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Traffic Video and VANET data fusion algorithm

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ABSTRACT

Modern Intelligent Transport Systems incorporate the traffic control strategies that are based not only on long term traffic analysis and forecasts, but also on the real time events detection like accidents or high congestion. The flexibility of these systems depends on accurate and precise data set describing the current state of road network. To estimate it, the data from various sources like: video surveillance, induction loops or vehicles itself (Vehicle to Infrastructure communication –V2I) is gathered. Excluding detection errors, the video surveillance data is a reliable source of general information about the traffic flow. On the other hand, the vehicle communication can provide less reliable, but more detailed information about a particular vehicle like: its engine state or planned manoeuvre. Unreliable or forged C2I information can be used to disturb traffic or to gain a higher priority on the road. The paper reviews the fusion algorithms that are used to merge data from video tracking algorithms and vehicular networks. Based on the survey, a weighted fusion algorithm is proposed that estimates the acquired data reliability. The algorithm uses the video surveillance data as a filter for C2I communication. Finally, applications for microscopic traffic models and safety issues are taken into consideration.

KEYWORDS: VANET, video detection, fusion algorithm

1. Introduction

Acquiring data for optimal road traffic control or surveillance is a very complex issue. In case of big cities, where ITS systems are implemented, the video detection is a major source of information about the traffic. However, data provided by these systems are not detailed enough and inaccurate to be used in most traffic microscopic simulation models. The major drawback of video surveillance is a detectors quantity. Moreover, the traffic cameras are not present at every intersection or are working as virtual loop at selected traffic lanes, some intersection inlets or outlets. Finally, road constructions, which are changing road network characteristic is not followed by changes in ITS monitoring infrastructure. This drawbacks led to considering ad-hoc vehicle networks (VANET) as data inconsistence solution.

VANET offers a lot of opportunities for application's development. Modern OBUs with connection interfaces are not only able to communicate with traffic participants, send or receive warnings, but also to analyse complex messages and to generate their own safety assessments. The application possibilities of OBU are vast: avoiding traffic jams and accidents, warning about the weather threats like ice, fog or strong wind. GPS systems, used in several routing algorithms, can utilise and validate the received data. The drawback of this technology is an ability to forge information which can disturb a traffic flow. Therefore, fusion of data from various sources is required.

The paper proposes the real-time solution that aggregate data from multiple sources and filter them at the same time.

2. Related works

The paper connects four research areas: video-detection, vehicle ad-hoc networks, traffic modelling as well as data processing algorithms – modelling and fusion algorithms in particular. Each of this areas will be briefly described next, in accordance to the researched topic.

2.1. Video tracking

The knowledge of a video-detection algorithms are essential to estimate their detection error. Moving objects, like vehicles, can be detected by their shapes, appearances and actions [1]. The most common and developed practice in object tracking is to identify it first. This task can be achieved by finding the object representation in a separate frame. The object can be represented as a set of points, set of geometric figures or defined silhouette.

While using points, object can be represented as a centroid [2] and in case of several points by their spatial relations [3]. This methods are used for tracking small objects. While processing bigger objects a shape representation can be used [1]. The most advanced and time consuming are silhouette operations. They can be constructed by simple geometric shapes fusion or obtained as a result of background subtraction [2]. Despite the selected method the changes in direction and scale are managed by adaptive filters or homography transformations. The introductive surveys was made [4]. The data provided by video-detection algorithms are noised, however the most precise detection is achieved using virtual detection loops ~1m accuracy. In case of tracking objects the accuracy change with distance from the camera and is equal $(1,\infty)$ meters.

2.2. VANET solutions

Vehicular ad-hoc networks are becoming more and more reliable tool to exchange data between vehicles. The vehicles and road side units can communicate to create unified network. There are many standards and propositions how to store, secure and process the information in vehicular networks [5] [6].

According to Dedicated Short Range Standard (DSRC) to be able to create the network its nodes must be within each other's range. In case of Japan it is 30 m, in Europe it is 15-20 m and in the USA it is up to 1000 m [5]. In Europe and the United States of America 5.8 GHz bandwidth is dedicated to the vehicular communication, providing 7 or 4 channels with transmission rate 250 kbit/s for upload and 500kbit for download (in USA: 1-4 Mbit). One of the channels is strictly for security and safety purposes. Second standard is based on 802.11p transmission protocol and WAVE/ IEEE1609.3 specification[6]. Its effective transmission range is usually estimated at 100 m. However, some research shows outdoor usage for range from 400 m up to 1200 m [xx1].

Dynamic changes of the structure (reconstruction approximately every 6 s [7]) are a characteristic feature of vehicular networks. Network is usually build with redundant connections in order to stay consistent.

VANETs are built basing on the following communication standards: Wi-Fi IEEE 802.11p, WAVE IEEE 1609, WiMAX IEEE 802.16, Bluetooth, IRDA or ZigBee.

VANET is considered as a vital part of modern Intelligent Transport System (ITS). In this case we can distinguish: Inter-vehicle communication (IVC) and road-to-vehicle communication (RVC).

VANET using road-side units is able to generate position data with accuracy 3-10 m in open space and 5-20 m in urban districts (where buildings and noises are most frequent). Using video surveillance data we can verify position and pinpoint it even more precisely. To acquire data for experiments VANET simulation model was developed in [8]. Experiments shows that the ability to send message to VANET, based on 802.11 standard and at 1200 veh/h traffic volume, is 91%.

2.3. Traffic modelling

The traffic flow can be modelled both in mesoscopic, macroscopic and microscopic scale. The paper focus on separate vehicle data estimation, thus microscopic model will be considered. There are many traffic models that evaluate the positions and velocity of vehicles. The paper will use the basic kinetic traffic equations and Cellular automata to provide data and for verification purposes.

Cellular automata have become a useful tool for microscopic modelling of road traffic processes, due to its low computational complexity and high performance in computer simulations. Cellular models are limited to discrete time, space and state representation. However, despite limitations, a traffic process can be simulated with sufficient precision. The detailed implementations was thoughtfully described in [9, 10]. The model has many application and extensions for:

- urban road networks [11],
- signalised urban networks [12],
- traffic modelling [12],
- the fuzzy cellular model[13].

The paper will adopt the Kosinski ordered numbers, which proved to be potent representation in transport solutions [13].

2.4. Fusion algorithms

In century, where ITS and VANET technology is used for more and more critical applications like: Vehicle Collision Warning Systems (CWS) and Autonomous Vehicles [14], it is vital to create robust and precise localisation system. Unfortunately, all widely available systems such as GPS receivers or cellular networks alone are not the best solutions. Therefore, fusion of following technologies is required: GPS localisation, Dead Reckoning, Cellular Localization or Image/Video Localization systems. There are many works concerning the linear models with noise: gaussian/ nongaussian. To predict/ filter them Kalman Filter, which presenting highest performance in polynomial computation complexity, (classical/extended) and Particle Filter are used. Unfortunately they constantly requires position and its error estimation. The paper proposed to simplify evaluation using fuzzy numbers.

3. Model proposal

The paper introduces a model to connect data from following sources: video-detection, kinetic equations and VANET. Each data source characterise with variation and trust level. The overall relation model was presented in Fig. 1.

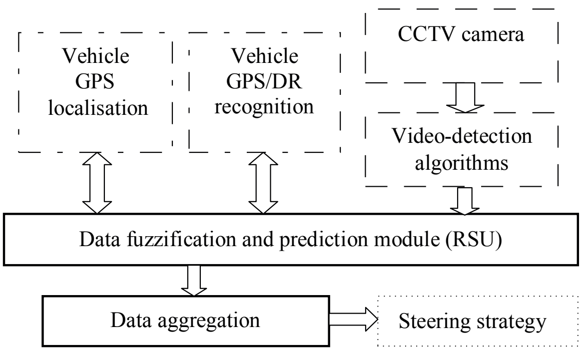

Fig. 1. The model external dependencies

The dash-dot elements are a part of VANET. Data, which are acquired from it, could be obtained continuously, however the forged as well as bias data can be sent to disturb traffic. The dashed line modules represent reliable data from surveillance system, which can be treated as a verification element. Despite reliability, video surveillance is not monitoring all traffic roads, therefore fusion of this sources is needed. The road side units collect a data from many sourced according to the scheme in Fig. 2.

Based on the model state the control functions can be performed. The traffic control strategies are described in [13]. Therefore this model will focus on bolded block, which performs data gathering and its representation in a road model.

Proposed solution reduces possibility to react on faked warnings, that could be forged in VANET.

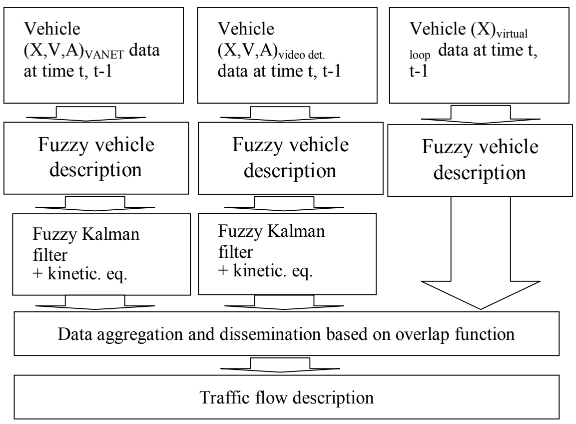

Fig. 2. Overall data aggregation model scheme

3.1. Model definition

Proposed model is flexible and it can be adapted to any VANET standard e.g. WAVE or CAR2X. The model allows system to gain data either from RSUs or from external network via GSM. In both cases the additional fuzzy vehicle description is added. The model consists of three functional blocks: the data inquiry, data aggregation into road model, and data verification procedure.

The model acquire data from multiple sources. Based on preliminary survey two types of vehicle description was distinguished:

$$c_i' = [x_x, v_x, a_x, x_y, v_y, a_y, w_a, w_v],$$
$$c_i'' = [x_x, x_y, v_y, \alpha_y, a_y, \alpha_a, w_a, w_v].$$

Vectors c_i' and c_i'' are data provided form vehicle navigation. Vectors can be shortened to describe virtual loops or video tracking data. To unify data the c_i' vector, which represents Cartesian coordinates, will be transformed to polar coordinates. The trivial transition $(v_x,x_y) \rightarrow (v,\alpha_v)$ and $(a_x,a_y) \rightarrow (a,\alpha_a)$ is performed. The vector c_i'' is considered as an unified description.

To represent vehicle data and source noise, the Kosinski ordered numbers [15] were used. A vehicle position, velocity and accuracy is defined as fuzzy ordered number. All values are represented using pair of f and g functions and four parameters $a=[a^1, a^2, a^3, a^4]$:

$$f\colon \forall a_i \in [a_i^1, a_i^2] \rightarrow [0,1], \quad (1)$$
$$\forall a_i', a_i'' \in [a_i^1, a_i^2], a_i' < a_i'' \rightarrow f(a_i') \le f(a_i''), a_i^1 < a_i^2$$
$$\forall a_i', a_i'' \in [a_i^1, a_i^2], a_i' < a_i'' \rightarrow f(a_i') \ge f(a_i''), a_i^1 > a_i^2$$
$$g\colon \forall a \in [a_i^3, a_i^4] \rightarrow [0,1], \quad (2)$$
$$\forall a_i', a_i'' \in [a_i^3, a_i^4], a_i' < a_i'' \rightarrow f(a_i') \ge f(a_i''), a_i^3 < a_i^4$$
$$\forall a_i', a_i'' \in [a_i^3, a_i^4], a_i' < a_i'' \rightarrow f(a_i') \le f(a_i''), a_i^3 > a_i^4$$

and the fuzzy ordered number, which can be defined as a pair:

$$\left(a_i, \mu(a_i)\right), \mu(a_i) = \begin{cases} 1 & : \ a_i \in [a_i^2, a_i^3] \\ f(z) & : \ a_i \in [a_i^1, a_i^2) \\ g(z) & : \ a_i \in (a_i^3, a_i^4] \\ 0 & : \ a_i \in R - [a_i^3, a_i^4] \end{cases} \quad (3)$$

The basic operation for f and g functions were defined in [15]. To simplify evaluation process trapezoid representation for vehicles was chosen (Fig. 3). Each vehicle vector c_i is defined within a lane set (L_j):

$$L = \cup L_j, j \in N$$
$$L_j = \{c_i\}, i \in N \quad (4)$$

where: L_j – j lane within road network L.

The vehicle vector c_i is further simplified to represent motion within lane:

$$c_i = [x_i, v_i, a_i, q_i, u_i] \quad (5)$$

where:
x_i , v_i , a_i – position/velocity/ acceleration within L_i lane,
q_i – accuracy [0,1] of fitness of vehicle i within lane L_j,
u_i – trust function of i-th vehicle.

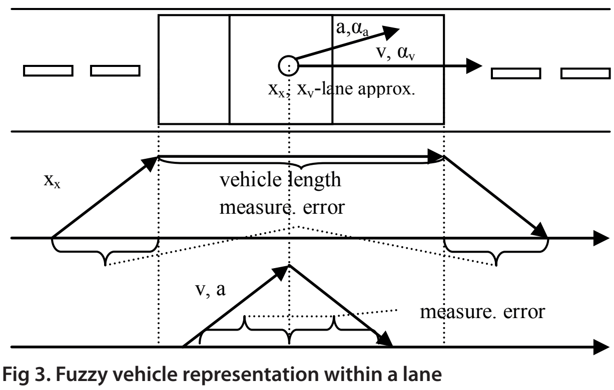

Fig 3. Fuzzy vehicle representation within a lane

The function of location determination of vehicle within a lane for video-detection is based on virtual loop and defined by one-dimension value – displacement within L_j (for vehicle tracking – several detection fields). The data aggregation for VANET is performed in accordance to the closest set of traffic lanes L' (Fig. 4).

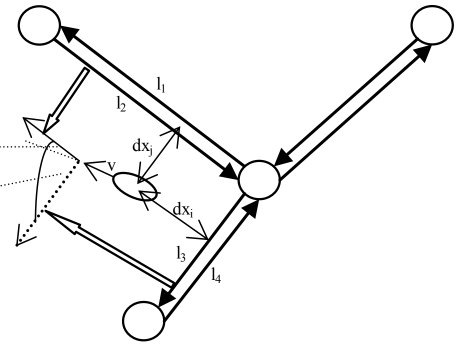

Fig. 4. Approximation of vehicle to the specific lane.

To find a probable lane the distance measure with angle between lane direction and vehicle velocity was used. The vehicle can appear on two and more lanes if they are close to each other.

The localisation detection using GPS systems has Gaussian noise, therefore the following equation was proposed:

$$q_i = \frac{k^2\ (\gamma_i,\sigma_i) dx_i{}^2}{\sum_{j=1}^{L} k^2\ (\gamma_j,\sigma_j) dx_j{}^2}, \tag{6}$$

where:

$$k(\gamma_i, \sigma_i) = \frac{1}{2\sqrt{2\pi}} e^{-\frac{\gamma_i{}^2}{2\sigma^2}},$$

σ_i – standard deviation of a measure,
γ_i – angle between lane and vehicle direction,
dx_i – perpendicular distance between lane and vehicle.

The value is decreased along with prediction horizon with dq rate. The q_i value influence detection process. The model was enriched by kinetic equation and Kalman filter to predict the vehicle state, which is not constantly updated. The Kalman filter was adopted to fuzzy ordered numbers processed by the following equations for rough estimation:

$$c_i(dt) = \begin{bmatrix} 1 & dt & \frac{dt^2}{2} & 0 & 0 \\ 0 & 1 & dt & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & dq & 0 \\ 0 & 0 & 0 & 0 & du \end{bmatrix}^T c_i \tag{7}$$

Next step require Kalman gain evaluation using fuzzification degree of x_i and x_i'(the fuzzified measure of vehicle i after dt time interval), for right side(h_r) and left side(h_l) separately:

$$h_l = \frac{(x_i^2 - x_i^1)^2}{(x_i^2 - x_i^1)^2 + (x_i^{2'} - x_i^{1'})^2} \tag{8}$$

$$h_r = \frac{(x_i^4 - x_i^3)^2}{(x_i^4 - x_i^3)^2 + (x_i^{4'} - x_i^{3'})^2} \tag{9}$$

Final estimation is performed using following equation for every c_i within L_j:

$$\widehat{x_i} = \begin{cases} x_i + h_l(xi' - x_i) : x_i^b, b \in [1,2] \\ x_i + h_r(xi' - x_i) : x_i^b, b \in [3,4] \end{cases} \tag{10}$$

The prediction process is performed for each data source separately. Based on the received data aggregation process is performed.

3.2. Data aggregation

The aggregation process is based on the sum of lane sets L_j from distinct sources. The sum is performed according to *ui, qi* and overlap function, which define the mutual correspondence between each vehicle. To reduce algorithm complexity, it can be assumed that overtaking manoeuvre is not performed, however it is a big simplification and this algorithm will take overtaking manoeuvre under consideration. The overlap function is defined as follows:

$$f_{overlap}(x_i, x_j) = \begin{cases} \frac{x_j^3 - x_i^0}{x_i^3 - x_i^0} & : \quad x_j^0 < x_i^0 \wedge x_j^3 < x_i^3 \wedge x_j^3 < x_i^0 \\ \frac{x_j^3 - x_j^0}{x_i^3 - x_i^0} & : \quad x_j^0 > x_i^0 \wedge x_j^3 < x_i^3 \\ \frac{x_i^3 - x_j^0}{x_i^3 - x_i^0} & : \quad x_j^0 > x_i^0 \wedge x_j^0 < x_i^3 \wedge x_j^3 > x_i^3 \\ 1 & : \quad x_j^0 < x_i^0 \wedge x_j^3 > x_i^3 \quad (*) \\ 0 & : \quad otherwise \end{cases} \tag{11}$$

The final position of a vehicle is defined using following general adaptation filter steps:

1. vehicle c_i are removed from lanes L_i if its value is not maximal among alternative lanes,
2. data trust value u_i is evaluated using video-surveillance data (x_i) and VANET data (x_j) using following equation: $f_u(x_i, x_j, u_i) = u_i * \min\left(f_{overl.}(x_j, x_i), f_{overl.}(x_i, x_j)\right)$
3. Remove every c_i, if its $q_i < eq$ (def: 0,1),
4. The overlap function was performed for vehicles from the same lane and various sources: L_i'+L_i".
5. If vehicles c_i and c_j overlaps more than eo=1/3, remove vehicle with lower u value, if it is not possible perform comparison for q value.
6. If there is more sources for L_i go back to point 4.

The aggregation is performed for every lane separately. After simple mathematical transformations forth rule in equation 11(eq. *) was modify to reduce *fu* complexity:

$$\frac{x_i^3 - x_i^0}{x_j^3 - x_j^0} : x_j^0 < x_i^0 \wedge x_j^3 > x_i^3 \tag{12}$$

4. Model evaluation

To verify the model a Cellular automata was used [9]. The model is enhanced by the VANET simulation platform described by author in [8]. Signal propagation from RSU to other cars via car-to-car communication takes place every second. The transmission range was defined based on European standard to 20m (100m for 802.11 standard), which is equal to 4(20) cells in the presented model. Furthermore the vehicle video-detection based on preliminary survey of algorithms is able to detect vehicles with success rate 97%. The lifetime of package in network was estimated to 5 seconds. The algorithm process data provided from a car-to-car communication, RSU or paid GSM communication. The modelled network grid was defined in fig 5.

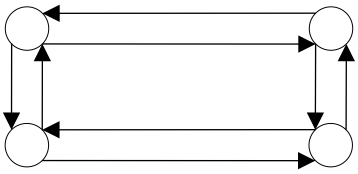

Fig. 5. The road network model

The network was tested in 1200 veh/h traffic volume,10m precision of GPS localisation and video-detection devices (accuracy 2m). Survey shows minimal impact of traffic volume on prediction of vehicle state. However, noise value from various sources is a key parameter influencing detection rate. Its relation is presented in Fig. 6. The aggregation possibility of model was also shown (as *sum* data series).

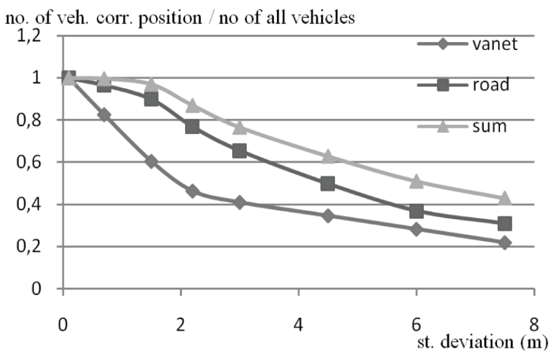

Fig. 6 The tracking error in comparison to cellular model

The research firmly shows, that fuzzification process does not influence the model precision. The low value of VANET is obtained, due to Kalman filter usage, which is responding to rapid changes in velocity of cellular model. In next experiment, the time interval between next localisation process was changed. The Fig. 7 shows description precision changes.

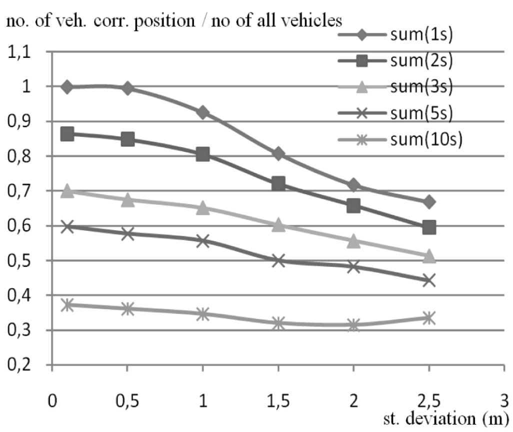

Fig. 7. The prediction abilities for various time intervals

Finally, a number of trusted vehicles in comparison to all vehicles was researched according to *du* value and supervised road area(%) (fig. 8).

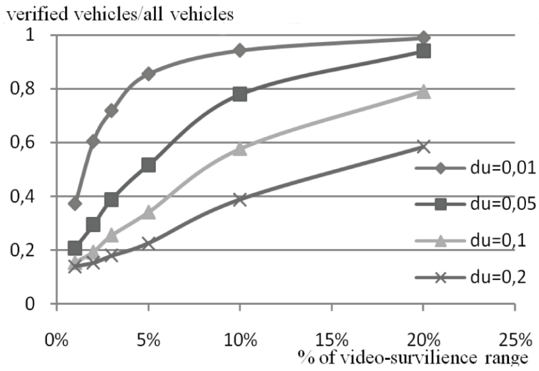

Fig. 8. Vehicle video supervision accuracy

The performed research shows, that it is possible to authorise the VANET data using video-detection, if the balance in infrastructure is maintained.

5. Conclusion

The paper proposes the adaptive filter to aggregate and validate data for VANET. The data authorisation method was proposed based on trust level (u) and data accuracy (q). Additionally, ordered fuzzy numbers was used to include data noise using its variance. Moreover, kinetic restrictions were placed using Kalman filter, thus data from various sources can be predicted. The prediction is simplified by processing data and its noise simultaneously. The model is robust, simple and can be adopted to real-time processing. The data sources accepted by model are various: video surveillance, induction loops or vehicles itself. Using model unreliable or forged C2I information can be detected, if they overlap with trusted vehicles position. The model was verified using cellular model as source data and verification data.

Further research will consider the model enhancement and experiments on real traffic data. Additionally, more advanced aggregation and verification algorithms will be developed – enhanced by driver behavioural model data.

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