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Computers as Brains: A Robot's Tale

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ABSTRACT
The computer metaphor of mind and brain states broadly that the brain is the control organ for the body. This implies that brain (including mind) and physical body are separable from each other and the physical and social environment. Given the dominance of computing technology in daily life, many brain researchers and subsequently also engineers are furthermore compelled to take brain-computer analogies not as metaphors but as literal descriptions of brain function. These two fundamental assumptions manifest as overwhelming challenges when pursuing synthetic rather than analytic approaches, i.e., when we attempt to computationally control artificial bodies such as robots, especially when co-located with humans. I will discuss the computational brain metaphor from the perspective of bodies for whom computational control is a reality – robots, and their creators – engineers. Rather than presenting new metaphors, I will use evidence from control engineering and human-robot interaction to argue for a shift of thought: if we can enrich how engineers approach robotic control, new robots could offer powerful momentum to shifting the scientific opinion towards embracing a less dualistic, more holistic view of the brain's embedding in body and world.

1 WHAT DO WE UNDERSTAND BY THE COMPUTER METAPHOR OF THE MIND AND BRAIN?

We all agree that the brain is a conglomeration of cells, white and grey matter, neurons, hormones, etc. Opinions, however, differ on how the brain is involved in cognitive function and the creation of intelligent behavior. According to cognitivist views, the *computer metaphor* of the mind and brain is the idea that the mind works like a computer program that is running on the brain, i.e. the biological computer hardware, *controlling* a peripheral body. Here, the cognitivist theory goes such that humans sense their environment through the body's sensory systems (eyes, ears, skin, tongue, nose), i.e. the input. Because what is sensed does not in itself carry meaning yet, the sensory information must be combined with knowledge we store about the world in our memory. From that, the brain forms a representation, or internal model, of the situation, which is the basis for decision making, i.e. processing, and ultimately motor control, i.e. the output. Thus, the computer metaphor of the mind and brain is that of an *sense-model-plan-act* (SMPA) controller. Obviously, nobody really thinks that the brain is literally a computer. After all, it must be a lot more complex, and we are facing the problem that computers do not have minds of their own (yet). Nevertheless, the analogy is so powerful that its principles dominate how we think about the role of the brain (and mind): in the feedback loop of human motor control, the brain sends a motor command (efference) to the peripheral nervous system and the muscles. At the same time, an efference copy of this signal is generated so that the brain can update the internal model with the intended outcome of the action. Once the action is in execution, the information from the senses is used to calculate an update of the current state (afference/re-afference) in the brain so that the expected outcome (efference copy) can be compared with the action outcome (re-afference) and any potential error can be corrected in the motor program. In this analogy, the mind is composed of non-substantiated metaphysical processes like perceptions, awareness, thought, and so on, that solely exist in the brain as an internal model that includes an updateable representation of the world around us. The body, in that notion, has nothing to do with the creation of the mind and emotions are treated as a nuisance or weighting/shaping factor. The implication of this metaphor is that while the brain and the body are connected through tissue, neural and other bio-physiological pathways, in theory, the brain could exist without it, if it was adequately nourished, and its connections could be rewired to control a different body. The best illustration I have ever found for the idea that the brain can be independent of the body are the *Heads in Jars*[1] in the animation series Futurama (20st Century Fox, 1999). These heads survive in a nutrient liquid and have full perception, cognition, and language capacities. They can also be attached to robotic bodies that they then control to move around in the world[2]. The fundamental idea these illustrations very poignantly convey is that emotion and intelligence, and with-it perception, cognition, and motor control, can be separated from the replaceable body. After all, we are just meat (Clark, 2016).

While there has been a long tradition to explaining brain function with control theory of the newest technology of the time (clockworks, steam engines, computers, quantum etc.) the computer has lent itself as a hard to eradicate metaphor of our times, as computer technology and neuroscience have advanced hand in hand in an interesting circular argument forming the cognitive science of our days. It was Newell and Simons 1960s General Problem Solver that was intended to replicate the internal thought processes of solving a logic problem in the brain (Newell & Simon, 1961; Shapiro, 2011) and thus created an analogy between brain and computer early on in the cognitive debate. Fueled by Wiener's approach to cybernetics and feedback loops (Wiener, 1961), this has also led to the use of metaphors of linear and dynamic control theory for bio-inspired machines that entails that there is one single processor that executes instructions and controls input/output operations of a peripheral machine. This central controller monitors one or several process variables (e.g. position) and compares it with a reference variable (e.g. goal location). If a difference between intended outcome and real outcome is detected, this *error* is returned as feedback to generate a control action that brings the controlled process variable to the same value as the reference. In control theory, this is known as closed-loop or feedback control.

Unfortunately, many researchers have since lost sight of the brain-computer analogies in fact being a metaphor, and hence, in circular fashion, adopt it as the literal description of brain function (Daugman, 2001). Today, researchers in artificial intelligence (AI) claim, without thinking twice, that neural networks are inspired by how the brain works, as much as neuroscientists and cognitive psychologists claim that the brain processes information and controls the body. This is also true for most engineers, who typically have minimal exposure

[1] https://futurama.fandom.com/wiki/Heads_in_Jars; https://theinfosphere.org/Head_jars
[2] https://futurama.fandom.com/wiki/A_Head_in_the_Polls; https://theinfosphere.org/Bendin%27_in_the_Wind;

to cognitive psychology and neuroscience during their education. Consequently, they are mostly unaware of the existence of different meta-theories on perception, action, and cognition[3] and trust the most dominant and hence most easily traceable theory, which is the computational metaphor of mind and brain (e.g. Yang et al., 2018). Adding to this is that knowledge of computing and computer architectures eases the understanding and implementation of computational theories of brain and mind.

In practice, this means that traditional robotic engineering typically controls robotic actions with a central control architecture. Given the historical entanglement of control theory with neuroscience and cognitive science, it is not surprising the robot designers have turned to what we seemingly already know about human action, perception, and cognition. The resulting cognitive architectures are sequential information-processing functional units made up of complex data structures that constitute models, plans, and goals, usually includes sensing, modeling, planning, and acting stages (Brooks, 1986; Hill, 2006). Thus, the classic robot control scheme, also for robots who are supposed to interact with humans, is SMPA. For robots to move, they must execute a control program that is implemented on that central computer and sends control signals to the motors. While a fully automated robot can operate without outward-facing sensors, the robot that is supposed to interact with the world with some level of autonomy must sense the world. This input data is typically obtained from sensors as analogue signal that is then filtered and digitalized. Interpretation of this data is then done using either logic processing or artificial intelligence and machine learning based on features and patterns detectable in the digital signal. The input is augmented with stored knowledge compared to an ideal model of the current situation, and error terms are calculated to determine subsequent action. As multiple action commands are typically possible given the often-redundant degrees of freedom of the robot's body, some kind of action selection is also part of the decision-making process. In robotics, this is typically done with optimizing the trajectory from the current to a goal location – both for the entire robot (navigation) or its body parts (e.g. arm movement). If adaptation to the environment is necessary, online corrections can be made by updating the internal model parameters. Thus, the classic robot control scheme is in fact the implementation of the computer metaphor of the human brain and mind with the goal to intelligently and autonomously control a peripheral body.

2 What are some of the limitations of the computer metaphor, and are there any empirical findings that make it nonviable?

The purpose of robots is primarily to take over dull, dirty, and dangerous tasks for humans. In this capacity, robots traditionally act outside of human-occupied spaces. For pre-programmed applications such as in manufacturing, central SMPA control is a brilliantly working approach, even though problems arise based on processing capacity when large amounts of data must be e.g. visually identified and evaluated for action planning. More recently however, robots are also envisioned to support humans directly, be it in educational, home, health, public or social settings (Christensen et al., 2021; Feil-Seifer & Mataric, 2009; Goodrich & Schultz, 2007). Thus, the goal of robotic design has shifted from work in uninhabited environments to work in environments that are particularly designed for (able-bodied) humans, and with that came the necessary shift from designing mere robotic *action* to designing human-robot *interaction* (Bartneck et al., 2024). As the general assumption is that human-like appearance and behavior

[3] I want to emphasize that this is not the fault of the interested engineer, but a shortcoming of integrating existing education systems of humanistic and applied cultures (Snow, 1959) within approaches to engineering and STEM education. In addition, also many researchers in cognitive science are unaware of different existing meta-theories as the computational perspective is the dominant theory about mind and brain of our times (Chemero, 2009) and often the only one that is taught in cognitive science programs.

of a robot is more intuitive and interpretable for people, the trend is also rapidly moving towards general purpose humanoid robots (Giger et al., 2019; Sciutti et al., 2018; Vianello et al., 2021). To program these behaviors, robotic researchers again draw heavily on what we "know" about human intelligence, i.e. computational metaphors of the mind and brain.

Interestingly, vast problems arise when building robots that are supposed to interact with the world, i.e. are situated in a dynamically changing environment, when they are controlled in a classic central control architecture, which is inspired by the computer metaphor of the brain and mind (Pfeifer & Bongard, 2006). The phenomenon in question is *Moravec's paradox* (Moravec, 1998): tasks that are easy for humans, such as motor control or social skills, are difficult for machines to replicate, especially considering multiple different contexts and dynamic environments in which they can be applied[4]. Robots must interpret and respond to social and behavioral requirements in real time, such as turn-taking, appropriate approaches, and acknowledgments, which are intuitive for humans but challenging for machines.

For HRI to be successful, the robot is ideally able to make sense and reciprocate task related behaviors and communicative acts in real time, such as coordinate movements, react to gaze cues or pointing gestures, adjusting its behavior for affective states from body language or facial expression, etc. To accomplish that, the computational idea of SMPA dictates that humans interpret both action and context via comparison to an internal model, a representation. The resulting approach in robotics for HRI is therefore to build a cognitive architecture (an internal model) which interprets inputs from the environment and the human for robot control (Clodic & Alami, 2021; Lemaignan et al., 2017; Mutlu et al., 2016; Thomaz et al., 2013). As the complexity of everyday interactions settings is infinite, the robotic engineer very quickly encounters what is known as the frame problem (Dennett, 1984/2006), i.e. the problem of deciding what actions are relevant and need to be considered? The typical approach in HRI is therefore to limit the interaction space to a specific setting and focus on the execution of a limited set of possible actions (i.e. building blocks, Belhassein et al., 2020). Yet even within these limits, any interpretation of context or situation-dependency must be given to the robot explicitly and is hence subject to either the programmer's informed or intuitive interpretation of a situation or based on context-dependent data-driven methods such as black-box machine learning (Semeraro et al., 2022). The relatively obvious problem with this approach is that both the internal model of the robot and the learned behavior are situation-specific and limited to a controlled lab setting. Neither the internal model nor the resultant interactive behavior can be generalized to other situations (Brooks, 2018; Mutlu et al., 2013). The learned behavior is additionally subject to the quality of the available training data. If sufficient training data is available, complex behaviors are possible. Yet, the system fails as soon as a situation arises that was not part of the training set[5]. Thus, with cognitive architectures we are actually far from addressing the frame problem, especially when we consider the robot's capability (or lack thereof) with respect to autonomous interaction with humans (Clodic et al., 2024; Clodic & Alami, 2021).

Although researchers in HRI claim that "the unit of analysis in HRI is always some form of interaction between human and robot" (Bartneck et al. 2024, p.161), the actual unfolding of the interaction between human and robot is rarely subject of analysis. Reflecting the idea that

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[4] At the same time, tasks that are difficult for humans, such as mathematical calculations or big data analysis, are relatively easy for machines given enough processing power, while humans require years of training and executed such tasks over much more time – this misalignment of abilities is the full paradox.

[5] Even generative AI cannot react to every situation correctly, as evident in numerous anecdotes on "hallucinations".

cognition is the main component of intelligent behavior and interaction, and cognition happens within the individual brain, once a control scheme is implemented, successful HRI is considered confirmed on the robot-centric side if the robot can adapt its own behavior according to how the interaction unfolds within the limits of the narrowly parameterized or learned situation (Bartneck et al., 2024). From the human-centric side, interaction is considered successful if the robot elicits in the human a targeted response (e.g. a reduced reaction time, an emotional response, etc.) that is typically assessed with questionnaires, via observation, or behavioral measures of human action. Thus, the assessment focusses on the outcome, not on the dynamics of the interaction limiting the understanding of behaviors arising from the coupling between agents and their task-relevant environment, including other agents.

As any interaction between two agents is necessarily adaptive, such that the actions of one agent affect the actions of another agent (Lorenz et al., 2014; Martins et al., 2019; Rossi et al., 2017), the other important question is, how does this approach affect the interaction partner, i.e. the human? Let's consider a hand-over task, a typical task that is often studied in human-robot interaction (Ortenzi et al., 2021). An object is supposed to be handed from a giver to a receiver. The computational assumption is, that in order to engage in such tasks, the actions of the respective other have to be represented together with one's own, and the adaptation of movements towards the handover point is happening as a continuous updating of the observed and simulated action (Kourtis et al., 2013; Sebanz et al., 2003, 2006). Other requirements for success are that both giver and receiver attend to the same object, and the receiver needs to predict the intended hand-over position that the giver communicates verbally or non-verbally through cues in gaze, body stance, arm pose, etc. Meanwhile, the giver relies on visual and tactile feedback to perceive and track the object as well as the state of the receiver. While classic robot controllers struggle to provide a complete handover implementation that is fluid and seamless as they focus on sequential implementation of the different phases: initiation, approach, passing, retraction (Ortenzi et al., 2021), HRI research shows that the more task-relevant features included in the decision-making process leading to robotic action, the better the interpretability of the robot, and hence adaptation by the human. For robot control that means that besides the basics of scene and object recognition, movement planning, obstacle avoidance, the actual non-trivial phase of object release, etc. a lot of different "soft feature" packages must be considered, implemented, and integrated for action planning (Clodic & Alami, 2021). Considering the complexity of this endeavor, it is very likely that one or several aspects of an interaction are ignored, deliberately omitted, or overlooked, leading to a potentially *human-like*, but not quite *as-human* interaction (Papadimitriou, 2016).

As progress is made in integrating different cues to create the multi-modal interaction partner humans expect (Belhassein et al., 2022; Sarthou et al., 2021), further evidence is suggesting that it is not about the generation of cues alone, but that both the morphology of the robot and its movement kinematics affect the ability of a person to anticipate a robot's action: the more human-like the movement and the appearance of the robot are, the more of its full-body degrees-of-freedom are coordinated meaningfully towards the intended outcome, e.g. heading direction, head position, and gaze, the more fluid and immediate are the human's reaction to it (Abubshait & Wiese, 2017; Huber et al., 2013; Saygin et al., 2012).

Attempts in implementing both appearance and naturalistic behavior are undertaken in the creation and study of naturalistic looking humanoid robots, e.g. geminoids (Ishiguro, 2006; Ishiguro & Dalla Libera, 2018). Geminoids are modelled after a real person and allow for human-robot interaction studies that literally compare a person's reaction to a human's behavior and to that of their robotic "twin". Interestingly, these studies overwhelmingly reveal the problem of uncanniness, i.e. the theory that people will act in a more intuitive way towards robots as those exhibit increasingly human-like characteristics until the increasing human-likeness leads to the agent being considered strange, unfamiliar and disconcerting (Mori et al., 2012; Saygin et al., 2012). (Saygin et al., 2012) explored this phenomenon comparing the pre-programmed movements of a geminoid with and without its human-like appearance[6] to the actions of the human it was modelled after. Studying the reaction of participants observing the same actions performed by the mechanical robot, the human-like robot, and the human, shows that to avoid uncanniness, congruency is key, i.e. a mechanical looking robot is expected to perform mechanical movements, while a human-looking android is expected to move as a human, i.e. it is important to display plausible motion patterns given the body's morphology. Related to this is the problem that the robot may appear capable, but cannot deliver intelligent or context-relevant behavior, which leads to frustration and potentially abandonment of the interaction (Abubshait & Wiese, 2017). Thus, the limitation is that the body of the robot is treated as separate from its behavior, even though evidence is pointing towards the necessity to derive the robot's action capabilities from its form (or vice versa) if intuitive interaction is the goal.

Consequently, the interaction with current robots that interact with people autonomously with respect to a given task is always to some extent impoverished in comparison to interaction with people. Interestingly, this impoverishment has great benefits for therapy and training of children with ASD (Cabibihan et al., 2013), as they benefit from not being overwhelmed by competing social task demands. However, while impoverished interactions may be otherwise acceptable for mostly controlled settings such as manufacturing, it seems very problematic to consider such interactions for care-taking of typically developing children who are still very much shaped by imitation learning, or care-taking of the elderly, who are already often isolated from human connection (Prescott & Robillard, 2021).

3 WHAT METAPHOR SHOULD REPLACE THE COMPUTER METAPHOR, OR BETTER YET, DO WE NEED A METAPHOR FOR THE MIND AND BRAIN AT ALL?

We not need a new metaphor for brain and mind, but a different way of thinking. If we want to gain insight into human intelligent behavior, we need to move from reductionist thinking to holistic thinking and embrace the complexity and dynamic of the world we evolved with. Instead of identifying the building blocks of behavior, and their cues, and potential adaptive mechanisms, we need to emphasize research on lawful relations between ongoing processes that unfold on different time scales (neural, individual, social, organizational, political, etc.) and understand how they affect each other across time scales. While we typically accept that the physical environment and even the interaction dynamics of small organisms are governed by the laws of physics and chemistry, we somehow do not accept that for people. So, what we also need to let go off is the idea that the human brain is special and remember that the brain lives in a body. This body has co-evolved and co-developed with the environment we are currently experiencing and hence looks and feels the way it looks and feels to enable our survival. This includes that the material make-up of our bodies as well as the form we evolved into serves a purpose. As we are an inherently social species, our ability to engage with other people has also evolved and developed to improve our chances of survival by group membership. Our behavior (and emotion) is therefore attuned in service of belonging, and we constantly adapt to each other, and the environment, to maintain physical, physiological, and

[6] In one condition they stripped it of its skin to reveal its mechanic appearance, while in the other condition the skin was on, making the robot look like its human counterpart. How the movements were implemented is not disclosed in the paper. Geminoids are however typically teleoperated.

social balance. In return, our physical and social environment, including our technical environment, shapes us.

The theoretical foundation for such an approach is laid out in the study of embodied cognition (Chemero, 2009; Wilson & Golonka, 2013). Embodied cognition is not a different metaphor, it is an entirely different way of conceptualizing the role of the brain and the emergence of mind. Here, representations are rejected, and it is assumed that cognitive function emerges from *nested brain-body-environment interactions* (Brooks, 1991; Favela, 2024). Importantly, this includes the assumption that the ambient array our senses perceive in the environment is already structured such that it provides meaningful and actionable information (Gibson, 1979; Stoffregen & Bardy, 2001), eliminating the need for an internal model as a necessary component for information processing. Instead perception and action are directly coupled (Warren, 2006). Action execution in an always changing environment is conceptualized as dynamical systems in which attractor landscapes define appropriate behavior (Chiel & Beer, 1997; Richardson & Chemero, 2014; van Gelder, 1998). Finally, embodiment also entails that the body morphologically enables and constrains possible activities by its form and make-up (Pfeifer et al., 2007; Profeta & Turvey, 2018), and behavior emerges by continuously engaging that body in an environment providing context for action in form of affordances (Gibson, 1977; Stoffregen, 2003), which shape goal-directed behavior.

Embodied cognition has found its way into robotics in the form of situated, behavior-based, or bio-inspired systems (Beer, 2003; Brooks, 1997; Brooks, 1991; Jordanous, 2020; Pfeifer et al., 2007; Pfeifer & Bongard, 2006). The goal is to build robots that can intelligently engage with their environment without representations or higher-level reasoning, simply based on layering task achieving behaviors, i.e. parallel loosely coupled processes, in what (Brooks, 1986) introduced as *subsumption architectures*. Here, the available outward-facing sensors collect relational information between robots and the environment by exploiting the laws of physics (e.g. optics, kinematics, etc.) that directly trigger motor responses that result in observable by means of layered task-achieving behaviors such as wander, avoid objects, identify objects, etc., that each have a function of their own yet affect each other. Interestingly, (Prescott et al., 1999) liken subsumption architectures to layered functional mechanisms in the mammalian brain, providing a direct link to neuroscience.

Importantly, both embodied cognition and behavior-based robotics consider changes over time at different time scales. For example, the theory of direct perception implies that perception is for action, and action is for perception – meaning that while perception has evolved to expand and enable our action capabilities, our also evolved action capabilities enable and limit our perceptions. For example, one needs to move to perceive depth non-ambiguously. Both embodied cognition and behavior-based robotics therefore also exploit the unfolding of sensations and actions over time by focusing on lawful dynamic relations between the agent and its environment. Following (Beer, 2023), the role of science is therefore to characterize the structure of agent-environment interactions and the underlying dynamics by which this structure is generated in order to understand intelligent behavior. I concur.

4 WHAT EMPIRICAL FINDINGS SUPPORT YOUR PREFERRED ALTERNATIVE METAPHOR?

That intuitive interactive behavior requires dealing with complexity and paying attention to nuances is not a matter of debate, no matter which camp one is on. We also all agree that more human-likeness in behavior and appearance improves the outcome of the interaction with artificial agents, and that fluency is key. The debate rather centers on the question of how this can be accomplished, i.e. how brain, body, and environment factor into the generation of intelligent behavior. While evidence exists that the individual performance of behavior-based robots demonstrate the feasibility of embodied cognition as a theory of intelligent behavior for the individual agent (e.g. Pfeifer & Bongard, 2006), the question I am addressing here is if implementing theory of embodied cognition, brain-body-environment coupling, and dynamical systems theory, triggers the emergence of improved or more intuitive interactions with human interaction partners than those operating with SMPA cognitive architectures.

As an earlier demonstration of the subsumption architecture, Rodney Brooks and his team built Herbert, a mobile robot with arm and gripper, which could find, grasp, and dispose of cans by layering task-specific behaviors (Brooks et al., 1986, 1988). Both the mobile platform and the gripper have visual sensors (IR and laser-range scanners) that provide the robot with information about distance to objects in its environment. Intelligent behavior is accomplished by directly using information in the environment for motor control in different task-relevant layers. If the laser-range finder and identify object layer identifies a can, this object becomes the goal location and Herbert navigates towards it. Meanwhile, the IR scanner and AVOID layer makes sure that on the way there, no obstacles are hit. Interestingly, action selection is not done via comparison to a model, but via passing on of task-relevant information and inhibition/suppression of irrelevant information. Once the robot is in the object's vicinity, the depth sensor in the gripper enables grasping the object. The payload of the object determines the grasping force via "proprioception", i.e. using the joint angle errors given a known motor transfer function to determine the weight of the object. Herbert then carries the can back to the bin by retracing its own path along walls and other objects in the environment based on the distance it recorded of its way towards the goal via encoders in its base. Once the object is deposited, the weight lift is noticed in the arm, which then triggers the renewed search. Thus, without a plan or model of the world, Herbert's behavior does not just enable it to navigate the world and fulfill its task. Importantly, Herbert can, within the limits of the capabilities of its sensors, motors, and hardware, act in any environment. Interestingly, a similar architecture was used in the design of iRobot's Roomba which, instead of cans, detects dust. It successfully cleans millions of different households. By successfully managing this complexity, Roomba does not just elicits emotional responses by the way it moves - and fails (Sung et al., 2007), it also demonstrates how implementing principles of embodied cognition can lead to useful applications and ubiquitous acceptance of a robot.

While classic representational approaches assume that one needs to extract features from the environment, create a representation and use information from memory to understand the intentions and emotions of a person, Cynthia Breazeal has demonstrated a different approach deploying a subsumption architecture to control her anthropomorphic robot head Kizmet (Breazeal, 2003a; Breazeal & Fitzpatrick, 2000; Brooks, 2002). Her goal was to create a sociable robot that can display intelligent behavior in a complex, unpredictable (social) environment, can recognize and express affect and emotion, and can respond to humans with social adeptness. Therefore, Kizmet's embodiment allows it to express a continuum of emotive states though facial expressions, body posture adjustments, gaze direction, and quality of voice. Its subsumption architecture features a tight integration of an emotion system with a (non-representational) cognitive system guided by a social-/stimulation/-and fatigue drives, and the motor system (Breazeal & Brooks, 2004). Based on perceptions from the environment, the drives shape the "internal agenda" of the robots to fulfill its "needs". The motor system then expresses the emotional stance outward to "get the robot what it needs" from interaction partners to stay homeostatically balanced and satisfied. Enabling what Breazeal calls *social amplification*, Kizmet can, for example, establish its own personal space by using expressive behaviors: if someone comes too close, making their face difficult to fully view due to the narrow field of view of its high-acuity cameras, Kismet becomes more fearful. That emotional state is also reflected in its posture; it draws back. This withdrawal not only increases the physical distance but also acts as a social trigger, prompting humans to adjust their proximity. In HRI studies, humans responded intuitively to this behavior, often apologizing or backing away without needing explicit instructions (Brooks, 2002). Thus, humans interpret Kismet's movements as natural and intentional and adjust their behavior accordingly.

While it is known that biological motion is important to ensure natural human-robot interaction, the complexity of possible perceptual motor control solutions lets many researchers in HRI prefer to use Wizard-of-Oz settings, i.e. telemanipulated robots to study the effects of as-human movements. While the general approach is appropriate for studying HRI, telemanipulation is subject to mapping of human motion to a robotic body, the resulting behavior is not always as intended and can hence not be used to reliable judge human reaction in every situation. Attempting to actually model biological motion, research in biological motor control shows that many human perceptual motor behaviors are based on two fundamental dynamical motor primitives: discrete movements -e.g., reaching, tapping, or throwing, and rhythmic movements -e.g., walking, waving, or hammering (Degallier & Ijspeert, 2010; Hogan & Sternad, 2007, 2012). These findings suggest that human perceptual motor behavior, including multiagent coordination, can often be modeled using two types of dynamical systems: point attractors for discrete movements (Saltzman & Kelso, 1987) and limit cycles for rhythmic movements (Haken et al., 1985; Kugler & Turvey, 1987). Dynamical movement primitives have been successfully used to model various human actions (e.g., reaching, drumming, obstacle avoidance) (Degallier et al., 2006; Fajen & Warren, 2003; Saltzman & Kelso, 1987) and as well as dyadic social motor coordination (Lamb et al., 2017; Richardson et al., 2015). Consequently, low-dimensional dynamical systems combining point attractor and limit cycle primitives offer a potential control architecture for artificial agents to exhibit human-like behavior. Implementing this approach to human-agent interaction in a virtual dynamic shepherding task, (Nalepka et al., 2019) demonstrate that people cannot differentiate if they are interacting with another human, or in fact with an artificial agent following the suggested nonlinear hybrid coupling. Furthermore, after engaging in a goal-directed pick-and-place task with an anthropomorphic robot that was coupled to the human interaction partner (Mörtl et al., 2014), people who noticed the coupling reported that this behavior makes the robot more lively, and fosters smoother interaction.

Let us as a final perspective return to object handover. After noticing that traditional approaches of implementing handover in human-robot interaction fail to provide a fluid and seamless experience for people, (Medina et al., 2016) conducted human-human handover experiments to understand the interaction from a kinematic and kinetic perspective. Their key insights show that people control both their hand and arm during all handover phases in proportion to the object load they carry, and that for fluid interaction one needs to consider the reciprocal coupling of giver and receiver arm movements as well as the dynamic transfer of giver grip force to load share with the receiver. Lastly, they also show how the hand-over force dynamics are supported by the arm motion dynamics and configuration. Based on this, they develop a fluid controller that captures the entirety of the interactive process and considers the coupled underlying dynamics and kinetics between giver and receiver in which the handover point is modelled as an attractor that governs both giver and receiver arm and hand motion until the object is passed on. In a subsequent human-robot interaction study they demonstrate that the fluid controller significantly reduces the duration of the passing phase, the internal forces, as well as the required work for both human and robot in comparison to a traditional thresholdbased controller. Thus, their coupled dynamics model results in more natural, fluid, and seamless hand-over situations.

In summary, implementing the principles of embodied cognition and interaction dynamics to artificial agents does indeed result in natural, smooth, and fluid interactions demonstrating that the underlying mechanisms may be one step closer to what is going on. Unfortunately, as comparatively few implementations exist, the sample size for my evaluation was small. Considering that this approach is, however, very promising given its ability to deal with complexity without relying on black box machine learning, I am hoping for the inclined roboticist to expand from bio-inspired robots for animal models to contribute to the ongoing debate about artificial intelligence – as it seems indeed, it should be an embodied one.

However, I want to emphasize that while I truly believe that a more embodied and dynamic approach to HRI will allow us to learn more about ourselves and will provide great insights into the embodiment and emergence of intelligent behavior, I am not trying to make the case for more sophisticated robots alone, but more importantly for a more holistic consideration of the *impact* the robot has. If we consider not just a robot in isolation, but the human-robot-environment interactive system, we have a chance to study the consequences of robot designs before deploying them to the public.

This is very important as there is an *enormous* risk: If we in fact succeed in building robots that are intuitive to interact with because we got the brain-body-environment coupling right, we also build robots that are certainly anthropomorphized or humanized (Balkenius & Johansson, 2022; Giger et al., 2019). This can lead to serious problems with respect to appropriate behavior and emotional attachment to robots (Prescott & Robillard, 2021; Robert, 2017). As robots are already often anthropomorphized, especially if they have a human-like appearance[7], such as the multi-purpose humanoids about to be unleashed into public at large scale, people will have no guardrails against deception and manipulation. If our actions are reciprocated by the robot, or the robot displays *as-human* behavior, we are biologically wired to engage (Brooks, 2002; Ye et al., 2023). This biological wiring makes us highly vulnerable to being "moved around", both in the sense of physical guidance though cleverly designed motion guidance nudging, as well as emotionally (Fuchs & Koch, 2014). At the same time, we know that our quality of life and wellbeing in our circles, at school, at work, when we need care, all highly depend on human contact. Strangely, because we assume that interaction happens in the brain, we tend to assume that interaction does not affect the body. Opposing that notion, there is overwhelming evidence that our social interactions greatly affect our bodies, including our brains, and our health (e.g. Cacioppo, 2008; Chiel & Beer, 1997; Van der Kolk, 2014). If we instead of engaging with humans, engage with robots, the problem is, that we are engaging with a machine that is, factually, unable to empathize (van Wynsberghe, 2022) and in most cases is controlled by proprietary algorithms, i.e. by for profit companies. So, while I firmly believe that robots could be an invaluable tool to gain insight into the working of brain-body-environment couplings, and the emergence of intelligent behavior, and that there is a way to use robots as a valuable supportive tool to improve the way we live and work (Prescott & Robillard, 2021) – we need to take precautions such that we design robots for good (Šabanović et al., 2023). One way forwards may be to limit the robot's appearance to a more functional form (Balkenius & Johansson, 2022; Brooks, 2002) and instead focus on the function-movement relation while

[7] But not only when they appear human-like. People tend to anthropomorphize objects in general, and machines in particular - especially when they act somehow unpredictably as this invokes the illusion of agency and aliveness (Reeves & Nass, 1996).

still enabling goal-directed, intention-communicating and supportive robot behavior via embodied and situated control.

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