Artificial Intelligence and Location Verification in Vehicular Networks

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Abstract—Location information claimed by devices will play an ever-increasing role in future wireless networks such as wireless vehicular networks, 5G, and the Internet of Things (IoT). Against this background, the verification of such claimed location information will be an issue of growing importance. A formal information-theoretic Location Verification System (LVS) can address this issue to some extent, but such a system usually operates within the limits of idealistic assumptions on a-priori information on the proportions of genuine and malicious users in the field. In this work, we address this critical limitation by using a Neural Network (NN) showing how such a NN based LVS is capable of efficiently functioning even when the proportions of genuine and malicious users are completely unknown a-priori. We demonstrate the improved performance of this new form of LVS based on Time of Arrival measurements from multiple verifying base stations within the context of vehicular networks, quantifying how our NN-LVS outperforms the stand-alone information-theoretic LVS in a range of anticipated real-world conditions. We also show the efficient performance for the NN-LVS when the users’ signals have added Non-Line-of-Sight (NLoS) bias in them. This new LVS can be applied to a range of location-centric applications within the domain of the IoT.

I. INTRODUCTION

We are at the verge of new wireless networks that aim to bring communication revolutions in homes, hospitals, education, transportation, and other aspects of society. Emerging Intelligent Transportation Systems (ITS) are particularly exciting due to their potential to save many lives. The success of these new technologies in general, and ITS in particular, find their roots in the true location information of the clients (e.g., devices, users, vehicles) involved. In many scenarios, it is anticipated that clients can directly obtain their location information [1], [2] through the Global Navigation Satellite System (GNSS). This location information is then usually provided by the clients to other clients or to some central Processing Center (PC), for other network functionality purposes. But what if a client provides incorrect information about its true location intentionally in an attempt to obtain some advantage over other users [3], [4]? Such circumstances could also occur unintentionally due to difficulty in recording the GNSS location information or hardware issues.

The focus of the work in this paper is location verification in the Internet of Things (IoT), in general, and in ITS (a sub-application of IoT) in particular. The location verification framework proposed in this work is applicable to all IoT applications whose performance is related to a user’s reported location. Within ITS, if a malicious user provides inaccurate location information and this goes unnoticed, the possible aftermath could range from sub-optimal traffic routing all the way through to life-threatening collisions [5], [6]. Verification of a user’s reported location information is hence critical for successful operation in ITS [5], [7]–[10]. Due to this, Location Verification System (LVS) performance has been a research focus in ITS for well over a decade. Recently, several information-theoretic LVSs have been devised [11]–[14]. These LVSs operate under a set of well-defined rules and conditions. Additionally, they have limitations in addressing various anomalies, since they usually assume idealized channel conditions [12]. As such, information-theoretic LVSs usually possess performance limitations in real-world situations. One of the most important of these limitations is the a-priori lack of knowledge on the proportion (fraction) of vehicles in the field that will be malicious (alternatively, the fraction that will be genuine).

Neural Networks (NNs) have recently brought breakthroughs into many aspects of modern society. Web mining [15], content filtering [16], image recognition [17], [18], speech processing [19], language identification [20], speaker verification [21], object detection [22], [23], advanced genomics [24], and drug discovery [25] are just a few of the fields impacted. NNs also lay the foundation for many aspects of the self-driving car paradigm [26]. Many of these breakthroughs are achieved through the development of new NN algorithms [27]. We consider an LVS based on Time of Arrival (ToA) measurements [28] under the influence of Non-Line-of-Sight (NLoS) biases. The novel contributions in this work are summarized as below.

- We show that the NN-LVS proposed in this work outperforms an information-theoretic LVS [28] when the ToA of the users’ signals have added NLoS bias in them.
- We also show that unlike the information-theoretic LVS which assumes an a-priori knowledge about the proportion of malicious vehicles in the field, the NN-LVS works satisfactorily in the complete absence of this knowledge.

Recent advancements in digital signal processing and hardware design now provide us with very accurate physical-layer timing information for wireless networks [29], [30]. These developments provide us with the clock synchronization that enables the LVS we study here. As such, we suggest our new NN-LVS can offer a viable and pragmatic solution to the important task of location verification for many IoT
applications under real-world conditions and uncertainties.

The remainder of this paper is organized as follows. Section II presents the system model. Section III details the performance analysis using information theory and neural network techniques. Section IV provides numerical results, and Section V highlights future prospects. Section VI concludes this work.

II. SYSTEM MODEL

We outline the system model and assumptions considered in this work as below:

1) The system model consists of \( N \) trusted Base Stations (BSs) as verifiers with publicly known locations that are assumed to be in the range of the prover (the vehicle whose claimed location is to be authenticated). The location of the \( i \)-th BS is \( X_i = [x_i, y_i] \) where, \( i = 1, 2, ..., N \).

2) The true location from a genuine or malicious vehicle (the prover) is denoted by \( X_c = [x_c, y_c] \). For a legitimate vehicle, the claimed location is exactly the same as its true location. On the other hand, a malicious vehicle spoofs its true location to the BSs (to potentially obtain an advantage over other vehicles or to disrupt the system performance). The true location of a malicious vehicle is unknown to the wider network.

3) We refer to the announced (reported) location from a legitimate or malicious vehicle as claimed location and denote it by \( X_c = [x_c, y_c] \). For a legitimate vehicle, the claimed location is exactly the same as its true location. On the other hand, a malicious vehicle spoofs its true location to the BSs (to potentially obtain an advantage over other vehicles or to disrupt the system performance). The true location of a malicious vehicle is unknown to the wider network.

4) One of the \( N \) BSs is chosen as the PC. Measurements from all BSs are collected at the PC before being processed into a binary decision related to a vehicle’s claimed location.

5) Under the null hypothesis \( \mathcal{H}_0 \), the framework assumes a vehicle to be legitimate, i.e.,

\[ \mathcal{H}_0 : X_c = X_t, \]  

(1)

6) Under the alternate hypothesis \( \mathcal{H}_1 \), the framework considers a vehicle to be malicious, i.e.,

\[ \mathcal{H}_1 : X_c \neq X_t, \]  

(2)

Under \( \mathcal{H}_0 \), the ToA value measured by the \( i \)-th BS from a legitimate vehicle is given by

\[ Y_i = U_i + Z_i, \quad i = 1, 2, ..., N, \]  

(3)

where \( Z_i \), the BS’s receiver thermal noise, is a zero-mean normal random variable with variance \( \sigma^2_i \). \( U_i \) is the ToA and is given by

\[ U_i = \frac{d^2_c}{c^2}, \]  

(4)

where \( d^2_c \) is the Euclidean distance from \( i \)-th BS to the legitimate vehicle’s true location, and is given by

\[ d^2_c = \sqrt{(x_c - x_i)^2 + (y_c - y_i)^2}, \]  

with \( c \) as the speed of light.

We assume the measurements made by the \( N \) BSs to be independent of each other. Under \( \mathcal{H}_0 \), they collectively form a vector \( Y = [Y_1, Y_2, \ldots, Y_N]^T \). Vector \( Y \) follows a multi-variate normal distribution given as

\[ Y|\mathcal{H}_0 \sim \mathcal{N}(U, R), \]  

(5)

where \( U = [U_1, U_2, \ldots, U_N]^T \) is the mean vector under the null hypothesis, and \( R = \sigma^2_i I_N \) is the covariance matrix.

Under \( \mathcal{H}_1 \), a malicious vehicle claims to be at a location removed from its true location. In a real-world scenario, we can think of this as if the malicious vehicle pretends to be on the road when he actually is placed off the road in a street or in a building. The ToA value measured by the \( i \)-th verifier from a malicious vehicle is given by

\[ Y_i = T_x + W_i + Z_i, \quad i = 1, 2, ..., N, \]  

(6)

where \( T_x \) is a time bias potentially added by the malicious vehicle that impacts the overall ToA value. \( W_i \) is given by

\[ W_i = \frac{d^2_i}{c^2}, \]  

(7)

where \( d^2_i \) is the Euclidean distance from \( i \)-th BS to the malicious vehicle’s true location, and is given by

\[ d^2_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}. \]

We assume the measurements made by \( N \) BSs to be independent of each other. Under \( \mathcal{H}_1 \), they collectively form a vector \( Y = [Y_1, Y_2, \ldots, Y_N]^T \). Vector \( Y \) follows a multi-variate normal distribution given as

\[ Y|\mathcal{H}_1 \sim \mathcal{N}(W + T_x 1, R), \]  

(8)

where \( W + T_x 1 = [W_1 + T_x, W_2 + T_x, \ldots, W_N + T_x]^T \) and \( 1 \) is a vector equal to the length of the number of BSs \( N \) with all its elements set to 1. For later convenience we set \( V = W + T_x 1 \) and rewrite (8) as

\[ Y|\mathcal{H}_1 \sim \mathcal{N}(V, R). \]  

(9)

III. PERFORMANCE ANALYSIS

The outcome of an LVS is a binary result, i.e., the prover is legitimate or malicious. This is different from a localization system where the output is an estimated location. We consider LVS using two methodologies in this work: through the information-theoretic analysis followed in [28], and through our newly designed NN method which makes use of the machine-learning techniques. In both cases, a Bayes average cost function is chosen as the performance metric for LVS in terms of the ‘Total Error’. The information-theoretic method is based on the a-priori assumption that the proportion of malicious vehicles is known. Usually this is set to 0.5 in the absence of any other information. On the other hand, the NN-LVS determines the Total Error irrespective of any such a-priori assumption and it can function with any proportion of malicious vehicles in the field. The Total Error is given by

\[ \xi = P_0 \alpha + P_1 (1 - \beta), \]  

(10)
where \( P_0 \), and \( P_1 \) \((P_0 + P_1 = 1)\) are the \textit{a priori} probabilities of occurrences of \( \mathcal{H}_0 \) \(\text{(i.e., legitimate vehicle)}\), and \( \mathcal{H}_1 \) \(\text{(i.e., malicious vehicle)}\), respectively, and are set equal, \(\text{i.e.}, 0.5\). \(\alpha\) represents the false positive rate \(\text{(the rate of legitimate vehicles being detected incorrectly)}\) and \(\beta\) represents the detection rate \(\text{(the rate of malicious vehicles being detected correctly)}\). Equation (10) then takes the form
\[
\xi = 0.5\alpha + 0.5(1-\beta). \tag{11}
\]

**A. LVS Using Information Theory**

It has been proven earlier that the Likelihood Ratio Test \(\text{(LRT)}\) achieves the optimum detection results for a given false positive rate \([31]\). This leads to the conclusion that the LRT minimizes the Total Error and maximizes the mutual information between input and output of LVS \([32]\). We write the decision rule for the LRT as
\[
\Lambda(Y) = \begin{cases} 1 & \text{if } \frac{p(Y|\mathcal{H}_1)}{p(Y|\mathcal{H}_0)} \geq \lambda, \\ 0 & \text{otherwise}, \end{cases} \tag{12}
\]
where \(\Lambda(Y)\) is the likelihood ratio, \(\lambda = \frac{D_0}{D_1}\) is the decision threshold, and \(D_1\) and \(D_0\) are the binary decision values \(\text{(i.e., whether the vehicle is legitimate or malicious)}\). Given the multi-variate normal form of the observations, (12) can be reformulated as \([33]\)
\[
\Lambda(Y) = \frac{e^{-\frac{1}{2}(Y-V)^T R^{-1} (Y-V)}}{e^{-\frac{1}{2}(Y-U)^T R^{-1} (Y-U)}} \geq \frac{D_1}{D_0} \geq \lambda. \tag{13}
\]

**B. LVS Using Neural Networks**

This section highlights the novel approach used to design a classification framework for the verification of a vehicle’s claimed location through supervised machine-learning techniques. The framework uses a multi-layer feed-forward NN for the binary classification of a vehicle as either legitimate or malicious.

For uniformity, the framework considers the same inputs as considered for the information-theoretic method. These inputs include the user’s claimed location, and \(Y\) \(\text{(the observation vector influenced by the thermal noise} \ Z_i\). Based on a series of trials with changing architectures for the NN-LVS, we finalise a framework that has an input vector, a hidden layer \((\text{with 10 neurons})\), and a binary output layer as shown in Fig. 1. The NN LVS achieved optimum performance through the use of the Hyperbolic tangent sigmoid and linear transfer functions in the hidden, and output layers, respectively.

**IV. NUMERICAL RESULTS**

We now present some numerical results based on our analysis from the information-theoretic and NN-based LVSs. In carrying out these simulations, BSs are located in a 1000 meters by 500 meters area at fixed publicly known locations. This area closely resembles a small district of a city and corresponds to the context of ITS where the BSs are trusted verifiers located on the roadside or in the nearby parking lots. The claimant vehicle \(\text{(the prover whose location is yet to be verified)}\) resides in a 500 X 500 meters area in between the BSs. In order to simulate the attacking scenario and thus study the performance of both the LVSs, we assume that there are two claimants that are within the communication range, namely a legitimate vehicle which is reporting its true location to the BSs and a malicious vehicle which is performing the location-spoofing attack. Both the vehicles can overhear the communication between the BSs and thus both acquire the locations of the BSs. If malicious, the vehicle can also overhear the communication between legitimate vehicles and the BSs so that it can forge its claimed location to that of the legitimate vehicle’s true location.

The malicious vehicle sets its true location at a far-off point so that its transmitted signal \(\text{(with the appropriate timing offset)}\) has equal ToA at all the BSs \(\text{(in the limit of the true location of a malicious vehicle being much greater that any other scale all NLoS biases at all BSs are the same)}\). Under this approximation the mean ToA at the BSs is just the mean of the timings anticipated from a vehicle at the claimed location. The resultant alteration in ToA due to the receiver’s thermal noise is extracted from a Gaussian random distribution with fixed standard deviation. The value of standard deviation considered in our simulation is set to 300 nanoseconds.

We use simulated ToA data in our numerical experiments. The claimed locations for genuine and malicious vehicles in equal proportion are generated randomly in the specified area. The ToA from the claimed locations at the 4 BSs is calculated using equation (4). The receivers in the BSs are under the influence of independent thermal noise \( Z_i \) and thus the ToA measurements they make have a certain degree of variation. We extract this variation \(\text{(in nanoseconds)}\) from a Gaussian random function that has a fixed standard deviation. The area around the vehicles have blockings and therefore their transmitted signals cannot reach the BSs directly hence, their ToAs have additional NLoS bias \(\phi_i\) in them. To mimic reality,
we extract \( \phi_i \) from an exponential distribution as given below

\[
f(\phi_i) = \rho_i e^{-\rho_i \phi_i},
\]

where \( \rho_i \) is the scale parameter.

For the information-theoretic LVS, we determine the Total Error, the false positive rate, and the detection rate using equations (11) and (13). The data considered for the information-theoretic LVS analysis is used to also train the NN-LVS. We call this data the training data.\(^1\) In the training phase, we feed the NN-LVS with random vehicles data at a speed of one vehicle data per second. During each second, the NN-LVS is trained with the available training data. The backpropagation algorithm has a set of internal parameters to terminate the training phase for the NN-LVS. We observe that in most of the cases, the maximum validation failures; which is the maximum number of iterations in a row during which the NN-LVS’s performance fails to improve or remains the same, terminates the training phase. We set this parameter to 6. The weights and biases are considered as optimised once the training phase has concluded. The NN-LVS afterwards can be used to classify a vehicle as genuine or malicious in the test data.\(^2\)

The NN-LVS is trained during the 1st second with an input training data from a single random vehicle. At the end of 1st second, we subject the NN-LVS (with its weights and biases optimized) to calculate a Total Error for the test data. In the 2nd second, we add another random vehicle training data to the previously available single vehicle training data. The combined data forms a new training data set which is used to retrain the NN-LVS (from 1st second). After a re-training, the NN-LVS is used to determine a new Total Error for the test data. We add yet another random vehicle training data to the previously available training data in the 3rd second and use the updated data set to once again train the NN-LVS. At the end of the third second a revised Total Error is calculated for the test data. This process of updating the training data set, retraining the NN-LVS and recalculating a new Total Error for the test data continues in the following seconds. The Total Error keeps on decreasing with the passage of time.

In Fig. 2 we initially determine the Total Error for a data set that has genuine and malicious vehicles in equal proportions (i.e., \( P_0 \) and \( P_1 = 0.5 \)). The standard deviation for \( Z_i \) (extracted from a Gaussian distribution) is 300 nanoseconds while the standard deviation for NLoS bias (extracted from an exponential distribution) is indicated by the different curves. The number of BSs used is 4. The LRT (i.e., the Total Error arising from the information-theoretic LVS) corresponding to each NLoS curve is indicated by the dashed arrow lines. We can see that performance for the information-theoretic LVS deteriorates as the NLoS bias increases, while the performance for the NN-LVS improves with an increase in the NLoS bias in the ToA data. It is clear that the NN-LVS is able to accommodate the NLoS conditions significantly better than an information-theoretic LVS.

Next, we study the impact of changing \( P_1 \) (the proportion of malicious vehicles) on the performance of LVS. We train a NN-LVS through similar procedures as described earlier but change the proportion of malicious vehicles in the test data. In one of the experiments, we fix the standard deviation for \( Z_i \) and the NLoS bias both to 300 nanoseconds. The number of BSs is 4. We can see in Fig. 3 that NN-LVS performs consistently even when \( P_1 \) is different in the test data. We can see that NN-LVS performance is satisfactory even when the test data has 99.95\% genuine vehicles and 0.05\% malicious vehicles. The red line in the Fig. 3 shows the Total Error for the information-theoretic LVS when the genuine and malicious vehicles are in equal proportions in the data (with no changes to \( Z_i \) and NLoS bias). Our study shows that unlike the information-theoretic LVS whose performance is conditioned on the \( a-priori \) knowledge of \( P_1 \), the NN-LVS’s performance is largely independent of \( P_1 \).

In Fig. 4, we change the standard deviation for NLoS bias to 500 nanoseconds. \( Z_i \) still is extracted from a Gaussian random distribution with a standard deviation of 300 nanoseconds. We can observe that NN-LVS’s performance is independent of the \( P_1 \) value.

In Fig. 5, we change the number of BSs to 6 while the standard deviation for NLoS bias and \( Z_i \) are kept the same.
Fig. 3. Total Error performance of the NN-LVS with 4 BSs. The test data has different proportions for genuine and malicious vehicles as highlighted by the different colour of curves. $Z_i$ is extracted from a Gaussian random distribution with a standard deviation of 300 nanoseconds. The NLoS bias is extracted from an exponential distribution with a fixed standard deviation of 300 nanoseconds. The red line shows the Total Error for the information-theoretic LVS (based on LRT method) for a data (realised under same settings of standard deviation for $Z_i$ and NLoS bias) which has both $P_0$ and $P_1$ equal to 0.5. We can see that the NN-LVS performs consistently with different $P_1$ values in the test data.

Fig. 4. Total Error performance of the NN-LVS as in Fig. 3 except the standard deviation for NLoS bias now is 500 nanoseconds.

Fig. 5. Total Error performance of the NN-LVS as in Fig. 4 except the number of BSs now are 6.

from the vehicle was measured at 3 BSs. The performance results for the NN-LVS using input RSS measurements were consistent with the claims of this work, showing our NN-LVS’s adaptability to other metrics beyond ToA.

The NN-LVS framework proposed in this work can be applied to many sub-applications within IoT and 5G whose performance largely depends on the true and verified locations of users. Map services, smart parking, massive MIMO, enhanced beamforming, coverage enrichment, and interference mitigation are just a few of the applications which can benefit from a NN-LVS. The same framework can also assist in defence-related operations where location and its verification is of prime importance.

V. FUTURE WORK

We aim to add more prominent features related to the channel environment so as to further investigate gains achieved by NN-based LVSs. These additional features will better capture the real-world channels. We also plan to compliment ToA systems by adding RSS and Angle of Arrival (AoA) measurements thus enhancing the reliability of NN-based LVSs. A combination of ToA, RSS and AoA will make the NN-LVS even more reliable and efficient in its location verification. We also plan to extend the NN framework to more complex channel fading models such as Rician fading channels. Estimating channel parameters through machine-learning will also result in an extended performance for the NN-LVS. In this case the neural network architecture will need to be extended so as to accommodate the additional unknowns that must be learned. Finally, additional flexibility that allows for the dynamic re-training of the NN-LVS will be investigated. The above future work will help us develop a more robust state-of-the-art artificially intelligent LVS, an LVS which will be wholly practical in terms of its location.
verification performance in a wide range of future wireless networks beyond the ITS we have studied here.

VI. CONCLUSION

Information-theoretic LVS frameworks, due to their operating limitations, are not practical in many real-world scenarios. To address this gap, we have proposed the use of a NN approach to location verification. This approach is particularly useful when we consider that one of the key inputs to any LVS is knowledge on the proportion of vehicles anticipated to be malicious - an input usually known. Using simulated ToA data, we have shown how a NN-based LVS outperforms a state-of-the-art information-theoretic LVS. Unlike the information-theoretic LVS, the working of the NN-LVS is shown to be largely independent of the proportion of malicious vehicles in the area. Unknown channel conditions, such as NLoS bias effects, were also shown to be better accommodated by the NN-LVS approach. We believe the novel approach for enhancing the performance of real-world LVSs that we have developed here potentially forms the foundation for all future works in this important area.

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