RF-based Traffic Detection and Identification

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***Abstract*—Road traffic congestion estimation is a critical function that affects both developed and developing countries alike. In this paper, we present *Monitor* as a novel RF-based traffic detection and identification system. Compared to the current approaches for traffic estimation, *Monitor* is low-cost, does not disrupt traffic during installation, works for non-laned traffic, and does not require active user participation. Our approach is based on the fact that the presence of an object in an RF environment affects the signal strength, and hence can be used for detecting and identifying objects.**

We present the *Monitor* system architecture and how it uses statistical techniques, based on the mean and variance of the received RF signal strength, to both detect the presence of objects and differentiate between humans and cars to reduce the traffic estimation outliers. Implementation of *Monitor* on standard RF equipment shows its capability of detecting the presence of objects and identifying their type with high accuracy highlighting its promise for different vehicle-related applications.

I. Introduction

Traffic estimation is an important problem that affects different aspects of the social, ecological, and economical aspects of a society. A study made in 2007 [1] estimated a loss of $78 billion in the form of 4.2 billion lost hours and 2.9 billion gallons of wasted gasoline in the United States alone due to traffic congestion.

A number of systems over the years have been proposed for congestion estimation. These systems can be categorized into two groups: infrastructure-based and distributed approaches. Infrastructure-based techniques include loop detectors [2], magnetic sensors [3], acoustic sensors [4], and computer vision techniques [5]. These systems have the advantage of not depending on input from the users. However, they require special hardware to be installed at the points where cars are to be detected. In addition, some of them do not work for non-laned traffic, which is the norm in developing countries, and may disrupt traffic during installation. On the other hand, distributed estimation techniques depend on sensors attached to the cars or the users [6], [7], [8], [9]. These systems have the advantage of not requiring special infrastructure to operate. However, they suffer from the limited availability of cars and high-end phones with GPS receivers, which is even worse in developing countries. In addition, provider-based techniques suffer from the accuracy of determining the location of the users and the granularity of congestion estimation.

In this paper, we present *Monitor* as a novel RF-based traffic detection and identification system based on the fact that the presence of objects in an RF environment affects the received signal strength in different ways based on their size, material and/or geometry, and hence can be used for detecting and tracking objects in an area of interest. Compared to previous systems, *Monitor* uses nominal RF equipment, reducing its installation cost significantly, does not disturb traffic during installation, works with non-laned traffic, and does not require user participation. *Monitor* depends on applying statistical techniques to the received signal strength to detect the presence of objects in an area of interest. Moreover, it can differentiate between cars and humans which helps in determining the degree of traffic congestion accurately without wrongly considering humans as vehicles.

Evaluation of *Monitor* in an actual environment shows a good probability of detection of objects and differentiation between humans and cars using nominal RF equipment.

The remaining of this paper is organized as follows. Section II presents the design of *Monitor*. Section III shows our testbed and evaluation results. Finally, we conclude the paper and give directions for future work in Section IV.

II. The *Monitor* System

In this section, we give the details of *Monitor* and how it leverages the received signal strength for object detection and identification.

A. System Overview

Our system is based on the fact that RF signals are affected by changes in the environment [10]. The existence of an object within the wireless signal coverage affects the received signal strength (RSSI) based on the object's size, geometry and material making it possible to differentiate object type, i.e. human or car. The RSSI experiences significant temporal and spatial variability. The spatial variability is caused by the multi-path effect and changes of distance between the transmitter and receiver. The temporal variability is caused by the movement of objects within the signal range. Since the human body is made mainly of water and cars are made mostly of metal, our hypotheses is that their effect on the RSSI should be different. Metallic objects tend to reflect the signal, while water tends to absorb and refract the signal [11].

Figure 1 shows the raw RSSI for three cases: silence, car, and human based on real experiments. The figure shows that both the human and car lead to changes in the mean

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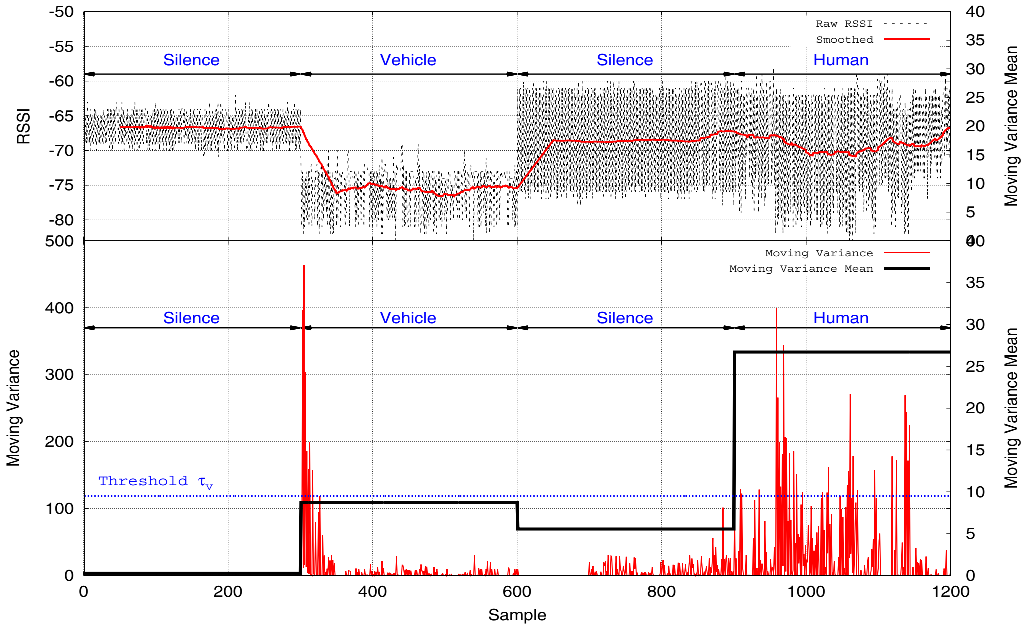


Fig. 1. Raw RSSI readings, mean , and variance for the three cases of silence, human, and car presence.

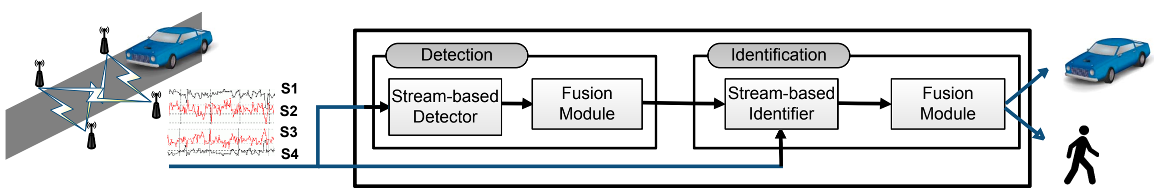


Fig. 2. *Monitor* system architecture.

RSSI, which can be positive or negative in general, due to constructive and destructive interference between different signal paths, especially in the case of human presence. The figure also shows that RSSI variance in the case of human is the largest. In general, RSSI variance is directly proportional to mean RSSI [12], [10]. This confirms our hypothesis that RSSI can be used to differentiate between the three cases.

Monitor leverages this behavior to both detect and identify different objects as shown in Figure 2. The installed nominal RF equipment sends periodic RF frames that are received by the other nodes and whose RSSI is recorded. These streams are then processed by the detection module to detect the presence of an object. The detection decision along with the raw RSSI values are then forwarded to the identification module to further identify the object type.

B. Object Detection

The RSSI pattern in silence periods is stabilized around an average value with some noise and fluctuation (Figure 1). The existence of an object affects the RSSI pattern causing it to shift up or down, based on the constructive of destructive interference of the multipath effect induced by the object's presence. Therefore, for detecting the existence of an object within an area of interest, *Monitor* compares two moving averages of the RSSI of a single stream with different window sizes. The intuition is to compare the long term signal behavior, representing the static environment, to the short term behavior, representing the current state. If there is significant change, based on a threshold, then an object is detected.

More formally, let S_i represent the RSSI sample i from one wireless stream. The long term ($\alpha_{l,k}$) and short term ($\alpha_{s,k}$) averages are defined as follows for time index k:

$$\alpha_{l,k} = \frac{1}{w_l} \cdot \sum_{i=k}^{k+w_l-1} S_i \tag{1}$$

$$\alpha_{s,k} = \frac{1}{w_s} \cdot \sum_{i=k+w_l}^{k+w_l+w_s-1} S_i \tag{2}$$

where w_l and w_s are two parameters representing the long and short window sizes respectively.

When the relative absolute difference[1] between the two

[1]The absolute value is used to take into account the constructive and destructive signal interference patterns as discussed in Section II-A.

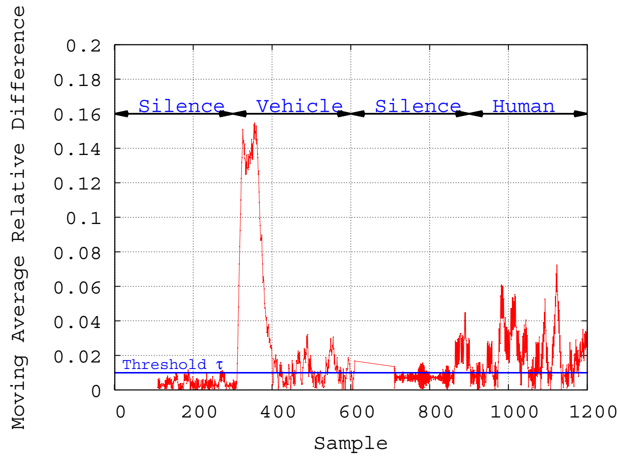


Fig. 3. Effect of applying the moving average technique to the raw RSSI of one stream.

averages, $\alpha_{l,k}$ and $\alpha_{s,k}$ exceeds a threshold τ , *Monitor* detects an object at time $t = k + w_s$. Figure 3 shows the effect of applying the moving average technique to the raw RSSI values. The figure shows that the moving average technique can detect the presence of objects with high accuracy (spike above the threshold). However, there are some false positive and negative cases due to the signal noise. To further reduce this noise, *Monitor* uses two techniques: time latching and stream fusion. The idea behind the time latching technique is to wait for the signal to become positive or negative for a certain time before the signal is considered above/below the threshold. This way, instantaneous fluctuations due to noise will not affect the overall accuracy. Since each stream is noisy by itself, *Monitor* adds a fusion step that combines the detection output of the individual streams for better detection accuracy. This is based on a new parameter (N) that represents that number of concurrent streams voting for detection at the same time to declare a global detection.

C. Object Identification

To differentiate between a human and a car, *Monitor* depends on the variance of the RSSI. A stationary car in an area of interest will affect the mean signal strength. However, since it is an inanimate object, its effect on the variance of the RSSI is minimal (increases only at the moment of change). On the other hand, a human in the area of interest will lead a larger variance due to his involuntary movement (Figure 1).

Once an object is detected using the technique in Section II-B, *Monitor* calculates the moving variance of the RSSI data of one stream (v_t) as:

$$\bar{S_t} = \frac{1}{w} . \sum_{i=k}^{k+w-1} S_i \tag{3}$$

$$v_t = \frac{1}{w-1} . \sum_{i=k}^{k+w-1} (S_i - \bar{S_t})^2 \tag{4}$$

TABLE I
DEFAULT VALUES FOR THE DIFFERENT PARAMETERS.

Detection				**Identification**	
w_l	w_s	τ	N	w	τ_v
50	15	0.01	3	50	9.5

where w is the window size and $t = k + w$ *Monitor* compares the average of moving variance $\bar{v}_t$, from the time an object is detected until it moves out, to a threshold τ_v. If $\bar{v}_t > \tau_v$, then a human is detected, otherwise a car is detected.

Figure 1 shows the effect of applying the moving variance technique to the raw RSSI values. The figure shows that the mean variance in the case of car presence is significantly lower than the case of the human.

Similar to the detection module, to *Monitor* fuses the identification output of the different modules to further enhance accuracy. However, in this case, since the human may not cut all the streams concurrently, *Monitor* detects a human if any of the streams exceeds the threshold. A car is detected otherwise.

D. Discussion

In the operation phase, after collecting RSS readings, the event detection module uses the moving average technique to detect the existence of an object. Then, the object identification module, based on the moving variance technique, differentiates between the detected objects categorizing them into humans or vehicles.

The finite state machine shown in Figure 4 describes the different states of the system. We have four main states: silence, detected object, car, and human. The system starts in the silence state. Once an object is detected, based on the moving average technique, the system moves to the detected, but unknown, object state. Finally, the moving variance technique is used to differentiate between the two object types.

III. Evaluation

In this section, we evaluate the performance of *Monitor* in an actual testbed. To show the feasibility of *Monitor*, we assume a single object, i.e. a human or vehicle existing in the area of interest, and leave the cases of multiple objects for future work. Table I summarizes the default values for the different system parameters.

A. Testbed

Figure 5 shows the experimental testbed. We used two Cisco Aironet 1131AG series access points (APs) to represent the transmitting units and two Dell Latitude E6510 laptops with Intel Centrino N 6200 AGN wireless NIC to represent the monitoring points (MPs). MPs record the RSSI from each AP leading to four streams of raw data for processing.

B. Data Collection

As discussed in Section II, we use the Received Signal Strength Indicator (RSSI) as the raw values. In the infrastructure mode of the 802.11 protocol (WLAN/WiFi), APs broadcast beacons typically every 100 ms. When a frame is

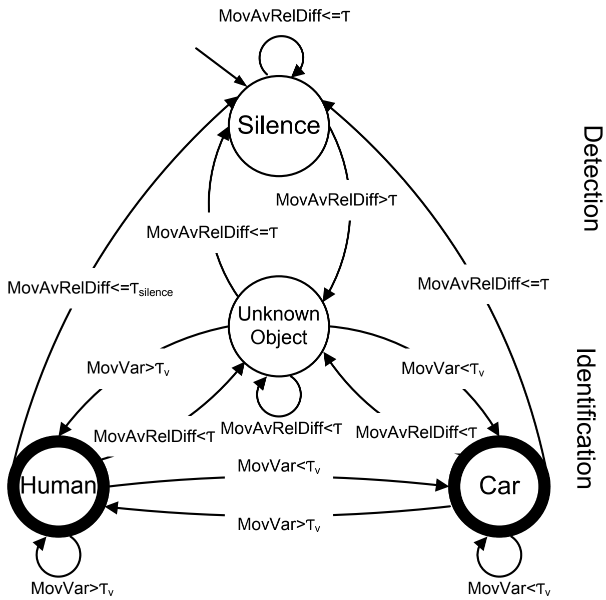


Fig. 4. The finite state machine for *Monitor* object detection and identification.

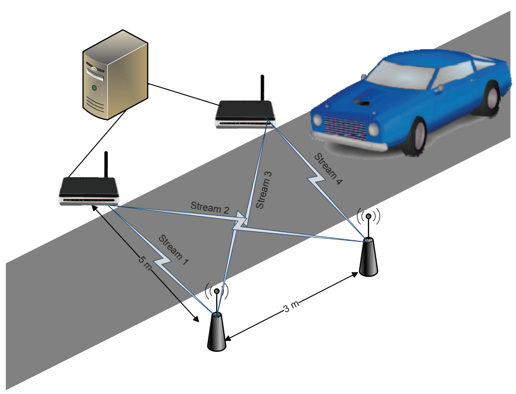
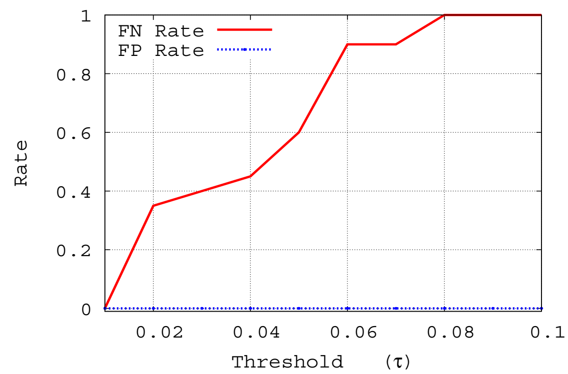
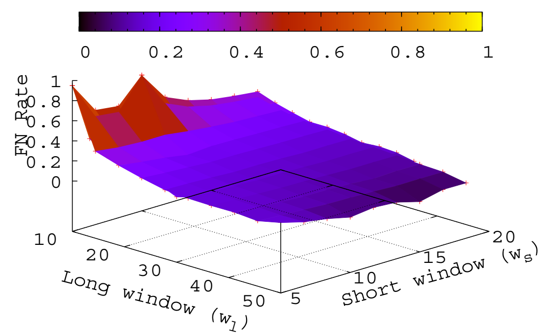


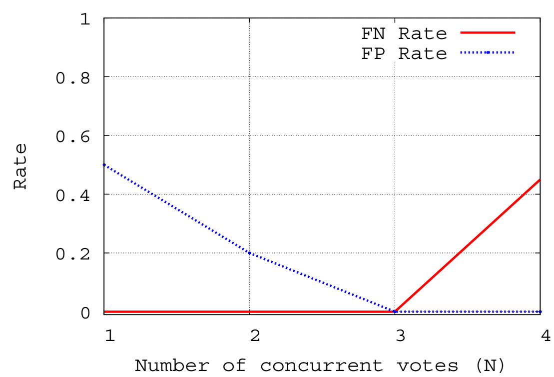
Fig. 5. Experiment layout.



(a) Threshold



(b) Window size



(c) Number of votes

Fig. 6. Effect of the different parameters on the moving average detection technique.

received by a card, it not only extracts and supplies data to the higher layers, but also notes the RSSI values which are reported in the header of the link layer frame [13].

We have a total of 30 experiments representing three cases: silence period (10 experiments), a human entering the area of interest (10 experiments), and a car entering the area of interest (10 experiments). For each case, 600 samples are collected.

C. Evaluation Metrics

We use three metrics to quantify the performance of *Monitor* detection and identification:

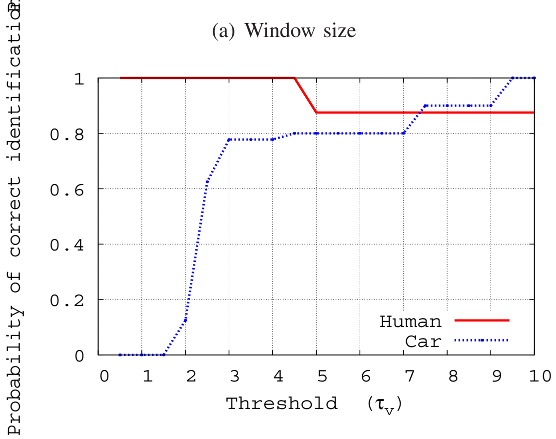
- *False negative rate*: This is the number of times the system misses the detection of an object.
- *False positive rate*: This is the number of times the system incorrectly identifies a silence period as an object.
- *The probability of identification*: which is the probability that the system will correctly identify the object type.

D. Detection Results

In this section, we evaluate the effect of the parameters on the performance of the detection module: the threshold (τ), window sizes (w_l and w_s), and the number of concurrent streams required for detection (N).

Figure 6 shows the results. The figure shows that as we increase the detection threshold, i.e. impose more constraints on the detection, the false positive rate remains at zero while the false positive rate decreases. We note that we can achieve both probability of detection equals one and zero false positive rate ***concurrently*** for $\tau = 0.01$.

(a) Window size



(b) Threshold

Fig. 7. Effect of the different parameters on the performance of the moving variance identification technique.

For the effect of the window sizes, Figure 6(b) shows that a small long window (w_l) fails to capture the long term behavior. A value for $w_l = 50$, $w_s = 15$ lead to both probability of detection equals one and zero false positive rate ***concurrently***.

Finally, increasing the number of concurrent streams voting for detection (N) imposes more constraints on the detection process, leading to reduced false positive rate and increased false negative rate. A value of $N = 3$ leads to an optimal performance of probability of detection equals one and zero false positive rate.

E. Identification Results

In this section, we evaluate the effect of the parameters on the performance of the identification module: the threshold (τ_v) and window size (w).

Figure 7 shows that increasing the window size will lead to decreasing the moving window variance, favoring the detection of humans and reducing the probability of detecting cars.

Similarly, increasing the identification threshold (τ_v), adds constraints on identifying the human, reducing the human detection probability compared to the car.

Depending on the application, the designer can achieve different values for the probability of detecting the human and the car. For example, *Monitor* can achieve 100% human detection and 89% car detection for $w = 50$ and $\tau_v = 9.5$.

IV. Conclusion

We presented *Monitor* as an RF-based traffic detection and identification system. *Monitor* depends on the fact that the presence of objects in an RF environment affects the received signal strength based on the object properties. We presented the *Monitor* system architecture and the moving average and moving variance techniques for detection and identification of humans and cars respectively.

Evaluation of *Monitor* in a real testbed shows that it can achieve accurate detection with zero false negatives and positives concurrently. The system designer can tune the parameters to achieve different identification probability. This paper showed the feasibility of *Monitor* as a traffic estimation system that is low-cost, does not disrupt traffic during installation, works for non-laned traffic, and does not require active user participation. Currently, we are expanding *Monitor* in different directions including larger scale experiments, identifying other properties such as the number and speed of objects and other types of objects and experimenting with other RF technologies.

Acknowledgment

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