Reducing Unnecessary Pedestrian-to-Vehicle Transmissions Using a Contextual Policy

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ABSTRACT

The safety of vulnerable road users (VRU) (e.g., pedestrians, bicyclists) can be improved by sharing their position and context information with vehicles over a wireless communication channel. However, challenges exist in managing transmission in densely populated areas with large numbers of VRUs, since these transmissions may overload the wireless channel leading to transmissions errors and increased battery consumption of the VRU device. This paper hence proposes a contextual transmission policy to address the above challenges. The policy leverages the GPS information available at a personal VRU device to control the message transmission rate for the VRU device. VRUs walking across a street are deemed highly vulnerable and use a larger message transmission rate. Others on the sidewalk are less vulnerable and transmitting fewer messages per time interval. Simulations of a Manhattan VRU scenario show that even with inaccurate GPS readings, significant numbers of transmission can be reduced, which results in a reduction of information age from being 90% of the times less than 1700 msec to 90% of the times less than 710 msec.

KEYWORDS

Pedestrian; Safety; Contextual; P2V; DSRC

1 INTRODUCTION

Vulnerable Road Users (VRUs) are traffic participants who are at higher risk for serious injury or death in case of an accident than car occupants. Examples are pedestrians, pedalcyclists, and road workers. Among them, pedestrians represent 84% of the 6421 total United States VRU fatalities during 2015 [22]. Research by the National Highway Traffic Safety Administration (NHTSA) also shows a 10% increase in the VRU fatality rate from 2014 to 2015 [21]. These trends and the significant number of accidents motivates the quest for technology solutions to improve VRU safety.

One line of work to improve VRU safety explores the use of smartphones or other personal devices to send Personal Safety Messages (PSM) which inform surrounding vehicles of the presence and location of VRUs. For example, Tahmasbi et al. [29] developed a Dedicated Short Range Communications-based collision detection system wherein a vehicle and a smartphone can directly communicate. To ensure that approaching vehicles have the most recent information about a VRU, including its location, speed and heading, such PSM messages must be sent repeatedly. Specifically, previous work [28] suggests transmissions of PSMs at rates of up to 5 messages per second. Concerns over the battery consumption of the VRU device and a congested wireless channel make long operation at high rates undesirable. In fact, our prior simulation results [26] from a Manhattan model show that such PSM transmissions could exhaust the capacity of the communication channel and lead to packet reception errors due to high interference levels. This raises questions about the performance of communication-based pedestrian safety technologies in crowded areas in the absence of a congestion mitigation method.

For vehicle-to-vehicle (V2V) safety messages, prior work has addressed channel congestion through a congestion control algorithm. It focuses on adjusting the message rate of each vehicle based on vehicle dynamics or parameters such as Channel Busy Percentage (CBP) measurements (e.g.,[15, 19]). The characteristics of PSM transmissions differ from V2V transmissions, however. First, the density of pedestrians can be higher than that of vehicles, which lead to even more congested channels. Second, the risk distribution for pedestrians is significantly more biased than that for vehicles. Many VRUs move in inherently more safe locations, such as a sidewalk, where the risk of colliding with a vehicle is very small. Other pedestrians, for example those crossing the street, are at higher risk and information about them is significantly more valuable to nearby vehicles for safety applications. Existing V2V congestion control algorithms do not account for this and would lead to relatively uniform reductions in message rate over all pedestrians. Naively applying them here could lead to unnecessary transmissions from pedestrians that are safe and potentially too few transmissions from pedestrian at risk.

To address this challenge, this work proposes a Contextual Transmission Policy (CTP) for VRUs based on a smartphone sensor-based

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classification algorithm to detect when VRUs are on the road. The CTP is orthogonal to the congestion control algorithms and can be viewed as a prioritization strategy that maintain high rates for pedestrians at risk but seeks to reduce unnecessary message transmissions from those who can be determined to be at very low risk. To assess risk, the classifier uses several contextual parameters such as movement and type of motion but primarily relies on location of the VRU. It estimates the VRU distance from key crossing points, locations that are frequently used by pedestrians to cross the street. Since Global Positioning System (GPS) readings are frequently inaccurate in urban canyons, where the error is more than tens of meters, the algorithm uses additional guard zones around these crossing points based on positioning error estimates. If the VRU is located sufficiently far away from the crossing point at the road border, that is outside the guard zone, the VRU is judged at low risk and assigned a low message rate. The guard zone is determined adaptively based on GPS error estimates to maximize the reduction of the unnecessary PSM transmissions while not missing any VRUs that cross the street.

While CTP is compatible with different communication architectures, the simulation implementation and evaluation assumes Dedicated Short Range Communication (DSRC) technology, which enables low-latency message transmissions. A full implementation could build on smartphone prototypes capable of transmitting PSMs that have been demonstrated by industry [2]. The contributions of this work can be summarized as follows:

- Introducing a contextual transmission policy that adjusts transmissions rate for VRUs primarily based on their location and can tolerate GPS positioning inaccuracies
- Evaluating the risk classification accuracy of the algorithm in a Manhattan-derived simulation model
- Examining the reduction in PSM transmissions and improvements in pedestrian-to-vehicle communication performance by applying the contextual transmission policy in a Manhattan simulation scenario

2 BACKGROUND

Recent activities from the Intelligent Transportation System (ITS) community demonstrated growing interests in using wireless communication to improve the safety of VRUs. For example, the Volpe National Transportation System Center (NTSC) analyzed the national crash database and prioritized pre-crash scenarios that lead up to traffic accidents involving pedestrians and vehicles [3]. The project helps lay the foundation to develop new wireless communication-based pedestrian-to-vehicle (P2V) cooperative safety applications. Meanwhile, the US Department of Transportation (USDoT) funded the city of Tampa in Florida through its Connected Vehicle Pilot program to explore a proof-of-concept P2V solution [5]. The goal of the effort is to provide a safer traveling experience for pedestrians at intersections. Further, a working group of the Society of Automotive Engineers (SAE) recently worked to publish a P2V communication standard J2945/9 [27] which defines a set of preliminary technical specifications for using the Dedicated Short Range Communication (DSRC) technology to transmit PSMs. This standard will serve as a guidance for manufactures to build devices supporting P2V communications in the U.S.

2.1 Challenges

While the above activities help advance the P2V communication technology, the majority of the ITS community in the past decade has focused on inter-vehicle communications and P2V is still at an early stage. Several technical challenges remain to be addressed before such technology can be deployed. For example, the DSRC community aims for lane-level accuracy in its messages but the localization technology required to provide at least lane-level accuracy [27] is not available to today's portable devices (e.g. smartphones), which will likely be the main type of equipment transmitting PSMs. This affects the performance of any P2V communication-based warning system that needs relative position between a VRU and approaching vehicles to assess risks of having a traffic accident. This calls for further work on P2V algorithms that are less dependent on precise positioning information.

Another technical challenge, as reported in [26], is high channel usage which is caused by an overwhelming amount of VRU devices transmitting PSMs through a channel of limited bandwidth. The overloaded channel results in significant transmission errors for PSMs and may degrade the networking performance for all other types of messages sharing the same wireless medium. However, it is nontrivial to address this scalability challenge for PSM transmission by simply applying congestion control algorithms from the V2V cooperative safety community which has extensively investigated the scalabiilty issue for Basic Safety Message (BSM) transmissions. The primary reasons are twofold:

First, a VRU device usually has a limited capacity of battery, making it undesirable to transmit PSMs at a high message rate all the time, in other words, regardless if a VRU is exposed to a possibility of a traffic accident. This is different with V2V communications that are not subject to energy constraint and could transmit BSMs independent of the presence of a vehicle crash threat. As a result, the developed V2V congestion control algorithms, which allow vehicles to always transmit BSMs at a large rate when the channel is not deemed congested, do not directly suit management of PSM transmission.

Second, VRU experiences a set of safety contexts for which the V2V congestion control algorithms may not have an appropriate wireless resource allocation when channel is overused. More specifically, popular V2V congestion control solutions emphasize fairness when allocating wireless resource to vehicles [15, 19, 25]. This leads vehicles with equal chances to transmit BSMs since it is both important to hear others and to be heard on the road. For PSM transmissions, however, VRUs have no interests in hearing each other for road safety purpose. They instead need to be known by vehicles. Their vulnerability with respect to oncoming vehicles, as compared to fairness, could be a better metric based on which wireless resources allocation can be determined, particularly since the risk of collision with a vehicle is very unevenly distributed for pedestrians (located in-street vs sidewalk, for example).

2.2 A Contextual Approach

The above analysis highlights the need to pursue a new PSM-oriented congestion control solution. A promising research direction is to understand VRU safety context and focus transmission of PSMs more on the critical moments where such a message is necessary. This direction, given the above discussion, could enable an algorithm to reduce both battery consumption for a VRU device and congestion on the wireless channel. In our previous work [26], we have demonstrated that if the pedestrian's contextual information can be collected accurately, it could help significantly reduce the communication traffic load over the channel.

To extract pedestrian's contextual information, prior work has focused on using data from smartphone's built-in sensors. Our previous work [13, 16, 17] have studied the feasibility and limitations of using built-in sensors to identify pedestrian risk scenarios. In [16], we analyzed the performance of positioning and inertial sensing techniques for in-street pedestrian detection in both rural and urban scenarios. Further in [13], we demonstrated the data obtained from multiple sensors (e.g. GPS, gyroscope, compass, etc.) on the smartphone can be explored to detect pedestrian's movements, such as turning left or right, and then predict when the pedestrians are about to cross the street. However, both work identified that the performance of the proposed detection techniques can get potentially affected by the high-rise buildings in the urban area due to large errors in the positioning.

To tackle the positioning challenges, we created a new detection technique based on shoe mounted inertial sensors which can characterize pedestrian's on-ramp walking and the process of stepping down from a street curb without fine-grained GPS information [17]. Although the performance of the system was demonstrated encouraging, the requirement of additional shoe-mounted inertial sensor may limit the large-scale deployment of the system.

Tang et al. [30] proposed an algorithm to detect street crossing attempts of pedestrians by using images from their smartphone camera. The algorithm detects distracted pedestrians who cross a street while using a phone, e.g. texting. However, this algorithm requires pedestrians to hold their smartphones while walking, which may not be the case in many situations. Bujari et al. presented in [11] an algorithm which leverages the accelerometer on the smartphon to detect street-crossing events after pedestrians waited for the green phase of a traffic light. The algorithm was cost effective. However, unpredictable human behavior lead to a high false positive and negative rates.

This paper pursues an approach that relies on the sensory data on the smartphone to extract pedestrian's contextual information without any special interaction between the smartphone and the pedestrian. The information is further used to develop a CTP that sends PSMs for a pedestrian based on his/her perceived safety level. Our design goal for the CTP is to reduce the transmission of PSMs as much as possible without compromising the safety of a pedestrian.

3 CONTEXTUAL TRANSMISSION POLICY

The key idea of the proposed CTP is to track multiple context clues that indicate that a smartphone user is not currently a vulnerable road user and to reduce or eliminate personal safety message transmission in this case. In particular, the design focuses on the key challenge of identifying the many smartphone users who are in relatively safe location on sidewalks or in pedestrian zones even when the positioning data available to the smartphone is affected by errors on the order of tens of meters, as frequently the case in urban canyons. It accomplishes this through a map of common street crossing points, where pedestrians walk onto the street, and an adaptive guard zone around these crossing points that is adjusted based on the positioning error estimate.

3.1 Idealized Candidate CTP

For the sake of clarity, let us first ignore possible measurements errors and consider a CTP for operation under ideal conditions.

The first context rule of the algorithm eliminates transmissions when the smartphone remains stationary for a longer period of time t_s, a time interval which would be configured on the order of several minutes. Vulnerable road users usually move and very rarely sit or remain stationary for an extended period of time. In contrast, smartphone users inside buildings, restaurants, or cafes may sit or put aside their smartphone for longer periods of time. Modern smartphone contain low-power inertial sensors that can efficiently track such movement, further motivates this baseline rule.

When motion is detected, the transmission policy uses inertial techniques to determine the type of motion (walking, running, bicycle, in-vehicles, train) using algorithms as discussed in prior work [25]. The CTP will transmit PSMs when walking, running, and bicycle transportation modes are detected but not for vehicle or train occupants, which are not considered vulnerable road users (and vehicles are expected to have their own DSRC transmitters). When running or bicycle modes are detected, the transmitter can remain in higher-risk mode (i.e. more frequent transmission) due to the higher speeds involved and the shorter duration of such activities compared to time spent walking.

The primary challenge then lies in assessing risk in the walking context. The walking context may be further refined by using indoor/outdoor classification techniques [24], in which case transmissions can be disabled indoors. These algorithms generally consume more power than movement detection, which motivates their use as a secondary algorithm that is only periodically active when a user is walking. Note though that complete deactivation of indoor transmissions may create risks in indoor parking garages.

Ideally, the walking context should also be further refined by using in-street context information, since the majority of pedestrians usually moves in relatively safe sidewalk or pedestrian plaza locations. With ideal sensor and map information, the CTP could use the VRU's location to examine if the VRU is located on the road simply by comparing the most recent GPS location L_{latest} reported by the smartphone, with the borders of nearby sidewalks and streets. To perform such a comparison, L_{latest} would need to be accurate to about one meter. Moreover, a carefully calibrated map is required, where boarders of streets and sidewalks are accurately marked. There are two primary challenges with the aforementioned method: 1) Many electronic maps define streets only with their centerline and do not precisely delineate sidewalks. 2) GPS sensors on smartphones exhibit tens of meters of error in urban canyons. Therefore, a direct comparison between L_{latest} and road-sidewalk borders is unlikely to work. Since no sufficiently accurate in-street detection algorithm exist that can operate in dense urban areas and only rely on smartphone sensors, we focus the remainder of the discussion on this aspect.

3.2 CTP with Walking Risk Assessment

Without access to the detailed map and accurate location of VRUs, the proposed design uses a proximity heuristic, to compare VRU's noisy GPS location with the locations where VRUs frequently cross the street. Such crossing points, C_i, can be manually marked on a map stored in the phone, or can be potentially determined automatically by overhearing the positions reported in others' PSMs over a longer span of time. The rationale is that if a pedestrian is in proximity of any such crossing point, there is a higher chance of crossing the street. Conversely, if the pedestrian is sufficiently far away from these crossing points and the risk of a mid-block or random crossing is low, the frequency of PSM transmissions can be reduced. Generally, the algorithm is intended to be conservative, it errs on the side of classifying pedestrians as $HighVulnerable$ while still located on the sidewalk rather than putting vulnerable pedestrians in danger by misclassifying them as safe.

More precisely, as shown in Algorithm 1, the CTP's main part (line 3-13) executes only if the VRU is moving/walking (line 1). Otherwise, the VRU is marked $LowVulnerable$. In our work, the accelerometer on smartphones is used to analyze VRU movement which, once detected, triggers the algorithm to update the proximity threshold d_{Thr} (line 2), as discussed later. Then, the classifier algorithm calculates a distance d_i between the latest reported location L_{latest} and each nearby crossing location C_i from the map, where $i = 1, 2..N$ and N is the number crossing points stored in the phone's map within a predefined radius around the device. If the condition $d_i < d_{Thr}$ is satisfied for at least one i, then the VRU is marked as $HighVulnerable$, otherwise as $LowVulnerable$.

Algorithm 1: CTP Algorithm

Data: C_i, L_{latest}, $err_{L-latest}$, w_{max}
Result: Vulnerability level
1 **if** $VRUIsMoving$ **then**
2     $d_{Thr} \leftarrow$ maximum($\alpha \times err_{L-latest}, w_{max}$)
3   **foreach** *Crossing point* C_i **do**
4         $d_i \leftarrow$ distance between L_{latest} and C_i
5   **if** $d_i \leq d_{Thr}$ **then**
6   mark this VRU as $HighVulnerable$
7   **return**
8   **end**
9   **end**
10   **if** *RandomCrossingDetection* **then**
11   mark this VRU as $HighVulnerable$
12   **return**
13   **end**
14 **end**
15 mark this VRU as $LowVulnerable$
16 **return**

The key to addressing positioning inaccuracies lies in the choice of the threshold d_{Thr} which defines a guard zone around the crossing points. While a fixed, conservative d_{Thr} would simplify the algorithm, we consider an adaptive threshold to address the changing GPS error magnitude over time. The algorithm monitors the GPS error $err_{L-latest}$ reported by the smartphone[1] and multiplies it with a safety coefficient α to obtain d_{Thr}. Note though that the street-width w_{max} should be a lower bound for d_{Thr}. The maximum nearby street width w_{max} can be obtained from maps such as OpenStreetMap [23] or could potentially be calculated using differences between nearby crossing points C_i.

To accommodate possible mid-block crossing and stepping into the street at other random locations, the algorithm can incorporate additional heuristics (line 10-13). First, stepping off a curb results in larger acceleration measurements than regular steps [17]. Second, in areas with sidewalks, stepping off the curb other than at an intersection is often preceded by a change in direction, which can be monitored using inertial sensors on phones. The algorithm should revert to $HighVulnerable$ classification when such conditions are detected. This is indicated in the algorithm with the *RandomCrossingDetection* condition (line 10).

4 EVALUATION

We study the risk classification accuracy and the impact of the CTP algorithm on network performance using a simulation model spanning several blocks around Times Square in Manhattan with pedestrian movements generated using the SUMO traffic generator.

4.1 Evaluation Metrics

To measure how well the proposed CTP classifier can detect the VRUs crossing streets, we select Recall and Specificity metrics. Recall is defined as:

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{1}$$

A greater Recall value indicates that more pedestrians who are crossing the street have been correctly classified as $HighVulnerable$. To err on the side of safety we choose a minimum threshold of 95% for Recall. Parameter choices that led to Recall values below this threshold, were not further evaluated.

Instead of Precision, Specificity is considered the secondary criterion. Specificity, or the true negative rate, directly represents the ratio of outcomes that correctly classifies VRUs on the sidewalk, which better reflects our goals. The Specificity is defined as:

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives} \tag{2}$$

A greater Specificity value indicates a higher true negative rate, i.e. more pedestrians who are safely walking on the sidewalk were correctly classified as such. Higher Specificity means that more unnecessary PSM transmissions can be avoided. Specificity is therefore another indirect indicator of energy efficiency.

4.1.1 Network Performance. We evaluate the impact on network performance in terms of the channel busy percentage, packet error rate, and information age. Since we focus safety applications, the PER and Information Age calculation only considers transmissions where the transmitter is actually at risk (in the street) as determined by ground truth simulator data.

[1]Android, for example, provides the `getAccuracy()` method, which returns a floating point number indicating the radius of 68% confidence for the phone's position [7].

Channel Busy Percentage (CBP) rises with channel load and very high CBP is undesirable because it degrades communication performance due to higher chances of collision. It is defined in Eq. 3.

$$CBP = \frac{t_{Busy}}{t_{CBPwindow}} \tag{3}$$

where $t_{CBPwindow}$ is the CBP measurement window and t_{Busy} is the time period during which the channel is considered as busy by the simulator.

The Packet Error Rate (PER) combines errors due to low received signals (large distance) and due to collisions. To allow separating these, we calculate PER separately for different transmitter-receiver distances using 30m distance bins. In our simulations, the PER is calculated based on the transmissions carried out in Times Square area (the red box in Figure 2). That is, if the transmitter is within the red box the transmission is accounted for, regardless of the receiver location.

The Information Age reflects how fresh the pedestrian's information is at the receiver [18]. The information age is the time since the last successfully received message, which contains the last position update from the pedestrian. To illustrate this, Figure 1 shows a time diagram for communication between two transceivers. The information age increases linearly with time and resets to zero every time a message is successfully received. The simulator samples information age periodically, illustrated by samples 1-4 shown on the right side of Y axis. We further calculate the cumulative distribution function (CDF) of these values over all transmitter-receiver pairs where the transmitter is a VRU located on the street and transmitter-receiver distance is less than 150 meters. Information age increase when unnecessary transmission lead to channel congestion due to the associated collisions. It also increases when an in-street VRU is misclassified since this reduces the message rate of that node. It therefore reflects overall CTP performance.

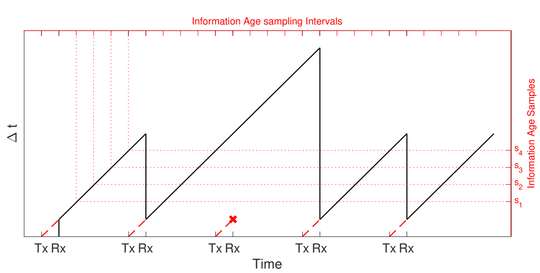


Figure 1: Communication between two transceivers and Information Age sampling over time

We also report the total number of transmissions by all the VRU devices during 85 seconds of simulation, which is approximately proportional to the energy overhead of these techniques. The proposed CTP, VRU devices neither need to communicate with each other nor receive information from vehicles. They can operate in TX-only mode, fall back into power-save modes immediately after each transmission.

4.2 Simulation Setup

The proposed classifier and its impact on network performance is evaluated by using the ns-3 simulator [4]. To generate more accurate results, the simulator is modified to implement frame capture [6, 12]. PSMs are broadcasted over one-hop on a 10 MHz channel at 5.9 GHz band. As for the path loss model, different models are used depending on the link type between the transmitter and receiver at the time of the communication. If there is no building between the pair, a log distance model plus Nakagami fading is used. If at least one building is in between, but the locations of the pair are on different legs of the same intersection, then the proposed loss model of [20] is used. Finally, if the pair are located on parallel street with at least one building in between them, then it is assumed that the packet is lost due to the attenuation from the structure of the building. More detail can be found in [26]. Table 1 shows important simulation parameters.

Table 1: Simulation parameters

Parameter	Value
$t_{CBPwindow}$	200 msec
CW_{min}	15
AIFSN	2
Packet size	316 bytes
Data rate	6 Mbps
Transmission power	20 dBm
Noise floor	-98 dBm
Energy detection threshold	-85 dBm
Channel bandwidth	10 MHz
GPS error model	Gaussian dist. $\mu = 20$ m
Simulation time	90 sec

Since the performance of the proposed classifier depends on the position information reported by the GPS devices, an urban canyon environment is considered as the simulation scenario due to its challenging signal propagation situation for GPS signals. Figure 2 shows the neighborhood around Times Square in New York city. The movements of cars, pedestrians, and bicyclists are simulated by SUMO [9]. The aforementioned model has been extended from work [26] in that the mobility traces are simulated for every road way highlighted in blue while retaining the focus on high node density around Times Square. Another reason for choosing Times Square neighborhood is its high density of pedestrians in the area which helps to evaluate network performance under a near worst-case network load.

The generated scenario includes approximately 400 vehicles, 2300 pedestrians, and 30 bicycles across 7th avenue, 45 Street and Broadway. Note that only pedestrians and vehicles which are outdoors are modeled, that is people inside buildings, and vehicles parked in parking areas are not transmitting and receiving PSMs. Also, we do not evaluate mid-block and random crossings because it is not supported by the SUMO mobility simulator used in this work and we do not yet have suitable location traces.

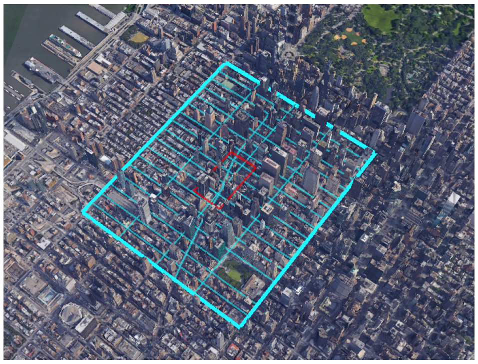


Figure 2: Simulation scenario map - Times Square, NY, USA

4.3 Algorithms and Baselines

Our CTP algorithm assigns $1Hz$ as PSM message rate to pedestrians which are classified as $LowVulnerable$, i.e. located on sidewalk, and $5Hz$ to pedestrians which are determined to be $HighVulnerable$.

We compare the achieved performance by the proposed CTP, with an ideal oracle classifier that relies on accurate simulator information and maps to determine whether a VRU is located in the street or on a sidewalk. In addition, a baseline algorithm where all pedestrians transmit PSMs at $5Hz$ is used.

4.4 GPS Error Model

The implemented GPS error model in this work is using a magnitude positioning error with Gaussian distribution with mean of 20 meters, and angle of the error with uniform distribution between 0-360 degrees. The error samples are assumed uncorrelated. While not ideal for the urban canyon environment, this model provides a first approximation of expected errors. GPS measurements in urban canyons are distorted because of attenuation, multipath, and shadowing effects. Multipath occurs when signals from satellites bounce off buildings and reach the receiver's antenna via different paths where the traveling times for those paths are longer than that of the Line-Of-Sight (LOS) path. Attenuation and shadowing can block the LOS path. GPS error distribution under LOS reportedly follow a normal distribution or Rayleigh distribution with no correlation between samples [1]. Under Non-Line-Of-Sight (NLOS) the error depends mostly on the obstructions' structures [10]. Related studies report 20 meters average and up to 40 meters GPS error for urban environments [14, 17]. Real GPS measurement will be incorporated in future work.

5 RESULTS

We begin with risk classification accuracy and then examine the impact on network performance. Note that all results have been obtained from five simulation runs with different mobility traces, each 90 seconds simulation runtime. The results are furthers averaged across all five runs where 5 seconds of transient state of each simulation has been excluded from the metric calculation. The error bars are showing the minimum and maximum values obtained across different simulation runs.

Figure 3 shows comparison between the Recall metric and the Specificity metric for the proposed proximity-based classifier for different d_{Thr} configurations. A trivial fixed proximity threshold is also examined, where $d_{Thr} = 10m$ in order to show the drawbacks of such approach. To plot this figure, the classifier decision is examined every 200 msec for all the VRU devices in the simulation. Then Recall and Specificity are calculated and collected for each interval. At the end, the collected values are further averaged across the simulation duration.

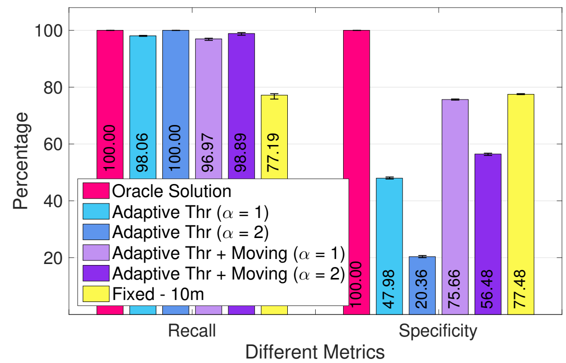


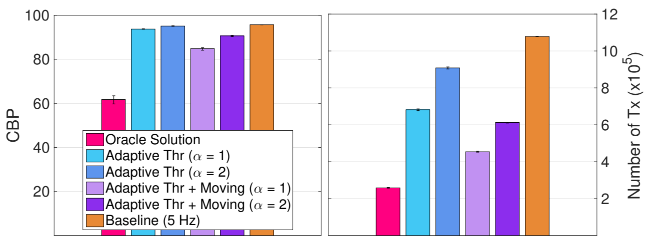
Figure 3: Classifier evaluation

Note that 68% confidence for the reported GPS error by the device is not modeled when generating GPS errors in the simulations. Therefore, the CTP algorithm is simulated where $\alpha = 1$ and $\alpha = 2$. Moreover, in order to show the impact of movement monitoring before marking a VRU as $HighVulnerable$, two cases are considered for simulation. The first case is where the CTP considers the movement as the prerequisite to be marked as $HighVulnerable$, labeled as $+Moving$, and when it overlooks the movement. All these configuration options result in four variations of CTP. These configurations are further compared with baseline and the Oracle Solution. Each figure includes a red bar/curve representing the Oracle solution as well as a bar/curve for the baseline where applicable.

The left side of Figure 3 shows the comparison of classifier's Recall. As expected, the Oracle solution has 100% Recall. The outlier, however, is the configuration where $d_{Thr} = 10m$. In this case, shown by the yellow bar, almost 25% of VRUs on the road are marked as virtually safe by mistake. The result is not greater than the threshold described in 4.1, as this type of wrong classification potentially puts the VRU's safety in jeopardy. Moreover, even if better results can be achieved by further optimizing the predefined fixed threshold, this solution is not reliable since in some challenging scenarios, e.g. in an urban canyon, GPS errors are time-varying and can be biased for several tens of meters [14]. Therefore, a constant threshold based solution, i.e. $d_{Thr} = 10m$, is incompetent in these scenarios and is not considered for further analysis.

As discussed earlier, we consider the Recall value of 95% as the minimum performance, which all of the four adaptive approaches can meet. This indicates that most of the VRUs who are crossing the street have been correctly identified by the proposed CTP classifier as $HighVulnerable$. The second priority is to reduce the cases where VRUs in virtually safe situations are misclassified as

HighVulnerable, i.e. VRUs located on the sidewalk are wrongly identified as in-street. Looking at the right side of Figure 3, we observe the configuration where $\alpha = 1$ and movement monitoring is applied, outperforms the other configurations with a degraded Recall value of 1-4%. The simulations results show that our classifier is able to achieve more 96% Recall and 75% Specificity.



(a) **(b)**

Figure 4: Channel load indicators; a) Channel Busy Percentage, and b) The number of transmitted PSMs during the simulation

Figure 4a shows the average CBP for different configurations of the proposed CTP. The CBP values are measured every 200 msec at the center of 7th avenue and 45th street intersection, and then are averaged over the simulation duration. Figure 4b shows the total number of transmissions sent by all the VRU devices in the simulation. We observe that although the total number of transmissions sent by VRUs differs from one configuration to another, the CBP values remain close to each other. For example, the difference of CBP values between baseline $5Hz$ and adaptive threshold using reported GPS as d_{Thr} is only 2%, but latter sends 50% more PSMs. This is because when the channel load is high, CBP values are no longer linearly (or near-linearly) proportional to the number of transmissions on the channel. Therefore, in these high channel load scenarios, the number of transmissions is a better indicator than the CBP for energy consumption. In general, the proposed CTP solution can reduce the number of transmissions by 15%-58% depending on the different configuration and different trade-off objectives. However, due to the very dense scenario of this work, the wireless channel is over-saturated and even reducing transmissions by half does not mitigate the CBP as much.

Figure 5 shows the age of information contained as discussed in 4.1. The Information Age is sampled every 10 msec and the calculation is limited to the cases where the transmitter is a VRU in the street and is less than 150m away from the receiver. The observation is that with Oracle solution, about 90% of age samples are less than 440 ms. However, baseline 5Hz algorithm provides 1700 msec for the same criteria. As our CTP solutions, for the CTP configuration, where $\alpha = 1$ and the movement condition is considered, 90% of samples are less than 710 msec.

Such improvement when CTP is used is primarily because of the unnecessary transmission reduction that consequently reduces the packet collision on the wireless channel. Figure 6 shows the calculated PER for in-street VRUs. The comparison between different CTP configurations and the baseline algorithms shows that our CTP solution with the configuration with $\alpha = 1$ and the movement condition checker can improve the PER up to 18%.

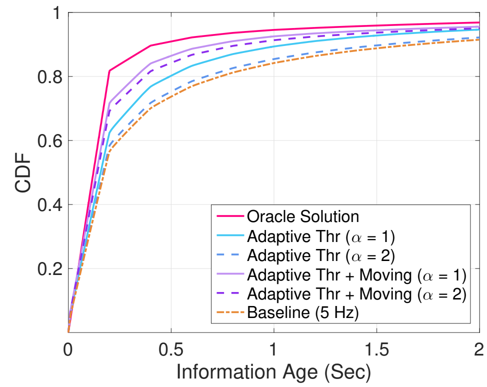


Figure 5: Information Age comparison for in-street VRUs

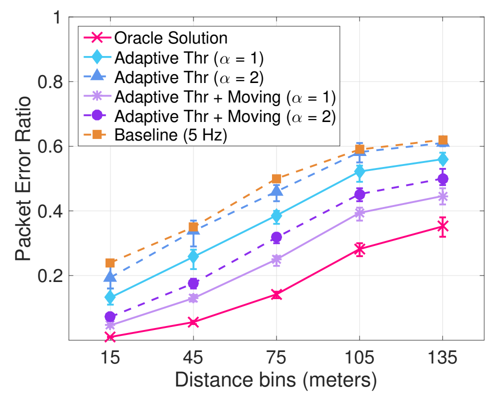


Figure 6: Packet Error Ratio comparison for in-street VRUs

Since the distribution of GPS errors could potentially affect the results, a question may arise about the impact of the general accuracy of the GPS locations provided by smartphones on the proposed CTP algorithm performance. Table 2 presents the impact of the GPS accuracy on the CTP algorithm where the $\alpha = 1$ and movement checker is employed. The general observation is that the performance of the classifier is preserved with different levels of GPS accuracy assumptions. However, for the configuration that the reported GPS error is not compared with the maximum width of nearby streets in the process of adjusting d_{Thr} (look at the two rightmost columns), the Recall is degraded and the Specificity is improved as more accurate GPS locations provided. The main reason for this change is that the extremely low d_{Thr} values would not satisfy the distance comparison of line 5 in Algorithm 1. Consequently, many in-street VRUs are misclassified as *LowVulnerable*.

Table 2: Impact of GPS accuracy on CTP classifier performance

Classifier Conf.	μ_{err}	Comparing with Street Width?			
		yes		no	
		Recall	Spec.	Recall	Spec.
$\alpha = 1$ & Mov.	20 m	96.90	75.61	95.88	76.75
$\alpha = 1$ & Mov.	10 m	98.69	79.53	91.86	87.73
$\alpha = 1$ & Mov.	5 m	98.93	78.68	79.89	93.62

6 DISCUSSION AND FUTURE WORK

Further Congestion Mitigation. Note that after applying CTP the chosen message transmission rate can be further regulated through a channel congestion control mechanism. CTP primarily separates smartphones into distinct priority classes. The message rates assigned to each class could then be adjusted to the current channel load. To achieve this goal, one possible future step would be examining weighted message rate based congestion control algorithms such as Bansal and Kenney's work [8], on top of the presented classifier. This could result in further improvements in network performance metrics.

Bicyclists with Smartphones. In future, some bicycles could also be equipped with a dedicated VRU device which can be activated when moving instead of simply relying on the bicyclist's smartphone to transmit PSMs. One remaining challenge would be avoiding duplicate transmissions from both the smartphone and the bicycle device. This can be resolved at the cost of higher energy consumption by making smartphones periodically listening to the channel and monitoring it for matching movement profiles, i.e. speed, heading, and location.

Energy Trade-offs. In our current design, smartphones are not assumed to listen to the channel to save energy. This allow their wireless chipsets to enter sleep mode while not transmitting. However, there is a trade-off in that it also causes the smartphone to miss information, for example about the presence of vehicles, which could also enable energy management techniques such as not transmitting when no vehicles are nearby. In the current simulation scenario, this would not have been effective since the scenario is so dense that there are a lot of cars in the communication range of every VRU in the scenario. More generally, though, this remains an interesting topic for future work.

7 CONCLUSIONS

In this paper, we argued that the safety of Vulnerable Road Users (VRU), in particularly pedestrians, depends on their location more than their speed and designed a Contextual Transmission Policy (CTP) to account for this. While the overall CTP relies on multiple forms of context, we have focused on risk classification of pedestrians that are walking outdoors. To give priority to VRU's in the street, the CTP identifies potential in-street VRUs with a classifier that checks for proximity to common crossing points and can also incorporate additional crossing detection heuristics. VRUs that are potentially in the street maintain a higher message rate while those determined to be relatively safe off-street use reduced message rates. Simulation results show classifier accuracy of more than 96% Recall and 75% Specificity and an improvement in information age from less than 1700 msec to less than 710 msec in 90% of the times.

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