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User Intent-Based Proximity Unlock: A Novel Approach For Secure Vehicle Unlocking

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Abstract—
Autonomous vehicles are a rapidly evolving field of research and development, with several innovations aimed at en- hancing their functionality. One such innovation under research is Proximity Unlock, an Internet of Things (IoT) solution that enables safe and efficient locking and unlocking of autonomous vehicles. In this paper, we propose an approach for Proximity Unlock using deep learning methods to identify the intent of the rider walking towards the vehicle. Our approach introduces a novel method that analyzes the rider's walking behavior in addition to RSSI data. We integrated and tested our proposed approach, which demonstrated great accuracy in identifying the rider's intent. This solution has the potential to provide a seamless and secure experience for riders who need to access their autonomous vehicles. Our developments have implications for the wider autonomous vehicle industry and contribute to its ongoing development.
Index Terms—*Robotics, Time Series classification, Autonomous vehicles, IoT).*

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I. INTRODUCTION

The Internet of Things (IoT) [1] has revolutionised the way we interact with our environment, bringing us ever closer to the physical world around us. In recent years, advances in deep learning algorithms have enabled the development of new IoT solutions, allowing for more efficient and reliable access control. Proximity Unlock is one such feature that allows users to experience a convenient unlock mechanism whereby the vehicle unlocks automatically when the user reaches or is about to reach his/her ride usually with the paired phone as the trigger generator.

The problem boils down to how can we trigger a timely response based on proximity of a paired phone? Much de- velopments have been done for key-less unlocking of vehicles involving techniques like face detection [2], but they all require much human interactions like passwords or face scans. We aim for a seamless unlocking mechanism for which all the rider needs is his phone with our app, no need for pressing buttons typing in passwords or face recognition, just walk towards the vehicle with you phone in had or in pocket and the vehicle automatically gets unlock. Such a feat has not been achieved by any of the current research works and IoT powered vehicles in the market. For this we need to be able to precisely predict the intent of the user based on his movement around the vehicle. Only when we are sure that the user is moving directly towards the scooter, we need to transmit an unlock command at least 3 seconds before he reaches the scooter.

To help with all this, we have many sensors provided in a typical cell phone, for example : BLE(Bluetooth Low Energy), accelerometer, gyro-sensors, magnetometers, light-sensors etc [3]. All these sensors can be used to get data which can in turn help to precisely locate the movement(acceleration), the direction(gyro) and whether the phone is in pocket or not(light- sensor). However the conventional sensors are not reliable in the long term, the irregular and noisy signals are not much help in identifying the user behaviour. Moreover sensors like accelerometers require much more processing, and gyros are not available in all mobiles. In our study we find that finally BLE is the sensor to rely on, the signals however are noisy and need to be processed.

In this paper we provide a time series classification approach using some deep learning algorithms for building a proximity unlock mechanism for a scooter using simple BLE sensors paired between the vehicle and the phone of the user.

II. DATA COLLECTION AND ANALYSIS

A processed RSSI(Relative Signal Strength Indicator) [4] signal from BLE, if analysed properly can act as a time series, to depict the intent of the customer, as utilised in [5] for human to human proximity. The strength of the refined signal increases rapidly when the Bluetooth sensor gets in proximity and vice versa when it moves away. This is thus a viable option for building a proximity unlock mechanism for our scooters. We used BLE in proximity because of it's low battery consumption and sustained signal at longer range. It was efficient and reliable in our case while reducing carbon emissions and making it eco-friendly for use. Further BLE protocol is supported on most modern devices at a very low cost.

Source and collection

The collection was done on 2 major scenarios for unlocking a vehicle, underground parking lots and open ground regions. This accounted for variations in the signal caused by humidity and temperature. Data was collected for different directions of approach towards the scooter, in a radial formation the directions were front 0 degree, front 45 deg, right 90 deg, back 135 deg, back 180 deg, back 225 deg, left 270 deg, front 315 deg. The direction of approaches were registered as towards and away from the scooter. Variations such as phone in front pocket and back pocket as well as phone in hand were also introduced.

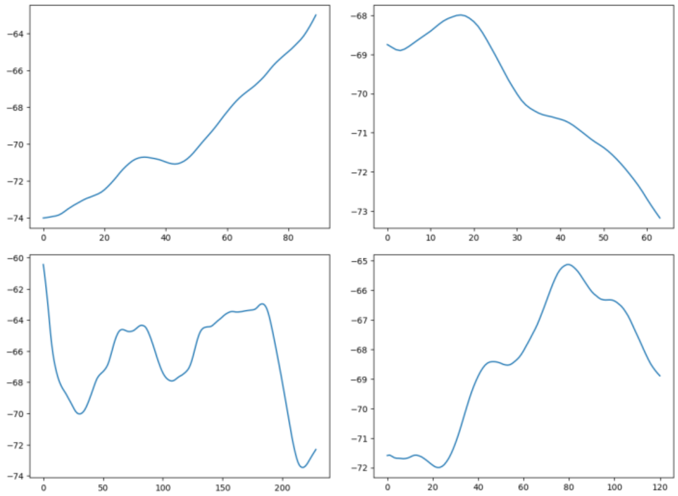


Fig. 1. Smoothened RSSI values for all different variations, move towards (top left), move away (top right), move around(bottom left), move past (bottom right)

The positive class were walks that were down with an intent of unlocking the scooter, i.e they started at 20 feet and stopped 0 feet from the scooter. Other walks like walk around at 6 feet, walk past from 6 feet or walk away from 0 feet to 20 feet were negative classes. In total there were 64 total variants of data for which the data was collected for N number of vehicles. The data collection was done such that for each second we got 10 RSSI values. A depiction of different classes of walks is shown in Fig. 1. Walk pasts and Walk arounds have high peaks and increasing slopes at points where the rides is close by, thus identifying the right intent becomes a hefty task.

Analysis and Insights

The RSSI signals are full of fluctuations, there are ir- regularities and spikes caused by multitudes of reasons like humidity, obstructions in the path of the user and minor disturbances caused by the sensor pairing itself. It was found that a specific phone(various different brands were used) and a specific scooter once paired provided a different RSSI value distribution than any other pair, i.e, the RSSI value were different for the same scooter when paired with different phone brands at the same distance. To tackle this problem we shuffled the pairs regularly so that the data is much generalised.

Finally we had a dataset of about 3000 walks after the data collection. Each walk data represented a single walk in one of the 64 variations either from a 20 feet radius to the scooter or from the scooter to a 20 feet point. These walks constituted of unclean data as well, walks which are too small for classifying their intents, walks with irregularities, etc.

CLEANING THE DATA

To start with cleaning we need to understand that the target is a time series classification, each walk is a time series of RSSI values, the target is to predict at least 3 sec prior to reaching the scooter whether the person is actually moving to the scooter or just passing by.

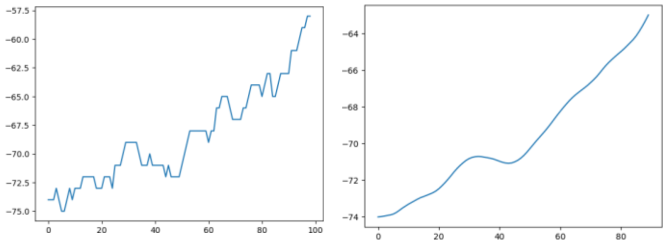


Fig. 2. Raw RSSI values compared to smoothened RSSI values, Raw data for a sample move towards walk(left) and its Kalman filter and rolling window processed image(right).

Passing by walks have a spike in the middle of the walk due to their proximity at its apex, whereas walking towards the scooter with an intent of riding it will have a increasing slope until the rider reaches the vehicle. We aim to trigger an unlock around 6 feet Any walks with less than 7 seconds or 70 data points of data are discarded as the last 2-3 seconds of data is withing the 6 feet radius. We need to predict before that, so that data is of no use except confirm whether the person was inside the radius, ie unlocked the scooter or if not then he just passed by.

The walk data is still noisy as RSSI values fluctuate, a simple smoothening of the values is not the right option since, there are fluctuations that will affect the running mean of the values. Kalman filter [6] is the best option here, it provides a sequential, unbiased, and minimum error variance estimate under the assumption of known statistics of system and measurement errors, which allows us to remove some of the spikes in the data points caused by noise, shown in Fig.

2. The rest of the irregularities can be smoothened over by using a 10 range sliding window smoothening technique. After removing the mislabelled and other invalid walks we have our cleaned data, of about 2000 walks.

III. TIME SERIES CLASSIFICATION

LSTMs

Given the time series nature of our data, LSTM [7] was considered a suitable choice. In the data preparation phase, we employed diverse approaches. Initially, we trained an LSTM model using raw BLE data from various walks, regardless of their duration. Through experimentation, we determined that the optimal length of BLE data to be sent to the model during inference is 8.7 seconds i.e. 87 values. Notably, the model effectively handled cases where individuals walked around the scooter without intending to approach it. The LSTM model considered contextual information, ensuring that the scooter remained locked during such instances. However, a significant challenge arose when individuals walked away from the scooter and then returned with the intent to approach it. Even if they were far away, a spike in the BLE values caused the LSTM model to interpret it as an approach. Although achieving an accuracy of 96%, real-world scenario testing revealed performance below the expected level.

TABLE I
SLOPES AND INTERCEPTS FEATURES FOR THE 2 CLASSES

slope median	intercept median	slope max	intercept max
0.446	-0.319	0.126	0.027
-0.447	0.320	-0.127	-0.028

TABLE II
PHONE MODEL VARIATIONS WHILE PAIRING

RSSI value	phone 1	phone 2	phone 3	phone 4	phone 5
max	-42	-61	-57	-55	-44
min	-79	-85	-77	-84	-88

CNNs

Unlike LSTMs, CNN [8] based models rely on convolu- tional operations for extracting meaningful features from the sequential data and make predictions based on those features, treat each value in the time series independently. This makes 1D CNNs suitable for tasks where the temporal feature is not crucial or when capturing long-term dependencies is not a primary concern. As discussed reducing the length of the input sequence may not help in addressing the challenges posed by irregular slopes in time series data when using LSTMs. In such cases, 1D CNNs can be a better solution as they are less affected by the irregular slopes and focus on extracting relevant features directly from the input data.

Our model is a simple CNN based model constituting of 3 1D CNN layers, each followed by Batch-norm [9] and ReLU

[10] activation layers. Finally followed by Dense layers to provide a binary classification to whether the intent of the walk is to unlock or not. Once trained on the data discussed in section III we have a test accuracy of 94.3%. Results on actual testing done using app and other combination of methods for refining the RSSI values will be discussed in the Results section IX.

IV. SLOPE OF THE RSSI VALUES

The analysis provided above gave a clear bifurcation of the intents of the walks in our data, slopes of the slopes tell a lot about the walk intent. A monotonically increasing slope till the very edge of the 6 feet mark is almost always an indication of a unlock intent. Sudden increases in slope and sudden dips are usually for walk around and walk past approaches and decreasing slopes for moving away of unlock intent, shown in Fig. 1. Intercepts also play a role in providing insight into the initial condition or value before any changes.

We have tried to incorporate these features as well in our model to boost its performance further. For this we calculated slopes and intercepts for every 5 processed RSSI values. Since there are minor fluctuations that might effect majorly

in calculating the slope and intercepts, we take an average of the previous 5 slopes and intercepts, i.e we use the past 25 values or 2.5 seconds of the data to determine 4 features

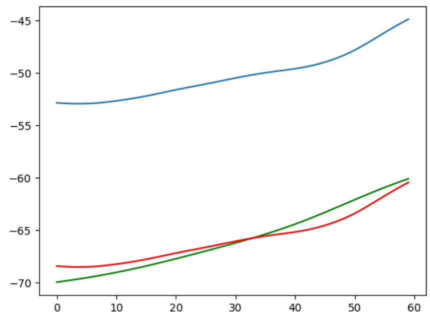


Fig. 3. Shifting of the input series using an ideal curve to normalize the data. Ideal curve(green), shifted series(red), and original series(blue).

after some analysis, namely median slope, median intercept, max slope and max intercept. Together with these 4 values, a total of 54 values are provided to our simple CNN model. Feature importance showed slope and intercept features to be in the top 6 most important features for the CNN model, due to their clear value distinction between the positive and negative classes as shown in Table I.

V. PROBLEM OF UNIQUE PAIRS FOR PHONE AND SCOOTER

It was found that each pair of phone and vehicle connected with it provides its own range of values for the series of RSSI values, a similar walk can have completely different range of values from 2 different phone as shown in Table III, affecting the models output. Different manufacturers had different implementations and quality of chips which caused this instability. Thus normalizing the data becomes essential so that the model can be applied generically for all the combinations of phones and scooters. An early attempt was to provide the average values of each phone type from the collected dataset and use it to scale the RSSI values in the specified range of the unique pair.

Shifting the input series range

Another important contribution was to compare and scale the ongoing time series to a pre calculated ideal “move towards” walk. This ideal walk of 50 values was calculated using the mean of all the “move towards” walks. Every 50 value time series input is scaled to this ideal walk’s range, taking an average of difference of each of the 50 RSSI value between the ideal and current series, we get a ’shift value’ which then could be used to normalise the input series. This idea itself helped in dealing with outliers and cases where the range of various phone models is varying. As shown in Fig. 3 the original ”move towards” series has too high RSSI values reaching -45 causing an outlier in our data, out ideal curve shows the usual values are around -65, thus we shift the range, generalising our model outputs.

Exponential Weightage

The slope values varied with every upcoming RSSI values, it was found upon experimenting that the recent values of the slopes had more effect on the timing of the unlocking,

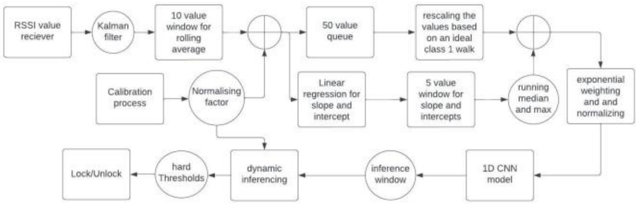


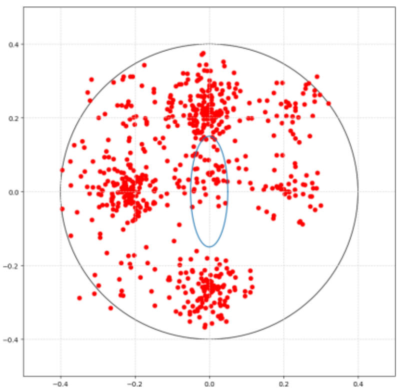
Fig. 4. A distribution of unlocking and point where the values change and so does the intent from negative to positive class. The black radius depicts 6 feet from the blue ellipse(scooter).

especially for the cases of walk past and walk arounds. Of the 50 RSSI values used, slopes for the latest and oldest values gave most information. For better usage of the slopes an exponential weightage of the 50 processed RSSI values was calculated, after multiplying the move towards approaches were modified to have a better and more profound slope, walk past intents had a increasing slope but quickly dissipated and was not as high in RSSI values as move towards and walk had a decreasing slope. This provides a faster response for unlocking the vehicle and reducing the irregularities and delays.

VI. CALIBRATION OF THE PAIR

The need for a calibration mechanism arose the moment it was clear that each pair of phone and scooter has its own range of values. Because of this irregularity there is a huge problem in unlocking the scooter from all directions, as shown from the Fig. 4, there is a high concentration of sudden changes in values from a few feet front, left and back, its find right side RSSI values are more steady and thus provide less information on such sudden changes and irregularities in each pair. Thus a calibration needs to done by walking around the vehicle at different distances and capturing the respective RSSI values. A normalising factor was calculated based on values at the following distances : 0 feet from vehicle front, 2 feet from front, 2 feet from left, 0 from left, 0 from right and 0 from behind.

These values provide a crucial information, in some pairs, the left values are lower than the right, causing delayed unlocks from left side, some have very low values in the front, causing undesired unlocks before the 6 feet because of their high RSSI values. By taking an average of the above location values we use it fro normalising the upcoming RSSI values thus solving the irregular unlocking problem.



Dynamic Inference

A sure way to ensure that there are no undesired un- locks(unlocks outside the 6 feet radius and for intents that are not 'move toward'), is to change the rate of inference. We look Fig. 5. Our testing app data flow.

for the latest 'n' predictions by our CNN model for unlocking the vehicle. Inference rate for calling the model initially fixed to 0.2 seconds, can cause trouble in scenarios where there are RSSI values really high outside 6 feet. To encounter this we have introduced dynamic inferencing, the model is called at

0.6 seconds as long as a specific threshold is not reached. This threshold is easy after we have already done calibration as discussed above. Of all the values at different locations, the minimum value acts as the threshold, for values above this values the inference rate is changed to 0.2 seconds. Thus achieving swift safe and reliable unlocks in the 6 feet vicinity.

VII. VARIATIONS IN HANDLING THE PHONE

Finally thinking about an ordinary person availing our Proximity Unlock mechanism we dive into different ways the phone can be handled by the user, since the phone is the only way we are safely linked to the scooter and the only way we receive RSSI value data in our app.

There are 3 ways in which the user can handle the phone, in his hand, in his front pocket and in his back pocket. So far all our algorithms have been combined and put in place to work fabulously for in hand usecases. It was found that due to the clothing fabric RSSI values are lowered and this causes delayed unlocks, however our 'ideal shift' technique discussed in section VI is able to handle this problem. Back pockets however are a problem still unsolved. In back pockets the value change is very insignificant, machine learning methods are not appropriate for solving this case. Another approach utilised for front pocket was to detect whether the phone is in a pocket using the light sensor which is available in most phones these days, if yes increase the normalising factor by a threshold to account for the delayed unlocks.

VIII. TESTING

All the above methods and ideas have been implemented over the CNN model trained on the collected data were tested using an app built for real-time testing. An unbiased and generalised environment was created for testing the unlocking behaviour based on the user walk and his phone handling.

Locations for testing were done on both basement and ground-level to account for all possible cases and variation in RSSI caused by environmental factors.

TABLE III
RESULTS ON VARIOUS STRATEGIES

Strategy	Desired		Undesired		Desired Unlock				Undesired Unlock			
	Walks	Acc.	Walks	Acc.	Phone 1	Phone 2	Phone 3	Phone 4	Phone 1	Phone 2	Phone 3	Phone 4
CNN	451	82.48%	368	82.05%	81.37%	83.10%	72.87%	92.58%	80.37%	96.10%	91.87%	67.74%
CNN+dynamic	1060	81.46%	810	88.40%	81.25%	94.38%	73.08%	96.88%	90.81%	70.53%	86.65%	85.79%
LSTM	768	78.78%	764	90.97%	80.73%	73.44%	72.25%	89.53%	95.29%	86.39%	100.00%	96.32%
LSTM + dynamic	336	67.20%	320	91.41%	80.00%	82.81%	56.25%	70.31%	100.00%	70.31%	95.31%	100.00%
CNN dynamic (4 to 1)	1648	81.04%	1494	92.84%	85.55%	84.48%	82.50%	71.63%	93.73%	94.23%	98.43%	95.80%
CNN dynamic in pocket	256	89.84%	318	88.05%	90.63%	89.06%	81.10%	92.67%	91.6%	87.56%	82.23%	91.76%

IX. RESULTS

As shown in Table III, the results indicate CNN models performing better than LSTMs for short duration signal classi- fication. Addition of methods like dynamic inference improves the results, specifically undesired unlocks. The phone and vehicle pairing issue is easily solved by the calibration method and shows promising results for a variety of pairs.

X. CONCLUSION

In this paper, we have discussed a novel method for un- manned vehicle unlocking and introduced methods that can improve on the security of this approach, We have provided evidence that generic and static algorithmic based methods are not accurate enough and thus understanding and capturing the walking trend and analysing the approach of the user is not only important but also crucial for a quick unlock and great user experience. We found that a generic algorithm can not be deployed across a multitude of vehicles for Bluetooth based unlocking of vehicles, a dynamic and calibration enforced method outperforms them. The results indicate that within a radius of 6 feet our method is able to capture the walking pattern of the user and unlock the vehicle.

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