In-Vehicle Localization System for BLE Enabled Devices

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ABSTRACT
This paper proposes an in-vehicle localization system for Bluetooth low-energy (BLE) enabled devices to improve passive-entry passive-start functionality. The system includes BLE sensor modules, a fusion processor, a telematics unit, and a Firebase server integrated with a user-friendly mobile app. The BLE modules are located at the optimal positions in the vehicle to monitor the received signal strength indication (RSSI) from the user's mobile phone. The fusion unit processes the RSSI readings using the Kalman filter and the trilateration techniques and then calculates the accurate position of the mobile device to the vehicle. The telematics unit communicates with the Firebase server for user login and access control. The mobile application features include setting up accounts, verifying identities, and interacting with a vehicle via the BLE. The proposed system ensures vehicle security and allows authorized users to unlock/lock doors and control the vehicle. The experimental results showed that the developed key achieves safe vehicle access and control, and enables integration with the smart vehicles.

Keywords
In-Vehicle Localization, Received Signal Strength indication, Bluetooth Low-Energy, Firebase, Mobile Application, Kalman Filter, Trilateration, Passive-Entry Passive-Start.

1. INTRODUCTION
The large prevalence of smartphones and wearable technologies offers unprecedented improvements in the quality of life and comfort. Automotive manufacturers seek to employ these technologies in vehicle-to-phone communications such as the localization of a device position relative to a vehicle and then locking/unlocking doors depending on a phone distance. So, many drivers are expected to utilize their smartphones as secure digital keys by 2030 [1].

The development of Bluetooth low-energy (BLE) technology has enabled various applications for localization-based systems. In [2], different BLE-based fingerprint localization techniques have been studied for vehicular applications. The authors highlighted varying accuracy levels achieved with the proposed algorithms. Despite that, they concluded the need for enhanced techniques to overcome limitations in identification accuracy. In [3], BLE beacons for passenger localization within vehicles have been illustrated by tracking passenger positions, and the design faced challenges such as signal interference, and the need for precise calibration to ensure accurate localization. Researchers in [4] explored the integration of geomagnetism with BLE signals. They found that combining these technologies could potentially enhance vehicle in-out detection accuracy. Nevertheless, they pointed out the complexity of implementation and the need for further optimization to address environmental factors that might affect geomagnetic readings. In [5], the use of multi-channel BLE for in-vehicle localization has been examined. This approach emphasized the importance of leveraging multiple BLE channels to improve the robustness and accuracy of BLE-based localization. However, it also identified issues related to signal fluctuations and the necessity for sophisticated filtering techniques to mitigate noise. A relay attack resistance in passive Keyless entry and start systems has been studied. The study proposed methods to enhance security by detecting user context. It acknowledged that additional computational overhead and system complexity could be potential drawbacks [6].

The paper presents a system comprising BLE sensor modules strategically distributed within the vehicle to sense the received signal strength indication (RSSI) from the user's mobile device. The readings are collected by a fusion processing unit, which applies the Kalman filter and trilateration techniques, to determine the position of the mobile device. The system also includes a connectivity module, linked to a server, and a mobile application for managing user authentication and privileges. The proposed system addresses the limitations identified in the previous works by incorporating advanced filtering techniques to mitigate signal noise and fluctuations and optimizing beacon placement for better accuracy. Besides, using commercially available hardware components ensures a cost-effective solution without compromising performance and reliability.

2. SYSTEM ARCHITECTURE
Figure 1 shows the proposed BLE-based in-vehicle localization system. The designed hardware includes four ESP32 sensor modules placed within the vehicle. The ESP32 modules sense the received signal strength indication (RSSI) from the user's mobile. The ESP32 modules communicate according to the Bluetooth 5 protocol with minimum power consumption and exchange data at a distance of around 100 meters. The system also has a Tiva-C-based fusion processing unit, that consists of an ARM-based microcontroller running at frequencies up to 80MHz. The measured RSSI values from the BLE modules are transmitted to the fusion processor via a controller area network (CAN) bus. Then, the fusion processor uses the trilateration algorithm and sensor fusion techniques to determine the mobile

phone's location. There is also a telematics unit based on the Raspberry Pi 4 Model B, which behaves as a connectivity module, interfacing with the Firebase cloud server and a mobile application for managing user authentication and privileges. The architecture in Figure 2, has blue pill units (STM32F103), which are used for engine start, locking/unlocking doors, and NFC reader. It also contains CAN bus transceivers (MCP2551) for continuous data exchange.

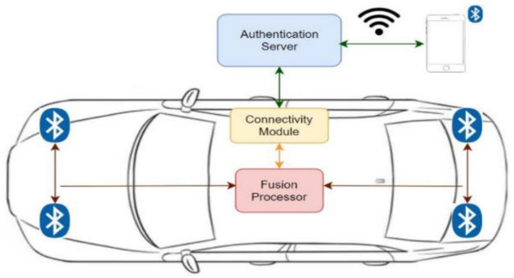

Fig 1: Block diagram of the in-vehicle localization system

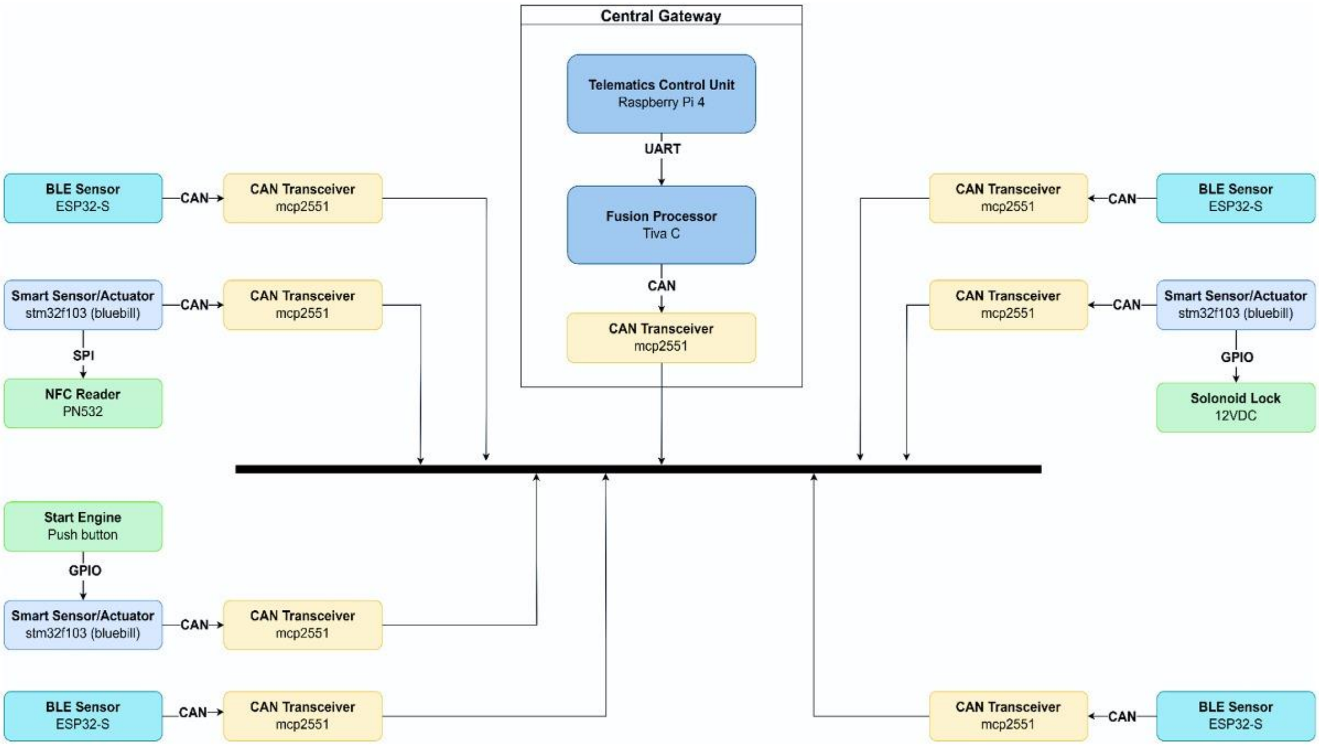

Fig 2: Hardware architecture of the proposed in-vehicle localization system

3. SYSTEM IMPLEMENTATION

The distributed ESP32 BLE modules in the vehicle measure the RSSI signals from the user's phone, to calculate the phone location in real-time. Then the distance between the BLE sensors and the mobile device is estimated by the path loss model [7]:

$$\text{Distance} = 10^{\frac{RSSI_0 - RSSI}{10 \cdot n}} \quad (1)$$

where $RSSI_0$ is the value of RSSI calibrated at one meter and RSSI is the measured value by the ESP32 sensor. The path loss rate n depends on the environment and varies between 2 and 6.

The validity of the measured RSSI signals is tested by placing the mobile phone and the ESP32 module at one meter as shown in Figure 3. The distance from the measured RSSI data is recorded in Figure 4. It can be seen that the measured distance differs from the expected value and has an amount of error due to environmental interference and multipath errors.

Fig 3: Testing the ESP32 module and a phone positioned at one meter

Fig 4: Measured distance with some errors

As the RSSI value and its corresponding distance fluctuate, the measured RSSI must be filtered from surrounding noise. Therefore, the Kalman filter technique is applied to minimize noise and errors in RSSI reading sensed by the BLE modules. Kalman filter provides more accurate and stable measurements since it incorporates the process dynamics and measurement noise and it's adaptable to environmental changes. The Kalman filter algorithm is implemented in the system by the following steps [8-11]: Prediction,

$$\hat{x}_{k|k-1} = \hat{x}_{k-1|k-1} \quad (2)$$

$$P_{k|k-1} = P_{k-1|k-1} + Q_k \quad (3)$$

Measurement update,

$$K_k = P_{k|k-1} H^T \left(H P_{k|k-1} H^T + R \right)^{-1} \quad (4)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - H \hat{x}_{k|k-1}) \quad (5)$$

$$P_{k|k} = (I - K_k H)\, P_{k|k-1} \quad (6)$$

for $k = 1, 2\ldots,$ where $\hat{x}_{k|k-1}$ is the predicted state given the knowledge of the process prior to time-step k, $\hat{x}_{k|k}$ is the estimated state given z_k, K_k is the Kalman gain, and I is the identity matrix. $P_{k|k-1}$ and $P_{k|k}$ are the covariance matrices of the prediction and estimation errors.

The RSSI reading and the corresponding distance are processed by the Kalman filter technique. Figure 5 shows better distance measurements, at one meter after applying the Kalman filter than the results obtained in Figure 4.

The next stage in operation flow is the Tiva-C-based processing unit. ESP32 modules are connected to the Tiva-C processor through a CAN bus (Figure 6). The bus consists of two lines, the CAN low (CANL) line and the CAN high (CANH) line, and is terminated with 120 ohm resistance at each end. Each ESP32 module sends CAN packets (Figure 7) to the processor containing the measured distance for the mobile phone. Figure 8 shows the construction of the CAN frame sent from the ESP32 node and received by the processor. The frame starts with the identification and control fields, followed by four data bytes for the measured distance by the ESP32 node. The end of the frame is the cyclic redundancy check (CRC) sequence and the acknowledgment (ACK) field.

Fig 5: Measured distance after applying the Kalman filter

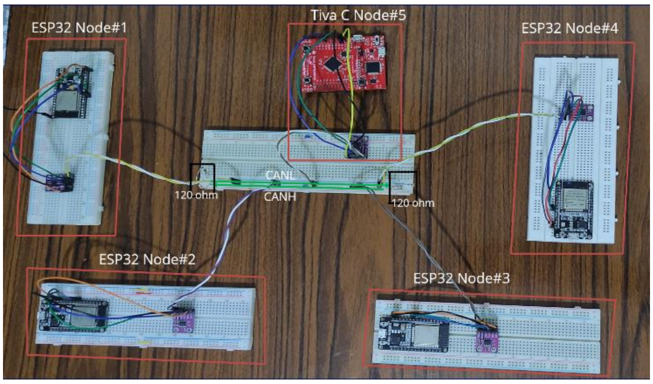

Fig 6: Testing ESP32 modules and the Tiva-C processor through the CAN bus

Fig 7: Testing CAN bus packets of the five nodes using Saleae logic analyzer [12]

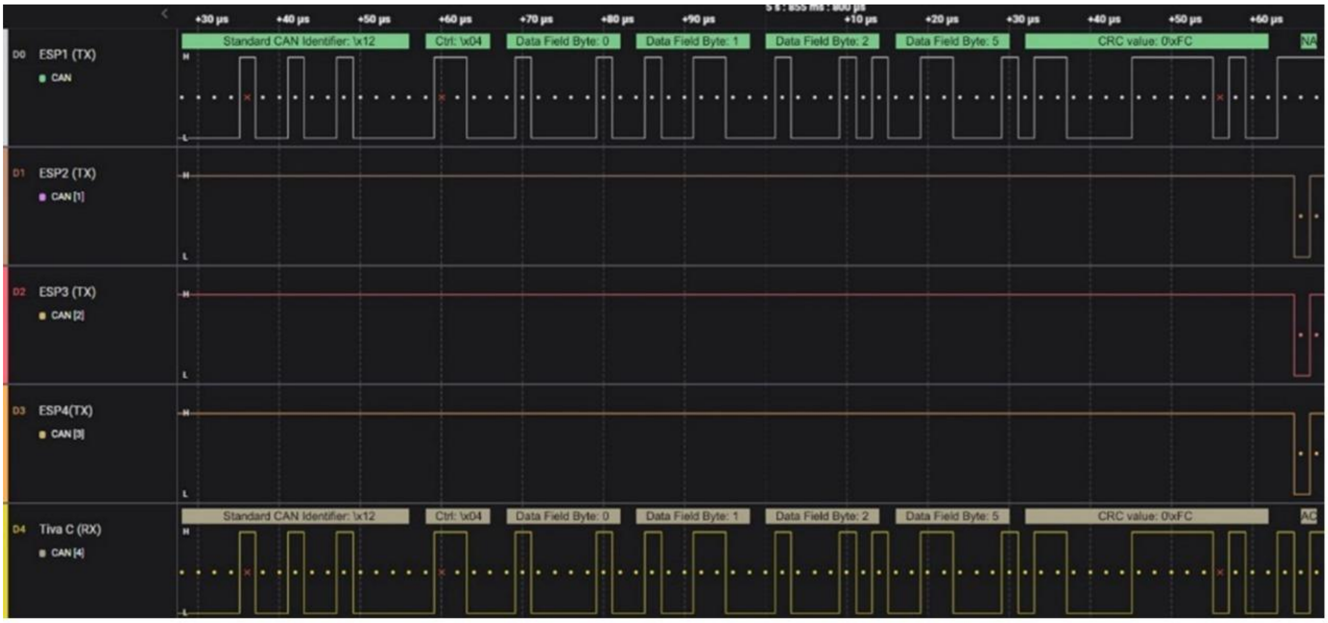

Fig 8: Structure of CAN frame in the system

After that, the Tiva-C processing unit applies the trilateration technique on the received distance, to determine the actual phone's location. The trilateration algorithm is applied to the three BLE modules closest to the mobile device. If the coordinates of the closest three ESP32 modules (Figure 9) are (x_1, y_1), (x_2, y_2), and (x_3, y_3), the position (x, y) in meter, of the user's mobile is given by [13, 14]:

$$x = \frac{d_1^2 - d_2^2 + l^2}{2\,l} \quad (7)$$

$$y = \frac{d_1^2 - d_3^2 + m^2}{2\,m} - x \quad (8)$$

Variables d_1, d_2, and d_3 are the distances between the phone and the BLE modules. Variable l is the side if the environment is a square, and the variable m is half of the side (0.5l).

The trilateration algorithm is implemented on Matlab-Simulink as shown in Figure 10, and the position of the mobile device is tested at various distances outside and inside the vehicle.

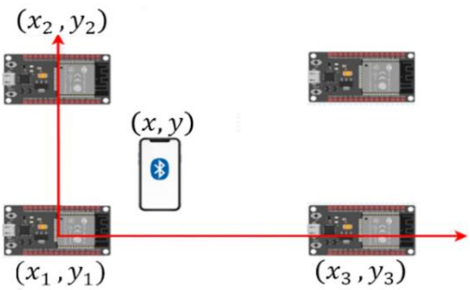

Fig 9: Positioning using the trilateration technique

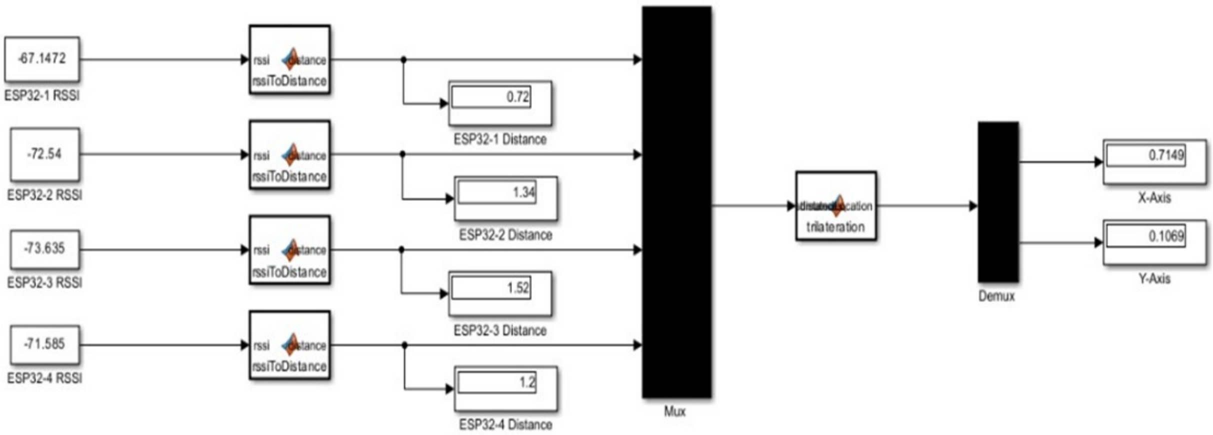

Fig 10: Detection of phone location using the trilateration method on Matlab-Simulink [15]

A mobile application has been implemented to enhance user acceptability. Figure 11 to Figure 16 exhibit some features of the designed application. Figure 11 displays the entry page of the application, and asks whether the user is new and must create a new account (Figure 12), or if the user already has an account and will log in (Figure 13). After successful login and authentication, the user is navigated to the home page in Figure 14 which displays the vehicle details and enables access to different settings pages. The user can update the account details (Figure 15), and the vehicle details (Figure 16) to ensure the database on the backend side is updated and synchronized with the application. Figure 17 shows the Firebase console panel, which allows administrators to monitor the user data, manage documents, oversee user registrations, enable or disable accounts, and request user confirmations.

Fig 11: Welcome page

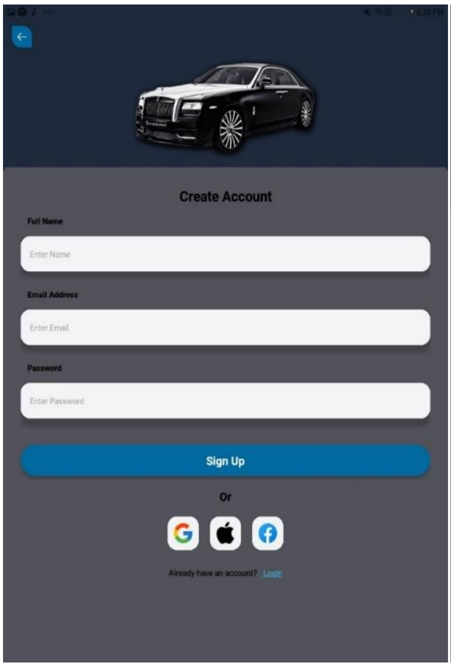

Fig 12: User registration page

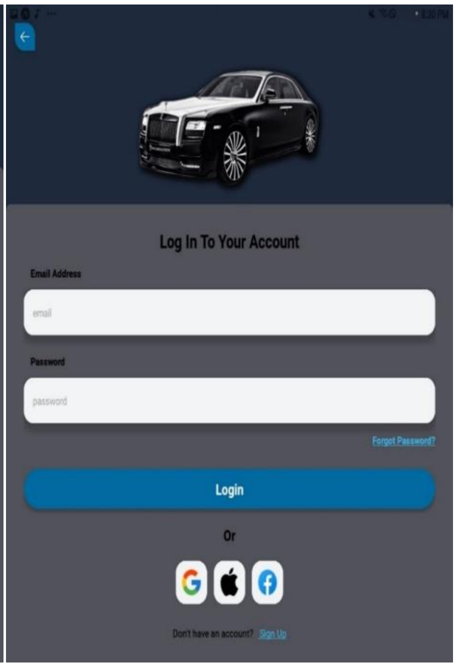

Fig 13: User login page

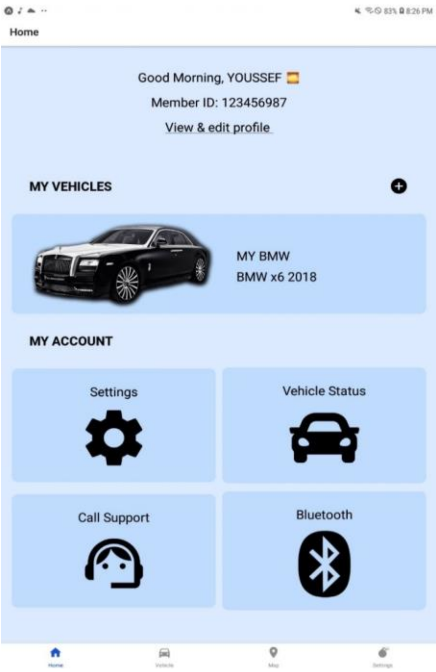

Fig 14: Home page

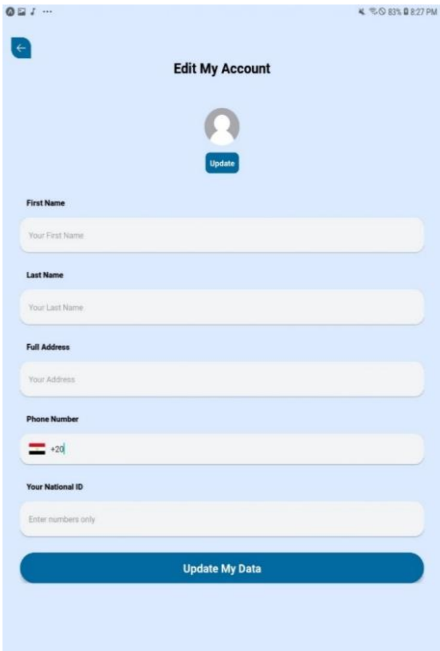

Fig 15: User profile page

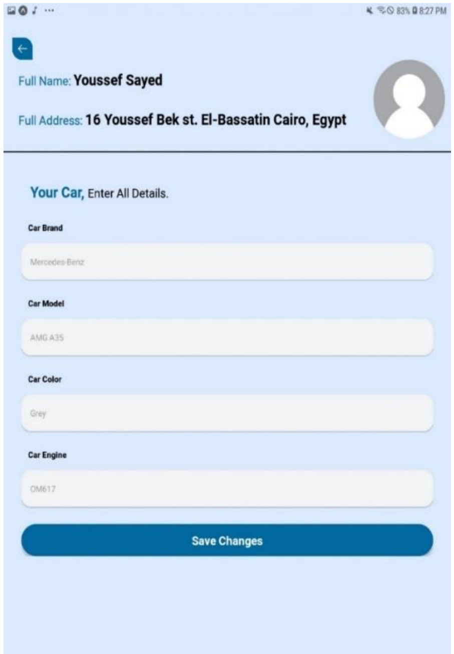

Fig 16: Car details page

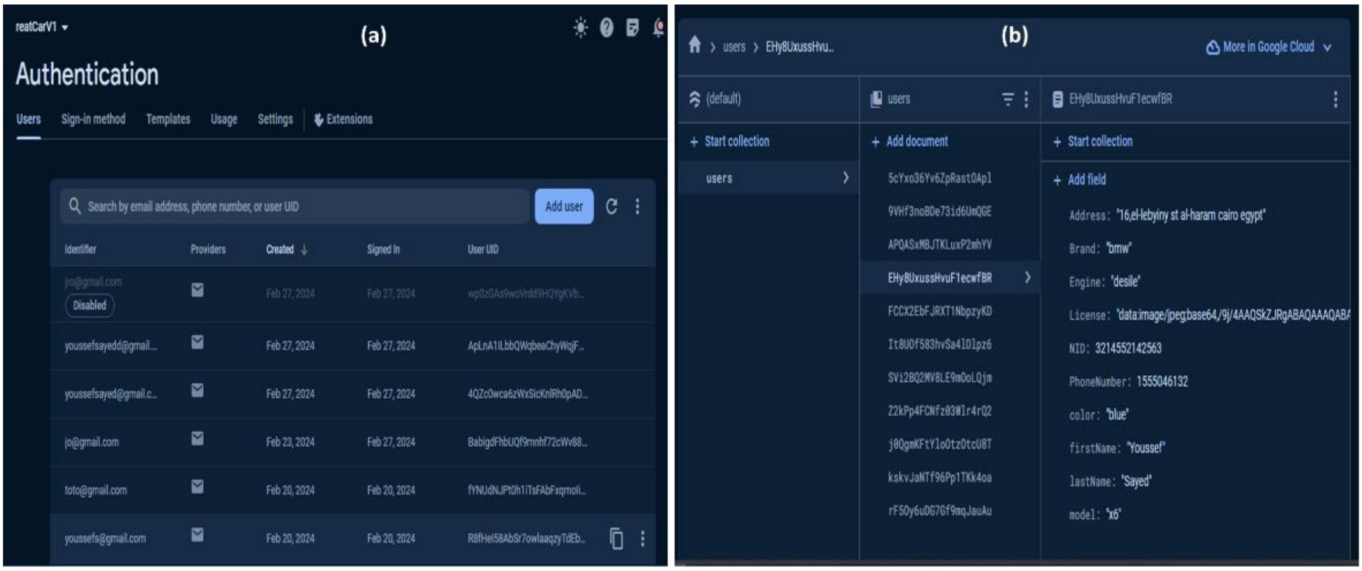

Fig 17: Firebase console panel: (a) authentication tab and (b) database tab

4. EXPERIMENTAL RESULTS

The proposed system is implemented as shown in Figure 18, and tested in different operation conditions. The localization of the phone to the vehicle and controlling the vehicle's door locking/unlocking mechanism based on the user proximity is experimented in Figure 19. Figure 19(a) displays that if the user is outside the authentication zone of the vehicle, the doors are still locked. Figure 19(b) shows the user can unlock the door if the mobile is inside the specified range. Figure 20 shows after unlocking the vehicle door the authorized user can start/stop the engine, or open the trunk. Figure 21 displays the available privileges for the user. The full-access user can unlock the door and start the engine (Figure 21(a)). While the limited-access user can only open the trunk and not allow him to start the engine (Figure 21(b)). Figure 22 shows unlocking the vehicle door with the authorized NFC card and preventing access to the unauthorized card.

Fig 18: Real-time network of EPS32 modules with Tiva-C and Raspberry Pi units

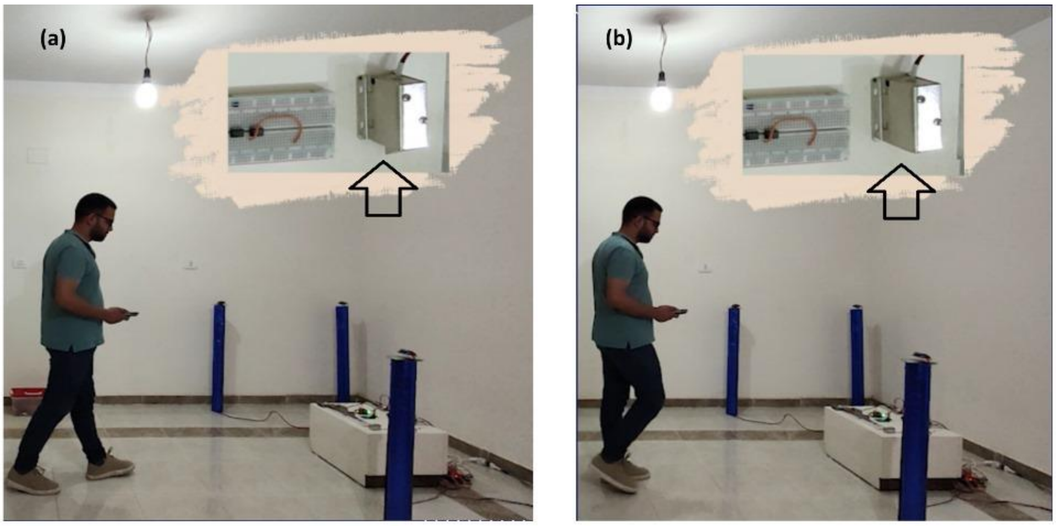

Fig 19: Testing (a) locking and (b) unlocking, the vehicle door according to the user's location

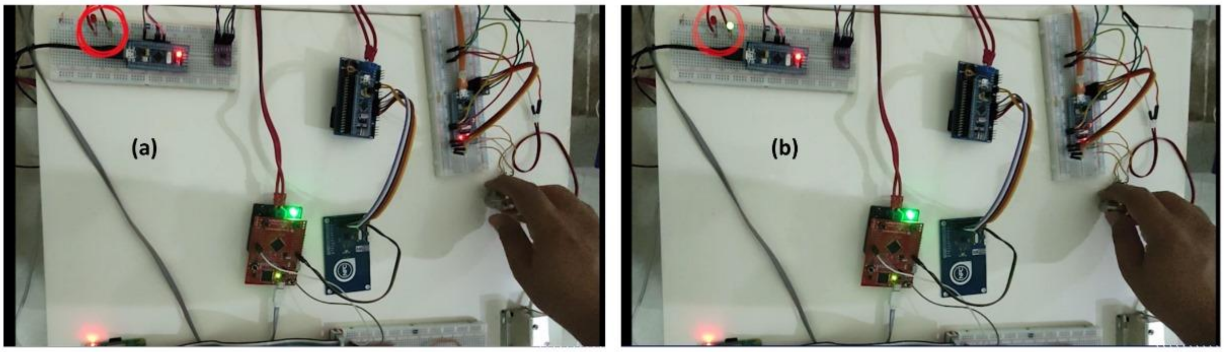

Fig 20: Testing (a) stopping and (b) starting the vehicle engine

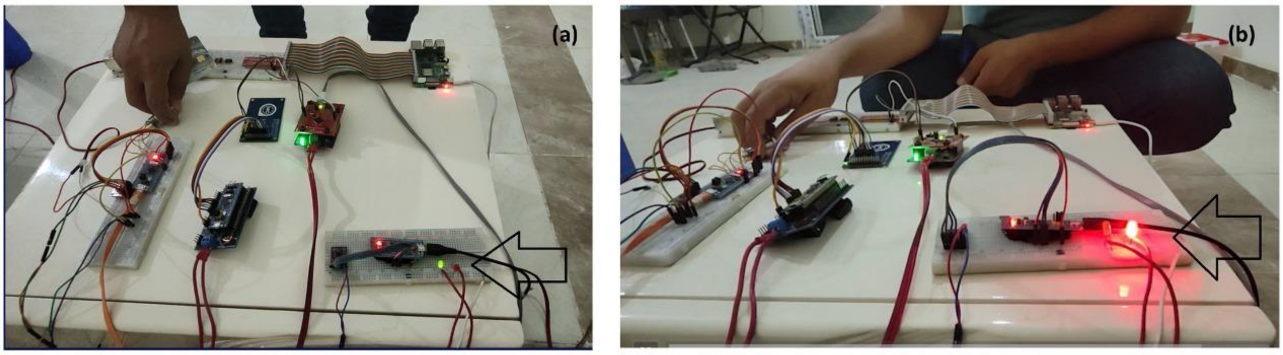

Fig 21: Testing (a) full and (b) limited accessibility of user

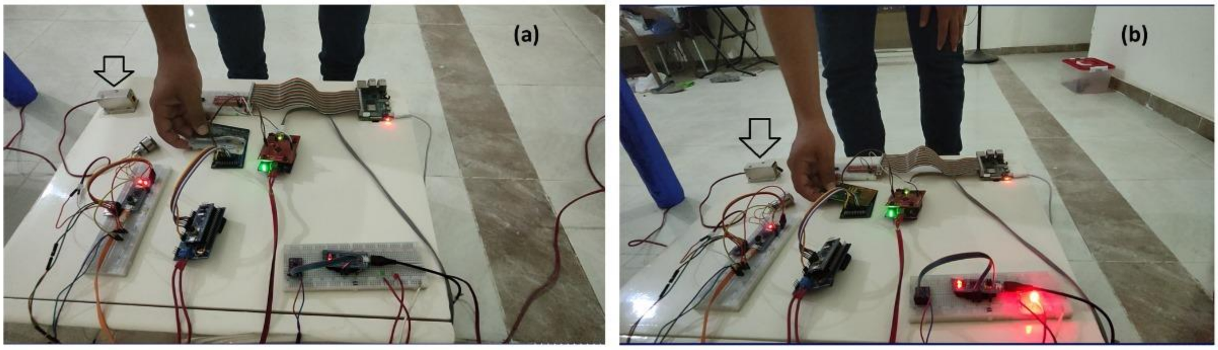

Fig 22: (a) The user can unlock the vehicle with an NFC card, (b) the user can't open with an unauthorized card

5. CONCLUSION

In this paper, a real-time in-vehicle localization system with BLE technology has been designed to improve vehicle security and user convenience in a passive-entry passive-start setup. The trilateration and the Kalman filter algorithms have been utilized to verify the accurate location of the mobile device. A user-friendly mobile application for convenient interaction with the vehicle and a secure-access Firebase server for authentication and privilege management have been developed. The results confirm the effectiveness of the proposed system as keyless vehicle access and control and can be used as an assisted solution for smart vehicles.

6. REFERENCES

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