# On the Information Theoretic Implications of Embodiment – Principles and Methods

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**Abstract.** Embodied intelligent systems are naturally subject to physical constraints, such as forces and torques (due to gravity and friction), energy requirements for propulsion, and eventual damage and degeneration. But embodiment implies far more than just a set of limiting physical constraints; it directly supports the selection and processing of information. Here, we focus on an emerging link between information and embodiment, that is, on how embodiment actively supports and promotes intelligent information processing by exploiting the dynamics of the interaction between an embodied system and its environment. In this light the claim that "intelligence requires a body" means that embodied systems actively induce information structure in sensory inputs, hence greatly simplifying the major challenge posed by the need to process huge amounts of information in real time. The structure thus induced crucially depends on the embodied system's morphology and materials. From this perspective, behavior informs and shapes cognition as it is the outcome of the dynamic interplay of physical and information theoretic processes, and not the end result of a control process that can be understood at any single level of analysis. This chapter reviews the recent literature on embodiment, elaborates some of the underlying principles, and shows how robotic systems can be employed to characterize and quantify the notion of information structure.

**Keywords:** Embodiment, Information Processing, Morphology, Materials.

## 1 Introduction

The stance taken here strongly differs from the still widely held traditional one of "cognition as computation" where intelligence is considered to be algorithmic and the result of abstract symbol manipulation. While this computational perspective has led to many important theoretical insights and applications, most of the emphasis has been on exclusively internal mechanisms of information processing. Contrasting the computational perspective, there has been a considerable amount of research demonstrating that cognition is embodied and best understood as a situated activity.

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The extensive conceptual and empirical groundwork for embodied cognition laid within psychology, cognitive science, philosophy artificial intelligence, and robotics has been reviewed elsewhere [1–16]. Building on this body of empirical and theoretical work, here we address a specific set of issues surrounding the potential link between embodiment and information processing.

Our main thesis is that the interaction between physical and information processes is central for the emergence and development of intelligence. When talking about agents in the real world, it is important to realize that information is not just “out there”, an infinite tape ready to be loaded and processed by the cognitive machinery of the brain. Instead, through physical (embodied) interactions with the environment, information structure (e.g., spatio-temporal correlations in a visual input stream, redundancies between different perceptual modalities, or regularities in sensory patterns that are invariant with respect to changes in illumination, size, or orientation) is actively induced in sensory inputs. In the context of this review, we will use the term information structure to refer to the structure in the sensory data typically induced by and meaningful with respect to some purposive or intended action such as grasping or walking. As suggested here, the presence of such structure might be essential for the acquisition of a broad range of cognitive and motor abilities such as multimodal sensory integration, cross-modal learning, perceptual categorization, reaching, object manipulation, language, and locomotion.

We first discuss a case study, categorization, illustrating the main concepts, and we formulate two pertinent principles. Subsequently, we expand on the notion of information structure and information self-structuring, and show how quantitative measures can be used to provide corroboration and theoretical groundwork. We will then briefly discuss the role of these ideas in learning and development and look at how dynamics can be exploited to structure sensory stimulation. Finally, we discuss the implications of the ideas developed in this chapter for theories of cognition and cognitive development.

## 2 Categorization in the Real World

For autonomous embodied agents acting in the real world (animals, humans, robots), perceptual categorization – the ability to make distinctions – is a hard problem. First, based on the stimulation impinging on its sensor arrays (sensation) the agent has to rapidly determine and attend to what needs to be categorized. Second, the appearance and properties of objects or events in the environment being classified vary continuously, e.g., owing to occlusions, and changes of distances and orientations with respect to the agent. And third, the environmental conditions (e.g., illumination, viewpoint, and background noise) fluctuate considerably. There is much relevant work in computer vision that has been devoted to extracting scale- and translation-invariant low-level visual features and high-level multidimensional representations for the purpose of robust perceptual categorization [17–19]. Following this approach, however, categorization often turns out to be a very difficult if not an impossible computational feat, especially when adequate information is lacking. A solution that can only be pursued by embodied agents, but is not available when using a purely computational (i.e., disembodied) approach, is that through their interaction with the environment, agents generate the sensory stimulation required to perform the proper categorization and thus drastically simplify the problem of mapping sensory stimulation onto perceptual categories. The most typical and effective way is through a process of sensory-motor coordination.

Because of its almost universal presence in behaving organisms, sensory-motor coordination has been widely studied in psychology, neuroscience, and robotics [20–31]. Studies indicate how sensory-motor coordination, for instance, simplifies category formation (for a review, see [30]), influences visual experience [25], and determines concept acquisition [32]. One demonstration of the idea of exploiting coordinated interaction with the environment is a study by Pfeifer and Scheier [23] in which it is shown that mobile robots can reliably categorize big and small wooden cylinders only if their behavior is sensory-motor coordinated. The artificial evolution experiments by Nolfi [26] and Beer [27] illustrate a similar point: the fittest agents, i.e., those that could most reliably find the category to which different kind of objects belonged, were those engaging in sensory-motor coordinated behavior. Intuitively, in these examples, the interaction with the environment (a physical process) creates additional (that is, previously absent) sensory stimulation which is also highly structured thus facilitating subsequent information processing. Computational economy and temporal efficiency are purchased at the cost of behavioral interaction, so to speak.

## 3 Information Self-structuring

The idea that the synergy between the world and the observer's actions plays a primary role for the emergence and development of cognition is much in tune with previous work on direct and active perception [33–35], animate, interactive, and enactive vision [36–38]. From an information theoretical point of view, embodied agents generate information structure in their sensory stimulation as they – actively – interact with the environment. It is important to note that in this process, the specific morphology (type and placement of the sensors and actuators) and the materials used unavoidably determine the resulting information structure. Because of the high density of touch sensors on the fingertips and because of the shape of the hand, for instance, grasping automatically leads to rich, structured tactile stimulation. The coordinated sensory-motor action of grasping induces stable patterns of stimulation characterized by correlations between the activities of receptor neurons within a sensor modality, as well as correlations between receptor neurons in different modalities (vision, touch, audition, and proprioception). Such correlations or statistical dependencies (which are instances of information structure) create redundancy across sensory channels, which may help reducing the effective dimensionality of the input, and which in turn – given the typically staggering number of possible configurations that the input system can assume – significantly simplify perception. We call this idea the "principle of information self-structuring" [28,29,39].

Theoretical studies and robot models provide quantitative evidence for the notion that self-generated motor activity can create information structure in sensory-motor data [23,24,26,28,29,39,40]. For instance, in [28] it is shown how a simple robot capable of saliency-based attentional behavior – an instance of an active vision system – self-structures the information present in its sensory and motor channels (Fig. 1). The results exposed in the article also demonstrate that sensory-motor coordination leads to a better embedding of the visual input into a low-dimensional space, as compared to un-coordinated behavior. Traditionally, such dimensionality reduction is seen as the result of internal processing of a neural architecture, for example through mechanisms in early visual processing that lead to efficient low-dimensional (sparse) encoding by exploiting input redundancies and regularities [41–43]. We suggest that the generation of structured information through embodied interaction provides an additional mechanism contributing to efficient neural coding. In this context we also point out a distinct advantage of using robotic devices rather than working with humans or animals. Robots allow for comprehensive recording and analysis of complete histories of sensory stimulation and motor activity, and enable us to conduct precisely controlled experiments while introducing systematic changes in body morphology, materials, and control architectures [44,45].

The theoretical concepts outlined in this section receive support from experiments with human subjects showing that most of our sensory experiences involve active (i.e., sensory-motor) exploration of the world (e.g., through manipulation or visual inspection) [25,37]. Such exploration promotes not only object recognition [46–48], but also, for instance, the learning of the three-dimensional structure of objects [49], and depth perception [50].

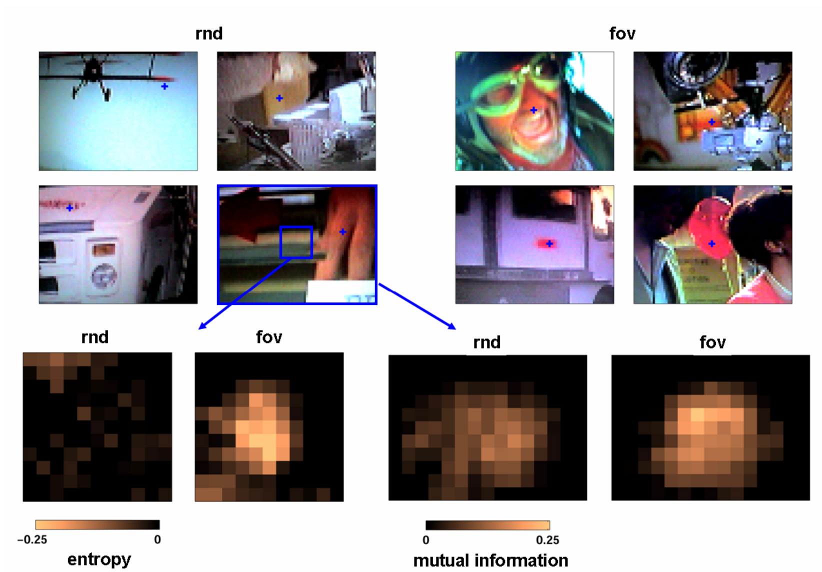


**Fig. 1.** Information structure in the visual field as a function of embodiment**.** Images show sample video frames obtained from a disrupted (a; “rnd”, “low embodiment” – no sensory-motor coupling) and normally tracking (b; “fov”, “high embodiment” – high sensory-motor coupling) and active vision system. Plots at the bottom show spatial maps of entropy and mutual information, expressed as differences relative to the background. There is a significant decrease in entropy (c) and an increase in mutual information (d) in the center of the visual field for the “fov” condition, compared to little change in the “rnd” condition. (Data replotted from [28]).

## 4 Learning and Development

There is an interesting implication of information self-structuring for learning. Information structure does not exist before the interaction occurs, but emerges only while the interaction is taking place. However, once it has been induced, learning can pick up on it such that next time around, the responsible sensory-motor information structure is more easily reactivated. It follows that embodied interaction lies at the root of a powerful learning mechanism as it enables the creation of time-locked correlations and the discovery of higher-order regularities that transcend the individual sensory modalities.

These ideas also extend to development. It is generally recognized that structured information and statistical regularities are crucial for perception, action, and cognition – and their development [4,32,41,51,52]. At a very young age, babies frequently use several sensory modalities for the purpose of categorization: they look at objects, grasp them, stick them into their mouths, throw them on the floor, and so on. The resulting intra- and intermodal sensory stimulation appears to be essential for concept formation [4,32,53,54]. As they grow older, infants can perform categorization based on the visual modality alone which implies that they must have learned something about how to predict sensory stimulation in one modality using the information available through another modality, for instance, the haptic from the visual one. By virtue of its continuous influence on the development of specialized neurons and their connections that incorporate consistent statistical patterns in their inputs, information structure plays a critical role in development. It is easier for neural circuits to exploit and learn sensory-motor patterns containing regularities and recurrent statistical features.

## 5 On Morphology, Dynamics, and Control

We have argued that coordinated sensory-motor interaction can impose consistent and invariant (that is, learnable) structure on sensory stimulation. It is important to realize that such information structure can also result from the dynamics of the interaction of a given morphology with the surrounding environment. Several studies with robots, for instance, indicate that computational processes involved in control can be partially subsumed (or taken over) by the morphological properties of the agent [55–59]. A paradigmatic example is provided by passive dynamic walkers which are robots – or rather mechanical structures without microprocessors or motors – that walk down a slope without control and actuation [56]. The walker's morphology (center of mass, length of the limbs, and the shape of the feet) and its materials are carefully designed so as to exploit the physical constraints present in its ecological niche (friction, gravity, inclination of the slope) for locomotion. To get the robot to learn to walk on level surfaces, one can use the mechanical design obtained during passive dynamic walking and endow it with actuators (e.g., located in the ankles or hips) [60]. The natural dynamics of the (body-environment) system provides the target for learning the control policy for the actuators by stabilizing the limit cycle trajectory that the robot follows – the dynamics structures the output of the angle sensors located in the joints, so to speak – and the robot learns to walk adaptively on flat ground within a relatively short period of time.

It is interesting to observe that as a consequence of the different data distributions resulting from different sensory morphologies a dependency exists between morphology, dynamics, and learning speed [60–62]. For example, by exploiting the non-homogenous arrangement of facets in the insect eye (denser in the front than on the side), the phenomenon of motion parallax can be “compensated away” and the adaptability of neural controller can be greatly improved [62]. We infer that the design of controller and morphology are, in a sense, inseparable, since the structure of both impacts information processing. However, while some progress has been made to optimize the design of robot controllers, robot morphology still largely remains a matter of heuristics. Future progress in the design of intelligent robots will require analytical tools and methodologies to exploit the interaction between morphology and computation [59].

The specific morphology of the body and the interaction of body and environment dynamics also shape the repertoire of preferred movements: a loosely hanging bouncing arm moves in a complex trajectory, but its control is extremely simple (the knowledge of how to move the limb seems to reside in the limb itself), whereas moving the hand in a straight path – a seemingly simple trajectory – requires a lot of control. It follows that part of the “processing” is done by the dynamics of the agent-environment interaction, and only sparse neural control needs to be exerted when the self-regulating and stabilizing properties of the natural dynamics can be exploited (see Fig. 2). The idea that brain, morphology, materials, and environment share responsibility in generating information structure has been called the “principle of ecological balance” [57] because there is a “balance” or task distribution between the different aspects of an embodied agent.

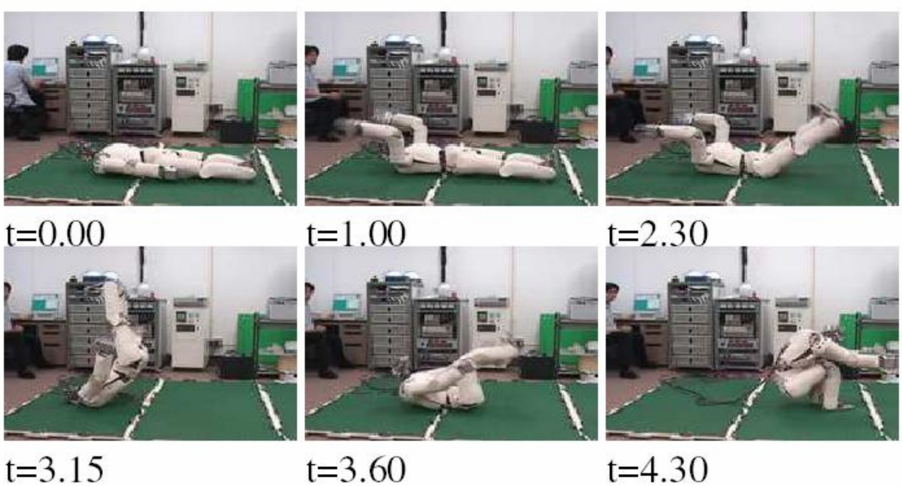


**Fig. 2.** Humanoid exploiting natural dynamics of body-environment interaction**.** Note that the robot is underactuated with respect to the ground which makes the equations of motion intractable analytically. By applying sparse but well-timed control actions the system transits from a lying (t=0) to a squatting position (t=4.30).

## 6 On the Interaction of Physical and Information Processes

The importance of the interaction between physical and information processes can hardly be over-estimated. The complexity of perceptual categorization in the real world, for instance, cannot be managed by computational means only. We have therefore stressed the significance of sensory-motor coordination. The principle of information self-structuring illustrates that physical interaction with the real world, in particular sensory-motor coordinated interaction, induces structured sensory stimulation, which, given the proper morphology, substantially facilitates neural processing, and hence sets the foundations for learning and development of perception and cognition in general.

We can take the idea of interaction of physical and information processes a step further by looking at the dynamics of embodied systems. We mentioned that because of the constraints provided by their embodiment, the movements of embodied systems follow certain preferred trajectories. It turns out that in biological agents such dynamics typically leads to rich and structured sensory stimulation. For example, as grasping is much easier than bending the fingers of the hand backwards, grasping is more likely to occur, and owing to the morphology (e.g., the high density of touch sensors on the fingertips), the intended sensory stimulation is induced. The natural movements of the arm and hand are – as a result of their intrinsic dynamics – directed towards the front center of the body. This in turn implies that normally a grasped object is moved towards the center of the visual field thereby inducing correlations in the visual and haptic channels which, as we pointed out earlier, simplify learning. So we see that an interesting relationship exists between morphology, intrinsic body dynamics, generation of information structure, and learning.

The idea of action and cognition constrained by embodiment can be applied within a developmental framework. For instance, it is possible to explain the infant's immaturity and initial limitations in morphology (e.g., wide spacing of photoreceptors in the retina), as unique adaptations to the environmental constraints of the ecological niche [63]. The specific effect of this arrangement is to filter out high spatial frequency information, and to make close objects most salient to the infant and hence reduce the complexity of the required information processing. Such complexity reduction may, for instance, facilitate learning about size constancy [64]. That is, the developmental immaturity of sensory, motor, and neural systems which at first sight appears to be an inadequacy, is in fact of advantage, because it effectively decreases the "information overload" that otherwise would most certainly overwhelm the infant [53,65]. A similar phenomenon occurs at the level of the motor system where musculo-skeletal constraints limit the range of executable movements and hence implicitly reduce the number of control variables. The neural system exploits such constraints and control is simplified by combining a rather small set of primitives (e.g., synergies [66] or force fields [67]), in different proportions rather than individually controlling each muscle.

Here, we have outlined a view of sensory-motor coordination and natural dynamics as crucial causal elements for neural information processing because they generate information structure. Our argument has revolved mainly around brain areas directly connected to sensory and motor systems. It is likely, however, that embodied systems operating in a highly coordinated manner generate information structure and statistical regularities at all hierarchical levels within their neural architectures, including effects on neural activity patterns far removed from the sensory periphery. This hypothesis leads to several predictions, testable in animal or robot experiments. For example, activations or statistical relationships between neurons in cortical areas engaged in sensorimotor processing should exhibit specific changes across different states of sensorimotor coordination or coupling. Increased structuring of information through embodiment would be associated with increased multimodal synchronization and binding, or more efficient neural coding.

## 7 Conclusion

The conceptual view of perception as an active process has gained much support in recent years (e.g., [25–29,38,57]). The work reviewed in this chapter provides additional evidence for this view and proposes a new link between embodiment and information. Perception cannot be treated as a purely computational problem that unfolds entirely *within* a given information processing architecture. Instead, perception is naturally embedded within a physically embodied system, interacting with the real world. Thus, the *interplay* between physical and information processes gives rise to perception. We identified specific contributions of embodiment to perceptual processing through the active generation of structure in sensory stimulation, which may pave the way towards a formal and quantitative analysis. The idea of inducing information structure through physical interaction with the real world has important consequences for understanding and building intelligent systems, by highlighting the fundamental importance of morphology, materials, and dynamics.

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