Data Dissemination in Cooperative ITS from an Information-centric Perspective

Matthias Röckl, Patrick Robertson

Institute of Communications and Navigation,
German Aerospace Center,
D-82234 Wessling/Oberpfaffenhofen,
Germany

{Matthias.Roeckl|Patrick.Robertson}@dlr.de

***Abstract*— The success of cooperative Intelligent Transportation Systems (ITS) applications such as collision avoidance or adaptive cruise control stands or falls with the exchange of information between distributed and usually moving nodes. The extensive transmission of information contrasts with a limited channel bandwidth which has to be shared between all nodes. Thus, a tradeoff is required which cooperatively selects pieces of information for dissemination according to their worth for the receivers under consideration of the communication channel conditions.**

The tradeoff is achieved by an entropy-based evaluation of evidence in a dynamic probabilistic filter system. With this approach the dissemination priority is based on the uncertainty reduction which can be achieved by the reception of a piece of evidence in contrast to a pure prediction. The novelty of the approach as presented in this paper is exceptional due to its information-centric evaluation of the worth of evidence which has not been performed so far for cooperative ITS applications. It outperforms current state of the art by its generic and theoretically grounded approach for diverse applications, its inclusion of measurement uncertainty, its context-adaptability and its optimized cooperative radio bandwidth utilization.

I. Introduction

The deployment of transceivers for wireless ad-hoc communications to road vehicles (e.g. cars, trucks, motorcycles) and road infrastructure (e.g. traffic lights, traffic signs, warning signs/cones) enables the spontaneous exchange of information between these nodes. Through their cooperation they build a so called *Vehicular Ad-hoc Network (VANET)*. Respective protocols are currently in standardisation by IEEE 802.11p/1609.1-4 [1], [2] in the U.S., ASV3/4 in Japan and ETSI TC ITS [3] in Europe. The basis for every group is IEEE 802.11 WLAN [4] with enhancements to support longer ranges, faster setup, better error resistance and higher reliability required for the outdoor environment with fast moving nodes.

Using the additional information which becomes available by *Vehicle-2-X communications (V2X)* a multitude of cooperative applications can be realized, such as:

- Cooperative Collision Avoidance
- Traffic Jam Detection
- Black Spot Warning (ice, aquaplaning, obstacles, potholes, etc.)
- Cooperative Adaptive Cruise Control (CACC) [5]

More examples for cooperative applications can be found in [6], [7]. For their realization, information on position, velocity, heading, wheel slip, bumper compression, acceleration/braking activity, etc., has to be exchanged between the nodes.

The availability of remote information for each node brings cooperative applications to life. Thus, the task of every node shall be to benevolently (in the sense of achieving an overall optimum) disseminate evidence which is gathered from its local sensor system (e.g. GNSS, odometer, brake pedal, rain sensor, wheel sensors). The best results with the highest state of knowledge for every node would be achieved if every piece of evidence is disseminated to all other nodes. Since the bandwidth of the wireless channel is limited, effectively only a subset of all evidences can be selected for dissemination. Thus, a tradeoff has to be found between a extensive data dissemination and an economical usage of the available bandwidth. This local tradeoff inside each node has to be extended for a global tradeoff inside the whole VANET because the bandwidth has to be shared between all nodes in each other's communication range.

The objective of this work is to achieve an optimized exchange of evidence between nodes in the VANET. Therefore, for every single piece of evidence the worth for becoming disseminated is evaluated. The remainder of this paper hence is stuctured as follows. Section II provides an overview of current algorithms for data dissemination in VANETs. The following section proposes our novel information-centric data dissemination algorithm. The implementation for the prioritized channel access is introduced in section IV. Section VI shows evaluation results. The paper ends with conclusions in section VII.

II. State of the art

A. Car-2-Car Communication Consortium Demo

Data dissemination as currently applied in a recent demonstration event of the Car-2-Car Communication Consortium [6] was based on fixed defined message sets referred to as *Cooperative Awareness Message (CAM)* and *Decentralized Environmental Notification (DEN)*. CAMs are time-triggered messages with a periodic update rate between 0.5 and 2Hz. They include a fixed set of information on position, heading, velocity, etc. DENs are event-triggered messages which are sent whenever a certain event (e.g. switching on the hazard lights) is detected. All messages have the same priority

This kind of data dissemination does not take into account uncertainty in the sensor data, context-dependent importance of evidence (e.g. a standing vehicle does not change its position → disseminating position information with a high update rate is improvident) and bandwidth availability.

B. ETSI TC ITS

ETSI TC ITS took over the enhanced specifications of the CAM and DEN messages from the Car-2-Car Communication Consortium. These enhancements include a so called tagged list which allows the attachment of further evidence to the message according to a selection algorithm which is to be defined. ETSI TC ITS further defined priority classes for every message type which is used on MAC layer for IEEE 802.11e [8] prioritization.

According to [9] the update rate $1/t_c$ of CAMs has been refined to:

$$1/t_c = \max(0.5s, 5s - v_{max\_objects} \cdot 0.1 \frac{s}{km/h}) \qquad (1)$$

$0 \leq v_{max\_objects}$ is given by the velocity of the fastest known object in the single hop neighborhood. Therefore the frequency ranges from 0.2Hz (0km/h) to 2Hz (45+ km/h).

The proposed data dissemination algorithm does not consider uncertainty in the sensor data. It merely adapts to velocities of nearby vehicles without taking into account any other context information, its applicability is merely suitable for the exchange of CAMs and it does not consider bandwidth availability.

C. CASS

In [10] Rezaei introduced an adaptive communication scheme for the Cooperative Active Safety System (CASS) which estimates the vehicle position, first, with all gathered evidence (self-estimation) and, second, only the evidence which has been disseminated (remote estimation) with two distinct estimators. If the difference between both estimations exceeds a threshold, evidence is disseminated. According to Rezaei, the actual message update rate needed can be reduced to 1/6th in contrast to static broadcasting schemes with 10Hz update rate. The algorithm presented by Rezaei is based on point estimations (e.g. maximum likelihood or minimum mean squared error) and does not take into account uncertainty of evidence explicitly. Since the actual divergence of the point estimations is independent of the inherent uncertainties, e.g. self- and remote estimator calculate great divergence of the positions but do not detect a high measurement uncertainty, it is less suitable to explicate the actual worth of a single piece of evidence. The application of the algorithm requires the definition of a threshold which is specific for the kind of information. Thus, it cannot be used as a generic approach for all kinds of evidence.

III. Worth of Information

Information theory tells us that information is more interesting for a node if it does not know it, or, for the case of intelligent nodes, if it cannot predict it. The outcome of tossing an unbiased coin has a very high relevance to interested parties because nobody can predict the outcome. If this coin is loaded and in the majority of cases shows the same side, the outcome provides less new information to the observers. If we transfer this example to the cooperative situation estimation in future ITS, information which is almost obvious to other nodes - because it is predictable - is probably not worth sending. It would consume bandwidth and may collide with other messages which may be more relevant. Thus, an intelligent system has to differentiate the degree of "surprise" which is the level of uncertainty reduction of the information it can communicate to other nodes.

Based on this informal description a theoretical framework to estimate the worth of disseminating information will be elaborated in the following.

A. Model Description

In general, we have to differentiate two kinds of random variables: the evidence which is subject to dissemination and the situational information. Whereas the evidence E represents a concrete ascertainable quantity (e.g. a GPS or wheel slip measurement), the situational information S stands for the hidden process which caused the evidence (e.g. the real vehicle position or an icy road segment). Due to measurement inaccuracy and incompleteness, the causal connection normally is no "hard" dependency (e.g. ice on the road causes wheel slip) but has to be considered as an *elastic constraint* [11] (e.g. ice on the road makes a wheel slip more probable). It can be described by the conditional probability distribution $P(E|S)$ with S as the pavement condition and E as measurements from the wheel sensors.

B. Sender Expected Receiver Utility

In the following we assume the exchange of concrete evidence e (e.g. the position [48.06°,11.35°]) which has been gathered from a respective source of information such as a GPS receiver. The value of this evidence received by a node via V2X communication can be determined by the additional utility the receiver can gain from it. For instance, a new GPS measurement received from the preceding vehicle can be used by the following vehicle to initiate a braking action if the distance is too short. This increases its safety utility by maintaining a safe following distance. If evidence e is not received, the distance may be assessed as sufficient which decreases the safety utility. Formally, the utility gain $U(S:e)$ by the reception of evidence e measured by the situational information S is defined by:

$$U(S:e) = U(S|e) - U(S) \qquad (2)$$

with $U(S): S \rightarrow \mathbb{R}$ as the utility function which maps the situational information S to a real number, e.g. a collision risk measure. $U(S|e)$ thereby defines the utility of the situation S given the evidence e. Since S is subject to uncertainty, equation 2 can be enhanced to calculate the expected utility gain:

$$EU(S:e) = \sum_S P(S|e)U(S|e) - \sum_S P(S)U(S) \qquad (3)$$

The decision to disseminate evidence is performed at the sender. Since the sender is a priori unaware of the utility function(s) of the receiver, equation 3 is only valid under the assumption that the sender knows the single true utility function U of the receiver. Otherwise, correctly, it has to take into account the uncertainty over the receiver's utility functions by performing an expectation over all possible utility functions U:

$$SERU(S:e) = \sum_U P(U) \left[\sum_S P(S|e)U(S|e) - \sum_S P(S)U(S) \right] \qquad (4)$$

SERU defines the **Sender Expected Receiver Utility** for the situational information S by the evidence e. More general, if the concrete state e of the evidence E is unknown, SERU can be determined by:

$$\begin{aligned} &SERU(S:E) = \\ &= \sum_U P(U) \left[\sum_S \sum_E P(E)P(S|E)U(S|E) - \sum_S P(S)U(S) \right] \\ &= \sum_U P(U) \left[\sum_S \sum_E P(S,E)U(S|E) - \sum_S P(S)U(S) \right] \qquad (5) \end{aligned}$$

If we assume a single utility function which decreases exponentially with greater uncertainty, the logarithm of the probability represents a suitable objective utility function as used by Shannon in [12]:

$$\begin{aligned} SERU(S:e) &= \sum_S P(S|e)\log_2 P(S|e) - \sum_S P(S)\log_2 P(S) = \\ &= -H(S|e) + H(S) \quad \textit{[in bits]} \qquad (6) \end{aligned}$$

with $H(S)$ being the entropy of the random variable S and $H(S|e)$ being the conditional entropy of S given e.

Given any evidence E the receiver can expect a utility gain of:

$$
\begin{aligned}
&SERU(S:E) = \\
&= \sum_S \sum_E P(S,E)\log_2 P(S|E) - \sum_S P(S)\log_2 P(S) = \\
&= -H(S|E) + H(S) \geq 0
\end{aligned} \tag{7}
$$

$SERU(S:E)$ is equivalent to the mutual information $I(S:E)$ [12] which is a measure for the expected uncertainty reduction of S if E is known. According to [13] the mutual information is non-negative which means that the change in uncertainty which can be expected by additional evidence never degrades a node's state of knowledge.

C. SERU in dynamic systems

In case of periodically occuring evidences (e.g. GPS position solutions every second) the evidences are caused by a dynamic process which is for instance the vehicle movement. In a time-discretized inspection, the situational information S^k at time step k causes the evidence e^k. If this evidence is not disseminated by the sender, the receiver has to rely on a pure prediction with the previously received evidences $e^{1:k-1}$ from time step 1 to $k-1$. The $SERU$ for evidence e^k in a probabilistic dynamic system therefore is defined as follows:

$$
\begin{aligned}
&SERU(S^k : e^k|e^{1:k-1}) = \\
&= \underbrace{H(S^k|e^{1:k-1})}_{\substack{\text{Uncertainty of } S^k \\ \text{without } e^k}} - \underbrace{H(S^k|e^{1:k})}_{\substack{\text{Uncertainty of } S^k \\ \text{with } e^k}} = \\
&= -\sum_S P(S|e^{1:k-1})\log_2 P(S|e^{1:k-1}) + \\
&\qquad + \sum_S P(S|e^{1:k})\log_2 P(S|e^{1:k})
\end{aligned} \tag{8}
$$

To determine the conditional probability distributions in this equation, probabilistic dynamic filters can be applied to the first-order Markov model with situational information S and evidence E as shown in fig. 1; see the following section for an explanation of terms.

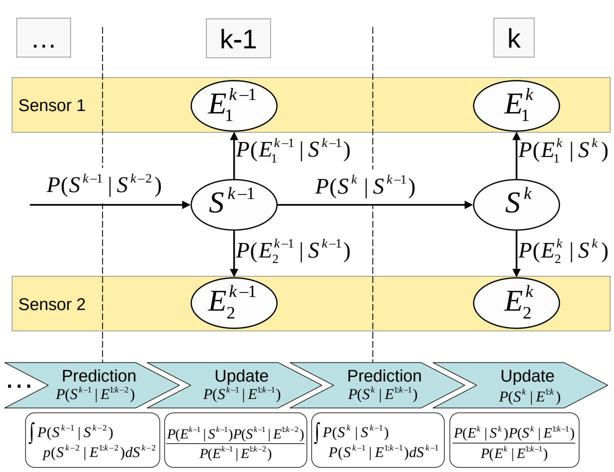

Fig. 1. Dynamic probabilistic filter model for two sensors and respective filter equations for the recursive prediction correction

Generally, probabilistic dynamic filters are based on a recursive prediction-correction process with updates every time evidence becomes available. The prediction is based on all past evidences $e^{1:k} = \{e^1, \ldots, e^k\}$ whereas evidence $e^j \in e^{1:k}$ at time slice j can as well represent a set of evidences $e^j = \{e_1^j, \ldots, e_m^j\}$ composed of evidences from the sensors $1, \ldots, m$. According to [14], [15] the **prediction** of a discrete situational information S^k (e.g. position, rain, pavement condition) for the next time slice k, where $k-1$ is the past time slice, is defined as follows:

Prediction step from $k-1$ to k:

$$
\underbrace{P(S^k|e^{1:k-1})}_{\substack{\text{Prediction of } S^k \\ \text{given } e^{1:k-1}}} = \sum_{S^{k-1}} \underbrace{P(S^k|S^{k-1})}_{\substack{\text{Transition from} \\ S^{k-1} \text{ to } S^k}} \cdot \underbrace{P(S^{k-1}|e^{1:k-1})}_{\substack{\text{Update of } S^{k-1} \text{ from eq. 10} \\ \text{of the previous time slice}}} \tag{9}
$$

With the prediction the observation window is shifted to the next time slice k. When recent evidence e^k becomes available the probability of S^k gets an **update** by:

Update step at k:

$$
\underbrace{P(S^k|e^{1:k})}_{\substack{\text{Update of } S^k \\ \text{given } e^{1:k}}} = \alpha \cdot \underbrace{P(e^k|S^k)}_{\substack{\text{Likelihood of} \\ e^k \text{ given } S^k}} \cdot \underbrace{P(S^k|e^{1:k-1})}_{\substack{\text{Prediction of } S^k \text{ from} \\ \text{eq. 9 of the current time slice}}} \tag{10}
$$

$\alpha = P(e^k|e^{1:k-1})$ is a normalization constant which ensures that the posterior probability over the entire state space sums up to one.

Since the evidences may be different in their representation length the burden which has to be carried by the communication channel differs. Thus, the resource consumption required to transmit the evidence has to influence the final data dissemination decision. In order to guarantee equality between different kinds of representation lengths the gross expected utility of the evidence has to be reduced by the costs that emerge due to the resource consumption. Thus, we define the **NetSERU** of the evidence gathered in time slice k as:

$$
NetSERU(E^k) = SERU(S^k : e^k|e^{1:k-1}) - C(e^k) \tag{11}
$$

$C(e^k)$ generally defines the costs associated with the transmission of evidence e^k. The costs depend at least on the representation length, e.g. $C(e^k) = length(e^k)$, may scale with the current channel load to spare a residual bandwidth for urgent messages and may incorporate further costs such as monetary costs if a transmission in GSM/UMTS cellular networks is considered.

IV. Prioritization

The actual decision of the transmission of evidence can be based on a hard threshold (e.g. $NetSERU > 0.5$) or, preferably to merely assign a priority value to the message which contains the evidence. Based on this priority value the communication system then performs a priority-adapted handling of the message. As an example, the $NetSERU$ can be used to assign an *access category (AC)* according to IEEE 802.11e [8] to the message. The communication system then maps this access category to the respective duration of the *Arbitrary Inter-Frame Space (AIFS)* as fixed waiting time and the *Backoff* chosen from the *Contention Window (CW)* as random waiting time and handles it with a respective transmission queue. Each transmission queue then performs a first-in/first-out (FIFO) scheduling independently. In case the backoff counters of more than one queue reaches zero the virtual collision handler resolves the concurrent transmission attempt. The reason to have independent queues is to prevent starvation of low priority messages and guarantee fairness requirements.

This is the standard procedure for IEEE 802.11e-based systems but is not appropriate for the data dissemination objective which applies for future cooperative ITS with safety aspects. In these kinds of systems high priority messages always have to be privileged in comparison to low priority messages. This concept does not only apply for transmission requests within a single node (local prioritization) but has to be applied to the whole set of nodes which are within each other's communication range (global prioritization).

Consequently, instead of several independent FIFO queues an improvement can be achieved by introducing a single fixed-length priority queue which allows an insertion of messages at arbitrary queue positions according to the $NetSERU$ value of the contained evidence. With this approach unimportant messages will be placed at the top of the queue (i.e. low priority) and will be discarded eventually if higher priority messages are inserted at lower queue positions. Since the length of the queue is limited and overflowing data will be discarded, unimportant information will neither dissipate queue positions nor waste storage resources. With the implementation of the proposed approach in every node a global prioritization of messages will be enabled since messages with high priority on any node in the network will get access on the channel before messages with lower priority.

A further improvement compared to state of the art is the handling of outdated messages. The problem arises when a message does not get access to the channel due to the existence of higher priority messages until a message arrives in the queue which contains the same kind of evidence but with a newer date. In this case the older evidence is less relevant. That does not mean that its worth is zero as it might contain useful information (e.g. movement information within a turning maneuver) but in most cases the newer evidence will have a higher worth due to its higher up-to-dateness. In order to avoid an inappropriate queue growth, our solution to this problem is to substitute the older message for the newer message and add both priorities to the new message:

$$\begin{aligned}&CNetSERU(S^k : e^k|e^{1:k-1}) = \\ &\quad NetSERU(S^k : e^k|e^{1:k-1}) + \\ &\quad \begin{cases} 0 & , e^{k-1} \text{ already transmitted} \\ CNetSERU(S^k : e^{k-1}|e^{1:k-2}) & , \text{otherwise} \end{cases}\end{aligned} \tag{12}$$

$CNetSERU$ defines the **cumulative net sender expected receiver utility** and represents the major parameter to optimize data dissemination in this work.

V. Implementation

The worth of evidence calculation (sec. III) and message prioritization (sec. IV) has been implemented within a sequential monte carlo estimator (SMC) which is also known as particle filter (more details can be found in [16] and [17], [14]). In contrast to Kalman and grid-based filters the particle filter is an approximative filter which can be used for the estimation of the posterior probability of random variables with continuous value spaces, e.g. the vehicle position given input from GNSS, odometer and compass, with non-Gaussian noise. In the following analyses the particle filter approximates the posterior probability with 1000 particles, each representing a potential hypothesis.

The state space which is estimated by the particle filter is defined by $S = \{X, Y, V, H\}$ with X as the position in X direction, Y as the position in Y direction, V as the velocity and H as the heading. The dynamic state transition model for eq. 9 is depicted in fig. 2. It is based on the following equations:

$$\mathtt{X}^k = \mathtt{X}^{k-1} + (\cos(\mathtt{H}^{k-1}) \cdot \mathtt{V}^{k-1} \cdot \Delta t) \tag{13}$$
$$\mathtt{Y}^k = \mathtt{Y}^{k-1} + (\sin(\mathtt{H}^{k-1}) \cdot \mathtt{V}^{k-1} \cdot \Delta t) \tag{14}$$
$$\mathtt{V}^k = \mathtt{V}^{k-1} + (v \cdot \Delta t) \tag{15}$$
$$\mathtt{H}^k = \mathtt{H}^{k-1} + (h \cdot \Delta t) \tag{16}$$

with

$$v = \mathcal{N}(0, 10m/s)$$
$$h = \mathcal{N}(0, 2rad)$$
$$\Delta t = \text{time}(k) - \text{time}(k-1)$$

$\mathcal{N}(\mu, \sigma)$ represents a normal distribution with mean μ and standard deviation σ. For the measurement model Gaussian distributed errors for all sensors have been assumed. Thus, the likelihood $P(e^k|S^k)$ from eq. 10 is calculated using:

- $\mathcal{N}(0, 3m)$ for GNSS measurements in UTM coordinate system,
- $\mathcal{N}(0, 0.1rad)$ for the compass, and
- $\mathcal{N}(0, 2m/s)$ for the odometer.

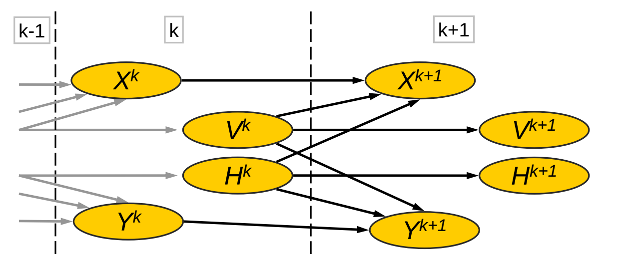

Fig. 2. Position-Heading-Velocity state transition model for the ego vehicle with the states position (X, Y), velocity V and heading H for the time slices $k-1$, k and $k+1$

VI. Evaluation

For the evaluation we implemented a time-triggered simulation enviroment which generates sensor output for simulated vehicles with 10Hz update rate. The evaluation scenario used in this work is a straight and a “zig-zag” road with two vehicles referred to as ego vehicle and target vehicle. Both vehicles move according to the Krauss model [18] with maximum velocity of 20m/s, a maximum acceleration of 2m/s^2 and a maximum deceleration of 5m/s^2. Each vehicle is assumed to be equipped with a GNSS, an odometer and a compass with the previously defined error models. The target vehicle sends out evidences gathered from these sensors according to the algorithms defined in section III and IV.

Fig. 3 shows the $SERU$ value (eq. 8) of the target vehicle during a simulation run on the “zig-zag” road. During the straight road segments the SERU varies about 0.2bit around 1.1bit. Thus, there is no significant change and the message priority is low. After each sharp bend the SERU shows distinguishable peaks since the prediction of the future position acts on the assumption of an ongoing straight movement because the map is unknown and the mean of the heading transition in eq. 16 is 0. The update with recent evidence provides an unexpected change in this movement and thus has a high SERU. The peak height depends on the current measurement quality which is not shown in the figure.

Fig. 4 shows the progress of the SERU for the target vehicle driving on a straight road. Due to faults in the positioning system,

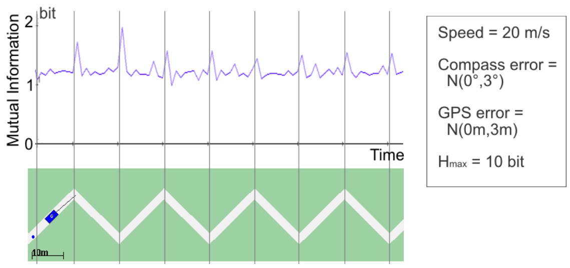

Fig. 3. Mutual information on a "zig-zag" road with sharp 90° bends

GNSS updates arrive only with an update rate of 0.4Hz. Every time a new measurement becomes available a peak in the SERU can be recognized since the uncertainty of the prediction is significantly reduced by the new measurement.

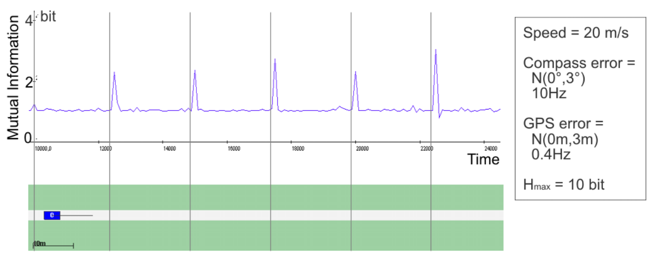

Fig. 4. Mutual information on a straight road with GNSS position fixes every 2.5 seconds

Up to now only the variation of the SERU depending on the measurement value and its uncertainty has been inspected. In fig. 5 the actual resulting update rate is evaluated when the $CNetSERU$ value of eq. 12 is used. The threshold for the dissemination decision in this figure was set to 10. Thus, every time $CNetSERU > 10$ the message containing the evidence position, velocity and heading is disseminated. The continuous line depicts the velocity of the target vehicle. The vertical bars show the mean update rate during the acceleration, the constant high speed, the deceleration and the standstill phase. During the standstill the update rate is the lowest with ca. 0.4Hz. During the acceleration and deceleration phase the update rate raises to 0.9-1Hz and during the high speed movement the update rate reaches its maximum with ca. 1.1Hz. This is justified due to the higher uncertainty of the movement prediction with higher speeds in the movement model defined in eq. 13-16.

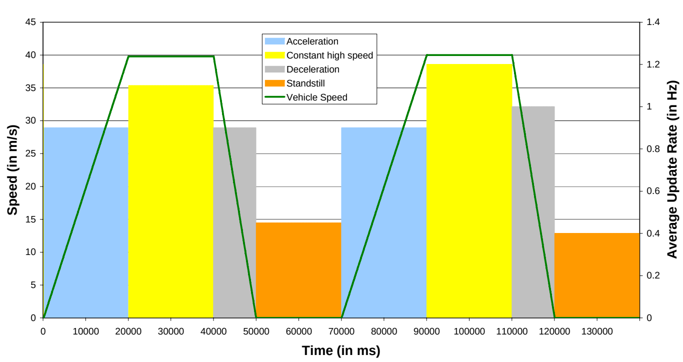

Fig. 5. Average update rate during the driving maneuvers *acceleration*, *constant high speed*, *deceleration* and *standstill*

In fig. 5 it was assumed that all other nodes in communication range have a priority equal or less than 10. The target vehicle thus was allowed to access the channel whenever $CNetSERU > 10$. In reality this value will change according to the criticality of the current situation (e.g. two vehicles on collision course have to exchange messages with very high priority). With a varying update rate the estimation uncertainty for the ego vehicle which tracks the target vehicle for collision avoidance or automatic following varies. Fig. 6 shows the mean error of the position of the target vehicle as the mean distance between the estimated position and the real position over the simulation run of 300s. The values are given for the $CNetSERU$ values (0,1,...,10) required to access the channel which represents the actual message appearance of all nodes in communication range. Additionally, the figure shows the effective transmission rate which results from the varying minimum $CNetSERU$ values. For instance, an update rate of 1Hz is the result of a high channel load where a message can only be sent if its $CNetSERU > 8$.

A major conclusion which follows from this figure results from the comparison with the uncertainty without filter application which is also shown in the figure. The minimum mean error without filter is around 3.8m which is reached with an actual update rate of 10Hz. With the application of the filter and our information-centric data dissemination scheme the same error is achieved with 1Hz. Thus, by the application of our algorithm a significant economy in the message transmission rate can be achieved if a certain maximum error shall not be exceeded. On the other hand, the error can be reduced from 3.8m to 1.2m with our algorithms if a 10Hz transmission rate can be used.

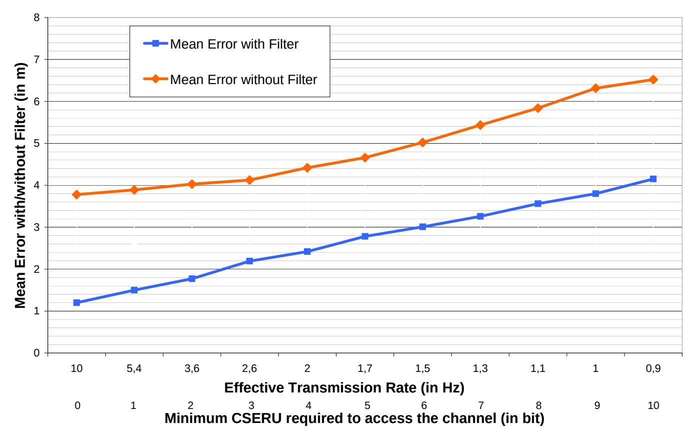

Fig. 6. Mean error with/without filter and message update rate against different transmission rates

VII. Conclusions

In this paper we introduced a novel data dissemination scheme which distinguishes itself from existing state-of-the-art by taking into account the uncertainty inherent in the measurements, the current context and the available bandwidth. Applied to a particle filter it shows promising results. One of the major results is the significant reduction of the update rate without loss of estimation quality.

It is important to note that the reduction of the update rate as shown in fig. 6 does not allow to draw the conclusion that a static reduction of the update rate has the same results. It is important to select evidence for dissemination wisely as its individual worth varies significantly (see fig. 3 and 4). The proposed algorithm incorporates all these factors into a single generic decision process which can be applied to every node which actively participates in the VANET. By making a global trade-off between benefit and costs the system scales with increasing penetration rate and is hence perfectly suited to accompany the introduction of cooperative ITS in the world.

ACKNOWLEDGEMENT

This work has been partly funded by the European Commission through FP7 ICT Project iTETRIS: *An Integrated Wireless and Traffic Platform for Real-Time Road Traffic Management Solutions (No. FP7 224644)*

REFERENCES

[1] "Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications - Wireless Access in Vehicular Environments (WAVE) - IEEE 802.11p," IEEE, Tech. Rep. IEEE P802.11p/D4.02.

[2] "Wireless Access in Vehicular Environments (WAVE)," VTS/ITS Committee of IEEE ITS Society, Tech. Rep. IEEE1609.1-4, 2005.

[3] "European Telecommunications Standards Institute (ETSI) - Technical Commitee (TC) - Intelligent Transportation Systems (ITS."

[4] "Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) specifications - High-speed Physical Layer in the 5 GHz Band (Part 11)," LAN/MAN Standards Committee of IEEE Computer Society, Tech. Rep. IEEE Std 802.11a-1999(R2003), June 2003.

[5] M. Röckl, J. Gacnik, and J. Schomerus, "Integration of Car-2-Car Communication as a Virtual Sensor in Automotive Sensor Fusion for Advanced Driver Assistance Systems," in *International Federation of Automotive Engineering Societies (FISITA)*, A. of German Engineers (VDI), Ed. Munich, Germany: Springer Automotive Media, September 2008.

[6] "Car-2-Car Communication Consortium - Manifesto," 2008.

[7] C. A. M. P. (CAMP), "Vehicle Safety Communications Project Task 3 Final Report: Identify Intelligent Vehicle Safety Applications Enabled by DSRC," Tech. Rep., March 2005.

[8] "Medium Access Control (MAC) Quality of Service (QoS) Enhancements (Amendment 7)," LAN/MAN Standards Committee of IEEE Computer Society, Tech. Rep. IEEE P802.11e/D10.0, September 2004.

[9] European Telecommunications Standards Institute (ETSI) - Technical Commitee (TC) - Intelligent Transportation Systems (ITS, "Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; [Part 2: Specification of Cooperative Awareness Basic Service;]."

[10] S. Rezaei, R. Sengupta, H. Krishnan, and X. Guan, "Adaptive Communication Scheme for Cooperative Active Safety System," in *NewsBITS*, vol. 4, no. 2. Institute of Transportation Studies, University of California, Berkeley, December 2008.

[11] J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Francisco, USA: Morgan Kaufmann, 1988.

[12] C. E. Shannon and W. Warren, "A Mathematical Theory of Communication," 1949.

[13] D. J. C. MacKay, *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, 2003.

[14] Z. Chen, "Bayesian filtering: From Kalman filters to particle filters, and beyond," Adaptive Systems Laboratory, McMaster University, Tech. Rep., 2003.

[15] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Prentice Hall, 1995.

[16] M. Röckl, K. Frank, T. Strang, M. Kranz, J. Gacnik, and J. Schomerus, "Hybrid fusion approach combining autonomous and cooperative detection and ranging methods for situation-aware driver assistance systems," in *IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC) 2008*, September 2008.

[17] S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A Tutorial on Particle Filters for On-line Non-linear/Non-Gaussian Bayesian Tracking," *IEEE Transactions on Signal Processing*, vol. 50, 2001.

[18] S. Krauß, "Microscopic Modeling of Traffic Flow: Investigation of Collision Free Vehicle Dynamics," Ph.D. dissertation, 1998.