Adaptive Negotiation Model for Human-Machine Interaction on Decision Level

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Abstract: Our work is a contribution to automation design for human-machine cooperation with explicit emancipated cooperative decision making. We propose an adaptive negotiation framework as a model for human-machine interaction on decision level. This expands modeling of human-machine cooperation, starting at the stabilization and trajectory level with approaches such as shared control, towards higher levels of interaction as guidance and navigation. In essence, the framework extends the well-known basic negotiation model of multi-agent systems by an explicit adaptation of the agent's negotiation behavior. The adaptation is based on an opponent model using a Bayesian learning approach. An exemplary implementation for the application of human-automation interaction in autonomous driving is introduced. First results prove the high flexibility of the framework to model human negotiation behavior.

Keywords: human-machine cooperation, cooperative decision making, negotiation theory, opponent modeling, adaptation, autonomous driving

1. INTRODUCTION

Human-machine cooperation has been studied extensively over the past decades, resulting in a wide range of models, automation design approaches and applications (Flemisch et al., 2016; Della Penna et al., 2010; Mortl et al., 2012; Flad et al., 2014). One major class of approaches is haptic shared control. These approaches often aim at identifying the goal of the human and support his actions towards this goal while working towards secondary objectives, cf. Della Penna et al. (2010) and Mortl et al. (2012). Other approaches consider the automation as an emancipated partner, e. g. whenever a differential game is applied to model the human-machine cooperation, cf. Flad et al. (2014), and assume a common goal or reference trajectory. Furthermore, all of these models consider interactions that incorporate a haptic component and take place via some object, e. g. a table (Mortl et al., 2012), or some system interface, e. g. the steering wheel of a car (Flad et al., 2014) or an active joystick (Oguz et al., 2012).

In summary, these approaches tackle assistance design and cooperation modeling on the stabilization layer of human behavior, see Fig. 1. However, a higher degree of automation leads to a different kind of human-machine interaction on decision level (Flemisch et al., 2016). This pushes the development of automation designs for cooperation into the guidance and navigation layer. One aspect of cooperation on higher levels is cooperative decision making. Usually, the master-slave principle with the human ultimately in the lead is applied, cf. Mortl et al. (2012). However, with an increasing reliability of sensors and automated systems in general, it is beneficial to design the automation intrinsically as an equal partner to the human in order to achieve an emancipated cooperative decision making process. As an example for the need of emancipated automation design, consider RADAR sensors and the networking of cars that yield higher insights in long-range traffic situations that are incomprehensible for humans. Another example are infrared sensors that may provide vital environmental data for firemen operating in exoskeletons. In both cases, the information obtained by the automation adds real value to human decision making.

Consequently, the aim of this work is to provide an intuitive interface for human interaction with such elaborate systems on decision level. In contrast to simply presenting all available information to the human, an intuitive interface avoids a potential mental overload within the human (Landau, 2002). Hence, the automation must present condensed and interpreted information to the human while taking part in the cooperative decision making process.
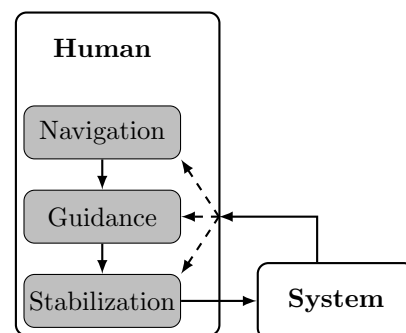

Fig. 1. Three human behavioral layers introduced by Donges (1999)

Furthermore, our systems design is inspired by human-human cooperative decision making. This is motivated by our preliminary work that found high agreement rates among humans in cooperative decision making (Rothfuss et al., 2018) and studies on stabilization level that indicate potentially high acceptance rates in case of equal modeling of human and automation (Groten et al., 2013).

In summary, the proposed approach includes an inherent emancipated modeling of the cooperative decision making situation between human and automation that is close to a human-human decision making setting. Similar to the stabilization layer, the approach on decision level has to consider challenges that come with human-machine interaction which are explained in the following.

1.1 Challenges of Human-Machine Interaction

The automation design for an emancipated human-machine cooperation offers a variety of challenges:

- the choice of the appropriate theory for modeling emancipated partners
- the model has to adequately describe human interaction capabilities, i. e. interaction based on discrete events at random times, cf. Mell and Gratch (2017)
- the design of identification methods due to the expected small number of exchanges with few communication symbols until an agreement is reached, resulting in potentially insufficient information gain for behavior identification, i. e. model fitting
- modeling of human reflection and adaptation techniques to change decision making behavior, cf. Vahidov et al. (2014)

In our approach we tackle all of these challenges and adapt state-of-the-art approaches to better suit human behavior in cooperative decision making.

1.2 State-of-the-art Approaches

The two major theories that provide models for cooperative decision making are negotiation theory (e. g. Baarslag et al. (2015)) and game theory (e. g. (Altendorf and Flemisch, 2014)). In this paper we focus on negotiation theory due to its explicit form of interaction modeling.

There are several active negotiation models available for multi-agent systems with autonomous agents. Examples are collision avoidance for airplanes (Sislak et al., 2011) and vessels (Yang et al., 2007). Similarly, some models are available for human-machine negotiation, e. g. the postmen problem (Zlotkin and Rosenschein, 1989) and the buyer-seller scenario (Vahidov et al., 2014).

However, these models are unsuitable for the targeted form of human-machine interaction and resulting challenges given in Section 1.1. Reasons are mainly the models' assumption of a high rate of communication and the lack of an explicit adaptation mechanism. Therefore we introduced in previous work a new negotiation model in the context of driving assistance (Rothfuss et al., 2019). It contains both an asynchronous communication protocol to suit the discrete event character of human action and communication as well as an opponent model to draw advantage from deeper insights into the opponent's reasoning. However, the identification model is underperforming in case of limited communication.

1.3 Contribution

In this paper we propose a generalized framework for cooperative decision making in human-machine interaction that incorporates the event-based negotiation model of Rothfuss et al. (2019) and an identification approach for identifying opponent's behavior. The new framework also allows a generalized, explicit strategy for adaptation of negotiation tactics. In addition, the paper provides an application of the introduced framework to the context of autonomous driving and simulation results that show the ability of the framework to cope with the challenges of cooperative decision making involving humans.

The autonomous driving scenario is an exemplary scenario for demonstrating the adaptive negotiation framework. More complex driving situations and other human-machine negotiation scenarios, e. g. in robotics, are also in the scope of the proposed framework.

The remainder of this paper is structured as follows: Section 2 introduces the adaptive negotiation framework and its exemplary application to autonomous driving. This is followed by some simulation results of an exemplary negotiation setting in Section 3 and the conclusion in Section 4.

2. ADAPTIVE NEGOTIATION FRAMEWORK

The following section introduces the adaptive negotiation framework based on the negotiation model introduced by Rothfuss et al. (2019). That model is now enhanced by an suitable opponent model based on Bayesian Learning and the generalized adaptation concept. For a more conclusive view on the framework, the general description is presented alongside an exemplary application to a scenario in the context of autonomous driving.

2.1 Framework Overview

Fig. 2 gives an overview of the introduced framework and the interaction between its components. The objective of this framework is to model a single-issue human-machine
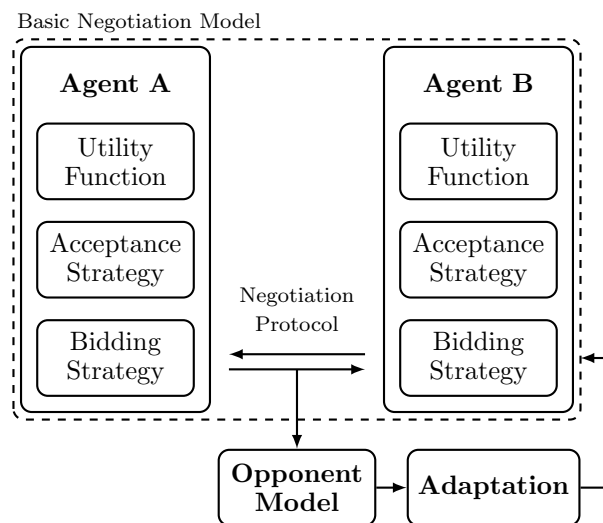

Fig. 2. Overview of the adaptive negotiation framework

negotiation over a set of decision options $\mathcal{D}$ by exchanging offers o^ν among participating agents $i \in \{A, B\}$ (automation & human) at time ν. Within the basic negotiation model, agents interact according to the negotiation protocol, evaluate offers by means of an individual utility function and accept or generate offers via acceptance and bidding strategies. Through an opponent model and the explicit adaptation component, agents are able to adapt their negotiation behavior w.r.t. the previously observed behavior of their opponent. In order to give a detailed explanation of the framework's components alongside the implementation, we first introduce the exemplary application scenario.

2.2 Exemplary Driving Scenario

The exemplary application scenario is set in the context of autonomous driving. Hence, we assume a fully autonomous vehicle. However, the human driver is able to interact with the vehicle via a maneuver interface, e.g. a touch pad, that allows intuitive changes of the vehicle's path by cooperative deciding on an appropriate driving maneuver. The aim of this form of interaction is to add value to the overall outcome of the driving task in terms of human comfort and acceptance. In this setting, both agents, driver and vehicle, are emancipated, i.e. there is no hierarchy, w.r.t. cooperative decision making which is modeled by the adaptive negotiation framework.

The exemplary road scenario is a Manhattan grid navigation setting depicted in Fig. 3. The aim is to reach the intersection marked with a green dot. At the time of the negotiation the vehicle is traveling along the black solid arrow. At the intersection three decision options d are available for both agents: turn left (d_1), drive straight ahead (d_2) and turn right (d_3). In addition, each decision option can be offered with one of three intensity levels $s_i \in \mathcal{S}$. These levels increase the number of available communication symbols to provide more information about agents' reasoning.

The gray boxes indicate traffic delays. The options d can be rated w.r.t. to the time loss due to a local traffic delay t_l at the current intersection and to the estimated time to reach the target intersection t_g taking into account all relevant traffic delays on the way.

Note, more complex driving situations could be considered by including additional external influences like in a parking lot search situation or a ride-sharing context. Furthermore,

one could think of various other interface designs, allowing for more and complex communication symbols.

The following sections introduce the adaptive negotiation framework alongside its application to this exemplary scenario.

2.3 Basic Negotiation Model

An overview of the reasoning of one agent i in the basic negotiation model is given in Fig. 4. In each cycle of decision making the agent evaluates its own current offer o_i and the opponent's offer $o_{\neg i}$ with its utility function U_i. Then he decides whether the opponent's offer should be accepted or rejected according to its acceptance strategy A. If the opponent's offer is declined, the agent determines a new counter offer in line with his bidding strategy. This offer is presented to the opponent. The next cycle starts according to the chosen interaction protocol.

In a more formal description the basic negotiation model consists of the following parts (Baarslag et al., 2015):

(1) An utility function U for evaluating offers o
$$U : o \rightarrow \mathbb{R}$$
(2) An acceptance strategy A determining whether to accept or decline an opponent's offer $o_{\neg i}$ based on the offer's utility compared to the utility of an own offer o_i
$$A\left(U\left(o_i\right), U\left(o_{\neg i}\right)\right) \rightarrow \text{accept/decline}$$
(3) A bidding strategy for determining a counter offer o_i w.r.t. to a concession strategy C. There are three classes of concession strategies:
   (a) Behavior-based strategies reflecting opponent's behavior, e.g. tit-for-tat
   $$C\left(U, o_{\neg i}\right) \rightarrow o_i$$
   (b) Time-based strategies modeling an increasing concession behavior over time
   $$C\left(U, \nu\right) \rightarrow o_i$$
   (c) Meta strategies combining behavior- and time-based strategies
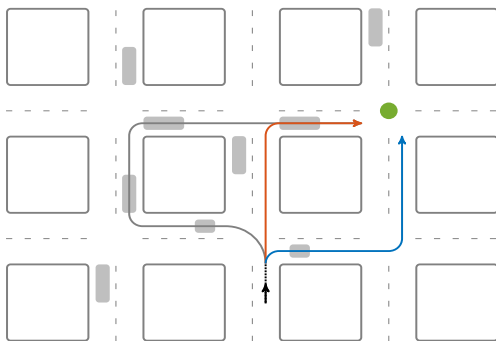 $$C\left(U, o_{\neg i}, \nu\right) \rightarrow o_i$$

Fig. 3. Evaluation scenario with shortest path to goal in blue, path avoiding local delays in orange and longest path with short local delay in gray.
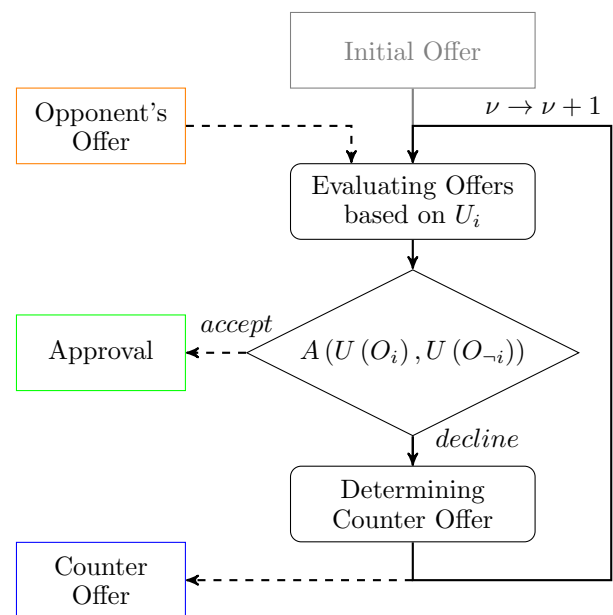

Fig. 4. Overview of reasoning of agent i

(4) A negotiation protocol for the agents. There are three major classes:
   (a) In the simultaneous protocol, agents exchange their offers simultaneously.
   (b) The alternating protocol describes agents placing offers in an alternating sequence.
   (c) The asynchronous protocol, introduced by Rothfuss et al. (2019), enables agents to place offers at random points in time.

Participating agents of one negotiation agree on the same negotiation protocol and are characterized by their structure and parameters of the introduced functions U, A and C. Usually, it is assumed that all agents possess the same function structure and only differ in their parameters θ.

Applying this basic negotiation model to the introduced scenario in Section 2.2 the offer space is defined as

$$\mathcal{O} = \mathcal{D} \times \mathcal{S} = \{d_1, d_2, d_3\} \times \{s_1, s_2, s_3\} \qquad (1)$$

Utility Function In line with state of the art approaches we propose a linear combination of evaluation functions to set up an exemplary utility function for evaluating the decision option d of offer $o = (d, s)$:

$$U_i(d) = w_{g,i} \cdot e_g(d) + w_{l,i} \cdot e_l(d) \qquad (2)$$

with weights $w_{g,i} + w_{l,i} = 1$ and evaluation functions

$$e_g(d) = \frac{\min_{\forall d_i \in \mathcal{D}} t_g(d_i)}{t_g(d)}, \; e_l(d) = 1 - \frac{t_l(d)}{\sum_{\forall d_i \in \mathcal{D}} t_l(d_i)}$$

that also perform a normalization of U. $e_g(d)$ penalizes the time for reaching the target intersection, referred to as the time-to-goal t_g, of a decision option d w.r.t. the fastest alternative. $e_l(d)$ penalizes the local traffic delay t_l of decision option d by comparing it to the sum of all local traffic delays.
The agents were parameterized as follows: Agent A, resembling the automation, focuses on the time to goal whereas Agent B, the human, tries to avoid local traffic delays.

Acceptance Strategy The acceptance strategy A_i of both agents $i \in \{A, B\}$ is set to:

$$A(U(o_i), U(o_{\neg i})) = \begin{cases} \text{accept} & U_i(o_{\neg i}) \geq U_i(o_i) \\ \text{decline} & U_i(o_{\neg i}) < U_i(o_i) \end{cases} \qquad (3)$$

Offers $o_{\neg i}$ are accepted if they yield a higher or equal utility as the own offer o_i, otherwise they are declined.

Bidding Strategy In order to ensure the termination of the negotiation process, we propose a time-based concession strategy. The concession is modeled via a target utility $U_t(t)$ that is decreasing over time:

$$U_{t,i}(\nu) = \max_{d \in \mathcal{D}} U_i(d) \cdot (1 - \nu^{1/\varepsilon_i}) \qquad (4)$$

ε is called the concession rate.
The agent tries to track his target utility with his offers utility values. This tracking is defined in the following two step optimization problem for determining offers o_i of agent i at time instance ν.
First, the optimal direction is determined by

$$d^* = \arg\min_{d \in \tilde{\mathcal{D}}_i} \{U_i(d) - U_{t,i}(\nu)\} \qquad (5)$$

with $\tilde{\mathcal{D}}_i = \{d \in \mathcal{D} : U_i(d) \geq U_{t,i}(\nu)\}$. On this basis and if $|\mathcal{S}| > 1$, the intensity is determined in the second step through

$$s^* = \arg\min_{s \in \mathcal{S}} \{U_i(d^*) - c_i(s) - U_{t,i}(\nu)\}. \qquad (6)$$

$c_i(s)$ models the influence of the intensity value, which gives a measure for the deviation between the utility of the chosen direction $U_i(d)$ and the target utility $U_{t,i}$.

$$c_i(s) = \begin{cases} w_s \cdot \left(1 - \frac{s - \min(\mathcal{S})}{\max(\mathcal{S}) - \min(\mathcal{S})}\right) & \text{if } w_{c,i} = 1 \\ w_s \cdot \left(\frac{s - \min(\mathcal{S})}{\max(\mathcal{S}) - \min(\mathcal{S})}\right) & \text{if } w_{c,i} = -1 \end{cases} \qquad (7)$$

$w_s \in \mathbb{R}$ is a design parameter of the scenario. If $w_{c,i} = 1$ the agent will start with maximum intensity and decrease it in the course of the negotiation, whereas for $w_{c,i} = -1$ the agent will start with small intensities and gradually increase the intensity. Either way, the intensity is a communication parameter that indicates how much an agent clings to the chosen direction, i.e. the effort the agent has to put in to stay with the chosen direction.
The resulting optimal offer at time instance ν is given by: $o_i^\nu = (d^*, s^*)$.

Interaction Protocol Due to the use case of human-machine interaction, we propose to use the asynchronous protocol of Rothfuss et al. (2019) in order to allow for a more appropriate modeling of human event-based communication. The automation is still able to operate at a constant update rate whereas the human is able to communicate at any time.

2.4 Opponent Modeling

In order to influence the outcome of the negotiation, agents may use the information from their opponent's offers to identify an opponent model and apply this information within their bidding strategy. In literature, various opponent models are available (Zeng and Sycara, 1998; Coehoorn and Jennings, 2004; Hindriks and Tykhonov, 2008; Hao and Leung, 2014). Facing the challenge of little communication among automation and human within one round of negotiation, we propose to apply an opponent model that is able to identify human behavior over several rounds. One possible method of opponent modeling is the Bayesian learning approach (Hindriks and Tykhonov, 2008).
Bayesian learning requires some assumptions about the opponent's strategy. In our approach we assume that the agents follow the same basic negotiation model and only differ in their parameters of utility, concession and acceptance functions. Upon this assumption and observed opponent's offers, Bayesian learning identifies the unknown parameters θ of the opponent's utility function and bidding strategy. In a first step, n_h combinations of parameters θ are set up as hypotheses h_j, $j \in [1, n_h] \subset \mathbb{N}$. Then, based on the usually small number of observed opponent's offers $o_{\neg i}$, the likelihood of parameter hypotheses $P(h_j)$ is updated by means of Bayes' rule

$$P(h_j | o_{\neg i}) = \frac{P(o_{\neg i} | h_j) P(h_j)}{P(o_{\neg i})}. \qquad (8)$$

For all j the probabilities $P(h_j)$ are initialized with a uniform distribution. To avoid the persistent exclusion of hypotheses with $P(h_j) = 0$ in a changing behavior setting, hypothesis probabilities are reinitialized at the beginning of each new round of identification by adding a small offset c followed by normalization. The offset c is set w.r.t. the

application, in our case $c = 0.001$.

The current estimate of the opponent's parameters in step ν can be determined as the expected value of θ w.r.t. to all h_j.

In a practical application the hypotheses for Bayesian learning can be set up via a discretization of the assumed range of opponent's parameters of utility function and bidding strategy w_g, w_c, ε. This leads to a set of hypotheses

$$
\begin{aligned}
\mathcal{H} &= \mathcal{W}_g \times \mathcal{W}_c \times \mathcal{E} \\
&= \{w_g^1, ..., w_g^{n_{w_g}}\} \times \{w_c^1, ..., w_c^{n_{w_c}}\} \times \{\varepsilon^1, ..., \varepsilon^{n_\varepsilon}\}
\end{aligned}
$$

each resembling a specific and unique combination of parameters $h_j = (w_{gj}, w_{cj}, \varepsilon_j) \in \mathcal{H}$.

Next, a probability $P(h_j)$ is assigned to each hypothesis. For the update of this probability based on the observed offer $o_{\neg i}^\nu$ at time instance ν, (8) is reformulated to

$$
P(h_j \mid o_{\neg i}^\nu) = \frac{P(h_j)P(o_{\neg i}^\nu \mid h_j)}{\sum\limits_{k=1}^{|\mathcal{H}|} P(h_k)P(o_{\neg i}^\nu \mid h_k)}. \tag{9}
$$

In order to calculate the update, $P(o_{\neg i}^\nu \mid h_j)$ has to be determined. This likelihood depends on a-priori knowledge on opponent's behavior and observed offers and can be reformulated to:

$$
\begin{aligned}
P(o_{\neg i}^\nu \mid h_j) &= P(d_{\neg i}^\nu, s_{\neg i}^\nu \mid h_j) \\
&= \frac{P(d_{\neg i}^\nu, s_{\neg i}^\nu, h_j)}{P(h_j)} \\
&= \frac{P(s_{\neg i}^\nu \mid d_{\neg i}^\nu, h_j) \cdot P(d_{\neg i}^\nu \mid h_j) \cdot P(h_j)}{P(h_j)} \\
&= P(s_{\neg i}^\nu \mid d_{\neg i}^\nu, h_j) \cdot P(d_{\neg i}^\nu \mid h_j)
\end{aligned} \tag{10}
$$

To determine these likelihoods we follow the assumption that both agents follow the same bidding and acceptance strategy. $P(d_{\neg i}^\nu \mid h_j)$ depends on the bidding and acceptance strategy, i.e. (5) and (3). Therefore, the offer of the opponent has to fulfill the following condition:

$$
\begin{aligned}
U_h(d_{\neg i}^\nu) &= \min_{d \in \mathcal{D}} U_h(d) \\
&\text{w.r.t. } U_h(d) \geq U_{t,h}(\nu) \text{ and} \\
&U_h(d) > U_h(d_i^\nu)
\end{aligned} \tag{11}
$$

The index $(\cdot)_h$ indicates the parameterization of the corresponding function with the parameters of hypothesis h. Besides ensuring that the opponent's utility of the chosen direction lies above target utility, condition (11) also takes into account that this utility must be higher than that of the last own offer w.r.t. the opponent's utility measure. Otherwise this offer would have been accepted by the opponent.

All hypotheses fulfilling this condition explain the current chosen direction of the opponent. Therefore a uniform distribution is assigned to these hypotheses:

$$
P(d_{\neg i}^\nu \mid h_j) = \begin{cases} \frac{1}{|\mathcal{D}^*|} & \text{if (11) holds} \\ 0 & \text{else} \end{cases} \tag{12}
$$

$$
\text{with } \mathcal{D}^* = \{d \in \mathcal{D} \mid (11) \text{ holds}\}
$$

$P(s_{\neg i}^\nu \mid d_{\neg i}^\nu, h_j)$ depends on the intensity determination (6). Therefore the following condition has to hold:

$$
s_{\neg i}^\nu = \arg\min_{s \in \mathcal{S}} \{U_h(d_{\neg i}^\nu) - c_h(s) - U_{t,h}(\nu)\} \tag{13}
$$

All hypotheses that fulfill this condition explain the current chosen intensity at the current direction. Due to the

fact that only one intensity per direction is valid, the probability is set to

$$
P(s_{\neg i}^\nu \mid d_{\neg i}^\nu, h_j) = \begin{cases} 1 & \text{if (13) holds} \\ 0 & \text{else} \end{cases} \tag{14}
$$

Based on the computed hypothesis probability distribution $P(h \mid o_{\neg i}^\nu)$, the estimated expected parameters $\hat{\theta}_{\neg i}$ of the opponent and their variance σ can be calculated.

2.5 Adaptation

In the following we introduce the explicit adaptation component of our negotiation framework that alters the parameters of the basic negotiation model of an agent from Section 2.3 based on the insights given by the identified negotiation behavior of the opponent (cf. Section 2.4). Usually, the opponent model information is directly included in the bidding strategy, cf. Hao and Leung (2014), e.g. to choose an offer that suits the opponent best in case one is indifferent towards multiple potential offers (Fukuta et al., 2016, p. 137). Other approaches use utility predictions to adapt the target utility and thus concession behavior with the aim to maximize utility (Chen et al., 2013). However, in our framework, we include a more powerful adaptation principle that is based on an explicit evaluation of the agent's current negotiation behavior (described by parameters θ) w.r.t. e.g. potential outcome $U(\theta)$ and required effort $E(\theta)$ to achieve this outcome:

$$
\theta^* = \arg\min_\theta J(U(\theta), E(\theta)) \tag{15}
$$

This structure allows to model an overall negotiation behavior that factors in the opponent's behavior e.g. giving in immediately if the opponent model indicates a strong resistance towards the own preference or insisting on one's preference if the corresponding costs are worth the effort. In essence the adaptation component optimizes the parameters of the bidding strategy w.r.t. an objective function J. The adaptation process does not have to be simultaneous to the offer exchange. Instead, it could take place at the end of a negotiation round. That way one can think of the behavior within a negotiation round as the *tactics of negotiation* and the adaptation as the *strategy of negotiation*, see Fig. 5. Furthermore, this approach offers increased modeling flexibility due to the fact that the adaptation strategy can be exchanged without changing the basic negotiation model.

For the adaptation strategy in the described scenario we propose to evaluate the effort of persuading the opponent in relation to the expected utility gain. Furthermore, we propose to adapt only the concession rate of an agent, not the weights of the utility function. Hence, the negotiation *behavior* is changed, not the *values* of the agent. This is achieved by refining the general adaptation objective of (15) to
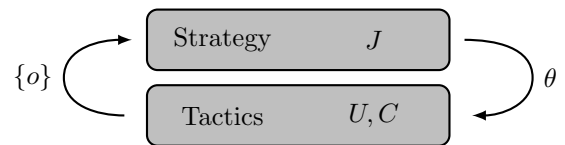

Fig. 5. Tactical and strategical layer of the adaptive negotiation framework

$$\epsilon_i^* = \arg\max_{\epsilon \in \mathcal{E}} U_i^T\left(\theta_i, \hat{\theta}_{\neg i}\right) \cdot \delta^{\nu^T\left(\theta_i, \hat{\theta}_{\neg i}\right)} \qquad (16)$$

w. r. t. $\epsilon \in \theta_i$.

$\delta \in\,]0, 1]$ is an adaptation design parameter and $\nu^T(\cdot)$ represents the time at which the negotiation is expected to end assuming a specific parameterization of the agents. $U_i^T(\cdot)$ is the utility at time $\nu^T(\cdot)$ for agent i.

To actually update the concession rate we consider the variance of the identification result and a risk disposition r_i of agent i:

$$\epsilon_i^{\nu+1} = \epsilon_i^{\nu} + \alpha(\sigma, r_i) \cdot (\epsilon_i^* - \epsilon_i^{\nu}) \qquad (17)$$

The risk disposition factor $r_i \in\,]0, 1]$ is a design parameter that influences the adaptation behavior of the agent. The higher the factor the more prepared the agent is to take risks. The proposed function $\alpha : \sigma, r_i \rightarrow [0, 1] \subset \mathbb{R}$ evaluates the variance of the current parameter estimation and balances this with the risk factor:

$$\alpha(\sigma, r_i) = \frac{1}{n_\sigma} \sum_{k=1}^{n_\sigma} \max\left(1 - \frac{\sigma_k}{r_i}, 0\right) \qquad (18)$$

n_σ is the number of estimated parameters (and corresponding variances).

In summary, the higher the risk disposition of an agent, the faster his behavior, i. e. concession parameter, will converge to the optimal one regarding the adaptation objective, also accepting higher variances of the estimated parameters.

3. RESULTS

3.1 Setup

The simulation results for the proposed framework are based on the times in Table 1 and the scenario of Section 2.2 with $|\mathcal{S}| = 3$ intention levels and corresponding weight of $w_s = 1$. The negotiation time t_N is normalized, i. e. $t_N = 0$ represents the time the first agent places a bid. At $t_N = 1$ the negotiation deadline is reached at which the vehicle has to start one of the potential maneuvers.

The agents are parameterized as follows (cf. Section 2.3):

$$\epsilon_{A/B} = 1, w_c = 1, w_{g,A} = 1, w_{g,B} = 0.$$

Both agents are able to identify the negotiation behavior of the opponent. In addition, agent A is able to adapt its negotiation behavior with $\delta = 0.8$ and $r_A = 0.3$, (cf. Section 2.5). Furthermore, agent A is set to propose offers at a constant update rate whereas agent B, representing the human, interacts at random times.

3.2 Description

Fig. 6 shows a negotiation process without adaptation. The agreement on option d_2 is indicated by a yellow circle. The vertical bars represent different levels of intensities. Note that due to the asynchronous protocol the agents

Table 1. Times for local traffic delay and time to goal intersection

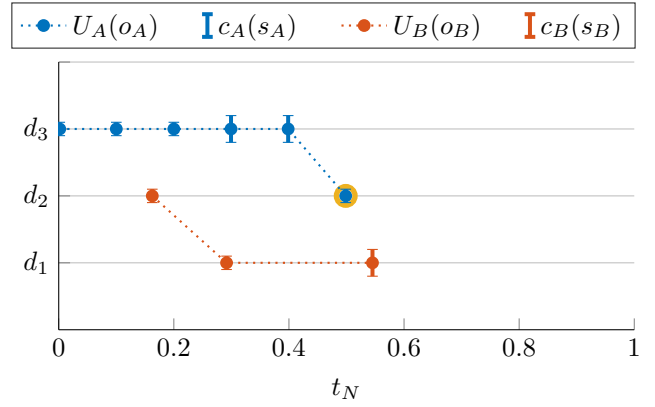| $\mathcal{D}$	t_g	t_l
d_1 (left)	390	10
d_2 (straight)	140	0
d_3 (right)	80	40

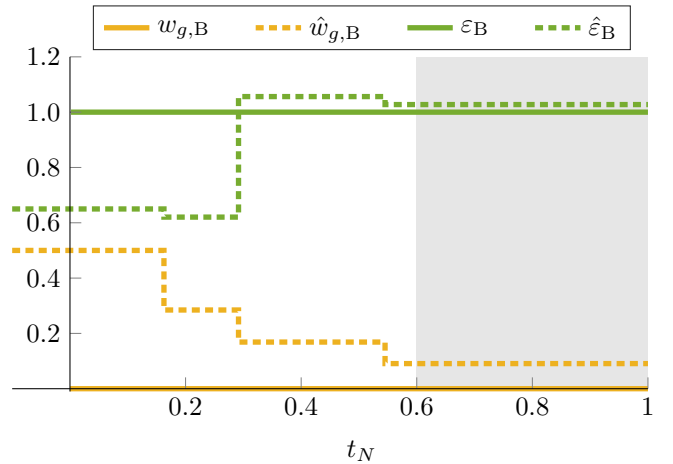Fig. 6. Negotiation process without adaptation.

Fig. 7. Identification process of agent A without adaptation. Actual parameters are depicted with solid lines, dotted lines are the estimates.

are allowed to interact at random times. Therefore, agent B detects the agreement only at his next interaction time. The corresponding performance of the identification method of agent A is depicted in Fig. 7. The estimated values (dashed lines) converge from their starting values at $t_N = 0$ towards the real values (solid line). Note that changes in direction offered or in intensity values contribute most to improvements regarding the parameter estimation, as they provide a high information content. Furthermore, note that the identification results for w_c are not depicted as this parameter was always identified correctly.

Fig. 8 shows a negotiation round in which agent A adapts its behavior. He becomes more intransigent and therefore is able to convince agent B with his offer for option d_3. Fig. 9 presents the identification performance of agent B of the changing behavior of agent A. The adaptation process is visible regarding the changing green trajectories of the concession parameter ϵ_A from high to low values, i. e. from concessive to intransigent behavior. Also the identification ability of changing negotiation behavior is visible as the estimates follow the actual values with a small delay.

3.3 Discussion

The proposed adaptive framework is able to model negotiation scenarios that lead to an agreement between
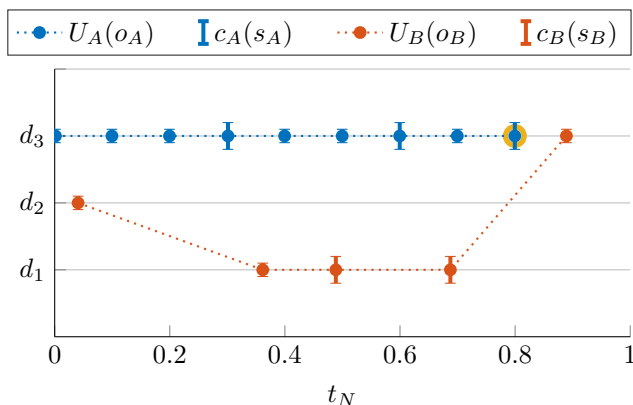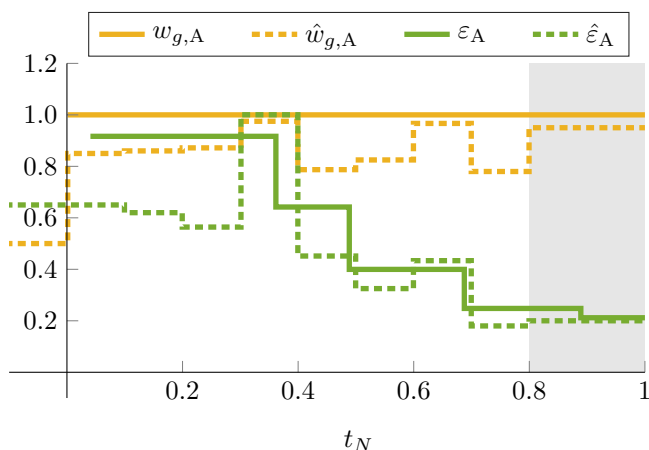
Fig. 8. Negotiation process with adaptation.

Fig. 9. Identification process of agent B showing adaptation of agent A

emancipated agents. The agents are allowed to communicate at different rates and with intensities as additional communication symbols. Furthermore, the proposed identification method is able to identify the behavior of the opponent (cf. Fig. 7), even if it is changing (cf. Fig. 9). The explicit adaptation strategy allows the agent to change his negotiation behavior based on the estimated effort and outcome of persuading the opponent (cf. Fig. 8). As a result the outcome of the negotiation may be different to the one without adaptation. The ability to adapt w. r. t. some objective function, in this case the trade-off between outcome utility and effort to achieve it, is a great advantage of our framework. In comparison to existing adaptation techniques that e. g. adapt the target utility for only maximizing the outcome utility our approach is more generalized and allows for more efficient negotiations. Furthermore, we are able to evaluate different objective functions in order to determine an appropriate adaptation behavior in the context of human-machine interaction.

4. CONCLUSION

A new framework to model emancipated cooperative decision making is proposed. The scope of the framework is the automation design for human-machine cooperation on a decision level. The framework extends state-of-the-art negotiation models by an explicit adaptation strategy of negotiation behavior. This yields a high modeling flexibility

as the adaptation strategy can be changed independently of the negotiation model. Furthermore, the challenges of little communication with few symbols in human-machine negotiation is addressed by an adequate opponent modeling and identification method based on Bayesian learning. The demonstrated variability and identification abilities of the framework encourage the automation design based on the proposed model and its implementation in a real application in order to study user acceptance and validate the generalized negotiation model. A suitable application could be a highly automated vehicle in which the human is able to interfere with the vehicle guidance automation on a maneuver command basis via e. g. a touch pad. Each maneuver is associated with a certain utility that is individual for both agents based on their information about the scenario. Hence, the resulting cooperative decision making is an intuitive cooperative maneuver selection based on information fusion of both, human and automation.

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