Towards pedestrian-AV interaction: method for elucidating pedestrian preferences

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Abstract— **Autonomous vehicle navigation around human pedestrians remains a challenge due to the potential for complex interactions and feedback loops between the agents. As a small step towards better understanding of these interactions, this Methods Paper presents a new empirical protocol based on tracking real humans in a controlled lab environment, which is able to make inferences about the human's preferences for interaction (how they trade off the cost of their time against the cost of a collision). Knowledge of such preferences if collected in more realistic environments could then be used by future AVs to predict and control for pedestrian behaviour. This study is intended as a work-in-progress report on methods working towards real-time and less controlled experiments, demonstrating sucessful use of several key components required by such systems, but in its more controlled setting. This suggests that these components could be extended to more realistic situations and results in an ongoing research programme.**

I. Introduction

The potential future deployment of full Autonomous Vehicles (AVs) is currently creating much enthusiasm, as such vehicles would change our daily life through making transportation more efficient. Huge improvements have been made on robotic localisation and mapping problems using Simultaneous Localisation And Mapping (SLAM) algorithms [26], [5] together with new, cheap sensors and computation technologies [15] [30]. 'Self-driving' cars can navigate safely on roads, promising a future society with a better mobility system with less accidents and traffic in cities.

But before the fully autonomous driving (SAE Level 5) revolution happens, AVs must share space with and will be challenged by human drivers and pedestrians, who are much harder to model and act upon than passive environments. Decades' of research in the fields of Transport Psychology and Human Factors have not yet been translated into robotic control systems, and leave many questions still unanswered. For safety and legal reasons, pedestrians are considered as obstacles, such that the vehicle always stops for them, in most current 'self-driving' systems. Recent on-road studies have shown that pedestrians may then take advantage over AVs due this predictable behaviour [22] [20] [13] [8] [4], pushing in front of them for priority eventually in *every* negotiation such that the vehicles can then make no progress. This has become known as the 'Freezing Robot Problem (FRP)'. Real human driving is massively more complex than simply mapping, localising and path planning. It is considered an art form by advanced practitioners such as members of the Institute for Advanced Motorists and other advanced drivers such as high-speed police and ambulance drivers. In their training, these practitioners generally emphasise the human psychological processes involved in predicting the behaviours of other road users as the most important skill of human drivers. Can you tell if a pedestrian is assertive enough to risk stepping out in front of you from their body language, their facial expressions, even their clothes and demographics? Road users have different utility functions, ranging from timid pedestrians likely to give way to all oncoming traffic, though to business-people late for a meeting or patients for an urgent medical appointment becoming much more assertive and risk-taking. Drivers must also consider the psychological effects of their own actions. Speeding up and slowing down are not just ways to control one's progress but also send information about our own personality and risk preferences to pedestrians engaged in such negotiations for priority, along with other possible signals including lateral road positing, and more conventional signals such as flashing indicator lights and headlights, and driver face and arm expressions.

Fig. 1: Two agents negotiating for priority at an intersection

The new EU H2020 interACT project has been created with a consortium of European partners [14] to investigate the role of interaction in future deployment of AVs in mixed traffic environments with human drivers, cyclists and pedestrians. The project will aim to understand the behaviour of other road users, and how AVs could interact with them in a safe and efficient manner, and propose eHMI solutions that could facilitate the communication between AVs and people.

As first steps towards these goals, we recently proposed [10] and solved a very simple game-theoretical mathematical model of the unsigned road-crossing scenarios represented in figs. 1 and 2, based on the famous game of 'chicken' and called 'sequential chicken'. In this simplest-possible model, two agents (which may be pedestrians and/or vehicles) compete for space at an unsigned intersection, using only their positions to signal information to one another. Time, space and actions are discretized and it is assumed that both players have equal utility functions and know this to be the case. The model leaves open free parameters specifying the utility function for human players. We proposed [10] only as a mathematical model but suggested that its parameters could be found via human experiments. In [6], we experimented the model with human participants and asked them to play the sequential chicken game as a board game to measure their behavioral parameters.

The present study extends this idea to present a new protocol using physical subjects' bodies in a semi-structured interaction scenario together with person tracking and Gaussian Process Regression analysis, to infer their preferences in a slightly more

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This project has received funding from the European Union's Horizon 2020 Research and Innovation programme under grant agreements No 723395 (InterACT) and No 645376 (FLOBOT).

realistic setting. As such it respresents additional progress moving the model closer to the real world, though of course there are many more needed in the future as the work progresses, until we reach a real-time continuous version suibable for use in AVs. First, it makes use of pedestrian tracking to estimate the trajectories of the agents involved in semi-structured human-human interactions while playing the sequential chicken model. Second, it computes the optimal strategies using a meta-strategy convergence method [10]. Lastly, it infers the parameters of the interactions using Gaussian Process Regression. To our knowledge there is no previous work fitting tracking-based semi-structured game-theoretic models to human motions and to infer behaviour parameters.

A. Related work

The problem of self-driving cars interacting with other road users is raising interest in both the Robotics and Transport Studies communities. Game Theory offers a framework to model conflict and cooperation between rational decision-makers. It was developed in the 1940s by von Neumann and Morgenstern. Its core concept is (Nash) *equilibrium* which is the pair of strategies (probability distributions over actions to be played) such that none of the players would change their strategy if they knew the other's strategy. Previous work in Transport Studies and highway design has applied game theory to several driver behaviour modelling tasks as reviewed in [9]. [16] and [21] developed game theoretic methods for lane changing manoeuvres. In [16] for example, a mixed-motive game theory model is used for deciding the strategy made by two AVs equipped with Adaptive Cruise Control (ACC). Their simulation has shown that game theory provides better results as payoffs obtained are larger and the differences smaller for the two cars. Similar to our work, the model in [19] computed Nash equilibria using Fictitious Play. Their method differs from ours that not only their model takes into account pedestrians' position from a single image but also some visual features from their appareance as part of the utility function to improve their trajectory predicition. [1] presents an algorithm for intersection management involving up to four self-driving cars communicating with each other. Two motions choices are available for each player (move forward or stop) and an optimised solution using game theory to solve the discrete intersection problem is presented. [2] makes use of game theory model such as the Prisoner's Dilemma to propose a decision making system for AVs in a roundabout. Alternative variants of the game of chicken are proposed in [22], [24] and [7] to solve conflicts between agents at intersections. A cellular automata-based approach is implemented in [24] and [7] to represent the conflict between two agents. [22] focuses on the interaction between an AV and a pedestrian. [23] proposes a game theory approach for intersection conflicts management with reactive agents (the automated vehicles) equipped with Adaptive Cruise Control systems and a manager agent is used to decide the optimal strategy that increases the overall performance of all the agents. This approach prevents from a crash to occur and it also minimises the time delay in the intersection. [29] and [28] proposed a non-cooperative game theoretic approach to human collision avoidance. Their method differs from ours that they used a motion capture system to record human motions, a Bootstrap algorithm to compute the confidence intervals and applied a Dynamic Time Warping (DTW) algorithm to measure similarity between the trajectories. Gaussian proccess models of continuous trajectories have been applied to pedestrian path modelling and FRP in [27].

When multiple equilibria are present in games, standard game theory does not specify how the players should choose the best one. In the above studies, no method is proposed for players to select which equilibrium to use. Typically this is because Transport Studies seeks to describe macroscopic flows of traffic rather than prescribe actions for individual vehicles, and considers that *any* possible equilibrium is a good description of observed data. For example in [22] the choice for the best solution depends on 'local social norms' which assumes that drivers should have prior knowledge of local customs. Unusually, [10] proposed a novel approach for optimal strategy prescription, called *meta-strategy convergence*. This method begins by choosing an equal-weighted mixture of strategies from all rational equilibria (after removing dominated and asymmetric equilibria where possible). The resulting strategies do not in general form an equilibrium themselves, but by applying fictitious play until convergence, a single equilibrium is obtained upon which it is argued that two rational players should agree without communication. Most of the game theory models reviewed above outperform non-game theoretic predictive models [29], [7], [19], [23].

Pedestrian tracking plays an important role in many commercial applications. Several tracking approaches are described in [12] [11]. Tracking is still a challenge for computer vision systems because of the multiple uncertainties (e.g. occlusions) due to complex environments. Tracking of pedestrians requires the estimation of non-linear, non-Gaussian problems due to human motion, pedestrian scales, and posture changes. Monte-Carlo methods such as particle filtered-based approaches draw a set of samples assigned to a target and perform the data association for multiple targets using probabilistic techniques such as Nearest Neighbor (NN), Multi-Hypothesis-Tracking (MHT), JPDAF and PHD-filter [18]. Pedestrian tracking is composed of two steps: (*i*) a prediction step to determine the expected position and motion state and (*ii*) an update step to refine the prediction using sensor observations.

Tracking has been often combined with game theory for problems of multi-robot system coordination. [25] used the approach of non-cooperative games to control a team of mobile robots for a target tracking. When multiple equilibria are present, an arbiter module based on the min-max method is used to fairly distributes the costs among the robots. [17] applies cooperative game theory to improve tracking performance for a group of robots. Their method allows communication between the robots in order to minimise tracking costs and maximise the interests of the overall system of robots. [32] proposes a cooperative nonzero sum game approach for the problem of multi-target tracking for a multi-robot system in a dynamic environment.

II. Methods

The present study shows how to fit parameters of the Sequential Chicken model to human behaviour collected from a semi-structured experimental environment. This environment is designed to enable the simplest possible mapping of physical human motions onto the model, as a step towards more naturalistic interaction modelling based on extensions of the model.

A. Sequential chicken model

In Sequential Chicken, two agents (e.g. pedestrian and/or human or autonomous driver) called Y and X are driving straight towards each other at an unmarked intersection as in fig. 1. In the model this process occurs over discrete space as in fig. 2 and discrete times ('turns') during which the agents can adjust their discrete speeds, simultaneously selecting speeds of either 1 square per turn or 2 squares per turn, at each turn. Both agents want to pass the intersection as soon as possible to avoid travel delays, but if they collide, they are both bigger losers as they both receive a negative utility U_{crash}. Otherwise if the players pass the intersection, each receives a time delay penalty $-TU_{time}$, where T is the time from the start of the game and U_{time} represents the value of saving one turn of travel time. The model assumes that the two players choose their actions (speeds) $a_Y, a_X \in \{1,2\}$ simultaneously then implement them simultaneously, at each of several discrete-time turns. There is no lateral motion (positioning within the lanes of the roads) or communication between the agents other than via their visible positions. The game is symmetric, as both players are assumed to know that they have the same utility functions

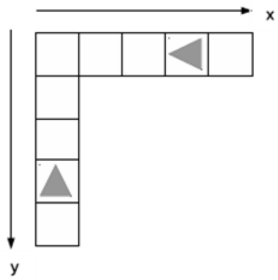


Fig. 2: Sequential Chicken Game

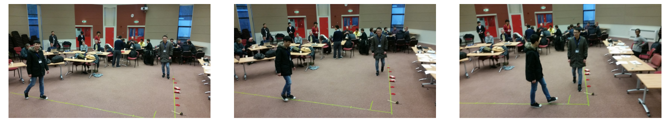


Fig. 3: Approaching Phase

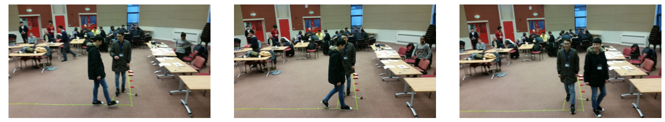


Fig. 4: Crossing Phase

(U_{crash}, U_{time}), hence they both have the same optimal strategies. These optimal strategies are derivable from game theory together with meta-strategy convergence, via recursion. Sequential Chicken can be viewed as a sequence of one-shot sub-games, whose payoffs are the expected values of new games resulting from the actions, and are solvable by standard game theory.

The (discretized) locations of the players can be represented by (y,x,t) at turn t and their actions $a_Y, a_X \in \{1,2\}$ for speed selection. The new state at turn $t+1$ is given by $(y+a_Y, x+a_X, t+1)$. Define $v_{y,x,t} = (v^Y_{y,x,t}, v^X_{y,x,t})$ as the value (expected utility, assuming all players play optimally) of the game for state (y,x,t). As in standard game theory the value of each 2×2 payoff matrix can then be written as,

$$v_{y,x,t} = v(\begin{bmatrix} v(y-1,x-1,t+1) & v(y-1,x-2,t+1) \\ v(y-2,x-1,t+1) & v(y-2,x-2,t+1) \end{bmatrix}), \quad (1)$$

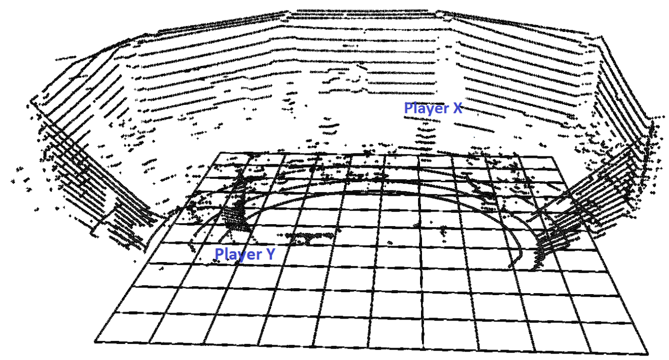
which can be solved using dynamic programming assuming meta-strategy convergence equilibrium selection. Under some approximations based on the temporal gauge invariance described in [10], we may remove the dependencies on the time t in our implementation so that only the locations (y,x) are required in computation of $v_{y,x}$ and optimal strategy selection.

In the sequential chicken model, if the two players play optimally, then there must exist a non-zero probability for a collision to occur. Intuitively, if we consider an AV to be one player that always yields, it will make no progress as the other player will always take advantage over it, hence there must be some threats of collision.

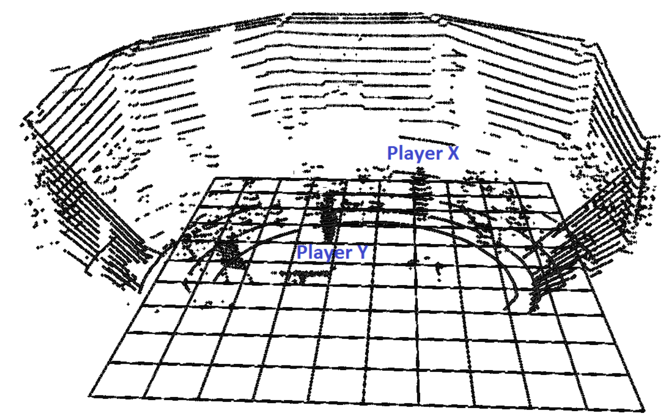
B. Human experiment

Eighteen human volunteer subjects (University of Lincoln Computer Science staff and students) were divided into 9 pairs, one designated as player Y and the other as player X. Each pair was asked to play a physical version of the Sequential Chicken game on a plus-maze shaped playing area drawn on an indoor floor as 0.4m grid squares as shown in fig. 2. Player Y was starting from $y = 10$ and player X from $x = 10$ such that they were both starting 10 squares away from the intersection. Players were instructed that their objective was to pass the intersection as soon as possible, 'as if they were trying to reach their office entrance in a busy pedestrian area'. Each pair played 5 games. In each game, the players were each given two cards containing the numbers 1 and 2. To prevent cheating, they were instructed that at each turn, called by the experimenter about every 2 seconds, they should select one card in secret, then both hold them up together (as in the game 'scissors, paper, stone') then both move together by that number of squares towards or beyond the intersection.

The players' motions were recorded using a Velodyne 3D lidar while an experimenter called the turns. Fig. 5 shows examples of the lidar output during the games.



(a) Approaching phase

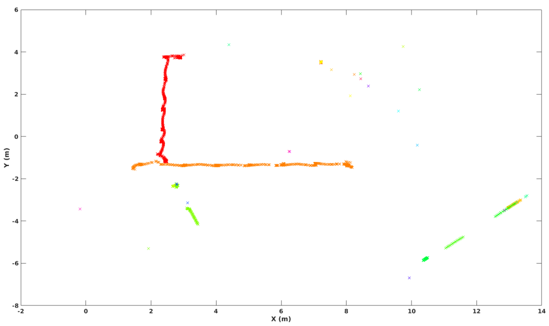


(b) Crossing phase

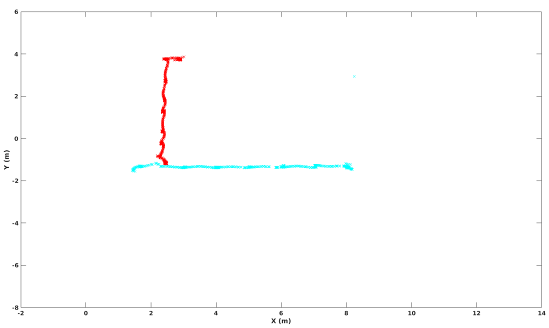
Fig. 5: 3D lidar output in approaching (a) and crossing (b) phases

C. 3D lidar-based pedestrian tracking

Pedestrian positions and velocities are provided by a robust Bayesian multi-target tracking systems based on 3D lidar detections[33], suitable for real-time, long-range tracking of multiple people in dynamic scenarios. Non-overlapping clusters of adjacent points are extracted based on their 3D Euclidean distance. An adaptive threshold accounts for the variation in shape and size of the human body in 3D LiDAR point clouds, which is a function of the person's distance from the sensor. Finally, clusters too large or too small to be humans are discarded by the detector, which outputs the distance and bearing of the cluster's centroid projected on the floor. The information from the detector is processed by a multi-target tracker, including an efficient implementation of Unscented



(a) Before filtering



(b) After filtering

Fig. 6: Pedestrian trajectories extracted from the 3D lidar before (a) and after (b) filtering

Kalman Filter (UKF) and Nearest Neighbour (NN) data association to deal with multiple detections simultaneously [3]. The tracker estimates the 2D coordinates and velocities of each pedestrian using a standard prediction-update recursive algorithm. The prediction step is based on the following constant velocity model,

$$\begin{cases} x_k = x_{k-1} + \Delta t \ \dot{x}_{k-1} \\ \dot{x}_k = \dot{x}_{k-1} \\ y_k = y_{k-1} + \Delta t \ \dot{y}_{k-1} \\ \dot{y}_k = \dot{y}_{k-1} \end{cases} \tag{2}$$

where x_k and y_k are the Cartesian coordinates of the target at time t_k, $\dot{x}_k$ and $\dot{y}_k$ are the respective velocities, and $\Delta t = t_k - t_{k-1}$. (The variables x, y, t in this section measure the same quantities in the game theory model, but here take continuous values while the game theory model uses quantised values.) The update step of the estimation use a 2D polar observation model to represent the position of a detected cluster,

$$\begin{cases} \phi_k &= tan^{-1}(y_k/x_k) \\ \gamma_k &= \sqrt{x_k^2 + y_k^2} \end{cases} \tag{3}$$

where ϕ_k and γ_k are, respectively, the bearing and the distance of the cluster's centroid with respect to the sensor. For sake of simplicity, noises and coordinate transformations are omitted in the above equations. Tracks set were then filtered to locate the two longest tracks in the game grid area as shown in fig. 6. More details can be found in [3], [33]. Discrete player positions (grid squares) were then extracted from the tracks for each turn.

D. Gaussian Process parameter posterior analysis

We use Gaussian Processes Regression [31] to fit the posterior belief over the behavioural parameters of interest, $\theta = (U_{crash}, U_{time})$ from the observed data, D. Under the Sequential Chicken model, M, these are,

$$P(\theta|M,D) = \frac{P(D|\theta,M)P(\theta|M)}{\sum_{\theta'} P(D|\theta',M)P(\theta'|M)}. \tag{4}$$

We assume a flat prior over θ so that,

$$P(\theta|M,D) \propto P(D|\theta,M), \tag{5}$$

which is the data likelihood, given by,

$$P(D|\theta,M) = \prod_{game} \prod_{turn} P(d_Y^{game,turn}|y,x,\theta,M')P(d_X^{game,turn}|y,x,\theta,M'), \tag{6}$$

where $d_{player}^{game,turn}$ are the observed action choices, and y and x are the observed player locations at each *turn* of each *game*. Here M' is a noisy version of the optimal Sequential Chicken model M, which plays actions from M with probability $(1-s)$ and maximum entropy random actions (0.5 probability of each speed) with probability s. This modification is necessary to allow the model to fit data where human players have made deviations from optimal strategies which would otherwise occur in the data with probability zero. Real humans are unlikely to be perfectly optimal at anything as they may make mistakes of perception and decision making. This is a common method to weaken psychological models to allow non-zero probabilities for such mistakes if present.
For a given values of θ we may compute the optimal strategy for the game by dynamic programming as in Algorithm 1. Optimal strategies are in general probabilistic, and prescribe the $P(d_Y^{game,turn}|y,x,\theta,M), P(d_X^{game,turn}|y,x,\theta,M)$ terms to compute the above data likelihood. We then use a Gaussian Process with a Radial Basis Function (RBF) kernel to smooth the likelihood function over all values of θ beyond a sample whose values are computed explicitly. In practice this is performed in the log domain to avoid numerical computation problems with small probabilities. The resulting Gaussian Process is then read as the (un-normalized, log) posterior belief over the behavioural parameters $\theta = \{U_{time}, U_{crash}\}$ of interest.

Algorithm 1 Optimal solution computation

for U_{crash} in range(U_{crash}^{min}, U_{crash}^{max}) **do**
  for U_{time} in range(U_{time}^{min}, U_{time}^{max}) **do**
    S ← strategy matrix (NY*NX*2) for P(player X chooses speed $2|y,x$)
    loglik = 0
    for each game in data **do**
      for each turn in game **do**
        loglik $= \prod_{game} \prod_{turn} (1-s)P(d_Y^{game,turn}|y,x,\theta,M)P(d_X^{game,turn}|y,x,\theta,M) + s(\frac{1}{2})$
      end for
    end for
    Store loglik(U_{crash}, U_{time})
  end for
end for
maxloglik ← max of loglik(U_{crash}, U_{time})

III. Results

After applying Gaussian Process Regression and optimising s to maximise the likelihood at the Maximum A Posteriori (MAP) point of θ, the posterior distribution over $\theta = \{U_{crash}, U_{time}\}$ is shown in fig. 7. The MAP estimate of the parameters is then around $U_{crash} = -30, U_{time} = 45$, at $s = 0.11$. The -2:3 ratio in the utilities means that assuming the noisy model M' the subjects value a 2/3 turn time delay equally to a crash, and the s value means that the subjects make mistakes from optimal behaviour in 11% of actions. Significance of the results can be seen by inspection of the thin standard deviation widths of 1D slices through the 2D posterior as in fig. 8.

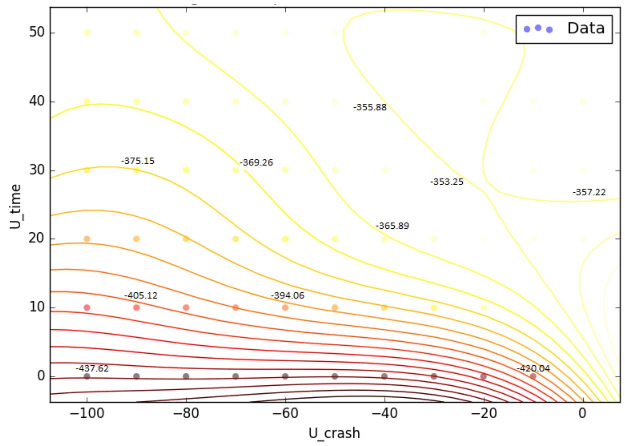


Fig. 7: Gaussian Process log-posterior over behavioural parameters. (Un-normalized)

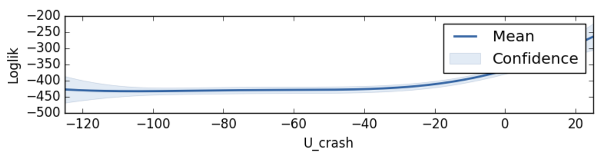


Fig. 8: Slices through the Gaussian Process showing 1 standard deviation log-posterior confidence.

The low (for Psychology models) deviation rate from optimal behavior, $s = 11\%$, suggests that the model is a good fit to what human pedestrians actually do in priority negotiations. The behavioral parameter results then show that in the semi-structured scenario the participants have a preference for time saving rather than collision avoidance. This was unexpected – in real life, a collision is intuitively much worse than almost any time delay to almost everyone. While the game was structured as a sequence of discrete turns to simplify model fitting, it was designed to closely resemble a real-world interaction in continuous time as much as possible. This high-risk appetite of the pedestrians is perhaps best explained by: (1) the high safety of the environment – the players know the study is set up in a laboratory environment operating under health and safety policies, and that all the other subjects are also just playing a game, so they are less concerned about colliding than they would be with strangers in a real public place such as an office corridor intersection; (2) the environment of the experiment may lead some players to view it as a zero-sum competion (a race) rather than attempting to maximise only their own utility; and (3) the utility of colliding with other experimental subjects is less bad than colliding with real strangers or with robots or autonomous vehicles, which is also harder to emulate in a safe laboratory environment that symetric pedestrian-pedestrian interactions.

IV. Conclusion

Despite showing an unexpected and unrealistic result as a consequence of the lab enviromnet used, this Methods Paper has demonstrated sucessful use of a new Method for elucidating pedestrian preferences in the Sequential Chicken model from a real-world scenario and empirical data. It was conducted in a deliberately simplified, semi-structured environment, designed to simplify and test model-fitting whilst still demonstrating all the essential components required for future more realistic experiments: protocol, tracking, parameter fitting, and posterior parameter analysis. Building on the components from this protocol demonstration, future experiments could now take further steps towards elucidation for realistic environments, including replacing the semi-structured discrete turn-taking with unstructured, continuous time and space movements but also using signalling methods (gestures, sounds etc.). They should also move away from the simplifying assumption of shared known and symetric utility functions, for example by using augmented reality to safely simulate interactions with heavy vehicles (e.g in 3D driving simulations) whose damage in a collision is less to themselves than to the pedestrian. This current model would not be affected by conflicts related to driving conventions (such as left- and right-hand driving) as only one single driving convention can run at a time in a precise location. The proposed approach could be easily extended to multi-lane roads and it would become a multi-target traking problem for the AV. Future work should consider less computational optimization methods than the gaussian process (GP) regression for the real-time behavioural parameter fitting.

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