IN-CAR DRIVER AUTHENTICATION USING WIRELESS SENSING

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INTRODUCTION

Driver authentication enables automatic adjustment of internal settings in automobiles such as seat and mirror positions, temperature etc., that are specific to an individual and can be operated without the need for a key.

Traditional approaches using image processing or computer vision have the drawback of potential privacy leakage whereas keys or passwords can easily be forged or forgotten.

In this work, we investigate and attempt to solve this problem by leveraging radio signature collections of drivers for different in-car environments.

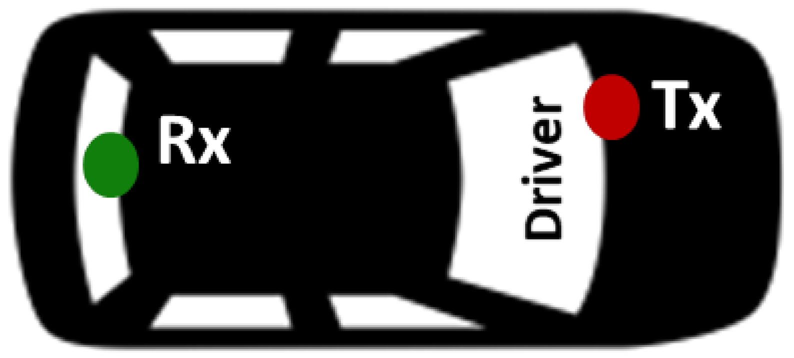

Figure 1: Location of transceivers in the car

CONTRIBUTIONS

- We propose the first in-car driver authentication system using WiFi.
- We build the first in-car driver radio biometric dataset consisting of radio signatures of five people collected over a period of two months.
- Using the above dataset, we develop machine learning (ML) models which can adapt to in-car environmental changes and improve the accuracy of driver authentication.

CHALLENGES AND METHOD

The procedure of recording a radio signature is called radio shot[1]. The similarity of two CSIs can be defined by the TRRS. For two Channel Frequency Responses (CFRs) $\boldsymbol{h_1}$ and $\boldsymbol{h_2}$, the TRRS in the frequency domain is given by [1]:

$$TRRS(\boldsymbol{h_1}, \boldsymbol{h_2}) = \frac{max_{\phi}|\sum_{k=0}^{L-1} h_1[k]h_2[k]^* e^{jk\phi}|^2}{(\sum_{l=0}^{L-1} |h_1[l]|^2)(\sum_{l=0}^{L-1} |h_2[l]|^2)}$$

where L is the number of sub-carriers. The higher the TRRS is, the more similar the two CFRs are.

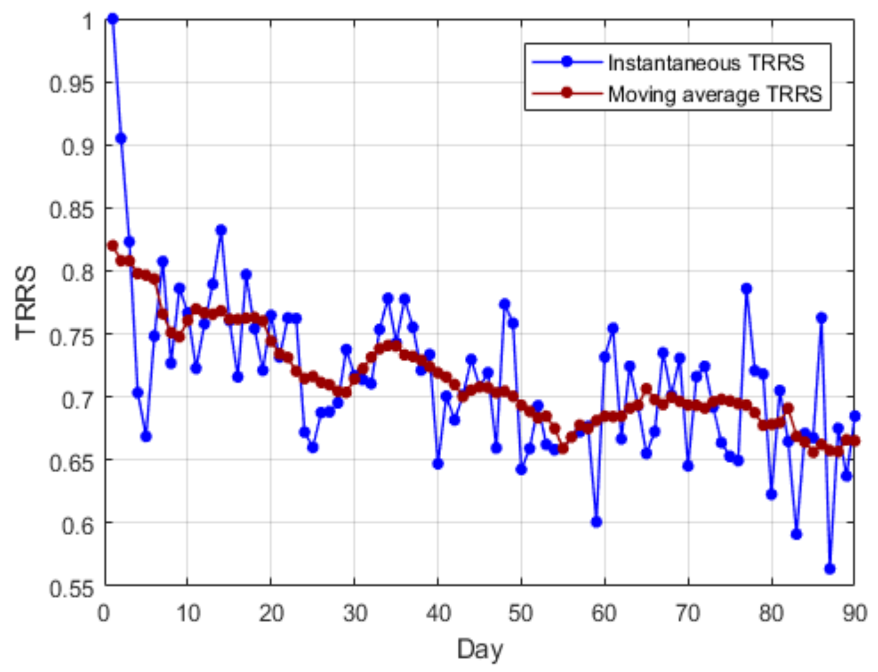

Figure 3: Degree of environment change inside the car

Existing wireless sensing based human identification algorithm assumes static background and fails when the environment changes[1]. For example, in Fig. 3, human 2 on day B will be recognized as human 1 since TRRS of radio shots is higher(i.e., 0.73) than that between same person(i.e., 0.57).

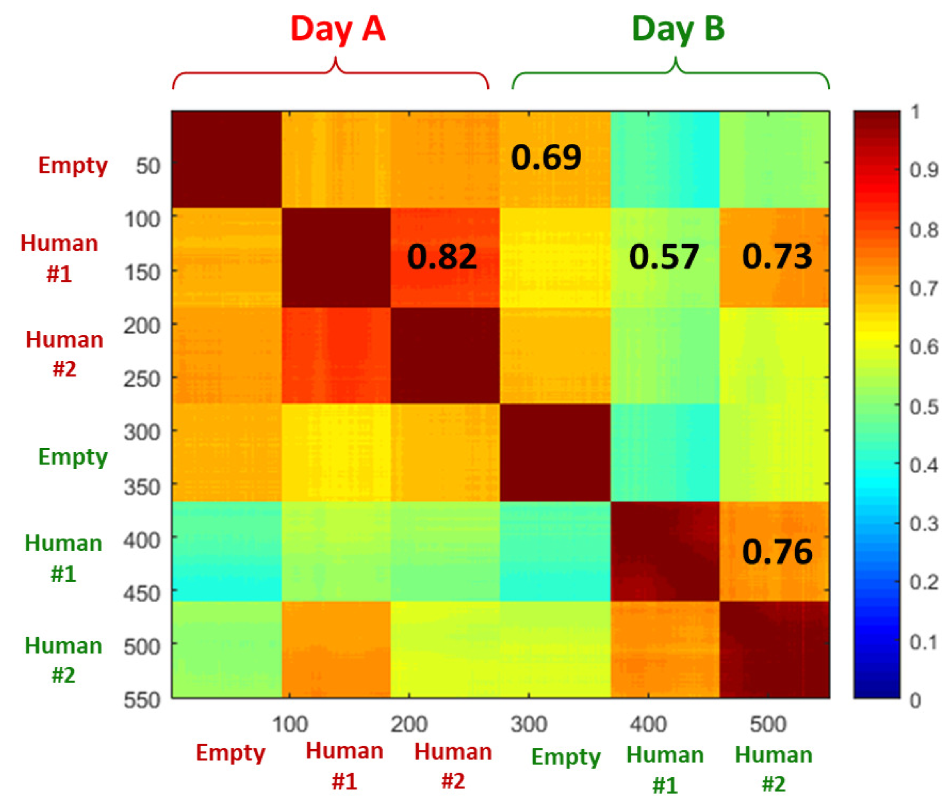

Figure 4: TRRS matrix

In-car driver radio biometric dataset was built using radio shots of five people collected over a period of two months. Grouping technique and machine learning methods are used to account for small changes in seating postures and adapt to changes in the in-car environment.

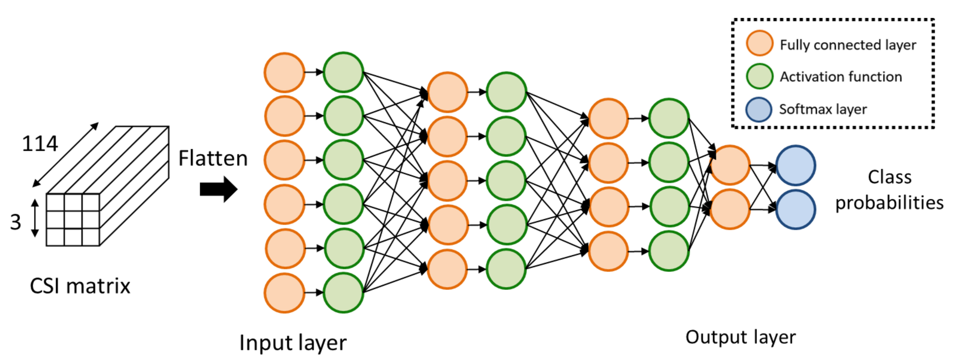

Figure 5: Neural network architecture

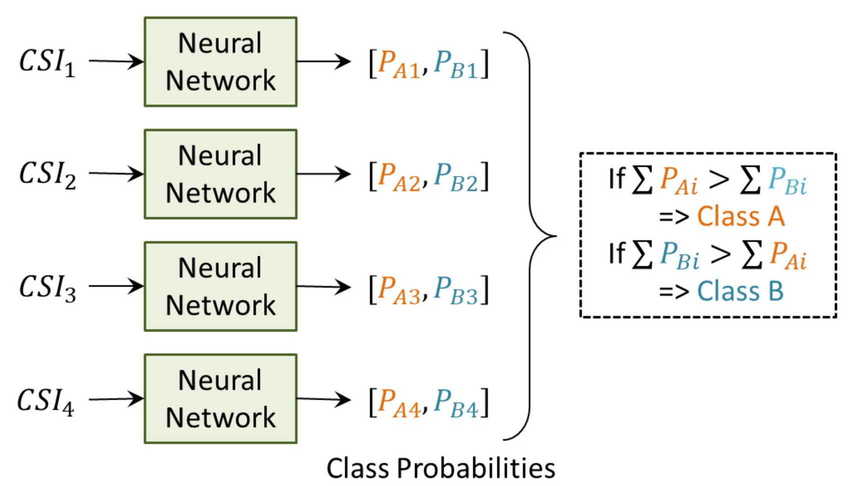

Figure 6: Grouping technique

RESULTS 1

Two-driver authentication

Classes	KNN	SVM-RBF	NN
A-B	86.40	91.45	96.58
A-C	91.00	94.17	**99.36**
A-D	88.81	93.54	98.08
A-E	89.25	95.21	**99.36**
B-C	87.06	87.91	96.37
B-D	74.12	89.37	95.51
B-E	85.53	93.33	94.88
C-D	83.77	89.17	95.10
C-E	65.57	73.33	84.19
D-E	80.70	91.04	96.80

Table 1: K_v-fold validation accuracy results for classifying two drivers.

Single Driver Authentication : An accuracy of 90.66% was achieved in validating a single driver(**A**) using RBF-SVM.

Train	A	B,C,D
Test	A	E,F

RESULTS 2

The proposed system is 'smart', in the sense that, it learns more and more with time. Overall, we speculate that the ML models learn more environment independent and human specific features with time. This became possible by training the model using radio biometrics collected from a large number of different environments present in the driver radio biometric dataset.

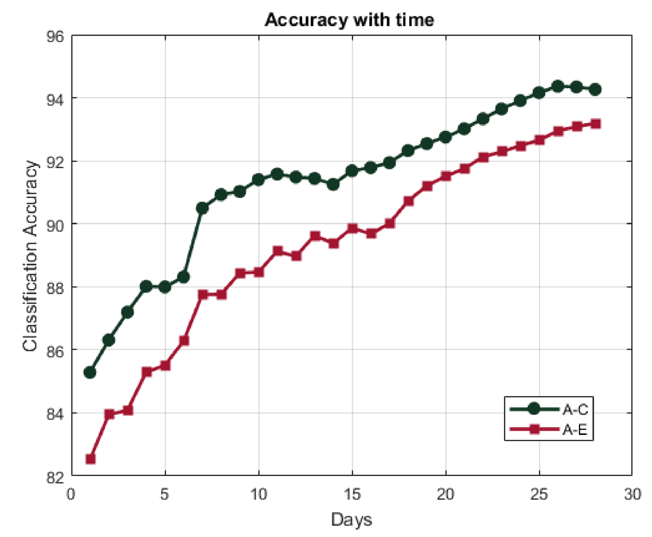

Figure 2: Smart learning: The performance of the driver authentication system improves as it learns more with time

REFERENCES

[1] Q. Xu, Y. Chen, B. Wang, and K. J. R. Liu. Radio biometrics: Human recognition through a wall. *IEEE Transactions on Information Forensics and Security*, 12(5):1141–1155, May 2017.

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