, the smartphone has to be aligned to the direction of vehicle, with positive z-axis pointed upwards as explained in the following subsection.



(a) Phone Axes (b) Vehicle Axes

Figure 1: Smartphone and Vehicle Axes

5.1. Accelerometer orientation: Euler Angles

An android application is designed and installed on the smartphone as shown in Figure 2.

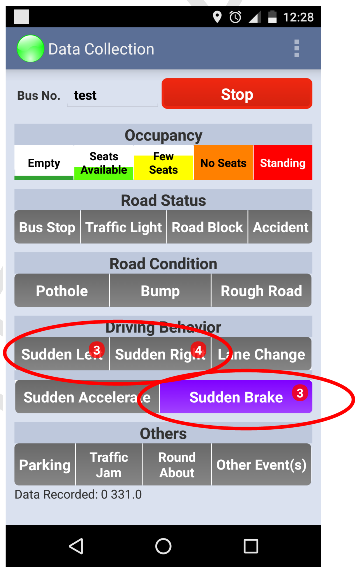


Figure 2: An Android application designed for data collection

The android application interacts with the in-built sensors of the smartphone, reads the data and send the values to the central server. The UI [6] of

[6]User Interface

the application interacts with the user in an interactive manner. To collect the ground truth, user taps the button as soon as he experiences the brake or sudden left/right turn while sitting inside the vehicle. This can be used to manually mark the database, which can further be used for defining template references for the events for DTW algorithm.

The accelerometer sensor in the smartphone can detect linear accelerations along the 3-axes that is X, Y and Z-axis, by measuring the inertial forces. The accelerometer detects accelerations a_x, a_y, a_z along their axis respectively. According to the SAE [29], the x-axis identifies the longitudinal direction, y-axis identifies the transverse one and the z-axis identifies the perpendicular direction to the xy-plane.

The reorientation can be achieved by using Euler Angles, in which three independent parameters are allowed to define the orientation in space of any body through a succession of elementary rotations [30], [31]. In this work, the Z-X-Y sequence was used where the rotation around x axis (roll angle) represented as α, around the y axis (pitch angle) as β and one around the z axis (yaw angle) as γ, whose rotation matrices are represented as following:

$$R(\alpha) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & c(\alpha) & -s(\alpha) \\ 0 & s(\alpha) & c(\alpha) \end{bmatrix}, R(\beta) = \begin{bmatrix} c(\beta) & 0 & s(\beta) \\ 0 & 1 & 0 \\ -s(\beta) & 0 & c(\beta) \end{bmatrix}, R(\gamma) = \begin{bmatrix} c(\gamma) & -s(\gamma) & 0 \\ s(\gamma) & c(\gamma) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathrm{R} = \mathrm{R}(\gamma) * \mathrm{R}(\alpha) * \mathrm{R}(\beta)$$

$$R = \begin{bmatrix} c(\gamma)c(\beta) - s(\alpha)s(\beta)s(\gamma) & -s(\gamma)c(\alpha) & c(\gamma)s(\beta) + s(\gamma)s(\alpha)c(\beta) \\ s(\gamma)c(\beta) + c(\gamma)s(\alpha)s(\beta) & c(\gamma)c(\alpha) & s(\gamma)s(\beta) - c(\gamma)s(\alpha)c(\beta) \\ -c(\alpha)s(\beta) & s(\alpha) & c(\alpha)c(\beta) \end{bmatrix}$$

X’, Y’ and Z’ are represented by eq. (1), (2) and (3)

$$X' = (c(\gamma)c(\beta) - s(\alpha)s(\beta)s(\gamma))X + (s(\gamma)c(\beta) + c(\gamma)s(\alpha)s(\beta))Y - (c(\alpha)s(\beta))Z \quad (1)$$

$$Y' = -(s(\gamma)c(\alpha))X + (c(\gamma)c(\alpha))Y + (s(\alpha))Z \quad (2)$$

$$Z' = (c(\gamma)s(\beta) + s(\gamma)s(\alpha)c(\beta))X + (s(\gamma)s(\beta) - c(\gamma)s(\alpha)c(\beta))Y + (c(\alpha)c(\beta))Z \quad (3)$$

where s and c represents sine and cosine respectively.

X', Y' and Z' are the new computed reoriented values of the accelerometer which can be further used to draw a manual pattern of the braking event. When the commuter applies brakes, the accelerometer will record the acceleration in all the 3-axis, out of which only Y-axis was chosen because only along that axis the deflection of reading is visible.

6. System Design

The objective of this paper is to detect the brakes and lateral maneuvers when applied on the vehicle using smartphone. When the vehicle experienced multiple brakes in a short span of time on some segment of the road, it may indicate congestion on the road. Also on a large scale, when multiple smartphones detect the braking event in same geographical area using crowd-sensing, it may indicate congestion on the road. This can be used to distinguish braking due to congestion v/s sudden braking due to harsh driving. The system design is divided into two sections i.e. brake detection and lateral maneuvers detection, whose working model has been explained in further subsections 6.1 and 6.2 respectively.

6.1. Proposed Model of Bake Event Detection

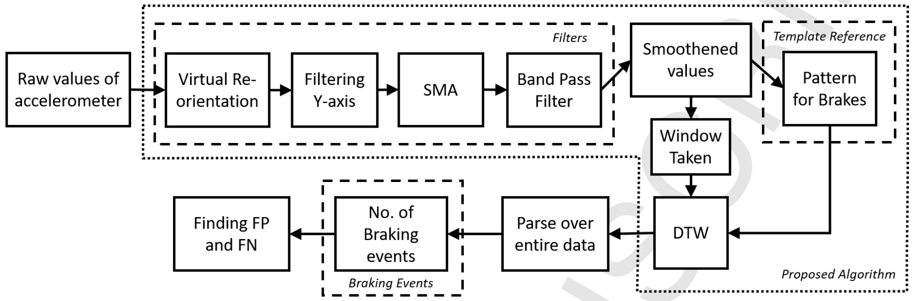


Figure 3: Working Model of Brake Event Detection

The working model of brake detection is illustrated in Figure 3. The raw values of the accelerometer are fed to the filter where the values are normalized / smoothed, before determining the braking event patterns. Some processing filters were applied on the Y-axis of accelerometer (reoriented) because of the need to filter out the noise or gravity component which gets added to the accelerometer data.

6.1.1. Filters

In the working model, filters play an important role because they are used to eliminate the noise and gravity component from the raw accelerometer data which got added during data collection. As shown in figure 3, each filter tries to smoothen / normalize the raw values of accelerometer in different manner. Filters like Virtual re-orientaion, filtering Y-axis, SMA and band-Pass filter have been used and are described as below:

Virtual Orientation. As discussed in section 5.1, virtual orientation has to be done to re-orient the accelerometer axes to its original axes using Euler's Angle.

Filtering Y-axis. After re-orientation, only Y-axis of the accelerometer is taken into consideration for braking detection because the braking event influences only on Y-axis. Thus the values along X and Z-axis are discarded using this filter.

SMA. SMA has been used to smoothen the values of accelerometer and also to remove the noise which gets added to the accelerometer data due to vibrations of the vehicle. SMA is an arithmetic moving average which is calculated by taking the average of data series.

Band Pass Filter. Sometimes it has been observed that the accelerometer sensor carries noise due to its hardware sensitivity. These values have to be normalized or eliminated to find an event. The smoothening of data is done using low and high pass filters known as Band Pass Filter (BPF). It is well known that low pass filters are used to pass low-frequency signals and reduce the amplitude of signals with frequencies higher than the threshold frequency whereas high pass filters are used to pass high-frequency signals and reduce the amplitude of signals with frequencies lower than the threshold frequency.

6.2. Proposed Model of Lateral Maneuver Detection

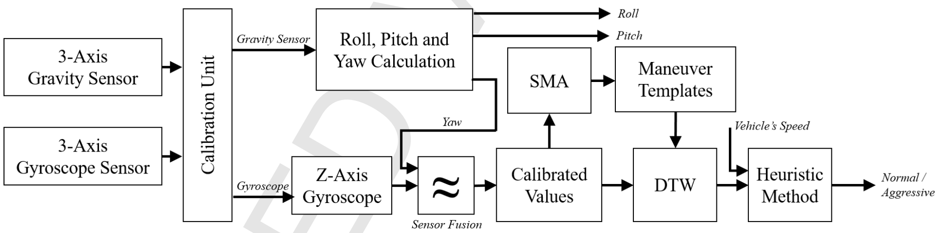


Figure 4: Working Model of Lateral Maneuver

The working model of lateral maneuver detection is depicted through Figure 4. The raw values of the gravity sensor and gyroscope are fed into the calibration unit where the values are normalized / smoothened, before determining the template references for lateral event patterns. Data along the Z-axis of gyroscope and yaw angle (calculated from gravity sensor) are fused together to acquire angular velocity w.r.t. direction, which were then further normalized using SMA filter (to smoothen the values) to determine the lateral event patterns (shown in figure 9, 10 & 11). This requires use of two filters in the proposed model i.e. fusion sensor and SMA. The working of fusion filter is explained further in subsection 6.2.1 whereas the explanation of SMA has already been explained in the previous subsection 6.1.1.

6.2.1. Fusion of Sensors

The fusion of sensors is often called data fusion (multi-sensor) where two or more streams of sensory data are fused together to get the normalized values. In our proposed model we have fused gravity and gyroscope sensors as described in the later section.

6.3. DTW (Dynamic Time Warping)

DTW is a dynamic pattern matching technique which measures the similarity between two patterns independent of time and space. It is different from traditional pattern matching techniques because in DTW each point of pattern is matched with each and every point of other pattern, having the complexity of O(n^2) (for readers not familiar with DTW, details of the technique is explained in Appendix - I for reference).

6.4. Template Reference

After applying the filters, the values from the accelerometer were smoothened / normalized and saved into a file. Specific experiments as explained in section 7 were conducted to determine template references / patterns from the ground truth data. To recall, the accelerometer readings corresponding to the braking event were extracted and saved into a database of patterns called Template References after generating events: braking and lateral maneuvers as a part of experimentation. The Template Reference for lateral maneuvers have also been derived using fusion filter.

One of the most important step in Dynamic Time Warping (DTW) based pattern recognition systems are the preparation of reliable reference templates for time series data to be recognized. In this paper, we have used a simple technique for preparing reliable reference templates to improve the event detection rate. The accuracy of DTW based event detection systems greatly relies on the quality of the prepared reference templates [32]. The usual procedure in selecting the reference templates is to select one sample and then test its recognition rate against another sample data. The pair that has the smallest "path sum value" close to zero indicates the detected event and is given by similarity score already explained in Appendix-I. If the recognition rate for many different test samples is high then this reference is kept, otherwise chosen template reference is discarded and another template has to be selected.

7. Evaluation

This section is divided into two subsections where the detection of braking events and lateral maneuvers are discussed in subsection 7.1 and 7.2.

7.1. Evaluation of Braking Events

The proposed algorithm has been developed to detect braking events which is based on the analysis of the acceleration signals. Some processing filters have been applied on the Y-axis of the accelerometer (reoriented) to filter the noise and eliminate the non-braking events from braking events. The data is collected on the roads of Chandigarh city using Nexus 5 smartphone mounted on Hero Honda Deluxe motorbike (2-wheeler). The smartphone was placed on the vehicle as shown in Figure 1 i.e. the smartphone was aligned parallel to the direction of vehicle. The experiment was conducted on a smooth road having no potholes and bumps. The data was collected with several events of braking at 20kmph and 30kmph. In our proposed method, DTW technique was used which is simple to implement and doesn't require any extensive training as required in other machine learning based techniques. The inputs streams to DTW (template reference and real time sensory data) are considered to be of same window size i.e. 7 data points (smaller the window size lower is the overall computation of the algorithm).

Table 3: Parameters considered for experimentation

Parameters	**Values taken into consideration**
Accelerometer axis taken into consideration	Y-axis
Delta(δ)	0.8
SMA (window size)	10 values
Pattern & Window size	7 values
Sliding / Shifting Window	Sliding Window

The parameters considered during the experimentation have been described in Table 3. 'δ' in the virtual reorientation process is called the smoothing factor (constant value) whose value is considered to be 0.8 (explained later in this section). SMA of window size of 10 values is considered which is based on experimentation where it was found that large window size smoothens the values but results in information loss. Although there is a signal loss due to application of this filter but it doesn't affect the detection rate of an event from the collected data. It rather helps in removal of noise from the data. These patterns are then fed to DTW technique to find the similar patterns or similarity score from the data collected.

The raw values of the accelerometer are passed through various filters (discussed in section 6.1.1). After passing through the third filter, the newly computed values are fed to the fourth filter that is band-pass filter, which passes the low and high frequencies. It was used to eliminate the gravity component which gets added to the accelerometer data. So as to find the gravity component from the accelerometer reading and to eliminate those values from the actual readings, band-pass filter was used. Mathematically, low and high pass filters have been denoted by equations (4) to (9), as given below:

Using `Low pass filter`: [33]

$$g_{x_n} = \delta * g_{x_{n-1}} + (1-\delta) * a_x \quad (4)$$

$$g_{y_n} = \delta * g_{y_{n-1}} + (1-\delta) * a_y \quad (5)$$

$$g_{z_n} = \delta * g_{z_{n-1}} + (1-\delta) * a_z \quad (6)$$

where a_x, a_y, a_z are the original values of accelerometer.

Using `High pass filter`: [33]

$$a_x^{'} = a_x - g_{x_n} \quad (7)$$

$$a_y^{'} = a_y - g_{y_n} \quad (8)$$

$$a_z^{'} = a_z - g_{z_n} \quad (9)$$

where $a_x^{'}$, $a_y^{'}$, $a_z^{'}$ are the new accelerometer values after passing through high pass filter.

The newly computed values are smoothened values (noise removed) and can be used for further analysis. The comparison of the different filters namely SMA and SMA with BPF when compared against the raw accelerometer values is shown in figure 5:

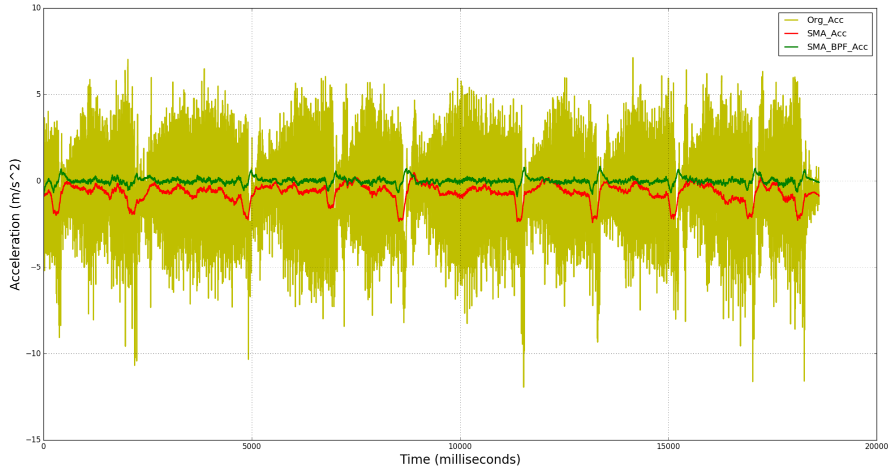
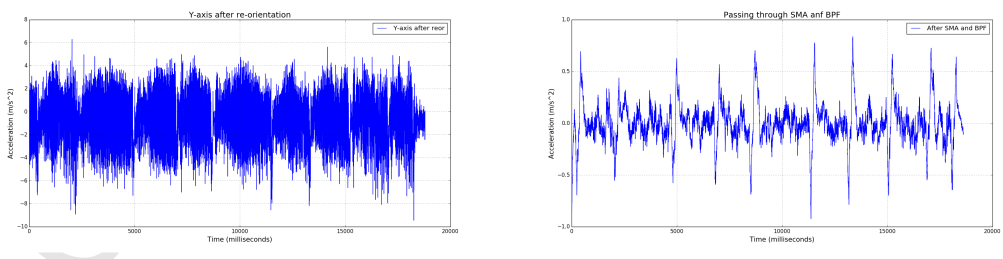


Figure 5: Comparative of raw and filtered accelerometer values

The output of smoothened / normalized accelerometer values when compared with the actual accelerometer data is shown in Figure 5. The raw accelerometer values, output of SMA and output of Band Pass filter are represented as yellow, red and green lines. From figure 5, it is clearly evident that the green line is much smoother signal when compared to SMA filter and raw values of accelerometer.

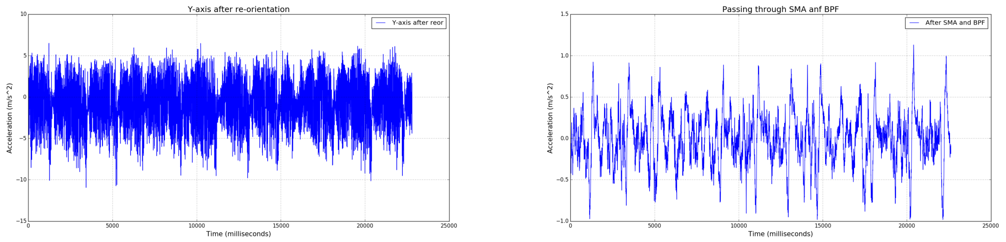
Comparison of the raw accelerometer data with data passed through all the filters is shown in Figure 6 and Figure 7 respectively.



(a) Raw Y-axis of accelerometer

(b) Y-axis of accelerometer after pasing through BPF

Figure 6: Raw Vs Filtered Y-axis of accelerometer at 20 kmph



(a) Raw Y-axis of accelerometer (b) Y-axis of accelerometer after pasing through BPF

Figure 7: Raw Vs Filtered Y-axis of accelerometer at 30 kmph

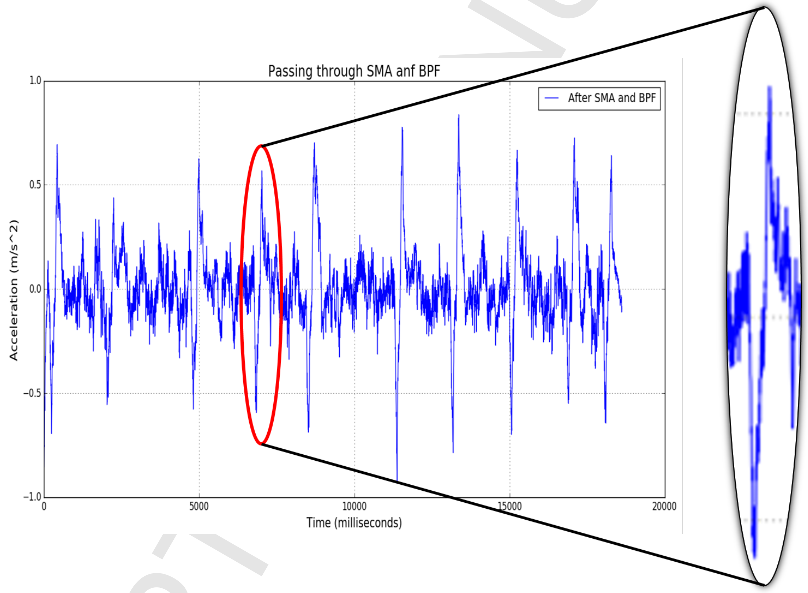


Figure 8: Selection of pattern as Template Reference

From Figure 6(b) and Figure 7(b), it is clearly evident that an event is clearly detected along Y-axis of accelerometer when passed through various filters. Patterns of the braking event are chosen manually as shown in Figure 8 and stored in the database named "template reference". That template reference is then parsed over entire data collected from the accelerometer to find the similar patterns using DTW technique (details explained in Appendix - I).

Table 4: Comparison of FPR and FNR with various existing techniques

Techniques	**Speed (Kmph)**	**False Negatives**	**Detection Rate**
DTW	20	0%*	100%
	30	0%*	100%
Wolverine	20	28%	72%
	30	20%	80%
Nericell	20	44%	56%
	30	48%	52%

* The false negative is 0% because our proposed technique is able to find all the manual marked events in comparison.

It has been observed that the filters used in the signal analysis of the accelerometer allows us to detect 100% of braking events with false positive rate of 4.35% and 8.7%, with speeds of 20kmph and 30kmph respectively. Results of proposed algorithm have been compared against the existing techniques and shown in Table 4. It is clear from the results that the proposed technique outperforms the existing techniques for the detection of braking events detected using the smartphone mounted on vehicles. Wolverine system [27] used SVM machine learning technique for training purpose whereas Nericell [24] used fixed threshold values to detect the braking events. Both systems produces the results with the false negative rate of 21.6% and 31.1% respectively, which is much higher than our proposed technique. It is thus evident that the use of DTW technique and fusion of sensors outperforms existing machine learning and threshold based techniques and is more efficient.

7.2. Evaluation of Lateral Maneuvers

The proposed algorithm has been developed to detect lateral maneuver events which is based on the fusion of gyroscope and gravity sensor signals. The data is collected from the roads of Chandigarh city using Nexus 5 smartphone mounted on Hero Honda Deluxe motorbike (2-wheeler) and Maruti Swift car (4-wheeler). The smartphone was placed in the vehicle as shown in Figure 1 i.e. the smartphone was aligned parallel to the direction of vehicle. The experiment was conducted on smooth road having no potholes and bumps. The data was collected with several events of lateral maneuvers both normal and aggressive. In our proposed method, DTW technique was used which is simple to implement and doesn't require any extensive training as other machine learning technique does, as already explained in previous sections.

Table 5: Parameters considered for experimentation

Parameters	**Values taken into consideration**
Gyroscope axis taken into consideration	Z-axis
Delta(δ)	0.98
SMA (window size)	10 values
Pattern & Window size	10 values
Sliding / Shifting Window	Sliding Window
No. of Drivers	6
Distance covered	13KM
No. of Left and Right turns	11, 11

The parameters that are considered during the experimentation have been described in Table 5. 'δ' in the virtual reorientation process called the smoothing factor (constant value) whose value is considered to be 0.98 (explained later in this section). SMA of window size of 10 values is considered which is based on experimentation where it was found that large window size smoothens the values but results in information loss. Although there is a signal loss due to application of this filter but it doesn't affect the detection rate of an event from the collected data, it rather helps in removal of noise from the data. These patterns are then fed to DTW technique to find the similar patterns or similarity score from the data collected.

The raw values of the gravity sensor and gyroscope are passed to the calibration unit where the X, Y and Z-axis of gravity sensor and Z-axis of gyroscope are filtered out for further fusion. However, roll pitch and yaw angles are computed from the gravity sensor whose equations are shown from (10) to (12).

$$roll = atan\left(\frac{g(x)}{\sqrt{g(y)^2 + g(z)^2}}\right) \tag{10}$$

$$pitch = atan\left(\frac{g(y)}{\sqrt{g(x)^2 + g(z)^2}}\right) \tag{11}$$

$$yaw = atan\left(\frac{g(z) * s(roll) - g(y) * c(roll)}{g(x) * c(pitch) + g(y) * s(pitch) * s(roll) + g(z) * s(pitch) * c(roll)}\right) \tag{12}$$

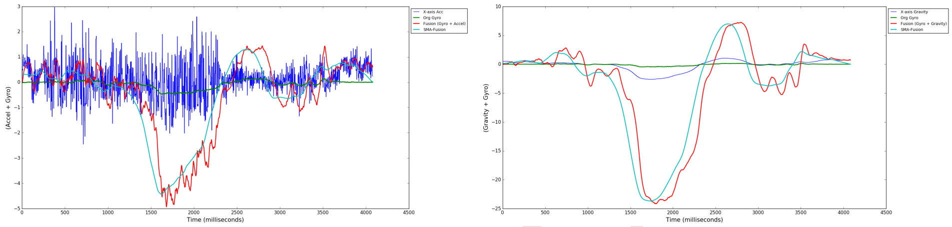
where $g(x)$, $g(y)$ and $g(z)$ are the values of X, Y, Z-axis of gravity sensor respectively, c and s represents cos and sin.

The fusion of gravity sensor and gyroscope is represented in the following equation (13).

$$\theta_{t+1} = \delta * (\theta_t + \omega \triangle t) + (1 - \delta) * \phi \tag{13}$$

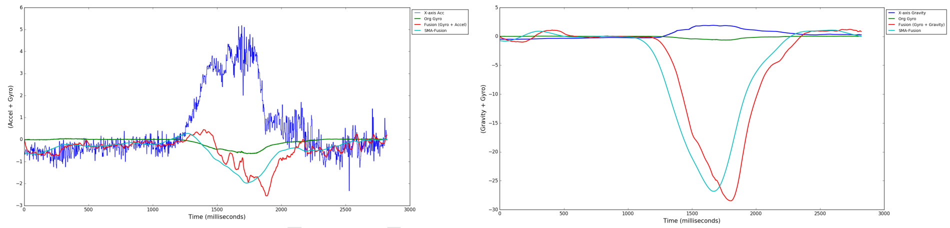
where θ, ω, ϕ are the current angle value, gyroscope values and gravity sensor values respectively. In every iteration, the pitch and roll angle values are updated with the new gyroscope values by means of integration over time. The filter then checks if the magnitude of the force observed by the gravity sensor has a significant value that could be the real g-force vector. If the value is too small or too big, we know for sure that it is a disturbance and we don't need to take into consideration. Afterwards, it will update the pitch and roll angles with the gravity data by taking 98% of the current value, and adding 2% of the angle calculated by the gravity. This will ensure that the measurement won't drift over time, but is very accurate on the short term.

We also performed an experiment by choosing the accelerometer or gravity sensor fused with gyroscope when the data was collected from bike and car. Figure 9(a) and 10(a) shows the output of right turn taken by bike and car respectively by considering accelerometer sensor. Figure 9(b) and 10(b) shows the output of right turn taken by bike and car respectively considering gravity sensor. Figure 11(a) and 11(b) shows the output of left turn taken by the vehicle considering accelerometer and gravity sensor respectively.



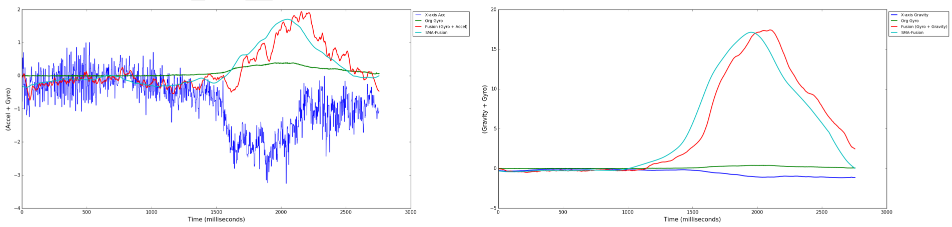
(a) Calibration using Accelerometer (b) Calibration using Gravity Sensor

Figure 9: Calibration using Accelerometer and Gravity sensor using bike



(a) Calibration using Accelerometer (b) Calibration using Gravity Sensor

Figure 10: Calibration using Accelerometer and Gravity sensor using bike (Right Turn)



(a) Calibration using Accelerometer (b) Calibration using Gravity Sensor

Figure 11: Calibration using Accelerometer and Gravity sensor (Left Turn)

From the above figures 9, 10 and 11, it is clearly evident the an event is clearly detected by fusing gravity sensor and gyroscope readings. However, after fusing accelerometer with gyroscope and gravity with gyroscopic values, no major difference is found in the output as shown but more fluctuations are observed in the accelerometer data. In the further analysis we therefore chose the fusion of gravity sensor with gyroscope to obtain smoothened values as output.

In figure 9(b) and 10(b), green, blue, red and cyan line represent the output of gyroscope sensor, x-axis gravity sensor, fusion of gravity sensor & gyroscope and SMA of fusion output respectively. It is evident that the red line shows the left turn taken by the vehicle, which was further smoothened using SMA filter. A pattern is chosen depicting the left and right turn and saved into the database called "Template Reference". The template reference and window from real time sensory data was taken and is then fed to DTW (explained in Appendix-I) to find the similar patterns.

The data was collected from 6 drivers driving vehicles on the roads of Chandigarh city. The route of 13KM was chosen having 11 right and 11 left turns. The drivers were asked to encounter every left and right turns on the way. The raw data from the smartphones was successfully extracted having total 66 right and 66 left turns. Our proposed algorithm successfully detected 97% of left and right turns. The average speed of the vehicle was 60kmph through these road segments.

We have also collected the data of aggressive turns. In this experiment only one driver was chosen who possessed good driving skills and his job was to take aggressive turns. Total of 15 aggressive turns were recorded by the smartphone. After applying our proposed technique, 13 aggressive turns were correctly identified which leads to the detection rate of 86.67%.

8. Conclusion

In this paper, a prototype of detecting the reckless driving behavior has been proposed and validated on the roads of the city Chandigarh. The results from the proposed prototype have been compared with the existing techniques.

Sensory data from the accelerometer, gravity sensor and gyroscope has been used to detect the reckless driving events. DTW has been used to detect events out of the data streams collected using sensors of the smartphone. Fusion of two sensors has also been done to enhance accuracy of event detection. The output of DTW gives the closeness score of two patterns. Although there are other based Machine Learning and statistical Markov model based techniques which have been used in the past research such as Support Vector Machines, Hidden Markov Modeling (HMM) and Artificial Neural Network (ANN) techniques. The DTW is widely used in the small-scale embedded hardware such as those embedded in smartphones. The simplicity of the hardware implementation of the DTW engine, capability of comparing time-series data and requirement of relatively small number of template references makes it suitable for many resource-constrained mobile devices. Additionally, the training procedure in DTW is very simple and fast, as compared with the SVM, HMM and ANN. DTW can also automatically cope with time deformations and different speeds associated with time-dependent data makes it apt for our chosen application. The detection rate of our proposed algorithm was found to be 100%, 97% and 86.67% in case of detecting braking event which is higher in comparison to the existing techniques, detecting left & right turns and aggressive right & left turns respectively. The proposed DTW based detection technique outperforms the existing techniques when applied on same dataset (real time accelerometer, gyroscope, gravity sensor data collected using smartphone from the roads of Chandigarh City). Our proposed prototype enhances accuracy of detection of braking as well as normal or aggressive driving events and is based on crowd-sensing, which is more efficient in comparison to the existing techniques.

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Appendix - I

DTW (Dynamic Time Warping)

DTW measures the similarity among two sequences that may differ in time or space. It can be applied for all types of data that are represented linearly according to time such as audio, video and graphics. It is well-known in the various applications like speech recognition applications, e.g. [34] and gesture recognition [35]. The working of DTW is explained as in figure 12:

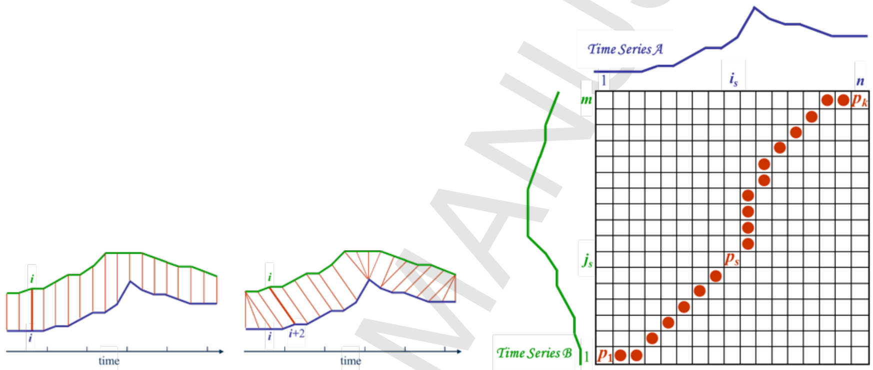

Figure 12: Working Model of DTW [36]

Suppose we have two time series, a sequence A of length n and a sequence of length b, where

A = a_1, a_2, a_3, , a_i, , a_n

B = b_1, b_2, b_3, , b_j, , b_n

To align these two sequences using DTW, we first construct an n-by-n matrix where the (i^{th}, j^{th}) element of the matrix corresponds to the squared distance, d(a_i , b_j) = (a_i - b_j)^2, which is the alignment between points a_i and b_j. To find the best match between these two sequences, we retrieve a path through the matrix that minimizes the total cumulative distance between them as illustrated in Figure 1. In particular, the optimal path is the path that minimizes the warping cost

$$\text{DTW(A, B)} = \min\{\sqrt{\textstyle\sum_{k=1}^{K} w_k}\}$$

where w_k is the matrix element $(i, j)_k$ that also belongs to k^{th} element of a warping path W, a contiguous set of matrix elements that represent a mapping between A and B. This warping path can be found using dynamic programming to evaluate the following recurrence.

$$\gamma(\text{i, j}) = \text{d}(a_i,\, b_j) + \min \{\ \gamma(\text{i-1, j-1})\ ,\ \gamma(\text{i-1, j })\ ,\ \gamma(\text{i, j-1})\ \}$$

where d(i, j) is the distance found in the current cell, and γ(i, j) is the cumulative distance of d(i, j) and the minimum cumulative distances from the three adjacent cells.

Many researchers use the DTW for pattern recognition with variable length and time and also tries to speed up the algorithm. Since these has been proven by the [37], that the inputs to DTW the patterns should be of equal length and defining the bounds to DTW will speed up the algorithm.