RFTraffic: Passive Traffic Awareness Based on Emitted RF Noise from the Vehicles

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***Abstract*—In this paper, a new traffic monitoring technique is introduced which works based on the emitted RF noise from the vehicles. In comparison with the current traffic sensing systems, our light-weight technique has simpler structure in both terms of hardware and software. An antenna installed to the roadside receives the signal generated during electrical activity of the vehicles' sub-systems. This signal feeds the feature extraction and classification blocks which recognize different classes of traffic situation in terms of density and flow. Different classifiers like *Naive Bayes*, *Decision Tree* and *k-Nearest Neighbor* are applied in real-world scenarios and performances higher than 95% are reported. Although the electrical noises of the various vehicles do not have the same statistical characteristics, experimental analysis shows that they are applicable for traffic monitoring goals. Due to the acceptable classification results and the differences between the proposed and current traffic monitoring techniques in terms of interfering factors, advantages and disadvantages, we propose it to work in parallel with the current systems to improve the coverage and efficiency of the traffic control network.**

I. Introduction

Gradually increasing of the traffic demand is saturating the capacity of the transportation network especially in developed countries represented by the EU, USA and Japan. Due to some reasons like limited possibility of the roads' extension, limited land resources and environmental pollution problem, the development of more efficient traffic management systems has absorbed great attention. Along with the development of ubiquitous computing in different aspects of the everyday life and advances in processing and communication technologies, automated management systems are advancing the human-based ones. Therefore, Intelligent Transport System (ITS) is one of the key necessities of the future smart cities.

The ITS integrates effectively the technologies like information processing, data communication, electronic sensor, electronic control and computer processing into the traffic management, in order to establish a comprehensive, real-time transport management system [1], which is accurate and efficient for large-scale applications. Smart transportation elements including intelligent vehicles, intelligent roads and intelligent infrastructures help the drivers efficiently to gain higher level of safety and maneuver capability.

Traffic monitoring is an important part of the ITS. Various road-specific parameters are aggregated to sense the traffic flow. Currently, vision-based methods are widely used in this regard. Cameras together with the advanced image/video processing techniques extract various features about traffic like density and flow or about the individual vehicles like color, shape, length, speed, etc. However dynamic outdoor situation degrades their performance [2]. Therefore, vision-based traffic monitoring systems depend more or less on sensor positioning [3].

In this paper a new traffic awareness system is introduced. Because of the electrical activity of various sub-systems like combustion or electrical motors (to derive the pumps or fans), each car emits RF (radio frequency) signals. These signals are different from the environmental noise. This phenomenon enables us to extract the traffic situation information from these signals. To achieve this, we install a RF receiver close to the road to aggregate the emitted RF signals from the vehicles. Various classification algorithms are applied on the aggregated signal in the computer attached to the receiver to classify the traffic situation.

The proposed RF-based traffic awareness system is robust against dynamic illumination or the movement of the background objects. Since it is based on the signals emitted from the cars, this system is passive and in comparison with the other RF-based or vision-based traffic/vehicle monitoring technologies has a simpler structure. Moreover, together with array processing schemes, it is able to sense the traffic density in different directions. Due to its capabilities and advantages, we propose this technique to be used parallel to or instead of the other traffic sensing systems.

The rest of the paper is organized as follows: In the next section, we will review the state of the art in traffic density sensing methods as well as RF-based context recognition applications. Moreover, in this section the effective sub-systems to generate the RF signal of the vehicles are introduced. In Sec. III, we focus on the proposed traffic awareness system. The results of the application of the context recognition algorithms on the aggregated signals are represented in Sec. IV. In Sec. V we discuss about the proposed system, its characteristics and future opportunities. Finally, Sec. VI concludes the paper.

II. Related Work

In this section, we offer a brief overview of the state of the art for traffic density sensing approaches and RF-based context recognition, then we introduce relevant sources of the RF signal in the vehicles.

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A. *Traffic Density Sensing Approaches*

Several methods like push button, magnetic sensors, ranging devices (*e.g.* RADAR), loop antenna embedded to the road and acoustic- or visual-based systems are used to sense the traffic density. But in this section we focus on the techniques which are capable of being used in the future ITS.

Application of the cameras and images/video processing techniques on the captured data refers to the most popular traffic sensing technique [3]–[7]. Depending on the processing capability, various parameters like the vehicle size, speed, color or the traffic density and flow are detectable. Moreover, video processing techniques are able to track a vehicle even in complex junctions [2].

Nevertheless, vision-based traffic monitoring systems are highly sensitive to the environmental changes: light density and shadows vary continuously or snow, rain and fog limit the vision range of the camera [2]. Most of the image processing techniques are based on the detection of changes in the sequence of images. Therefore, movement of the background objects like trees (because of wind) and people degrades the performance. Moreover, physical movement because of the wind or other parameters may degrade the monitoring performance.

By development of the inter-vehicle communication capabilities [8] in the vehicles, traffic sensing techniques are proposed based on car-to-car communication (C2C) [9]. But such methods need the collaboration of each unit of the vehicles. However, there is no guarantee about the performance of such systems due to lack or defection of the proper communication features (old vehicles) or due to deactivation of the C2C communication subsystems by the drivers.

B. *RF-based Context Recognition*

Context awareness is starting to play an increasingly important role in different areas of pervasive computing, especially in recognition applications, which are able to adapt their operations to the current situational context without explicit user intervention [10]. Context, according to Dey and Abowd, is any information that can be used to characterize the situation of an entity, where an entity is a person, place or object that is considered relevant to the interaction between a user and an application [11].

The most researched context recognition scenarios are often cited as applications of activity recognition, situation recognition, motion detection, etc., which usually utilize wireless sensor nodes equipped with various sensors to detect situation. Due to several constraints of wireless sensing with sensors, like power consumption, communication bandwidth and deployment costs, now researchers have begun investigation of different features in RF propagation for the purpose of context recognition [12]. The RF signal is generated by nearly every electronic device such as mobile phones, notebooks, watches, motors, etc., so the additional cost for using this signal in a recognition application is considerably low.

Woyach *et.al* [13] present a sensor-less sensing approach to detect the motion of objects based on received signal strength measurements on MICAz nodes, which illustrates that the motion of objects with respect to the velocity can be estimated by means of a signal strength pattern analysis. Another similar work [14] achieves WiFi-based motion detection by analyzing spectral characteristics of WLAN radio signal strength and its fluctuations. Fluctuations in GSM signal strength have also been used for detecting user mobility [15], [16]. Besides observing the absolute RSSI values like [13], Lee *et.al* [12] employ the fluctuation counting in RSSI values on a restricted frequency band for motion detection. Other classification applications, such as electrical event detection in a home environment through sensing the electromagnetic interference [17] and room situation classification based on RF-channel measurements [18], show also a great potential of RF signal features for activity recognition.

We note that in most of the previous RF-based context recognition systems, a RF signal is transmitted through the target and receiver uses the shape and strength of the reflexes for classification. Our method for detecting traffic situation proposes to extract information about for instance traffic density by using only emitted RF signals from the vehicles passing by.

C. *Sources of RF Noise in the Vehicles*

Modern vehicles are composed of various electronic components like: electric ignition, motors to drive different pumps (oil, water or fuel) or fans, other sub-systems like communication sub-systems (radio receiver/transmitters), microprocessors, sensors, entertainment facilities and wires that route the signals among the electronic sub-systems. Some of these sub-systems are expected to have RF emission with specific patterns, *e.g.* during ignition procedure, relatively strong impulses are generated or a periodic behavior from the electric motors is expected. Despite of the complexity and variety of the emitted RF signal from the vehicles, this signal contains information about the vehicles' situation (*e.g.* in [19], [20] RF emission is used to detect various car models).

III. Proposed Traffic Awareness System

Our proposed traffic awareness system is designed to investigate traffic information extraction on the road intersection. While most traffic congestion or traffic flow estimation approaches rely on only sensory data of observed road segments [21] and do not consider other surrounding context. Our approach focuses on simply utilizing emitted RF signals from the vehicles to discover current traffic situation context instead of relying on only sensory data of observed road segments. The context that is investigated in this paper for the traffic flow estimation will be defined in Sec. III-C.

A. *Feasibility Study*

In this section, we will illustrate some features of the RF noises from the vehicles based on the first dataset. Firstly we calculate the Mean value of all captured data, which correspond to either environment or cars moving by. It is easy to see in Fig. 2, the Mean value of environment situation is

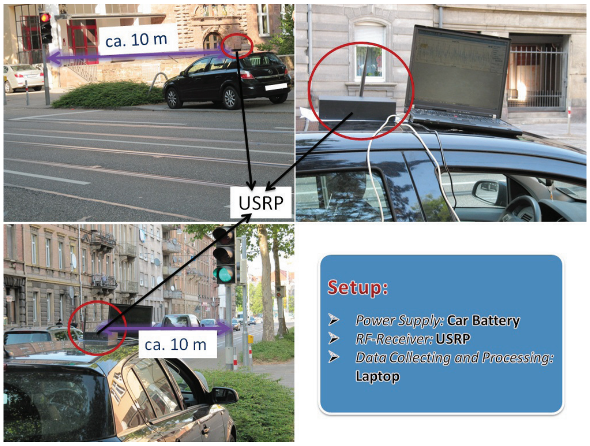

Fig. 1. Experimental setup for the proposed traffic awareness system

averagely greater than the Mean value of car-moving situation. Thanks to the different Mean value levels (see magenta and green dash lines in the figure), the Mean value of RF noises can be used as a classification feature to distinguish car movement from the environment.

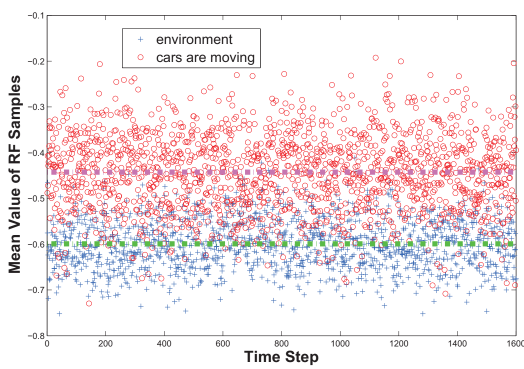

Fig. 2. The Mean Value of RF signal features different behaviors in different situation

Then we investigate the FFT amplitude of the RF noises. Fig. 3 shows two FFT curves corresponding to the environment and cars without movement respectively. The different curve progressions prove clearly that the FFT amplitude of the RF noises can be considered as another feature for classifying different traffic situations.

Through such a simple feasibility study, we believe that the RF noises from the vehicles can be used as the only information source for traffic sensing.

B. Experimental Setup

We used a USRP[1] software radio equipped with a 2.4 GHz transceiver board (RFX2400) and a VERT2450 antenna module with 3dBi antenna gain is used to receive the emitted RF signal from the vehicles. We tested the emitted signals in limited frequency bands, but the signals at 2.4 GHz matched

[1]www.ettus.com

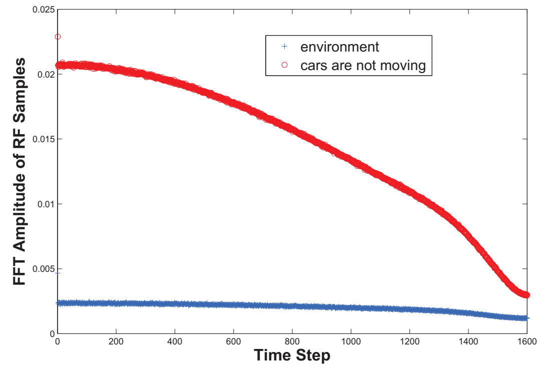

Fig. 3. The FFT Amplitude of RF signal features different behaviors in different situation

to our application more (To minimize the set up, higher frequencies are considered). A laptop PC is connected to the USRP which is responsible for data acquisition and application of the feature extraction and classification algorithms. The basic illustration of this experimental setup is depicted in Fig. 1.

Furthermore, the USRP device is configured to listen to the channel continuously while calculating the features used for classification at a sampling rate of 320000 samples/sec. As the power supply for the USRP device in our prototype is a car battery, a preprocessing step is designed for extracting the environmental context without any traffic but this power supply car, in order to avoid further interference to the received signal and so achieve more accurate classification results.

C. Context Recognition

We study the feasibility to obtain an awareness on traffic situations in experimental instrumentation with only an USRP software radio as described in Sec. III-B. In general, the proposed approach refers to a context recognition system for traffic awareness of road segments, which consists of four functional modules illustrated in Fig. 4:

- **Data Acquisition:** the first step in any data analysis task is naturally data collecting, so is in our traffic awareness scenario as well. As described before, the data acquisition for the proposed traffic awareness system is accomplished only through a light-weight RF signals received with an USRP node at 2.4 GHz instead of conventional sensor-based sensing.
- **Feature Extraction:** the next step is to derive features from the raw RF measurements using statistical and signal processing techniques. To feed the next module (classification), we sampled the *Mean Value*, *Standard Deviation*, *Root Mean Square (RMS)* and *FFT Amplitude* of the received signals.
- **Classification:** after feature extraction, a feature vector is forwarded to the classification process in both learning phase and real-time estimation phase. As illustrated in the system schema (Fig. 4), we employ Naive Bayes

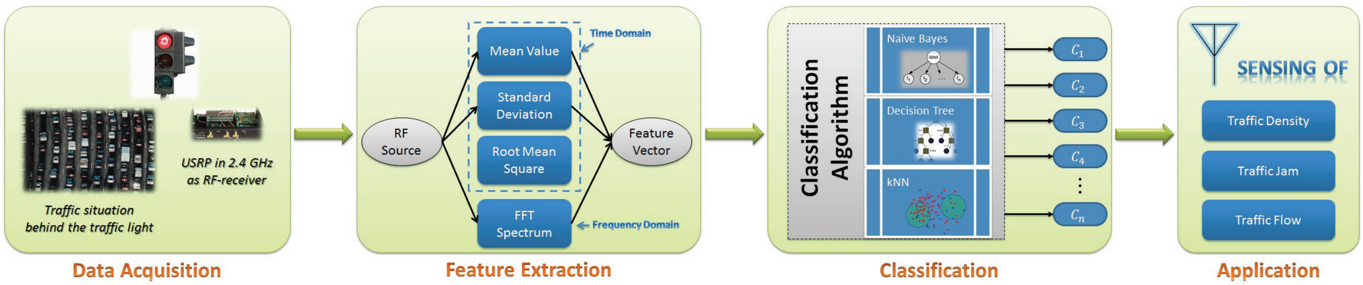

Fig. 4. Architecture of context recognition process for our traffic awareness application

(probabilistic classifier), Decision Tree (predictive model) and k-NN (k-nearest neighbor algorithm: instance-based learning) for the classification module and compare the results.

- **Application:** to ease the further processing of the classified contexts for traffic awareness, certain high-level contexts can be interpreted based on the classified low-level traffic contexts and then integrated into the existing traffic sensing applications (*e.g.* traffic density and traffic jam/flow).

The precondition of a real-time traffic awareness is the predefined context attributes for the traffic situation estimation, which is the only step in the proposed architecture that requires user interaction in the proposed architecture. Correlation of the context attributes to the observed road segment can not be neglected. So we limit the definition of context attributes only for the traffic density with respect to the traffic light as follows, which are five different traffic density situations demonstrated in Fig. 5.

- ***Environment*** (C_1): which means no traffic flow/jam at all, see Fig. 5(a).
- ***Smooth traffic with one car*** (C_2): which means only few cars drive by the green traffic light at that moment and corresponds to no congestion, see Fig. 5(b).
- ***Smooth traffic with many cars*** (C_3): which means lots of cars drive by the green traffic light at that moment and corresponds to low congestion, see Fig. 5(c).
- ***One car stopped*** (C_4): which means only few cars wait right now behind the red traffic light and corresponds to medium congestion, see Fig. 5(d).
- ***Many cars stopped*** (C_5): which means lots of cars wait right now behind the red traffic light and corresponds to high congestion, see Fig. 5(e).

IV. Evaluation

The experiment was conducted for a road segment with two lanes in each direction. In the experiment we attempted to derive the five context classes of the traffic density described in Sec. III-C. To gather meaningful performance data, we must firstly determine the requirements for the dataset capturing. On the one hand, with respect to the average duration of the red light (ca. 15 s), we restrict the size of each dataset for 10 s, so that these five context classes can be distinguished from each other without temporal overlap. On the other hand, in order to differ the dataset of red traffic light scenarios from green ones, we set a stop time for the data gathering during the red light just when the red light turns to green.

For each classification we set a window size of 2000 samples in the feature extraction, *i.e.* for training, each dataset is fetched for 1600 feature values. In general, the traffic awareness system is now evaluated off-line. As mentioned in Sec. III-C, we adopt Naive Bayes, Decision Tree and k-NN for our situation classification module and compare the results in terms of the accuracy and confusion matrix. To avoid any bias caused by the particular sampling chosen for training and testing, we validate all three classification algorithms with a stratified 10-fold cross-validation, through which the dataset is partitioned randomly into 10 subsamples. Each subsample is held out in turn for testing and the remaining nine subsamples are used as training data [22].

	Predicted (%)				
Actual	C_1	C_2	C_3	C_4	C_5
C_1	98.1	1.6	0.3	0	0
C_2	1.2	98.7	0.1	0	0
C_3	0.6	4.7	94.7	0	0
C_4	0	0	0	99.9	0.1
C_5	0	0	0	16.7	83.3

TABLE I
Classification accuracy achieved with Naive Bayes Classifier for traffic density awareness using one USRP device in the setting depicted in Fig. 1

The accuracy of the traffic density awareness using different classification algorithms is shown in Table I, II and III respectively. We observe that the average accuracy for the situation awareness with all three classifiers is rather high, which is over 95%. From the point of view of the results, especially the first four situation classes, *i.e.* C_1, C_2, C_3 and C_4 could be detected very well with an average false negative rate of 1.4%, 2.0% , 6.2% and 2.8% respectively. As we see, the fifth class, C_5, *i.e.* "many cars stopped", whose recognition rate is still considerably high with an average accuracy of 87.6%. But compared to the other four classes, the average classification accuracy of C_5 drops about 10%. While a loss in accuracy for

(a) Environment without any traffic flow (b) Smooth traffic flow with only one car driving by (c) Smooth traffic flow with many cars driving by (d) Only one car behind the red traffic light (e) Many cars behind the red traffic light

Fig. 5. Five different traffic situation scenarios behind a traffic light

	Predicted (%)				
Actual	C_1	C_2	C_3	C_4	C_5
C_1	99.3	0.6	0.1	0	0
C_2	0.7	98.9	0.4	0	0
C_3	0.5	1.9	97.6	0	0
C_4	0	0	0	98.1	1.9
C_5	0	0	0	2.1	97.9

TABLE II
CLASSIFICATION ACCURACY ACHIEVED WITH DECISION TREE CLASSIFIER FOR TRAFFIC DENSITY AWARENESS USING ONE USRP DEVICE IN THE SETTING DEPICTED IN FIG. 1

	Predicted (%)				
Actual	C_1	C_2	C_3	C_4	C_5
C_1	98.5	1.4	0.1	0	0
C_2	1.5	96.4	2.1	0	0
C_3	0.8	10	89.2	0	0
C_4	0	0	0	93.6	6.4
C_5	0	0	0	18.4	81.6

TABLE III
CLASSIFICATION ACCURACY ACHIEVED WITH K-NN (K=1) CLASSIFIER FOR TRAFFIC DENSITY AWARENESS USING ONE USRP DEVICE IN THE SETTING DEPICTED IN FIG. 1

the class of "many cars stopped" was expected due to the RF signal strength and receiving range.

As mentioned before, we provide *Mean Value*, *Standard Deviation*, *Root Mean Square (RMS)* and *FFT Amplitude* of the received signals as features for the classification process, the last two contributed more. Fig. 6 shows finally the distribution of five defined traffic density situations with respect to for instance two features of *Mean Value* and *FFT Amplitude* after classification using Decision Tree algorithm.

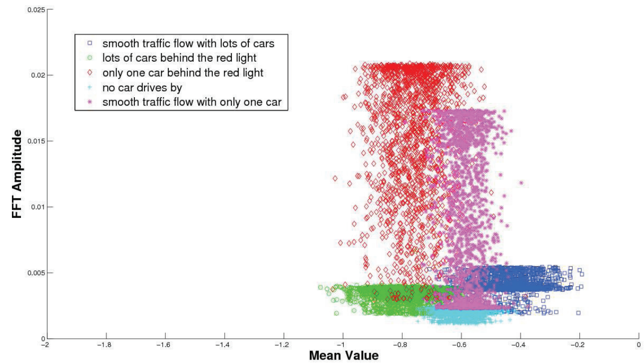

Fig. 6. Classification results of five different traffic situations using Decision Tree Learning (regression trees): X-axis and Y-axis are Mean Value and FFT Amplitude of the RF-signals respectively, which are two features of the context classification process.

V. DISCUSSION

Simplicity is one of the positive aspects of our proposed technique. At hardware part, there is only one receiver together with the antenna whereas in the software part, the applied classification algorithms are relatively simpler than those used in vision-based techniques. Although limited classes of traffic density and flow are detectable, but as seen in tables I-III, the performance is relatively high. This simplicity which directly affects the price, would be beneficial to more expansion of the traffic sensing and monitoring network. Moreover, the proposed method is more suitable for miniaturized applications like covert traffic monitoring.

The performance of the vision-based systems is highly dependent on the light density and the background objects. Although RF signals are also affected by the transmission channel and interfering signals, we did the test in daytime (between 14:00 and 16:00) to have relatively worse case of interference level. More accurate tests to compare the variation of the negative transmission channel effects by time on the classification performance are needed.

The main goal of this paper was to introduce a new traffic monitoring technique. Due to its performance, flexibility, and robustness, the proposed technique has lots of potential applications which are under research. There are various kinds of antennae with different patterns [23], most of them are applicable to receive the emitted signals from the cars. It enables our traffic sensing system to sense the traffic situation at a certain direction. Moreover, together with array processing schemes [24], the proposed system can change its pattern by modification of the phase shifts of the antenna elements or to process the signals of more than one direction at the same time. Multiple antennae are also applicable in another form. Each receiver can sense the traffic density of a limited area around itself due to its limited reception capability, *i.e.* the proposed traffic monitoring has limited range depending on the receiver sensitivity. Installation of the multiple antennae along the street behind the traffic light allows us to figure out the exact length of the traffic jam.

Other forms of classification of the vehicles like based on their dimensions: motorcycle, car, van, bus or based on their location: city or highway (primary tests show its feasibility) are also possible. Various location aware applications can be then defined based on this possibility.

Comparison of proposed traffic monitoring technique with current video-based ones shows that due to their independence in terms of interfering or distorting factors, capabilities, advantages and disadvantages, as well as the potential extensions of the proposed system, it can be used in parallel with the current traffic monitoring systems to cover their drawbacks.

VI. Conclusion

Traffic situation recognition is one important component for Intelligent Transport System (ITS). In this paper, we represented the feasibility of a new traffic awareness technique. It uses the RF signals emitted from the cars. The proposed technique has a simple structure, and other than most of the previous RF-based context recognition methods, it does not need reflection of a certain signal from the vehicles. The signals are generated inside the motor during combustion, in the (oil or water) pumps, fans and connections of the sensors to the processing unit. The signals are received by a roadside receiver and classified to extract the traffic situation.

To show the performance of the proposed technique, we focused on the traffic density and traffic flow. Our classifiers could detect five different classes of traffic situation: no car, no traffic congestion, light traffic congestion, light traffic jam and heavy traffic jam. Different classifiers are tested and performances more than 95% are achieved.

Differing from the current traffic sensing techniques, we propose our system to work in parallel with current vision-based traffic monitoring techniques. Because of its novelty, the proposed technique has various potential extensions, such as recognition of various classes of vehicles, development of a traffic surveillance network based on multiple antennae or directional traffic sensing by directional or array antenna.

Acknowledgment

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