Creating driving behavior for artificial agents in a social augmented micro-world

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Abstract. This paper presents first results on the implementation of driving agents in the socially augmented micro-world (SAM). Time series analysis are used for comparing the agent behavior with human behavior. We will discuss the results from time series analysis/clustering and compare them with classifications done by hand. Further approaches for future research are presented and discussed.

Keywords: artificial agents, driving behavior, micro-world, time series

1 Introduction

This paper presents the current work on the ongoing interdisciplinary project of Psychology and Informatics in the field of human factors. The central goal of the work in this paper is to construct artificial agents which can replace humans in a socially augmented micro-world. The socially augmented micro-world (SAM), was developed by the group of H. Wandke at the Institute of Psychology at Humboldt-Universität zu Berlin [1]. The aim is to study design problems for complex human operated systems.

Fig. 1 shows the setup of the ATEO lab system (ALS), consisting of two humans which interact with SAM through a joystick, as seen in the left part of the figure. The humans are called micro-world inhabitants (MWI).The human operator sits on the right in the figure, hidden from both MWI. He supervises both MWI through the ATEO Master. ATEO refers to the German title of the umbrella project for developing the ALS: ArbeitsTeilung Entwickler-Operateur. So far, determinism has been the main deficit of simulations. To avoid determinism there are two humans included, to cooperatively performing a pursuit tracking task. Each human partially influences a vehicle, which drives a long a street. Both MWI are instructed with different orders, to drive fast or to drive accurately. The operator's task is to improve the overall performance of the MWI's by visual or acoustical hints. For a broader range of experiments, it shall be possible to replace human MWI by artificial agents.

In the next chapter we will review previous work. Then we will show the final architecture of the agent. The next two parts focus on the two approaches which were made to analyze the human MWI behavior. We thank the colleages from Department of Mathematics and Informatics, University of Novi Sad, for

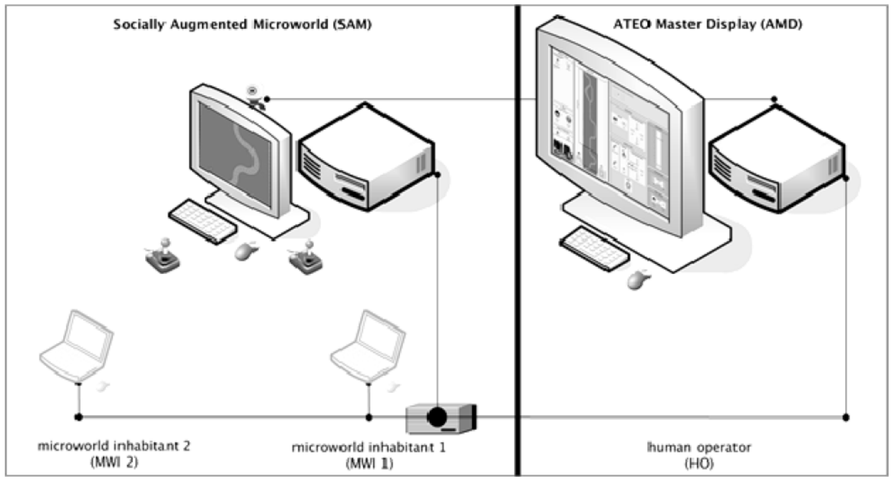


Fig. 1: setup of ATEO lab system

providing the data of their series analysis. The last chapter presents the results of the comparison of both approaches and the first results of artificial agents and outlines future work.

2 Earlier Work

2.1 Agent architecture

In the last year we finished the proposed architecture [2] [3]. The architecture focuses on usability, efficiency, maintainability and portability. Usability can be understood as clarity of the used concepts and the effort needed to use the agents. Efficiency concerns the real time behavior of each component. The next point is the maintainability, which refers to the cost of finding and correcting errors. Modifiability is also part of maintainability and is the cost of changing parts of the agent architecture. The last part is portability and describes the difficulty to port the agent from one environment to an other.
One important aspect of the usability is the effort which is needed to implement new agent behavior. To simplify the architecture we use a design pattern called strategy [4]. This design pattern gives a lot of possibilities, new agents can easily be added and the behavior can be changed during run time.

2.2 Classification by hand

As mentioned in [2], the behavior of human MWI need to be analyzed, as a prerequisite for the development of artificial agents. There are 26 data sets from former studies with human probands. One data set contains 11 tracks. For each

track there exists one file in the csv data format, which contains information about the state of SAM, taken every 39ms.
The first approach focused on only one track, because this track exhibits characteristics like forks or obstacles for the first time and has no intervention from the operator. We only analysed the critical situations (forks, the avoiding of obstacles). Data gained in the situations provides more variance and hence supports the identification of selective types of interaction behavior. Six different steering behavior were found:

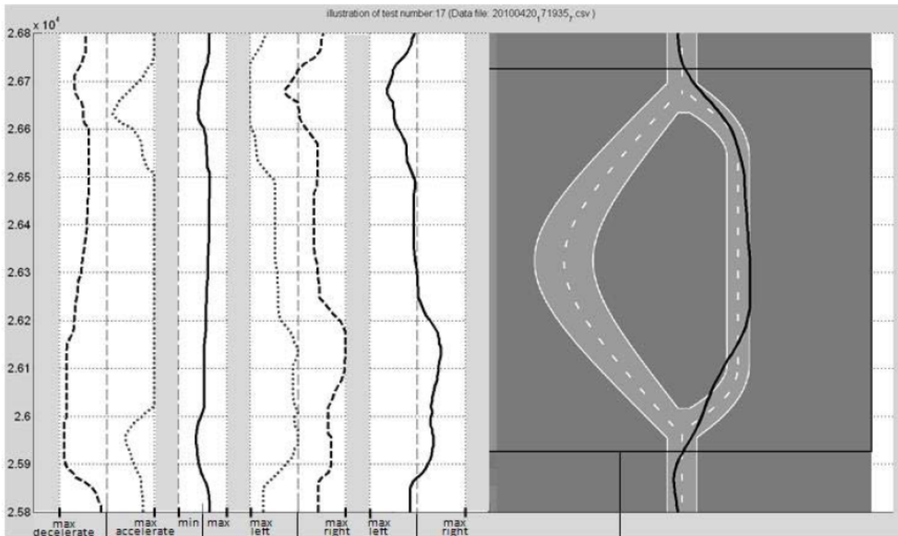
1. Adapted navigator: MWI adjusts his steering to characteristics of the track.
2. Extreme steering navigator: steers with maximum deflection alternating extremely from one direction to the other within a short time.
3. No steering navigator: this MWI hardly shows own steering, the partner steers.
4. Parallel navigator: produces comparable navigation lane to an adapted driver. The parallel navigator exists only in combination with a second parallel navigator.
5. Indecisive navigator: makes no decision or decides too late.
6. Residue: remaining data sets which did not fit in any other classification or does not show any characteristic steering behavior.

Fig. 2 shows an example for the visualization that support the classification by hand. The driver types were classified by similarities of the curves.

2.3 Classification with time series

Instead of analysis by hand as described above, the analysis of time series could lead to automatized classification. Such an approach was done with the help of FAP [5]. FAP is a system for time-series anlysis, developed at Department of Mathematics and Informatics, University of Novi Sad [6]. Three time series have been investigated which described the path, the acceleration and the deviation from the ideal path. The data have been derived from the CVS file. Three different similarity measures were chosen: Dynamic Time Warping (DTW), Edit Distance on Real sequence (EDR) and Edit Distance with Real penalty (ERP). For each of the three time series a distance matrix was calculated. A hierarchical clustering algorithm was used for clustering and creating dendrograms. This can be seen in Fig. 3.

As each of the three similarity measures follows a different methodology, they lead to different clusters. Two distinct clusters were to be identified distinguishing navigators focusing on speed from those focusing on accuracy. To do this, the appropriatness of the three similarity measures was investigated. The different instruction should result in different navigation styles. This difference should be observable by related clusters derived from the time series. As result the ERP measure is the most suitable to group the MWI. The ERP measure is defined as:



acceleration		speed		steering		resultant conjoint steering	relativized route on the track
direction	intensity	0	very slow	direction	intensity	--> important when	--> needed to find
accelerate	0 =none	1	slow	right	0 =none	operator take part	the critical parts
decelerate	1 =low	2	middle	left	1 =low	(so it was ignored in	of the track
none	2 =middle	3	fast	none	2 =middle	this analysis)	
	3 =high	4	very fast		3 =high		

Fig. 2: The acceleration-, speed- and steering curves of a data set at a fork (left). The road segment with fork (right). The classification sytem of parameters (below).

$$ERP(R,S) = \begin{cases} \sum_1^n |s_i - g| & \text{if } m = 0 \\ \sum_1^m |r_i - g| & \text{if } n = 0 \\ min\{ERP(Rest(R), Rest(S)) + dist_E RP(r_1, s_1), & \\ \qquad ERP(Rest(R), S) + dist_{ERP}(r_1, gap), & \text{otherwise} \\ \qquad ERP(R, Rest(S)) + dist_{ERP}(s_1, gap)\} & \end{cases}$$

$$dist_E RP(r_i, s_i) = \begin{cases} |r_i - s_i| & \text{if } r_i, s_i \text{not gaps} \\ |r_i - g| & \text{if } s_i \text{is a gap} \\ |s_i - g| & \text{if } r_i \text{is a gap} \end{cases}$$

This measure borrows ideas from the domain of strings. Two strings are aligned so that they become identical with the smallest number of added, deleted or changed symbols.

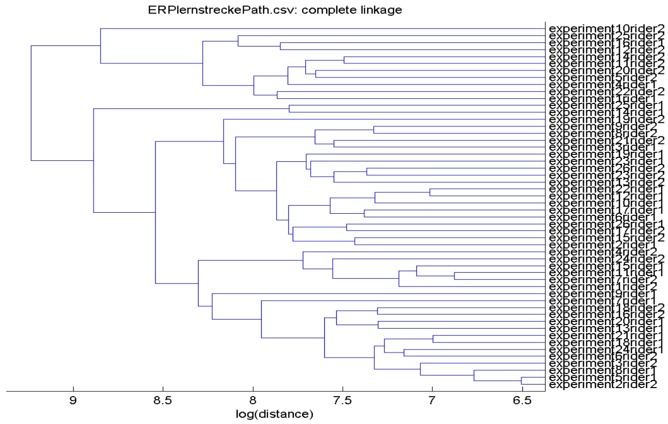


Fig. 3: A dendrogram created from hierarchical clustering, with ERP as similarity measure for the path series on "learning track"

3 Results and Discussion

3.1 Comparison between classification by hand and classification with time series

As described in the introduction, the goal is to create artifical agents which can be substituted human MWI. Those artifical agents should show characteristic human driving behavior.

The ERP similarity measure is used to compare the human and agent behavior. We looked to confirm the hypothesis that MWI in the same classification, which was done by hand, are more similar to each other by the ERP similarity measure. In the first approach, the MWIs were compared using ERP by tracks were they have interacted separatledly with SAM (track 1-4). The classification by hand was done by another track (track 7) where steering were done cooperatively. The tracks 1-4 were used since there was no interdependence between the drivers just that their characteristic behavior could be observed more clearly. As a negativ result, the MWIs in one of the classes found by hand did not show more ERP similarity than the others. The question stands, if other results could be achieved by comparing the same tracks.

3.2 Artifical agents first results

We decided to use P-controller for our agents because of its simplicity. We want to start from a simple and easy to understand agent and add more complex concepts step by step. Ehlert et. al. [7] shows that with a reactive agent and simple rules it is possible to create human-like driving behavior.

P-controller, or proportional controller, is well know as a control system and can mathematically described.[8]

$a_t = K_p(y_t - x_t)$

- a_t is the resulting controller signal
- K_p is the propotional gain
- y_t is the desired position of the vehicle at time t
- x_t is the actual position at time t

In general, the agent behavior can be called seeking behavior, since it tries to reach a desired point, in this case, the middle of the street. We take the difference from the actual position of the vehicle to the desired position as input for a p-controller. So we get the following equation:

$$steering = K_{p_s} * (position_{desired} - position_{current})$$
$$acceleration = K_{p_a} * (1024 - 2 * |steering|)$$

Both functions have a value range from -1024 till 1024. We tested two different value pairs.

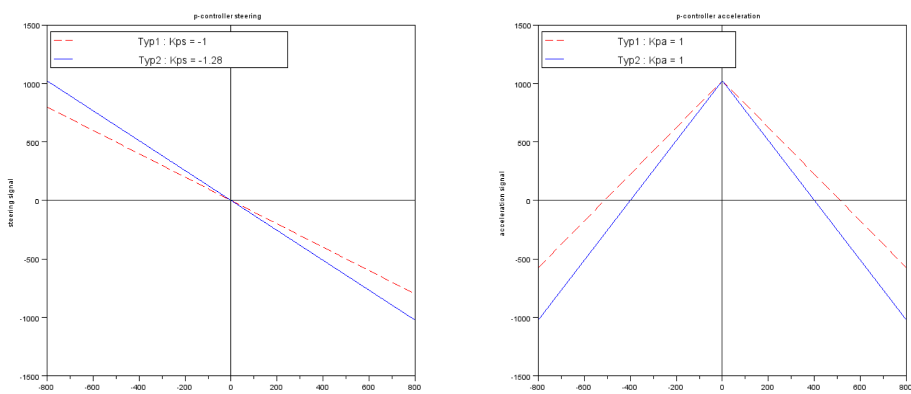


Fig. 4: steering P-controller (left) and acceleration P-controller (right)

Fig. 4 shows the P-controller function for both Typs, Typ1 ($Kps = -1, Kpa = 1$) and Typ2 ($Kps = -1.28, Kpa = 1$). For the steering P-controller deviation (x-axes) was printed against the steering (y-axes) and for the acceleration P-controller deviation (x-axes) was printed against acceleration (y-axes).

We calculated the ERP distances for those two artificial agents compared to the human MWI. As result we got that the ERP distance of the artificial agents to any of the human MWI is greater then 18000. For example the greatest distance between two human MWI is 10237 (between Experiment 10 Rider 2 and Experiment 25 Rider 2). This means that the human MWI are far away from P-controller.

3.3 Future work

In this paper, we presented the first attempts to create artifical agents which show human-like driving behavior. To compare the performances, we used the ERP similarity measure. In the end, we showed a first result for the artificial agents compared to human MWI. To improve the performance of the artificial agents foresight will be used. In this way, we come from a pure reactive agent to more deliberative agent. A further point is the step from P-controller to PID-controller. We will add more parameters which have to be tuned, but in the end we should get a more human like steering behavior and more parameters to create different navigation behavior. With human-like we mean a lower ERP similarity value. Further work is necessary for the usage of time series for analysis.

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