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Extracting dashcam telemetry data for predicting energy use of electric vehicles

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A R T I C L E I N F O

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A B S T R A C T

Prior to the acquisition of an electric vehicle, pre-evaluation of vehicle energy use is desirable to assess whether the intrinsic vehicle electrical storage capability is satisfactory. However, inconsistency in general vehicle modelling may provide unreliable predictions concerning energy usage. To increase the prediction reliability, the use of route-specific driving cycle data is essential.

This paper presents a case study of a novel method of extracting vehicle telemetry data from archived dashcam videos without the need to deploy conventional telemetry techniques. Utilising dashcam videos as input, and employing image processing and recognition technology, textual en-route driving data embedded in the video can be extracted. This data can then, in-turn, be used to model the performance of the vehicle, or an electric equivalent in terms of energy use and emissions. Results from preliminary testing with real-life dashcam videos, demonstrate negligible errors with regards to energy requirements and pollutants emitted from an EV operating on the modelled routes. Consequently, the proposed solution opens up the possibility to gather a significant amount of new data in order to better assess the transport sector's energy requirements. This is especially important for situations where conventional telemetry is difficult to obtain. In addition, results from vehicle fleet modelling may inform policy decisions with regard to the impact of introducing low emission zones.

1. Introduction

Increasing environmental concerns, especially Greenhouse Gas (GHG) and air pollutant emissions, particularly from transport are driving significant changes with respect to transportation policy. For example, in Europe, more than a quarter of the total urban GHG emissions are attributable to Public Service Vehicle's (PSVs), such as goods transportation and municipal services (European Commission, 2013). By 2050, the European Commission (EC) proposes a 60 % reduction in transportation related GHG emissions (European Commission, 2016), where vehicles that rely on conventionally fuelled internal combustion engines (ICE) are to be halved and targeted for phasing out by 2050 at the latest (European Commission, 2016). To support this target, the United Kingdom will prohibit the trading of new combustion-engine vehicles by 2035 (Department for Transport & Office for Zero Emissions Vehicles, 2021). Similarly, the EU's European Commission has launched regulations that target a carbon emission reduction of 50–55 % for new vehicle models by 2030, and a complete 100 % reduction by 2035, effectively imposing a sales ban on internal combustion engine-powered vehicles (European Council, 2022).

In the past decade, EVs have been promoted with both global and European strategic endorsements as the emerging technology to reduce air pollution (Dijk et al., 2013). Therefore, as a critical solution to lower air pollution and GHG emissions, among the different options proposed by relevant stakeholders (BESTFACT, 2016; Lebeau et al., 2016, Kirschstein and Meisel 2015), electric vehicles (EVs) are being increasingly adopted and supported by policy-makers (U.S. Department of Energy, 2011a,b; Canter, 2008). Recent statistical studies suggest a year-on-year increase in fully electric vehicle sales of 100 % in the UK, with an expectation that road-ready electric vehicle numbers will reach 300,000 by 2030 (UK Government – Department for Transport, 2022). Similar trends can be observed in other world regions, with the EU's European Environment Agency consistently reporting EV registrations doubling each year, with up to 750,000 battery electric vehicles on the road in 2020 (European Union, 2021).

Additionally, promoted by its zero tailpipe emissions (Morrissey et al., 2016; Driscoll et al., 2013; Casalset al., 2016), the adoption of battery-powered vehicles has been expanded into both urban

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commuting and more recently, urban municipal services and commercial transportation (Cen et al., 2018; Zhao et al., 2020). This aligns with increased and more widespread introduction of air quality related transport policy initiatives. For example, Low Emission Zones (LEZ) and Clean Air Zones (CAZ) in the UK, which aim to penalise the operation of the most polluting vehicles in controlled geographic areas (Ballantyne and Heron, 2020).

Several studies have performed comparative assessments of both energy use and tailpipe emissions between battery-electric and ICE vehicles. Outcomes have demonstrated the contributions from detailed EV sub-systems (Kim et al., 2016; Notter, 2010; Ambrose and Kendall, 2016), and presented macro research concluding the positive differences, such as significantly reduced GHG emission and particle pollution, between EVs and ICE vehicles (Hawkins, 2012; Burnham, 2012; CARB, 2012). In general, EVs are shown to produce fewer greenhouse gas emissions and be less polluting than ICE vehicles (Encarnação et al., 2018). However, to pre-evaluate the efficacy of electrification and environmental contribution, accurate and case-based figures of power consumption and emissions reduction are required by the potential user, prior to a commitment to providing electric alternatives to replace their existing vehicle(s). This is especially true if the user is to be a fleet vehicle operator, for example a local refuse collection operator and their fleet of PSVs (Zhao et al., 2020), due to the increased emissions produced by the types of ICE vehicles normally employed. Currently, environmental contribution or energy consumption performance predictions are generally approximated from semi-qualitative studies based on urban layout and road length (Andreassi et al., 2019). Such estimations not only give rise to lower prediction accuracy but significant errors during post-implementation evaluation. Additionally, this approach could result in the recommendation to invest in unsuitable vehicles and infrastructure due to lack of accurate prediction of vehicle energy performance and requirements (Pelletier et al., 2017; Schoch et al., 2018).

Prior to the deployment of EV replacements for ICEVs, accurate energy usage and environmental contribution can be assessed. This can be obtained by simulating the desired EV using designated vehicle driving data and route / geographical information. These case-based, city-distinctive predictions could significantly enhance the accuracy and authenticity of the pre-deployment evaluation results (Tamor et al., 2015; Nocera et al., 2018). However, these analyses have to-date been conducted using "typical drive cycles" due to lack of data, for example high-resolution route information and driving data for all possible routes (Zhao et al., 2018). Even though research has shown improved accuracy and applicability can be obtained by utilising simulated drive routes and a comprehensive vehicle model (Basso et al., 2021; Zhao et al., 2020, Daina et al., 2017), the assurance and accuracy of results could be further increased with real-life driving data, where driving behaviour and traffic conditions are involved.

However, to obtain this route-specific energy usage prediction, two data inputs are required: an accurate model that mathematically represents the energy consumption of the proposed vehicle, and high-resolution recordings of the vehicles en route driving data, consisting of a vehicle's manoeuvre, and driving track across all routes of interest (Zhao et al., 2020). The vehicle model could be established using the drivetrain information and auxiliary information sourced from the vehicle manufacturer (Daina et al., 2017). The en route driving data that represents each vehicle's speed, position, and elevation, however, is more problematic to obtain, since it is preferable to predict the energy consumption of an EV on a driving route before an EV has been purchased or deployed. Therefore, no such data is available from an actual electric vehicle on the given targeted route.

Interestingly, potential telemetry data recordings are routinely compressed and archived, especially by fleet operators, as a dashcam video library for driver training and accident prevention (Mehrish et al., 2019). Therefore, both current and historical driving data that covers multiple routes of interest may actually be readily available in the format of dashcam videos. As such, by using the overlaid information available in those videos, route information and en route driving data, such as speed and location, can be obtained and exploited alongside an EV model to predict an EV's energy usage under different seasons or weather conditions. However, the data cannot be directly used by electric vehicle simulation modelling technologies and other feasibility analysis tools. This is due to the format of the data and its limited reliability, since the required video data is presented only as an image instead of the required strings or numbers. Therefore, to convert the video data from the image format into a usable format, sequentially linear textual data need to be extracted from the dashcam videos using pattern recognition, which itself presents challenges, such as those caused by fast-changing background and compression-incurred blur.

This paper presents a novel application of optical character recognition software technology for telemetry extraction from vehicle dashcam videos. The methodology utilises dashcam videos as raw data input, through an emergent image processing and recognition technology, the en route driving data overlaid on the dashcam video can be extracted to establish a dataset of textual information over a specified time period. Detailed image processing and data extraction methodology and technology will be presented in section 2 of this paper, along with the approximation algorithm used for intermittent recognition results. The proposed solution aims to provide data that accounts for factors that would normally be difficult to model artificially. The employed approach, which is based on analysing visual information through utilising a visual recognition algorithm is a novel method, based on optical character recognition (OCR), and has been chosen in order to determine its efficacy in estimating values.

Moreover, this data would normally be unavailable for investigations into vehicle emissions and costs, thus it effectively supports decision making with greater accuracy of information. A case study example of experimental evaluation using a real-life archived dashcam is provided in section 3, thus validating that the energy required, and pollution emissions from operating a replacement EV on the same route shown in the dashcam video may be calculated and used for pre-electrification feasibility evaluation.

Finally, the work presented in this paper represents an evolution and expansion of previous early-stage research on electric refuse collection vehicle (eRCV) energy use modelling by Zhao et al. (2021). Furthering the work to allow the required input data collection through the use of pre-existing in-cab dashcam videos enabling wider applicability of the modelling technique developed across a range of different vehicles and operating routes.

1.1. Literature review

The research featured in this paper is at the crossroads of many fields of expertise found in different research areas, including transport logistics concerning novelty (Amaya et al., 2021; Chung, 2021). The methodology itself relates to geometry and computer vision, however, the underlying principles, although in a niche field, aim to present data-driven solutions to generating energy usage predictions for situations where a lack of conventional telemetry data exists. Therefore, this represents a novel approach to data acquisition for energy modelling and transport and logistics research.

1.1.1. Telemetry

The concept of telemetry is represented by the ability to record and automatically communicate accurate measurements of physical parameters of entities in an in-situ fashion (Altvater, 2017). Telemetry systems have seen recent increases in usability in the automotive and transport sectors, with a range of wide applications proving their effectiveness. For example, they have been extensively used to better understand potential improvements of logistic fleet usage, such as improved mileage through better vehicle routing and decreased carbon dioxide emissions (De Oliveira Neto et al., 2019). Similarly, telemetry data has been proven useful for creating semantic, high-resolution data for maps of urban areas, as highlighted by Wei et al. (2022). The accuracy of artificial intelligence (AI) based driving assistants has also been proven to be positively affected by integrating vehicle telemetry in prediction operations, indicated in the work of Terán et al. (2020).

Since the 1980s, the concept has been extensively used in high-performance subsectors of transport, such as motorsport. It has been employed as data-driven feedback for the design of key elements, such as aerodynamics and powertrain sizing (Miller, 2021). Additionally, telemetry principles have been successfully employed to develop optimised controllers for torque split and velocity scheduling in hybrid vehicles (Manzie et al., 2012). Evidence represented by improved aerodynamic efficiency as well as increased power-to-weight ratio of motorsport vehicles (Carpentiers, 2016), indicate that telemetry has positively contributed to the vehicle design process, together with other sources of feedback, such as driver comments and computational simulation. This demonstrates that similar ideas have been successfully applied in previous studies for different applications, therefore validating the aims of the presented material.

In order to better understand the purposes of this research, traditional telemetry data application limitations must be considered. Conventionally, this data may be extracted for energy usage estimation from driving data obtained from an in-service conventionally fuelled ICE vehicle. Since the electrified vehicles will operate on the same routes under the same or similar road restrictions, such as speed limits and time restrictions, the on-road EV driving data is the equivalent to that from an available ICE vehicle. Traditionally, this data could be collected by using an on-board GPS logging device installed on the in-service vehicle. However, most logging devices are primarily installed for anti-theft and trip detection purposes hence cannot achieve the essential resolution and logging frequency required to collect data for simulation (Joubert and Meintjes, 2015; Lappanitchayakul, 2019). In addition, the introduction of data logging is often viewed with suspicion by operatives, whereas in-cab video recordings are now commonplace.

Finally, video acquisition of data using dashboard-mounted video cameras (dashcams) has been widely used and has recently gained popularity in vehicles, especially in PSVs (Taccari et al., 2018). However, the videos captured from these dashcams are primarily used to provide witness and testimony during traffic violations and accidents (Mental Floss, 2014). This includes collecting evidentiary journey and real-time vehicle data, such as speed and geographic coordinates, which are overlaid onto the video feed together with time stamp, such as the capture shown in Fig. 1. Since the overlaid real-time vehicle data includes a near-constant update of the vehicle's speed and direction, as well as providing a video reference of the vehicle's route, dashcam footage may be used as a good source of telemetry data (Stincescu et al., 2021).

Fig. 1. Example of frame from a dashcam recording, with an overlay displaying real-time vehicle data.

1.1.2. Computer vision for transport applications

Another important factor in the literature that has been examined is represented by the principles of computer vision. These have been extensively employed and explained further in the methodology section. The concept of computer vision is based on several scientific fields and is concerned with enabling computers to gain high-level, human-like understanding from digital material (Ballard et al., 1982). It is an evolution of AI principles that employs metaheuristic prediction techniques, such as machine learning, to generate predictions based on information with a high degree of complexity, as indicated by Sonka et al. (2008). Whilst at its creation the concept was fairly limited in terms of capability, it has gained significant interest due to the most recent leaps in computational power. Some of the most popular first-order applications of computer vision include object recognition and detection, image restoration and event detection and reconstruction (Morris, 2004). For example, Automatic Number Plate Recognition (ANPR) has become an established method of traffic monitoring and surveillance (Coifman et al., 1998).

Finally, optical character recognition (OCR) technology has been developed for several years and its latest iterations manage to have very high degrees of prediction accuracy, as indicated in the works of Sajedi (2016) and Amin et al. (2022). Additionally, applications of this technology have seen multiple adoptions in many fields of expertise, ranging from live traffic vehicle identification (Tian et al., 2015; Safaei et al., 2016) to natural sciences (Khalil et al., 2021). Consequently, the use of OCR computer vision technology is widely proven and could be the basis for a novel approach to telemetry data collection.

2. Materials and methods

To analyse the energy usage and emissions reduction that could be achieved from an electrified vehicle in each location prior to its actual deployment, comprehensive analyses and vehicle emission calculations are undertaken. To perform this analysis, telemetry data may be employed to generate energy predictions for electric vehicles. Fig. 2 shows a simplified flowchart of the model which will be used for this purpose. This model is based on the eBike model previously introduced in (Stincescu et al., 2021) which in turn is a variation of a previous model iteration published in (Zhao et al., 2020). The model is capable of simulating a battery-electric powertrain that may have its characteristics set according to the given technical specification of the vehicle (in this case, an electric motorbike).

The proposed simulation model was developed using Simulink and SimScape versions in the base workspace and environment. Several model approaches were developed in order to estimate different capabilities of various simulation blocks within Simulink. Compared to basic Simulink blocks for which the output can be seen only if an observer block is attached to the signal line (e.g., scope, bar, final value), SimScape allows for complete parameter observation thanks to the Solver Explorer application. In this implementation, time-based evolution of all system and subsystem parameters can be seen down to a library-defined block level. This also allows for a much quicker and better understanding of the model.

The model simulates the aspects of the drivetrain and aerodynamics, allowing the losses of the system be calculated and consequently the total energy requirement of the vehicle to be calculated for a given journey. The difference between the speed output of the model and the speed from the telemetry data gives an indication of the accuracy and reliability of the model, with a smaller difference showing greater model accuracy.

However, the use of this model requires telemetry data of the vehicle's speed, preferably at a high resolution. Whilst there are a number of ways that telemetry data like this can be collected, a novel and simple way of collecting such data, potentially without requiring any further equipment, is provided in this paper. The proposed approach overcomes the difficulties in reconstructing a vehicle's speed and driving profile from a compressed dashcam video and can produce a dataset consisting

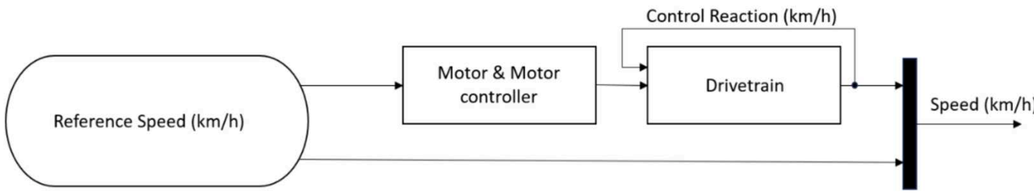

Fig. 2. Simplified system diagram of EV energy usage estimation model.

of the vehicle's speed and GPS coordinates in millisecond resolution.

The processed dataset may then be fed into a model, such as the discussed MATLAB-based electric vehicle model, to calculate the energy usage of an electric vehicle with a given technical specification. The results can then be compared with the current energy performance figures of a comparable conventionally fuelled vehicle, hence an evaluation of the reductions in carbon footprint and other emissions may be performed.

A simplified system diagram for the process of obtaining telemetry data is shown in Fig. 3. This shows how the video data is processed prior to character recognition, how polynomials are used for error checking and interpolation, and how the telemetry data is fed into a model to predict energy usage.

The video analysed for telemetry extraction is encoded using the Phase Alternating Line (PAL) format, with the resolution of 1280*720 pixels at 25 frames per second. The conversion process begins by extracting the video frames that are multiples of 25, along with 6 adjacent frames. These frames improve the prediction confidence in a scenario where the reference frame is blurred out due to inter-frame compression or bitrate limitation. The targeted frames for extraction may be detected by modelling a function based on equation (1):

$$f(t)^* = \begin{cases} f(0)^* = 0 \\ [25t-3, 25t+3], 1 < t < \tau - 1 \\ f(\tau)^* = [25\tau], \end{cases} \tag{1}$$

where t is time in seconds and τ is the length of target video (in seconds) until the last valid whole second. A dashcam video typically starts and ends with the vehicle stationary and at a fixed location, hence the first and last frame group consists only of a single frame.

Next, the extracted frames are cropped using a reference mask area such that only the instantaneous speed is displayed. This helps with minimising image information and consequentially decreasing the time spent identifying the relevant digits. An example of this may be seen in Fig. 4.

Similarly, Fig. 4 shows two major constraints to be addressed before Optical Character Recognition (OCR) can be used to generate the displayed digits. Initially, the speed display is transposed onto the dashcam video using a semi-translucent background. This obfuscates the edges of the speed digits through the reduction of the relative contrast. This is most apparent in the second, fourth, and sixth frames. Furthermore, the speed values may be significantly obscured by inter-frame video compression, as can clearly be seen in the fourth frame. Moreover, the original confidence prediction rate observed by the OCR algorithm on the original frames, as presented in Fig. 4, is particularly low, set at 15 %. This further confirms that image enhancements are required to increase OCR prediction rate.

Following the initial image modifications, a multi-progress frame enhancement procedure is utilised. This is based on inter-frame approximation in order to improve the pattern matching of displayed speed values. Fig. 5 shows the frame data being processed in groups. Initially, masked input frames are used to target the zone where the speed is displayed. Additionally, Fig. 4 suggests that having a high contrast background is essential to achieve high digit recognition confidence. Thus, in order to minimise the negative effect caused by

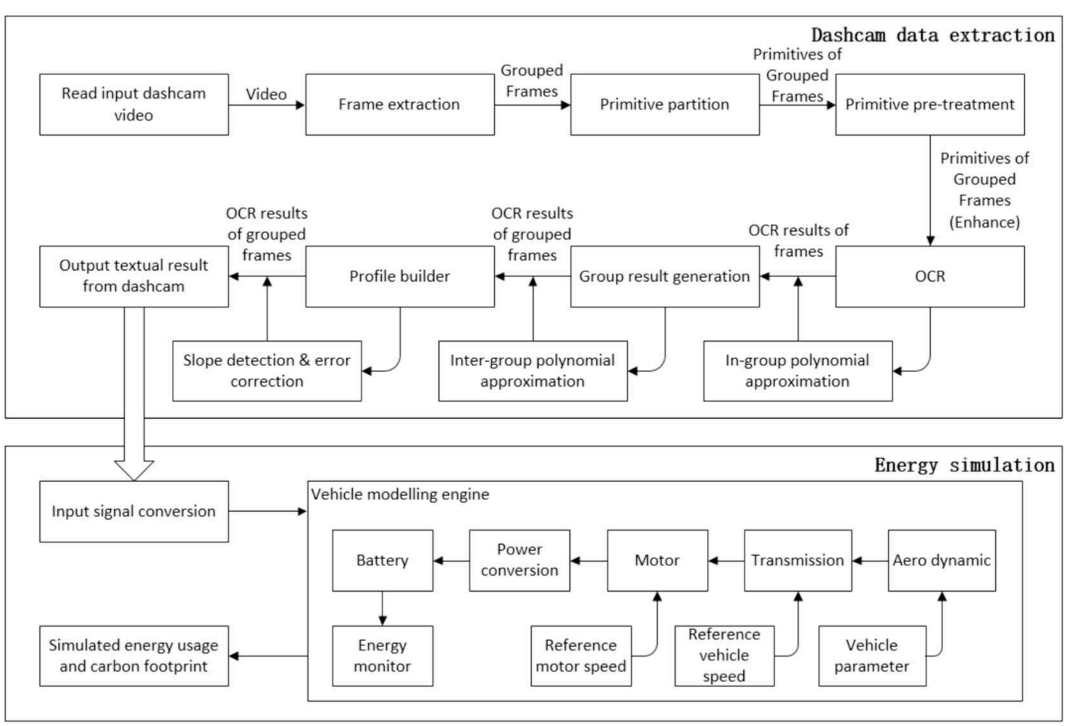

Fig. 3. Concept system diagram of the proposed dashcam video and EV energy consumption simulation methodology.

Fig. 4. Example of trimmed extracted frame group (the example is centred at the 600th frame).

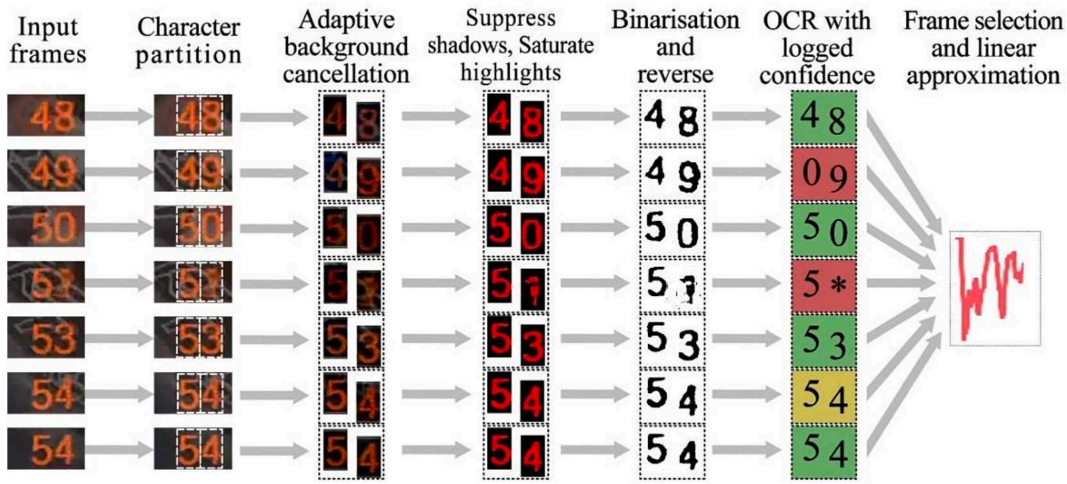

Fig. 5. Proposed image processing procedure showing an example input frame group and the resulting OCR metrics with their respective level of confidences coloured in Green (High), Lime Green (average) and Red (Low).

background contrast variation an adaptive background cancellation filter is applied, Fig. 6.

As indicated in Figs. 6, 4 pixels are sampled at each corner of a given primitive with its Red-Green-Blue (RGB) values. Gradients are then established so that interpolations are calculated to fill the intermediate pixels within the area specified by these 4 pixels. Finally, an output primitive image with its background attenuated can be obtained by subtracting the virtual background from the original. Finally, a filter is applied with the purpose of saturating the bright pixels and further reducing the shadows. The enhanced images are then filtered and reversed in order to be passed through OCR engine identification.

Text recognition is carried out using the proposed OCR algorithms, a number of which have been studied and benchmarked previously. (Yin et al., 2016; Ye and Doermann, 2014; Liang et al., 2005; Jung et al., 2004). Here, a state-of-the-art OCR engine based on the Tesseract (Smith, 2007) software has been applied. Results of the OCR algorithm are recorded alongside a confidence metric; depending on the predicted confidence level, a variable polynomial approximation algorithm is deployed.

In the example shown above (Fig. 5), only 4 frames have a high confidence value. In situations where not all results have a high confidence value, the results generated by the remaining frames can be enhanced through the application of a polynomial approximation algorithm based on a cubic equation. The generated polynomial as generated for this example is shown in Fig. 7.

Following the procedure presented previously, each frame group is processed, and its OCR result obtained. Hence, a speed reading of the 25th, 50th… frame, that is equivalent to the end of each second of the proposed video can be obtained. During the situation where the OCR engine is unable to generate a robust result for an entire frame-group, the similar polynomial approximation will be deployed which utilises results obtained from its adjacent frame-group to predict a result for this pending frame-group. In this case, the result is a speed profile that is exported to the vehicle model, where the energy usage and corresponding carbon footprint can be evaluated.

3. Results and discussion

In order to overcome issues with publishing commercially sensitive data, an example of publicly available dashcam video and telemetry data from a road sports vehicle has been used here, as shown in Fig. 8. This evaluation only serves to verify the methodology of the proposed dashcam video-based information extraction method, and is conducted using a vehicle-designated simulation model. Hence the specific video

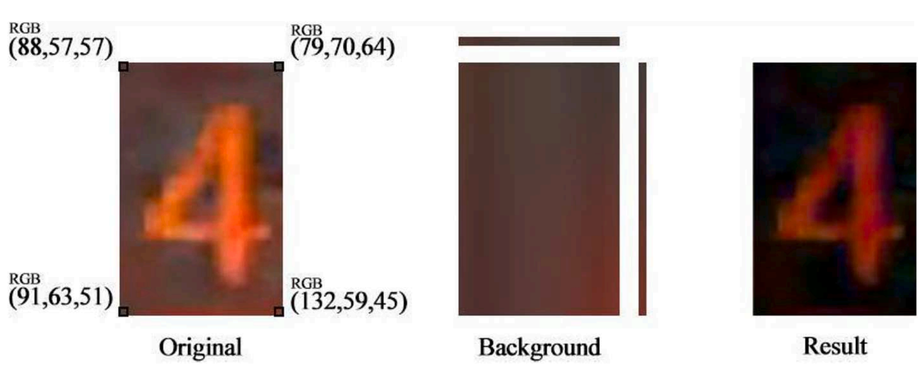

Fig. 6. Example of background cancellation through filtering using a virtual background coloured as the reference corner pixels.

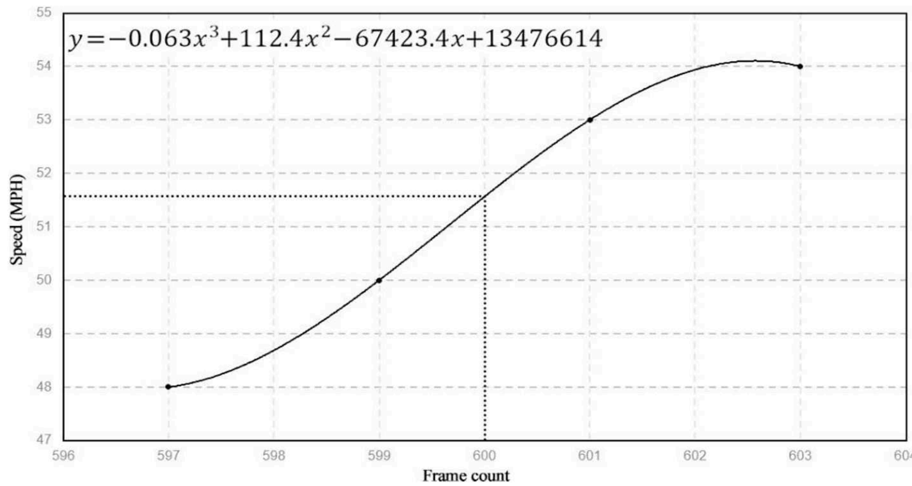

Fig. 7. A plot of the polynomial approximation performed on initial OCR. The equation describing the curve is stated on the top left side of the image.

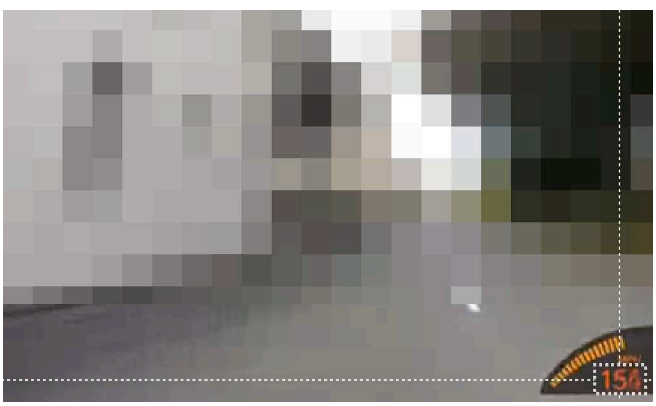

Fig. 8. Example of frame compression.

chosen and the difference in vehicle type have a negligible effect on the evaluation result, with the expected conclusion being the real-time and total energy usage calculation for this vehicle, which is equally applicable to any vehicle type.

Table 1 shows technical information relating to the video. The video has been compressed with a blur filter to reduce the time spent identifying the speed values (Fig. 8).

To test this approach, a group of seven frames were extracted from each one second time period of video. The fourth image from each group was chosen as a reference. Following this initial image extraction, the image section showing the speed values is cropped using the mask as above, as highlighted by the dotted area in Fig. 8. This is then further broken down to three areas sized at 34*60 pixels, where each of the speed digits will appear. Fig. 9 demonstrates the overall confidence metric distribution, grouped by digit representation of each digit output from the OCR Tesseract process. As can be seen, the confidence of the hundreds digit is the highest. This is likely because, in the input data used, it only ever takes the value of zero or one. Furthermore, it is the least likely to change and therefore the least likely to be blurred or otherwise obfuscated by the compression process or simply by changing during the time the analysed frames are taken. This reason is also the likely cause of the least confidence being in the ones digit, which is most likely to be changing during the frames being analysed.

Table 1
Video information.

Parameter	Value
Resolution	1280x720
Framerate	25
Data of interest	Vehicle speed in Miles Per Hour (MPH)
Total video frames in the original file	115,382
Video codec	0H.264
Average bitrate of the original file	481 kb/s
File size of the original file	266 MB

Based on the OCR algorithm-identified values and their relative time from the start of the video, a speed-time profile representing vehicle telemetry is produced (Fig. 10). The vehicle speed readings have been converted from Miles per Hour (MPH) to Kilometres per Hour (km/h) in order to ensure consistency with the metric measurement system. This is a graphical representation of an example of telemetry data which can be input into the vehicle model, which along with vehicle parameters, can be used to calculate the resultant vehicle energy use from the dashcam video data.

Fig. 11 shows the output of the model shown in Fig. 2 when the telemetry data obtained in Fig. 10 is used as an input. This graph shows a comparison between the video dashcam produced telemetry and the model control reaction. It can be observed that, because the model output very closely matches the telemetry speed data, the system response is consistent, tracking the input telemetry well, with minimal control errors.

The output model speed data is then processed together with the input vehicle specification to generate predictions concerning efficiencies related to energy conversion, motor driving, motor transmission and other phenomena that influence electrical energy usage. Based on these predictions, precise energy usage monitoring may be obtained. The simulated cumulative energy consumption for the obtained dashcam telemetry may be observed in Fig. 12. Finally, using the results for total trip energy usage, together with the emissions of the sources of national electricity generation, carbon dioxide and noxious gas emissions can easily be approximated.

Using this novel method, data presented in a dashcam video captured from any given vehicle on a given route can be successfully evaluated and used as telemetry data, where conventional telemetry information is difficult or impossible to obtain. The driving data can then be fed into a vehicle model, such as the one provided, so that energy usage information may be calculated. The previously presented results demonstrate the consistency and accuracy of the proposed procedure of employing OCR technology for digit recognition. This successfully validates the methodology described in this paper. This solution can be applied in the evaluation of the environmental impact of deploying a specific EV replacement vehicle for use on a given route or set of routes. As such, this will be invaluable in supporting future urban planning and transport decision making within a city with regards to potential electric vehicle

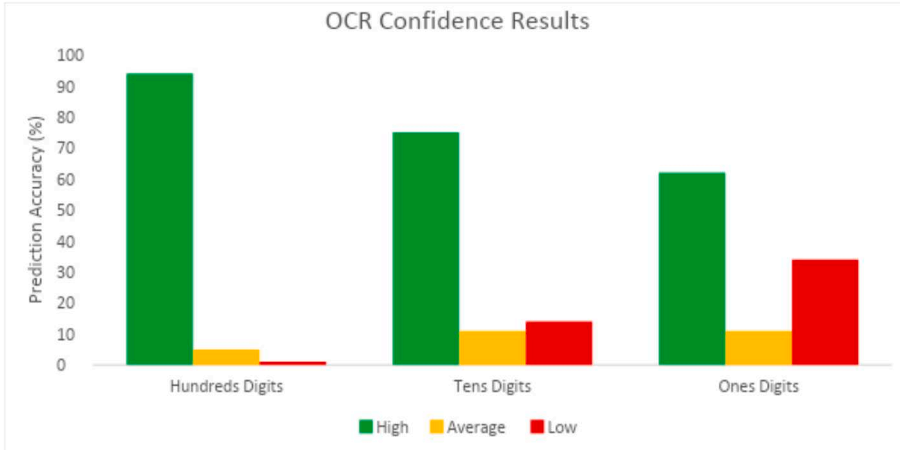

Fig. 9. OCR confidence results.

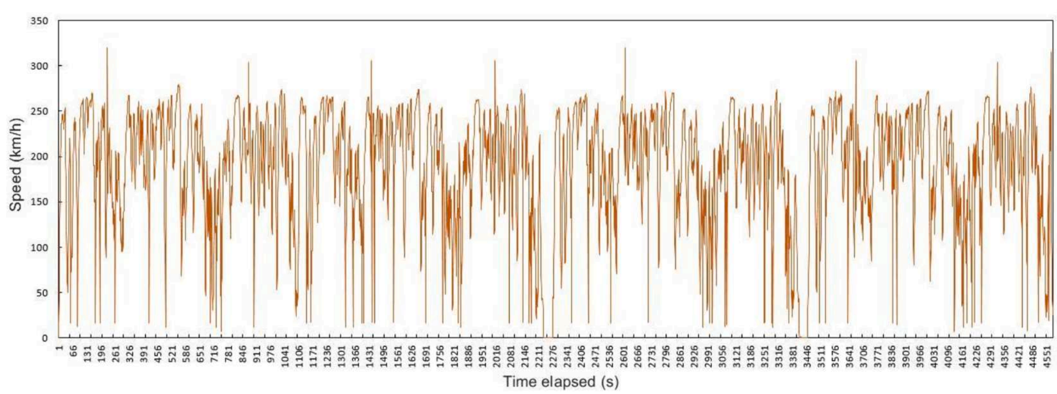

Fig. 10. OCR-generated vehicle telemetry.

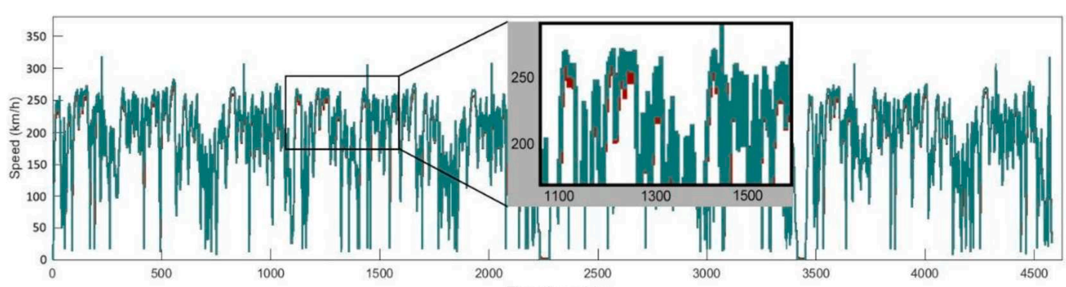

Fig. 11. Comparison between input OCR-generated telemetry data and system control response.

fleet usage as part of the transition to alternative fuelled vehicles. This is in line with transport policy aimed at reaching net zero carbon emissions, for example the UK government's 'Road to Zero' Strategy (Department for Transport, 2018).

The presented methodology can be used to help make informed decisions about the upgrade of ICEV fleets to EV fleets. As well as providing an estimation of the environmental savings that could be made, it also can be used to estimate running costs, and consequently, financial savings. The methodology can also be used to better specify electric vehicles in terms of required battery size, top speed, and acceleration requirements, so that the transition to an electric fleet can be made as easily as possible without specifying the vehicles and unnecessarily increasing cost.

There are some limitations to the proposed methodology, both in terms of creation of the telemetry data, and the findings from the model. Whilst the described method for obtaining telemetry data from dashcam recordings could theoretically provide second or sub-second accuracy, this relies on the speed data on the dashcam recording being similarly accurate and updated as quickly. However, if the speed data is updated at this rate, there is a greater chance of the interframe compression causing low-confidence in the recognition of the speed data. Additionally, depending on the way in which speed data is displayed on the video recording (font, colour, size, etc.), some footage, and consequently some dashcams, may be better suited to this purpose than others.

Some limitations in terms of raw data-driven results must also be noted. The dataset upon which the methodology was built does not have a direct comparison based on conventional telemetry recorded via standard vehicle data loggers. However, the process has been validated against data logged from other vehicles. The main sources of error that may influence the overall accuracy of the presented concept have been

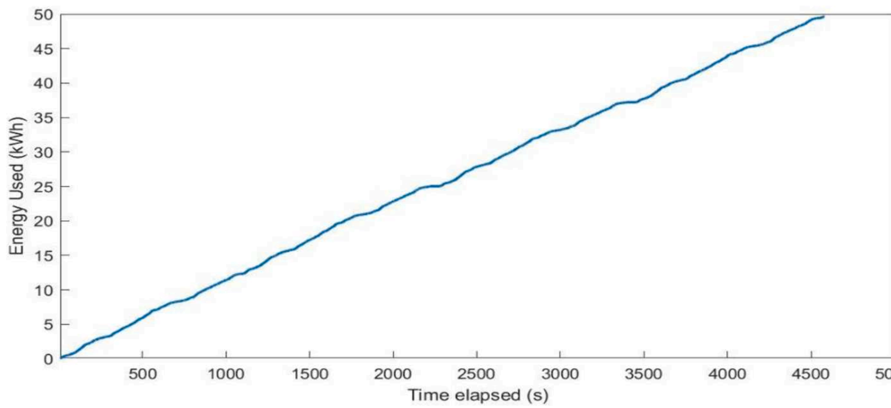

Fig. 12. Simulated energy consumption.

identified within the image processing stages of the methodology. These are represented by the signal-to-noise (SNR) ratio of the captured image and the accuracy percentage of the trained OCR algorithm.

Furthermore, in order to produce an accurate prediction of energy usage from the telemetry data, parameters related to the vehicle such as weight, drive efficiency and aerodynamic information are required to be provided to the model. These may not be known, or may not be accurate, causing an error in the energy usage prediction. Finally, in order to calculate the carbon emissions from a particular EV journey, the carbon emissions of the National Grid at the time of charging must be known. It is possible to approximate emissions based on average emissions from the grid, however, since electricity generation carbon emissions are based on the time of day, the time of year and the weather, it is impossible to accurately predict.

4. Conclusions

In this paper, a novel approach to evaluating the efficacy of replacing fuel-powered vehicles with battery-powered EV counterparts is presented. The proposed approach relies on dashcam videos captured, or retrieved from an archive, from an ICE-powered vehicle in normal operation. This has been achieved using an improved OCR methodology and a state-of-the-art data processing and modelling algorithm. Utilising the proposed image processing and OCR technology, textual information, including geographic coordinates and vehicle speed that are overlaid on the video, are decoded and re-organised to create time-based profiles such as a dataset of vehicle speed against time. A vehicle model is then used to simulate the vehicle's energy usage utilising the dataset obtained from dashcam videos to calculate the energy consumption for a battery-power replacement vehicle to cover the same route shown in the dashcam video. Using this approach, it is possible to ascertain the environmental impact of electrifying an ICE-powered vehicle and obtaining its energy use, along with technology-respective statistics for potential reductions in carbon footprint and other pollutant emissions. This may be estimated using extrapolation techniques. Moreover, if a higher degree of precision is required, simulations of energy usage benchmarking may be performed with the aid of modern state-of-the-art simulation solutions. This paper demonstrates how vehicle energy use may be inferred from (potentially pre-existing) in-cab video recordings, and hence may be further used to map the impact of replacing conventional vehicles and fleets with electric alternatives.

To further improve the accuracy and authenticity of the energy estimation, work is on-going to introduce additional variables into the energy prediction. The variables under development include various weather and road conditions, which could also be identified from the same dashcam videos. Moreover, the telemetry acquisition through OCR may be improved by employing better trained algorithms, as well as applying other unconventional algorithms, such as AI-based neural networks (Hu and Hwang, 2002). Some work in this regard already exists and potential further applications can be developed on top of existing research (Ganis et al., 1998; Wang and Hu, 2017).

Whilst the presented research indicates that OCR technology may be successfully applied to the question of EV energy usage, more work is required in order to fully determine its potential as a robust application. Future work based on the proposed solution can be directed to further refinements that may be brought to the visual prediction algorithm, through better training the predictive technologies. Similarly, alternative predictive technologies based on *meta*-heuristic prediction algorithms may also be investigated and benchmarked against the presented OCR approach.

This paper features an investigation into the feasibility of using state-of-the-art OCR technology to extract data from dashcam videos to generate vehicle telemetry. Results presented above demonstrate the success of applying image processing techniques to understanding energy requirements of deploying electric vehicles in the transport industry. Furthermore, it enhances the available data for predicting energy usage in transportation and logistics by facilitating the usage of a significant amount of data that normally would be unusable. Moreover, the proposed solution presented in this case study, enables large amounts of previously unsuitable telemetry data information to be used in EV energy consumption estimation. This is also likely to have a strong, beneficial impact on macro-level analyses, for example providing more refined feasibility investigations of various EV fleets, for example eRCVs and eBuses, which may positively influence the pro-EV and decarbonisation transport policies that are currently being adopted.

CRediT authorship contribution statement

George W.M. Hind: Writing – review & editing. **Erica E.F. Ballantyne:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Tudor Stincescu:** Writing – original draft, Validation, Investigation, Formal analysis. **Rui Zhao:** Writing – original draft, Visualization, Software, Methodology. **David A. Stone:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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