# Chapter 6
# Bridging Minds and AI for Enhanced Autonomous Driving

**Roveri Nicola, Silvia Milana, Antonio Culla, Gianluca Pepe, and Antonio Carcaterra**

**Abstract** This paper studies some aspects of a larger a ground-breaking research initiative aiming to advance autonomous driving through the integration of neurotechnology. This multidisciplinary approach combines mechanical engineering with cutting-edge monitoring technologies to develop autonomous driving algorithms that closely mimic human behaviour and reactions. By equipping drivers with state-of-the-art sensors to monitor brain activity, eye movements, heart rate, and skin conductivity, comprehensive data on driver responses is gathered in realistic driving scenarios.

The primary objective is to bridge the gap between human understanding of driving and the capabilities of autonomous systems. Through the detailed analysis of the collected data, the project aims to identify patterns and reactions that can be incorporated into autonomous driving algorithms, enhancing their intuitiveness, safety, and alignment with human behaviour. This project addresses significant gaps in the current literature and opens new avenues for the development of more effective autonomous driving systems. With this purpose, the paper studies the opportunity to integrate information from brain signals, extracted from a dataset, into the control system of the vehicle guidance system.

**Keywords** Neurotechnology · Brain activity · Autonomous driving · Optimal control theory · Dynamics

## Introduction

In this article, an adaptive control strategy that integrates neurofeedback into vehicle guidance systems is proposed. The objective is to evaluate the efficacy of a brain-assisted control system by simulating a simplified two-dimensional obstacle avoidance problem. The vehicle is modeled as a point in a plane, tasked with moving from a starting point A to a target point B while avoiding obstacles[1, 2]. Obstacles are represented using a potential field model, where attractive forces guide the vehicle toward the goal and repulsive forces push it away from obstacles.

In recent years, the integration of brain signals into autonomous driving systems has generated increasing interest within the scientific community. Several studies have explored the use of Electroencephalography (EEG) to enhance the safety and efficiency of autonomous vehicles. Another noteworthy approach was presented in [3], where the driver's brain waves were used to improve emergency braking by combining EEG signals with information from environmental sensors. Additionally, in [4] , a semi-autonomous control system was developed in which the vehicle can be driven through mental commands detected by EEG.

Other studies have investigated human-vehicle collaboration through hybrid brain-computer interfaces (BCIs) and computer vision systems. In [5], a collaborative driving system was proposed where decisions on the path are entrusted to the driver via BCI, while the computer vision system keeps the vehicle on the road and avoids collisions. Furthermore, in [6], the use of EEG was studied to monitor brain activity related to errors during driving, both in a simulator and in a real car, highlighting the potential of EEG in detecting mental states critical for road safety. Finally, in [7], the applicability of a dry EEG system in passive BCI for autonomous driving was evaluated, demonstrating the feasibility of using non-invasive and user-friendly EEG devices in real driving contexts.

Despite these advancements, challenges remain in effectively integrating brain signals into vehicle control systems. This work distinguishes itself by utilizing neurophysiological signals to modulate in real time the parameters of the vehicle's adaptive control, rather than merely monitoring the driver's state or issuing discrete commands. This deep integration

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between neurotechnology and control engineering represents a step forward toward the development of more intuitive and safer autonomous vehicles.

For this study, the MPDB dataset [4] was considered. Physiological signals measured through EEG, Electrocardiography (ECG), Electromyography (EMG), Galvanic Skin Response (GSR), and eye movement data in a six-degree-of-freedom (6DOF) driving simulator were correlated with driving behavior categorized into five groups: Smooth Driving (SD), Acceleration Driving (AD), Deceleration Driving (DD), Lane Changing Driving (LCD), and Turning Driving (TD) [8]. The trajectories obtained from a classical Linear Quadratic Regulator (LQR) control system are compared with the solution provided by an adaptive version of the LQR [9, 10] where the control gains are modulated based on the vehicle's proximity to obstacles.

## Background

The obstacle avoidance problem is formulated using a potential field approach, which defines a composite potential $U(\underline{q})$ for the vehicle at position $\underline{q} = (x, y)^T$ in a two-dimensional space. The potential is a combination of an attractive field guiding the vehicle toward the goal $\underline{q}_{goal}$ and a repulsive field pushing the vehicle away from obstacles.

The total potential at position is defined as:

$$U(\underline{q}) = U_{att}(\underline{q}) + U_{rep}(\underline{q}) \tag{1}$$

where $U_{att}$ is the attractive potential toward the target, and $U_{rep}$ is the repulsive potential generated by obstacles.

The force acting on the vehicle at the position $\underline{q}$ is due to the gradient of the total potential defined before:

$$\mathbf{F}(\underline{q}) = -\nabla U_{att}(\underline{q}) - \nabla U_{rep}(\underline{q}) \tag{2}$$

where $\nabla$ is: $\nabla(\bullet) = (\partial(\bullet)/\partial x,\ \partial(\bullet)/\partial y)^T$.

Let be $\underline{q}_{goal}$ the target point, the attractive force is modelled as:

$$\underline{F}_{att}(\underline{q}) = -k_{att}(\underline{q} - \underline{q}_{goal}) \tag{3}$$

where $k_{att}$ is a scalar that acts as a weight by defining the strength of attraction and has to be set adequately.

The repulsive force is active only when the vehicle is within a certain distance $\rho(q)$ from an obstacle. The repulsive force is defined as:

$$\underline{F}_{rep}(\underline{q}) = \begin{cases} k_{rep}\left(\dfrac{1}{\rho(\underline{q})} - \dfrac{1}{\rho_0}\right)\dfrac{\underline{q} - \underline{q}_{obs}}{\rho(\underline{q})^3} & if \quad \rho(\underline{q}) < \rho_0 \\ 0 & if \quad \rho(\underline{q}) > \rho_0 \end{cases} \tag{4}$$

where $\underline{q}_{obs}$ is the point of the obstacle with minimum distance, *i.e.* the nearest obstacle, $\rho(\underline{q}) = |\underline{q} - \underline{q}_{obs}|$ is the distance from an obstacle, $\rho_0$ is distance threshold, $k_{rep}$ is a weight factor and has to be set adequately.

The resultant force $\underline{F}(\underline{q})$ acting on the vehicle is given by: $\underline{F}(\underline{q}) = \underline{F}_{att}(\underline{q}) + \underline{F}_{rep}(\underline{q})$. This force governs the direction and magnitude of the vehicle's movement in the plane.

The system state is represented by $\underline{z}(t) = \left(\underline{\dot{q}},\ \underline{q}\right)^T$. The state dynamics is described by the linear system:

$$\underline{\dot{z}}(t) \;=\; \mathbf{A}\,\underline{z}(t) \;+\; \mathbf{B}\,\underline{u}(t) + \underline{n}(t) \tag{5}$$

where $\underline{u}(t)$ is the control input, directly related to $\underline{F}$, and $\underline{n}(t)$ is an external noise.

The objective of control is to impose on a system a desired behaviour. The studied type of control is the feedback control: that is, one must determine the law that binds $u(t)$ with the state vector $z(t)$. The theory of optimal control has as its objective the minimisation-maximisation of some performance criterion. To realise optimal control a variational approach consisting in the minimisation of a functional $J$ is performed.

In general $J$ is defined as an integral that extends throughout the observation time of the phenomenon, T, the whose integrand is the Lagrangian function $\mathcal{L}(z,\ u,\ n)$ which depends on the state, the control and the external noise.

In the classical Linear Quadratic Regulator (LQR) framework, and the objective function $J$ is: $\underline{z}^T\,\mathbf{Q}\,\underline{z} \;+\; \underline{u}^T\,\mathbf{R}\,\underline{u}$. The term $\underline{z}^T\,\mathbf{Q}\,\underline{z}$ measures the benefit, the smaller it is, the better the performance; the term $\underline{u}^T\,\mathbf{R}\,\underline{u}$ measures the control cost to obtain the benefit. Therefore, the problem can be written as follows:

$$\begin{cases} \min\ J = \displaystyle\int_0^T \left(\underline{z}^T\,\mathbf{Q}\,\underline{z} \;+\; \underline{u}^T\,\mathbf{R}\,\underline{u}\right)\ dt \\ \underline{\dot{z}} \;=\; \mathbf{A}\,\underline{z} \;+\; \mathbf{B}\,\underline{u} + \underline{n}\,, \quad \underline{z}(0) \;=\; \underline{z}_0 \end{cases} \tag{6}$$

By using the Lagrange multipliers the following relationship is obtained:

$$\tilde{J} = \int_0^T \left[ \underline{z}^T \, \mathbf{Q} \, \underline{z} \, + \, \underline{u}^T \, \mathbf{R} \, \underline{u} + \lambda^T \left( \dot{\underline{z}} \, - \, \mathbf{A} \, \underline{z} \, - \, \mathbf{B} \, \underline{u} - \underline{n} \right) \right] \, dt \tag{7}$$

A solution strategy using feedback control allows to write:

$$\begin{cases} -\dot{\mathbf{K}} \, + \, \mathbf{A}^T\mathbf{K} \, + \, \mathbf{K}\mathbf{A} \, + \, \mathbf{K}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\mathbf{K} \, - \, \mathbf{Q} \, = \, 0 \, , \quad \mathbf{K}(0) \, = \, 0 \\ -\dot{\underline{p}} \, + \, \mathbf{A}^T\underline{p} \, + \, \mathbf{K}\mathbf{B}\mathbf{R}^{-1}\mathbf{B}^T\underline{p} \, + \, \mathbf{K}\underline{n} \, = \, 0 \, , \quad \underline{p}(0) \, = \, 0 \end{cases} \tag{8}$$

The first equation is the Riccati's equation and $\mathbf{K}$, solution of the Riccati's equation, is the gain matrix.

In this formulation, the matrices $\mathbf{Q}$ and $\mathbf{R}$ are constant, meaning that the controller uniformly balances trajectory tracking (reaching the goal) and control effort throughout the entire task.

## Analysis

Numerical simulations are performed to compare the performance of the standard LQR controller with constant $\mathbf{Q}(\underline{z})$ and $\mathbf{R}(\underline{z})$ matrices against an adaptive LQR controller with state-dependent matrices. The scenarios involve a vehicle navigating through a field of obstacles to reach a predefined target. Metrics such as time to target, control effort, and proximity to obstacles are analyzed to assess the effectiveness of the adaptive controller.

To simulate the effect of brain signals, we introduce a state-dependent LQR controller. The idea is that brain signals modulate the vehicle's behaviour based on its proximity to obstacles. As the vehicle approaches an obstacle, the driver becomes more alert, and the control system prioritizes obstacle avoidance. Conversely, when the vehicle is far from obstacles, the system focuses on target tracking. In this adaptive LQR, the matrices $\mathbf{Q}$ and $\mathbf{R}$ become functions of the distance to the nearest obstacle $\rho(\underline{q})$. Matrix $\mathbf{Q}(\rho)$ penalizes the vehicle deviation from the desired state more heavily when near obstacles:

$$\mathbf{Q}(\rho) \, = \, \mathbf{Q}_0 \, + \, \Delta\mathbf{Q} \, \sigma(\rho) \tag{9}$$

where $\mathbf{Q}_0$ is the nominal weight matrix, $\Delta\mathbf{Q}$ is the additional penalty when near an obstacle, $\sigma(\rho)$ is a *sigmoid* function of the distance $\rho$ to the nearest obstacle.

Matrix $\mathbf{R}(\underline{q})$ reduces the penalization on control effort near obstacles to allow for more aggressive corrections:

$$\mathbf{R}(\rho) \, = \, \mathbf{R}_0 \, + \, \Delta\mathbf{R} \, (1 \, - \, \sigma(\rho)) \tag{10}$$

where $\mathbf{R}_0$ is the nominal control cost, $\Delta\mathbf{R}$ is the reduction in control cost near obstacles.

The control input is still of the form $\underline{u}(\underline{z}, \, t) \; = \; \mathbf{R}^{-1} \, \mathbf{B}^T \; (\mathbf{K}(z, \, t) \, \underline{z})$, but the gain matrix $\mathbf{K}(\underline{z}, \, t)$ now depends on the state-dependent matrices $\mathbf{Q}(\rho)$ and $\mathbf{R}(\rho)$, calculated in real-time by solving the Riccati's equation. As the vehicle approaches an obstacle, the controller automatically shifts its behavior, focusing more on avoiding the obstacle and less on reaching the goal. This dynamic adjustment simulates the heightened alertness of a human driver in critical situations.

### *Physiological signals and driver behavior*

The brain signals are extracted by the MPDB dataset. This one gives a set of physiological signals correlated to corresponding driver's reaction. The environment where the experiment is performed is a 6DOF driving simulator and the signals are measured by EEG, ECG, EMG, GSR and eye track [8]. The experiment is performed showing a set of events to the driver and registering his reaction. The event and the driving behavior are correlated as shown in the following correspondence table (1).

**Table 1** Corresponding table [8]

| Driving behavior | Corresponding events |
|---|---|
| Smooth driving | Normal straight line driving |
| Acceleration | Overtaking<br>Congestion relief |
| Deceleration | The front emergency brake<br>The slide front cut-in<br>Pedestrian crossing |
| Lane-change | Static obstacle on right<br>Static obstacle on left |
| Turning | Left-turn sign<br>Right-turn sign |

## Conclusion

This paper introduces a novel adaptive LQR control strategy that integrates simulated brain responses into a vehicle's obstacle avoidance behaviour. By dynamically adjusting the weight matrices $\mathbf{Q}$ and $\mathbf{R}$ based on the vehicle's proximity to obstacles, the controller mimics the human driver's heightened attention in critical situations. Numerical simulations demonstrate the potential of this approach in improving both safety and navigation efficiency.

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## References

1. Roveri, N., Carcaterra, A., Molinari, L., and Pepe, G. "Safe and secure control of swarms of vehicles by small-world theory". *Energies*, 13(5):1043 (2020)
2. Pepe, G., Roveri, N., and Carcaterra, A. "Experimenting sensors network for innovative optimal control of car suspensions". *Sensors*, 19(14):3062 (2019)
3. Bi, L., Wang, H., Teng, T., and Guan, C. "A novel method of emergency situation detection for a brain-controlled vehicle by combining eeg signals with surrounding information". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 26(10):1926–1934 (2018)
4. Tao, X., Gao, D., Zhang, W., Liu, T., Du, B., and Zhang, S.e.a. "Driving behaviour multimodal human factors raw dataset" (2023)
5. Zhang, Z., Han, S., Yi, H., Duan, F., Kang, F., Sun, Z., Solé-Casals, J., and Caiafa, C.F. "A brain-controlled vehicle system based on steady state visual evoked potentials". *Cognitive Computation*, 15(1):159–175 (2023)
6. Zhang, H., Chavarriaga, R., Khaliliardali, Z., Gheorghe, L., Iturrate, I., and d R Millán, J. "Eeg-based decoding of error-related brain activity in a real-world driving task". *Journal of neural engineering*, 12(6):066028 (2015)
7. Zander, T.O., Andreessen, L.M., Berg, A., Bleuel, M., Pawlitzki, J., Zawallich, L., Krol, L.R., and Gramann, K. "Evaluation of a dry eeg system for application of passive brain-computer interfaces in autonomous driving". *Frontiers in human neuroscience*, 11:78 (2017)
8. Tao, X., Gao, D., Zhang, W., Liu, T., Du, B., Zhang, S., and Qin, Y. "A multimodal physiological dataset for driving behaviour analysis". *Scientific data*, 11(1):378 (2024)
9. Pensalfini, S., Coppo, F., Mezzani, F., Pepe, G., and Carcaterra, A. "Optimal control theory based design of elasto-magnetic metamaterial". *Procedia Engineering*, 199:1761–1766 (2017) X International Conference on Structural Dynamics, EURODYN 2017.
10. Pepe, G., Paifelman, E., and Carcaterra, A. "Feedback volterra control of integro-differential equations". *International Journal of Control* (2023)