Route tracking diagnosis algorithm for EV energy prediction strategies

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***Abstract*—Current pollution issues generated by internal combustion engine (ICE) based vehicles have lead to their progressive introduction of electrified transport systems. However, their main drawback is their poor autonomy when compared to conventional vehicles. In order to mitigate this issue, the scientific community is extensively researching on energy optimization and prediction strategies to extend the autonomy of electric vehicles (EV). In general, such strategies require the knowledge of the route profile, being of capital importance to identify whether the vehicle is on route or not. Considering this, in this paper, a geo-fence based route tracking diagnosis strategy is proposed and tested. The proposed strategy relies on the information provided by the Google Maps API (Application Programming Interface) to calculate the vehicles reference route. Additionally, a Global Positioning System (GPS) device is used to monitor the real vehicle position. The proposed strategy is validated throughout simulation and experimental tests.**

***Index Terms*—BEV, PHEV, energy consumption estimation, optimization, geo-fence**

I. Introduction

During the last decades, the revolution in the automotive industry has generalized the purchase of internal combustion engine (ICE) based vehicles for personal use. Such significant increase of the vehicle fleet has become a serious problem, as it implies a considerable increase of pollution in urban areas [1]. Consequently, the legislation has become restrictive in a great number of city centres. As a consequence, end users are looking for alternative powertrain solutions, being battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) the current preferred options.

One of the most important barriers that prevents the widespread of electrified vehicles is their limited energy storage capacity, which results in poor driving ranges. In order to overcome this limitation, a significant amount of research is being carried out regarding efficient energy management. These strategies aim to predict the vehicle energy consumption during the whole trip to optimize the control of the drivetrain components [2]. In this context, a variety of forecasting methods have been developed to meet this target. For example, The research studies conducted in [3]–[5] focus on driving pattern identification (speed profile, acceleration or roadway grade) to estimate the energy consumption. In [6], methods for the characterization of the driver influence are conducted. Other studies include the journey planning information (traffic signs, traffic flow) [7], or propose advance driver assistance systems to minimize the energy consumption along the route [8]–[10].

All these energy prediction approaches rely on the knowledge of the route profile to estimate the amount of energy consumed during a trip. In order to obtain an accurate energy prediction, these techniques need to be complemented with a route tracking diagnosis strategy. This information is valuable for the energy prediction strategy to update the route profile and characteristics if the vehicle is out of the reference route.

Considering all the previous, a geo-fence based route tracking diagnosis strategy is proposed and tested in this paper. The proposed strategy relies on the information provided by the Google Maps API (application programming interface) to calculate the vehicle's reference route. Additionally, a Global Positioning System (GPS) device is used to monitor the real vehicle position. The proposed strategy is validated throughout simulation and experimental tests.

II. Impact factors of an energy prediction strategy

The processes required for accurately estimate the energy consumption in an EV are not straightforward. The influence of various factors such as the driver behaviour, weather, traffic congestion and vehicle characteristics affect the prediction algorithms and, therefore, cannot be neglected [11], [12]. In this context, a general diagram of the main impact factors that have influence on energy prediction algorithms are summarized in figure 1. In the following, the three main aspects that influence the vehicle power consumption are introduced.

A. Route information

Route information is one of the most significant factors that influence the vehicle energy prediction. This includes both basic route information (speed and altitude profile), and also advanced data such as traffic flow, traffic signals or environmental information (weather conditions, wind speed, etc.) [13]. In order to get the required information, live data can be collected using cloud platforms such as Google, and such data can be gathered in a database for further analysis during the desired time interval.

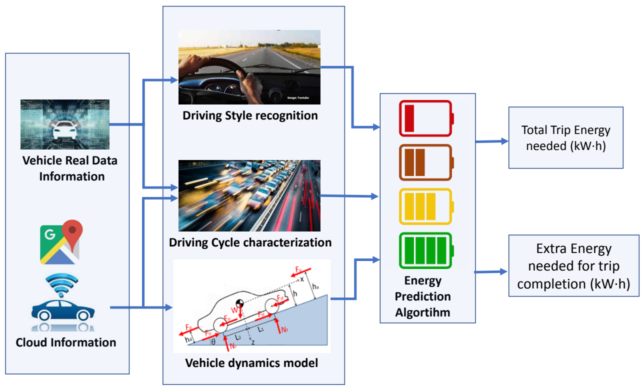


Fig. 1: General diagram of the main factors that have influence on an energy prediction strategy.

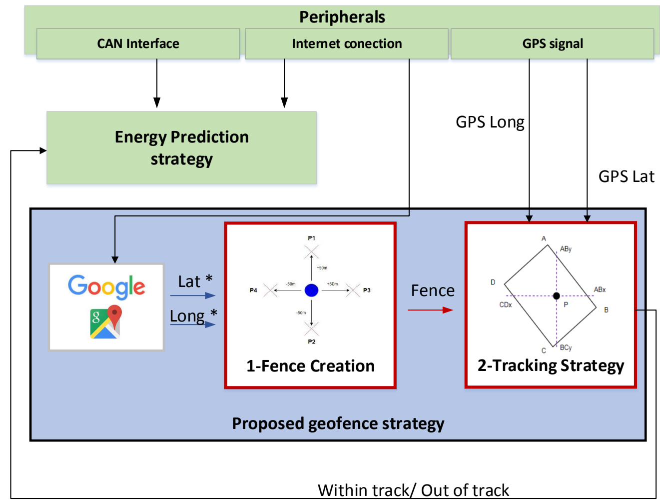


Fig. 2: General diagram of the proposed geo-fence strategy.

B. Vehicle information

Apart from route information, a good knowledge of the vehicle dynamic performance is required to achieve an adequate energy consumption estimation, i.e., by means of an adequate:

(a) Vehicle parametrization;
(b) Vehicle real data acquisition through a controller area network (CAN) protocol.

It is important to point out that an accurate vehicle parametrization is required to simulate its performance [2], [14], [15]. A vehicle simulation model aims to determine the required torque for a given speed profile:

$$T_{wheel} = r_{wheel}(F_{Roll} + F_{Aero} + F_{Inertia} + F_{Grade}), \quad (1)$$

where F_{Roll}, F_{Aero}, $F_{Inertia}$ and F_{Grade} are the rolling resistance, aerodynamic resistance, inertia forces and grade forces, respectively. These last four can be defined as:

$$F_{Roll} = \mu a_g M_{car}, \quad (2)$$

$$F_{Aero} = \frac{\rho v^2 C_d A_f}{2}, \quad (3)$$

$$F_{Inertia} = \{M_{car}(1 + M_{rot})\}a_{car}, \quad (4)$$

$$F_{Grade} = M_{car} sin(tan(\delta)), \quad (5)$$

where, M_{car} is the total vehicle mass; v is the speed (m/s); a_g is the gravity acceleration; μ is the rolling friction coefficient; ρ is the air density; C_d is the drag coefficient; A_f is the vehicle cross section; M_{rot} is the equivalent mass of the rotating parts of the car, a_{car} is the car acceleration and δ is the grade slope of the route profile.

On the other hand, vehicle CAN Bus data such and battery state of charge (SoC), and DC-link current and voltage status are required to monitor the vehicle performance online.

C. Driving style

The driving style of the driver has a great impact on the energy consumption of the vehicle. In this context, driving styles can be classified as follows [16]–[18]:

(a) Steady driving;
(b) General driving;
(c) Radical driving.

D. Energy consumption estimation algorithm requirements

An energy estimation strategy should be based on the aforementioned pillars (subsections II-A, II-B, II-C). It is of great importance to remark that the more impact factors are considered, the more accurate will be the conducted energy prediction.

As a knowledge of the route information is mandatory, it is important to ensure that the vehicle is following the route calculated at the beginning by the energy estimation (and optimization) algorithm. Thus, these techniques should rely on a route-tracking diagnosis, in order to provide further reliability to the prediction calculations as, if the vehicle deviates from the defined route, the new route should be recalculated to obtain a good energy consumption estimation.

The main goal of a route-tracking diagnosis is to carry out, efficiently, out-of-track detections. In the following, a geo-fence based route-tracking strategy is proposed and fully validated.

III. Proposed geo-fence based route-tracking strategy

A general diagram of the proposed geo-fence strategy is shown in figure 2. The strategy relies information provided by the Google Maps API to determine the reference profile of the route. A polygon shape virtual barrier (fence) is then created around it. Finally, a GPS based feedback tracking strategy is presented to determine whether the vehicle is inside or outside the boundaries of the predefined route.

A. Fence generation

The route profile provided by the Google Map API is expressed in both latitude and longitude coordinates. For each of them, the distance of the virtual fence is firstly determined within the proposed algorithm. The procedure is shown in figure 3, where the boundaries `P1`, `P2` and `P3`, `P4` represent the reference location displacement along the longitude and latitude axes, respectively.

The relationship between meters and decimal degrees can be achieved by applying the following:

$$Latitude\ (lat) : 1^{\circ} = 111.12\ km, \tag{6}$$

$$Longitude\ (long) : 1^{\circ} = \frac{E_{perim}}{360^{o}} cos(lat)\ km, \tag{7}$$

where E_{perim} is the Equatorial perimeter and is defined as $E_{perim} = 40074, 78$ km. A conservative fence distance of 50 m has been considered in this particular application, due to the constraints of current GPS technology precision.

Once the boundaries `P1`, `P2`, `P3` and `P4` are determined, a rectangle shaped fence is created between two consecutive locations of the reference route profile (figure 4(a)). The general procedure to assign the polygon vertices is the following:

- `A` corresponds to the boundary located at the highest latitude value;
- `B` corresponds to the boundary located at the highest longitude value;
- `C` corresponds to the boundary located at the lowest latitude value;
- `D` corresponds to the boundary located at the lowest longitude value.

Two particular scenarios have been considered. The first one corresponds to the situation where the consecutive locations remain at the same longitude, i.e., vertical direction (figure 4(b))). Under this circumstance, the polygon vertices are assigned as follows:

- `A` corresponds to the `P4` located at the highest latitude;
- `B` is the highest longitude located `P3`;
- `D` is assigned to the `P4` located at the lowest longitude;
- `C` corresponds to the `P3` located at the lowest latitude.

The second and last particular situation considers two consecutive locations at the same latitude, i.e., horizontal direction (figure 4(c)). Here, `A` and `B` are the `P1` boundaries with the lowest and highest longitudes, respectively. Similarly, `D` and `C` are the `P2` boundaries with the lowest and highest longitude, respectively.

B. Tracking strategy

An Out-of-track detection strategy has been implemented to monitor and track the vehicle real route. As stated before and based on a GPS location feedback, the proposed strategy aims to notify the energy prediction system if the vehicle trajectory remains out of the reference track for a defined period of time.

The proposed method aims to determine if a certain location `P` (GPS position) lies inside or outside the boundary area (polygon based fence), as shown in the example depicted in figure 5. The resolution of the geometrical problem consists on two steps:

1) The determination of the rectangle side equations `AB`, `BC`, `CD` and `DA`.
2) The projection of the point `P` into a line. It can be concluded that the GPS position `P` lies inside of the fence when the following is fulfilled:

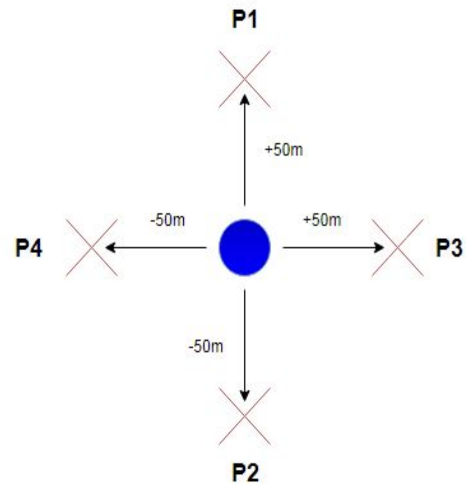


Fig. 3: Boundary determination around a reference location.

$$(BC_Y < P_Y < DA_Y)\ \&\ (CD_X < P_X < AB_X), \tag{8}$$

where BC_Y is the projection of the `BC` segment on the y-axis, DA_Y is the projection of the segment `DA` on the y-axis, CD_X is the projection of the segment `CD` on the x-axis, AB_X is the projection of the segment `AB` on the x-axis, and P_X and P_Y are the projections of `P` on the x- and y-axes, respectively.

Additionally, the algorithm determines the vehicle direction, comparing the distance between the GPS position and the next closest reference at different time intervals.

An out-of-track indicator is enabled if one of the above situations occurs. The proposed strategy includes a counter to register consecutive out-of-track situations in order to discriminate incorrect position measurements and prevent false positives.

IV. Simulation results

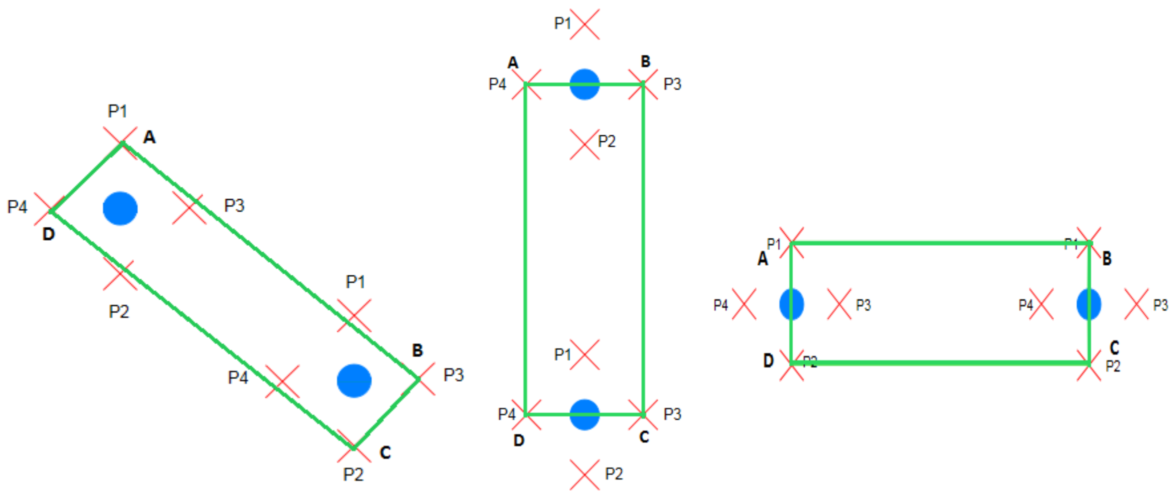
As a first step, the proposed geo-fence strategy has been implemented in the Matlab/Simulink simulation environment. Simulation results are shown in figure 6. In such figure, the polygonal fence detailed in section III-A has been included in green.

The analysis of the results of the tracking strategy are shown in table I for a given validation test case. When the GPS locations are outside the fence (figure 6 and table I, position numbers 6, 7, 11, 12 and 13), the tracking strategy increases the out-of-track indicator counter. The counter is reset once the GPS position remains inside the fence.

V. Experimental results

A. Experimental platform description

An electronic device powered by an ARM Cortex processor running open software operation system (Linux) has been used for the geo-fence algorithm experimental validation. A fully open source hardware has been selected, i.e., the Beaglebone



(a) General scenario. (b) Vertical direction. (c) Horizontal direction.

Fig. 4: Polygon based fence determination.

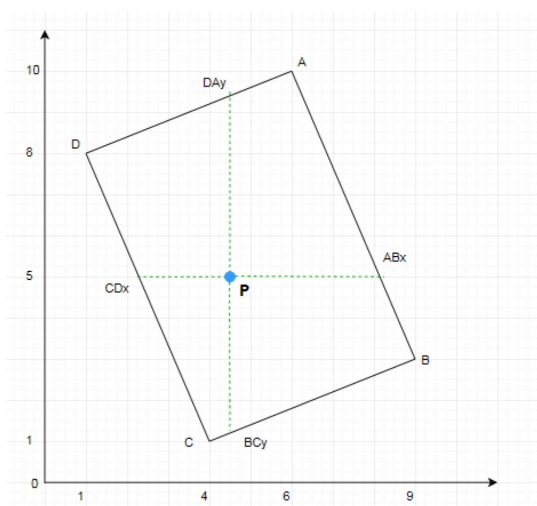


Fig. 5: Strategy to determine whether or not a point lies inside the defined boundaries.

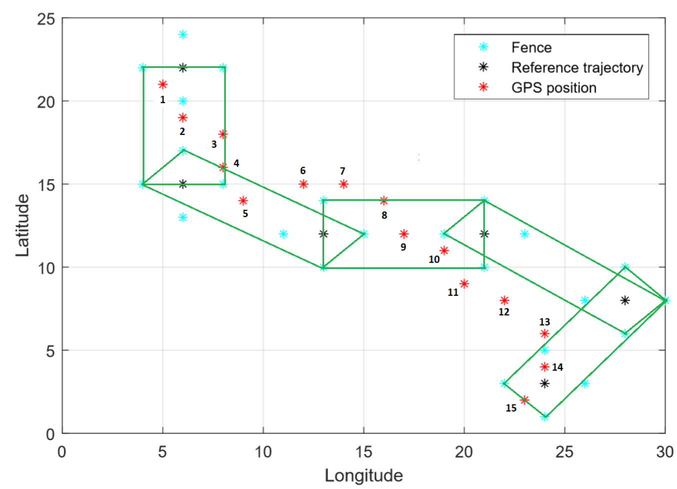


Fig. 6: Simulation results of the proposed geo-fence route tracking strategy.

TABLE I Tracking strategy analysis (simulation results).

GPS position	Fence	Out-of-Track counter
1	Inside	0
2	Inside	0
3	Inside	0
4	Inside	0
5	Inside	0
6	Outside	1
7	Outside	2
8	Inside	0
9	Inside	0
10	Inside	0
11	Outside	1
12	Outside	2
13	Outside	3
14	Inside	0
15	Inside	0

Black Wireless platform. This device contains the Octavo Systems OSD335x System-in-Package, which integrates the Texas Instruments Sitara ARM Cortex-A8 AM335x Processor, DDR3 memory, TPS65217C PMIC, TL5209 LDO, and all needed passive components into an small package. All this allows for a vastly simplified final system design. A G-STAR IV GPS device is used and plugged to the Beaglebone Black USB port. The experimental platform is shown in figure 7.

Regarding the firmware, the well-known model based design (MBD) approach has been followed in Simulink for the development of the proposed geo-fence algorithm. The framework has been developed in Python, which allows to easily manage high level task such as CAN bus and wireless communication trough bluetooh, wifi or 3G, web services iteration (Google Maps) and GPS.

B. Experimental results

For the experimental validation, the proposed strategy has been embedded in the Beaglebone Black target, and the GPS

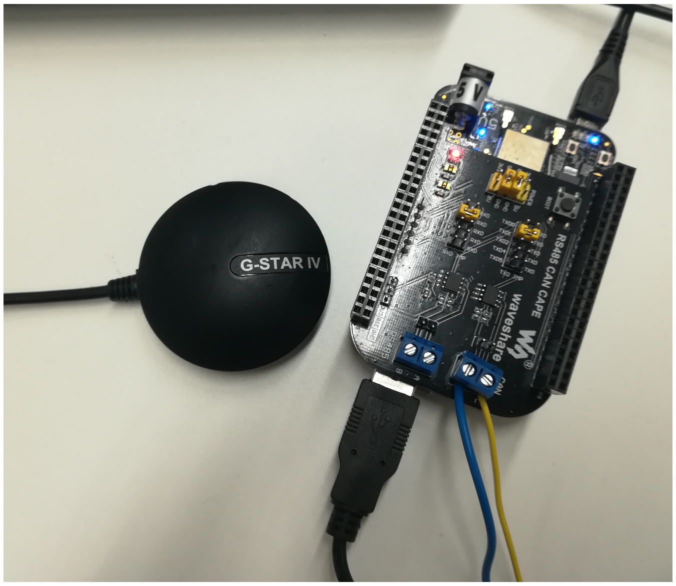


Fig. 7: Experimental platform: GPS device and BeagleBone Hardware.

TABLE II Tracking strategy analysis (experimental results).

GPS pos.	Fence	OoT counter	GPS pos.	Fence	OoT counter
1	Inside	0	17	Outside	6
2	Inside	0	18	Outside	13
3	Inside	0	19	Outside	19
4	Inside	0	20	Outside	26
5	Inside	0	21	Inside	0
6	Inside	0	22	Inside	0
7	Inside	0	23	Inside	0
8	Inside	0	24	Inside	0
9	Inside	0	25	Inside	0
10	Inside	0	26	Inside	0
11	Inside	0	27	Inside	0
12	Inside	0	28	Inside	0
13	Inside	0	29	Inside	0
14	Inside	0	30	Inside	0
15	Inside	0	31	Inside	0
16	Inside	0	32	Inside	0

speed was set to around 5 km/h. In this context, figure 8 shows experimentally obtained validation results. The selected path, from `A` to `B`, shows 8 blue tickers, indicating the desired route (i. e., route profile provided by Google Map API). Data of 32 GPS locations was taken, obtaining the out-of-track experimental results shown in table II. From this experimental test, it can be seen that, until GPS location number 17 is reached, all the positions are located inside the virtual fence described in section III-A. From GPS location 17 to 20, the GPS trajectory is considered out of the reference trajectory, as shown in table II.

Taking into account the GPS device average speed, the execution time of the task running in the Beaglebone and the GPS refresh data (1 Hz), it can be concluded that the out-of-track counter is increased in each location in around 6-7 times. At GPS location 21, the system remains inside the virtual fence of the desired route trajectory, so the out-of-track counter is reset.

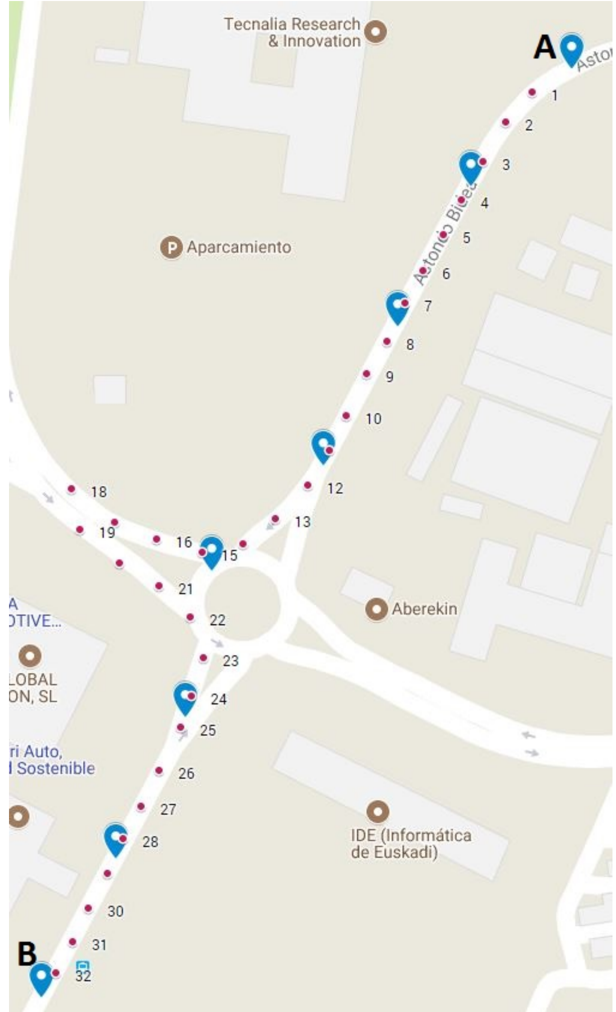


Fig. 8: Experimental results of the proposed geo-fence route tracking strategy for a given test.

VI. Conclusions

In this paper, a review of current EV energy consumption estimation algorithms has been carried out, and the importance of relying on out-of-route detection algorithms has been confirmed. Additionally, a geo-fence based route-tracking strategy has been proposed.

Experimental results shows that the proposed method can provide accurate information related with the direction and the real position of the vehicle in the desired route. The proposed solution is capable of being executed in a low cost device. As cost is a major concern of the automotive sector, the proposal can be considered adequate. In the future, the geo-fence based route-tracking algorithm will be integrated in a real vehicle, testing its operation through real driving routes.

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