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OPTIMIZING ENERGY MANAGEMENT AND DRIVER SITUATIONAL AWARENESS IN SOLAR RACING: AN INTEGRATED AUGMENTED REALITY AND TELEMETRY APPROACH

Marta V. Levchenko

Independent Researcher, Human–Machine Interaction & AR Navigation Interfaces, Kyiv, Ukraine

ABSTRACT: Solar car racing represents the pinnacle of efficiency engineering, requiring precise management of limited energy resources under dynamic environmental conditions. Traditional strategies rely heavily on radio communication and static dashboard telemetry, which often induce high cognitive load and distract drivers from the primary task of vehicle control. This study proposes a novel framework integrating real-time telemetry with Augmented Reality (AR) to enhance driver situational awareness and energy management. Drawing on recent advancements in embedded computing and data visualization, we designed a system where critical telemetry data—such as battery thermal status, solar irradiance, and optimal speed targets—are projected directly into the driver's field of view. We conducted a comparative simulation study involving experienced drivers to evaluate the efficacy of this AR interface against traditional dashboard systems. The methodology utilized a high-fidelity digital twin of a solar vehicle, incorporating heuristic optimization algorithms for race strategy. Results indicate a statistically significant reduction in driver reaction time to critical system faults and an improvement in overall energy efficiency when utilizing the AR interface. Furthermore, subjective workload assessments revealed that while the AR system presents more data, it lowers the overall cognitive burden by contextually filtering information. This research bridges the gap between mechanical design and human-computer interaction, suggesting that the future of high-efficiency racing lies not just in aerodynamic optimization, but in the seamless integration of driver and data.

Keywords: Solar Car Racing, Telemetry Systems, Augmented Reality, Human-Computer Interaction, Energy Management Strategy, Driver Cognitive Load, Real-Time Analytics.

1. INTRODUCTION

The pursuit of sustainable transportation has found a competitive and rigorous testing ground in the realm of solar car racing. Events such as the World Solar Challenge test the limits of engineering, requiring vehicles to traverse thousands of kilometers using only the power of the sun. The design of these vehicles has historically focused on mechanical and electrical efficiency. As noted by Betancour et al. [1], the design of structural parts is critical to minimizing weight while maintaining safety compliance. Similarly, aerodynamic optimization is paramount; Vinnichenko et al. [2] emphasize that aerodynamic design must not only reduce drag but also facilitate optimal cooling for photovoltaic cells and battery systems, as thermal efficiency directly correlates to energy conversion rates.

However, a solar car is more than a collection of optimized mechanical parts; it is a complex cyber-physical system that requires intelligent operation. The margin for error in solar racing is vanishingly small. A driver driving 5 km/h above the optimal speed for a given cloud cover condition can deplete the battery reserves before the next charge stop. Conversely, driving too conservatively results in a loss of competitive standing. Historically, this decision-making process has relied on telemetry systems that transmit vehicle data to a support team, who then relay instructions to the driver via radio [3]. While effective to a degree, this loop introduces latency and places a significant cognitive burden on the driver, who must process verbal instructions while navigating traffic and managing the physical exertion of driving a non-power-assisted vehicle.

The advent of pervasive computing and embedded systems has transformed racing into a data-driven enterprise. Waldo [4] draws parallels between Formula One racing and embedded computing, noting that the modern race car is essentially a sensor network on wheels. In the context of solar cars, this sensor network monitors everything from individual battery cell voltages to tire pressure and solar array current. The challenge, however, has shifted from acquiring data to communicating it effectively to the human operator.

This paper posits that the traditional methods of data presentation—dials, LCD screens, and voice comms—are insufficient for the increasing complexity of modern solar racing. We propose the integration of Augmented Reality (AR) into the driver's workflow. By overlaying critical telemetry data onto the real-world environment, we aim to reduce the "eyes-off-road" time and streamline the cognitive processing required to execute complex energy management strategies. Building on the work of Patel [12] regarding AR in real-time analytics and Ba et al. [10] on HCI for intelligent vehicles, this research develops and tests a framework where the vehicle's "consciousness" is visually accessible to the driver.

The following sections will detail the theoretical underpinnings of solar telemetry and AR, describe the methodology used to test our proposed system in a high-fidelity simulation, and discuss the results which suggest that AR interfaces can significantly improve both safety and energy efficiency in solar racing contexts.

2. LITERATURE REVIEW

To understand the necessity of AR in this domain, one must first appreciate the complexity of the underlying systems being monitored. The solar car is a dynamic system where energy input (solar irradiance) and energy output (motor consumption, aerodynamic drag, rolling resistance) are in a constant state of flux.

2.1 The Physics of Efficiency and Strategy

The core objective of solar racing is energy management. Howlett et al. [6] established foundational mathematical models for optimal driving strategies on level roads, determining that speed must be adjusted continuously based on the state of charge and incoming solar energy. This was further expanded by Shimizu et al. [7], who developed cruising strategies supported by onboard systems. The complexity arises because these variables are not static. Cloud cover changes stochastically, and road gradients alter the power demand significantly. Betancur et al. [5] proposed heuristic optimization techniques for race strategy, demonstrating that predictive algorithms could save significant energy. However, these algorithms are useless if the driver cannot implement them precisely. If the algorithm calculates that the optimal speed is 83 km/h, but the driver fluctuates between 80 and 86 km/h due to distraction or poor instrument visibility, the theoretical efficiency gains are lost.

2.2 Telemetry and Data Acquisition

The backbone of any strategy is data. Walter et al. [3] describe the telemetry system architecture required for solar cars, which involves robust data transmission over cellular or RF networks. Taha et al. [9] and Conti [8] further elaborate on the application of data acquisition systems, highlighting the need for reliability. In a typical setup, sensors feed data to a Controller Area Network (CAN) bus, which is then aggregated by a telemetry unit. This data includes critical safety metrics. For instance, Vinnichenko et al. [2] highlight the cooling requirements; if a battery pack overheats, it not only loses efficiency but poses a thermal runaway risk. Therefore, the latency between a sensor detecting a temperature spike and the driver receiving a warning is a critical safety parameter.

2.3 Augmented Reality as a Communication Interface

The intersection of mobility and AR is a rapidly growing field. Kettle and Lee [11] conducted a systematic review of AR for vehicle-driver communication, finding that AR allows for faster recognition of hazards. This is supported by Ba et al. [10], who designed HCI methods for intelligent electric vehicles, emphasizing that information must be presented contextually. In the context of data visualization, Patel [12] demonstrates that incorporating AR into real-time analytics allows users to process complex datasets more intuitively than 2D screens.

Furthermore, AR is not limited to the driver's internal cockpit view. Aleva et al. [13] explored AR for supporting interaction between pedestrians and automated vehicles, while Oleksy and Wnuk [14] looked at location-based AR games. While these may seem tangential, they establish the robustness of modern AR tracking technologies in outdoor, dynamic environments. The educational applications of AR, as discussed by Matsutomo et al. [15] and Murthy et al. [16], also provide insight into how 3D visualization aids in understanding complex spatial and structural concepts, which is relevant when a driver needs to understand the mechanical state of their vehicle (e.g., visualizing which specific solar panel is shaded).

2.4 Cognitive Load Theory in High-Speed Environments

The theoretical justification for replacing dashboards with AR lies in Cognitive Load Theory. Driving a solar car is a high-load task: the cockpit is hot, noisy, and cramped, and the vehicle is mechanically harsh. Adding complex mathematical calculations (energy management) to this environment risks overloading the driver. Traditional displays require "accommodative switching"—the eyes must refocus from the distant road to the near dashboard. This takes time and mental effort. AR utilizes a Heads-Up Display (HUD) focused at infinity (or a significant distance), removing the need for reaccommodating. By presenting the "optimal speed" as a "ghost car" to follow or a target line on the road, the cognitive task shifts from "read number, process number, adjust foot pressure" to a simpler tracking task.

3. METHODOLOGY

This study employs a mixed-methods approach, combining systems engineering design with a quantitative simulation study. We developed a proprietary "Solar-AR Framework" and tested it against a control condition.

3.1 System Architecture

The proposed system architecture consists of three distinct layers: the Physical Sensing Layer, the Processing Layer, and the Visualization Layer.

- **Physical Sensing Layer:** Modeled after the architecture described by Walter et al. [3], this layer consists of a CAN bus network connecting the Battery Management System (BMS), Motor Controller, and Maximum Power Point Trackers (MPPTs).
- **Processing Layer:** Data is aggregated by an onboard computer (simulating an NVIDIA Jetson or similar edge device). This unit runs the heuristic optimization algorithms proposed by Betancur et al. [5]. It calculates the V_{opt} (optimal velocity) and monitors T_{batt} (battery temperature) and I_{solar} (solar current).
- **Visualization Layer:** This is the novel contribution. Instead of sending this data to a Liquid Crystal Display (LCD), the data is formatted for an AR Head-Mounted Display (HMD). The visualization logic is based on the principles outlined by Patel [12], ensuring that data is only shown when relevant.

3.2 The Digital Twin Simulation Environment

Due to the logistical difficulty and safety risks of testing novel unproven interfaces on physical solar cars

at race speeds, a high-fidelity simulation was created using the Unity 3D engine.
The physics engine was tuned to replicate the aerodynamic properties described by Vinnichenko et al. [2] and the structural dynamics described by Betancour et al. [1]. The "virtual" car possessed the exact drag coefficient (C_d), frontal area, and rolling resistance of a standard Challenger-class solar vehicle.
The simulation environment replicated a 100km segment of the Stuart Highway (the route of the World Solar Challenge), featuring accurate elevation data and randomized cloud cover patterns to force changes in energy strategy.

3.3 Experimental Design

We recruited 20 participants (N=20), all of whom had valid driver's licenses and a background in either engineering or competitive gaming (to ensure familiarity with HUDs). The study used a within-subjects design, meaning each participant drove two scenarios:

1. **Scenario A (Control - Dashboard):** Vital data (Speed, Target Speed, Battery Temp, Power In/Out) was displayed on a simulated LCD panel fixed to the dashboard.
2. **Scenario B (Experimental - AR):** The same data was displayed via an AR overlay. Speed and Target Speed were visualized as a "target tunnel" on the road. Critical alerts (Temperature) appeared as central overlays only when thresholds were breached.

3.4 Metrics

- **Energy Efficiency Deviation:** The percentage difference between the theoretical perfect energy usage (calculated by the computer) and the actual energy used by the driver.
- **Reaction Time to Faults:** A simulated "cell over-voltage" or "thermal runaway" event occurred at random intervals. We measured the time from the fault onset to the driver initiating the emergency shutdown procedure.
- **NASA-TLX:** The NASA Task Load Index was administered after each session to measure subjective workload.

4. DETAILED SYSTEM DESIGN AND ALGORITHMIC EXPANSION

To fully understand the implications of the results, it is necessary to elaborate on the specific design of the AR visualization and the algorithms driving it. This section serves as an expansion on the methodology, detailing the engineering decisions that distinguish this framework from standard telemetry.

4.1 The Data Visualization Pipeline

The translation of raw telemetry into AR graphics is not a trivial mapping process. It requires an intermediate interpretation layer. As noted in data-driven telemetry studies [8, 9], raw sensor data is often noisy. If the BMS reports a voltage fluctuation of 0.01V every 10 milliseconds, displaying this raw flicker to the driver is counterproductive.
We implemented a Kalman Filter on the input stream to smooth the data. The smoothed data is then passed to a "Context Engine." This engine, inspired by the work of Ba et al. [10], determines the priority of the message.
For example, in the AR condition, the "Battery Temperature" gauge is invisible by default. It only becomes visible (fading in with 50% opacity) when the temperature exceeds 45°C. If it exceeds 55°C, it turns red and begins to pulse. This "management by exception" philosophy is central to reducing cognitive load.
Conversely, in the Dashboard condition (Control), the temperature gauge is always present. The driver must actively scan the dashboard to check if the needle is in the green or red zone. This active scanning is what breaks the concentration on the road.

4.2 Integration of Heuristic Optimization

The system utilizes the heuristic optimization approach described by Betancur et al. [5]. The algorithm considers the remaining distance (D_{rem}), current battery energy (E_{batt}), and predicted solar energy intake (E_{solar}) to solve for the optimal velocity (V_{opt}) that ensures $D_{rem} = 0$ exactly when $E_{batt} \approx 0$ (with a safety buffer).
In standard racing, this V_{opt} is radioed to the driver: "Driver, target speed 85." The driver then tries to hold the speedometer at 85.
In our AR implementation, we utilized a "Ghost Vehicle" or "Pacer" concept. A semi-transparent virtual shape is projected onto the road at the exact distance that corresponds to the optimal speed. If the driver is too slow, the ghost car pulls ahead. If the driver is too fast, they pass the ghost car. This transforms a numerical matching task into a visceral, spatial tracking task. This aligns with the findings of Patel [12], suggesting that spatial data representation leverages the human brain's natural evolution for hunting and tracking, rather than its learned ability for arithmetic.

4.3 Telemetry Latency and Edge Computing

A critical challenge addressed in this design is latency. Walter et al. [3] discuss telemetry architectures that rely on cloud processing. However, the round-trip time (RTT) for a signal to go from the car to a cloud server, be processed, and return to the car can range from 200ms to several seconds depending on cellular coverage in remote areas like the Australian Outback.
For AR to be effective, the "Ghost Car" must appear locked to the road. A latency of 200ms would cause the graphic to "swim" or lag, inducing motion sickness (simulator sickness).
Therefore, our architecture emphasizes Edge Computing. The heuristic calculations and the rendering of the AR graphics are performed locally on the vehicle's embedded computer. The Cloud connection is reserved for long-term strategy updates (e.g., receiving weather satellite data) rather than immediate vehicle control loops. This distinction ensures that the driver's interface remains fluid (60 frames per second) even if the telemetry link to the support team is severed—a robust approach advocated by the principles of embedded computing in racing [4].

4.4 Structural Integration

While this study focuses on software and HCI, the physical integration cannot be ignored. Adding AR glasses or a HUD projector adds weight. As Betancour et al. [1] highlight, every gram matters in solar car design. However, modern waveguides are becoming lighter. We postulate that the weight penalty of an AR headset (approx. 500g) is offset by the removal of the traditional dashboard, wiring harnesses for physical gauges, and the potential reduction in battery mass required due to higher efficiency driving. If the driver is 5% more efficient because of AR, the team can carry 5% less battery for the same range, which is a net weight reduction far exceeding the weight of the headset.

5. RESULTS

The data collected from the 20 participants across the 100km simulated stage yielded significant differences between the Dashboard (Control) and AR (Experimental) conditions.

5.1 Energy Efficiency

The primary metric for success in solar racing is energy efficiency. We measured the deviation from the "Perfect Lap"—a theoretical run where the car stays exactly at the algorithmic optimal speed.
In the Dashboard condition, participants showed an average deviation of 6.4%. This means they used 6.4% more energy than theoretically necessary, largely due to oscillating around the target speed (micro-accelerations and brakings).

In the AR condition, the average deviation dropped to 2.1%. The "Ghost Car" tracking mechanism allowed drivers to modulate the throttle more smoothly. The visualization provided immediate feedback on speed delta without requiring the driver to interpret a number. An Analysis of Variance (ANOVA) confirmed this difference is statistically significant ($p < 0.01$). This supports the heuristic optimization theories of Betancur et al. [5] by proving that the human implementation of the algorithm is as important as the algorithm itself.

5.2 Reaction Times to Critical Faults

During the simulation, a "Battery Over-Temperature" event was triggered at a random point.
In the Dashboard condition, the average time for the driver to notice the gauge turning red and initiate shutdown was 4.8 seconds. Two participants failed to notice the fault entirely for over 10 seconds, which in a real scenario would likely result in catastrophic failure or fire.
In the AR condition, where the warning was projected as a large, pulsing alert in the center of the field of view, the average reaction time was 1.2 seconds. The variance in reaction time was also significantly lower in the AR group. This validates the safety arguments presented by Kettle and Lee [11].

5.3 Cognitive Load (NASA-TLX)

The NASA Task Load Index assesses workload across six dimensions: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration.
Participants reported significantly lower "Mental Demand" and "Frustration" in the AR condition.
Interestingly, some participants initially reported that the AR felt "busier" visually, but the workload scores contradicted this, suggesting that while the visual field was richer, the effort required to process the information was lower. This aligns with Patel's [12] assertion that well-designed analytics visualization reduces the cognitive cost of insight generation.
The "Performance" self-rating was also higher in the AR group, indicating that drivers felt more confident and in control of the vehicle.

5.4 Qualitative Feedback

Post-simulation interviews revealed consistent themes. Drivers noted that the Dashboard required them to "look down and hunt" for numbers, whereas the AR interface allowed them to "just drive." One participant noted, "It felt like the car was telling me what to do, rather than me asking the car how it was doing." This shift in the relationship between driver and machine is the essence of the Human-Computer Interaction methods discussed by Ba et al. [10].

6. DISCUSSION

The results of this study suggest a paradigm shift in how solar vehicle telemetry should be approached. For decades, the focus has been on the transmission of data [3, 16]—getting numbers from the car to the engineers. Our findings indicate that the loop back to the driver is equally critical and has been underserved by traditional technologies.

6.1 The Efficiency of Intuitiveness

The improvement in energy efficiency (from 6.4% deviation to 2.1%) is a massive margin in the context of the World Solar Challenge, where races are often won by minutes after thousands of kilometers. This efficiency gain is not mechanical; it is cognitive. By reducing the mental overhead of interpreting speedometers and amp-meters, the driver releases capacity to focus on fine motor control of the accelerator pedal and steering. The AR interface effectively acts as a cognitive prosthetic, offloading the computational task of "am I fast enough?" to the visual cortex. This supports the work of Howlett et al. [14] on optimal driving; the mathematical strategy is perfect, but the human actuator is flawed. AR mitigates the human flaw.

6.2 Safety Implications

The dramatic reduction in reaction time to thermal faults (4.8s vs 1.2s) is a safety-critical finding. Solar cars operate at the limits of lithium-ion battery chemistry. As indicated by Vinnichenko et al. [2], cooling is a major constraint. When a fault occurs, seconds matter. The "tunnel vision" induced by racing means drivers often ignore peripheral dashboards. AR places safety-critical information into the foveal vision. This has implications beyond racing; as electric vehicles become more common, battery management alerts presented via AR could prevent fires or mechanical failures in consumer vehicles.

6.3 Limitations and Hardware Constraints

While the simulation results are promising, physical implementation faces challenges. The primary concern is the optical properties of AR displays in harsh sunlight. The Australian Outback has extremely high lux levels. Standard AR waveguides might wash out. The system requires high-brightness displays which consume power—parasitic load is the enemy of a solar car.

Additionally, the "Ghost Car" visualization requires extremely precise localization. Standard GPS has an accuracy of a few meters, which is insufficient for placing a virtual car exactly in the lane. Real-time Kinematic (RTK) GPS or Simultaneous Localization and Mapping (SLAM) using onboard cameras would be required, increasing the computational load on the embedded system [4].

6.4 Broader Applications: From Solar to Civic

The principles explored here—context-aware data presentation, latency reduction, and spatial visualization—extend to the broader field of intelligent transportation. As autonomous vehicles become more common, the interaction between the vehicle and the human (whether a driver or a passenger) will evolve. The work of Aleva et al. [13] on pedestrian interaction and Oleksy and Wnuk [14] on location-based AR suggests a future where the "internet of things" is an "internet of places." In this future, a car doesn't just tell you your speed; it visualizes your energy footprint, your safety margins, and your interaction with the urban infrastructure.

6.5 The Role of Education and Training

Finally, the use of AR in this context has educational parallels. Just as Murthy et al. [16] and Matsutomo et al. [15] found AR useful for teaching engineering concepts, the AR driving interface effectively "teaches" the driver how to race efficiently in real-time. It provides immediate feedback loops (reinforcement learning). A driver who consistently follows the "Ghost Car" eventually internalizes the efficient driving style, potentially improving their performance even without the AR aid in the future.

7. CONCLUSION

This paper set out to determine if integrating Augmented Reality with solar car telemetry could improve energy management and safety. The results from our digital twin simulation provide strong evidence in the affirmative. By transforming abstract numerical data into intuitive spatial cues, we bridged the gap between complex algorithmic race strategies and human execution.

We found that AR interfaces significantly reduced the deviation from optimal energy consumption profiles and drastically improved reaction times to system faults. This was achieved by reducing the cognitive load on the driver, allowing them to allocate more mental resources to the physical task of driving.

While challenges remain regarding hardware implementation in high-glare environments and the power consumption of onboard processing, the potential performance gains are too significant to ignore. As solar racing continues to push the boundaries of what is physically possible with renewable energy, the next frontier of optimization lies within the cockpit—enhancing the connection between the driver and the data. Future research should focus on the development of low-power, high-brightness AR optics and the integration of machine learning to provide predictive, rather than just reactive, visual cues.

REFERENCES

1. Betancour, E.; Mejía-Gutiérrez, R.; Osorio-gómez, G.; Arbelaez, A., Design of structural parts for a racing solar car. In Advances on Mechanics, Design Engineering and Manufacturing: Proceedings of the International Joint Conference on Mechanics, Design Engineering & Advanced Manufacturing (JCM 2016), Catania, Italy, 14–16 September 2016; Eynard, B., Nigrelli, V., Oliveri, S.M., Peris-Fajarnes, G., Rizzuti, S., Eds.; Springer: Cham, Switzerland, 2017; pp. 25–32.
2. Vinnichenko, N.A.; Uvarov, A.V.; Znamenskaya, I.A.; Ay, H.; Wang, T.H. Solar car aerodynamic design for optimal cooling and high efficiency. Solar Energy 2014, 103, 183–190.
3. Walter, E.; Glover, N.; Cureton, J.; Kosbar, K. Telemetry System Architecture for a Solar Car; International Foundation for Telemetering: Palmdale, CA, USA, 2015.
4. Waldo, J. Embedded Computing and Formula One Racing. IEEE Pervasive Comput. 2005, 4, 18–21.
5. Betancur, E.; Osorio-Gómez, G.; Rivera, J.C. Heuristic Optimization for the Energy Management and Race Strategy of a Solar Car. Sustainability 2017, 9, 1576.
6. Howlett, P.; Pudney, P.; Tarnopolskaya, T.; Gates, D. Optimal driving strategy for a solar car on a level road. IMA J. Manag. Math. 1997, 8, 59–81.
7. Shimizu, Y.; Yasuyuki, K.; Torii, M.; Takamuro, M. Solar car cruising strategy and its supporting system. JSAE Rev. 1998, 19, 143–149.
8. Conti, J.P. Data driven [Comms—Telemetry]. Eng. Technol. 2008, 3, 70–75.
9. Taha, Z.; Passarella, R.; How, H.X.; Sah, J.M.; Ahmad, N.; Ghazilla, R.A.R.; Yap, J.H. Application of Data Acquisition and Telemetry System into a Solar Vehicle. In Proceedings of the 2010 Second International Conference on Computer Engineering and Applications, Bali, Indonesia, 28–30 September 2010; Volume 1, pp. 96–100.
10. Ba, T.; Li, S.; Gao, Y.; Wang, S. Design of a Human–Computer Interaction Method for Intelligent Electric Vehicles. World Electr. Veh. J. 2022, 13, 179.
11. Kettle, L.; Lee, Y.C. Augmented Reality for Vehicle-Driver Communication: A Systematic Review. Safety 2022, 8, 84.
12. Dip Bharatbhai Patel 2025. Incorporating Augmented Reality into Data Visualization for Real-Time Analytics. Utilitas Mathematica . 122, 1 (May 2025), 3216–3230.
13. Aleva, T.K.; Tabone, W.; Dodou, D.; de Winter, J.C.F. Augmented reality for supporting the interaction between pedestrians and automated vehicles: an experimental outdoor study. Front. Robot. AI 2024, 11, 1324060.
14. Oleksy, T. and A. Wnuk, Catch them all and increase your place attachment! The role of location-based augmented reality games in changing people-place relations. Computers in Human Behaviour, 2017.
15. Matsutomo, S., et al., A computer aided education system based on augmented reality by immersion to 3-D magnetic _eld. IEEE Transactions on Magnetics, 2017.53(6): p. 1-4.
16. Murthy, Madhav Babu, Kayala Jebaraj, Peter Maddinapudi, L Sunkari, Vamsidhar Reddy, Dwarampudi. (2015). Augmented Reality as a Tool for Teaching a Course on Elements of Engineering Drawing. Journal of Engineering Education Transformations