Timely Negotiation and Correction of Shared Intentions With Body Motion

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Abstract—Current robot architectures for modeling interaction behavior are not well suited to the dual task of sequencing discrete actions and incorporating information instantly. Additionally, for communication based on body motion, actions also serve as cues for negotiating interaction alternatives and to enable timely interventions. The paper presents a dynamical system based on the stable heteroclinic channel network, which provides a rich set of parameters to instantly modulate motions, while maintaining a compact state graph abstraction suitable for reasoning, planning and inference.

I. INTRODUCTION

Body language – the use of body motion and pose for the purpose of communication – is a fast, intuitive and widely available modality for negotiating shared intentions in physical human-robot interaction, especially for collaborative tasks. Usually, task goals such as handing over an object can be achieved in several ways But to succeed, both parties have to agree upon a mutually consistent course of action. Traditionally, robots determine that course of actions at a specific point in time (decision points) prior to executing actions, and only reconsider choices after completing the action, a behavior that follows directly from the use of state machines (e.g. hybrid automata, MDPs, grid worlds) to structure interaction patterns. While discrete state machines provide huge advantages for learning, reasoning and planning, they also discretize time which makes them particularly unsuited for acting smoothly and timely on continuous streams of perceptual information. They are also unable to perform a speculative execution of actions, i.e. to start an action (e.g. reach out for handover) for the purpose of signaling an assumed or preferred course of action to the interaction partner without committing to its completion, so that the outcome can still be negotiated. It buys the robot time to observe reactions to its motion and react accordingly, e.g. by aborting an action or by blending to another, alternative action. This way, robot and human can quickly negotiate courses of actions, and if guessed correctly the first time (a probable scenario due to cultural norms and individual preferences), then no extra time is spent on the negotiation at all, making the interaction fluent and swift. Modulation of body motion can also be used to effectively negotiate roles in interactions. By displaying decisive motion, the robot implicitly claims a leading role in an interaction, i.e. to determine the location of a handover. Conversely, displaying hesitant or ambiguous motions the human to take the lead and determine the location.

Although the behaviors mentioned above could greatly improve intuitiveness of human-robot interaction, implementation with discrete state machines is cumbersome, difficult, and often requires giving up their prime advantage: having a small state space. POMDPs are able to recreate some form gradual behavior e.g. by using the expectation of states for blending goals [3], [1], but they do not provide a notion of reversibility required to implement speculative execution and a notion of time (i.e. action phases) for continuous synchronization. With hybrid automata [8], controllers can provide continuous behavior, but nevertheless hybrid automata require decisions to be instant and irreversible. Also, any perception-mediated modification of time-related behavior, i.e. phase of a motion or relative importance of motions, has to bypass the hybrid automaton and be implemented within controllers. As a consequence, controllers are not reusable across tasks, state is fragmented across the system and consistent modification of state (i.e. for conditioning and learning) is difficult to achieve.

To remove these shortcomings we propose a novel system architecture to replace hybrid automata for robot behavior synthesis, one which behaves like a discrete state machine but actually is a continuous dynamical system. Additionally, it provides consistent activation weights and phase values for mixing and blending controllers.

The key conceptual difference to hybrid automata is that transitions are extended over time, are non-exclusive (if they share a common predecessor state), have a phase, and are reversible (i.e. are not Markovian). The semantics of a discrete state machine can be recovered by including transitions with their preceding state. So methods that require markovian states – most planning, probabilistic reasoning and learning algorithms – stay applicable.

Implementation as a dynamical system ensures that all information paths are time-continuous and analytically differentiable, a property that may especially be interesting for end-to-end learning approaches that need gradients for each component. But it also ensures that perceptual information can be integrated into the system state at any rate, any time.

For human-robot interaction specifically, we will show how the proposed system enables the robot to negotiate shared intentions on-the-fly using body motion, convey preferences (e.g. the propensity to lead or follow), and to synthesize timely and gradual feedback to cues from human body motion; all without compromising the simplicity of individual actions.

In the following sections we will first describe the implementation and then demonstrate its capabilities in an object handover scenario.
II. IMPLEMENTATION

The proposed system builds upon the work on sable heteroclinic channel (SHC) networks [2],[5]. SHC networks are dynamical systems that have saddle points which can be arbitrarily connected with limit cycles (heteroclinic channels). If the saddle points are interpreted as states, then SHC networks can be understood to act like a state machine. And used as such [2], Fig. illustrates the attractor of the simplest possible SHC network composed of three saddle points. In this paper, we additionally interpret the heteroclinic channels as representing transitions between states, propose a method to algebraically partition the state space into individual states and transitions as well as compute a phase variable for each individual transition. Further, the differential equation is modified to provide a *greediness* factor that modifies behavior during transitions.

\[
\dot{x} = x \circ (\alpha + (\rho_0 + \rho_\Delta \circ (T + G)) \cdot x^\gamma) \cdot \eta(t) + \delta(t) + \epsilon \cdot \mathcal{W}(t)
\]

Compared to the equation used in [2], we added the exponent \(\gamma\), explicitly introduce the state transition matrix \(T\) (\(T_{ij} = 1\) if transition \(i \rightarrow j\) exists, 0 otherwise), added a “greediness” matrix \(G\), and added a scalar \(\eta(t)\) to adjust the speed at which \(x\) evolves. The parameters \(\alpha\), \(\rho_0\) and \(\rho_\Delta\) are chosen such that \(n\) saddle points occur, each one placed on its exclusive coordinate axis. The signal \(\delta(t)\) is used to selectively push the system away from saddle points and \(\epsilon \cdot \mathcal{W}(t)\) adds stochastic noise with zero mean.

a) Matrices \(\rho_0\) and \(\rho_\Delta\): The \(n \times n\) matrices \(\rho_0\) and \(\rho_\Delta\) are constructed from three parameter vectors [2]: \(\alpha\) (growth rates), \(\beta\) (saddle point positions), and \(\nu\) (saddle point shapes):

\[
\rho_0 = [\alpha \otimes \beta^{-1}] \circ [I - 1 - \alpha \otimes \alpha^{-1}]
\]

\[
\rho_\Delta = (\alpha \circ (1 + \nu^{-1})) \otimes \beta^{-1}
\]

The matrices are chosen such that the matrix \(\rho\) constructed by Eq. 5 in [2] can be computed as \(\rho = -\rho_0 - T \circ \rho_\Delta\). The advantage of the given formulation is that \(\rho_0\) and \(\rho_\Delta\) do not change when transition matrix \(T\) or greediness matrix \(G\) is modified. For convenience, we can fix many parameters to obtain a canonical system:

\[
\alpha_i = \alpha_0 \quad \text{(growth rates)}
\]

\[
\beta_i = 1.0 \quad \text{(position of saddle point)}
\]

\[
\nu_i = 1.0 \quad \text{(channel asymmetry)}
\]

To illustrate, the matrices for the system in Fig. [1] are:

\[
\rho_0 = \begin{bmatrix}
-\alpha_0 & -2\alpha_0 & -2\alpha_0 \\
-2\alpha_0 & -\alpha_0 & -2\alpha_0 \\
-2\alpha_0 & -2\alpha_0 & -\alpha_0
\end{bmatrix}
\]

\[
\rho_\Delta = \begin{bmatrix}
2\alpha_0 & 2\alpha_0 & 2\alpha_0 \\
2\alpha_0 & 2\alpha_0 & 2\alpha_0 \\
2\alpha_0 & 2\alpha_0 & 2\alpha_0
\end{bmatrix}
\]

\[
T = \begin{bmatrix}
0 & 1 & 0 \\
1 & 0 & 0 \\
0 & 0 & 1
\end{bmatrix}
\]

Channel location: The factor \(\gamma\) determines the distance of the attractor to the vector space origin. With \(\gamma = 1\) channels approximately maintain constant \(L^1\) distance (as used in [2]), whereas with \(\gamma = 2\) they approximately maintain constant \(L^2\) distance (assuming a canonical system). The latter causes the attractor to lie on a hypersphere. For the canonical system, we chose \(\gamma = 2\).

B. Activations and Phases

The SHC network provides the notion of states (saddle points) and transitions (stable heteroclinic channels). In order to algebraically partition the vector space of \(x\) into regions for each state and each possible transition, we can leverage two mathematical properties of the system.

First, the coordinate vectors of each state/saddle point form an orthonormal basis. From this follows that the channels are located on the plane spanned by the basis vectors of predecessor and successor state, as can also be seen in Fig. [1].

Second, the coordinate vector of each state is sparse, all but one coordinates are zero. From this follows that functions specific to a state or transition can be computed from specific elements of \(x\).
a) Activation values of states and transitions: From these insights we can devise an “activation” value for each transition \( i \to j \), based on its respective successor and predecessor coordinate values and the norms of \( x \):

\[
\lambda_{\text{transitions}} = \frac{16 \cdot x \otimes x \cdot |x|^2}{(x \otimes 1 + 1 \otimes x)^4 + |x|^4} \circ T
\] (2)

The function \( \Lambda_{\text{transitions}} \) is chosen such that elements are limited to the range of \([0.0 \ldots 1.0]\), and invariant to scaling \( x \). Fig. 2 illustrates the function value for a single active transition \( i \to j \) w.r.t. coordinates \( x_i \) and \( x_j \). \( \Lambda_{\text{transitions}} \) is sparse in the sense that only few transitions are active at any time. If more than one transition is active, then \( \sum \Lambda_{\text{transitions}} \approx 1.0 \) (for systems with \( \gamma = 2 \)). Because of this, \( \Lambda_{\text{transitions}} \) can also be understood as a weight matrix.

For the states, activation is computed from the residual of the transition activations, so that all activation values sum up to 1.0. Additionally, \( x \) is squared to ensure sparseness of the state activation values and hence mutual exclusiveness:

\[
\lambda_{\text{states}} = x^2 \cdot (1 - \frac{\sum \Lambda_{\text{transitions}}}{|x|^2})
\] (3)

And as the diagonal of \( \Lambda_{\text{transitions}} \) is semantically not meaningful, we can combine all transition and state activations into a single activation matrix \( \Lambda \):

\[
\Lambda_{ji} = \begin{cases} 
\lambda_{ji}^{\text{transitions}} & j \neq i \\
\lambda_{ij}^{\text{states}} & j = i 
\end{cases}
\]

Fig. 3 shows an example of the resulting set of activation values for the minimal three-state system illustrated in Fig. 1 (using \( \alpha_0 = 10, \delta = 5 \cdot 10^{-5} \)).

\( \otimes \) denotes the outer vector product.

b) Transition Phases: Different to (markovian) states, transitions have a notion of time and progress, i.e. they possess a phase. As channels are located on a two-dimensional plane spanned by two coordinate axes, we can compute a phase for each possible transition \( i \to j \):

\[
\Phi_{ji} = \frac{|x_j|}{|x_i| + |x_j|}
\] (4)

The shape of the function is illustrated in Fig. 2 and yields values in the range \([0 \ldots 1]\). Note that \( \Phi_{ji} \) is only meaningful when transition \( i \to j \) is active, i.e. when \(|x_i| + |x_j| \gg 0 \).

Fig. 4 illustrates the phase over time.

1) Composition of Motion: So far, we established a dynamical system that provides us with a consistent set of activation values for transitions and states, and with phases for transitions. Eqs. 2 and 3 are chosen such that \( \sum \Lambda = 1 \), therefore \( \Lambda \) can be directly used for weighted...
averaging of control goals associated with each state and each transition. In terms of control, states and transitions have to be treated differently though. States are phaseless, so we can only associate static control goals with them. Transitions, on the other hand, have a phase, so we can also associate phase-parameterized movement primitives with them, such as DMPs [4], [6] and ProMPs [4], or simply planned trajectories. For the full system demonstration, we use the ProMP framework to learn and reproduce movements during transitions. In order to enable composition using the mixing method for ProMPs [4], state goals are defined as static normal distribution over position and velocity. It is important to note that even though usually only one or two control goals are activated, multiple goals may be active, e.g. when competing transitions (with common predecessor state) become active, or when subsequent transitions are blended into each other because of large values in $\delta$.

C. Inputs to influence system behavior

Terms of Eq. 1 is chosen such that some of them can be used as inputs to effect certain behaviors. The transition matrix $T$ is used to define which transitions exist, and can be updated during execution of the system, if desired. Matrix $G$ is used to adjust the behavior for active, competing transitions and for pausing or aborting transitions. Vector $\delta$ determines, when a state is left and which transition(s) is activated. The factor $\eta$ speeds up or slows down the system dynamics, which can be used for e.g. synchronization by entraining.

a) Causing transitions: When the system is exactly on a saddle point, e.g. $x = (1, 0, 0)$, then the system can potentially stay in this state forever. In order to cause a transition, a small positive velocity bias $\delta_j$ can be added, which pushes the system towards successor state $j$, or a negative $\delta_j$ to avoid it. Sometimes though, this level of granularity is not enough, and we want to set the velocity bias for each transition specifically. We can define an input biases matrix $B$ where each element $B_{ji}$ corresponds to the bias towards state $j$ in state $i$. A resolved vector $\delta$ can then be computed with $\Lambda$:

$$\delta = (\Lambda \circ B) \cdot x$$  \hspace{1cm} (5)$$

The matrix $B$ elements are the equivalent of control goals associated with each state and each transition. In terms of control, states and transitions have to be treated differently though. States are phaseless, so we can only associate static control goals with them. Transitions, on the other hand, have a phase, so we can also associate phase-parameterized movement primitives with them, such as DMPs [4], [6] and ProMPs [4], or simply planned trajectories. For the full system demonstration, we use the ProMP framework to learn and reproduce movements during transitions. In order to enable composition using the mixing method for ProMPs [4], state goals are defined as static normal distribution over position and velocity. It is important to note that even though usually only one or two control goals are activated, multiple goals may be active, e.g. when competing transitions (with common predecessor state) become active, or when subsequent transitions are blended into each other because of large values in $\delta$.

b) Decisiveness and Hesitation: A unique feature of the proposed system is the ability to transition from a predecessor state into the direction of several successor states at once, by setting positive biases for transitions with common predecessor. The attractor shape forces a decision at some point though and only one transition completes, i.e. the system converges to one heteroclinic channel, a behavior which ensures the mutual exclusivity of states. The dynamic behavior of two competing heteroclinic channels is illustrated in Fig. 6a. Depending on $\delta$, the system state $x$ will first progress in a specific direction on the hypersphere, but then...
The original SHC network is retrieved with $g = [1, 1, 1]$. (b) It can be very decisive ($g = [8, 8, 8]$). (c) With $g = [0, 0, 0]$ ongoing transitions are halted. (d) With negative values transitions are aborted and the system returns to the predecessor state $0 (g = [-2, -2, -2])$.

Fig. 6. Effect of changing the greediness parameter uniformly on two competing transitions $0 \to 1$ and $0 \to 2$. (a) The system can be reluctant to choose (original SHC behavior, $g = [1, 1, 1]$). (b) It can be very decisive ($g = [8, 8, 8]$). (c) With $g = [0, 0, 0]$ ongoing transitions are halted. (d) With negative values transitions are aborted and the system returns to the predecessor state $0 (g = [-2, -2, -2])$.

Reconsidering Decisions: The greediness can not only be used to alter mixing behavior during transitions, but it can also be used to make the system reconsider the successor state it is converging to. The ratio of $\frac{G_{ji}}{G_{j0}}$ for two competing successor states determines where the system bifurcates. By altering the ratio, a system that previously was set to converge towards one state can be made to converge towards another state. This effectively enables us to reconsider earlier decisions on which successor state to converge to. For illustration, Fig. 8 shows three systems where during a transition, elements of $g$ are changed asymmetrically. Depending on the absolute values, the system can be made to “reluctantly” move towards the new desired successor state (Fig. 8a), to respond gradually depending on how certain it was before (Fig. 8b), or to aggressively “backtrack” (Fig. 8c). It should be noted, that the greediness input provides a powerful method to alter the “flavor” of transitions, while keeping the overall state graph intact (as expressed by the transition matrix $T$).

III. EXPERIMENTS

In order to demonstrate the capability of the proposed system to quickly react to perceptual input, and to generate legible motion, all while maintaining a simple state graph abstraction of an interaction, we chose to apply it for a handover task. In this task, a robot arm picks up an object from a table surface, and then hands it over to a human interaction partner standing nearby. The object can be handed over to the left or the right hand of the human.

Reconsidering Decisions: The proposed system provides a consistent method to generate legible mixtures of phase based motions such as avoid mixing movements, which maintains their expressiveness. If $g$ is small then movements are mixed according to the accumulated $\dot{\delta}$, creating an ambiguous motion.

The matrix $\overrightarrow{G}$ encodes competitive greediness, i.e. mutual inhibition between competing successor states, while $\overleftarrow{G}$ encodes greediness w.r.t. the preceding state. When $\overrightarrow{G} = 0$ and $\overleftarrow{G} = 0$ the system behaves as in [2] and Fig. 6a, when $\overrightarrow{G}_{ji} = -1$, the gradient for the channel $i \to j$ is compensated, i.e. the transition halts. If $\overrightarrow{G} = \overleftarrow{G}$, then for simplicity we can define a single greediness vector $g$ with values for each (successor) state, from which we can construct both matrices:

$\overrightarrow{G}_{ji} = \begin{cases} 
-0.5 & g_j < -1 \\
\frac{g_j - 1}{2} & else \\
0 & g_j > 1 
\end{cases}
$

and

$\overleftarrow{G}_{ji} = 1.5 \cdot \frac{g_j - 1}{2} - 0.5 \cdot \frac{g_i - 1}{2}$

The equations are chosen such that the behavior of the original SHC network is retrieved with $g_j = 1$. (“default” greediness). With $g_j = 0$ (Fig. 7a), the system will completely halt ongoing transitions towards state $j$, i.e. the gradient along the heteroclinic channel drops to zero. With negative $g_j$ (Fig. 7b), the gradient along the heteroclinic channel reverses, which moves the system back to the preceding state.

The speed of transitions are not increased beyond the default speed because $\overleftarrow{G}$ is clamped. Values beyond $|g_j| > 1$ therefore only increases the competition between successor states. The net effect is, that for large values of $g_j$, the system becomes very decision-happy (Fig. 6b vs. Fig. 6b) and tries to converge towards a single transition early, while for low values of $g_j$, the system is reluctant to decide. This effect can be used to modulate the ambiguity of movements. If two expressive movements are associated with two competing transitions, then large values of $g$ will cause the system to

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probabilistic movement primitives [4] or dynamic movement primitives[6]

IV. Discussion

A. Conclusions

The paper presented a novel method to structure and execute robot motion, which is especially suited for implementing human-robot interaction based on body motion. The paper analyzed properties and parameters of the proposed system and related modulations to human-interpretable qualities such as decisiveness and hesitation, which can be used to negotiate decisions faster and more effectively than relying on turn-based interaction.

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