FP6-004381-MACS

MACS

Multi-sensory Autonomous Cognitive Systems Interacting with Dynamic Environments for Perceiving and Using Affordances

Instrument: Specifically Targeted Research Project (STReP)

Thematic Priority: 2.3.2.4 Cognitive Systems

D5.1.1 Overview of Existing Affordance Learning Approaches

Due date of deliverable: December 31, 2004
Actual submission date: February 8, 2005
March 24, 2005 (Revised version 2)

Start date of project: September 1, 2004 Duration: 36 months

Österreichische Studiengesellschaft für Kybernetik (OFAI)

Revision: Version 2

Project co-funded by the European Commission within the Sixth Framework Programme (2002–2006)		
Dissemination Level		
PU	Public	**X**
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

EU Project MACS

Deliverable D5.1.1

Overview of Existing Affordance Learning Approaches

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Number:	**MACS/5/1.1**
WP:	*5.1*
Status:	*final*
Created at:	*December 31, 2004*
Revised at:	*March 14, 2005*

Overview of Existing Affordance Learning Approaches

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This research was funded by the European Commission's 6th Framework Programme IST Project MACS under contract/grant number FP6-004381. The Commission's support is gratefully acknowledged.

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Contents

1 Introduction

The concept of affordances is used in many technical approaches to describe a coupling between environment and an agent with respect to actions. Thereby affordances are what the environment offers the agent to act upon. See [Gibson, 1986] and [Bærentsen and Trettvik, 2002] for a discussion on what affordances are.

The analysis of the different approaches to learning affordances is difficult, because many authors do not define very well, either what they regard as affordances or use different definitions. The most common aspect of the different definitions of affordances is that they form a relation between experienced percepts and potential actions. The finer nature of this relation is still under debate. For the purposes of this comparison, we take as our working hypothesis that

> Affordances are relations between *spatial-temporal* percepts and action capabilities of an agent as well as chains of action capabilities, whereby this relation does not need any symbolic object representation.

Unfortunately a lot of technical approaches claim to use affordances for the selection of behaviours but do not state where the knowledge about affordances comes from and how affordances are detected. In the following sections we provide an overview about publications related to the theory of affordances with a special focus on learning.

2 Selected Papers on Learning Affordances

2.1 Gibson, J. J. (1986). *The Ecological Approach to visual perception.* London, 1986.

Within the eighth chapter of his book [pp. 127-143] J.J. Gibson describes his view on affordances: “The *affordances* of the environment are what it offers the animal, what it *provides* or *furnishes*, either for good or ill.” [Gibson, 1986, p. 127] Typical examples are: stones afford *sitting-on* and *throwing*, sun affords *recharging energy*, and a door affords *going through*, *opening*, *closing* or *separating spaces*. Affordances are not properties of the object, nor are they part of the artefact. This means that affordances are not only properties that can be associated to internal representations of external objects or object classes. According to Gibson an object is perceived by perceiving its affordances not by perceiving its qualities. Affordances are perceived directly by an artefact: “An affordance is an invariant combination of variables, and one might guess that it is easier to perceive such an invariant unit than it is to perceive all the variables separately” [Gibson, 1986, p. 134f]

An agent can only perceive affordances that are related to any of its possible actions, e.g. it can only perceive that an object affords *lifting* if it is capable to *grip* and *lift* objects. “The observer may or may not perceive or attend to the affordance, according to his needs, but the affordance, being invariant, is always there to be perceived.” [Gibson, 1986, p. 139] Not only immobile objects provide affordance but also other agents can provide affordances, e.g. an animal can be a prey (and thus afford *eating*) for another animal, which is then a predator.[Gibson, 1986, p. 135] An animate has to include proprioception into perception of affordances: “... the information to specify the utilities of the environment is accompanied by information to specify the observer himself, his body, legs, hands, and mouth. This is only to reemphasize that exteroception is accompanied by proprioception - that to perceive the world is to coperceive oneself.” [Gibson, 1986, p. 141]. Gibson does not say much about how an artefact builds up its knowledge about affordances. In one section he talks about ecological niches and how animals adapted to them, whereby the animal acquires knowledge about affordances via evolution. Gibson mentions learning superficially: A child “must learn to perceive the affordances of things for other observers as well as for” [Gibson, 1986, p. 145] itself. He does not state *how* affordances are learned and which kind of affordances are learned.

See [Bærentsen and Trettvik, 2002] for an extended theory of affordances that includes learning.

2.2 Duchon, A. P., Warren, W. H., and Kaelbling, L. P. (1998). Ecological robotics. In *Adaptive Behavior, Special Issue on Biologically Inspired Models of Spatial Navigation*, volume 6:3/4, pages 473 507.

Duchon *et al.* present some theoretical background on affordances as well as on optic flow and control laws and present experiments on implementing these control laws on real robots. The authors follow the Gibbsonian approach, "that it is more desirable to put the animal in its environment than to put the environment into the animal" [Duchon et al., 1998, p. 3]. Thus one of the central statements of the authors is that no internal model is necessary to realise even complex behaviours interacting with the environment. They prove this through presenting their work on avoiding obstacles, the game of tag, and maze navigation.

A control law describes the change in the control of actuators, depending on the optic flow, e.g. the following example states, that the upthrust U changes proportional to the vertical optic flow: $\triangle U = \left(\frac{k}{c}\right) \triangle \vec{w}_v$

The authors state that there is a big difference between stimulus-response psychology and ecological psychology: the environment must not control the robot. "Rather, the animal is *using* information in the environment as a resource to control its own goal-directed actions. The animal perceives the environment in terms of affordances. A decision about the consequent behaviour must be made based upon the perception." [Duchon et al., 1998, p. 6] This means that a system, that is using affordances has to explicitly include a decision process and goal-directed behaviour.

The authors distinguish between the direct coupling of perception and action and the decision process, which action is to be performed. While the presented control laws (which deal with the direct coupling of environment and action) are static and not adaptable, the authors emphasise the role of learning in the context of affordances: "... the 'affordances of surfaces in the environment are constant for a particular animal (Gibson, 1979) and are discovered in the course of learning" [Duchon et al., 1998, p. 5]. Unfortunately the authors do not state how affordances of the environment are learned within their system. Their work focuses on experiments with control laws.

2.3 Bærentsen, K. B. and Trettvik, J. (2002). An activity theory approach to affordance. In *NordiCHI 02: Proceedings of the second Nordic conference on Human-computer interaction*, pages 51 60. ACM Press.

Bærentsen and Trettvik describe their view on affordances for the use in the field of Human-Computer Interaction (HCI). They state that the most essential aspect of the concept of affordances is activity and that this aspect is undifferentiated within Gibson's theory. Therefore they propose to extend the analysis of affordances from the *evolutionary biological* aspect to *cultural-historical* aspects. The authors explain that artefacts acquire knowledge about affordances through evolution (adaptation to the ecological niche), individual experience and socially acquired objective meaning [Bærentsen and Trettvik, 2002, p. 54], whereby the objective meaning encompasses the actual physical object as well as cognised and linguistically symbolised objects. Objective meaning "corresponds to the way the particular phenomenon would be defined in an encyclopaedia" [Bærentsen and Trettvik, 2002, p. 55].

The authors describe activity as part of the space spanned by the dimensions *Activity Motive* (Why?), *Action Goal* (What?) and *Operation Conditions* (How?). That means that "concrete activities are always motivated, goal directed and adapted to the conditions of action" [Bærentsen and Trettvik, 2002, p. 53]. There is a hierarchical relationship between the constituents, whereby the relation of these three constituents is not fixed and may alter (e.g. by learning).

Bærentsen and Trettvik differentiate conditions that the actor is aware of (mostly directly related to attainment of a *goal*) and conditions that the form of the activity has to be adapted to (unconscious). In contrast to Gibson the authors distinguish between natural objects and cultural objects as objects that are designed to provide specific affordances, because of the inclusion of cultural-historical aspects of affordances. All these aspects show that the authors deal with affordances and decisions at very specific level. Learning is a major part within the extended theory proposed by Bærentsen and Trettvik to achieve knowledge about affordances that is not explicitly innate. This learning leads to the argumentation, that the commonly criticised affordance of a mailbox, *communication with people far away*, becomes equal to the affordance *passable* (which seems to be explicitly built into the system) even though it is involved in much more complex environmental conditions and actions.

The authors state that learning affordances is realised as "adaptations of sensorium and perceptual systems that 'tune the perceptual system to invariants in flow/form/time patterns in the ambient sensory array" [Bærentsen and Trettvik, 2002, p. 58]. Proprioception is to be included into the learning process, because affordances relate the environment and the agent: "To learn whether an obstacle is passable is to learn the relative size of ones own body and limbs compared to the scales of the obstacle. [...] The way we learn to perceive this is by orienting ourselves in the environment, since perceiving the environment by active exploration, automatically informs about our own scales compared to scales in the explored environment "perception entail ego-perception" [Bærentsen and Trettvik, 2002, p. 58].

Very important is that the perception of affordances is said to be "not based on the momentary sensory input, but on the spatial-temporally extended and continuous activity of the perceptual system" [Bærentsen and Trettvik, 2002, p. 53].

2.4 Edwards, M. G., Humphreys, G. W., and Castiello, U. (2003). Motor facilitation following action observation: a behavioural study in prehensile action. In *Brain Cognition*, volume 53, pages 495 502.

In their paper Edwards *et al.* describe grasping and reaching experiments with humans. They investigated the effect of action and object observation on the later performance of actions. The result most relevant for MACS is their discovery that "observation of the object alone was as effective as observing an appropriate action to an object: both primed the subsequent reach to the target. This result is important because it contrasts with the properties of mirror neurons in the monkey as reported by Gallese *et al.* (1996)." [Edwards et al., 2003, p. 500].

The authors suggest, that "the presentation of the object in the observation stage of the experiment, afforded action towards it, and primed components of the subsequent reaching action (Gibson 1966)" [Edwards et al., 2003, p. 501]. Within additional experiments children imitated goals of actions instead of the actions themselves. Edwards *et al.* conclude that observation of an object may prime the goal representation, facilitating components of subsequent actions. They state that any affordance based system could be co-ordinated with mirror-neuron systems for achieving a similar imitation behaviour. Very important is that again the aspect of goal-directed behaviour is emphasised for an affordance based system.

The results support the theory of affordances and describe a way, how a system can imitate actions of another system of different physical structure: affordances lead to possible actions and these actions can be labelled/distinguished by their effects on the environment and thus associated with goals. The system can therefore choose a *possible action that leads to the same goal* as perceived from the imitatee.

2.5 Calderon, C. A. A. and Hu, H. (2003). Goal and actions: Learning by imitation. In *Proceedings of the Second International Symposium on Imitation in Animals and Artifacts.*

Calderon and Hu present a mechanism of imitation, which they expected to enable a robot to acquire new behaviours through the extraction of goals from perceived actions. Behaviours are learned by linking actions via pre- and post-conditions.

Thereby three units are used: *the perception unit*, which obtains the conditions of the imitatee and its relation with the environment, *the execution unit*, which carries out the actions that are expected to achieve similar effects like the one executed by the imitatee, and the *learning unit*, which is responsible for establishing the relation between the perceived imitatee's actions and the own possible actions to execute. The perception unit does not extract the exact movement of limbs etc. from the scene, but goals which can then be related to the own action capabilities by choosing an action which is most likely to produce a similar post condition and thus the same effect on the environment. The result of the learning procedure is a network of actions connected by pre- and post-conditions like shown in the figure below. Thereby chains of actions can become actions themselves. Such a network could directly be used to plan actions and chains of actions.

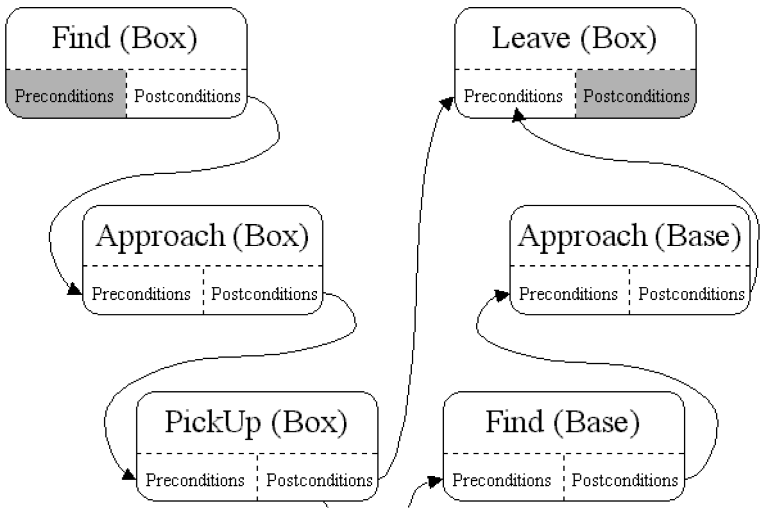


Figure 1: Net of actions that solves the task of finding boxes in an environment and moving them to a base.

This paper does not deal with affordances explicitly, but it provides a method which can be adapted to learning affordances by observation and is thus relevant for MACSs work package 5.4. Preconditions of an action include affordances, e.g. when an object does not afford gripping the action grip can't be performed. When an agent has learned a set of basic affordances, it can observe other artefacts and map perceived actions to its own action possibilities using the perceived states and affordances. The resulting chains of actions together with the necessary pre- and post-conditions provide new complex actions which result in new more complex affordances. E.g. a robot can learn by imitation to grip object A, lift it, move it to another location, and put it on top of object B; this chain of actions could be called piling and the objects that are used afford piling (which could be seen as a compilation of the affordances of *gripping*, *lifting*, *moving*, *lowering*, *unhanding* of object A and of *support* of object B). This relieves one from hard coding all possible actions and thus predefining the set of affordances that can be learned by the artefact.

2.6 Hugues, L. and Drogoul, A. (2001a). Robot behavior learning by vision-based demonstrations. In *Proc. of the 4th European Workshop on Advanced Mobile Robots.* Hugues, L. and Drogoul, A. (2001b). Shaping of robot behaviors by demonstrations. In *Proc. of the first International Workshop on Epigenetic Robotics: Modeling Cognitive Development in Robotic Systems.*

Hugues and Drogoul built a system that learns to map visual input to action output via demonstration by a teacher. All input image are analysed by a large set of artificial cells, which analyse certain regions with respect to colour and density, and contain information about the action that is typically performed when this cell becomes active (i.e. when the according percept was perceived). Including some additional values, a histogram of the set of cells is created and the most frequent action-value is transferred to the effectors. The system is implemented on a mobile robot. The association of cell and action is learned via demonstration, i.e. controlling the robot with a joystick.

The system presented within this paper derives actions directly from the perceptual input. According to Duchon *et al.* this work realises a learning response-stimulus approach and not an ecological approach using affordances, because there is no explicit decision process that is able to change the behaviour and no spatial-temporal aspects are included.

2.7 Maistros, G., Marom, Y., and Hayes, G. (2001). Perception-action coupling via imitation and attention. In *Proceedings of AAAI fall symposium on Anchoring Symbols to Sensor Data in Single and Multiple Robot Systems.*

Maistros *et al.* describe a system, that is expected to learn a direct link between perceptual input and actions. A self organising feature map (SOFM) clusters the input space and provides an attention mechanism. Motor schemata code internal targets, like joint angles or speeds of motors. These motor schemata can be transformed into concrete actions using a forward model of the kinematics of the artefact. During the learning phase, for each node of the SOFM a belonging motor schema is learned, so that in a recall phase these motor schemas are activated when the belonging SOFM node is activated. The developed system was tested within two simulations, e.g. within the second experiment a Khepera-Simulator was used to imitate the behaviour of wall following.

As the authors state, the presented system connects nodes and motor schemata one-to-one and the system is not yet extended to more than one motor schema per object. Furthermore the system operates on the current sensor state only and works in disjunctive learning and recall phases. These aspects lead to the conclusion that, according to Duchon's claim for a decision process, the designed system implements a stimulus-response mechanism rather than an ecological approach that uses the theory of affordances.

2.8 Nehaniv, C. and Dautenhahn, K. (1998). Mapping between dissimilar bodies affordances and the algebraic foundations of imitation. In *Proceedings European Workshop on Learning Robots.*

Nehaniv and Dautenhahn deal with the problem of imitating actions, whereby the actors have dissimilar bodies. They state that it is necessary to imitate goals and subgoals instead of the actions themselves. Thus a wheeled robot could imitate a dog-shaped robot. Thereby the quality of correspondence of the observed and imitated behaviour heavily depends on an external third party. An imitator observes an agent and chooses an action, depending on what the environment affords to it. This action has to change the environment as well as the imitator according to the behaviour to be imitated.

The authors develop a framework in which the imitation of a behaviour is described mathematically. Therefore they assume that both robots can be described as functions which calculate the next system state depending on the current system state and the sensor input. The equivalence of two behaviours can then be described in terms of equivalence-classes and a rational homomorphism. Chains of actions are thereby in the same equivalence class, if they transfer the robots state and the state of the environment into a similar state. Learning to imitate means to adapt the sequences of actions so that the transition-functions of the two robots are equivalent, even though they use different chains of actions to perform the transitions. Affordances are used to choose appropriate actions but unfortunately the authors do not state how these affordances are perceived and how they are coded.

2.9 Steedman, M. Formalizing An Ordance. In *Proceedings of the 24th Annual Meeting of the Cognitive Science Society.*

Steedman presents a representation of objects in terms of their affordances using Linear Dynamic Event Calculus. He intentionally ignores the perceptual aspect of affordances in his paper, which is against the theory of affordances [Gibson, 1986] that heavily relies on perception. The major principle of embodied AI is that interaction of artefact and environment is absolutely necessary to ground symbols and behaviour within the environment, but unfortunately the author does not state, where the rules and symbols he deals with come from.

Within his notation objects become functions that are applied to the embodied agent or the object itself.

E.g. the following rules transfer a door into a function that transforms states of its environment:

$$\begin{aligned} push(y,x) &\leadsto \left\{ \begin{array}{lcl} shut(x) & \multimap & open(x) \\ open(x) & \multimap & shut(x) \end{array} \right\} \\ go - through(y,x) &\leadsto \left\{ \begin{array}{lcl} in(y) & \multimap & out(x) \\ out(y) & \multimap & in(x) \end{array} \right\} \\ Affordance(door) &= \left\{ \begin{array}{l} push \\ gothrough \end{array} \right\} \end{aligned}$$

Steedman applies his logic system of transferring states to of internal symbols and to the processing of language. Since his grammar processing system is decoupled from the environment and the embodiment of the agent, the connection with affordances is not obvious. For the purposes of MACS the proposed logic manipulation of symbols does not seem to be applicable.

2.10 Want, R., Fishkin, K. P., Gujar, A., and Harrison, B. L. (1999). Bridging physical and virtual worlds with electronic tags. In *CHI*, pages 370 377.

Want *et al.* present a system for seamlessly blending the affordances and strengths of physically manipulatable objects with virtual environments or artefacts. They use a combination of radio frequency identification (RFID) tags and readers, radio frequency networking, infrared beacons, and portable computers to combine a physical object with an electronic counterpart. Real objects like books or business cards are tagged with RFID tags. When the tagged object is within reach of the portable computer the identifier is received by the tag reader and the corresponding virtual object provides its affordances, e.g. an e-mail program affords writing an e-mail when a business card is shown or a translation is afforded when a French book is presented. This link between physical and virtual world can be adapted. The idea of using RFID tags to cause a reaction within a technical system can be used within early experiments to bypass the perceptual system of a robot platforms and simulate perception as long as the perceptual system is not working properly.

2.11 Lewis, M. and Simo, L. (2001). *Certain principles of biomorphic robots.*

In this paper among other things Lewis and Simó are studying the question "How a neural system might learn an affordance". As test platform they use a 14 cm tall tethered biped robot, which faces the problem of visually triggered gait adjustments. The environment of the robot consists of flat surfaces and small obstacles. The described experiments are covering gait adjustments prior to and during stepping over these small obstacles. To surmount an obstacle the robot must accurately predict a collision with the obstacle and perform an appropriate behaviour, which means adapting foot placement and stepping over the obstacle at the correct time.

The real robot presented here is controlled by algorithms that were the outcome of previous work performed with a simulator by the same authors. It involves a Central Pattern Generator (CPG) based locomotor system, learning modules, visual perceptual modules, and tactile reflexes.

Objects are recognised with a dynamic attention mechanism which consists of three layers: a raw data layer, a prediction layer and a novelty layer. Depending on the perceived raw data layer a prediction layer is generated. The novelty layer receives the difference between both layers and generates a hard-limit threshold depending on a local feedback gain factor. With this dynamic attention mechanism the robot is able to detect unexpected features (objects) in the environment and distinguish between them and sensory consequences of its own movement. After the recognition of a novel event an activated novelty cell triggers a short-term memory signal which allows association between future an current events, namely an "eligibility trace" see also [Sutton and Barto, 1998].

A training signal is sent to a mapping from the novelty cells to a variable that adjusts stride length in the CPG if the robot's foot collides with the environment. After learning, a pattern of weights maps the novelty cells to modulation of the locomotor CPG.

The paper represents a valuable contribution in context to "learning affordances" in robotics. Valuable contributions are the dynamic attention mechanism evolved there, as well as the ability of recognizing the sensory consequences of the robots own movements and a learning mechanism that is able to create and adapt mappings between visual perceptions and actions. However it does not go into detail on learning affordances of different objects or on learning different affordances of one object or object class.

2.12 Cañmero, L. (1997). Modelling motivations and emotions as a basis for intelligent behavior. In *First Intl. Conf. on Autonomous Agents*, pages 148-155. ACM Press. Cos-Aguilera, I., Cañmero, L., and Hayes, G. M. (2003). Motivation-driven learning of object affordances: First experiments using a simulated khepera robot. In *9th International Conference in Cognitive Modelling* (ICCM'03). Cos-Aguilera, I., Cañmero, L., and Hayes, G. M. (2004). Using a sofm to learn object affordances. In *5th Workshop of Physical Agents* (WAF'04). Cos, I. and Hayes, G. (2002). Behaviour control using a functional and emotional model. In *8th Confererence of the Simulation of Adaptive Behavior* (SAB'02).

Cos-Aguilera *et al.* propose an approach which involves a biologically inspired model that endows an agent to relate objects regularities/invariants with the possibility of performing an action via interaction episodes [Cos-Aguilera et al., 2004]. In their point of view "learning affordances" can be defined as learning action potentials, which means to learn that an object exhibiting certain regularities offers the possibility of performing a particular action. To build a neural representation of regularities in the environment of the robot a "Growing When Required (GWR)" network is used. The experiments have been performed using a Webots simulator with a Khepera robot in a simple environment. The robot has different action potentials: grasping, touching (interaction) and shelter. These actions are selected via a behaviour selection architecture being a simplified version of the one proposed in [Cañmero, 1997] and [Cos and Hayes, 2002]. It consists of a set of homeostatic variables, survival-related internal variables, a set of drives, a repertoire of behaviours and an arbitrary mechanism to choose the appropriate behaviour as introduced in [Cos-Aguilera et al., 2003]. The arbitration mechanism for behaviour selection follows a winner-take-all policy, using the drive that exhibits the highest urgency. Following behaviours are possible: eating (grasping an object) which satisfies hunger, "shelter" satisfying fatigue and "interact" satisfying curiosity.

Additional to the hormone model introduced in [Cos-Aguilera et al., 2003] two hormones are used to indicate the success or failure of an interaction. These hormones (frustration and satisfaction) are used in the learning mechanism to learn if an object lacks or has the functionality it attempted to perform. The goal of the experiments was to demonstrate that artificial agents are able to learn to relate the invariants of the objects in the environment, (which are the clusters in the GWR) with the outcome of goal-oriented interactions. Thereby the robots are then able to compensate internal deficits proposed by their survival-related variables by selecting appropriate objects for the required action. This has been realised through two phases, a clustering phase and an exploitation phase. In the clustering phase the robot wanders around the environment, interacting with different objects and building the GWR network by taking snapshots of the objects and creating vector representations which are used to feed the Self Organizing Feature Map (SOFM). In the exploitation phase the behaviour of the robot depends on its internal survival-related variables. Once an object is encountered, its closest node in the GWR network is identified and the behaviour is carried out. The width of the gripper is the physical boundary to grasp an object or not. The boundary to succeed in sheltering has been simulated depending on the diameter of the base of the object. Touching is always possible. The outcome of the interactions depending on hormone satisfaction and frustration is used to update a set of weights, relating each node to every behaviour. This learning procedure is called one-step backup reinforcement.

Finally the learning results in a set of weights relating each node in the sensory space to each behaviour respectively possible action. Experiments have been performed with four different networks each with a different amount of nodes. Cos-Aguilera *et al.* are concluding that GWR is a flexible representation that may be extended in real time to add nodes when required and is sufficient to identify the invariants of the objects in the simple environment and furthermore that the used learning mechanism is appropriate for the binding between the cues in the environment and the internal needs of an the artificial agent.

According to the goals of our project the paper is able to contribute in two ways: as a valuable basis for discussion of the term “affordance” regarding to robots and their perceptual possibilities, as well as a description of a possible approach to learning of affordances.

2.13 Natale, L., Metta, G., and Sandini, G. (2004). Learning haptic representation of objects. In *International Conference on Intelligent Manipulation and Grasping.*

In this paper Natale *et al.* discuss their proposal that processing haptic information is crucial for learning affordances. For example two optically identical balls with different weights can have different affordances, which cannot be perceived by only looking at them. Natale *et al.* therefore propose an approach for learning haptic representations of different objects. As test platform for their experiments they use Baby(ro)bot, a humanoid torso with a 6 degree of freedom arm and a 5 finger hand. For each object the robot grasps, the posture of the hand reflects the physical size of the objects. The posture of the hand respectively the corresponding joint angles are fed into a Self Organizing Map (SOM). The network implicitly codes not only physical features like shape, which also could be perceived visually, but also intrinsic properties like weight. To extract such features seems to be a crucial element on the way to meet the requisites of affordance theory [Gibson, 1986] as well as in the task of generalising from objects, where perceived characteristics are used separately from objects "instead of object representations" to identify affordances. The paper also points out that the haptic perception of object features strongly depends on the mechanical design of the actuator.

2.14 Metta, G. and Fitzpatrick, P. (2002). Development of imitation in a humanoid robot. Technical report, MIT Artifcial Intelligence Laboratory.

The paper introduces the discovery of the neurophysiologic area of mirror neurons that were found in the frontal cortex of monkeys [Rizzolatti et al., 1996]. Mirror neurons are a specific class of neurons that are activated both when a monkey executes an actions as well as when observing the same action performed by another. The importance of this discovery lies in the possibility to relate these neurons to gesture recognition, language and learning by imitation.

As an experimental setup the humanoid robot COG was used to demonstrate goal directed mimicry behaviour by imitating "types of poking" that were previously perceived when executed by a human teacher. The object properties are then interrelated to the motor repertoire. The authors believe that these relations lead to a pragmatic description of objects according to the Gibsonian concept of affordances [Gibson, 1986]. Unfortunately none of the technical details are described, but as far as we got insight to the concepts described, the usage of affordances in this paper seems to be misleading since Gibson did not pursue the idea of describing objects or to deal with object representations.

2.15 Fitzpatrick, P., Metta, G., Natale, L., Rao, S., and Sandini, G. (2003). Learning about objects through action: Initial steps towards artificial cognition. In *2003 IEEE International Conference on Robotics and Automation (ICRA).*

In this paper "learning to act" is divided into two modes of learning. First the robots have to learn the consequences of a motor action in a so called "discovery mode" and after that learn to select a specific motor action to achieve a certain result in a goal-directed mode. The robots used are Cog, the upper torso humanoid robot developed at the A.I. Lab (MIT, Boston) and Baby(ro)bot an upper torso humanoid robot at the LIRA Lab (University of Genova).

Learning affordances was performed by reducing the action space to four possible actions: pull in, side tap, push away, and back slap. The test environment consisted of the following four objects: an orange juice bottle, a toy car, a cube, and a coloured ball. During the training phase, each of the objects was "poked" 25 times per object for each possible action. The extracted visual features represent the objects immediate direction of movement and their principle axis of inertia. Depending on these features a map for each <object, action> pair and a "motion signature probability map" is updated for every repetition. After this learning phase the robots are able to perform behavioural demonstrations of the learned affordances by choosing the one action for a presented object that is most likely to make the object roll. Fitzpatrick *et al.* describe this mechanism, respectively the specific structure of the robot that detects the affordance of the object and the conjunction to the generation of behaviour, as the first stage of the development of more complex behaviours relying on the understanding of objects as physical entities with specific properties.

Another MACS related question handled by this paper is how a system would be able to extract useful information from seeing an object manipulated by someone else. Again the visual processing as described before for active poking is proposed by the authors. The robot is comparing the observed displacement of the object with its own representations and is searching for the one of the four possible actions whose effect is closest to the observed action. This method is argued as magnitudes simpler than trying to completely characterise the action in terms of the observed kinematics of the movement.

The paper concludes with the statement that only repeated interactions, which can also be seen as playing with objects, can reveal how objects behave when performing a particular action. The same information retrieved during the two learning modes, when "learning to act" can be used for imitation as seen in the area of mirror neurons [Rizzolatti et al., 1996], to select an appropriate action to mimic the perceived manipulation for instance done my a human.

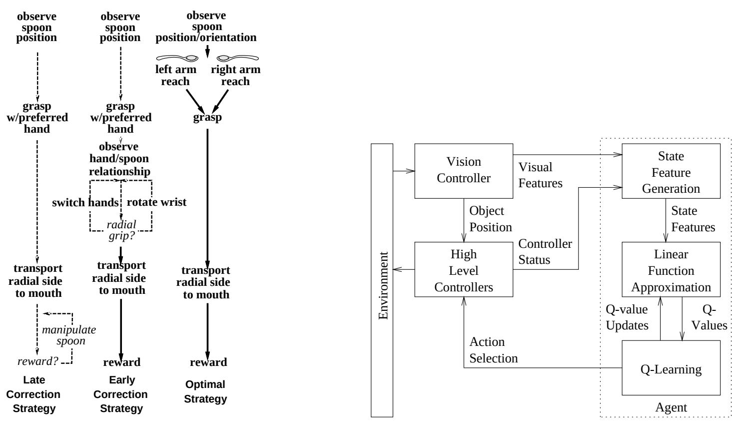
2.16 Wheeler, D.S., Fagg, A.H., and Grupen, R.A. (2002). Learning Prospective Pick and Place Behavior. In *2002 International Conference on Development and Learning (ICDL)*.

Wheeler *et al.* are inspired by studies of McCarthy *et al.* about the incremental acquisition of grasping strategies of young infants (9-19 months). The investigations focused on the initial reach made by infants to a spoon laden with applesauce, demonstrating that youngest infants (Fig. 2(a), 9 months) perform an almost reflexive strategy, doing a grasp with dominant hands disregarding the orientation of the spoon, while older infants increasingly evolve an anticipatory regrasping strategy which is later subsumed by a process that predicts which arm to use so that regrasping is not necessary. From these observations, Wheeler *et al.* hypothesize that human infants use exploration based learning to search for actions that will yield future reward, and that this process works in concert with the identification of features which discriminate between important interaction contexts.

They propose a control structure for acquiring increasingly sophisticated representations and control knowledge incrementally, suggesting that a robot can use Reinforcement Learning to write its own program for grasping and manipulation tasks. They present a concept on how robots learn to associate visual and haptic features with grasp goals through interactions with a sample task, i.e., to grasp an object and insert it into a receptacle. In particular, they propose a system architecture (Fig. 2(b)) in which a vision controller first provides visual features which are integrated with haptic features for state generation. A linear function approximator associates then states with preferable actions, applying Q-learning to incrementally converge towards an optimal policy for action selection.

In the experiments, the reinforcement control agent learned to select actions according to the video images of a peanut butter jar in two different orientations. Over time, the agent learned to distinguish between the two object orientations based on the visual features, and learned the optimal action sequence for each orientation.

Extended experiments were performed with a dexterous hand of a humanoid robot, developing haptic and visual categories for reaching and grasping in a similar framework.



(a) (b)

Figure 2: (a) Initial reach made by infants to a spoon filled with applesauce. (b) A system architecture integrating a vision controller with haptic features for state generation.

2.17 Shon, A.P., Grimes, D.B., Baker, C.L., Rao, R.P.N., and Meltzoff, A.N. (2004), A Model-based Goal-directed Bayesian Framework for Imitation Learning in Humans and Machines, submitted to Cognitive Science.

Shon *et al.* focus on imitation learning in stochastic environments where the imitator must learn and act under real-time performance constraints. The authors propose Bayesian algorithms based on Meltzoff and Moore's AIM hypothesis for infant imitation, that implement the core of an imitation learning framework, and demonstrate the system allowing real-time learning and imitation in an active stereo vision robotic head.

Imitation is a versatile mechanism for transferring knowledge from a skilled agent (the instructor) to an unskilled agent (observer) using direct demonstration rather than manipulating symbols. Children are seemingly highly adept at observing and imitating the actions of others. The utility in providing robots with the ability to imitate is to exhibit a drastically lower cost of programming than one which requires expert programming.

The active intermodal mapping (AIM) model for imitation of infants is based on the claim that imitation is a goal-directed, i.e., matching-to-target process. The active nature of the mapping process is captured by the proprioceptive feedback loop, the motor performance is evaluated against the seen target and serves as basis for correction. Imitation begins by mapping perceptions of the teacher and the infant's own somatosensory proprioceptive feedback into a supramodal representation, allowing matching to the target to occur. Meltzoff suggest that saliency determines the dimension that infants choose to imitate next.

The outlined Bayesian framework for goal-directed imitation learning involves a Forward model (estimates how actions affect state transitions), an Inverse model (models which actions caused specific state transitions), and a Prior model (models the policy to achieve a specific goal). The system starts with detecting features over time that produce state sequences. In turn, these sequences define actions (Prior model). Their next step is to transform state and action observations into instructor-centric values which are mapped to observer-centric values which will update observer-centric probabilistic forward and prior models. Combining these yields distributions over actions of an inverse imitation model that is learned from observation. The authors conclude that, in contrast to similar approaches on imitation learning, they advocate using probabilistic models to handle real-world, noisy data.

3 Conclusion

Even though J.J. Gibsons theory of affordances provides an interesting new view on how individuals perceive their environment, Gibson did not provide a biological foundation nor a concept how to implement the use of affordances in technical systems. There is no scientific theory yet that fills this gap properly. All papers evaluated in this deliverable, which claim to deal with affordances, use a lot of assumptions often without specifying them into detail or worse just use the label 'affordances' for traditional approaches.

From the presented work, the following major theoretical aspects with direct consequence for learning are:

1. Affordances are not properties of the artefact nor of an object [Gibson, 1986].
2. An artefact can only perceive affordances that are *connected to its action capabilities* [Gibson, 1986]. Thus *proprioception* has to be included in learning affordances [Gibson, 1986] [Bærentsen and Trettvik, 2002].
3. Affordances are not based on a momentary sensor input, but have to *include spatio temporal* aspects[Bærentsen and Trettvik, 2002]. Systems dealing with affordances have to use the perceived information about what the environment affords to *control their goal-directed actions* [Duchon et al., 1998] [Bærentsen and Trettvik, 2002].
4. There are affordances that are *explicitly innate* to the agent through evolutionary development and there are affordances that have to be learned [Gibson, 1986] [Bærentsen and Trettvik, 2002].
5. Learning chains of actions can lead to learning new, more complex affordances. This can be done either by an individual alone or, to limit the search space, by imitation. As [Edwards et al., 2003] and [Calderon and Hu, 2003] showed with their approaches, by imitating *goals* and *subgoals* an agent does not need internal models of itself nor of the observed agent to reproduce observed behaviour. The knowledge how its own actions affect its environment is sufficient. Even though an imitating agent must be capable to perceive that there are actions within its environment and must be able to perceive the goals of those actions in particular.

Regarding these aspects, partner OEFAI developed an extended view on affordances and a theoretical approach how affordances could be implemented within a robotic mobile agent. These approache will be published to the project partners within a technical report.

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