A Contribution to Integrated Driver Modeling: A Coherent Framework for Modeling Both Non-routine and Routine Elements of the Driving Task

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Abstract. This paper is concerned with computational driver modeling, whereby a particular focus is placed on mapping both non-routine and routine elements of the driving task in a theoretically coherent framework. The approach is based on Salvucci's [1] driver model and thus, the cognitive architecture ACT-R [2] is used for modeling non-routine matters; for routine activities, such as the longitudinal and the lateral control of the vehicle, a fuzzy logic approach is suggested. In order to demonstrate the applicability of this procedure, an empirical evaluation study is carried out and the steering behavior of a computational driver model is compared to that of human drivers.

Keywords: Fuzzy logic, cognitive architecture, ACT-R, driver modeling.

1 Introduction

During the last years a lot of research has been put into providing computational models of how humans drive a car. Usually these simulations are based on psychological principles and most of them are able to emulate certain aspects of the driving behavior in real-time (for a review see [3]). This research is not only useful for gaining a better understanding of how humans execute a rather common everyday task, but it is also helpful for improving current interfaces [1]: Within the context of usability studies, a computational driver model may be used as a rapid prototyping tool, which replaces human subjects in order to facilitate the evaluation process. Nevertheless, this information is helpful for predicting the intentions of drivers in order to design advanced driver assistance systems (e.g. lane-change detection).

Although driving a car is a quite common task, it turns out to be rather complex when breaking it down into its subcomponents in order to model the underlying psychological processes. Such, for instance, the following issues are to be addressed [4]: How do drivers allocate their limited attentional resources? How do they acquire situation awareness? To consider these topics, both a strong psychological theory and a programming environment are needed. For higher-level, *executive* processes such a framework is provided by a cognitive architecture. However, much of what we do

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when driving is a lower-level, *automated* skill, and hence may not be modeled within a cognitive architecture.

To make this distinction between executive and automated processes is common practice: Executive processing "is characterized as a slow, generally serial, effortful, capacity-limited, subject-regulated processing model that must be used to deal with novel or inconsistent information" [5, p. 2]. In contrast to this, the automatic mode is described as "a fast, parallel, fairly effortless process that (…) is not under direct subject control, and is responsible for the performance of well-developed skilled behaviors" [5, p. 1]. In the context of car driving there are some aspects, like navigation or route planning, which afford executive reasoning. Just the same there are also some automated skills, such as gear shifting or steering.

Although this separation between executive and automated activities is sensible, it must not be forgotten that both occur in one task simultaneously. Groeger [4, p. 65] assumes "that what we are observing (…) is the product of a *single continuum of control*, rather than separate control systems, separately involved in routine and non-routine activities". On this account a modeling approach is needed that is not only able to map these two distinct processes, but that is also able to integrate them into one coherent framework.

The reminder of the article is organized as follows: First an approach of integrated driver modeling is presented which is based on a cognitive architecture (Sec. 2). While this approach seems to be suited for modeling executive processes, it is suggested to improve the modeling of automated tasks by relying on fuzzy logic (Sec. 3). In order to demonstrate the applicability of this procedure, a fuzzy controller is realized, which models the steering behavior (Sec. 4). This controller is implemented in a driver model and compared to human data (Sec. 5); its outcome and issues for further research are discussed at the end (Sec. 6).

2 Integrated Driver Modeling

Due to the complexity of the driving task, Salvucci [1] suggested an integrated approach, in which the cognitive sub-tasks (e.g. plan to overtake, remember a vehicle in the blind spot) are modeled within a cognitive architecture (Sec. 2.1), whereas the automated sub-tasks (e.g. steer around a curve, follow a lead vehicle) are modeled by further theoretical assumptions (Sec. 2.2).

2.1 Modeling Non-routine, Executive Activities

A cognitive architecture is both a theory of human information processing and a computational framework for simulating human behavior. Here the architecture Adaptive Control of Thought – Rational (ACT-R) [2] is used; its main components are modules, buffers, and a pattern matcher (Fig. 1):

The architecture consists of perceptual-motor modules and memory modules. The first group of modules is concerned with the interface with the real world; there are visual, auditive, speech or motor modules. In addition, there are two kinds of memory modules; the declarative memory consists of factual knowledge (e.g. a red traffic light indicates to stop) and the procedural memory represents knowledge about how we do things (e.g. if you plan to overtake, then you have to accelerate).

The modules, except for the procedural memory, are accessed through buffers, and for each module, a dedicated buffer serves as the interface with that module. Although the processes within different modules can go in parallel, there is a serial bottleneck that corresponds to human limitations: The content of any buffer is limited to a single declarative unit of knowledge. Thus, only a single memory can be retrieved or a single perceptual object can be encoded at a time.

Additionally, there is a pattern matcher, which searches the procedural memory for a production rule that fits to the current contents of the buffers. Again there is a serial bottleneck, which is reasonable from a theoretical point of view: Only one such production can be selected at a given moment. That production, when executed, can modify the buffers and thereby change the state of the system. Thus, in ACT-R cognitive processing is characterized as a successive firing of productions.

Although only one production can be fired at a certain point in time, there may be several rules that match the state of the buffers (e.g. if there is a slower lead vehicle, then you have to brake / to overtake). For this reason, there is also a conflict resolution mechanism: the utility associated with each production is estimated by a sub-symbolic equation and only the production with the highest utility is selected for execution. To conclude, ACT-R is a hybrid architecture, which consists both of a symbolic production system and a sub-symbolic part. It includes various well-tested assumptions on human information processing and it has been used successfully in numerous domains.

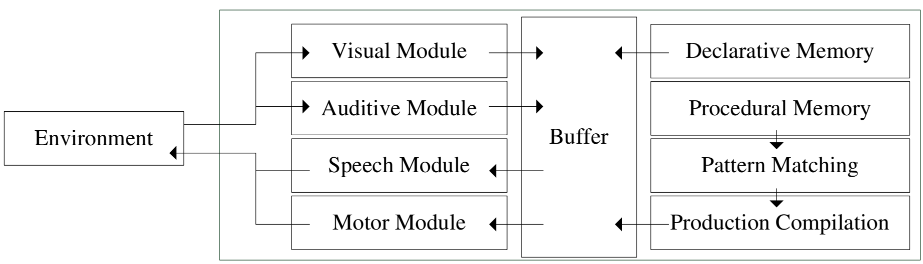

Fig. 1. The cognitive architecture Adaptive Control of Thought – Rational (ACT-R 6.0) [2]

As Salvucci's [1] driver model relies on this framework, too, it inherits the architecture's view on cognition. In addition, it makes further assumptions on the domain of driving, which become obvious when taking a look at how the model's control flow is defined or what production rules are used. Thus, for instance, the model states which information is needed for controlling a vehicle as it indicates where to allocate the attention and which objects to encode. Just the same, it specifies how a highway traffic environment is monitored in order to gain situation awareness, or how decisions, such as initiating a lane change, are drawn. As this article focuses mainly on the overall consistency of the modeling approach, these domain specific assumptions are not addressed in detail here.

2.2 Modeling Routine, Automated Activities

Salvucci's [1] model does not only consider executive tasks, but it accounts also for automated aspects of driving. In a highway environment most routine activities occur for the lateral (i.e. steering) and longitudinal control (i.e. accelerating, braking).

For modeling these activities Salvucci and Gray [6] suggest a closed-loop control approach is suggested, which is derived from a standard proportional integral, or PI, controller: While the lateral control law relies on the perceived visual direction of two salient points on the road, the longitudinal control law uses the time headway to a lead vehicle. As a subsequent motor execution of control, the vehicle's steering angle is adjusted (lateral control), and a depression of the accelerator or the brake pedal (longitudinal control) occurs.

As the automated activities are part of a larger driving task, the control laws have to be integrated into the cognitive architecture. Due to ACT-R's serial cognitive processor a discrete formulation of both control laws is needed. This is convenient from a computational point of view, but it has theoretical implications also: First, it matches the assumptions that humans operate on a discrete "clock" with a cycle time of 50 ms [2]. Second, the discrete form works with an irregular updating frequency; it is thus suited to cope with distraction or inattention while driving. Although this model has yielded good results in validation studies [1], some issues still have to be discussed:

Vagueness of perception. The modeling strategy is based on the assumption that drivers rely on exact values, such as the visual angle to salient road points or the time headway to a lead vehicle. In contrast to this, it is much more likely to assume that people rely on broader categories in which several instances are summarized. For example, when cruising on a highway it tends to be the overall belief of being too close to a lead vehicle that lets us brake rather than the observation that our distance has dropped below "20 m".

Coherent modeling framework. Groeger [4, p. 74] supposes that "conscious control (…) along with well practiced routines, is part of a single control architecture". However, in Salvucci's [1] model the automated elements seem to be "outsourced" of the cognitive architecture rather than being part of a coherent framework.

This becomes obvious when taking a look at how automaticity develops. According to Fitts [7] there are three stages in the acquisition of skills: The initial, *cognitive,* stage is seen as tightly linked to verbal descriptions. For instance, driving instructors usually provide some rules when explaining to a learner when to change gears. A common characteristic for the second, *associative,* stage is that verbal mediation is reduced. The final stage is *automatic* and verbalization is no longer needed nor possible. Salvucci's approach maps the initial stage with the cognitive architecture and the last stage with the control laws, but it is not obvious that these stages are part of one task.

3 Fuzzy Logic for Modeling Automated Activities

In order to overcome some of the problems mentioned above, an alternative approach, based on fuzzy logic, is suggested. After a brief introduction to fuzzy control

(Sec. 3.1) it is argued why this is suited to span a coherent modeling framework together with a cognitive architecture (Sec. 3.2).

3.1 Fuzzy Logic and Fuzzy Control

According to [8] the parallel processing of automated activities affords that different rules are evaluated at the same time and that their outputs are merged. Whenever more than one rule is applied at a certain moment, it is possible that the conditional parts of the rules are only partly met. The problem of combining rules, which apply to a certain context only to some degree, can be modeled by fuzzy logic:

Fuzzy logic was introduced by Zadeh [9] and it allows a mathematical representation of vagueness. Within classic set theory one element is either part of a given set or it is not part of it. In contrast, in fuzzy logic the membership of one element to a certain set is considered as a matter of degree. A fuzzy set A is specified by a membership function m_A defined on the universe of discourse X, commonly containing values in the interval from 0 to 1 (normalized). For control applications, for instance, X may be defined as the error value of the control problem, which has the linguistic meaning "error". If X is divided into various fuzzy sets, then there is a linguistic term that may be assigned to each single set and that describes the meaning of the specific values of the set in natural language. Thus, for instance, "large" may refer to a fuzzy set with large values of X.

Usually logic operations on fuzzy sets are carried out by relying on so called T-norms and T-conorms [10]. For the intersection (i.e. logical *and*) the minimum operator is commonly used, while for the union (i.e. logical *or*) the maximum is typically applied. Thereby, due to the loss of information, the product-operator is often preferred to the minimum [10]. By relying on such operators the *if*-condition of a rule can be expressed in a fuzzy way. In order to map a complete *if-then* rule a further operator is needed. For this purpose either the minimum or the product is suggested, whereby the membership function will be truncated when the first one is applied, whereas it will be scaled when the latter is used. Therefore, fuzzy logic allows to express and to conduct logical *if-then* statements with both the antecedents and the consequence being fuzzy.

The linguistic terms associated with each fuzzy set provides the opportunity to translate expert knowledge, stated in natural language, into a mathematic representation. According to this idea, Mamdani [11] suggested to use fuzzy logic for control applications. Since then fuzzy-controllers are commonly used in a wide field of technical applications [12]. The core element of such a fuzzy controller is the knowledge base, which consists of a rule base and a data base. The rule base contains a set of *if-then* rules as described above. The data base holds the membership functions of the fuzzy sets belonging to each linguistic variable that is used for the control problem. For a given input all rules, contained in the rule base, are evaluated individually. To be useful for control tasks, all individual fuzzy outputs have to be merged and a crisp value for the output has to be derived; these steps are labeled as aggregation and defuzzification, respectively (Sec. 4.1; [14]).

3.2 Fuzzy Logic and Cognitive Modeling

Against the background of this work the fuzzy approach is sensible for two reasons:

Vagueness of perception. In contrast to Salvucci's [6] approach, which relies on crisp input values, fuzzy logic is more in line with the human tendency of representing perceptual input in broader and vague categories in order to cope with the complexity of the environment. Thus, instead of braking because the time headway to a lead vehicle has fallen below a certain value, it is more likely to assume that this maneuver is initiated by reasoning of being "too close".

Coherent modeling framework. From a formal point of view fuzzy control is also more equivalent to a cognitive architecture than is common control theory. The idea of splitting the controller into a rule and a data base corresponds to the way of how knowledge is implemented in ACT-R, namely as procedural and declarative memory. Thus, the conjoint use of both approaches accounts to Groeger's [4, p. 74] and Fitts' [7] demand for processing both tasks in a single architecture. There is also a major difference that is essential from a theoretical point of view: Whereas rules are processed in a parallel manner by a fuzzy controller, these are processed serially by ACT-R (i.e. firing of one production at one point in time). The fuzzy approach is suited to map the automatic processing of routine activities, whereas ACT-R models are able to describe the executive processing of non-routine activities.

4 Implementation of a Fuzzy Controller in a Driver Model

To demonstrate that the fuzzy approach is of practical value also, both the structure and the configuration of such a controller (Sec. 4.1) are presented (for more details see [13]). As the controller consists of numerous parameters human data were recorded (Sec. 4.2) and optimal parameter values were derived empirically (Sec. 4.3).

4.1 Structure and Configuration of the Controller

According to [6], humans rely on the visual information of two points when steering a vehicle, a near point and a far point. Corresponding to these two sources of information, the controller consists of two PD like rule bases.

The inputs are the angles between the car heading and the near point or the far point, respectively, and their derivations. The output is the change of the steering angle. Each input dimension was partitioned into seven fuzzy sets that are arranged symmetrically around zero, using triangular membership functions and trapezoidal ones for the borders [10]. The support of the functions varied in size, being small around zero and larger in the extremes. In consequence, for small deviations from the set point more rules apply and thus a more differentiated response can be provided to these more frequent events. The input membership functions of two adjacent fuzzy sets were chosen to cross at a level of 0.5 as this has generally turned out to be optimal in terms of rise time and over/undershoot behavior of the controller [15]. For the outputs the same strategy was applied, but here only triangular membership functions were used. Due to the fixed cross-point level and the symmetry around zero, it is possible to limit the description of the seven output sets of each rule base to four parameters. These parameters are obtained by fitting the controller to empirical data obtained in an experiment via an optimization procedure (Sec. 4.3); the overall structure of the controller is summarized by figure 2.

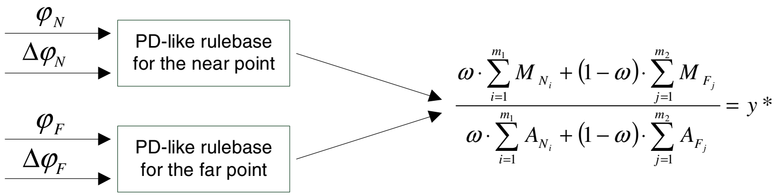

Fig. 2. Structure of the fuzzy controller with two independent rule bases and the center-of-sums method for defuzzification; *M* denotes the moments and *A* indicates the areas of the scaled output membership functions (N for near-, F for far-point)

Aggregating the individual rule outputs to a total output can be a rather complex and time consuming step. Therefore, defuzzification procedures are proposed, which skip the step of aggregation and rely directly on the individual outputs; within this work the center-of-sums method [14] [16] is used. Thereby, the crisp output is derived by dividing the sum of the (weighted) moments through the sum of the (weighted) areas[1] of the scaled output membership functions. As can be seen in figure 2, all rule outputs referring to one source of information (i.e. near or far point) were weighted equally. Due to the lack of prior knowledge, it is assumed that information from the near and the far contribute in equal parts, therefore ω was set to *0.5*.

4.2 Experimental Setup and Training Sample

In order to achieve a human-like behavior of the controller, empirical data were collected. Twelve human drivers were instructed to cover a round course in a driving simulation, based on the Microsoft XNA racing game and displayed in a VisionDome V4 (Elumens Corp.). The speed was set constant, thus the subjects only had to control the simulation via a steering wheel. Their driving behavior was logged and the variables of interest were computed. These were the current far and near point for every logging (as defined by [6]), the angles between the vectors from the car to these points, and the car heading, as well as the time discrete derivative of these angles. From each person's data set, a random sample of 1000 points was extracted, which together comprised the training sample.

4.3 Optimization of the Controller via Sequential Quadratic Programming

On the basis of this training set, the optimal values for eight parameters (Sec. 4.1) are to be derived. These parameters are restricted to be larger than zero. Because of the nonlinear behavior of a fuzzy-controller and the constrained optimization problem, sequential quadratic programming with active sets and default parameters was chosen

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[1] The area of a fuzzy-set on X is defined as $A = \int m(x)\, dx$ and the moment as $M = \int x\, m(x)\, dx$.

as optimization algorithm [17]. As error function, the sum of the squared deviation of the controller output and the values of the training sample was taken. Due to the problem that an optimization with specific starting values might fail to find the global minimum and instead end in a local one, the procedure was repeated 100 times with randomly drawn starting values. Finally, the parameter set with the minimal deviation from the training sample was applied.

5 Evaluation Study

In order to test the optimized controller an evaluation study was carried out. As it was done with the training sample, twelve participants were instructed to drive in the middle of a three-lane circuit in a smooth way. The same track was covered twelve times by the driver model. To challenge the robustness of the controller, a different track (Fig. 3) was used this time.

Two segments were analyzed in more detail, a curved and a rather straight one. For both segments two steering parameters were derived: To asses the accuracy of keeping the instructed course, the mean of the absolute deviation from the middle lane was computed. For quantifying the degree of flickering, the absolute heading errors (i.e. deviation of car and road heading) were assessed. The outcome of the study is presented (Sec. 5.1) and discussed (Sec. 5.2) below.

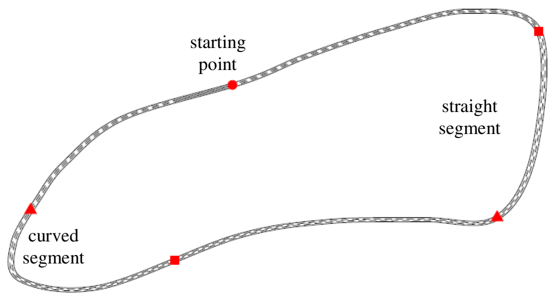

Fig. 3. Top view on the test track with a curved and a straight road segment

When comparing the steering behavior of the human participants to that of the computational driver model, one immediately notices two things: First, the driver model manages to remain within the middle lane as instructed, but by doing so it reveals a rather “sporting” driving style with a tendency to cut the corners. Thus, the mean deviation from the middle is $m_C = 0.71$ m on the curved segment, while it accounts for $m_S = 0.55$ m on the straight segment. In contrast to this, the human drivers deviate far less and their mean values account for $m_C = -0.04$ m and $m_S = 0.13$ m, respectively. Second, it seems that the driver model has to steer more often on straight segments compared to the human participants in order to remain stable; it appears to be more “nervous”.

For a more systematic analysis, an ANOVA for repeated measurement was carried out. As between-subjects factor, the data of the human participants were compared to that of the driver model and for both groups the two road segments were contrasted;

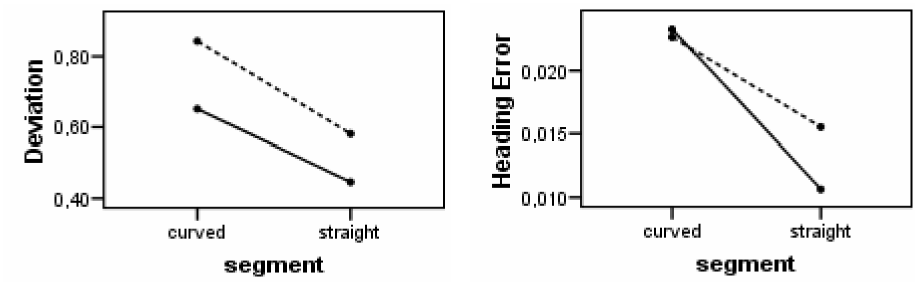

Fig. 4. Mean absolute deviation in meters (left) and mean absolute heading error in radian (right) for the human participants (continuous line) and the computational driver model (dashed line) as well as for two distinct road segments

as dependent variables both the mean absolute deviance (Fig. 4 left) and the mean absolute heading error (Fig. 4 right) were considered. Since the data are not normally distributed, they were Box-Cox transformed before being analyzed [18]. Significance values are reported based on the transformed data, whereas means and mean differences are derived from the original data set in order to facilitate interpretability:

For the mean absolute deviance the between-subjects factor was significant with $p = .007$ ($F_{(1, 22)} = 8.70$), whereby it was 0.2 m less for the human drivers than it was for the driver model. The within-subjects factor was also significant, whereby the mean deviation for the straight segment was reduced by 0.23 m ($p < .000$, $F_{(1, 22)} = 61.84$). The interaction was not significant with $p = .34$ ($F_{(1, 22)} = 0.94$).

The mean heading errors of the computational driver model were also significantly larger with an estimated difference of 0.002 rad, compared to the heading errors of the human drivers ($p = .004$, $F(1, 22) = 10.43$). The straight segment of the track also led to a reduced heading error, with a mean difference of 0.01 rad when compared to the curve ($p < .001$, $F(1, 22) = 57.67$). The interaction was also significant with $p = .007$ ($F(1, 22) = 8.91$).

6 Discussion

To summarize, the driver model was able to cope with the simulated driving task. Thus, enhancing a cognitive architecture, such as ACT-R, with a fuzzy approach is not only sensible from a theoretical point of view but it is also feasible. Three issues need to be addressed in future research: For one, due to the lack of prior knowledge, the two sources of information (i.e. near and far point) were weighted the same, with $\omega = 0.5$. By increasing ω a more centered position in curved segments may be achieved. This parameter may serve to shift the driving style from a “sporting” to a rather “comfortable” manner. However, despite the better fit between the hum an drivers and the computational model, this should not be done without relying on more empirical data or a sound theoretical basis. Second, Wilkie and colleagues [19] assume that different people also choose different strategies for acquiring far point information. In the case that not all drivers may refer to the tangential point when steering around a curve, a more centered driving behavior would occur, especially in sharp curves. Finally it has to be discussed whether the lateral road position has to be varied when running the model repeatedly, so as to produce a similar variance over the trials as shown by the study's participants.

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References

1. Salvucci, D.D.: Modeling driver behavior in a cognitive architecture. Human Factors 48, 362–380 (2006)
2. Anderson, J.R., et al.: An integrated theory of the mind. Psychological Review 111, 1036–1060 (2004)
3. Cacciabue, P.C.: Modelling Driver Behaviour in Automotive Environments. Springer, Heidelberg (2007)
4. Groeger, J.A.: Understanding Driving. Taylor & Francis, Philadelphia (2001)
5. Schneider, W., et al.: Automatic and controlled processing and attention. In: Parasuraman, R., Davies, D.R. (eds.) Varieties of attention, pp. 1–27. Academic Press, Orlando (1984)
6. Salvucci, D.D., et al.: A two-point visual control model of steering. Perception 33, 1233–1248 (2004)
7. Fitts, P.M.: Factors in complex skill training. In: Glaser, R. (ed.) Training research and education, pp. 177–197. Pittsburgh Univ. Press, Pittsburgh (1962)
8. Neisser, U.: The multiplicity of thought. British Journal of Psychology 54, 1–14 (1963)
9. Zadeh, L.A.: Fuzzy sets. Information and Control 8, 338–353 (1965)
10. Bandemer, H., et al.: Einführung in Fuzzy-Methoden. Theorie und Anwendungen unscharfer Mengen. Akademie-Verlag, Berlin (1990)
11. Mamdani, E.H.: Application of fuzzy algorithms for the control of a simple dynamic plant. In: Proc. IEEE, pp. 1585–1588. IEEE Press, New York (1974)
12. Seising, R.: The Fuzzification of Systems: The Genesis of Fuzzy Set Theory and its Initial Applications - Developments up to the 1970s. Springer, Heidelberg (2007)
13. Mihalyi, A.: Implementierung einer Fuzzy-Regelung in eine kognitive Architektur. Master Thesis. Ludwig-Maximilians-Universität, München (2008)
14. Driankov, D., et al.: An introduction to fuzzy control. Springer, Heidelberg (1996)
15. Boverie, S., et al.: Fuzzy logic control compared with other automatic control approaches. In: Proc. IEEE, pp. 1212–1216 (1991)
16. Leekwijck, W., et al.: Defuzzification: Criteria and classification. Fuzzy Sets and Systems 179, 159–178 (1999)
17. MatLab Optimization Toolbox 4, `http://www.mathworks.com`
18. Box, G.E.P., Cox, D.R.: An analysis of transformations. Journal of the Royal Statistical Society, B 26, 211–234 (1964)
19. Wilkie, R., et al.: Controlling Steering and Judging Heading. JEP: HPP 29, 363–378 (2003)