An Agent-based Sensor Grid to Monitor Urban Traffic

Maria Nadia Postorino and Giuseppe M. L. Sarné

***Abstract*— The growing of vehicular traffic in urban areas has worsened the citizens' quality of life. Therefore some actions to reduce their negative effects and to improve transport network performances have been implemented over the years. To this purpose, agent-based Intelligent Transport Systems can contribute to manage a transport network. In this work, a non-intrusive grid of agent-based sensors able to monitor traffic parameters is proposed. It exploits acoustic signatures of road vehicles and then analyses them to estimate traffic flows. Moreover, cooperating neighboring agent sensors implement a trust system to improve their performances. Some experimental results show the feasibility and the advantages of the proposed solution.**

***Index Terms*—Acoustic Vehicle Signature, Multi-Agent System, Sensors Grid, Transport System, Trust System.**

I. Introduction

Facing the increasing rate of vehicular traffic in most cities, government Authorities' new strategies is to manage the existing rather than to invest in new infrastructures [1]. This current tendency is also due to environmental awareness and reduced availability of budgets for new and more expensive investments [2], [3].

In this context, a relevant aid is coming from progresses in computer science, electronic, control systems, signal processing, communications and more and more sophisticated traffic models to realize Intelligent Transport Systems (ITS) that improves transport network performances [4], [5]. Therefore, nowadays it is easier (*i*) to assist drivers on their travel decisions by real-time traffic information systems (for instance, directly provided on their personal devices [6]) (*ii*) to adopt effective traffic control strategies (e.g., restricted traffic zones; speed limitation) starting from user travel preferences [7].

In this paper, a new approach is proposed to detect and monitor traffic flows in order to adopt suitable traffic control strategies. The system works in real time, requires inexpensive detectors and produces very low environmental impact. More in detail, a sensor grid detects passages of vehicles and then classifies them according to their acoustic signatures [8]. Each sensor of the grid is associated to a software agent [9], [10], an autonomous software entity coordinating all its activities and cooperating with the other sensor agents.

The detection of the acoustic signatures generated by moving vehicles (see Section II-A) is based on the adoption of simple and non-intrusive acoustic sensors, although it implies a complex signal processing phase that here has been based on the use of artificial neural networks (ANN) [11]–[13]. Each sensor agent manages a distributed trust system in order to refine its outputs (see Section II-D and III). More in detail: (*i*) the ANNs process the vehicle acoustic signatures and return the traffic flow measures by limiting potential loss of accuracy due to environmental noise signals [14]; (*ii*) each sensor agent which cooperates with its neighbouring sensor agents corrects and improves the ANNs outputs by using the Trust Reputation Reliability (TRR) model [15], [16] takes account of the existing interdependencies among their trust measures (i.e. each trust measure permeates all the other trust measures in order to obtain more reliable trust values).

A prototype of the proposed sensor agent grid has been realized by using the agent platform JADE [17] and some tests have been performed to verify its performances. To this aim, the real data of a transport sub-network were used.

In the following, Section II provides an overview of the proposed sensor agent. The trust system is described in Section III, while the results of the real data experiments are presented in Section IV. The Section V deals with related work and, finally, Section VI draws some main conclusions

II. The Sensor Agent

This Section presents an overview about the sensor agent, represented in Figure 1 according to: (*i*) the analogic signal detection; (*ii*) the A/D signal conversion and its pre-processing; (*iii*) the ANN pattern analysis to return some traffic measures; (*iv*) the traffic measure correction based on a distributed trust system locally implemented by each agent.

A. Signal Detection

Traffic detectors [18]–[20] are classified according to the adopted physical principle (i.e. radio frequency, pressure, magnetic fields, audio, etc.) and their positioning (i.e. on-board or in/over roadway).

On board traffic detectors include the GPS-based ones [21], able to collect many travel data (i.e. travel time, average speed, directions, etc.) for several transport applications [22], although GPS signal could be loss, mainly due to the land morphology. The in/over roadway class includes detectors recognizing vehicles (and other traffic parameters) that are moving across a detection zone. In turn, they are classified in *intrusive* (e.g. inductive loops and pneumatic or piezoelectric tubes) and *not intrusive* (e.g. video, audio, infrared or microwave detectors) [23].

The first ones are subject to deterioration, while the others are susceptible to the adverse weather conditions (e.g.severe

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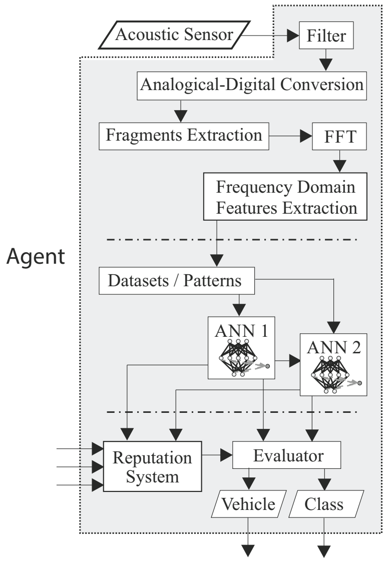

Fig. 1. The Tasks of the sensor agent.

fog blinds video sensors) but they: (*i*) avoid to trouble traffic for installation and maintenance issues; (*ii*) follow road direction or geometry changes easily; (*iii*) monitor more lanes also with a single sensor; (*iv*) have a low vulnerability to mechanical damages. However, the choice of the best sensor to use relies on many factors as required data, traffic composition, road geometry, intrusiveness, installation and life, weather conditions.

In this work, non-intrusive audio detectors (microphones) have been considered. They detect the acoustic vehicle signatures generated by the interactions tire-road and by other inside noise sources (e.g. the engine) [24], [25]. Indeed, they are cheap, easy to install or remove, return several traffic data (i.e. speed, vehicle category, vehicles gap, etc.) and their performances are quite good, although their accuracy might fail for adverse weather, stopped or very slow vehicles, high background noise level or for a wrong sensor location.

B. Signal Processing

Acoustic vehicle signatures main characteristic is its quick variation in time (see Figure 2) and frequency domains for: (*i*) kinematic, amount and traffic flow composition; (*ii*) road geometry; (*iii*) weather; (*iv*) reflecting obstacles (e.g. buildings, vehicles). Furthermore, the audio signal is apparently modified because of the Doppler effect [26]. Then, it grows in intensity and frequency when the vehicle approaches the sensor (i.e. microphone) and vice versa when it moves away.

The acoustic vehicle signature is very rich of information but not all of them need. To delete irrelevant information, the signal processing starts with a filtering phase to cut off (*i*) noise signals with a low intensity as, for instance, overnight and (*ii*) the frequencies over the 5 KHz (see below).

The resulting analogical signal is converted in digital one (A/D) [27], [28] by applying a Pulse Code Modulation (PCM) transformation including: (*i*) a sampling process to return a discrete-time signal with constant amplitude; (*ii*) a quantization on a finite number of levels; (*iii*) a codify. According to the

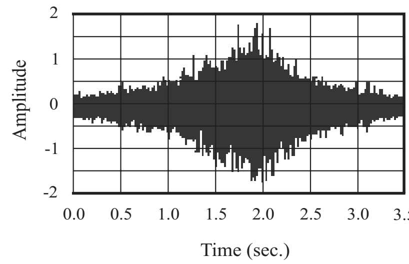

Fig. 2. The characteristic sound produced by vehicles moving with respect to a fixed point in the time domain.

hypothesis that about 90% of useful information belongs to the range $100 \div 5000$ KHz [12], this process[1] has been performed by adopting a 10 Khz sample frequency, a quantization on 16 bits and a Grey codify. When vehicles are spaced for more than 1 sec, a software procedure extracts a fragment (F) of 1.5 seconds (centred on the peak value) from each audio track enclosed between two gaps. According to the Doppler effect and the used ANNs (see below), some preliminary tests shown that a frequency spectrum analysis of such fragments allows the passage and the class of a vehicle to be identified. Then each audio fragment F is split into three equal slices (s_i, with $i = 1, 2, 3$) of 0.5 second (to consider the Doppler effect) and converted from the time to the frequency domain with a Fast Fourier Transformation (FFT) [29].

Finally, some features representing the most salient signal characteristics have been extracted from each slice. Their type and number depend on the adopted analysis procedure and then some tests have been performed by using a trial and error method (see Section II-C). Consequently, each slice s_i was split in some frequency bands (f_j) from which the mean values of the emitted signal power has been computed to represent it. Tests identified the best balance between computational costs and accuracy, showed a subdivision of the frequency range 100-5000 Hz in ten regions having boundary frequencies of 100, 149, 220, 325, 480, 709, 1047, 1548, 2288, 3383 and 5000 Hz. Note that any useful result is possible with less of nine frequency bands.

C. The ANN Component

ANNs, inspired to the biological neural networks, fit well the problem to recognize passage and class of a vehicle from its acoustic signature [25] without having knowledge on the specific function linking input and output data. According to some preliminary tests, two multilayer supervised ANNs, trained by a back-propagation (BP) algorithm [11], have been identified as the optimal solution in terms of architecture, topology and parameters calibration.

Briefly, the BP algorithm works for patterns (examples) and modifies iteratively its learning parameters based on the error between predicted and expected output values. The learning process ends if the unknown relationship between input and output is reached with the required precision. Then the trained ANN can be directly applied to unknown patterns.

[1]Note that a 0-20 KHz signal, 44.1 kHz sampled, 16 bit quantized and codify by using the Grey code, generates more of 40.000 samples for second.

Specifically, we adopted three-layer ANNs with hyperbolic tangent and sigmoid as neuron functions for the hidden and the output layers, respectively. Both the ANNs receive in input 30 values for pattern, i.e. the 10 feature values extracted by each slice s in which is split F (see Section II-B), and return real values ranging in $[0, 1]$. The first ANN identifies a vehicle passage, while the second one classifies it according to three pre-fixed categories (e.g., car, truck/bus or motorcycle). Therefore the first ANN has only 1 output neuron and the second one 3. Consequently, each training pattern of the first ANN dataset consists of 30 input and 1 output value, while that of the second ANN has 30 input and 3 output values. Moreover, 3 vehicle type and noise organized on 6 different categories (e.g., rain, wind, strong wind, noise, loud noise, background, respectively) have been considered for the training.

D. The Trust System Component

Each sensor agent calibrates its ANN outputs based on those of its neighboring agents (i.e. the agents directly connected to it on the transport network). To this aim, the sensor agent exploits a distributed trust system that, according to the trust the agent assigns to its neighboring agents, weight the traffic values provided by them. More details about the trust system are given in Section III.

III. The Trust Reputation Reliability Model

The Trust Reputation Reliability (TRR) model [15], [16], is an extension - particularly a distributed version - of the mathematical model described in [30]. Briefly, in TRR each agent has its perception of the trust (τ) of each other agent (in its community) providing a service, for instance data based on its reliability (ρ) and reputation (π) measures. In the following the TRR model will be described in the detail.

A. Reliability in the TRR model

In TRR each agent a has its own reliability model independently from the other agents. Therefore, the reliability of the agent b (i.e. $\rho_{ab} \in [0, 1] \in \mathbb{R}$) for the agent a is given by $\rho_{ab} = f_a(i_{ab})$, where i_{ab} is the number of interactions that a and b performed. In other words, the level of knowledge a has of b (i.e. i_{ab}) due to their past interactions is considered.

B. Reputation in the TRR model

The agent a computes the *reputation* of the agent b (i.e. $\pi_{ab} \in [0, 1] \in \mathbb{R}$) by asking to each other agent c of its community, different from a and b, an opinion about the capability of b in providing a service. In TRR the opinion of c, represented by the trust measure (see below) that c has in b (i.e. τ_{cb}), is weighted by the trust that a has in c (i.e. τ_{ac}). Therefore, in TRR the reputation of an agent is different for each agent depending on both its individual perception and on the opinions of the other agents. Formally, the reputation π_{ab} is computed as the *weighted mean* of all the opinions (i.e. the trust measures) of each other agent c, different from a and b, weighted by the value of the trust that a has in c as:

$$\pi_{ab} = \frac{\sum_{c \in C - \{a,b\}} \tau_{cb} \cdot \tau_{ac}}{\sum_{c \in C - \{a,b\}} \tau_{ac}} \tag{1}$$

C. Trust

Commonly, the trust measure that an agent a assigns to an agent b for its service (i.e. $\tau_{ab} \in [0, 1] \in \mathbb{R}$) combines the reliability measure ρ_{ab} with the reputation measure π_{ab}. Thus the direct knowledge that a has about b and the suggestions given from the other agents to a about b are taken into account in the trust measure. Some approaches require to specify the percentage of relevance given to the reliability with respect to the reputation. In TRR τ_{ab} is computed by using the parameter α_{ab} (i.e. $\alpha_{ab} \in [0, 1] \in \mathbb{R}$) to weight the reliability ρ_{ab} and $(1 - \alpha_{ab})$ to weight the reputation π_{ab}. Formally, the trust assigned by a to b is computed as:

$$\tau_{ab} = \alpha_{ab} \cdot \rho_{ab} + (1 - \alpha_{ab}) \cdot \pi_{ab} \tag{2}$$

Differently from the past, it is assumed that the relevance of the reliability with respect to the reputation increases with the number of interactions i_{ab} occurred between the agents a and b (i.e. $\alpha_{ab} = \alpha_{ab}(i_{ab})$). In particular, $\alpha_{ab} = 1$ only if i_{ab} is higher than or equal to a threshold N (a system parameter); otherwise, if α_{ab} depends on the ratio i_{ab}/N. More formally:

$$\alpha_{ab} = \begin{cases} \frac{i_{ab}}{N} & \textit{if } i_{ab} < N \\ 1 & \textit{if } i_{ab} \geq N \end{cases} \tag{3}$$

Consequently, τ_{ab} can be expressed as:

$$\tau_{ab} = \alpha_{ab} \cdot \rho_{ab} + (1 - \alpha_{ab}) \cdot \frac{\sum_{c \in C - \{a,b\}} \tau_{cb} \cdot \tau_{ac}}{\sum_{c \in C - \{a,b\}} \tau_{ac}} \tag{4}$$

This equation, written for all the agents, leads to a system of $n \cdot (n-1)$ linear equations containing $n \cdot (n-1)$ variables τ_{ab}, where n is the number of agents. This system is equivalent to that described in [30] and admits only one solution.

D. Distributed solution

When there is a wide agent community, the direct solution of this trust model is behind the computational capabilities of our sensor agent [31]. Therefore, we implemented a distributed approach where each agent applies the trust model only with respect to its neighboring agents. In such a way, we obtain a lot of small, handling and partially overlapped trust systems, were the trust values are propagated through the trust systems.

IV. The Experiment

This section presents the results of some experiments aimed at verifying the effectiveness of the proposed sensor agents both in (*i*) returning number and category of the detected vehicles and (*ii*) operating in a grid configuration on a transport network. The prototypes of the agents have been realized in JADE [17] and a sampling campaign has been carried out in the city of Reggio Calabria, in Southern Italy. Before describing the two experiment components, a brief overview of collected data and ANN training step is presented.

The sampling campaign involved 4 detection points, for 4 working days and 3 sessions for day (i.e. h. 8-9, 13-14 and 18-20, when the traffic reaches its peaks) on one-ways and one-lane roads in different traffic and weather conditions. Each detection point consisted of a microphone close to the road and a notebook to store data.

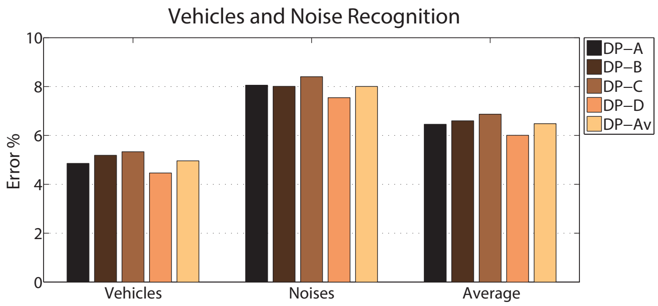

Fig. 3. Traffic and Noise Recognition performed by ANN_1 in recognizing vehicles and noises at each Detection Point (DP) A-D and the average error (DP-Av)

Part of the collected data have been used to train the ANNs (see Section II-B). Preliminary tests defined the optimal ANNs topologies (i.e. 30, 55 and 1 neurones and 30, 25 and 3 neurones for the input, hidden and output layers of ANN_1 and ANN_2, respectively). In particular, the input data are the feature values (see Section II-B), while the output, ranging in $[0, 1] \in \mathbb{R}$, for ANN_1 (resp. ANN_2) means a vehicle passage or a noise (resp. the membership to a vehicle class). The training datasets involved 2500 normalized patterns, 50% vehicles (e.g. cars, truck/bus and motorcycles with a prevalence of cars, likely to the real traffic, without affecting the performances [32]) and 50% noises shared on 6 noise classes in equal amounts (see Section II-C). The training phases ended after about 14500 iterations for ANN_1 and 9800 for ANN_2. Note that only one ANN was unable to detect a vehicle passage and/or its class with an acceptable precision.

a) Experiment 1: To verify the performances of our sensor agent, the trained ANNs received in input unknown patterns as a continuous flow of acoustic signals to process (see Sections II-B, II-C). As a result, 93.41% of ANN_1 and 88.46% of ANN_2 showed an average accuracy in respectively recognizing vehicle passages from noises and classifying the vehicles, see Figures 3 and 4. These results are interesting and close to those of the best (and more expensive) traffic detectors. However, note that: (*i*) some vehicles misclassification are due to their acoustic signatures similar to that of other categories, for instance some vans are similar to cars; (*ii*) ANN_1 mistakes (i.e. noises classified as vehicles) impact on the ANN_2 performances. (*iii*) idle cars or bad weather conditions made the sensor unable to provide useful results. More in general, tests have shown that each sensor unit overestimates slightly traffic flows and most part of the errors are due to noises recognized as vehicles.

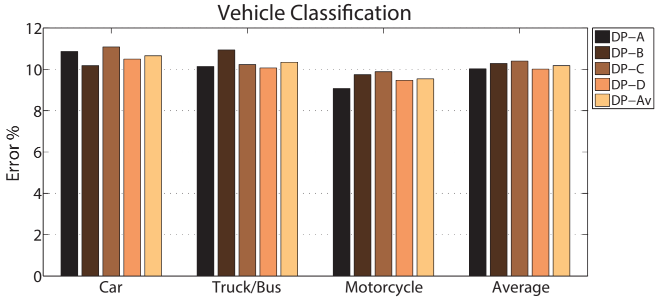

Fig. 4. Vehicle Classification performed by ANN_2 for the ANN_1 output at each Detection Point (DP) A-D and the average error (DP-Av)

b) Experiment 2: According to Figure 1, the second part of the experiment concerns the reliability of the sensor grid to limit unpredictable misleading (i.e. due to temporary obstacles) and the overestimation attitude of the ANN heuristic procedure. The test has been made on a small 4-detection point real grid, see Figure 4. To this purpose, each sensor agent computes periodically its traffic measures and sends them to each of its neighboring agent together with the last calculated trust values of their common neighboring agents.

Let F_x be the traffic flow detected by the sensor agent x in a time Δt and let $F_x^{'}$ be its weighted value computed as $F_x^{'} = \tau_x^x \cdot F_x$, where τ_x^x is the trust of x calculated by itself based on the TRR model. Note that if F_x and $F_x^{'}$ are greater than the maximum capability of the road (i.e. F_x^{max}) then we set them to F_x^{max}. Moreover, let FI_x (resp. FO_x) be the sum of all the incoming (i.e. ongoing) traffic flows for x provided by its neighbor agents and let $FI_x^{'}$ (resp. $FO_x^{'}$) be its weighted traffic flow computed as $FI_x^{'} = \sum_{i=1}^{n_I} \tau_i^x \cdot FI_{x,i}$ (i.e. $FO_x^{'} = \sum_{i=1}^{n_O} \tau_i^x \cdot FO_i^x$), where τ_i^x is the trust the sensor agent x has calculated for the i-th sensor about its capability of providing trusted values. Furthermore, let $\overline{F_x}$ be the estimated traffic flow of x computed as mean between its incoming and ongoing traffic flows above described (i.e. $\overline{F_x} = (FI_x^{'} + FO_x^{'})/2$) and let δ and ψ be two learning coefficients ranging in $[0, 1] \subset \mathbb{R}$.

Each sensor agent calibrates its weighted traffic measures (i.e. $F_x^{'}$) and reliability values (i.e. ρ_x) with respect to those of its neighboring agents on the grid by executing the following heuristic procedure:

- Any correction is performed on traffic measures and reliability values if: (*i*) $F_x^{'}$ (resp., $FI_x^{'}$, $FO_x^{'}$) differs for more than the 20% with respect to the previous step; (*ii*) $F_x^{'}$ or the i-th incoming (resp. ongoing) traffic flow $FI_{x,i}^{'}$ (resp. $FO_{x,i}^{'}$) is equal to $FI_{x,i}^{max}$ (resp. $FO_{x,i}^{max}$).
- Otherwise, the final traffic flow measure of x (i.e. $_x^{''}$) is updated as:

$$F_x^{''} = \begin{cases} F_x^{'} - \delta \cdot \frac{\overline{F_x} - F_x^{'}}{2} & \textit{if } F_x^{''} \le F_x^{max} \\ F_x^{max} & \textit{otherwise} \end{cases} \tag{5}$$

and the reliability value assigned by x to each involved sensor agent, including itself, is updated as:

$$\rho^x = \begin{cases} \rho^x + \psi \cdot \frac{F_x^{''} - F_x^{'}}{F_x^{'}} & \textit{if } \rho^x \le 1 \\ 1 & \textit{otherwise} \end{cases} \tag{6}$$

then x recomputes the trust of its neighboring agent.

The experiment has been performed as regards the detection point C of Figure 4 by setting $\Delta t = 2$ minutes, $\delta = 0.5$ and $\psi = 0.75$, while reliability and trust values of all the sensor agents was initially set to 1. In Figure 6 the obtained results in terms of overestimated number of vehicles for F, $F^{'}$ and $F^{''}$ with respect to the real traffic flows in the detection point C are represented. Results show that the implemented procedure is able to obtain traffic flow measures (i.e. $F^{''}$) closer to real data

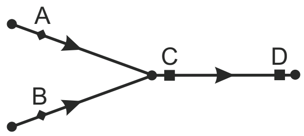

Fig. 5. The representation of the used transport sub-network.

than the other measures (i.e. F and $F^{'}$) by taking advantage of the use of a trust model in the agent grid.

V. Related Work

A complete literature overview on the different aspects handled in this paper is beyond our aim and, therefore, only those contributions coming closer to the matter presented here will be discussed in the following.

To monitor and manage a transport network, ITSs widely exploit the benefits provided by software agents to deal with large, uncertain and dynamic systems also in a distributed and cooperative way [4], [33]–[35]. Indeed, multi-agent systems are characterized by learning and adaptive capabilities when the complexity of the environments makes difficult to differently program agent behaviors [36]. Besides, agents can take advantage of helping other agents and reciprocally share data and experiences about other agents [37], as in our proposal.

Researchers are giving increasing attention to the application of multi-agent systems to transport network control and management. For instance, in [33] agents cooperate to: (*i*) improve the traffic management by allocating the network capacity; (*ii*) spread traffic information to drivers; (*iii*) take into account drivers' needs and preferences (in this case agents are embedded in vehicle route assistant devices). While in [34], [38], [39] the complex tasks involved in managing a transport network are decomposed into simpler agent-oriented tasks. Agents, dynamically distributed and replaced over the transport network to adapt its management to various scenarios, are hierarchically organized on a three level architecture to: coordinate agents tasks; execute the agents control; realize the agents activities.

However, these management tools require to be supported by algorithmic models able to simulate and to forecast users' path choices [4], [40], [41] but first, and foremost, it is required to know the state of the traffic on the transport network.

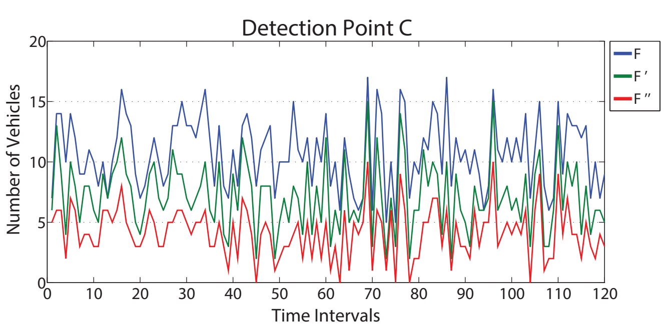

Fig. 6. Overestimated number of vehicles for F, $F^{'}$ and $F^{''}$ with respect to the real traffic flows in the detection point C

Since the knowledge of the traffic state on the transport network is a primary need for transport planners, a large number of sensors are currently available to detect traffic data [42], as discussed in Section II-A. Some of them are based on the analysis of acoustic vehicle signatures by ANNs, although different pre-processing phase and ANNs are used. In this context, in [24], [43] audio signals are processed by a Linear Predictive Coding conversion, autocorrelation analysis and Time Delay ANNs. The authors measure traffic flows on more lane roads and classify 4 classes of vehicles, but results are less satisfactory than those obtained in our work (although we tested only single lane roads). In [25] the vehicle detection exploits the audio signal peaks, while the classification is performed by multi-layer BP ANNs that use, as discriminative features, some characteristics of the emitted acoustic energy. Authors state the classification process as unreliable for vehicles different for class but similar for engine. Authors of [44] proposed to classify type and distance between vehicles based on their noises for different weather and speed conditions. From the recorded sound signals some features are extracted and, after a Discrete Fourier Transformation, processed by two probabilistic ANNs.

Finally, advances in communications, particularly wireless technologies, allow wide grids to be realized [45]. Such grids exploit more and more often agent technology [46] and trust systems for improving their effectiveness and performances. A comparison of different trust models for grid systems is provided in [47]. However, grids can adopt trust systems for privacy and security reasons [48] (e.g. in presence of wireless sensors) and not only to identify misleading sensors [49], [50], as in our case.

VI. Conclusions

To monitor urban vehicular traffic, we presented an agent-based sensor using information embedded into the acoustic vehicle signatures to identify both passage and class of detected vehicles. Moreover, this sensor agent has been designed to work in a grid configuration by cooperating with its neighboring agents in order to refine their measures. The proposed sensor agent takes advantage of the adoption of neural networks for processing the audio signals and the implementation of a distributed trust system to weight the collaboration of its neighboring sensor agents.

To test the performances of the proposed sensor agent, we built its prototype in JADE. Two different real data experiments have been realized. The first one considered the sensor agent in a stand-alone configuration. As result, the identification of passing vehicles and their class are close to those of the best (and more expensive) traffic detectors. The second experiment verified the effectiveness of the used heuristic algorithm to refine the computed traffic measures by exploiting a distributed trust system on a little grid of sensor agents.

Future researches will be addressed to test the performances of the proposed sensor agent on both multi-lane and/or two-way roads and the properties of a wider grid of sensor agent.

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