Deep neural network for lateral control of self-driving cars in urban environment

Abdelhafid El Farnane, My Abdelkader Youssefi, Ahmed Mouhsen, Abdelilah El Ihyaoui
Engineering Laboratory, Industrial Management and Innovation, Faculty of Sciences and Technics,
Hassan First University, Settat, Morocco

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ABSTRACT

The exponential growth of the automotive industry clearly indicates that self-driving cars are the future of transportation. However, their biggest challenge lies in lateral control, particularly in urban bottlenecking environments, where disturbances and obstacles are abundant. In these situations, the ego vehicle has to follow its own trajectory while rapidly correcting deviation errors without colliding with other nearby vehicles. Various research efforts have focused on developing lateral control approaches, but these methods remain limited in terms of response speed and control accuracy. This paper presents a control strategy using a deep neural network (DNN) controller to effectively keep the car on the centerline of its trajectory and adapt to disturbances arising from deviations or trajectory curvature. The controller focuses on minimizing deviation errors. The Matlab/Simulink software is used for designing and training the DNN. Finally, simulation results confirm that the suggested controller has several advantages in terms of precision, with lateral deviation remaining below 0.65 meters, and rapidity, with a response time of 0.7 seconds, compared to traditional controllers in solving lateral control.

Corresponding Author:

Abdelhafid El Farnane
Engineering Laboratory, Industrial Management and Innovation, Faculty of Sciences and Technics,
Hassan First University
Route de Casablanca, Km 3,5-B.P. 539. Settat, Morocco
Email: a.elfarnane@uhp.ac.ma

1. INTRODUCTION

With the rapid progress of autonomous driving technology, the field of self-driving cars has seen significant technological advances in the automotive industry in recent decades. These advancements are driven by joint ventures between car manufacturers and technology giants such as Google, Uber, Tesla, and General Motors, as well as the dedicated efforts of industry institutes and research centers [1]. Together, they are actively pushing forward the development of next-generation autonomous vehicle solutions. The integration of artificial intelligence [2], deep learning [3], and sensor technology [4] has enabled significant improvements in the safety, reliability, and performance of autonomous cars [5]. Moreover, significant advancements in machine learning have allowed innovative approaches to autonomous vehicles using deep neural networks [6], [7].

Achieving safe and precise self-driving car control in urban environments is a complex task, primarily due to the dynamic nature of urban traffic scenarios [8]. Autonomous driving systems require reliable and robust lateral control [9] to ensure that cars stay within lanes and perform smooth lane changes. Accurate lane detection, precise steering control, and adaptability to complex road geometries are critical factors for effective lateral control [10], [11]. Despite advancements in perception, decision-making, and control systems, traditional methods struggle to handle the intricacies and uncertainties present in urban environments.

Therefore, finding a solution that can consistently and accurately address these challenges is crucial for the widespread adoption and safe integration of self-driving cars into our transportation systems [12].

Several research studies have explored the topic of lateral control in self-driving cars, employing various techniques [13]. One notable approach involves the utilisation of image processing, where a study [14] proposes a system that uses a convolutional neural network to generate steering angles based on road images. Another study [15] proposes employing a deep learning model for autonomous vehicle lateral control, demonstrating proficient lane-keeping capabilities and achieving a notable 96% autonomy level, even in novel and challenging scenarios. In paper [16], a novel approach utilizing "mental simulations" is introduced for predictive control in self-driving car lateral dynamics. Inspired by natural cognition, it enhances autonomy by enabling robotic agents to independently learn predictive and inverse models. Additionally, research [17] integrates direct yaw stability control with lateral-longitudinal path-following for self-driving vehicles, employing a time-varying linear model predictive control (TVMPC) approach for lateral control. Simulations confirm the strategy's success in accurately tracking the desired trajectory, leading to enhanced car stability and performance. Another intriguing approach [18] focuses on adaptive tracking control for low-speed vehicles, utilizing the backstepping technique to enhance tracking accuracy within defined input limits. This strategy notably reduces tracking errors, particularly in cases of lateral deviations from the desired vehicle path, as validated through Matlab simulations. Furthermore, the study [19] suggests an improved version of the rapidly-exploring random tree (RRT) algorithm for autonomous vehicle trajectory tracking control, addressing directional constraints and enhancing feasibility. Results indicate a notable 10% enhancement in the coefficient of lateral position deviation compared to the conventional RRT algorithm. In the same way, the authors of [20] developed an adaptive MPC for lateral vehicle control. The controller is fine-tuned using an enhanced particle swarm optimisation algorithm. By incorporating neural networks and adaptive neuro-fuzzy inference systems (ANFIS), the adaptability of the standard MPC is improved in specific scenarios. Lastly, a robust nonlinear control approach [21] employing the barrier Lyapunov function accounts for lateral offset error constraints. It incorporates an extended state observer (ESO) and nonlinear controller, effectively managing disturbances and model uncertainties, leading to improved lateral control performance, as demonstrated in CarSim and Matlab simulations.

This paper presents an advanced deep neural network approach aimed at enhancing the lateral motion control of self-driving cars in urban environments. The fundamental difference of this work compared to the previous studies mentioned in the fact that our controller corrects both lateral and angular deviations, whether caused by the curved shape of the trajectory or by a deviation of the vehicle itself due to sudden braking or obstacle avoidance. Additionally, our method makes a significant contribution in terms of reducing the controller's response time. The structure of the paper is organised as follows: Section 2 presents the research method, section 3 describes the results of the controller simulation, and Section 4 provides the conclusion.

2. METHOD

2.1. System description and problem formulation

Self-driving cars are planned to move at a longitudinal velocity without lane departure. The objective is to keep the car on the central axis of straight or curved paths while effectively addressing disturbances or deviations by controlling the front steering angle. The trajectory is bounded by a left line and a right lane, which are detected by a camera mounted on the self-driving car. When the car deviates from its lane, three parameters become evident: lateral velocity, lateral deviation, and deviation angle. The values of these parameters should converge to zero through system regulation. The descriptive diagram of the system is presented in Figure 1.

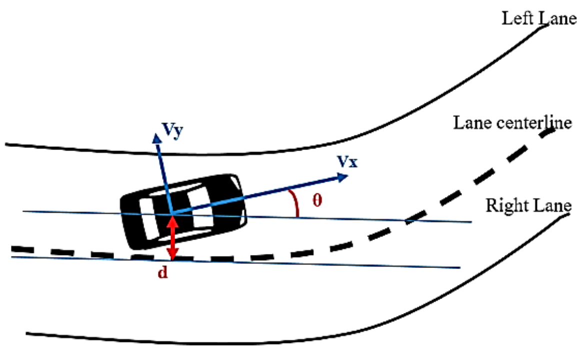


Figure 1. Kinematic model of self driving car movement

V_x : Longitudinal velocity (displacement velocity).
V_y : Lateral velocity (deviation velocity).
d : Lateral deviation.
θ : Deviation angle (angular difference between the centerline and the orientation of the car).
β : Orientation angle of the car.
α : Steering angle.

Initially, we assume that the self driving car has deviated from its lane. Different types of sensors mounted on car measure values of lateral velocity, lateral deviation, and deviation angle that correspond to this deviation [22]. A deep neural network exploits these values and generates an optimal value of front steering angle in order to keep the self driving car inside the lane. The system diagram is shown in Figure 2.

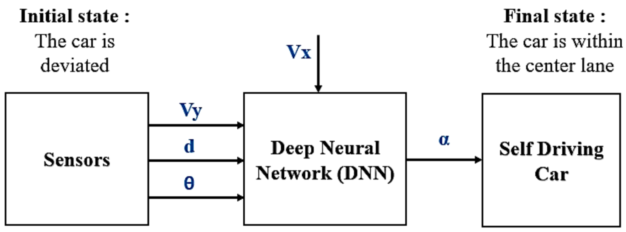


Figure 2. System block diagram

2.2. Self driving car modeling

Before developing the lateral trajectory controller, it is necessary to establish a dynamic model for the self driving car. Various mathematical models have been proposed to describe the interaction between the car and the road [23]. In this study, a linear model is adopted, where the lateral forces applied to the front and rear wheels are directly proportional to the sliding angles of the front and rear wheels, respectively [24]. This relationship is represented by (1).

$$\begin{Bmatrix} F_{yf} = C_f . k_f \\ F_{yr} = C_r . k_r \end{Bmatrix} \tag{1}$$

F_{yf} : lateral force applied to front wheels.
F_{yr} : lateral force applied to rear wheels.
C_f : proportionality coefficient for the front wheels (cornering stiffness).
C_r : proportionality coefficient for the rear wheels.
k_f : front wheels sliding angle.
k_r : rear wheels sliding angle.

Therefore, a simplified representation of the car, known as the Bicycle model [25], is used in this study. The model excludes the consideration of lateral acceleration and deviation angle, as shown in (2). The designation of the various vehicle parameters and their chosen values are given in Table 1.

$$\begin{Bmatrix} \ddot{d} = -\left[\frac{C_f + C_r}{m\, V_x}\right]\dot{d} - \left[V_x + \frac{C_f\, l_f - C_r\, l_r}{m\, V_x}\right]\dot{\theta} + \frac{C_f}{m}\alpha \\ \ddot{\theta} = -\left[\frac{C_f\, l_f - C_r\, l_r}{I_z\, V_x}\right]\dot{d} - \left[\frac{C_f\, l_f^2 + C_r\, l_r^2}{I_z\, V_x}\right]\dot{\theta} + \frac{C_f\, l_f}{I_z}\alpha \end{Bmatrix} \tag{2}$$

Table 1. The parameters of the car model

Symbol	Designation	Value	Unit
V_x	Longitudinal velocity	10 and 18	(m/s)
C_f	Cornering stiffness of the front wheels	19000	(N/rad)
C_r	Cornering stiffness of the rear wheels	33000	(N/rad)
M	Total car mass	1575	(kg)
I_z	Moment of inertia	2875	(kg.m^2)
l_f	Longitudinal distance from the centre of gravity to the front wheels	1.2	(m)
l_r	Longitudinal distance from the centre of gravity to the rear wheels	1.6	(m)

2.3. Deep neural network controller

The dynamic model of the self-driving car is implemented using Matlab software. In this study, a bicycle model of the car is chosen and created in Simulink. To maintain a constant longitudinal speed during the experiments, the longitudinal and lateral dynamics of the car were separated. However, it is important to note that in real-world scenarios, the longitudinal velocity can vary. This research primarily focuses on evaluating the performance of the deep neural network (DNN) controller. The deep neural network is created, designed, and trained using various features available within the Matlab software environment. Matlab provides a wide array of tools and functions for generating training data through the computation of control actions based on randomly generated states and past control actions. The root-mean-square error (RMSE) between the network output and the test data is approximately 0.032, as shown in Figure 3.

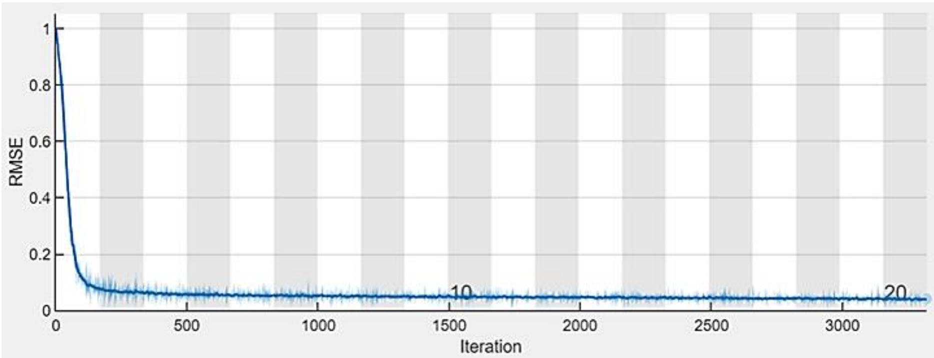


Figure 3. Training of the deep neural network

The different components of the system were modelled using Simulink, as depicted in Figure 4. The sensors block captures the lateral deviation and relative angle of deviation. The curvature preview is represented by a simplified block that provides the predicted curvature.

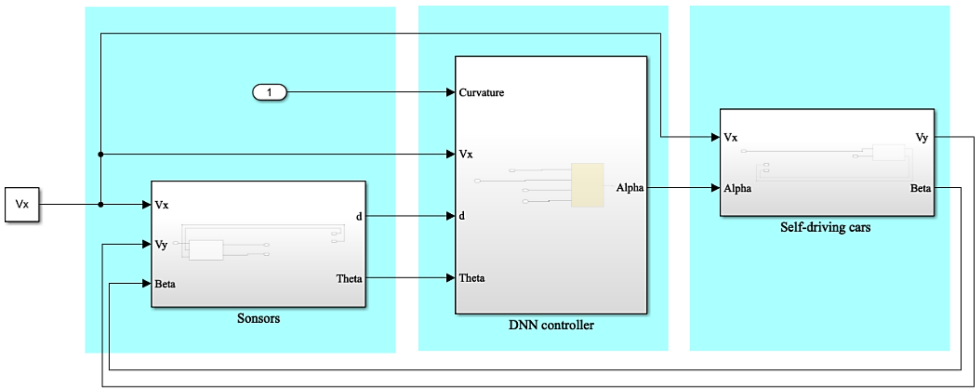


Figure 4. Simulink system model

3. RESULTS AND DISCUSSION

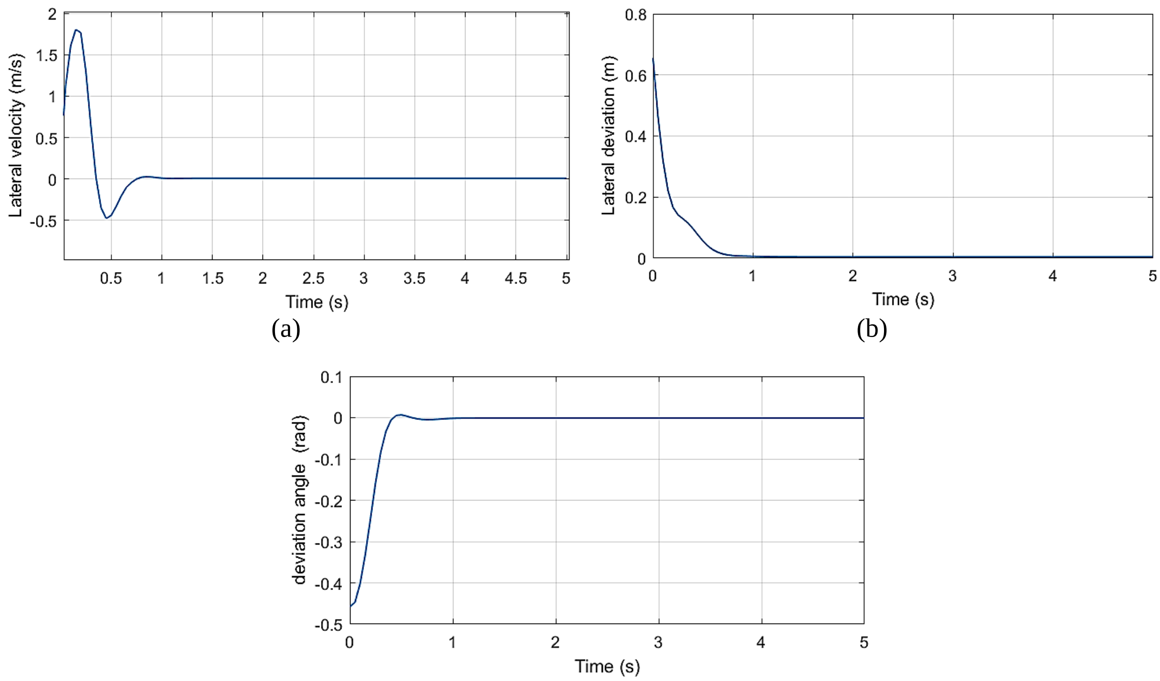
This section focuses on improving the performance of the deep neural network controller in repositioning a deviated vehicle. It presents the evolution of lateral velocity, lateral deviation, and relative yaw angle for two different longitudinal speeds. Additionally, the corresponding DNN response, representing the applied steering angle, is provided for both scenarios. The initial parameters are outlined in Table 2.

Table 2. Initial values of parameters

Time (s)	Lateral velocity (m/s)	Lateral deviation (m)	Deviation angle (rad)
3	1	0.65	- 0.45

The velocity of cars in urban environments varies depending on speed limits, traffic congestion, and road conditions. On average, it ranges between 30 and 50 kilometres per hour; however, it can be lower in congested areas and higher on wider roads. To evaluate the performance of the DNN controller in these scenarios, we chose two longitudinal velocity values: Vx = 10 m/s and Vx = 18 m/s, which correspond to speeds of 36 and 65 kilometres per hour, respectively.

In Figure 5(a), the lateral velocity initially increases until reaching 1.8 m/s, then decreases to -0.5 m/s. A positive sign indicates deviation towards the left line, while a negative sign corresponds to returning towards the centerline. After approximately 0.7 second, the system stabilises, and the lateral velocity becomes zero, indicating that the autonomous vehicle returns to its normal trajectory. Similarly, in Figures 5(b) and 5(c), the lateral deviation and deviation angle exhibit variations before converging to zero within less than one second, thanks to the corrective action of the DNN.



(a) (b)

(c)

Figure 5. Evolution of parameters corresponding to the deviated state of an autonomous vehicle at Vx = 10 m/s: (a) lateral velocity, (b) lateral deviation, and (c) deviation angle

Figure 6 represents the steering angle applied by the DNN to guide the vehicle back to the centre line. Initially, the angle reaches its peak value of 1.05 rad, corresponding to the maximum deviation (d = 0.65 m). Subsequently, it starts decreasing to -0.2 rad at 0.4 seconds, as a compensatory measure to counteract the effect of the maximum deviation angle observed at that particular time.

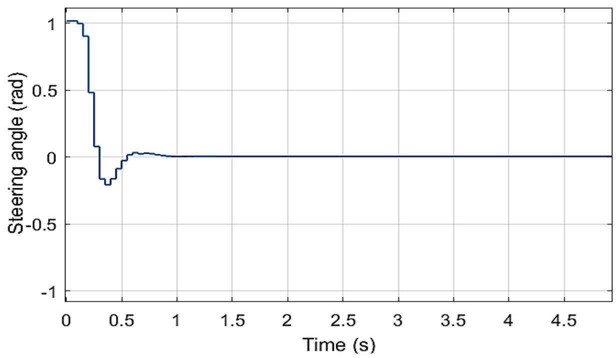


Figure 6. Evolution of steering angle

Through multiple simulations, it has been established that utilising a DNN is a more practical approach compared to model predictive control (MPC) and other methods for resolving deviation issues and achieving precise vehicle tracking. The DNN effectively assists the vehicle back to its intended trajectory within a short duration and with high accuracy. Consequently, we can conclude that the control action is both rapid and accurate. However, it is worth noting that the response time needed to realign the vehicle with its path increases as the longitudinal velocity rises. This aspect will be further examined by testing with a different, higher velocity value.

Figure 7 depicts the changes in various parameters at a longitudinal velocity of Vx = 18 m/s. It is observed that these parameters undergo multiple sign changes, indicating that the vehicle crosses the centerline several times before eventually tracking it accurately after 4 seconds. Notably, the lateral velocity, as shown in Figure 7(a), reaches 3.8 m/s before gradually decreasing to zero by the end of 2.75 seconds. In this case, a slight delay is evident compared to the previous case (Vx = 10 m/s). However, this delay remains acceptable in an urban environment setting, particularly considering that the chosen speed is already higher than the authorized speed in urban areas, which is approximately 16.5 m/s (60 km/h). In Figures 7(b), 7(c), and 7(d), we observe variations in the lateral deviation, deviation angle, and steering angle. These variations gradually converge to zero after 4 seconds, primarily due to the corrective action of the DNN.

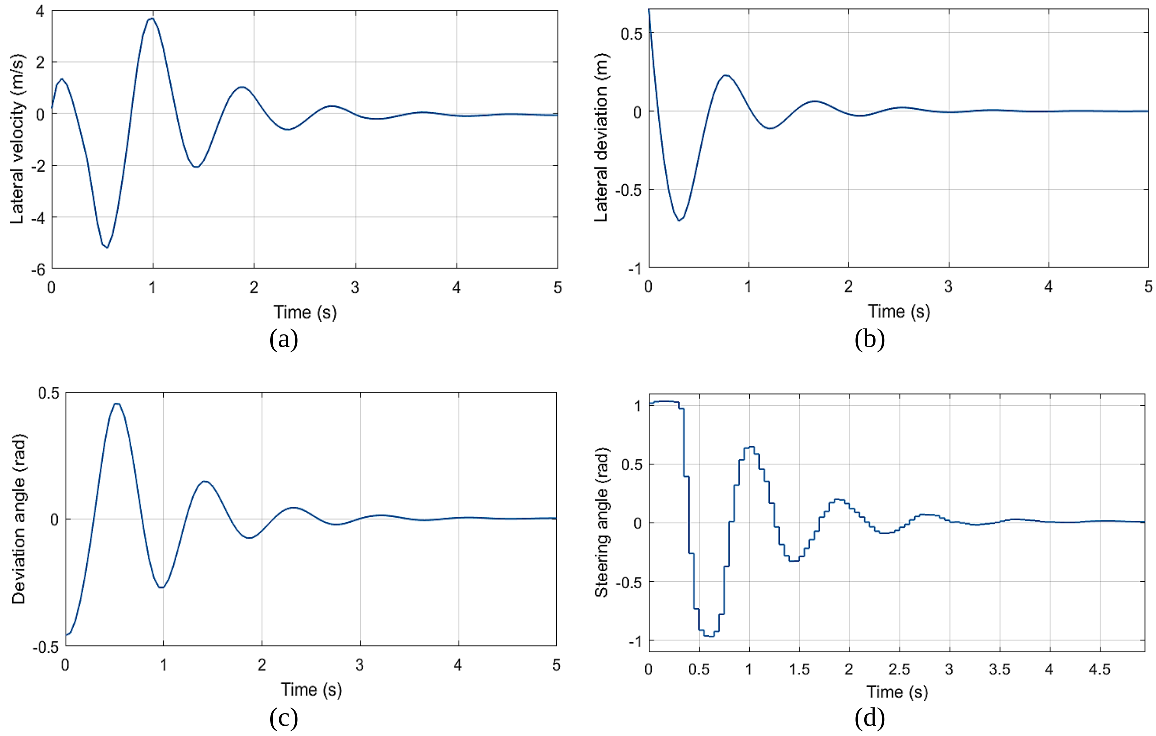


Figure 7. Evolution of parameters at Vx = 18 m/s: (a) lateral velocity, (b) lateral deviation, (c) deviation angle, and (d) steering angle

In both instances, the DNN demonstrates its remarkable capacity to accurately follow the trajectory and remedy disturbances quickly. Additionally, the results reveal that parameter fluctuations during the transient regime and before stabilization are acceptable within the urban scenario. The range of variation for various parameters is presented in Table 3.

Table 3. Variation intervals for different parameters

Longitudinal velocity (m/s)	Lateral velocity (m/s)	Lateral deviation (m)	Deviation angle (rad)	Steering angle	Tr 5%
Vx = 10 m/s	[-0.5, 1.75]	[0, 0.65]	[-0.45, 0.02]	[-0.2, 1.05]	0.7
Vx = 18 m/s	[-5.2, 3.8]	[-0.6, 0.65]	[-0.45, 0.45]	[-0.95, 1.05]	2.75

4. CONCLUSION

The objective of this paper is to solve the lateral control problem of trajectory tracking in self-driving cars through the implementation and optimisation of a deep neural network controller. The designed DNN controller aims to robustly manage the motion of autonomous vehicles while accurately tracking the centerline of the trajectory, even in the presence of perturbations. Simulation results demonstrate that the deviation error is completely corrected within 0.7 second for a longitudinal velocity of 10 m/s. In summary, the proposed lateral control method outperforms classical controllers, offering greater precision and a faster response time. Future research should focus on implementing and applying the controller to real-world systems while also exploring alternative approaches to enhance trajectory tracking for self-driving cars.

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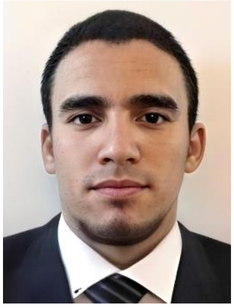
BIOGRAPHIES OF AUTHORS

Abdelhafid El Farnane received his Master's degree in electrical engineering from Hight Normal School of Technical Studies (ENSET) at Mohammed V University, Rabat, Morocco, in 2019. Currently, he is pursuing his Ph.D. degree from Faculty of Sciences and Technologies at Hassan I University, Settat, Morocco. His research interests include embedded systems, self-driving cars, and robot control. He can be contacted at email: a.elfarnane@uhp.ac.ma

My Abdelkader Youssefi was born in Tinghir, Morocco. He received his engineering degree in telecommunications from National Institute of Telecommunications (INPT), Rabat, Morocco, in 2003, and he received his Ph.D. degree from Mohammadia School of Engineers (EMI) at Mohammed V University in 2015. He is now a teacher at Hassan I University, Settat, Morocco. His research interests include embedded systems, self-driving, massive MIMO, wireless communications and internet of things. Pr. Youssefi has published more than 20 papers in peer-reviewed journals and referred conference proceedings. He can be contacted at email: ab.youssefi@gmail.com.

Ahmed Mouhsen received his Ph.D. degree in electronics from the University of Bordeaux, France, in 1992, and he is currently a Professor at Electrical Engineering Department, Faculty of Sciences and Technologies, Hassan I University, Settat, Morocco. His research interests focuses on Embedded Systems, wireless communications and Information Technology. Pr.Mouhsen has published more than 50 papers in peer-reviewed journals and referred conference proceedings. He can be contacted at email: ahmed.mouhsen@uhp.ac.ma.



Abdelilah El Ihyaoui ICT engineer graduated in 2013 from National Institute of Telecommunications (INPT), Rabat, Morocco. Ph.D. student at the Faculty of Sciences and Technologies at Hassan I University, Settat, Morocco. His research interests are computer science, software architecture and computer security. He can be contacted at email: abdelilah.elihyawi@gmail.com.