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An Object Tracking Based System at Rail-Road Crossing

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ABSTRACT: Now a day's safety and security are the most discussed topics in the rail-road and railway transportation field. While trains are more convenient for travel and for transporting goods, they have become a greater danger over the years as their speed has increased. On current railway system it, is becoming ever necessary to install safety elements to avoid accidents. One of the causes that can provoke serious accidents is the existence of obstacles on the tracks, either fixed or mobile. In this paper the system is tuned towards detecting and evaluating abnormal situations induced by users in railway road crossing. Then ideal trajectory of detecting objects will be identified which will help to discard dangerous situations. Four hazard scenarios are tested and evaluated with different real video image sequences: presence of the obstacle in the rail-road crossing, presence of the stopped vehicles line, vehicle zigzagging between two closed half barriers, and pedestrian crossing the area.

KEYWORDS: safety, transport system, railway-road crossings, tracking.

I. INTRODUCTION

Consider as a weak point in road and railway infrastructure, improving rail-road crossings safety became an important field of academic research and took increasing railway undertaking concerns. Improving the safety of people and road-rail facilities is an essential key element to ensuring good operation of the road and railway transport. Statistically, nearly 44% of rail-road users have a negative perception of the environment, which consequently increases the risk of accidents. The proportion of accidents at railway-road level crossings is not very high for the society, but these accidents are very dangerous.

The risk of fatal outcome in an accident at a level crossing is twenty to forty times greater than in an average road accident. Intensive users (mostly car drivers) are highly exposed to the risk, and the population living in the vicinity of level crossings is the most endangered one. Special cases are multi-fatality accidents and especially accidents involving school buses. In the case of a school bus accident, the emotional component of Promet-Traffic-Traffico, ten triggers public campaign requiring higher safety level, which often results in institutional improvements.

The method starts by detecting pixels affected by motion as a pretreatment phase. To detect and separate objects, this method consists in clustering moving pixels by comparing specific energy vectors associated to each target and each pixel affected by motion. Once the targets are extracted from the current frame, the objective is to track them. To achieve that, an object's tracking method based on optical flow is applied. The tracking process starts by computing optical flow of corner points, extracted by Harris operator, using the Lucas-Kanade algorithm.

II. EXISTING MEATHOD

The most reliable solution to decrease the risk and accident rate at level crossings is to eliminate unsafe Crossings in the LCs' and traffics. This avoids any collisions in the transport area. Unfortunately, this is impossible, due to location feasibility and cost that would be incurred. To overcome these limits, development of a new obstacle detection system is required. The proposed system is not intended to replace the present equipment installed on each level crossing. The purpose of such a system is to provide additional information to the human operator. This concerns the detection and tracking of any kind of objects, such as pedestrians, people on two-wheeled transport, wheelchairs and car drivers.

Passive vision model technique is not an appropriate for the object detections in the transport area. So use the CCTV camera in the two main systems. That will be discussed below: A level crossing obstacle detection system using



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one single camera: This system using video cameras has been developed by G.L.Foresti . This system uses one single CCD camera placed on a high pole in a corner of the level crossing. First, the object detection is computed based on the difference between current and background images. Then, with the knowledge of intrinsic camera parameters, calibration matrix and ground plane hypothesis, the 3D position of the different objects found are computed. Then objects are tracked with an Extended KalmanFiltre (EKF). Finally, object classification based on morphological statistical spectrum is performed in order to classify objects as car, bike, trunk, pedestrian, dog, paper, etc. Tests proved that the system works well in different situations (different camera points of view, bad environmental conditions, noise, object occlusions). But this system proved to be limited in low illumination and the presence of shadows can lead to false alarm.

III. PRAPOSED MEATHOD

In video surveillance, detection of moving objects from an image sequence is very important for target tracking, activity recognition, and behaviour understanding. Motion detection aims at segmenting foreground regions corresponding to moving objects from the background. Background subtraction and temporal differencing are two popular approaches to segment moving objects in an image sequence under a stationary camera. Temporal differencing calculates the difference of pixel features between consecutive scene frames in an image sequence. It is very effective to accommodate environmental changes, but generally can only detect partial edge shapes of moving object.

1 Localization Of object Detection

Stereo vision is introduced and has become one of the most extensively researched topics in computer vision. This research has partly solved some problems related to object detection and recognition in various types of scenes. The use of multi-camera systems provides additional information, such as the depth of objects in a given scene. Dense or sparse stereovision techniques can be used to match points. In dense stereovision, all points of an input image are taken into account for matching tasks. Each disparity, determined for each point of the scene, represents the coordinate gap of the same point between the two leftand right-hand images representing the same scene from two different points of view. A depth map is obtained from the two images. Each value of this obtained map is an estimation of the distance between a real point and the stereoscopic sensor and is given using intrinsic and extrinsic parameters related to the used sensors, such as the focal length and the baseline.

2 Trajectory Defining

Active safety systems and self-driving cars are a promising solution to reduce the number of traffic accidents. Some Advanced Driver Assistance Systems (ADAS) suchas Adaptive Cruise Control, Collision Warning System and Emergency Braking System, that already exist in series vehicles, are able to warn the driver and even to intervene on the state of the vehicle when a hazardous traffic situation is being developed. A Collision Avoidance System (CAS) needs to continuously make a prediction of the evolution of the scene, in order to detect any possible future collision with the ego-vehicle. This means that it is necessary to predict the trajectory of detected vehicles in the surroundings of the ego-vehicle and its own trajectory in the case of ADAS. Predicting the trajectory of a vehicle is not a deterministic task since it depends on each driver's intention and driving habits. However, certain considerations about vehicle dynamics can provide partial or fuzzy knowledge on the future. For instance it is known that a vehicle moving at a given speed will need a certain time to fully stop and that the curvature of its trajectory has to be under a certain value in order to keep stability.

Maneuver Recognition Module (MRM) is used in order to have a better prediction considering the whole prediction. In a set of trajectories corresponding to different maneuvers is predefined. Then, a Hidden Markov Model is used to select the most likely trajectory of an object, based on its current measurements sequence. Probabilistic Finite-State Machines are usedto model complex driving maneuvers as sequences of basic elements that are specified by a set of rules in a fuzzy logic system. The rules are obtained from a training data setincluding signals such as velocity, acceleration and steering angle. A Bayes filter approach is employed to recognize a driving maneuver by computing the probability of each basic element in the context of the maneuver model. In the ego vehicle trajectory is predicted by defining a *driving context* which is a vector containing relevant signals from sensors of the testbed such as light indicator or driver's gaze direction. The driving context is continuously recorded over a sliding time frame of 2 seconds and a trained classifier discriminates between *lane change* and *lane keeping* a few seconds before the maneuver starts.

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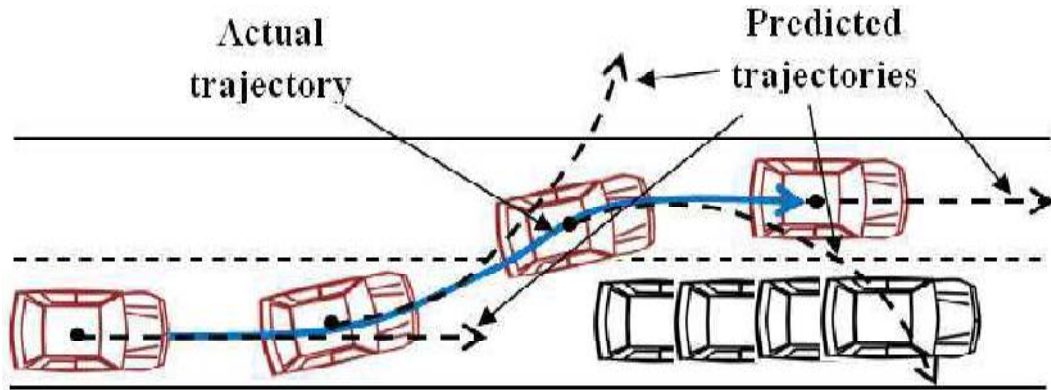


Figure 2.1 Lane changing

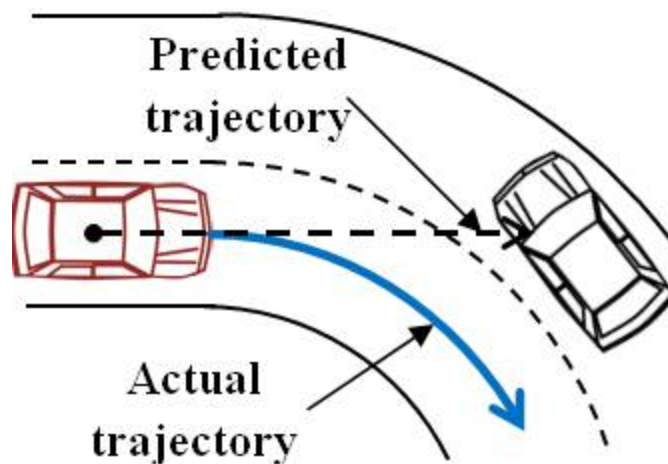


Figure 2.2 Entering a bend Bad trajectory predictions

3 Trajectory Identification

It is assumed that a target tracking system hosted by the ego-vehicle provides for each target vehicle the state vector $\zeta(\text{target})$ and its covariance matrix in a local Cartesian coordinate system:

$\zeta(\text{target}) = [x, y, \theta, v, a, \omega]^T$ (1) where x and y are the Cartesian coordinates, θ the yaw angle, v and a the longitudinal velocity and acceleration and ω the yaw rate. For one prediction operation, the working frame is static and corresponds to the current measurement frame. With the same parametrization, the ego-vehicle's state is thus defined as:

$$\zeta(\text{ego}) = [0, 0, 0, v, a, \omega]^T$$
 (2)

where v , a and ω are provided by proprioceptive sensors. It is also assumed that a camera based system detects roadmarkings and provides a local parabolic model of their centerlines in the same Cartesian frame :

$$y(x) = c_2x^2 + c_1x + c_0$$
 (3)

where c_2 , c_1 and c_0 are coefficients. The width of the lanes is also measured. The tracker and the road-markings detection system are called the Perception System in the following. For each vehicle, including the ego-vehicle, the MRM detects the current maneuver. Then, a first trajectory prediction is made, only based on the recognized maneuver. A second prediction is made by using CYRA motion model. The final predicted trajectory is obtained by combining those two predictions with a weighting-function.

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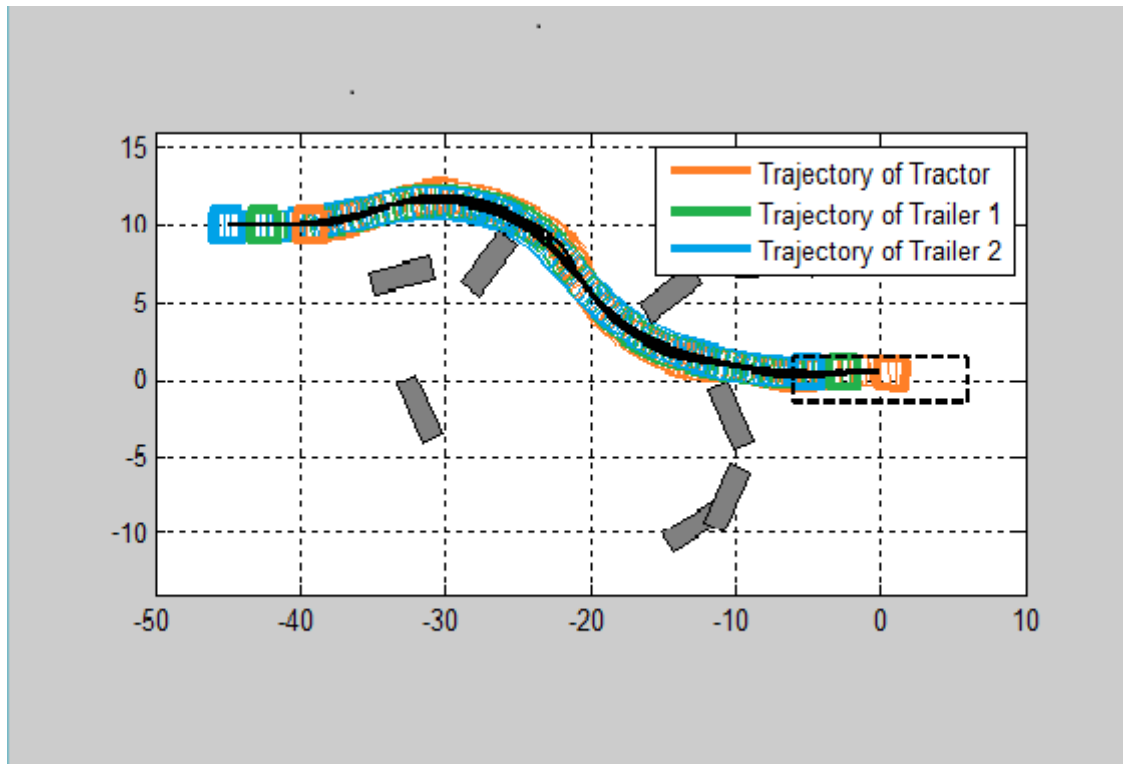


Figure 3.1 Trajectory Identification

4 Direction and Velocity Calculating

Recent advances in object tracking made it possible to obtain spatiotemporal motion trajectories for further analysis of concealed information. Although the extraction of trajectories is well understood and studied, relatively little investigation on the precise comparison of the trajectories and the secondary outputs of the tracking process is presented in the literature. A key issue in performance evaluation of tracking results is the distance metric that determines the similarity of the trajectories. Any additional analysis, such as action recognition, event detection, etc., highly depends on the accuracy of the similarity assessment. Most existing measures compute a mean distance of the corresponding positions of two equal duration trajectories. Supplementary statistics such as variance, median, minimum, and maximum distances are also suggested to extend the description of similarity.

In a recent work, Needham proposed an alignment based distance metric that reveals the spatial translation and temporal shift between the given trajectories, and introduced an area based metric that calculates the total enclosed area between the trajectories using trajectory intersections. Similarly, Ellis characterized several statistical properties of the tracking performance using the compensated means and standard deviations. One main disadvantage of the existing approaches is that they are all limited to the equal duration (lifetime) trajectories. By duration we refer the number of coordinate points that constitute the trajectory. These coordinates are sampled at different time instances. Since the existing measures depend on the mutual coordinate correspondences, they cannot be applied to trajectories that have different durations unless the trajectory duration is normalized or parameterized first.

However, such a normalization destroys the temporal properties of the trajectory. Conventional distance measures assume that the temporal sampling rates of the trajectories are equal. For instance, a ground truth trajectory labeled at a certain frame rate can be compared only with the trajectory generated by a tracker working at the same frame rate. These approaches do not cope with the uneven sampling instances, i.e. varying temporal distance between the coordinates, either. This is a common case especially for the real-time object trackers that process streaming video data. A real time tracker works on the next available frame, which may not be the immediate temporal successor of the current, whenever the current frame is processed. Thus, the obtained trajectory coordinates have varying temporal distance. Therefore, there is a need to develop other alternatives that can effectively measure the difference between unrestricted trajectories. Determine the similarity of trajectories using the conformity of the corresponding models.

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Construct a mixture of continuous Hidden Markov Models (HMM) that capture the dynamic properties of trajectory within a state transition matrix. The HMM based metrics enable the comparison of trajectories without any limitations of the previous measures.

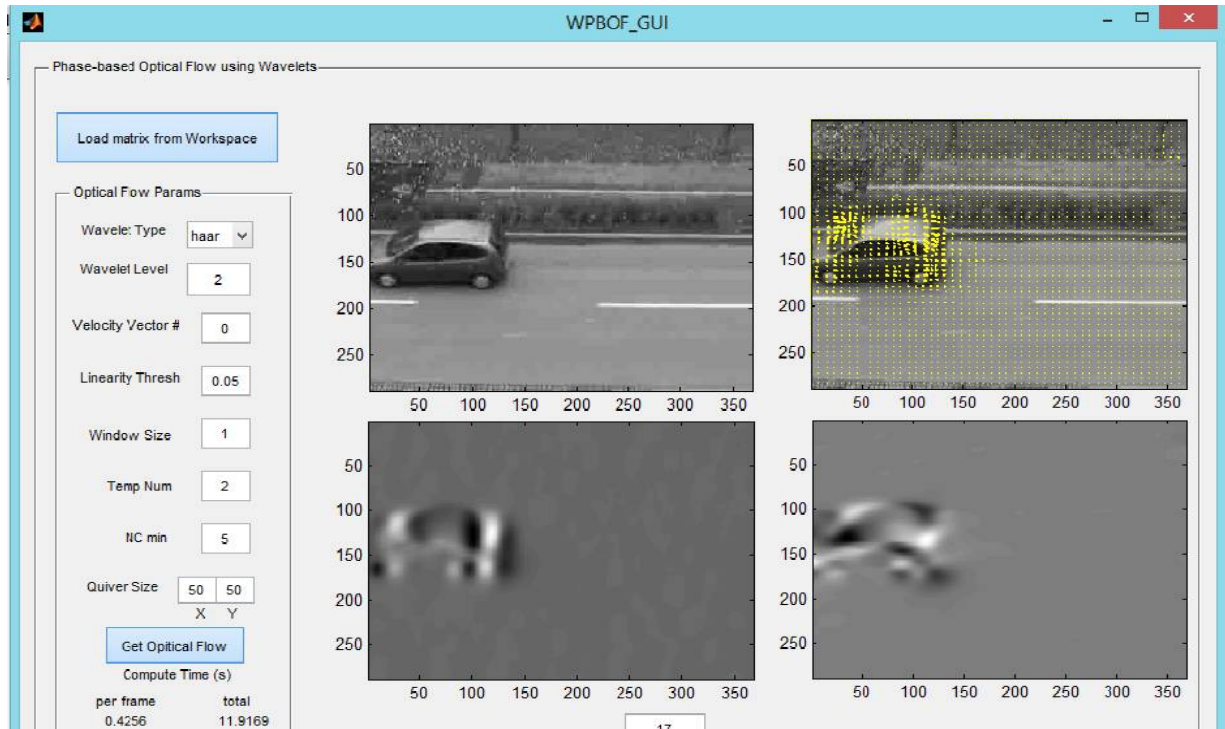


Figure 4.1 Direction and Velocity Detection Using Hidden Markov Model

IV. RESULT AND DISSCUSION

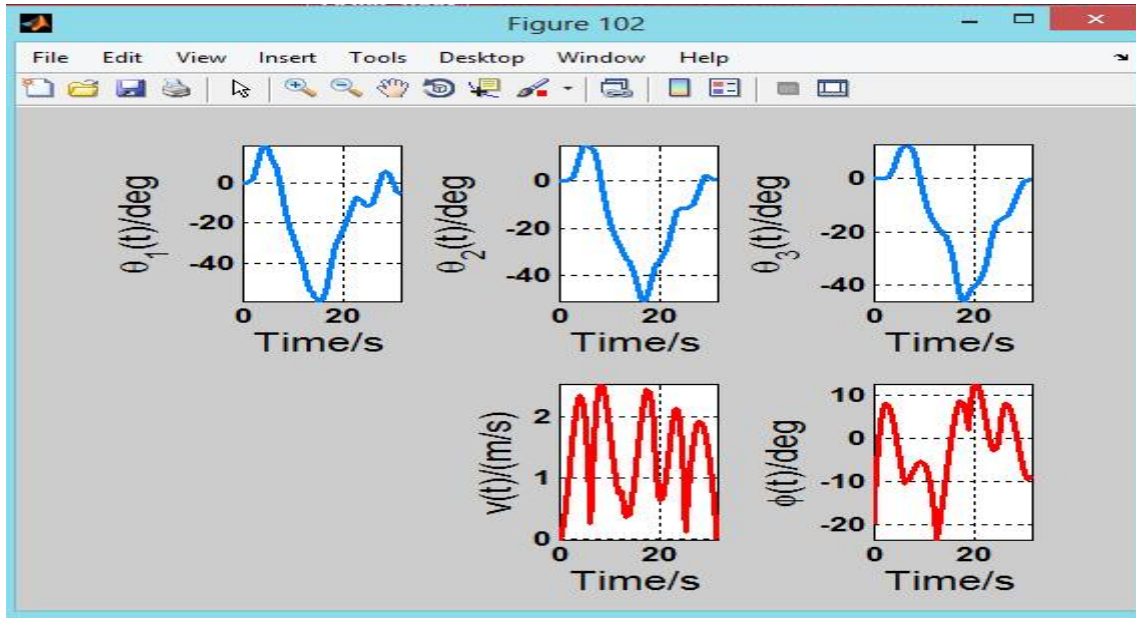
HMM based trajectory distance metrics that can accurately measure the coordinate, orient, and speed similarity of a pair of trajectories. These metrics measure different duration trajectories without destroying the temporal properties. They can be used not only for ground truth comparisons but also for further analysis of the tracking results, e.g. clustering and event analysis. Our experiments prove that the HMM distance metrics have superior discriminative properties than conventional metrics. The method includes a prediction based on CYRA motion model which is very accurate for a short term and a prediction based on maneuver recognition which is more adapted for longer term prediction. The experimental results on human real driving data proved the relevance of the method. The second contribution is a deterministic and efficient method for maneuver recognition. It is based only on kinematic measurements and road geometry detection. For real-time implementation, the complexity of the method can be kept low if the number of generated trajectories remains reasonable and if the curvature of the road is constant (in this case, the transformation from the Frenet frame to the Cartesian frame is trivial). Future works include the estimation of the uncertainty along the predicted trajectories in order to estimate the Time-To-Collision with an associated probability of collision for Collision Warning/Avoidance Systems.

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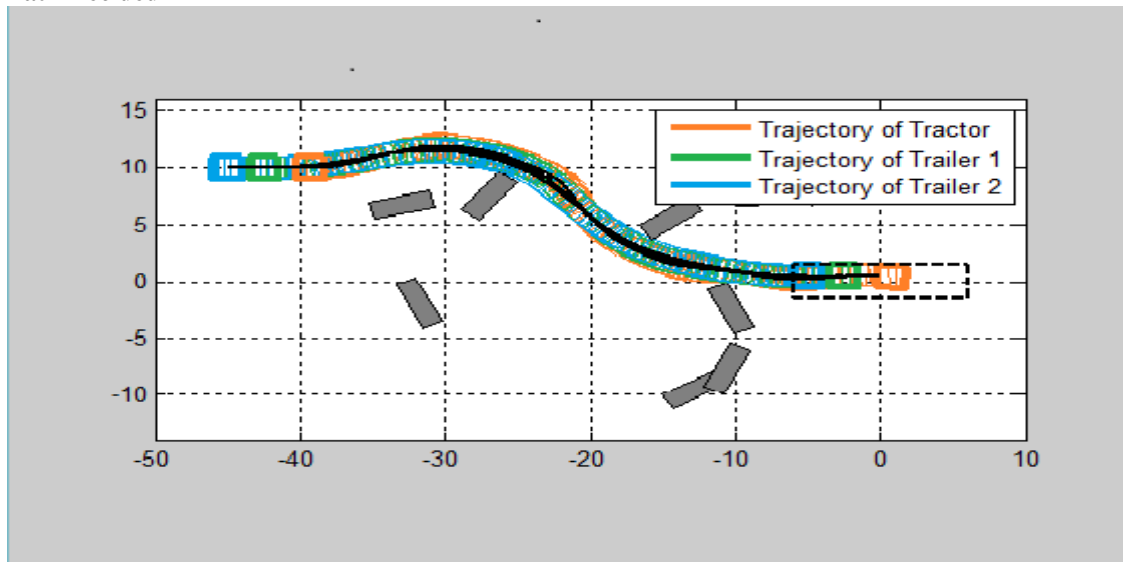
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1 Trajectory Defining And Parameters are evaluated



2 Path Decided

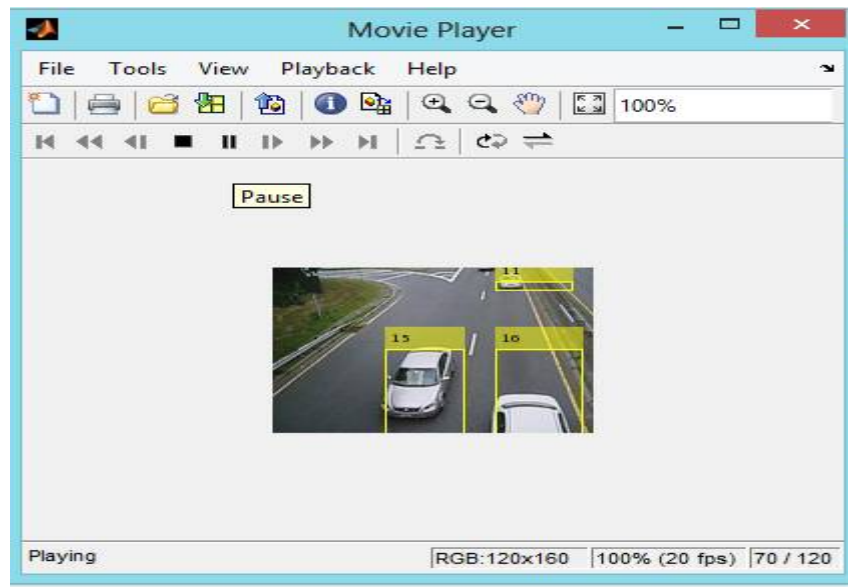


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3 Object Detection And Numbering The Objects



V. CONCLUSION

In this paper, the method starts by detecting and tracking objects seen in the monitored zone by a video camera. The second stage of the method consists in predicting for each tracked object the ideal trajectory allowing avoiding potential dangerous situations. The development carried out on the communication system within PANsafer allows us to define some perspectives in terms of progressive deployment.

This work can be extended by comparing with more existing techniques for behavioral analysis and by studying the effects of road segment sizes (or number) on the trajectory modeling. Four typical LC accident scenarios (presence of obstacles, zigzagging between the barriers, stopped cars line, and fall of a pedestrian) acquired in real conditions have been experimentally evaluated by applying the proposed dangerous situation recognition system. A risk index has been defined to assess the risk of objects detected in LC environment. The method starts by detecting and tracking objects seen in the monitored zone by a video camera. The second stage of the method consists in predicting for each tracked object the ideal trajectory allowing to avoid potential dangerous situations. The ideal trajectory prediction is based on an HMM. The third stage is concerned with the analysis of the predicted trajectory to evaluate the danger related to each tracked object. This stage is performed by considering different sources of dangerousness and applying a Dempster-Shafer-based combination.

REFERENCES

1. Nelson, "The UK approach to managing risk at passive level crossings," in *Proc. 7th Int. Symp. RailRoad-Highway Grade Crossing Res.Safety*, 2002,
2. L. Khoudour, M. Ghazel, F. Boukour, M. Heddebaut, and M. El-Koursi, "Towards safer level crossings: Existing recommendations, new applicable technologies and a proposed simulation model," *Eur. Transp. Res.Rev.*, vol. 1, no. 1, pp. 35–45, Mar. 2009.
3. J. J. Garcia *et al.*, "Efficient multisensory barrier for obstacle detection on railways," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 702–713, Sep. 2010.
4. N. Fakhfakhet *et al.*, "Background subtraction and 3D localization of moving and stationary obstacles at level crossings," in *Proc. Int. Conf. ImageProcess. Theory, Tools Appl.*, Paris, France, 2010.
5. Prioletti *et al.*, "Part-based pedestrian detection and feature-based tracking for driver assistance: Real-time, robust algorithms, and evaluation," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 72–74, Sep. 2013.
6. E. Schnieder, R. Slovak, E. M. El Koursi, L. Tordai, and M. Woods, "A European contribution to level crossing safety," in *Proc. FOVUS*, Stuttgart, Germany, Sep. 2008.



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7. Government's IT Strategy Headquarters: New IT Reform Strategy, The Realization of Society, in Which Everyone Can Benefit From IT, Anytime and Anywhere, Jan. 19 2006, 19.
8. L. Khoudouret *al.*, "PANsafer project: Towards a safer level crossing," presented at the 11th Level Crossing Symposium, Tokyo, Japan, 2010.
9. N. Fakhfakhet *al.*, "Background subtraction and 3D localization of moving and stationary obstacles at level crossings," in *Proc. Int. Conf. ImageProcess. Theory, Tools Appl.*, Paris, France, 2010.
10. Priolettiet *al.*, "Part-based pedestrian detection and feature-based tracking for driver assistance: Real-time, robust algorithms, and evaluation," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 72-74, Sep. 2013.

BIOGRAPHY

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