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ECORACER: GAME-BASED OPTIMAL ELECTRIC VEHICLE DESIGN AND DRIVER CONTROL USING HUMAN PLAYERS

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ABSTRACT

We investigate the cost and benefit of crowdsourcing solutions to an NP-complete powertrain design and control problem. Specifically, we cast this optimization problem as an online competition, and received 2391 game plays by 124 anonymous players during the first week from the launch. We compare the performance of human players against that of the Efficient Global Optimization (EGO) algorithm. We show that while only a small portion of human players can outperform the algorithm in long term, players tend to formulate good heuristics early on, from where good solutions can be extracted and used to constrain the solution space. Incorporating this constraint into the search enhances the efficiency of the algorithm, even for problem settings different from the game. These findings indicate that human computation is promising in solving comprehensible and computationally hard optimal design and control problems.

1 Introduction

Optimal design problems can still challenge our computational ability to solve them. A case in point is design of an electric vehicle combining topology (configuration) design, proportional design and control design for overall system optimization [1]. For example, this problem is NP complete, is not amenable to an all-in-one solution and also has a disjoint feasible domain. Other computationally hard design problems include material synthesis, drug design, and mechanical, electrical and structural topology design [2–7], and much effort has been expended to devise suitable algorithms in high-performance computing.

More recently, "human computation" [8] has been reported as a promising alternative to solving tough optimization problems. A seminal experiment was the Foldit [9] game, which gathers large numbers of non-expert players (a "crowd") to perform protein structure prediction by minimizing the protein's energy with spatial rearrangement of its structure. Since its launch in 2009, Foldit has attracted 300,000 players and has shown an advantage of human spatial reasoning for pursuing near-optimal solutions [10]. A follow-up study showed that the most popular folding strategy derived from the crowd is comparable in performance to an expert-developed computer algorithm for protein folding [11]. Inspired by this success, Lee et al. tackled the challenge of RNA synthesis, a combinatorial optimization problem [12], with the eteRNA experiment [13], showing that a human crowd with no knowledge of the underlying science improved their problem solving skills, outperformed existing computer algorithms, and even contributed knowledge to the creation of a more effective algorithm. Le Bras et al. proposed a way to expedite search in combinatorial problems by identifying the optimal values for a subset of variables through human-computer interactions. They demonstrated that a material discovery problem can be cast as an online game and solved visually by human players [14]. The Phylo game is another example that utilized human pattern recognition capability in solving an NP-hard optimization problem called Multiple Sequence Alignment, where players are set to identify similar genome sequences of animals

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by moving colored blocks around [15].

These results indicate the potential of using human intuition (sampling good design solutions [10, 12] and recognizing visual patterns [14,15]) and human intelligence (learning and generating design rules [11, 12]) for solving challenging optimization problems or enhancing numerical optimization solvers. Gamification, i.e., using games purposefully [16], is one way to engage large numbers of human participants in such tasks. The above studies do not provide analysis on whether investment in gamification is more cost-effective than improving existing computer algorithms. However, it appears that such "citizen science" can be valuable when (a) a group of trained human solvers can be gathered and maintained, and (b) efficient solutions to a *large number* of problems of similar mathematical nature is desired. At this point, the implementations of these existing games are case-dependent, and whether their individual success can be replicated in solving other problems remains an open question [17].

These successes and doubts regarding human computation motivated this paper. How much can gamification or "games with a purpose" [16] offer in solving computationally hard design optimization problems? And, is this approach cost-effective?

Motivated by the apparent promise of human computation,this paper describes an initial attempt at gamifying and crowdsourcing a design optimization problem. Specifically, we investigate the costs and benefits of using human crowd computation through games designed to address the aforementioned electric vehicle design problem. The basic idea is to "learn" (in computer science terminology) the problem's constrained solution space from successful and failed player attempts, and to search adaptively for an near-optimal solution within this constrained space. This idea is an extension of apprenticeship learning (see [18] for an example), where the machine apprentice follows or explores similar actions as the expert master.

The rest of the paper is structured as follows: We introduce the motivating problem of vehicle powertrain design and control in Section 2 and its gamification in Section 3. In Section 4, we look into computational solutions to the game problem with and without using information from human players. Section 6 compares performance of human players against the computational solution, and discusses the use of human computation as well as some technical details of the experiment. We conclude with Section 7.

2 Motivating Problem

A growing number of civil [19–22] and military [23–25] vehicle applications are being considered for electrification due to ever restrictive emission reduction and energy security requirements. With different driving conditions (speed and power demands), vehicle optimal powertrain design and control strategies can be quite different [26]. Therefore efficient design automation is desired to identify optimal solutions given the input vehicle specifications and driving conditions.

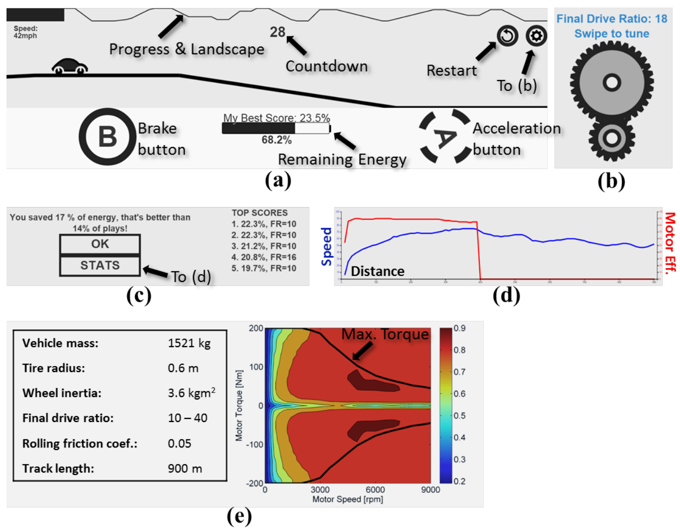
Fathy et al. [27] and Peters et al [28] investigated the combined design and control problem and showed that ignoring the coupling between design and control yields suboptimal solutions. One approach to handle the coupling is to formulate an all-in-one optimization problem to include both the design and the control [29, 30] problems in a single one; another approach is to nest optimal control within the design problem. This latter approach is more commonly used in hybrid electric vehicle configuration studies [1,31–33], where existing optimal control algorithms such as Dynamic Programming (DP) [21, 34], Pontryagin's Minimum Principle (PMP) [35,36] and Equivalent Consumption Minimization Strategy (ECMS) [37] can be applied. The DP method finds the control strategy with globally optimal energy efficiency by discretizing the state space and using optimal control to find a shortest path; PMP and ECMS have lower computation cost but can find only near-optimal solutions. The computational cost of DP grows exponentially with the size of the state space and the number of time steps, what is known curse of dimensionality [38]. The search for the optimal powertrain design and control policy can therefore become expensive, especially when a large variety of topology design candidates exist.

These optimal control algorithms commonly used for vehicle control require full information of the mechanical and electrical behavior (models), as well as future driving conditions, i.e., probability distributions of speed and power demand. When this information is (partially) unknown, learning mechanisms are required to guide the control strategy. In particular, when repeated trials are allowed, such as during the design phase, apprenticeship (imitation) learning algorithms [18,39] are developed for the controller to follow sample trajectories demonstrated by human experts. This paper is different from existing reinforcement learning studies in two aspects: (1) While existing work either utilizes an existing human expert [39] or learns a strategy (perhaps implicitly through a reward function) natural to human beings [18], here we examine a problem that is hard for individual players and is solved through crowd competition; (2) rather than developing a learning algorithm, here we focus on understanding the efficacy of human computation.

3 The ecoRacer Game

We introduce the ecoRacer game [40] that translates the powertrain design and control problem into a crowd competition. The game asks players to drive an electric car through a given track. Unlike traditional racer games that compete on speed, players must spend as little energy as possible to complete the track in 36 seconds[1]. To achieve this goal, players must employ good control strategies in combination with selection of a final drive ratio - a design variable. The final drive ratio range is

[1]This time limit is calibrated empirically so that the game is challenging enough to encourage replays, but not too difficult to appall new players away.



You saved 17 % of energy, that's better than 14% of plays!

OK

STATS

TOP SCORES
1. 22.3%, FR=10
2. 22.3%, FR=10
3. 21.2%, FR=10
4. 20.8%, FR=16
5. 19.7%, FR=10

Vehicle mass:	1521 kg
Tire radius:	0.6 m
Wheel inertia:	3.6 kgm^2
Final drive ratio:	10 – 40
Rolling friction coef.:	0.05
Track length:	900 m

FIGURE 1. The ecoRacer game interface (a-d) and settings (e). The game interface (a) is designed to work for computer and mobile screens. Touching the gear icon to the right enters the design screen (b), where the final drive ratio can be tuned. After each play, the score board (c) is shown, and the player can review speed and motor efficiency profiles of the current play in (d). Vehicle specifications, motor efficiency map, and maximum torque curves are shown in (e).

set between 10 and 40. A higher ratio will result in a larger output torque to the front wheels but lower maximum vehicle speed. After each completion of the track, the battery energy consumption is submitted as the player's score, and players are notified about their current ranking among all competitors. The leading scores along with their final drive ratios are shown to the players. We hypothesize that this last feature triggers competition among players, leading to more plays of the game. Game features are summarized in Figure 1.

The control only involves acceleration and braking, to ensure that the game is intuitive and easy to play on mobile platforms and for all audiences, including those with no driving experience. The controls are presented to the player at the beginning of the game. Energy consumption (regeneration) by acceleration (braking) is visualized on a battery bar. Chipmunk 2D physics engine [41] is incorporated to model the track, car body, motor, wheels and suspensions, with supplied motor efficiency map, maximum/minimum torque curve and other vehicle parameters. The physics engine simulates the scene once every 1/48 second, allowing precise control of the car by the player. For mobile devices with lower computing capability, this high frequency simulation may lead to slower car movement. Since the clock counts in real-time, the players on these devices become less competent. In order to address this issue, we defined "one second" in the game as the time spend on completing 48 simulation calls.

4 Computational Solutions of the ecoRacer Game

In order to benchmark the performance of human players, this section provides two computational solutions to the ecoRacer game. The first considers the game as a nested optimization problem: The outer loop searches for an optimal final drive ratio, while the inner loop solves a dynamic programming problem to find the optimal control policy for the given design. Through a nearly exhaustive search of the discrete control and design space we can obtain a solution close enough to the true global optimum. We should emphasize that this approach requires all models and parameters that constitute the game to be known. On contrary, the second approach treats the game as a black-box function that takes in control and design variables and outputs a score. The black-box function is learned based on existing trials through metamodeling (response surfaces). This latter approach is closer to how we usually solve optimization problems where simulations or experiments are involved; it is also a fair comparison to human players as both the machine and humans learn and improve through playing the game.

4.1 Optimal design and planning with full knowledge

Let P_{batt} be the instant battery power consumption, $\omega_{mot}(t)$ and $T_{mot}(t)$ the motor speed and torque at time t, v the vehicle speed and a the vehicle acceleration. Also denote by t_f time spent on finishing the race, $x(t_f)$ the distance covered at t_f, x_{final} the total track length, v_{max} the maximum speed limit and $a_{max/min}$ the limits on the vehicle acceleration. The objective is to minimize the battery consumption denoted by E_{batt} with respect to the final drive ratio ρ and the control of $T_{mot}(t)$, while completing the race within the time limit t_{max}. Note that t_f is not a free variable but it depends on the decision variables ρ and $T_{mot}(t)$. This minimization problem can be formulated as follows:

$$\begin{aligned} \min_{\rho, T_{mot}(t)} \quad & E_{batt} = \int_0^{t_f} P_{batt}(\omega_{mot}(t), T_{mot}(t), t) \cdot dt \\ \text{subject to} \quad & t_f \leq t_{max} \\ & x(t_f) = x_{final} \\ & v(0) = 0 \\ & 0 \leq v(t) \leq v_{max} \\ & a_{min} \leq a(t) \leq a_{max}. \end{aligned} \tag{1}$$

The vehicle speed and acceleration are determined by motor speed ω_{mot} and motor torque T_{mot} following:

$$\begin{aligned} v(t) &= \omega_{mot}(t)\, R_{tire}/\rho \\ a(t) &= \frac{T_{mot}(t)\, \rho/R_{tire} - F_{res}}{M_{veh} + 2\, J_{wheel}/R_{tire}}, \end{aligned} \tag{2}$$

where R_{tire} is the wheel radius; J_{wheel} the wheel inertia; M_{veh} the vehicle mass; and F_{res} the resistive force, including both road resistance and extra load from road inclination.

We solve the energy minimization problem in Equation (1) using a nested formulation described below.

4.1.1 Inner loop control problem The inner loop control problem for a given design is solved by DP. Specifically, we discretize the track into $N = 180$ equal steps, each corresponding to 5 meters. This setting provides an accurate enough solution while keeping a single call of the DP algorithm computationally affordable. We use the horizontal position and speed of the vehicle as state variables and the change of speed, Δv, as the decision variable. At each step i, Δv can take three values that correspond to the three actions players can take during the game: $\Delta v_{max,i}$ for acceleration, $\Delta v_{min,i}$ for brake, and 0 for no action. The values of $\Delta v_{max,i}$ and $\Delta v_{min,i}$ are determined by the motor torque limits based on the current state. To incorporate the time constraint, we first calculate time cost along with energy consumption for each decision at every state, and then treat the violation in the total time span as a penalty in the DP objective. With these assumptions, the DP formulation in Equation (1) for given ρ becomes:

$$\begin{aligned} \min_{\Delta v_i} \quad & \sum_{i=1}^{N} E_{batt}(x_i, v_i, \Delta v_i) + \lambda \sum_{i=1}^{N} t(x_i, v_i, \Delta v_i) \\ \text{subject to} \quad & x_1 = 0 \\ & x_N = x_{finish} \\ & v_1 = 0 \qquad (3) \\ & 0 \le v_i \le v_{max} \quad \forall i = \{1, 2, ..., N\} \\ & \Delta v_i \in \{\Delta v_{min,i}, 0, \Delta v_{max,i}\} \; \forall i = \{1, 2, ..., N\} \\ & \sum_{i=1}^{N} t(x_i, v_i, \Delta v_i) \le t_{max}, \end{aligned}$$

where $\lambda \ge 0$ is a penalty weight: Larger λ results in smaller t_f. We use a bi-section method to find the minimum λ that satisfies the time constraint. Note that this requires solving the DP problem multiple times.

4.1.2 Outer loop design problem The outer loop design problem searches for an optimal final drive ratio that minimizes battery energy consumption. The problem is discretized since players are only allowed to choose from a discrete set of final drive ratios. Starting with three initial ρ values, we fit a quadratic function to approximate the fuel consumption and iteratively minimize this function. We obtain convergence when two subsequent iterations give the same optimal solution. It is observed that for $\rho > 20$, no λ value yields a control solution to satisfy the time constraint due to low vehicle maximum speed caused by high final drive ratio. The optimal design $\rho^* = 18$ is identified, with 47.8% battery state of charge (SOC) upon finishing the track. Depending on the initial set of final drive ratios selected for the outer loop, the inner loop is called four to seven times with each call taking 1.7 to 2 hours to converge to a λ that satisfies the time constraint for the given final drive ratio [2]. Figure 2 summarizes the optimization results. As validation, we tested the same strategy using the game engine and obtained a final battery SOC of 43.4%. The difference between the game engine and the DP calculation is due to (1) the discrepancy between the physics engine and the DP model, e.g., vehicle jumping could happen in the game but is not modeled in DP, and (2) the discretization scheme involved in the DP solution. A finer discretization will reduce the difference with increased computation time.

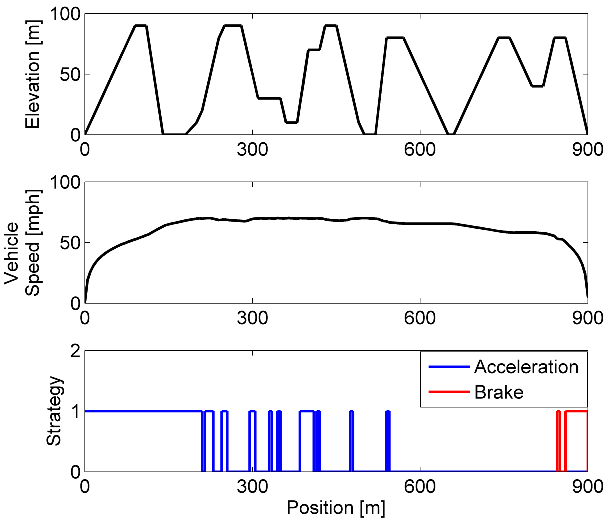


FIGURE 2. DP results for the optimal final drive ratio. Top to bottom: Road profile, optimal speed profile corresponding to $\rho^* = 18$, and optimal control decisions in terms of braking and acceleration.

4.2 Optimal design and control through Efficient Global Optimization (EGO)

We now discuss the EGO algorithm that iteratively learns a good design and control strategy without relying on the settings of the game.

4.2.1 Control parameters For each play by the computer (or a human player), we keep track of the control signals for acceleration and braking, denoted by c, along with the following four states: (1) track slope s ("1" for uphill, "-1" for downhill and "0" for flat ground), (2) remaining distance d, (3) remaining time $\bar{t}$, and (4) vehicle speed v. We assume that the control strategy can be parameterized by some vector $\mathbf{w}$, so that, given $\mathbf{w}$, the

[2]This simulation is performed using a desktop computer with Intel Xeon E5-2620 CPU clocked at 2.10 GHz and 128GB RAM.

control signal can be determined by the states:

$$c = \begin{cases} 1 \text{ (Accelerate)} & u(s,d,\bar{t},v,\mathbf{w}) \geq 1 \\ -1 \text{ (Brake)} & u(s,d,\bar{t},v,\mathbf{w}) \leq -1 \ , \\ 0 \text{ (No signal)} & \text{otherwise} \end{cases} \tag{4}$$

where $u(\cdot)$ is a mapping from the joint space of states and control parameters to the control signal. Denote the space of $\mathbf{w}$ as $\mathcal{W}$, which represents a subset of all control strategies that a human player can deploy. The formal determination of $u(\cdot)$ and $\mathcal{W}$ by using human data will be discussed in Section 5. For elaboration on the search algorithm, it suffices to consider $\mathcal{W}$ as a bounded vector space and $u(\cdot)$ as a bounded function defined on $\mathcal{W}$.

4.2.2 The score

Given a final drive ratio ρ and control parameters $\mathbf{w}$, the game can be simulated to output the battery charge consumed, denoted by e where $0 \leq e \leq 1$, and the remaining distance from the terminal, denoted by d_{end}. We define the following score as the objective to maximize for optimization:

$$f(\rho,\mathbf{w}) = \mathbb{1}(d_{\text{end}} = 0)(1-e) - d_{\text{end}}, \tag{5}$$

where $\mathbb{1}(\cdot)$ is an indicator function that returns 1 when its argument is *true*, or 0 otherwise. A successful play where $d_{\text{end}} = 0$ will output the final SOC that is $(1-e)$, while a failed play outputs the negative remaining distance. This objective favors the completion of the track, but also avoids evaluating failures indifferently.

4.2.3 The EGO algorithm

We can now employ the EGO algorithm, a search routine suitable for optimizing a black-box function defined on a continuous and bounded design space [42]. Denote the solution space as $\mathcal{S} := \mathcal{W} \times \mathcal{D}$, where $\mathcal{D} = [10, 40]$ is the one-dimensional design space. The algorithm starts by sampling $\mathcal{S}$. It then creates a kriging model using the initial samples and their responses. The next sample is chosen to maximize the expected improvement of the objective. Then, the kriging model is updated by incorporating the new sample and its response. The modeling and sampling procedure is repeated until some termination criterion is met. Figure 3 summarizes the EGO procedure. The nested maximum expected improvement problem is solved using a genetic algorithm.

5 Augmented EGO search using Human Plays

We now discuss parameterization of human plays and how the EGO algorithm can be improved based on these plays.

5.1 Parameterization of human plays

Recall that each play can be represented as a sequence of 5-tuples with control signals and corresponding states. To avoid over-burdening the server, we collect these 5-tuples at each unit distance during the play. We denote the total number of unit distances by N and each recorded play as $\{c_i, s_i, d_i, \bar{t}_i, v_i\}$, for $i = 1,\ldots,N$ [3].

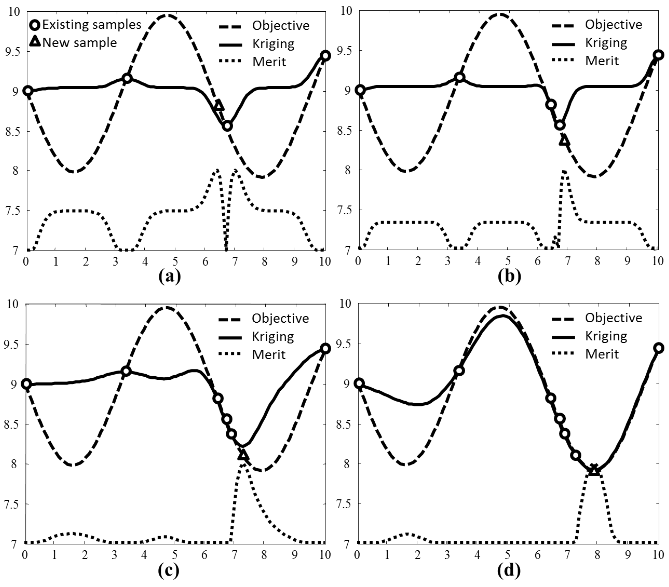


FIGURE 3. A one-dimensional example of EGO search (a-d). At each iteration, the algorithm updates the kriging model and chooses the next sample according to the maximum expected improvement function (Merit).

To parameterize the play, one would ideally define $u(\cdot)$ and fit $\mathbf{w}$ so that the actual control signals are preserved according to Equation (4). In practice, we manually tune the definition of $u(\cdot)$ so that replaying the best human play, i.e., with the highest recorded score, using the converted control parameters will yield a score close to the original one. This manual process led to the following choice of $u(\cdot)$:

$$u(s,d,\bar{t},v,\mathbf{w}) = [s,d,\bar{t},v,sd,sv,d/\bar{t},d^2,d^3]\mathbf{w}. \tag{6}$$

For a recorded play, the control parameters $\mathbf{w}$ are chosen by minimizing the discrepancy between the true control signals and those derived from Equation (4):

$$\begin{aligned} h(\mathbf{w}) = \quad & \sum_{i=1}^{N} \max\{(1-u(s_i,d_i,\bar{t}_i,v_i,\mathbf{w})),0\}^2 \mathbb{1}(c_i = 1) \\ & + \max\{(1+u(s_i,d_i,\bar{t}_i,v_i,\mathbf{w})),0\}^2 \mathbb{1}(c_i = -1) \\ & + \max\{(-1+u(s_i,d_i,\bar{t}_i,v_i,\mathbf{w})),0\}^2 \mathbb{1}(c_i = 0) \\ & + \max\{(-1-u(s_i,d_i,\bar{t}_i,v_i,\mathbf{w})),0\}^2 \mathbb{1}(c_i = 0). \end{aligned} \tag{7}$$

[3] The scores of replays using these recorded data are not the same as the original scores from players. This is because, while the game takes player inputs once every 1/48 seconds, we only record a subset of these signals at discrete distance values.

We then replay all human plays using the converted control parameters along with their corresponding final drive ratios to update scores.

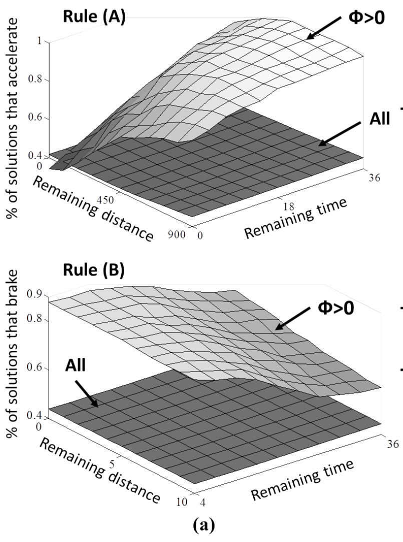
Note that instead of handcrafting the function $u(\cdot)$, we could also use a neural network to learn the mapping between states and control signals, and later consider network parameters as control parameters. On the other hand, introducing a nonlinear kernel (e.g., Gaussian kernel) to the handcrafted model may lead to better a fit to the observed control signals, but will also introduce infinite control parameters, which cannot be handled by an optimization algorithm.

In addition, the EGO algorithm requires bounds to be specified for the space of control parameters. Here we identified that the control parameters of the best human play are bounded in $[-3,3]$. Therefore setting $\mathcal{W} := [-3,3]^9$ will ensure that the best human solution is available to EGO.

5.2 Classification of human solutions

The parameterization step described above leads to a data set describing all human plays and their corresponding scores. To extract knowledge from this data, we create a one-class classifier for plays with positive scores. The classifier, denoted as $\phi([\rho, \mathbf{w}])$, predicts whether the input solution is likely to succeed ($\phi > 0$) or fail ($\phi \leq 0$) and can be used as a constraint during the search. The classifier is built using LIBSVM [43] with a Gaussian kernel. The kernel parameter γ is set to 0.1 and the training error parameter ν to 10^{-6}. Our rationale for training the classifier with all plays with positive scores rather than the few with top scores is that the former represent a broader range of strategies that *finish* the track. The resultant classifier will thus represent a more relaxed constraint in the solution space than the one derived from only the top plays, offering solution strategies that could be more generally applicable to the ecoRacer game with different game settings, rather than those specialized for the current track. To empirically demonstrate knowledge learned by the classifier from human plays, here we examine two basic control policies that should be applied universally to all game settings: (A) If the vehicle has zero speed when going uphill, it should accelerate in order to complete the track; and (B) if the vehicle is approaching the terminal with a high speed, it should restore energy by braking.

To verify that $\phi > 0$ captures these two, we uniformly draw 10^6 samples from $\mathcal{S}$. For each sample solution, we calculate its control signals under a variety of states specified in Figure 4. We consider each solution and states pair as a test point. The percentage of test points that give the correct control signal according to the two rules can be calculated, among all samples, or the ones that satisfy $\phi > 0$. Results are summarized in Figure 4, showing that incorporating $\phi > 0$ into the search results in a significantly higher chance of sampling reasonable solutions. In fact, the set $\mathcal{S}$ consists of a large number of irrational control strategies, e.g., braking while running out of time, or depleting energy to rush through the track. According to the one million samples, the sub-



Rule	(A)	(B)
Slope	Uphill	Downhill
Remaining dist. (m)	0-900	0-10
Remaining time (sec)	0-36	4-36
Speed (m/s)	0	80
Φ>0	**82.5%**	**76.2%**
All	42.9%	44.1%

(b)

FIGURE 4. The ’learned’ subspace of solutions provides more rational control strategies. (a) Percentage of test points that follow Rules (A) and (B) for a variety of states. The percentage is calculated for all uniformly sampled solutions in $\mathcal{S}$, and for those that satisfy $\phi > 0$. (b) A summary of tested states and percentages averaged across all states.

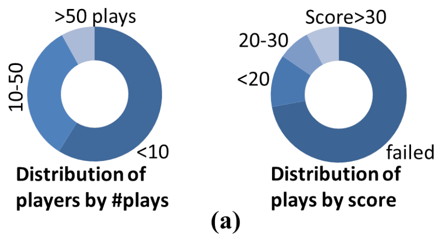
space of $\phi > 0$ accounts for only $0.2‰$ of the entire $\mathcal{S}$. We shall note that while certain heuristics (e.g., rule A) could be manually coded into the search by the algorithm designer, others cannot. Taking rule B as an example, while human players would decelerate towards the terminal to regenerate energy, the relationship between the timing of braking and the vehicle states (e.g., speed and distance from the terminal) is difficult to formulate explicitly, especially when neither the environment nor the vehicle model is assumed to be known.

6 Experiment and Results

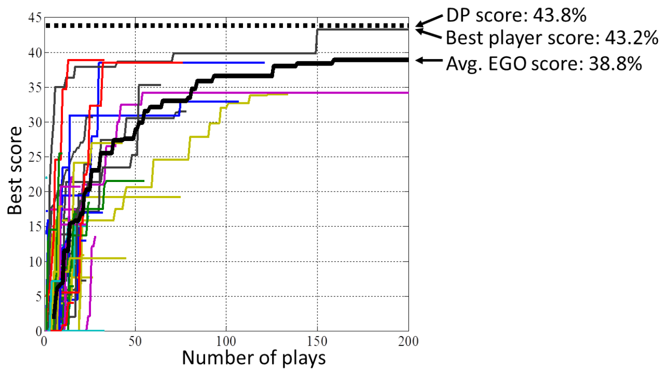
We can now summarize the experiment with human players and compare their performance with that of the EGO algorithm. We then apply the classifier learned from human plays to the same energy optimization problems with different track settings.

6.1 Comparison between human players and the algorithm

The ecoRacer game was launched on November 4th, 2014, to a sophomore engineering design class at the University of Michigan as well as broadcasted on Facebook and WeChat. The statistics and analysis in this paper are based on data received during the first week following the launch. A total number of 124 unique participants registered and played the game, with 2391 plays recorded. The best play (by user “ikalyoncu”) reached a score of 43.2%, only marginally worse than the DP solution of 43.8%. In addition, this player identified the actual optimal final



(a)



(b)

FIGURE 5. Statistics of the ecoRacer game. (a) Distribution of players by the number of games they played, and distribution of plays by their score. (b) History of improvement in score for each player. Results from EGO and DP are also shown for comparison.

drive ratio of $\rho^* = 18$. It is evident that the game is either hard or not interesting enough for most players as only 41% of players (51 out of 124) played more than 10 times. Also evident is the correlation between the number of attempts by each player and their best scores. Statistics of the game are summarized in Figure 5. In the same figure we compare human performance against that of EGO. One can see that the algorithm outperforms most players in a long run (since they quit early on), but is inferior to the elite players, especially during the early stage. This data, along with feedback from some of the players, provides us the qualitative understanding that human players are capable of learning quickly and creating good solutions, but only a few can optimize their solution by precisely executing the optimal control.

Note that the EGO implementation starts with five initial samples uniformly drawn from $\mathcal{S}$, thus the EGO trajectory starts at iteration number 5. Also due to the probabilistic nature of the initial sampling and the genetic algorithm employed to solve the maximum expected improvement problem, the reported scores are averaged over five independent EGO runs.

6.2 Search with and without crowdsourced knowledge

The comparison between the EGO algorithm and the players alone showed limited advantage of the latter in finding a good solution, largely due to the fact that only a small fraction of players have the necessary persistence to fine tune their strategy by playing repetitively. However, as we show in Figure 6, the method introduced in Section 5.2 allows us to turn player data into a constraint in the solution space and enhance the search for games that were not played by humans. Specifically, we tested three different tracks: The “inverse” track, “hill”, “zigzag” and “long" tracks[4]. For each track, we run the EGO algorithm with and without enforcing the constraint $\phi > 0$ during the search. In either case, the algorithm starts with five initial samples and terminates after a total of 200 samples. Since ϕ is created using a support vector machine, the initial samples are randomly chosen among the support vectors when the constraint is incorporated, or otherwise randomly sampled from $\mathcal{S}$. Figure 6 compares performance from the two algorithm settings, using the average values and standard errors from five independent EGO runs for each case. The result shows that while EGO without human plays can identify good solutions in long run, the algorithm can take a significant early advantage by using heuristics extracted from human plays. Further, we show that knowledge learned from human players are transferable to different track settings, and scalable to longer tracks, offering a promising solution to the curse of dimensionality.

6.3 Discussion

The experiment and simulation studies presented here help to answer questions regarding the use of human computation for engineering design.

Why would human beings be useful in an optimization task? Human computation, often in the form of crowdsourcing, has mainly been successful in batch tasks that rely on human intuition rather than computational resource, see [8] for examples. Nonetheless, human computation becomes especially beneficial when intuitive tasks are actually computationally expensive. As has been demonstrated by Foldit and eteRNA, some human players have excellent ability at solving spatial optimization problems, as their search efficiency outperforms that of computer algorithms. The ecoRacer game, similarly, is based on the hypothesis that some players are well trained at tuning their control strategy and design through trial-and-error. The hypothesis is reasonable considering that people around the world spend three billion hours training themselves in online games every week [17], and that a large portion of the games require players to perfect their control. As Figure 5 showed, some players learned good strategies much earlier than the algorithm did. It should, however, be noted that the underlying optimization problem must be well translated (and camouflaged) by the game so that people can appreciate the problem and enjoy the fun without facing the actual engineering problem. This requirement leads to the next question.

[4]The “inverse" track flips the original track from the game, and in the “long” track we duplicate the original track and the energy capacity five times.

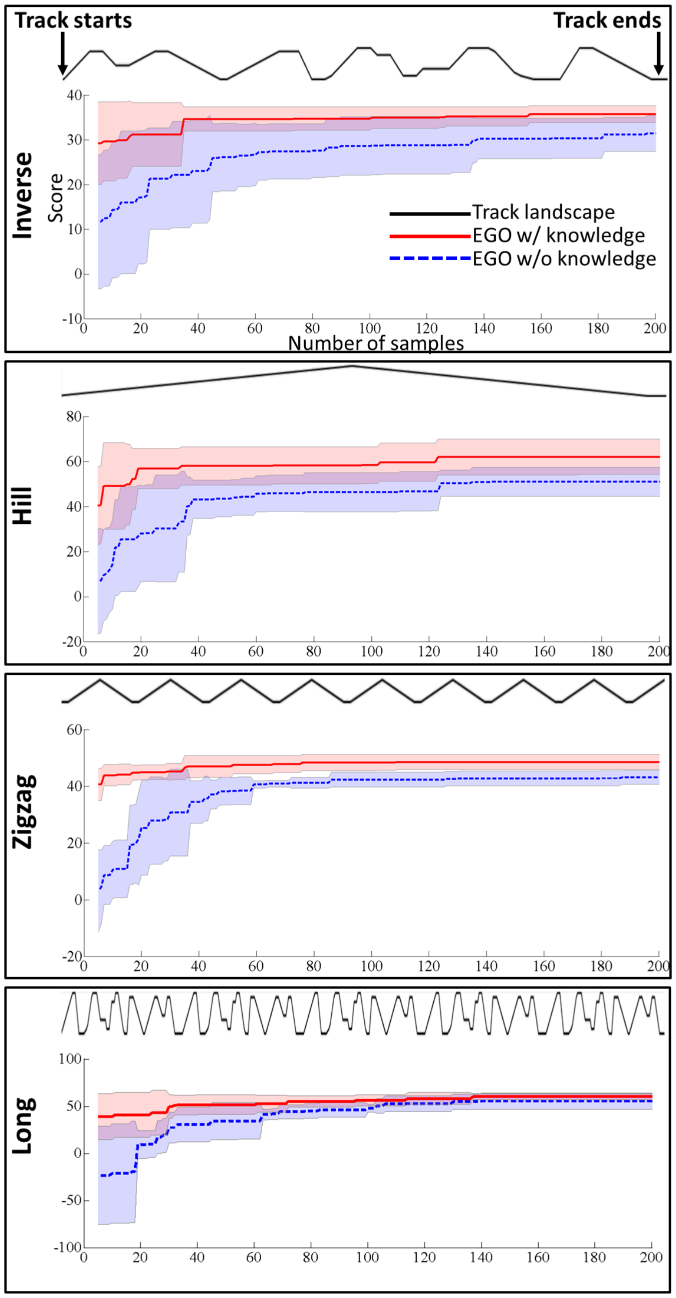


FIGURE 6. Comparison between EGO with and without human knowledge, using the "inverse", "hill", "zigzag" and "long" tracks. The "long" track is five times as long as the others.

Is it worth expending the effort of translating any particular problem and even building a game for it, in the hope that some talented people could solve it? Human computation experiments require significant effort to create the proper game environment and to establish sophisticated competition, collaboration and rewarding mechanisms. These efforts are necessary for continuously growing the player population in order to increase the chance of finding talented players. The efforts are not likely to be worthwhile if the underlying problem needs to be solved only once. Given sufficient computational resources, the computer algorithm is likely to outperform human players either by iterating long enough (see Figure 7 in [11] for an example) or by solving the problem via brute-force, e.g., shortest path in a discrete space[5]. Protein folding [10], RNA synthesis [12] and powertrain design for vehicles of particular usage may be tough enough problems requiring repeated solution and thus worthy of human computation investment. In addition, we should emphasize that extracting heuristics from human players and applying them to new problem settings, as demonstrated in [11, 12] and this study, could be of significant importance in solving problems facing the curse of dimensionality.

Given that players are more likely to spend their spare time on playing regular games than solving scientific or engineering puzzles, is human computation a realistic alternative?. For example, while Foldit attracted 300,000 players, there are hundreds of millions of active users of Angry Birds [17]. Given this reality, even if human computation is proven viable for solving computationally expensive design optimization problems, would there be enough players per problem for the strategy to be effective? Our experiment, as well as existing reports on human computation, showed that the problem can be efficiently solved by a small population of core players. In the case of ecoRacer, it was those players who contributed the successful plays. This finding implies that while the crowd attracted for any particular problem will not necessarily be large, these self-motivated participants may suffice to produce valuable data to expedite problem solving.

Some technical issues and remedies of the presented ecoRacer experiment are discussed as follows:

1. We note that converting user control signals to control parameters $\mathbf{w}$ caused discrepancy in the resultant scores. This is because the bases in the mapping $u(\cdot)$ are chosen so that the score derived from *the best* play's control parameters is close to its actual score. Therefore technically, the classifier ϕ is not derived directly from the genuine player data. This discrepancy can be reduced by choosing a better set of bases for $u(\cdot)$ that closes the gaps between *each* play's original score and that from the converted control parameters.

2. In this study we used a one-class classification that solely extracts knowledge from successful plays. An alternative approach to test would be to take failed plays into account and derive a binary classifier. It is also possible to create the classifier by utilizing the actual scores, as opposed to the binary "failed" and "successful" labels.

[5]While finding a shortest path is polynomial, generating the graph could be exponential with respect to the track length.

7 Conclusion

We examined the costs and benefits of incorporating game-based human computation versus a standard black-box search algorithm in the context of an optimal powertrain design and control problem. The results showed that, while only a small portion of human players outperformed the algorithm, useful heuristics can be extracted from the recorded plays and effectively applied to problem settings that were not presented to the players. This indicates the promising use of human computing in transferring knowledge learned from human-comprehensible problems to similar ones of larger scale or difficulty, to achieve scalable and effective search. The findings from this paper offer useful insights for future attempts at solving computationally expensive engineering optimization problems through human computation In future work, it would be also interesting to investigate how decomposition strategies involving problem partitioning and coordination that have been effectively applied to numerical solvers can be incorporated within a human computation framework. With a larger crowd of participants, we could also investigate the relationship between the crowd size and its performance. Lastly, it is valuable to explore game mechanisms that encourage players to improve their strategies in more efficient ways.

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