Cooperative Wireless Sensing for Characterization of Congested Traffic States

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***Abstract*— In this work we propose the use of vehicles as traffic sensors to quasi-synchronously measure both velocity and position of the probe. Those sensor vehicles wirelessly cooperate to relay that distributed information to a Data Fusion Center. That Data Fusion Center, in turn, calculates the Spatio-Temporal Velocity (STV) Field of the traffic from the gathered data. From the STV Field, it has been previously shown that Congested Traffic States (CTS) can be fully characterized. The actual distribution of stationary probes (induction loops, cameras, ...) used to reconstruct the STV Fields is usually very sparse with relation to the space-time variability of the CTS features of dense traffic. We propose the Wireless Sensor Network System for Early Detection of CTS. As a first result, we present the error incurred in reconstructing the STV Field with an increasing density of sensor vehicles. We show that with a fraction of sensor vehicles sensing communicating their position and speed as low as 10% is enough to stabilize the error. We also show the effect of including finite precision in the positioning system.**

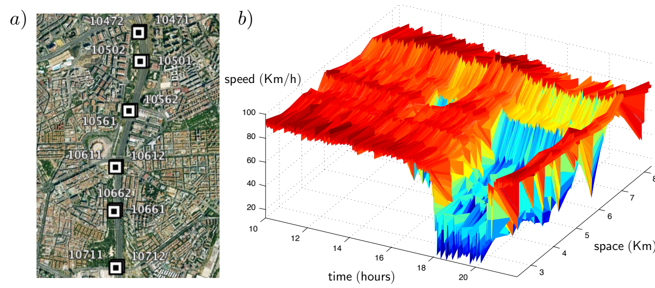

Fig. 1. a) Position of speed sensors in the north-to-south lanes of the M-30 beltway in Madrid, Spain, near the "Puente de Ventas" congestion point. The third digit in each identification number indicates the position of the coil in the beltway in kilometres. b) Spatio-temporal velocity field measured by the aforementioned sensors on November, 8, 2009.

I. Introduction

In high density traffic areas surrounding big cities such as belt highways, monitoring variations in the flow of vehicles is critical in many aspects ranging from economic impact to quality of life. The usual method to monitor these beltways is by means of induction coils laid under the tarmac which are able to count the number of cars per unit time, measure velocity and even discriminate between types of vehicles. This data is measured, averaged and communicated with a frequency of tens of seconds to the monitoring centre. However, the installation, operation and maintenance of these coils is costly and cumbersome as it can affect the normal flow of vehicles. Because of this economic aspect, the coils are usually spaced hundreds of metres apart (See Fig. 1).

However, it has been recently shown that, when metastable congested traffic states appear (e.g. without the need of bottlenecks) the spatial features of the oscillating traffic flow are but a few car lengths apart [1]. Therefore, it remains to be seen that the present accepted setup for measuring traffic flow in highways, with sensors placed hundreds of car lengths apart capture the essential features of those metastable states that usually precede highly congested traffic. On the other hand, the exact classification of Congested Traffic States (CTS) remains to be analytically described, but a few works have tried to characterize them in terms of microscopic (individual driver) behaviour of the traffic [2]. The distinction of the Space-Time Velocity (STV) field characteristics of CTS such as Stop-and-Go Waves (SGW), Oscillating Congested Traffic (OCT) or Widening Synchronized Patterns (WSP) is crucial to understand their causes and predict their transition times to Homogeneous Congested Traffic (HCT).

In this work we propose the use of the Wireless Sensor Network (WSN) paradigm that make use of a fraction of the vehicles as sensors the communicate via wireless measures of their individual velocities and positions to roadside wireless bridges or clusterheads. These, in turn, forward this space-time distributed information to a Data Fusion Center which accurately reconstructs the STV Field. This enables the accurate classification and characterization of CTS to predict congestions in the future.

The structure of the work stands as follows: In Section II we will describe the outline of the system of vehicular WSN, based on the communications system of IEEE 802.11p standard. The limits on the communication channel are described. The problem of the distribution of the sensor vehicles to accurately probe the STV field is addressed. In Section III we present the results of microscopic simulations of traffic and the attempt to reconstruct the STV Field with a varying Fraction of Sensor Vehicles (FSV). We also present the results of the Mean Squared Error (MSE) with an increasing FSV, evaluating the effect of finite precision in positioning systems. Finally in Section IV we present our conclusions and future extensions of the present work.

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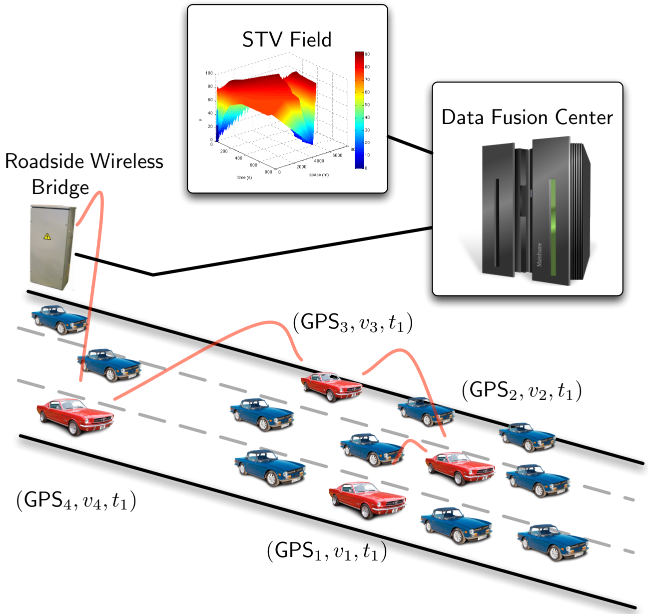

Fig. 2. Outline of the Vehicular Wireless Sensor Network along with the roadside and Data Fusion Centre infrastructure. Blue cars mark the passive cars while red cars mark the sensor vehicles. Red lines indicate the relay channel used to communicate the quasi-syncronous measurements of position (GPS_n) and velocity (v_n) of different vehicles at different sampling times (t_i). This data is provided to the Data Fusion Center for it to calculate the STV field.

II. System Model of Wireless Network of Sensor Vehicles

The system model of the WSN that we propose to probe the STV field of traffic in highways is presented in Fig. 2. The elements of the system are the following:

- Passive Vehicles (PV): Vehicles in the traffic with no communication capabilities.
- Sensor Vehicles (SV): Vehicles capable (index n) of sensing their position (GPS_n) and velocity (v_n) at times t_i. These measurements are relayed via the ad-hoc vehicular network of nearby SVs. The density of sensors is related to the total number of vehicles/time/lane. A constant Fraction of Sensor Vehicles is defined as $\mathsf{FSV} = \mathsf{Flow\ of\ SV}/\mathsf{Total\ Flow\ of\ Vehicles}$ where $\mathsf{Total\ Flow\ of\ Vehicles} = \mathsf{Flow\ of\ SV} + \mathsf{Flow\ of\ PV}$.
- Roadside Wireless Bridges (RSWB): Fixed Wireless aggregators of sensed data.
- Data Fusion Center (DFC): Center for processing spatio-temporal data gathered by the RSWBs to construct STV fields of the traffic flow of interest.

The operation of the WSN is as follows: each SV records its position and velocity periodically. The communication of the recorded variables is relayed via the wireless channel through other SVs to the RSWBs. These report the gathered data to the DFC which reconstructs the STV field from the measurements.

We will now address three specific issues within the proposed system, 1) the specificity of the Vehicular Ad-hoc NETwork (VANET) which is used as communication system to the traffic WSN and its limits, 2) the operation limits as a data gathering system and 3) the space-time distribution of the SV to accurately measure the STV field.

A. *Cooperative Communications in VANET and their limits*

VANETs have been proposed as a communication system where the cooperative wireless channel is the weakest link in the communication chain. So we have to address the specific problems that will affect the correct determination of the STV field. Late or lost data packets are determinant to the correct operation of the system. The main problems of the Quality of Service (QoS), i.e., delay and jitter in the data to the DFC (which affect the quasi-synchronous operation) and the Packet Loss Probability in this system are:

- The number of wireless hops to the nearest RSWB. This metric determines, not only the delay of the data stream, but its change in time determines the variation in delay, i.e., the jitter.
- The quality of the individual Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) wireless channels. These channels determine the end-to-end Bit Error Rate which, in turn, determines the end-to-end Packet Loss Probability.

We will now detail the specific features of the base protocol for VANETs (IEEE 802.11p) that could affect the operation of the proposed vehicular WSN.

The international standard IEEE 802.11p, also called Wireless Access for Vehicular Environment (WAVE), is a new amendment of the 802.11 family. WAVE uses certain mechanism provided by IEEE 802.11, properly modified to support Intelligent Transports Systems (ITS) services on Dedicated Short Range Communications (DSRC) band. DSRC band is centred in 5.9 GHz (U.S.) and 5.8 GHz (Europe). According to communication involving two nodes or link layer communication, there are two basic modes of operation: V2V and V2I communication. The stations on the roadside (RSU) and mobile radio units located on board of vehicles (OBU) can share information related to road and traffic conditions and use it to improve the safety and efficiency of the transportation system. The first mode is strongly related to Mobile Ad-Hoc Networks (MANETs), resulting in Vehicle Ad-Hoc Networks (VANETs), which have their own characteristics over them. IEEE 802.11p specifications covers the PHY layer and MAC layer. Upper layers, IEEE 1609.1, 1609.2, 1609.3, 1609.4, satisfy the WAVE connection setup and management, switching and routing, as well as the use of multiple channels without addressing PHY layer issues.

WAVE/DSRC adopts the same PHY defined for 802.11a, with 10 MHz channels instead of the usual 20 MHz, in order to decrease the inter-symbol interference caused by multipath delay and Doppler spread. Binary rate is, in consequence, reduced in a half. Typical modulation schemes (BPSK, QPSK, 16QAM and 64QAM) are legal in the Orthogonal Frequency-Division Multiplexing (OFDM) arrangement. Besides the reduction the bandwidth of each channel, there is a specialised use of them in order to provide reliability in safety and emergency applications. On U.S. Frequency allocation, the spectrum is structured into seven channels. Channel 178 (Control Channel or CCH) is mainly dedicated to safety communications. RSUs announces to On Board Units OBUs, 10 times per second, the applications it supports and the available channels. OBUs listen to channel 172, gathering to RSUs services. Ch 184 is reserved for high power and public safety applications. The rest is available for safety and non safety usage.

Medium access and sharing employs the same mechanism as 802.11 family with some essential improvements that dramatically reduces the connection setup. Joining a WAVE BSS only requires receiving a single WAVE Advertisement message from the initiating station. A station in WAVE Mode is allowed to transmit and receive data frames without pairing to a BSS, with wildcard BSSID only. This means, two vehicles can immediately communicate with each other through the same channel. The 802.11p MAC protocol is equivalent to the 802.11e Enhanced Distributed Channel Access (EDCA) with QoS support. Messages are then classified into different access categories (AC), where the lowest priority corresponds to AC0 and the highest to AC3. Thus, safety and critical messages uses AC3, both messages generated by the RSUs and the OBUs. The lowest priority may be given to non safety messages over the service channels.

The most noticeable effect of classical routing algorithms in VANETs [3] has been recently studied with experimental setups in the I-80 California freeway. It has ben shown that, as the VANET oscillates between fully connected to sparsely connected-state and free-flowing traffic, those algorithms were unable to cope with the re-healing times that generate the transition from one state to the other. In this work we will assume a fully connected network as congested traffic states are our main interest to characterize. Therefore, delay and jitter will be limited only by self-interference from the relaying path. As the PHY layer implemented by IEEE 802.11p standard is highly resilient to self-interference, the delay will be accounted for the individual transmission times multiplied by the number of wireless hops from SV to the RSWB. Delay can be assumed as negligible.

However, as CTSs imply a higher spatial density of vehicles in the VANET, if the deployment of RSWB is sparse (kilometres apart), the limits of consecutive relaying of digital information play an important part in the system. As it has been shown in [4], a scaling-law emerges to limit the end-to-end Bit Error Rate (BER) performance of a relaying fading channel. It follows that, whenever the number of consecutive hops reach the order of tens, for practical use, line-of-sight wireless channels, the end-to-end BER (and therefore, the Packet Loss Probability) increases exponentially.

Exhaustive simulation results show that IEEE 802.11p performance quantifies the Packet Loss Probability, for typical VANETS in CTS from 0.6% for nearest-vehicle distance of 5 m (1 car length) to 8% in free-flow traffic conditions [5]. Therefore, a Packet Loss Probability of less than 1% is to be expected for individual V2V communications. In this work we implement deployments of RSWB that do not allow for relay paths with a number above 15 hops.

B. Wireless Sensor Traffic Network

The Wireless Sensor Network (WSN) features a special case of MANET which results in the so called Data Gathering Channel [6]. The limits of such system, using a planar deployment of sensors are similar to those encountered for more general MANET, namely, that the traffic data goes to zero as the number of relaying sensors (with finite throughput) increase. Not only we find that problem if a hierarchical structure of the data gathering system (such as the one proposed at the beginning of this section) is not employed. The sensors are to be deployed to closely follow the variations of the probed field. As such a priori knowledge is usually not available, many techniques have been employed to determine the optimal spacing of sensors in a correlated field [7].

In the vehicular WSN studied in the present work, the probed field is the STV field. Abrupt changes are bound to happen once traffic congestion settles (see Fig. 1). The problem is further complicated because of the inherent non-equilibrium system which represents traffic flow in a freeway. To determine a measure of the variation of the STV field in sensible traffic conditions, we can study an approximate description of traffic flow as an steady-state system.

One possible approach to determine the space-time features of the traffic flow is the use of stochastic differential equations, such as the Fokker-Planck equation, to describe the vehicle statistics [8]. Within this approach, the behaviour of the vehicles is described by the coupled car-following equations

$$\frac{dv_i}{dt} = \frac{v_0 - v_i}{\tau} + f(s_i) - \gamma f(s_{i-1}) + \xi_i(t)\,, \tag{1}$$

where $v_i(t) = dr_i/dt$ is the speed of vehicle i at time t, v_0 the maximum velocity, $s_i(t) = r_i(t) - r_{i+1}(t)$ the distance, and $\xi_i(t)$ represents a white noise fluctuation term. The term $\gamma f(s_{i-1})$ with $0 \leq \gamma \leq 1$ can be understood in terms of two extreme cases: $\gamma = 0$ corresponds to the case of forwardly directed interactions of vehicles, while $\gamma = 1$ corresponds to symmetrical interactions of vehicles in forward and backward direction. This function can be related to a potential interaction function $U(s_i)$.

The above stochastic differential equation (Langevin equation) can be rewritten in terms of an equivalent Fokker-Planck equation. With the definitions

$$\begin{aligned}
W(s_i) &= v_0 + \tau[f(s_i) - \gamma f(s_{i-1})]\,, \\
f(s_i) &= -\frac{\partial U(s_i)}{\partial s_i}\,, \\
\langle \xi_i(t) \rangle &= 0\,, \\
\langle \xi_i(t)\xi_j(t') \rangle &= D\delta_{ij}\delta(t-t')\,, \\
\text{and } P &= P(s_1, \ldots, s_n, v_1, \ldots, v_n, t)\,, \qquad (2)
\end{aligned}$$

this Fokker-Planck equation reads

$$\frac{\partial P}{\partial t} = \sum_{i=1}^{n} \Bigg\{ -\frac{\partial}{\partial s_i}[\underbrace{(v_i - v_{i+1})}_{=ds_i/dt} P] - \frac{\partial}{\partial v_i}\left[\left(\frac{W(s_i)-v_i}{\tau}\right)P\right] + \frac{D}{2}\frac{\partial^2 P}{\partial {v_i}^2}\Bigg\}, \quad (3)$$

where periodic boundary conditions $v_{k+n}(t) = v_k(t)$ and $s_{k+n}(t) = s_k(t)$ are assumed for a highway of length L. A stationary solution to the Eq. 3 is the probability distribution

$$P(s_1, \ldots, s_n, v_1, \ldots, v_n) = \mathcal{N} \mathrm{e}^{-\sum_j [U(s_j)/\theta + B s_j]} \mathrm{e}^{-\sum_j (v_j - V)^2/(2\theta)} \quad (4)$$

where $V(t)$ represents the average vehicle velocity

$$V(t) = \langle v_i \rangle = \int ds_1 \ldots \int ds_n \int dv_1 \ldots \int dv_n \, v_i P(s_1, \ldots, s_n, v_1, \ldots, v_n, t) \quad (5)$$

$\theta(t)$ represents the variance vehicle velocity

$$\theta(t) = \langle (v_i - V)^2 \rangle = \int ds_1 \ldots \int ds_n \int dv_1 \ldots \int dv_n \, (v_i - V)^2 P(s_1, \ldots, s_n, v_1, \ldots, v_n, t) \quad (6)$$

and, finally, $\mathcal{N}$ is a normalization constant

$$\mathcal{N} = \left[\int ds_1 \ldots \int ds_n \int dv_1 \ldots \int dv_n \, \mathrm{e}^{-\sum_j [U(s_j)/\theta + B s_j]} \mathrm{e}^{-\sum_j (v_j - V)^2/(2\theta)}\right]^{-1} \quad (7)$$

The parameter B is required to specify the actual vehicle density (i.e. to ensure $\sum_j s_i = L$).

We can see from the probability distribution in Eq. 4 the vehicles in a highway tend to aggregate into clusters that depend exponentially decreasing on average and variance velocity. Thus, abrupt changes in a few vehicles lengths (as observed experimentally in [1]) are to be expected from small variances in velocity.

If a regularly spaced distribution of static sensors (induction loops) is used, for an accurate reconstruction of the STV to be performed, Nyquist theorem states that a spacing of more than double the highest frequency of the Fourier Transformed STV field (which would characterize the smallest aggregations of vehicle clusters) should be used. This would mean that, assuming a vehicle length of 5 metres, induction loops should be installed every few tens of meters. This is simply prohibitive.

On the other hand, if a vehicular WSN were to be used with a constant FSV, the deployment of SVs would closely match the variations in the STV field. The economy in the deployment of the infrastructure (the deployment of the RSWBs) would be a fraction of the cost of deploying induction loops. The OBUs would benefit from economy of scale and the sensorization of velocity and GPS positioning are negligible.

III. Results

A. Reconstruction of STV Fields from Sensor Vehicle Measurements

In the simulations used throughout this work, we have used a microscopic traffic model known as the Intelligent Driver Model (IDM) [2]. The reasons to choose this model over a macroscopic one, is the need for individual sensors (sensor vehicles) to exist in the simulation with its own distinct behaviour of position and velocity. This model is characterized by an acceleration function for each individual vehicle (or driver unit)

$$a_{\mathsf{IDM}}(s, v, \Delta v) = a\left[1 - \left(\frac{v}{v_0}\right)^4 - \left(\frac{s^*(v, \Delta v)}{s}\right)^2\right] \quad (8)$$

where

$$s^*(v, \Delta v) = s_0 + Tv + \frac{v \Delta v}{2\sqrt{ab}} \quad (9)$$

The state variables of the IDM model are s, the gap to the leading vehicle, v, the velocity and Δv, the velocity difference with the leading vehicle. The model parameters are the following: $v_0 = 95$ km/h is the desired velocity in the highway, $T = 1.6$ s, the desired time headway, $a = 0.73$ m/s^2, is the desired acceleration, $b = 1.67$ m/s^2 is the desired deceleration, $s_0 = 2$ m is the minimum gap with the leading vehicle. We assume identical driver units, with a length of 5 m. The initial flow of cars is fixed at 0.5 cars/s/lane. For a discussion of the stability of the collective behaviour that rises from this nearest-leading-neighbour model and the correspondence to measured CTS in actual highway traffic, please refer to [2]. In our simulations, in addition to the reconstruction of the STV field with no positioning, velocity or synchronization error (in order to establish a baseline for comparison), we introduce errors in synchronization of ≤ 0.2s and the precision of the in-car positioning systems as stated in Table I of [9]. We assume a sensing (and communication) rate of 1 Hz per vehicle. We introduce a time head inhomogeneity to force a CTS at $P = 5,550$ km such that the time head around that point is defined by the following expression:

$$T(s) = \begin{cases} T_0 & s < P - L/2 \\ T_0 + (T_1 - T_0)\left(\frac{s}{L} + \frac{1}{2}\right) & |s - P| < L/2 \\ T_1 & s > P + L/2 \end{cases}$$

where $T_0 = 1.6$ s, $T_1 = 1.75$ s and $L = 700$ m.

We show the results of the simulations in Fig. 3 where it can be seen that the actual STV field (Fig. 3a)) can be reconstructed pretty accurately (Fig. 3c)) from the trajectories of a FSV $= 10\%$, even allowing for GPS errors (Fig. 3b)). Even though the transition to a CTS is quite abrupt around $P = 5,500$ km, the main features of the CTS survive this sparse sampling in a simple linear interpolation reconstruction. Thus, we validate our premise that the distribution of SV closely follows the abrupt changes in the STV field when a CTS is met.

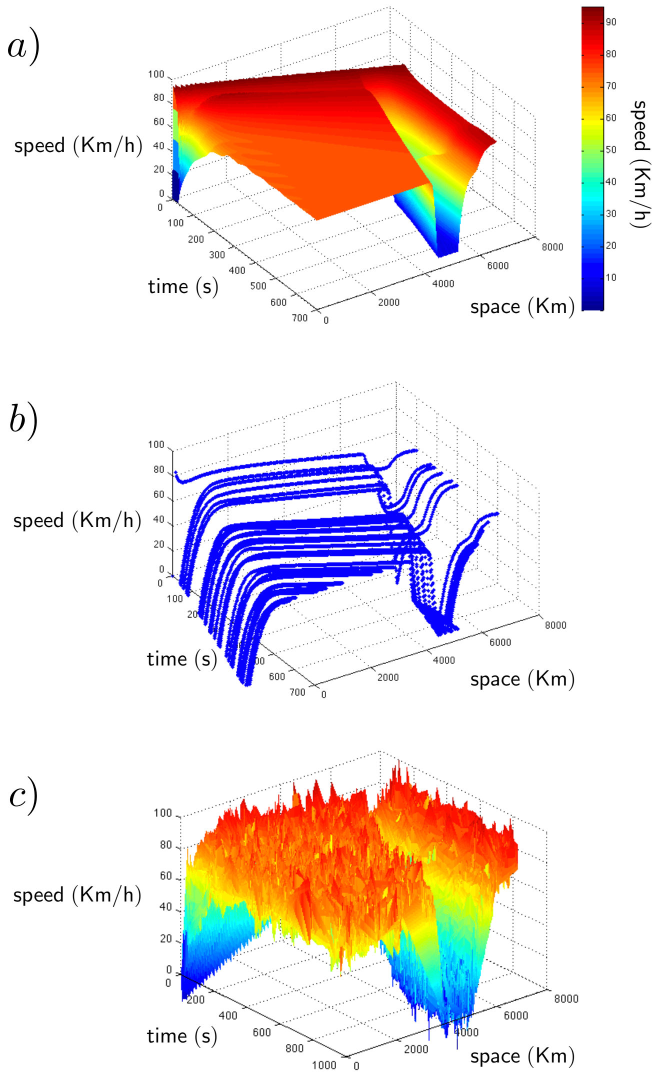

Fig. 3. a) Actual STV Field from a simulated traffic instance with the Intelligent Driver Model (IDM) with traffic flow variables extracted form the situation presented in Fig. 1. Precision of the STV Field is 5 m, *i.e.*, the length of the cars in the simulation. b) Phase-space trajectories from separate (random) sensor vehicles corresponding to a Fraction of Sensor Vehicles (FSV) of 10% reported every 1 s. c) Reconstructed STV Field from the measurements of the data recovered from b). A GPS error of 7 m in horizontal positioning is taken into account.

B. Accuracy of STV Fields with increasing FSV

We now pursue the minimum figure of FSV needed to allow for an accurate enough reconstruction. With the same configuration as the one described in the previous section, we increase the FSV from 1% up to 30% in 1% intervals. For each FSV, 20 random selections of SVs are separately carried out, allowing for statistical verification (up to within the error of the measure with a 90% confidence interval) of an inverse law for the Mean Squared Error (MSE) of the reconstruction (Fig. 4) with respect to the actual STV field.

Therefore, we can observe that, for a FSV = 10%, the MSE is stable up to within the error of the measure. This fact allows us to state that with a fraction of sensor vehicles

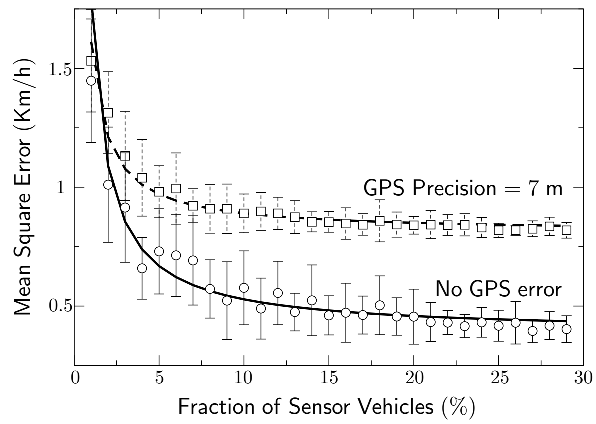

Fig. 4. Mean Squared Error (MSE) of the STV Field reconstruction from different instances of random sensor vehicles corresponding to the same FSV. Circles (with continuous error bars) indicate the MSE of different reconstructions if no positioning error is assumed. Square symbols (with discontinuous error bars) show the MSE of different reconstructions if the precision of the positioning system is limited to 7 m. Both the continuous and the discontinuous lines indicate the $a + b\,(\mathsf{FSV})^{-1}$ fit to each of the previous simulation results.

as low as one in ten vehicles, the error in obtaining the STV field of the Congested Traffic State with Cooperative Vehicular Wireless Sensor Network is within the error of the measure, have the measure been taken with a FSV = 100%. The comparison with respect to a deployment of fixed sensors with identical spatial density as the one shown in Fig. 1 can be up to four times as erroneous as the one shown in the present work.

IV. Conclusions and Future Works

A. Conclusions

In this work we have proposed a WSN for a vehicular networks to measure the STV field of traffic flow in highways. The data is relayed by means of the vehicular network to Roadside Wireless Bridges, which forward this information to a Data Fusion Center. We have shown that with a small fraction of the vehicles acting as sensors (as low as 10% of the vehicles), the reconstruction of the STV field is within a stable error margin. The reason for this accuracy is the inhomogeneous distribution of the sensor vehicles, which closely follows the defining patterns of the present Congested Traffic States.

B. Future Works

The work presented here is but the first step in a developing framework which will allow accurate reconstruction and prediction of CTS. Further developments are possible in order to allow the aforementioned feats. In the Data Fusion Center, linear interpolation techniques are to be substituted with advanced, nonuniform interpolation techniques [10]. This will allow a lowering in the difference between the MSE incurred when finite precision is taken into account, with the infinite precision positioning. The use of pattern recognition techniques, such as Support Vector Machines, in order to identify metastable features of CTS and predict future Congested Traffic is in the works.

In the field of the vehicular WSNs, we are to test the performance of the proposed system in transitions from free-flow traffic to specific CTSs, where a transition from a sparsely connected VANET to a fully connected one is expected to occur.

V. Acknowledgements

The authors would like to acknowledge the cooperation with SICE for the M-30 data and David Gutiérrez-Pérez for his aid in the data-processing.

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