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Detection of critical behaviour on roads by vehicle trajectory analysis

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ABSTRACT
Detecting restricted or security critical behaviour on roads is crucial for safety protection and fluent traffic flow. In the paper we propose mechanisms for the trajectory of moving vehicle analysis using vision-based techniques applied to video sequences captured by road cameras. The effectiveness of the proposed solution is confirmed by experimental studies.

KEYWORDS: vehicle behaviour analysis, trajectory analysis, road safety

1. Introduction

Illegal movements of vehicles are the major cause of accidents and roadblocks. Those movements can be detected using vision-based techniques applied to video sequences captured by road cameras. As a deterrent the system of critical behaviour detection can contribute to increase in awareness of drivers and their safe driving. Moreover, in case of the occurrence of unfortunate accident such system is capable of immediate (real-time) automatic response and alerting.

The advantage of using computer vision techniques is obviously non-intrusive approach [12]. In contrast, solutions such as inductive loops or piezoelectric cables (intrusive techniques) require the installation of the sensors directly onto or into the road surface [6]. Furthermore, the image-based techniques can be utilized in many ways for variety of tasks, providing complete traffic flow information for [15]: traffic management system, public transportation systems, information service systems, surveillance systems, security systems and logistics management systems. Tasks implemented successfully with vision-based techniques include: vehicle registration plates reading (ALPR - Automatic License Plate Recognition), vehicle counting, congestion calculation, traffic jam detection, lane occupancy readings, road accident detection, traffic light control, comprehensive statistics calculation and other.

It must be noticed, however, that not only are computer vision techniques used in Intelligent Transportation Systems (ITS) but they are increasingly utilized by driver assistant systems (ADAS - Advanced Driver Assistance Systems). Many vehicles are manufactured with on board cameras which form the basis for systems such as [9, 10]: TSR - Traffic Sign Recognition, CAV - Collision Avoidance (by pedestrians or surrounding vehicles detection and tracking), LDW - Lane Departure Warning (adaptive cruise control), and driver fatigue detection.

The main drawback of vision-based solutions is susceptibility to poor visibility conditions and occlusions. Researchers, however, actively respond to the challenge and propose solutions that deal with those difficulties (e.g. occluded traffic signs recognition [5]).

In the paper we propose mechanisms for the trajectory of moving vehicle analysis. We discuss the idea of the detection of critical behaviour on roads by the trajectory analysis. We briefly present state of the art algorithms found in the scientific literature. Then, we introduce our method, present appropriate examples and discuss the operation scenario for the system. The paper ends with a summary.

2. Restricted and security critical behaviour on roads

Analysis and identification of vehicles motion patterns are referred in the literature as Vehicle Behaviour Analysis [15]. Most solutions use motion trajectories obtained by vehicle tracking.

There are on-line systems which provide real-time analysis for anomaly detection or prediction. Another group uses the information in the off-line mode for statistics generation.

Vehicle trajectory analysis allows the following abnormal events detection:

- illegal left and right turns,
- illegal U-turn,
- illegal lane change and violation of the traffic line,
- overtaking in prohibited places,
- wrong-way driving,
- illegal retrograde,
- illegal parking.

Figure 1 presents examples of illegal movements. Each example represents a specific situation (scenario). Red dashed lines denote dangerous and forbidden movement.

The interesting part of vehicle behaviour analysis is the dual approach for the trajectory meaning. To form the pattern a forbidden trajectory or an appropriate one could be used (see the example presented in Fig. 2). Green lines denote a proper driving behaviour while red ones - those dangerous (the wrong-way driving). It is possible to use appropriate trajectories and compare vehicles movements to those trajectories. Any discrepancy will reveal restricted behaviour. On the other hand, the same discovery is possible with the similarity to forbidden trajectory. Making the right choice is determined by the road system and the specific traffic situation. If the hazardous behaviour is distinctive - the forbidden trajectory detection should works better. When there are many possibilities for the violation - e.g. overtaking in prohibited places which may occur in different parts of the road (see fig. 2) - the comparison with the appropriate trajectory gives more satisfactory results.

Fig. 1. Examples of restricted and security critical behaviour on roads: illegal left turn (left), illegal U-turn (right) [own study]

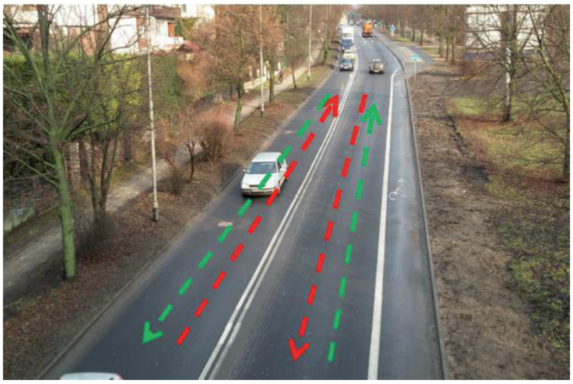

Fig. 2. Forbidden (red) and appropriate (green) trajectories [own study]

It is clear that the trajectory-based solution for illegal behaviour detection can be adopted to most locations. The trajectory may take a variety of shapes and may consist different number of points. Mechanism of trajectory comparison plays the vital role here.

3. Approaches for behaviour analysis

Behaviour analysis based on pattern matching and state estimating is preceded by two steps [7]: vehicle detection and vehicle description using static and dynamic parameters. After the successive vehicle detection the succeeding tracking algorithm follows the moving vehicle. As the result the trajectory is obtained. Object detection, classification and tracking belong to low level and middle level vision methods [3]. High level vision algorithms are reserved for activity perception and abnormal detection [3].

There have been varied approaches to handle trajectory of moving objects analysis based on video and some solutions have already been proposed. The algorithms for behaviour analysis proposed in the literature can be divided into supervised and unsupervised methods [3]. Supervised methods require manual intervention for specifying template patterns of behaviour. In an unsupervised mode the algorithm learns abnormal activity from the sample data. The process is automatic and the outcome might be sometimes unexpected. It requires a reasonable amount of data and is time consuming. Some method does not require a time-consuming learning step. A graph based approach for detecting abnormal behaviours is a good example here [2].

In more detail, for behaviour analysis the following techniques have been distinguished [15]: pattern recognition based, statistic based, traffic flow model based and artificial intelligence based.

Using velocity information it is possible to detect other dangerous vehicle behaviours. In [8] the rate of velocity variation and the rate of direction variation are used to detect: sharp brake, sharp turn, and sharp turn brake. In [13] trajectory analysis helps to detect the following traffic events: illegal lane change, stopping, retro gradation, sudden speeding up or slowing down. Template trajectories are modelled by straight lines. Comparisons are based on the angle and variance between the benchmark lane line and the trajectory of moving vehicle.

Interesting idea is presented in [7] where the aim is to predict accidents accurately in advance for a real-time system and generate appropriate warning. A fuzzy self-organizing neural network algorithm is applied to learn activity patterns from the sample trajectories. Then, vehicle activities are predicted based on the observed partial trajectory and utilized for accidents predictions.

Another interesting approach is presented in [1] where multiple camera views are used to remove occlusion and extract abnormal vehicles behaviour more accurately. The vehicles trajectory analysis is based on support vector machine (SVM) here. The system is constructed using the distributed architecture.

Many solutions found in the literature use the Hausdorff distance or its modifications (e.g. [3, 11, 14, 16]). This measure as one of the components is used in the method proposed in this paper.

4. The Hausdorff distance for trajectory comparison

Vehicle trajectories are defined as a set of points in the two dimensional space. Computing a measure of similarity between two sets of points associated with the trajectories can be computed using the Hausdorff distance. It is worth noticing that two trajectories might consists of different number of points coordinates. The Hausdorff distance is immune for such cases which represents a clear advantage. Assuming two sets of points coordinates $A = \{a_1, a_2, \dots, a_m\}$ and $B = \{b_1, b_2, \dots, b_n\}$ the directed Hausdorff distance from set A to set B is given as follows [4]:

$$h(A,B) = \max_{a \in A}\left(\min_{b \in B}\left(\|a-b\|\right)\right) \tag{1}$$

This measure is directional and its value is determined by the order of sets. The $\|a\text{-}b\|$ norm is most frequently defined as the Euclidean distance. The value $\min_{b \in B}(\|a-b\|)$ denotes the distance between a given point a and set of points $B = \{b_1, b_2, \dots, b_n\}$(distance to the closest one). For each point the closest from the other set should be found. From those values the maximal is the result.

Two directed distances $h(A,B)$ and $h(B,A)$ can be calculated between two sets. Different attempts have been taken to combine those values and define an undirected distance measure [4]. Widely accepted solution is given by:

$$H(A,B) = \max\left(h(A,B), h(B,A)\right) \tag{2}$$

Applying the Hausdorff distance directly to compare trajectories might lead to the problems with outliers. An individual coordinate (an outlier) can interfere and significantly increase the value of the calculated distance. Such case is possible when the vehicle tracking algorithm encounters some difficulties (e.g. occlusions). The trajectory can be smoothed and outliers filtered out to solve the problem. However, in situation when the car begins to be tracked in the middle of its movement (e.g. problems with detection at the first stage of its movement) the solution is not so straightforward. For that reason the better choice is to compute the Modified Hausdorff Distance (MHD) proposed by [4]:

$$MHD(A,B) = \max\left(h_{\text{mod}}(A,B), h_{\text{mod}}(B,A)\right) \tag{3}$$

where:

$$h_{\text{mod}}(A,B) = \frac{1}{|A|}\sum_{a \in A}\left(\min_{b \in B}\left(\|a-b\|\right)\right) \tag{4}$$

is the directional MHD. Directional MHDs are sometimes referred to as FHD (forward) or RHD (reverse).

The MHD averages individual value as depicted in Fig. 3 (where it is compared with the Hausdorff distance). There are two trajectories denoted by A and B. Two directional Hausdorff distances are visualized at the top. Two bottom ones present directional MHD.

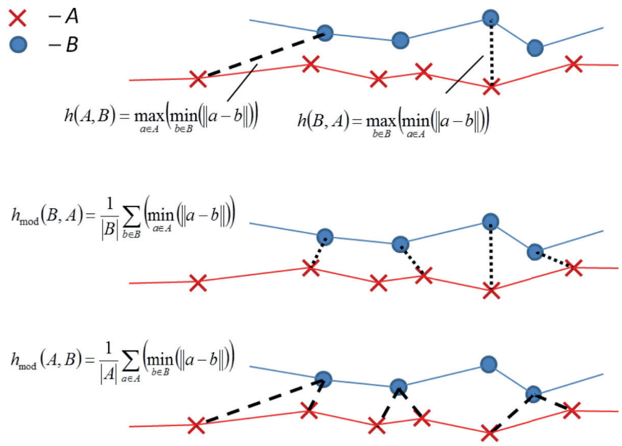

Fig. 3. Comparison of the Hausdorff distance calculation (top) and MHD calculation (middle and bottom) [own study]

Figure 4 presents three examples of the trajectory evaluation. Let the forbidden relation be the left turn considering the movement from the top (dashed red line). Dotted blue lines denote the investigated movements. Charts beside each case presents: MHD, FHD and RHD. The questioned trajectory was the second during computations. It was the question how to present changes over time. Vehicles speeds are different and subjected to individual variations (acceleration, slowing down). Different distances are traversed in constant time interval. Since it is the trajectory shape which is important we decided to show the results normalized to the distance travelled.

In all three cases the analysed trajectory in first few frames is similar. It corresponds to the forbidden trajectory. It is the reason why the FHD is small. From the point of view of the forbidden trajectory it is quite distant - hence the RHD is high. The differences occur in the second part of the examined movements. When the questioned trajectory moves away from the forbidden relation (the straight driving and the right turn) the FHD grows, giving high values to the MHD. Trajectories are not similar. In the third case and the second part of the movement the vehicle continues to move in the inappropriate manner. Its trajectory becomes more similar with each step giving the low value of the final MHD.

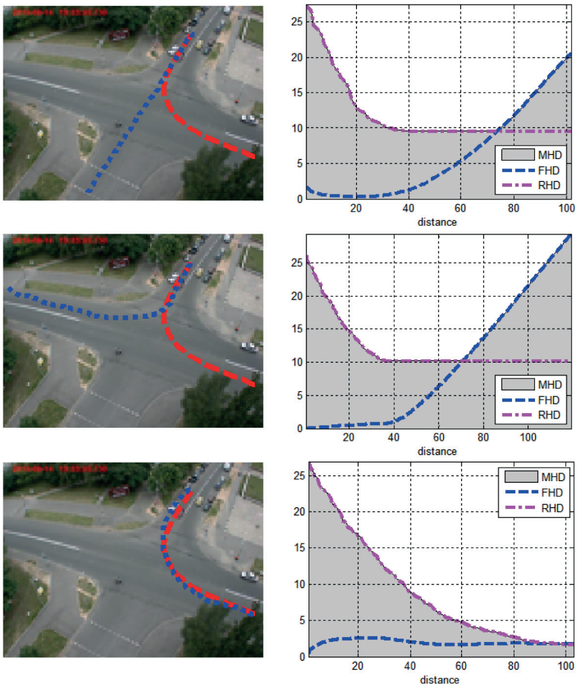

Fig. 4. Trajectories evaluation using MHD compared to FHD and RHD [own study]

5. The proposed solution

The MHD can expose the similarity between given trajectories satisfactorily. The influence from the outliers is reduced compared to the original Hausdorff distance. One problem, however, is still present. It is the result from the inherent definition of the measure - its separable treatment of trajectory points. The order of coordinate points in the trajectory is important. The MHD measure, unfortunately, only considers mutual relationships of trajectory points which are treated as a set. For that reason the MHD in unable to differentiate the direction of the movement. As the result, a properly moving vehicle in some cases can be classified as behaving illegally (see the example depicted in Fig.5). The forbidden trajectory starts at point no 1, includes the illegal left turn, finally ends at point no 2. Driving the opposite direction is safe and permitted but the vehicle trail leaves the trajectory matching the forbidden one.

Fig. 5. An example of illegal trajectory (from 1 to 2) which corresponds to the proper driving (from 2 to 1) [own study]

For the problem introduced above researches propose different solutions. The addition of velocity to the improved Hausdorff distance is considered in [3, 14]. In [16] the entire trajectory is treated as a sequence of the subtrajectories. We proposed the start and stop areas in our earlier studies [11]. Those areas are usually defined as patches at the calibration stage. The final result of trajectory comparison include the MHD match and trajectory extreme points (the beginning and the end) check for the correspondence with defined patches [11]. This solution proved to be effective in most cases as presented in the example depicted on the left hand side of Fig. 6. The problem, however, occurs when the beginning and the end of trajectory converge at the close area as depicted on the right part of Fig. 6. The forbidden trajectory for a roundabout and the right-hand traffic would be clockwise. Both extreme trajectory points converge. Similarly, start and stop patches form identical areas. The vehicle driving properly, turning back at the roundabout accordingly with the direction of movement will rise an alarm. Its trajectory and extreme trajectory points would comply. To overcome the problem we hereby propose the improved measure.

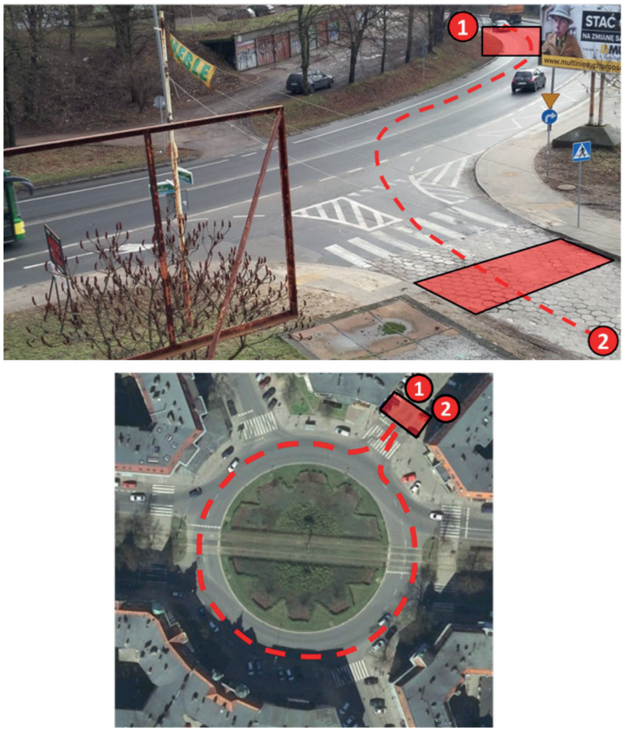

Fig. 6. Start and stop patches applied for differentiate the beginning and the end of trajectory. Successful application on the left and unfortunate on the right [own study]

To take into account the order of the trajectory points we propose to include the X and Y projections in the final trajectory matching algorithm. For close localization of extreme trajectory points the solution proves its value. Figure 7 presents an example of the roundabout problem. Starting position is on the left. The forbidden trajectory is clockwise and the questioned movement is counterclockwise. Both trajectories are similar and MHD measure decreases to very small values. During the movement the *X* coordinates rise and then fall for both trajectories (forbidden and questioned) which is shown in the lower left chart of Fig. 7. The *Y* coordinates act differently (the lower right chart of Fig. 7). For the forbidden trajectory the values first decrease, then increase, and finally decrease again (dashed red line). In the questioned movement, values of the *Y* coordinate: rise, decrease, and rise again (blue stem). Another example, for different intersection, is presented in reduced form in Fig. 8. The direction change is clearly visible in the *Y* projection.

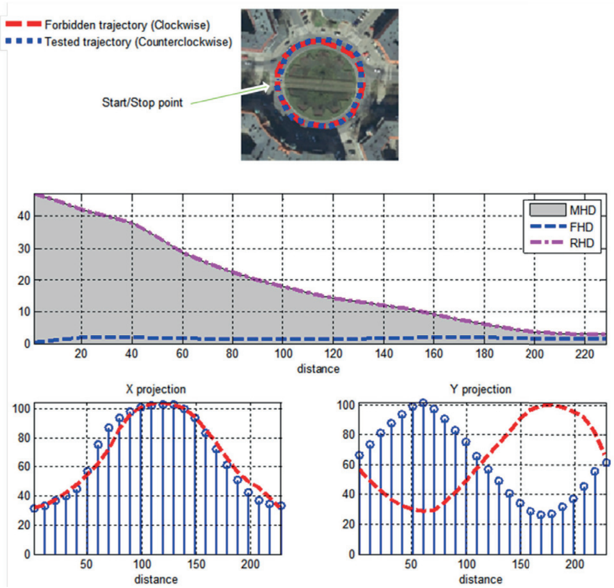

Fig. 7. Projections of trajectory points to *X* and *Y* axes for a roundabout [own study]

The projections of *X* and *Y* coordinates allow the discrimination of trajectory direction. We evaluated six different measures to recognize (dis)similarity of any two projections: L1, Euclidean, Chi-Square, Correlation, Intersection and Bhattacharyya distance. We used a scene from *A Public Video Dataset for Road Transportation Applications* [12] and generated 120 trajectories (10 trajectories for 4 directions by 3 possible movements). Figure 9 at the top presents the intersection and the aggregated traces of examined trajectories. We selected the left turn driving from the top as the forbidden trajectory to which all others have been compared. At the bottom of Fig. 9 the result of comparisons are shown. We present results by plotting the *X* projection comparison score by the *Y* projection comparison score for individual trajectories and a given method. The L1, Euclidean, Chi-Square and Intersection show very good clustering. Trajectories of abnormal behaviour form clear clusters (blue triangles) which prove the usefulness of the method.

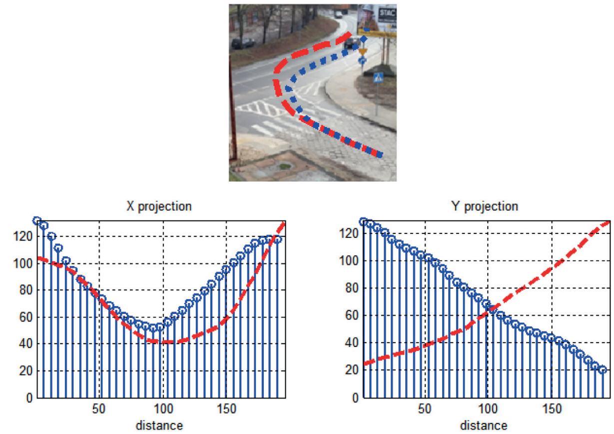

Fig. 8. Projections of trajectory points to *X* and *Y* axes for the turn case [own study]

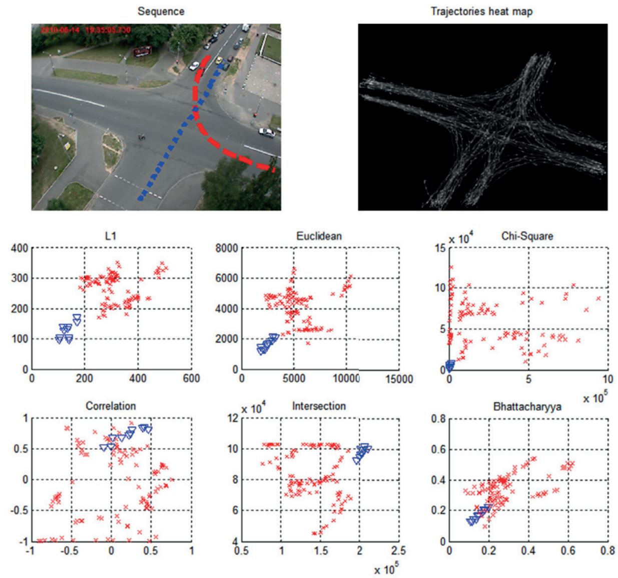

Fig. 9. Results of clustering using only *X* and *Y* projections [own study]

6. Conclusion

In this paper we proposed a method for detection of restricted or security critical behaviour on roads by vehicle trajectory analysis. Our proposal was to improve the original Modified Hausdorff Distance -based method by incorporating the *X* and *Y* projections in the final trajectory matching algorithm. Such solution solves the problem of the movement direction and specific trajectory configuration (found in e.g. roundabout case).

Accompanied with the ALPR technology the system can be a good deterrent from dangerous and illegal driving behaviour contributing for safety protection and fluent traffic flow.

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