Design for Multi-Vehicle Roadside Tracking Based on Radio Tomographic Imaging

Jarmo Theodore Wilkens and Anilton Salles Garcia

***Abstract*— With the increasing amount of vehicles on the road, traffic jams pose a growing global problem. Traffic surveillance is a crucial step into improving traffic flow. This paper proposes a design and methodology for the estimation of occupancy and velocity of multiple vehicles on a single lane road segment using Radio Tomographic Imaging (RTI). RTI is an emerging technology that produces images of the change in the electromagnetic field of a monitored area, making it possible to track device-free objects such as humans and cars. The proposal is based on the analysis of three works discussed in this paper, together with a newly introduced vehicle detection method. To the best of our knowledge, this paper is the first to propose the surveillance of multiple vehicles simultaneously using RTI sub-networks. We also propose a novel car detection and speed estimation method. The contribution of this paper is to stimulate research of the possibility of using RTI networks as being part of an Intelligent Transport System (ITS).**

***Keywords*— Radio Tomographic Imaging, Wireless Sensor Networks, Vehicle Traffic, Surveillance, Received Signal Strength.**

I. INTRODUCTION

Traffic jams limit a city's efficiency: people waste time by waiting and may arrive late at work or meetings, it is difficult for emergency services to pass and costly for industries as transportation time and fuel consumption increases. Hence it is essential for a city's efficiency to keep traffic flow optimal.

A solution to the described problem is to measure vehicle occupancy and traffic flow at high traffic density roads. These statistics may be made available online or directly relayed to navigation systems to inform people about traffic conditions. Furthermore, traffic data can be used to more efficiently control traffic lights in a smart city environment.

Due to the relatively high infrastructural costs of the already widely implemented roadside surveillance systems such as cameras, induction loops and radars [1], this paper seeks to explore the possibility of deploying a more cost-effective solution. More specifically, this paper proposes the application of *Radio Tomographic Imaging* (RTI). RTI is an emerging and promising technology, initially developed in 2008 by Patwari et al. [2], to localize and track stationary and moving device-free targets within a monitored area. The technology relies on a mesh network of simple and inexpensive stationary radio transceivers that are deployed on the border of the area of interest, where each radio is wirelessly connected in the 2.4 GHz ISM frequency band to all other radios. By obtaining the Received Signal Strength (RSS) of every link inside the network, the RTI system is able to image the location of a target in real-time, due to the targets present inside the Wireless Sensor Network (WSN) that attenuate the signals, also referred to as shadowing. Recent papers applied new techniques that lead to improved RTI performance [3], [4], [5]. Aside the cost-effectiveness offered by the RTI technology over the state of the art (cameras, induction loops, radars) is its scalable and easily configurable network. Moreover, the WSN offers a higher spatial resolution that will improve reliability of traffic modeling and accuracy of short-term traffic state prediction [1]. This paper discusses a theoretical deployment of a RTI network as a roadside surveillance application, hoping that future research and development would lead to improving traffic flow. This paper proposes a pragmatic set-up/methodology that estimates occupancy and velocity of two vehicles on a single lane road segment with radios positioned on the roadside that form an RTI network, as illustrated in figure 1 of section IV. The proposal is based on an analysis of three recent papers that demonstrated significant developments in the area of RTI and roadside surveillance. The proposal will also include data acquisition and processing procedures, including expected performance results with explanation.

The rest of this paper is organized as follows. Section II discusses related work concerning RTI and roadside surveillance, of which three are further analyzed in section III. Section IV contains the RTI proposal based on the analyzed articles, and section V concludes this article.

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II. RELATED WORK

Kassem et al. [7] investigated the application of Device free Passive (DfP) localization, a technology similar to RTI, to detect and estimate vehicle presence and velocity. They successfully differentiated between three states on a single lane road: empty street, a stationary vehicle and a moving vehicle.

Anderson et al. [8] aimed to improve RTI modeling and algorithms in a roadside surveillance environment. Three improvements were proposed, which includes an extra bias term to the existing image estimation solution [9], a way to remove negative observations and combining multiple frames to produce a more accurate final image. They compared their results to the first RTI network version by Wilson and Patwari [9], and show that their proposed approaches lead to greatly improved performance. Anderson et al. have shown it is possible to track a single vehicle passing through a single lane road and estimate its velocity using RTI.

Kaltiokallio et al. [5] developed an attenuation-based RTI system that localizes stationary and tracks moving people real-time. The authors reduce multipath interference and improve location estimates significantly by combining RSS fade level data on multiple channels. They also developed a model to determine link-channel specific parameters, thereby increasing localization accuracy further.

Alippi et al. [3] developed an outdoor RTI network method that detects and localizes multiple people real-time. Together with their proposed method, they combine several recent technologies with some adjustments, including measurements on multiple channels [5], spatial filtering for online calibration similar to [10], multi-target tracking [4] and background subtraction. They also develop an individual distance-RSS model for each node, further increasing robustness. They compare their results to the previously described system [5] with an RTI network deployed in a forested area, where they achieve an average localization error of a stationary person of 3.2 m, as opposed to 4.1 m using the method of [5].

Wei et al. [11] examined the use of Electronically Switched Directional (ESD) antennas to improve RTI performance. ESD antennas focus radiated power in a selected direction to reduce multipath propagation and thereby reduce interference in links. The authors proposed three methods to select the direction of each node, of which the fade level-based method yields highest performance. Compared to the multi-channel omni-directional RTI network in [12], their proposed system improves tracking performance by 42% in an open LOS-environment.

III. Article Analysis

The RTI implementation discussed in the selected articles are analyzed with respect to their computational complexity, localization accuracy and robustness. The proposed RTI system should be able to compute occupancy and speed of multiple vehicles real-time, fast enough to track vehicles moving at 50 km/h with sufficient accuracy. Moreover, the RTI system should be robust to multipath fading and time-varying intrinsic motion, which is the motion of objects that naturally belong to the environment. Intrinsic motion is seen as environmental noise, caused by, for example, wind that sways leaves, branches or the nodes themselves. Performance is greatly influenced if the receiver node is moved only by a fraction of its wavelength [11].

A. *"RTI Goes Wild: Radio Tomographic Imaging for Outdoor People Detection and Localization"*

Computational Complexity

Alippi et al. [3] demonstrate that every frequency channel of each link has varying RSS dynamics, which was modeled in [13] and referred to as *fade level*. A link-channel pair in deep fade and anti-fade is due to destructive and constructive interference respectively. Multipath fading is a result of reflected and scattered signals from surfaces in the environment. When no people are present in the monitored area, a link channel in anti-fade experiences a higher average RSS than a channel in deep fade. Anti-fade channels contain less interference and more reliably measure attenuation than deep fade channels. The number of links, nodes and voxels are given by L, N and V respectively.

Each estimated radio tomographic image $\hat{\mathbf{x}}_{V\times 1}$ in (1), depends on the regularized least-squares approach $\Pi_{V\times L}$ [2], [4], [12], and the change in RSS attenuation vector $\mathbf{y}_{L\times 1}$. Vector $\mathbf{y}$ consists of the RSS attenuation change measured from all fade-level based selected link-channels and is assumed to be a spatial integral of the propagation field of the monitored area. For all non-selected link-channels, the RSS change is set to zero. Matrix Π only required to be computed once before operation, which made real-time estimation of the image $\hat{\mathbf{x}}$ possible. Regularization is required, because the matrix $\mathbf{W}^T\mathbf{W}$ in (2) is typically not full rank (when $V > L$). Π consists of a simple weight matrix $\mathbf{W}_{L\times V}$ that relates the influence of each voxel on each link, regularization parameter σ_N^2 and *a priori* covariance matrix C_x (based on Poisson process):

$$\hat{\mathbf{x}} = \Pi\mathbf{y} \tag{1}$$

$$\Pi = (\mathbf{W}^T\mathbf{W} + \sigma_N^2 C_x^{-1})^{-1}\mathbf{W}^T \tag{2}$$

$$[C_x]_{j,i} = \sigma_x^2 e^{-d_{j,i}/\delta_c} \tag{3}$$

where σ_x^2 is the variance of voxel intensities, $d_{i,j}$ is the distance between the centers of voxels i and j, and δ_c is the voxels' correlation parameter. For the localization and tracking of multiple targets, the method of [4] was used. Image $\hat{\mathbf{x}}$ requires *VL* multiplications, meaning computational complexity increases linearly with amount of voxels and links.

RSS data from the complete network consisting of 20 Texas Instruments CC2531 nodes was collected every 340 ms, which they mention is sufficiently fast to track moving people. Computation time for an RTI estimate was not mentioned, but is assumed to be less than one network scan of 340 ms.

Localization Accuracy

The authors achieved an average location error of 3.2 m (Euclidian distance) in an RTI network deployed in a densely forested environment. They compared their results in the same measurement environment to the state of the art fade level-based model introduced by Kaltiokallio et al. [5], where they obtained a worse location error of 4.1 m.

Robustness

Alippi et al. have four methods to increase robustness against intrinsic motion. They achieve a 0.04% false alarm rate of a person present in the monitored area with wind. This is a significant improvement compared to the state of the art [5], where they achieved a 0.74% false alarm rate.

One of the methods is to select which links and which one of their channels are most reliable. After fixed time intervals, only link-channel pairs are selected that are in anti-fade and have an average RSS higher than the receiver sensitivity threshold. From these selected link-channels, only the channel that has the lowest variance of each link is selected. Intrinsic noise has high variance, which is filtered out this way.

The second method is an online calibration technique run for five seconds after each network scan, which applies a spatial filter that only updates the reference RSS of selected link-channel pairs not attenuated by stationary people [10].

The third method is a node-specific path loss model that is used to calculate fade level for each node. Fade levels are updated after each pre-determined fixed time interval.

The fourth method is background subtraction, which is a technique to better distinguish the blobs in the generated image representing real people from environmental noise.

B. "dRTI: Directional Radio Tomographic Imaging"

Computational Complexity

ESD antennas focus the radiated power in selected directions to reduce multipath propagation and thereby reduce interference in communication links. Wei et al. [11] used ESD antennas that have six selectable directions, meaning 36 possible transmit-receive antenna direction pairs are possible, which they refer to as *Pattern Pairs*. Communication in both directions leads to a maximum number of Pattern Pairs of 72 for each link. Using the proposed directional antennas comes at a cost of network scan time as each direction is sequentially switched, making the dRTI system difficult to scale to larger network sizes.

The authors proposed three methods to select the Pattern Pairs of each link, of which the fade level-based method yields highest performance. This method selects the top k Pattern Pairs with highest fade level. The change in RSS vector $\mathbf{y}$ is calculated as the sum of the absolute difference between the current and reference RSS for each selected Pattern Pair. Computational complexity hence increases with parameter k.

The RTI model used by Wei et al. is the same as in [9], which is a least-squares solution with Tikhonov regularization as shown by equations (4) and (5) in section III-C (without parameter β). In the work of Wei et al., however, the number of multiplications was reduced by approximately a factor 45. This provides strong evidence that images were generated real-time, but image generation time remains unknown.

Localization Accuracy

Compared to the multi-channel omni-directional RTI network in [12], their proposed system shows a tracking performance improvement of 42% in an open LOS-environment at the 90th percentile of the CDF representing tracking error. The authors, however, have not compared their results to the latest high performance multi-channel RTI network [3], which might have produced similar or even better results.

Robustness

The authors have not tested their proposed RTI system outdoors nor have they mentioned any effects of intrinsic motion. However, the authors do present system performance results with False Positive (FP) and False Negative (FN) figures, which is a way to evaluate system robustness. They show that their proposed dRTI method yields significantly lower FP and FN results compared to mean- and variance-based RTI, as well as multi-channel RTI.

C. "Radio Tomography for Roadside Surveillance"

Computational Complexity

Three improvements described below were proposed that all add to computational complexity compared to the initial RTI approach proposed by Wilson et al. [9].

Instead of the regularization term C_x in (2), Anderson et al. [8] applied a least-squares solution $\Pi_{V\times V}$ with *H1 regularization* in (5), which is a form of Tikhonov regularization [9]. Additional to this expression and using the Maximum A Posteriori (MAP) estimator, they added the bias term β for the estimation of a radio tomographic image $\hat{\mathbf{x}}_{MAP}$:

$$\hat{\mathbf{x}}_{MAP} = \Pi(\mathbf{W}^T\mathbf{y} + \beta\mathbf{1}_{V\times 1}) \tag{4}$$

$$\Pi = (\mathbf{W}^T\mathbf{W} + \alpha(\mathbf{D}_X^T\mathbf{D}_X + \mathbf{D}_Y^T\mathbf{D}_Y))^{-1} \tag{5}$$

where α is an empirically derived image smoothing parameter, $\mathbf{D}_X$ and $\mathbf{D}_Y$ are the difference operators for the horizontal and vertical directions respectively. Weight matrix $\mathbf{W}$ and RSS vector $\mathbf{y}$ represent the same as described in section (III-A). Computation of (4) requires $2VL$ multiplications, thereby making it twice as computationally expensive as in (1). The addition of the bias term β does not increase computational complexity notably.

Anderson et al. deal with negative data in the observations by iterating their proposed simple three-step method three times. The method is based on removing negative elements of $\hat{\mathbf{x}}_{MAP}$ and exclude the respective columns of $\mathbf{W}$ and $\mathbf{D}$, after which $\hat{\mathbf{x}}_{MAP}$ is recomputed until it does not contain any more negative entries. This method produces results similar to background subtraction, thereby denoising the image. Computation time increases proportional to the number of iterations, where the authors mention that three iterations were sufficient.

The authors combine three frames into a final, more accurate, image. A model to estimate vehicle velocity was proposed, which at the same time minimizes noise in the final image. However, it is not known how this model performs when multiple vehicles are in the monitored area.

Although the researchers mention RSS data is recorded real-time, is is not mentioned if the image was computed real-time, nor the computation time with their proposed approaches. It is also unknown what their network scan time is.

Localization accuracy

Using the method of removing the negative observations together with the optimized bias parameter β, the authors reduced the RMSE by 47% compared to the approach in [9]. By also integrating their multiple image combination method, they show performance is greatly enhanced compared to [9].

Robustness

Anderson et al. mention that weather and atmospheric effects had only a small impact on their RSS measurements at 2.4 GHz. Although they do not present any impacts of intrinsic motion on their system, they do show that robustness is increased compared to [9] using Receiver Operating Characteristic (ROC) curves.

IV. PROPOSED RTI SYSTEM

As briefly described in section I, this paper proposes a pragmatic methodology of a RTI network deployed on a roadside segment that determines occupancy and traffic flow of multiple family cars in real-time.

A. Experimental Design

To measure two cars in the same network traveling at 14 m/s (~50 km/h), maintaining a safe distance of two seconds means the distance between the cars should be at least 28 m. Assuming a car length of 4 m and assuming the cars are at least one second from the entrance/exit, the network length should span 66 m. This will require 72 radios, which are 36 nodes on each side, spaced 2 and 3 meters along and across the road respectively at a height of 0.5 m from the ground. Figure 1 illustrates the proposed design.

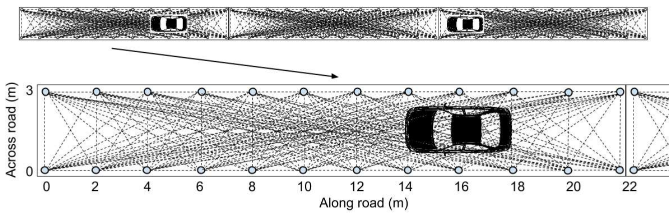

Fig. 1. Top view of roadside surveillance proposal

As opposed to conventional RTI networks where monitored targets are completely surrounded by radios, the proposed design only has radios deployed on two sides, thereby significantly reducing the number of links and consequently reducing system accuracy. Furthermore, network scan frequency should be considerably higher, since vehicles can move notably faster than people. The best case is where vehicle blurring does not occur, which is when the vehicle does not cross a voxel boundary during one network scan [8]. The maximum allowable velocity (m/s) is given by the product of the voxel width (m) and network scan frequency (Hz).

The average time of a transmission period per TI CC2531 node is around 3 ms [12], meaning for a WSN with 72 nodes operating on four frequency channels, the maximum scan frequency will be ~1.15 Hz. For a scan frequency of 1.15 Hz and a vehicle that moves 14 m/s (~50 km/h), a voxel width of ~12 m would be required. Such voxel width would be problematic to estimate velocities each second of vehicles moving slower than 12 m/s. To detect slow moving vehicles, maintaining a fairly high accuracy and still making use of multiple channels, the proposed RTI network design contains three sub-networks, each operating on two different frequency channels. The use of sub-networks was first described in [8]. In this case, a scan frequency of 7 Hz may be achieved, reducing the voxel width to 2 m, making it possible to estimate a minimum velocity of 7.2 km/h. A voxel width of 2 m means only a one-dimensional image can be generated, which is acceptable for the proposed application and also simplifies the tracking problem. Splitting up into sub-networks, however, comes at a cost of accuracy at the boundary areas, where there are relatively fewer links, as can be seen in figure 1.

For this proposal, it is chosen not to use directional antennas as described in section III-B, because they increase network scan time considerably. Data transmission and switching direction take 3 ms and 1 ms respectively. Switching and transmitting from six directions will take 23 ms per node. This is more than seven times longer than using omni-directional antennas, making it unfeasible to use directional antennas if image blurring is to be prevented for faster moving vehicles.

The network design proposes to use the same hardware and configurations as Alippi et al. [3], the only difference being the use of two unique channels per sub-network: $\mathcal{C}_1 = \{11, 14\}$, $\mathcal{C}_2 = \{17, 20\}$, $\mathcal{C}_3 = \{23, 26\}$. Using different frequency channels prevents co-channel interference within the RTI network. The protocol to be used for the RF sensors is the multi-Spin protocol [10]. Each sub-network has one node that transmits real-time data to the laptop, which stores all transmitting nodes' RSS data in one buffer.

A limitation of using a RTI system with omni-directional antennas operating in cities is co-channel interference with other 2.4 GHz ISM band networks. These networks include public Wi-Fi hotspots, 4G LTE, wireless cameras and bluetooth devices in vehicles. One method to reduce co-channel interference is using BPSK modulation, but the IEEE 802.15.4 standard only permits frequency bands 800/900 MHz utilizing this scheme, which comes at a cost of localization accuracy due to reduced wavelength. An alternative band could be the relatively interference-free 5 GHz ISM band, which, however, would increase multipath effects [14].

The proposed methodology of data acquisition is as follows. Drive one family car at a constant speed of 10 km/h on the RTI covered road segment and use the proposed method outlined in algorithm 1 to estimate occupancy and speed real-time. Repeat this for speeds of 20 km/h, 30 km/h, 40 km/h and 50 km/h. Reiterate the aforementioned procedure with two family cars, always driving at a safe distance of two seconds from each other. Save all recorded data to compare system performance for varying vehicle speeds and different amount of vehicles. Repeat all tests ten times to obtain more reliable results.

B. Radio Tomographic Imaging Method

The proposed novel roadside surveillance method is outlined in algorithm 1. It is mainly a combination of the method of Alippi et al. [3] and Anderson et al. [8].

Offline calibration is where the system records data without people or vehicles affecting the network. The fade level method of [3] filters out unreliable links, including the longer distance links that have an average RSS close to the receiver sensitivity threshold. Multipath fading in LOS signals is expected to occur due to signal scattering from the road surface.

The number of detected cars is given by the number of voxels darker than a voxel-specific threshold $\mathcal{T}_v$, where $\mathcal{T}_v$ is a newly proposed threshold given by:

$$\mathcal{T}_v = \rho \sum_{k \in \mathcal{A}} F_k \tag{6}$$

where ρ is a weighting parameter, $\mathcal{A}$ is the set of selected link-channels covering voxel v and F_k is the fade level calculated using the method of [3]. This threshold takes into account channel reliability and link density as can be observed in figure 1. If there are multiple neighboring voxels detected as a car, only the voxel representing the front part of the car is chosen. Vehicle speed is estimated as the number of voxels displaced per second, multiplied by the voxel width.

Algorithm 1: Proposed roadside surveillance method

Calibrate offline for 5 min. to obtain reference RSS [3]
Calculate fade level for each link-channel pair [3]
Apply link-channel selection method [3]
Determine threshold $\mathcal{T}_v$ for each voxel
Calculate projection matrix Π using (5) [8]
while *(1)* **do**
  At the completion of each network scan:
  Apply online calibration to update reference RSS [3]
  Update vector $\mathbf{y}$ (one vector for all sub-networks) [3]
  Compute RTI image $\hat{\mathbf{x}}_{MAP}$ using (4) [8]
  while $\hat{\boldsymbol{x}}_{MAP}$ *has negative observations [8]* **do**
    Set negative voxels of $\hat{\mathbf{x}}_{MAP}$ to zero
    Update Π using only the columns of $\mathbf{W}$ and $\mathbf{D}$ that correspond to the positive voxels of $\hat{\mathbf{x}}_{MAP}$
    Recompute image $\hat{\mathbf{x}}_{MAP}$ using (4)
  end
  Apply car detection and speed estimation methods
end

For this proposal, it is chosen not to use the frame combination method from [8], because the method seems computationally expensive and is expected not to improve vehicle detection and velocity estimation considerably.

Parameters α, β and ρ are found empirically. Since the amount of links is significantly higher than the number of voxels, regularization is theoretically not necessary, but may be included to smoothen the image.

C. Expected Results

Results from the proposed method are likely to be completely different from the results of papers discussed in this article. Not only does the design provide half as many links as in other networks, but the targets to be tracked are vehicles instead of humans, traveling at significantly higher velocities. The only work similar to this proposal is from Anderson et al. [8], who did not publish quantitative results concerning localization accuracy and how it is affected by vehicle velocity, nor system performance for the tracking of multiple vehicles.

Figure 2 shows a simulated RTI image in MATLAB of an arbitrary sub-network with a simulated car on voxels 7 and 8. The simulation procedure will be discussed in a future article. The brighter voxels represent the area occupied by the car.

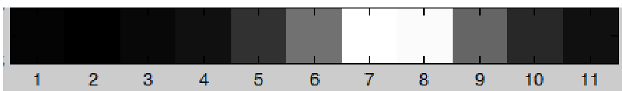

Fig. 2. One-dimensional RTI image

The proposed system is expected to be robust against intrinsic noise, due to the link-channel selection method and online calibration [3]. The image is significantly denoised by the removal of negative observations and the parameter β proposed by [8]. Localization accuracy is expected to decrease with increasing targets to be tracked [4]. This is due to the fact that some links may be attenuated by more than one object. Also, the number of multipath components is expected to be larger than in previous studies, due to the increased reflectiveness of metallic objects and size of targets, thereby making multipath interference a bigger problem.

V. Conclusion

In this paper, we propose a design and methodology for the estimation of occupancy and velocity of one and two vehicles on a single lane road segment traveling at speeds from 10 km/h up to 50 km/h using multiple RTI sub-networks. The use of multiple RTI sub-networks prevents blurring of faster moving vehicles. The proposed roadside surveillance method is mainly a combination of two recent works, together with a simple novel car detection and speed estimation method.

The contribution of this paper is to stimulate research of the possibility of using RTI networks as being part of an ITS in a smart city environment. Following the design and methodology presented in this paper, it is expected that more insight will be gained into how localization accuracy is affected by vehicle velocity, as well as system performance for the tracking of multiple vehicles. Future work will involve the practical implementation of the proposed methodology.

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