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# Leveraging Embodied Intelligence for Dexterous Robotic Manipulators Through Iterative Co-design

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**Abstract.** The role of embodied intelligence (EI) has the potential to overcome current limitations in the fabrication, control, and resulting behavior to create robust and effective dexterous robotic manipulators. To develop hands that truly exploit EI, we must design hands by considering the entire system: the physical body, sensory systems, and the brain (the controller). However, we lack clear approaches and methods that enable this system level design for hands. We introduce an iterative approach for co-design which seeks to utilize simulation and real world evaluation to maximize the performance by distributing EI across the different elements of the system. To achieve this vision we require hands that can be rapidly fabricated with variability in the design space. Thus, to further the development of robotic hands that utilize EI we need streamlined fabrication pipelines which incorporate spatially distributed sensors, complex geometries and materials, and control distributed at the sensory-motor and high task planning domains.

## 1. Introduction

Robotic manipulation has long been an active research field involving interdisciplinary researchers from domains including neuroscience, engineering, computer science, and materials science [30, 33, 1]. A key focus and open challenge is achieving more human like dexterity [24, 28]. Dexterity describes the ability to perform complex interactions with objects and the environment including in-hand manipulation, the ability to translate and rotate objects [31], and the ability to exploit environmental constraints, for example sliding a coin over a table to grasp it off the edge. Dexterous manipulation is particularly challenging as it inherently relies on complex interactions between the robot, object, and the environment [8, 23].

In recent years, there have been some notable examples of robot hands that showcase examples of this dexterous behavior [32, 7, 39, 34]. However, the capabilities of these hands are still limited when compared to our human counterparts. For example, they have limitations for error recovery, robustness to different environments, or behavioral diversity [11]. Extending the capabilities of robot hands will unlock many application ranging from service robots, prosthesis, medical or even agricultural robotics.

Many different approaches have been explored to move towards achieving dexterous manipulation [31, 40, 2, 26, 3]. This includes developing methods for fabricating complex bio-inspired hands and joints [38, 16], and developments in materials science and soft robotics to allow the creation of more compliant hands and manipulators [20, 27]. Deep learning, highly successful at many computational and learning tasks, has also been introduced to the field of

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manipulation [29, 32]. However, when compared with humans, AI based machines still struggle to exploit their physicality and situation with the environment, while introducing large complexities into the system [7]. In order to achieve a significant change in current dexterous manipulation capabilities, this "conventional-AI" must be augmented or combined with so called "embodied AI" which allows the computational power to be combined with exploitation of the physicality of the system. To move towards this approach we must understand how to design the "body" of robotic hands in conjunction with the algorithmic intelligence of the "brain" of these hands.

Considering human hands and fingers as a blueprint for highly dexterous manipulation, their "co-design" of the highly complex physical components (skin, sensors, bones, ligaments) and control system (nervous system and brain) has developed over millennia of biological evolution. Artificially developing hands and methods of design that rival evolution continues to be a significant challenge for engineers. Whilst complex multi-fingered hands have been developed numerously in the past, there is limited use of the design optimization, modeling, and controller development. In addition, due to complexity of the design and fabrication of sensory-motor systems, the exploitation and design of tactile sensors is also often not incorporated or considered as part of the design process for dexterous hands. This problem of negotiating complexity calls for a new approach towards designing and developing dexterous manipulation systems.

In this chapter, we introduce and expand upon the idea of iterative co-design: the simultaneous design iteration of the hardware and controller for multi-fingered hands. This concept aims to exploit embodied intelligence (EI) to provide behavioral advantages by designing the brain (controller) and body (mechatronic design) simultaneously. Importantly this extends to sensory systems at both the physical (sensory design and properties) and computational level (sensory-motor interactions). We hypothesize that a design methodology which simultaneously co-designs the EI and the computational intelligence of a system will be able to achieve behaviors that are otherwise not possible, or would require significantly more complexity or cost when designed separately. In the remainder of this chapter, we first address the challenges of design of robot hands, followed by a brief review of the related works with a discussion on what research directions are missing. A framework for iterative co-design of dexterous hands is then presented, before we conclude with a discussion on the challenges and future work.

## 2. Problem definition

A dexterous multi-fingered system is a highly complex system with multiple degrees of freedom (dof), intricate structures, actuators, and levels of control. Naturally, the process of designing and realizing such a system is therefore complex. Fig. 1 represents the progression of the development of a robot hand from the design stages to the use case. The brain and body of the hand is designed, fabricated, and the interactions planned. Through interactions between this hand system and the environment the behavior of the hand emerges. As labeled in the diagram, certain stages of the development incur "costs" $C$ while the output behavior can be considered a "reward" $R$. Examples of how these quantities could relate with a robotic hand are shown in Table 1.

The objective of the design process is to maximize $R_{behavior}$. However, simply aiming for the maximum behavioral reward is likely to result in a overly complex system which is challenging/resource-intensive to optimize at best and unable to optimize at worse. To combat the problem with complexity, we must take into consideration of the costs of development and devise a method to minimize those costs while maximizing the behavioral reward. This can be done at two levels within the robot development.

In other words, we must consider an objective function $\mathcal{Q}$ which simultaneously maximize the behavioral reward and minimize the costs constructed by some function $q(\cdot)$. We can consider the total cost to be the combination of various costs that arise throughout the full robot development stage and care about, given by $c(\cdot)$. The exact form of the function $q(\cdot)$ and $c(\cdot)$, and how the

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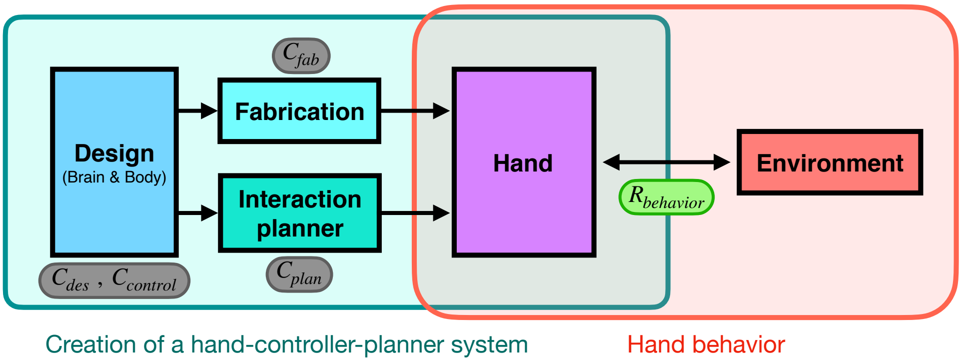


**Figure 1.** Simplified diagrammatic representation of the development and use of a robotic hand. The costs and rewards arising throughout the process is indicated by $C$ and $R$.

**Table 1.** Cost and rewards throughout the robot hand development and usage

| Quantity | Description | Example |
|---|---|---|
| $C_{des}$ | Cost of mechatronic design | Number of actuators<br>Time required to modify an existing design |
| $C_{control}$ | Cost of controller complexity | Number of gain parameters to tune<br>Number of layers in the neural network |
| $C_{plan}$ | Cost of planning and running the controller | Computational resource for planning or training |
| $C_{fab}$ | Cost of fabrication | Time taken to fabricate a hand<br>Monetary cost of purchasing a hand |
| $R_{behavior}$ | Reward of dexterous behavior | Reachable work space by the fingertip<br>Success rate for a task |

specific rewards and costs defined, is highly dependent on the situation.

$$\begin{aligned} \mathcal{Q} &= q\left(R_{behavior}, C_{total}\right) \\ C_{total} &= c\left(C_{des} + C_{control} + C_{plan} + C_{fab}\right) \end{aligned} \tag{1}$$

Using this analysis of the "cost" of hands we can analyze the role that EI can play in both the design, creation and use of hands. Typically, concepts EI is used to either maximize the behavioral output with minimal gains in cost (e.g. using soft materials to provide robustness) or, to minimize the costs whilst maintaining behavioral output (e.g. muscle synergies). However, if we can develop methods that allow us design systems where EI can be used to affect both the costs and rewards, we may be able to better optimize the use of EI across the entire system. Hence develop hands with both better performance and lower cost.

### *2.1. Approaches towards robot hand development*

In this section we discuss two high level approaches to the development of robotic hands: sequential and iterative co-design. We aim to highlight how the costs $C_{total}$ is closely linked to the structure of the approach itself, and therefore claim that the cost can be minimized by proposing an alternative robotic development approach: iterative co-design.

When designing any robotic system, and in particular a robotic hand, the standard/traditional approach has been a sequential process shown by the top flow chart of Fig. 2. In this approach, the robotic hand is developed step by step starting from the mechatronic design, to the fabrication, sensor addition, and finally a controller to operate the hand.

Iterative co-design presents an alternative robotic system development approach and is shown by the bottom flow chart of Fig. 2. Firstly, this approach is considered a *co-design* since the

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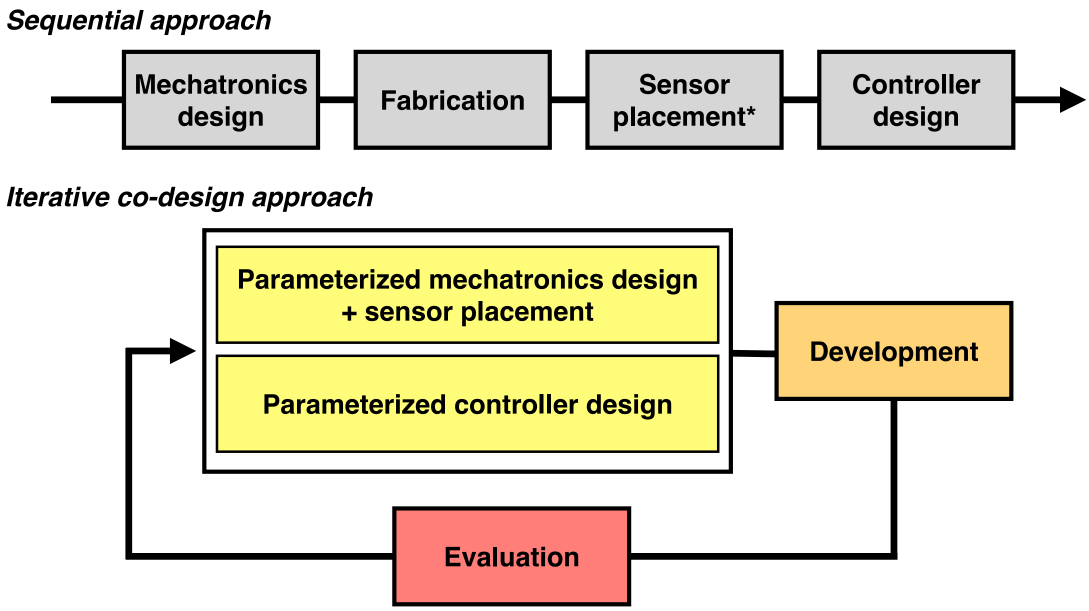


**Figure 2.** Block diagram of two methods of developing a robotic hand: Sequential approach and Iterative co-design approach. *Depending on the system, sensor placement can be included in the mechatronics design process

controller and the hardware is designed at once. Secondly it is *iterative* because after each development cycle, the robotic system is evaluated which can be used to update the parameters of the system. The development step refers to different ways a robot hand can be realized (e.g.: physical fabrication, simulated hand model, etc). Between the two approaches, there are trade-offs in costs incurred throughout the process. However, we claim that there are intrinsic properties within the iterative co-design approach that maximize $\mathcal{Q}$ and hence the preferred approach for the future of robotic hand design.

The sequential approach being the standard/traditional approach has a number of key benefits which should not be overlooked. The key advantage is to exploit specialization. Robotics being intrinsically multi-disciplinary, it is not scalable for a single individual or institutions to perform all aspects of the development. By distributing the development to different individuals/institutions with different tailored skills, one can argue the robot development is more efficient. Furthermore, the development process does not rely on multiple iteration, which further speeds up the process. However, with highly complex systems such as robot hands, there are clear disadvantages of this process. When a robot is developed sequentially, at any given step, design decision made earlier in the process affect the design decisions later in the process which has the tendency for the $C_{total}$ to increase significantly.

For robotic hands, commonly the mechanical system is designed to allow for maximum flexibility for the user since the use case is unknown. For example, by maximizing the number of joints and actuators, the designer of the controller is less constrained by the possible motion of the hand. However, such design decisions generate complexity which may not contribute to increasing the performance. In this same example, as the number of dof and actuators in the hand increase, the controller becomes inherently complex and difficult to adapt to new scenarios. Furthermore, certain design decisions made earlier in the process can be a hindrance unknowingly for later processes - an unintentional cost incurred due to the structure of the sequential approach. Especially if the hardware is purchased, the inability to modify the design in addition to the monetary cost of the platform all contribute to increase $C_{total}$.

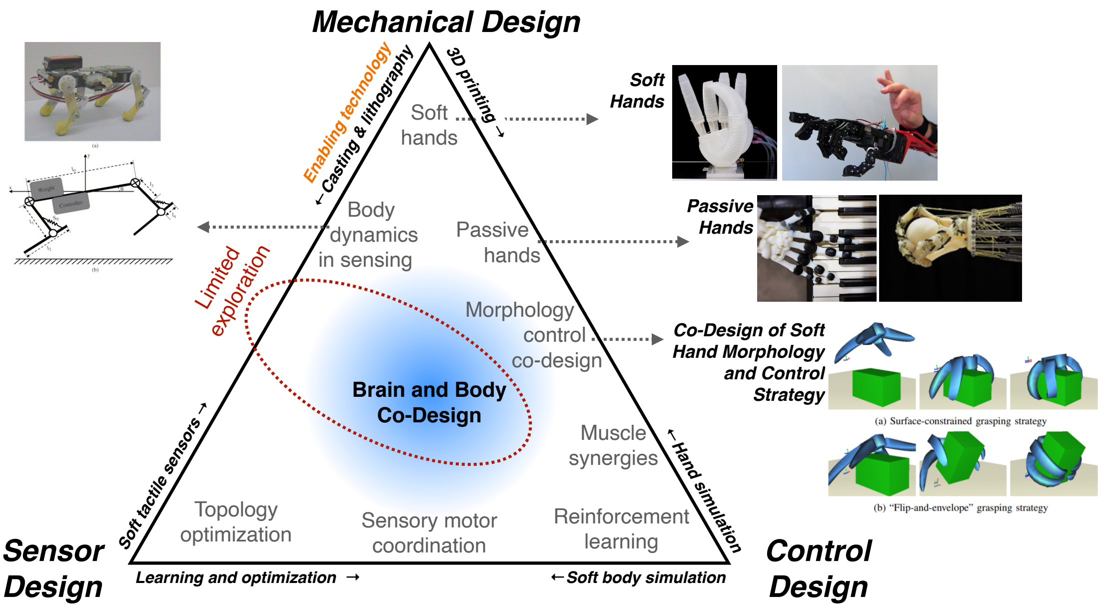


**Figure 3.** Organization of related work on co-design with a focus on robotic hands utilizing EI.

Iterative co-design offers an alternative approach to benefit from EI. Robotic systems and in particular robot hands have a strong coupling between the brain and body. The behavior of a robotic hand is hugely dependent on the mechatronics design (body): the number of fingers, how they bend, what sensors are placed and how they are placed, etc. Equally, the controller (brain) defines the interaction with the world and thus the behavior. We hypothesize that through co-design, the interaction between the brain and body can be captured and optimized, leveraging the advantages of EI. This would result in a system with a lower complexity/cost compared to a system developed through the sequential approach (e.g.: simpler controller, lower dof) but can achieve similar or improved behavior. In other words, by leveraging the EI of hands through the design method, we are able to systematically reduce $C_{total}$. Furthermore, the iterative nature of the approach allows for a optimization process to be defined, leading to increasing $\mathcal{Q}$.

## 3. Existing approaches to co-design

To understand the existing methods of co-design in robotic hand development, we consider the diagram in Fig. 3. This figure represents a three dimensional design space between mechanical, control, and sensor design where co-design sit at the center of this design space. This analysis allows us to identify key works that utilize co-design as a method of exploiting EI. Please note this is intended as a means to highlight notable works as opposed to a full review.

Soft hands are one significant area of research where EI is exploited through mechanical design to enable compliance or adaptive grasping approaches with minimal control [20]. Enabled by casting and lithography techniques made possible by 3D printing, key examples include the RBO hand [12, 36], or the anthropomorphic compliant DLR hand [10]. At the intersection of control and mechanical design, there has been progress made in recent years. This includes simulation work that enables the co-design of morphology and grasping control for soft robots [13]. This, and similar approaches [6, 37], are increasingly becoming feasible due to the development of simulators that can be accurately represent soft structures and complex contact with the environment. An alternative approach which focuses on fully exploiting EI is that of the passive

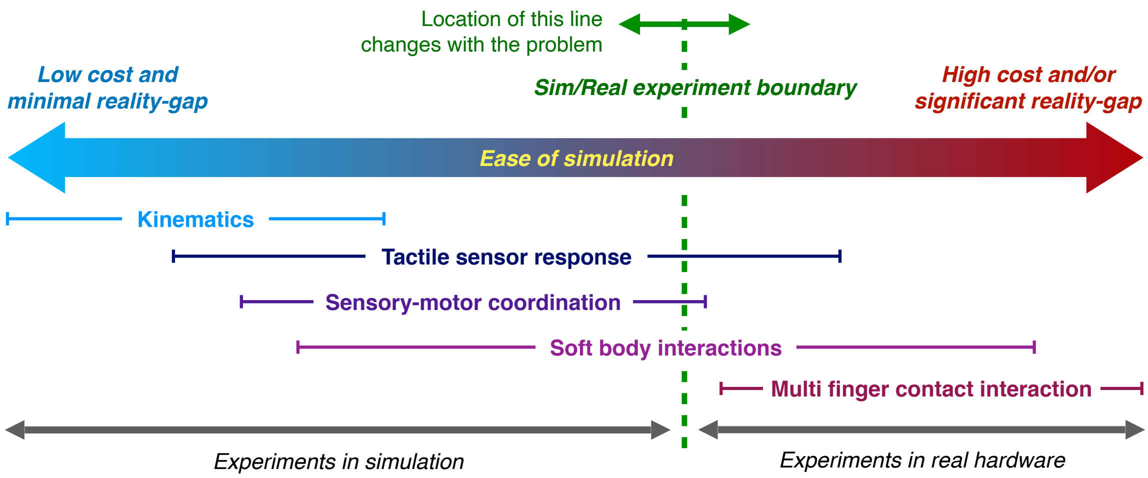


**Figure 4.** Qualitative placement of various robotics tasks on a spectrum based on the ease of simulating that task. Tasks on the spectrum can be split into two sections by the green dotted line: one where it is cheaper to experiment in simulation, another where it is cheaper to experiment using a physical setup.

hand – where only the wrist is actuated and the design or mechanical properties of the hand are designed or tuned to optimize the dexterity and range of motion [19, 16]. Control approaches leveraging this have been shown to enable piano playing and grasping of objects.

Moving towards the control domain, muscle synergies which focus on utilizing a low-dimensional representation or control input to achieve a high-dimensional rich behavioral/actuated output have been successfully demonstrated for manipulation [15, 17, 9]. This bio-inspired concept focuses more on exploiting the EI of control within the hands, but requires mechanical design that have sufficient complexity to allow such control methods to be exploited[14, 5].

Sensory-motor co-ordination sits at the intersection of sensor and controller design, and is necessary for many of the increasingly capable in-hand manipulation tasks being demonstrated [25]. Much of the research in this area focuses on developing controllers (including learning approaches) that leverage sensor design. There is limited exploration of how the sensory design affects the controller and the resultant performance. Whilst there has been some exploration of algorithms for topology optimization or morphology optimization of soft sensors [21, 35], this largely focuses on optimizing to improve the reconstruction of tactile information opposed to optimizing for control purposes.

As highlighted in Fig. 3, despite the developments in the area of co-design there appears to be limited work in the intersection of incorporation of sensor design into the design process and hands. Existing work in sensory topology has highlighted the gains that can be made solely through topology optimization, thus, there is an opportunity to combine and accentuate this other EI contributions. Equally works such as [22] show the importance to consider the body mechanics (in this case body dynamics) to assist sensing capabilities. We argue that to fully leverage and exploit EI within hands, we need to move to an approach for co-design that considers mechanical, control, and sensors, and that, to date, this design space has not been explored. We hypothesized that this is largely due to three current constraints or limitations which we discuss in detail in the following section.

### *3.1. The challenges in co-design*

Three key challenges can be identified when implementing the iterative co-design process for robotic hands. The first challenge is the limitation of cheap simulation tools with a minimal reality gap. While simulation capabilities have increasingly improved over the decade, for robotics research involving physical hardware, accurate and general purpose simulation tools are not widely available. The second challenge is the lack of a cheap, fast, and reliable fabrication method to iterate upon the hardware. While customizable hardware can be developed, it tends to incur a high cost in $C_{fab}$ (in the form of monetary cost and time) preventing multiple hardware iterations and exploration from being practical. The third challenge is the challenges in parameterization of the design. There are multiple ways of parameterizing both the hardware and the controller, and an effective method of doing so while maintaining real world constraints (such as the tolerances in manufacturability) is unsolved.

To better understand these challenges, consider Fig. 4. This figure aims to illustrate a spectrum of robotics tasks arranged by their general trend of qualitative "ease of simulation". Tasks which lie on the left side of the spectrum can be simulated cheaply and has a minimal reality gap. Such tasks only have a few well defined dof and modeling techniques are well-explored. Towards the right side, experimentation in simulation becomes challenging. This is because a) the simulation is computationally expensive, and/or b) the reality gap is so difficult to close such that the simulation is not meaningful. The full simulation of hands: complex multi dof mechanical interactions involving softness and friction with modeled sensors that match reality, is a highly challenging task which lies on the right side of this figure.

One way to combat the lack of simulation tools, is to look towards real world experiments. The green dotted line in Fig. 4 is a slider which divides robotics tasks on the "ease of simulation" spectrum between those which are suitable to execute in simulation or instead on a physical setup. The position of the slider is qualitative and depends on the task and resources available. Using real experiments, we are able to negotiate the limitation of simulation tools by offloading certain tasks to be evaluated in real life. Conceptually, this reduces costs of setting up and executing a complex simulation reducing $C_{total}$. This calls for a further need to tackle the second key challenge: the lack of cheap, reliable hardware.

Even if we are able to achieve a good experimental setup utilizing cheap simulation and cheap hardware, to leverage the best of both worlds, the third challenge remains. An effective method of identifying parameters of a complex system does not exist, and is usually left to the designer. Since the co-design process iterates on the parameters, their definition governs the final performance of the system. Furthermore, the parameter set must be tractable in both simulation and fabrication. If simulation and fabrication capabilities are improved, the constraints on parameters being tractable are loosened, allowing for more diverse exploration of the design space.

From this discussion, we see the three challenges in iterative co-design are loosely linked. If simulation capabilities are improved, more complex experiments can be conducted in simulation, reducing the need for hardware experiments. Conversely, if a low cost and reliable hardware can be fabricated, real world experiments can substitute the need for complex simulations. Improvements in simulation and fabrication techniques also allow for more diverse sets of parameters to be used. Although addressing one challenge would contribute towards solving the other challenge, we claim the development of a low cost and reliable hardware is most critical in the context of robotic hands. This is because regardless of the simulation capabilities or the definition of parameters the hardware must be fabricated at some point. With current simulation capabilities, even with the most computational intensive machines, there will always be some reality gap which requires calibration with a real system to close the gap.

Therefore, we believe the necessary steps to address the three key challenges are: a) accelerating the development of a low cost and reliable robotic hardware; b) construct an iterative

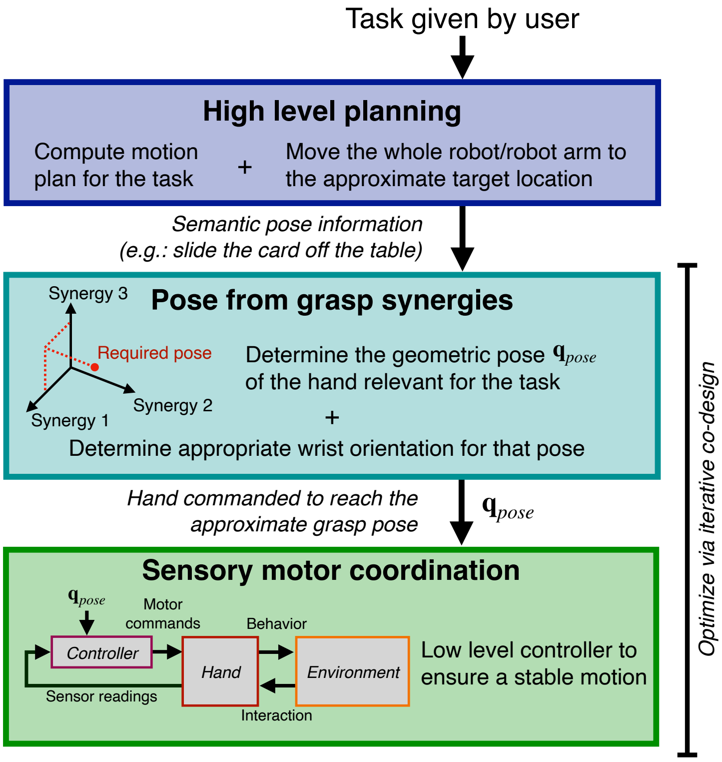


**Figure 5.** Three layers of abstraction to control a robotic hand system.

co-design process which utilizes simulation and real-life experiments and accounts for the cost of hardware development; and c) explore different methods of defining a suitable parameter set, while expanding/diversifying with improvements in simulation and fabrication.

## 4. A framework for iterative co-design

In the remainder of this chapter, a framework for implementing iterative co-design for robotic hands will be discussed. We first focus on how hand control and planning can be abstracted and divided into three layers of control. This is followed by an outline and discussion of a possible iterative co-design process.

### *4.1. Control abstraction of robotic hands*

*4.1.1. Overview of the abstraction layers* To begin the discussion of co-design, we must consider how the hand will be controlled. Fig. 5 presents three level of abstractions for controlling a robotic hand. This abstraction structure is directly inspired from how humans interact with objects using our hands. Take the example of opening a door. At the highest level of abstraction, we move our body, arm, and hand towards the object (the door handle). In the middle level of abstraction we make an approximate pose of our hand (power grasp of the handle). Finally, at the lowest level, we use our tactile and proprioceptive sensors to achieve a robust action (readjusting our grip, location of fingers, force applied to the door handle, etc).

In the first two layers, the motion is planned and adjusted primarily with visual feedback (e.g. adjusting your hand position with respect to the door handle). In the final layer however, the motion is more reactive and is purely based on the low level controller.

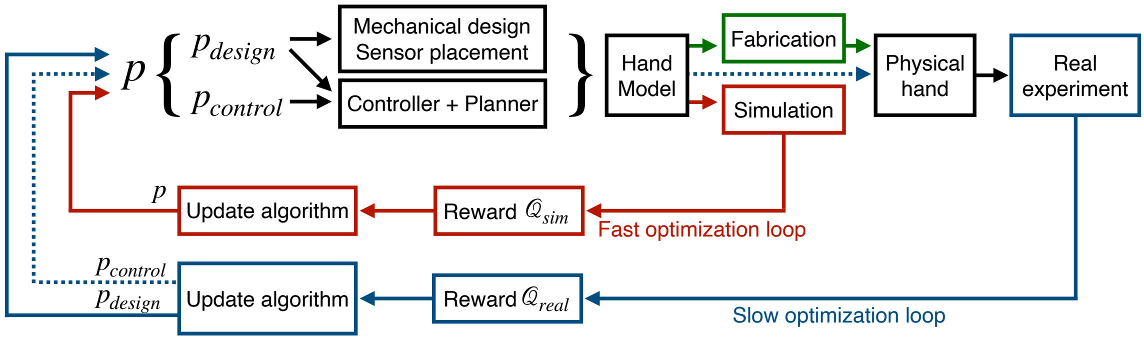


**Figure 6.** Block diagram of a possible implementation framework of iterative co-design.

*4.1.2. Abstraction layers in detail and its relationship to iterative co-design* For iterative co-design, the high level planner can be neglected (and will be neglected for the remaining discussion), as this planner is concerned with semantic understanding of the task and positioning of the hand, but not with the direct interaction of the hand with the environment. The final two layers depends largely on the morphology, sensing, and the sensory-motor control, and hence will be the focus of iterative co-design.

The middle layer of abstraction: "Pose from grasp synergies" are generated based on the semantic pose information. Grasp synergies are a collection of low dimensional representations of key *poses* of the hand, where a large collection of poses can be derived and chosen by the mid-level controller by "interpolating" between such synergies. In this way, the set of all poses becomes a continuous quantity - allowing possibilities of gradient based optimization to be incorporated in this co-design process. However, potential discontinuities and unreachable spaces due to the physical configuration of joints and actuators must be determined and optimized for the task.

The lowest layer: "Sensory motor coordination" focuses on how the sensors in the hands are used to make the approximate pose determined in the layer above into a reliable action which interacts with the environment. The structure and parameters of the low level controller is the quantity to be optimized through the iterative co-design process.

### *4.2. Iterative co-design framework*

Fig. 6 illustrates a high level framework for the implementation of iterative co-design. We assume to have access to a low cost and reliable hardware platform as discussed in section 3.1 where its design is parameterized. The core of this framework is $p$, the set of all parameters of the hand. $p$ can be divided into $p_{design}$ and $p_{control}$, the parameters for the hardware design and for the controller respectively. The aim is to maximize $Q$ by tuning $p$.

The *iterative* part of the block diagram takes the hand system based on $p_i$ (the set of parameters at some iteration $i$), evaluates the objective function ($Q_{sim}$ or $Q_{real}$ based on if the experimentation was in simulation or in real life), and then updates the parameters $p_{i+1} \rightarrow p_i$. The red "inner" loop updates $p$ by running simulated experiments while the blue "outer" updates $p$ by running real experiments. Through the use of a low cost hardware to run real world experiments, we aim to optimally exploit the relative advantages of simulation and real world experimentation as discussed in section 3.1.

In both loops the reward must be calculated. Defining a reward function mathematically is one of the most challenging tasks of the implementation since a universal performance metric for dexterous manipulation does not exist and the details are dependent on the task type and environment. Furthermore, matching the high level intention of the framework designer and form of the reward metric is challenging as we know from related challenges in artificial intelligence and

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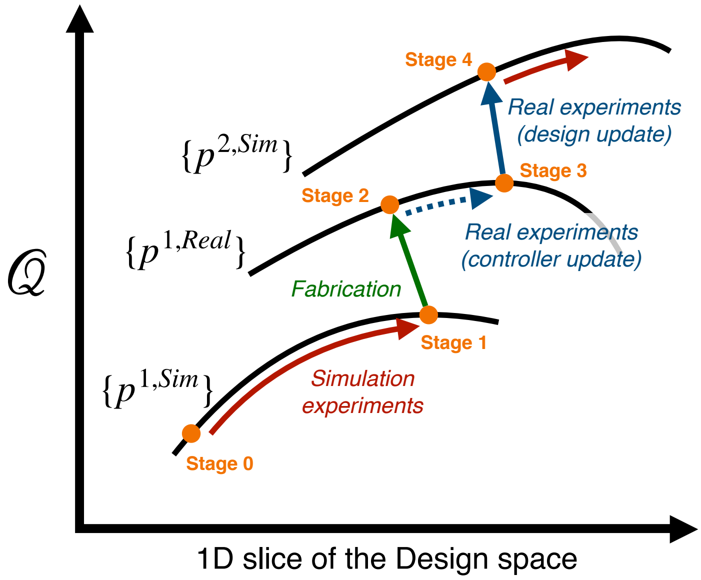


**Figure 7.** Conceptual plot to visualize how the iterative co-design process is expected to increase $\mathcal{Q}$.

reinforcement learning such as reward hacking [4] and misalignment [18]. The implementation of the updating algorithm is also a challenging yet key component of the framework. This updating algorithm can be completely model free such as Bayesian optimization, or include some information about the hand model to speed up the optimization process.

### *4.3. Iteration process*

The iteration and optimization process can be divided into three stages.

(i) Update $p$ through simulation

(ii) Update $p_{control}$ through real experiments after fabrication

(iii) Update $p_{design}$ through real experiments

Fig. 7 illustrates how we expect the reward to increase as we repeat the iteration process. The colors and formatting of the arrows match the that in Fig. 6. We start the process at **Stage 0** with some initial design parameter. We first use simulation to optimize the parameters (red solid arrow). We expect to use a low cost simulation, and hence this is the *fast optimization loop* which can run arbitrarily many times. A key point is that during this optimization process we only have "access" to a set of parameters of the design space the simulation can explore denoted by $\{p^{1,Sim}\}$ (the superscript number reflects the iteration count while *Sim* or *Real* reflects the optimization setting). The whole design space cannot be covered due to limitations of the simulation, computational costs, and how designs may get stuck in a local minima.

Once **Stage 1** is reached (the optimal point achievable via simulation experiments) the hand will be fabricated to conduct real world experiments (green solid arrow). Since the real world experiments allow further exploration of the design space, fabrication of the hand "unlocks access" to a new set of parameters $\{p^{1,Real}\}$ which can now be explored and reaching **Stage 2**.

Once the hardware is fabricated, multiple iterations to update $p_{control}$ can be performed (blue dotted arrow). We limit this step to $p_{control}$ because updating a controller is expected to be significantly faster than updating (re-fabricating) the hardware. Once **Stage 3** is reached we have exhausted the optimization possibilities using the current hardware setup. Finally, $p_{design}$ can be updated to reach **Stage 4** (solid blue arrow) - restarting the iteration process.

There are of course clear potential roadblocks with this iteration method. For example, the choice of updating algorithm is critical to produce meaningful improvements in $\mathcal{Q}$. Equally, as we expand $p$, exploration of the full search space becomes difficult. The trade-off between complexity and reward must always be considered.

## 5. Conclusion

Exploiting EI is one means by which the capabilities of current robot hands could be extended to improve their performance in increasingly complex and unstructured environments. In addition to core technologies that provide physical intelligence (fabrication methods, sensors, materials), we also require methods to optimize the design of hands to incorporate EI. In order to fully exploit the possibility of EI, we believe that co-design of the brain and body of the robotic system is critical. In this chapter we propose a method for this: iterative co-design, which leverages both the simulated and real world as a new method for hand design.

To implement this iterative co-design approach, one fundamental challenge is the need of a physical platform with complex structures and embedded sensors which can be fabricated rapidly and repeatably. The fabrication and design should be achievable on the timescale of hours. Such a hardware platform allows the parameterized design to be rapidly iterated and experiments conducted that can not be performed in simulation. We also require the hardware to have a significant design space that spans different materials, sensor, and geometries.

One aspect of this approach which we have only touched upon is the task definition and the evaluation or bench-marking metrics. The iterative optimization process relies on evaluating the hand performance and updating the design parameters. Likewise the aim of simultaneously developing the brain and body of hands, is to find a design solution which can perform increasingly complex, broad, and potentially even unseen tasks. Hence, evaluation metrics must be formulated that captures the performance of a range of tasks effectively and accurately.

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