A DEVELOPMENTAL APPROACH FOR AFFORDANCE AND IMITATION LEARNING THROUGH SELF-EXPLORATION IN COGNITIVE ROBOTS

By

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Dedicated to

my beloved wife Aysu,

and

my parents

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I. INTRODUCTION

Motivation and Goals

As robots are increasingly used outside the lab environment, they need to be more adaptable to increasingly challenging environments and exhibit robust performance in a wide range of situations. It is likely that in the future, robots will co-exist with people and they will be used in homes, workspaces and public spaces such as museums and hospitals. The role of robots in society is changing rapidly with recent advances, such that they will need to interact with people, help them with their jobs, and even take the responsibility of human beings in dangerous and harmful environments. Apart from being helpful in households with children and the elderly, robots will also need to adopt a wide range of roles including those of tour guides, factory workers, hospital nurses, and even astronauts. Robots will need to be used by a wide range of people from amateurs to the experts, therefore it is not efficient to pre-program robots for all tasks, which is infeasible in most circumstances.

Designing a robot controller would increase the amount of time and expertise, thus the focus should be on learning from experience registered through the robot's own sensors, so it can learn from a small set of trials. Designing controllers for particular tasks is a method which is very tedious and inflexible; instead it would be much more advantageous to design robots in a way that they could learn on their own in a manner similar to human beings. They need to be able to take decisions, adapt and learn how to act in an environment, and be able to invent solutions based on prior experience. It is likely that people will interact with robots in the future, so they need to be able to learn from humans. The robots of the future will not simply move based on pre-given commands, but they will perceive, categorize, understand and act. Such capabilities will give flexibility and efficiency to the system. It is impossible to consider all possibilities in advance and implant the robot with those hard-wired codes. Instead, if robots could simulate what happens in developing human beings, learn by trial and error much like a human baby does, and discover its action possibilities based on perceptual-motor interactions, then they would be able to handle complex problems. Currently, most engineering solutions used in robotic designs do not have this level of learning and adaptation.

A promising approach to advance robotic technology qualitatively is to enable robots to imitate humans, to learn affordance relations from them and update these relations by observing the outcomes of the behaviors learned during these processes. As robots come to learn from humans by adapting their repertoire, by mapping the perception of observed actions onto their own motor repertoire, they are more likely to perform adeptly in the service of their goals across the broad range of changing circumstances.

First of all, for robots to come to learn affordance relations from humans using limited experience, they need capabilities for discovering their own self-capacity so that they can generate their own action representations, and understand the accompanying sensory outcomes of those actions. Such an approach, which is based on attempts, errors and exploration, would fit better to their functioning than those hardcoded by the human programmers or interpreters. It has been successfully shown that Self-Organizing Maps [1] [2] can be used to extract the affordance relations between a robot's crawling motion video and its motor actions. This unsupervised vector quantization and dimension reduction algorithm can also enable the robot to learn from a human demonstrator and to visualize large bodies of high-dimensional data for finding limb/tool affordances from observing a human.

Second, robots should revisit and reconsider their own experiences to increase the efficiency and effectiveness with which they learn affordance relations on their own. Robots that can anticipate and account for the effects and expected performance of their behaviors will behave more like living beings that are aware and knowledgeable of their motor capabilities and shortcomings. Using physics engines, in which robots can learn and improve goal-subserving knowledge of affordance relations, will be a logical extension to imitation learning for robots. The robot can successfully imitate human actions and act in the actual world, by predicting its future state and the future state of the surrounding environment after having learned sensory-motor associations through self-exploration.

Imitation has a central role in human development and especially for learning and development of novel motor skills. Many studies show that imitation ability emerges early in life, and despite its complexity it is one of the major learning modes for infants as well as for adults [3]. Imitation requires encoding the observed task first, and then transferring this information onto one’s own motor representation of the same action. Before imitation ability emerges, affordance relations need to be learned and certain perceptual-motor associations need to be formed [3][4]. Developmental science and cognitive neuroscience point out how tightly action, perception and cognition are coupled in development [5]. Learning affordance relations, by autonomous experience requires learning to associate actions with corresponding sensory effects first, which then helps to close the action-perception loop so that infants can act accordingly to bring about desired action effects. This is mainly provided through a trial-by-error strategy through which infant explores own motoric capacities, biomechanical constraints, and discovers the possible contingencies between their limb movements and accompanying sensory effects. Self-exploration forms the basic building block for all kinds of action based learning. Beginning the first day of life babies engage in an active world where they observe and interact with others. However in order to be able to interpret the surrounding world and its action-effect relations. They need to discover their own bodies, and their motor capacities, which are mainly based on self-exploration of action-effect relations, where they actively get involved in random acts and observe the accompanying changes in the perceptual world, so they start forming associations between their action commands and accompanying perceptual effects. Affordance learning and imitation ability are built upon the ability to form perceptual-motor contingencies, and self-awareness of one's own body's limitations and capabilities. Applying this method, which is based on the way human beings learn, will advance the robotics field and increase the capacity and usefulness of robots greatly.

Research Objective

The objective of this dissertation is to implement human-inspired cognitive control abilities such as imitation learning and affordance learning within a Bioloid Humanoid Robot (BHR) [6]. Rather than using pre-programmed algorithms, we designed a flexible mechanism with which it could learn by a set of experience, and based on self-exploration of affordance relations it can learn to imitate actions on its own in a way much like a human baby does.

Research Approach

The approach described in this article takes additional steps towards allowing robots to systematically learn how to integrate perception, action, tasks and goal information from a relatively small number of experiences much like a human being does, so as to generate adaptive behaviors efficiently and flexibly.

Research Method

In our series of experiments we will show how our Bioloid Humanoid Robot (BHR) learned to imitate.

In **STAGE 1**, called LIMB AFFORDANCE LEARNING THROUGH MOTOR BABBLING, our humanoid robot provisionally discovered affordance relations between certain arm limb movements and corresponding motor units by exploring the outcomes of its random arm movements while in a crawling position. The purpose of this stage is to let the robot classify the right and the left arm based on self-exploration and a set of experience similarly to how a human baby discovers action-effect relations of his arm movements. Here, the idea behind motor babbling was to speed up the process of learning motion primitives by randomly executing, analyzing and gathering the outcomes of actions.

In **STAGE 2**, called IMPROVING LEARNED LIMB AFFORDANCES THROUGH SELF-EXPLORATION, the robot will provisionally learn a set of basic motion primitives, its own motor limits, biomechanical constraints and skills. In this phase, by performing random arm movements it will discover the associations between biomechanically possible arm movements and their spatial effects in the visual space. That is it will discover the link between joint angles for the left and right arm and the corresponding action effects in the environment in terms of the final position of the hands in the visual space. Using a neural network, the robot will learn the biomechanically possible work space.

Having learned the perceptual-motor coupling between certain actions and their resultant visual effects, then in **STAGE 3**, called IMITATION LEARNING FROM MOTION CAPTURE, the robot will learn to imitate a novel object-oriented action. In this case, by observing the spatial arm coordinates of a human being performing lift/push/pull actions oriented towards certain object, the robot will identify corresponding movement sequences in its own motor system that are suited for the spatio-visual effect being observed. In this final stage the robot builds upon its skill in limb affordance relations, and action-effect associations, and by bringing the perceptual-motor system a step further now it can imitate a novel action. This phase requires a direct mapping of the perceived sensory effects to the robot's own action system so it could choose the right joint angle combinations so as to bring about the perceived effect.

Organization of the Dissertation

This dissertation presents a design and implementation of imitation learning through affordances. The dissertation is organized into five chapters.

CHAPTER I is an introductory chapter to the research problem statement, method, objective and outline of this dissertation. Summaries of the subsequent chapters are given as follows:

CHAPTER II describes how imitation ability develops in human beings, and gives an overview of studies in cognitive science.

CHAPTER III provides a review of the relevant previous work in the area, presents background information related to motor babbling, affordance relations, and cognitive architectures for imitation learning.

CHAPTER IV provides an overview of the studies and the general approach.

CHAPTER V provides an overview of the first stage, and the tools used in the self-exploration stage which involves limb affordance learning through motor babbling.

CHAPTER VI describes an overview of the second stage, and the tools used in the self-exploration stage which involves improving learned limb affordances.

CHAPTER VII describes an overview of the third and last stage which involves a novel imitation task, and the tools used in this stage.

CHAPTER VIII provides the results of the imitation learning, as well as conclusions and future research discussion. This chapter summarizes and discusses the dissertation, and highlights contributions of this research. Directions for future research are offered.

II. HOW DOES IMITATION LEARNING DEVELOP IN INFANTS?

Self-exploration

Choosing appropriate action plans for a desired motor output requires learning the relationship between specific motor commands and accompanying sensory feedback (i.e. visual, proprioceptive, auditory, etc.) that result as a consequence of those movements. In other words, infants first need to learn to associate their actions with corresponding sensory effects in order to be able to act. Starting at birth infants engage in active exploration of their own body by touching it, moving it and they investigate the cross-modal contingencies of their action effects [7]. They move their arms and legs in an aim to explore the regularities in their sensori-motor system; they observe the link between their actions and the kind of perceptual consequences (i.e., visual, auditory, kinesthetic, haptic, etc.) those actions have in the body and in the environment as shown in Figure 1. Self-exploration promotes cross-modal calibration which is necessary for the emergence of complex action forms. This mechanism is systematic in the sense that the infant deliberately acts to see the perceptual effects, however it is also random because the actions are mostly uncontrolled, unskilled, and involve errors. Infants indeed get fascinated by the simultaneous experience of 'seeing' their body parts and 'feeling them move' in space [7].

Figure 1. Infants Exploring Actions and Resultant Sensory Effects. Self-exploration is necessary to develop perceptual-motor coordination.

For instance young infants spend almost 20% of their waking time by touching their face and mouth [8], an action which includes specific proprioceptive (due to arm movement) and haptic (from the face) action effects, which are integrated in the brain, thereby the infant discovers the contingency in such movement. Amsterdam [9] has found that especially in the first year of life infants observe their own movements in front of the mirror in an aim to explore the particular visual-kinesthetic contingency of their action results, and in later years this habit disappears gradually. Similarly Bahrick and Watson [10] using a habituation paradigm, demonstrated that 5 month old babies preferentially look at non-contingent views of their bodies which have conflicting visual and kinesthetic cues (i.e., upper torso belongs to the baby, but the leg movement belong to some other baby), because in this non-congruent view there is a violation of the familiar visual-proprioceptive expectation of body movements. Another example is, before being able to speak meaningful syllables and words, infants pass through a stage during which they experiment with uttering various sounds that resemble phonemes which are not meaningful and recognizable yet. The emergence of speech-like sounds is called BABBLING, and it begins at approximately 5- 7 months of age. This phase of experimenting with sounds and exploration of vocal capabilities is necessary for developing complex language skills in later development [11].

Moreover, very young infants were shown to alter their sucking rates in order to be able to hear their mother’s voice [12]. Another example is that two-five month old infants can form associations between leg kicks and the visual feedback from the contingent movements of a mobile, so they increase their rate of kicking in order to bring about the desired visual outcome: movement of the mobile [13]. It has also been shown that the infants start working on forming the sensorimotor link between the eye and the hand right after birth. Van der Meer et al. [14] [15]have found that newborns make an effort to view their hands. As also can be seen in one study [14] where they flashed light beams over various parts of the babies’ bodies, the surroundings otherwise being dark, and observed that the infants tried to control the position and velocity of their arms so as to keep them visible within the light. Even more interestingly, most of the babies started decelerating their arms before entering the light, suggesting that they wanted to and could form a link between the kind of arm movement they execute and the resultant visual effect: the spatial position of arm in the light. Thus, by exploring the contingencies between their movements and resultant environmental events, infants learn to associate their actions with corresponding changes in the environment, which is an important skill for the development of goal-directed and object-oriented action.

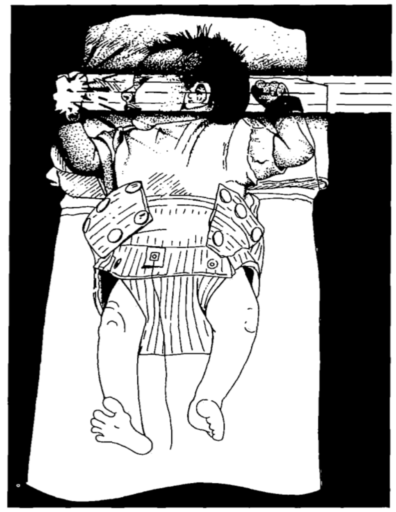


Figure 2. A Newborn Infant Taking Part in the Experiment [14]. He is making an effort to keep his hands visible in the beam of light.

Despite the restricted motor repertoire and muscle control of infants, they enjoy exploring those contingencies between their actions and action effects, and by doing so they learn about the capacity and limitations of their own body so that they can use it in the most efficient way to act on the environment and objects in a desired way. Moreover, the experience of contingencies between movements and their sensory events is a pleasing and arousing activity for infants [16] [17]. For instance, they enjoy it when they can correctly anticipate the contingent effects of their own movements, and get nervous when expected effects do not occur [17].

Self-exploration forms the basic building block for all kinds of action based learning. Beginning the first day of life babies engage in an active world where they observe and interact with others. However, in order to be able to interpret the surrounding world and its action-effect relations they need to discover their own bodies, and their motor capacities, which is mainly based on self-exploration of action-effect relations.

They actively get involved in random acts and observe the accompanying changes in the perceptual world, so they start forming associations between their action commands and accompanying perceptual effects. Imitation ability is built upon the ability to form perceptual-motor contingencies, and self-awareness of one's own body's limitations and capabilities.

Therefore, throughout development, infants start with exploring their own motor capacities, biomechanical constraints, and discover the possible contingencies between their movements and accompanying sensory effects. Self-exploration is based on a need to form spatio-temporal congruency of feedback from various modalities which are combined with appropriate motor plans. Self-exploration helps infants to close the action-perception loop and learn the relationship between motor commands and resultant sensory feedback (i.e., visual, proprioceptive, auditory, etc.) so that they can act accordingly to bring about desired action effects.

Hauf, Elsner & Aschersleben [4]and Aschersleben [3] favor the idea that newborns start with acquiring associations between actions and their effects. Then they build upon that to learn to form abstract goal representations in terms of action effects so that they can imitate, which they think develops at around 9 months of age. According to Hauf and colleagues, the acquisition of action-effect associations is the first step towards and an important prerequisite for acquisition of goal-directed action. For forming abstract goal-representations, infants need to go beyond instrumental learning and acquire a new level of understanding of action–effect relations. Tomasello [3] states that when infants begin to differentiate goals from the behavioral means to pursue the goal, then they can truly represent actions as goal-directed and can plan accordingly to produce desired action effects.

This ability further develops through infants' increased capability to map observed actions onto their own action repertoire. In other words, imitation ability, which requires understanding and encoding an observed task first and then transferring that information onto one's own motor representation, is built upon the ability to form those action-effect relations within one's own perceptual-motor system first.

Learning Affordance Relations

For infants as well as for adults, many actions are organized around a relation between the agent and some object. For instance during grasping, looking or pointing, the action is organized around a goal, i.e., a visual target, which affords some kind of an action type [18]. Affordances play an essential role for the perceptual-motor development in infancy. They encode the relationships between actions, objects, and their effects in the environment, and are important for cognitive capabilities such as motor planning and motor control.

'Affordances' is a term coined by Gibson [19], used to refer to action possibilities of an object with regard to the actor's action capabilities. For instance, a tennis ball is only throw-able for a human being of certain arm muscle power. Consider, for example, that a surface affords support comes to be understood by placing many different objects on many different surfaces, observing the perceptual effects of those actions, and discovering that level, non-compliant surfaces work best, and only then, away from their edges. With the onset of locomotion, children's own vestibular system informs them that horizontal acceleration and deceleration can destabilize their own vertical posture, however, its takes longer for children to appreciate the destabilizing impact of the instability they cause to objects that they push and pull, and far longer to appreciate this in the context of an acceleration caused by a machine that is not acting one-to-one with the child's own behavior. It takes years of many different kinds of experiences for a child to develop general knowledge of this simple affordance, such that the child, confronted with a conveyor belt of groceries, would apprehend the need to grab a carton of eggs more carefully if they are at the edge of the conveyor rather than the center. Another example is, for a ten year old child to realize that a chair affords a place to put a bag of groceries, she or he must marshal a more fundamental discovery, made when one year old, that stable horizontal surfaces afford placing objects on top of them.

Affordances are learned by autonomous experience and self-observation. The way an infant grasps a cup and a pencil, the kind of arm kinematics he uses might seem similar in the first year of life, but as affordance relations are learned and improved he would grasp two objects differently depending on their role in life. This is a skill that needs to develop in order to form accurate action representations. During the first year of life infants perceive actions as goal-directed, in other words, they represent human actions and object motions in relation to the particular objects to which they are directed and the kind of sensory feedback they would receive when they interact with those objects, rather than in terms of the superficial properties of those objects [20] [21]. In other words, affordance relations are developed by practicing action-effect relations in object oriented actions. By exploring actions and their perceptual effects in the environment, an infant would learn that a glass cup and a pencil would afford different actions towards them.

Thus, in parallel to the development in the capacity to detect goal structures, infants also develop affordance relations, an effective action-effect coupling and perceptual-motor coordination. Infants guide their actions and perceive affordances by exploring and learning action-effect relations [22].

Imitation Learning

Actions done by other individuals form a category of stimuli of great importance, in particular for humans. From an evolutionary point of view we must understand the actions of others if we want to survive, and our unique ability to imitate successfully seems to be a core faculty necessary for understanding the actions of others. Until recently, imitation ability was not considered to be associated with a high form of human intelligence, however, this perception has changed in such a way that it is now described as “a rare ability that is fundamentally linked to characteristically human forms of intelligence, in particular to language, culture, and the ability to understand other minds” [23]. Imitation has a central role in human development and especially for learning and development of novel motor skills. Imitation ability starts very early in life, and despite its complexity it is one of the major learning modes for infants as well as for adults.

We might think of imitation as copying in a reproductive way. During imitation, the observer transforms an observed action into an executed action that is very similar to the observed one. It requires encoding the observed task first, and then transferring this information onto one's own motor representation of the same action. Imitation also requires a precise matching of the performed action onto the observed one. Yet, close examination reveals that imitation is not as simple as it seems. For instance, which information must the observer extract from the model in order to imitate his behavior? Is it sufficient to understand the goal of the action or should its details also be coded? Most importantly, there is the translation problem. Sensory and motor systems are classically considered to be separate systems. Thus, how is the description of a visual event translated into muscle activity that accurately replicates the observed action? According to Rizzolatti, imitation is composed of two closely related cognitive phenomena. The first is the capacity to understand others' actions and the second is the capacity to replicate the action based on an understanding of the action [24]. Moreover, there is an important distinction between mimicry and imitation. Mimicry involves superficially copying the modeled behavior without understanding it [25]. However, according to Thorndike [26], true imitation is much more sophisticated and during imitation the observer not only truthfully transforms an observed action into an executed action, he also acquires a new motor behavior; thereby imitation implies learning.

It is well documented that imitation is one of the most important means by which infants and young children acquire a wide range of new behaviors. A growing body of research has now documented that imitation emerges early in life. In these studies with highly controlled conditions, newborns were shown to display facial gestures that matched those performed by an adult model [27], see Figure 3. However, it has also been suggested that the kind of action replication observed in those newborns resemble mimicking which is automatic and lack understating, rather than true imitation. Still it is remarkable that infants as young as a few months old seem to be capable of replicating actions despite the differences in body size, perspective of view and lack of conception of self-other distinction. Somehow these infants are able to relate the proprioceptive motor information about their own unseen body to an internal representation of the visual kinematics and create a match. What is more interesting is that infants show traces of a learning process though imitation. Meltzoff and Moore [28] conducted a study in which they looked at how 6-week olds temporally organize their behavior, and they found that the infants gradually corrected their imitative attempts over time through a sequence of repetitive trials [28].

Figure 3. Six-week old Infants Imitating the Large Tongue-protrusion Gesture. Demonstration from the Meltzoff and Moore study [27].

Infants' ability to learn about actions is restricted by their limited motor repertoire, and is constrained by their postural and muscle control ability, thus especially in the first year of life the range of actions an infant can perform is quite narrow. On the other hand, infants have ample opportunity to observe other people perform actions, as they try to acquire the capacity to produce those actions on their own. For instance, they watch other people (especially their parents and siblings) acting on the environment and on objects. They watch them to reach and grasp for objects, to lift boxes, to pull and push various objects, etc. Being able to transfer the knowledge of an observed action onto one's own action, i.e., true imitation, is a complex task which develops towards the end of first year of life as shown by the imitation paradigms performed on young infants [3]. In one such study by Carpenter [3] 10 and 12 month infants are asked to copy a target action that produced an interesting sensory effect. Both age groups copied the action correctly, but only the latter age group checked whether their own action resulted in a similar sensory effect, suggesting that 12 month olds had expected the same action-effect relations in their own actions.

Thus, it seems that although infants learn about contingencies between self-performed actions and their sensory effects starting in the first month of life, they seem to be able to detect action-effects relations from observed actions and mapping those relations onto their own motor representations towards the end of their first year of life, see Figure 4.

Figure 4. Infants Observing and/or Imitating various Actions.

Observational/imitation learning is an important part of learning goal-directed actions during infancy, and it remains very important during adulthood as well. Adults improve their motor skills by observing other people perform, and by trying to transfer the observed action onto their own action system. In order to imitate an action successfully, people need to transform the observed action into relevant motor codes so that a relevant motor representation could be formed in turn for use in imitation. That is, the perceptual characteristics of the observed action need to be mapped onto the motor repertoire of the observer.

Recent advancements such as the discovery of Mirror Neurons [24] and the Simulation Theory [29] [30] in the Cognitive Science field, bring new insights into our understanding of imitation learning. Mirror neurons, first discovered in the motor-related areas of the monkey brain, provide a neurophysiological basis for a direct matching system and the ability to map observed actions onto one's own action. Imitation might be based on a mechanism that directly matches the observed actions onto an internal motor representation through mirror neuron activation, because this set of neurons fire both when a monkey produces goal-directed action (such as breaking a peanut) and when the monkey observes the same action performed by another individual [31] [24]. According to Rizzolatti, this is a resonance mechanism through which "pictorial descriptions of motor behaviors are matched directly on the observer's motor representations of the same behaviors" [32]. Moreover, related findings in human beings using brain imaging techniques such as electroencephalography (EEG), transcranial magnetic stimulation (TMS), and functional magnetic resonance imaging (fMRI) reveal that common brain regions are activated when observing an action and when executing the same action oneself. They also show that observing an actor act primes the muscles the observer will need to use do the same action [33] [34]. Thus, this matching mechanism between observed and executed actions is a reasonable candidate for human imitation.

Moreover, this idea is further supported by the Simulation Theory, which states that we understand others' actions (and thus able to imitate) by using our own internal motor system as an emulator, in other words, by 'running an internal neural simulation of the observed action' [29] [30]. According to the theory, when humans observe an action, they internally simulate the observed action within their own sensori-motor system via their own internal model of action control and the simulated replica is a true internal action representation except for one fact: it is not covertly executed. Simulation Theory provides a basis for imitation learning as well as for mental training, where professional athletes and musicians, improve their skills by mentally rehearsing the action patterns. Mental simulation is based on a common activation pattern in the mirror neuron circuit for observed and executed actions, and it provides an explanation for how observed actions are directly mapped onto a corresponding action schema in observer's own internal motor repertoire: through running an internal simulation.

III. RELATED WORK

Affordance Relations Learning through Motor Babbling in Robots

A cognitive robot is likely to operate in a complex, often distracting environment, which provides many challenges to learning from experience. How should the robot focus its attention for best effect? Of all the features of the robot's environment, and the geometric explosion of relations between these features, which are those very few that warrant attention from the robot's limited processing resources? What aspects of the robot's experience are worth exploring in order to have good likelihood of learning something that will improve task performance? We believe affordances, or affordance relations, are the best candidates, because affordances are what an organism leverages toward successful completion of tasks that advance goals.

'Affordance' is a term coined by Gibson [19] initially to refer to features of the environment that offered (afforded) "good or ill" to an organism attempting to complete a task. For example, Gibson would have said that a ball affords throwing in a game of catch; thus, to perceive a ball is to perceive that it affords throwing. Subsequent thinking [35] has recognized that affordances are not static properties of objects but rather are emergent properties of the goal-object relationship. When an individual wants to play catch, a ball affords throwing. When an individual wants to play golf, a ball affords hitting. When an individual wants to prevent friction, a ball affords use as a bearing. None of the many known uses that balls afford, as well as none of the afforded uses yet to be discovered, perceived when perceiving a ball. Rather, the afforded utility of a ball is imputed in the context of accomplishing a goal, where an afforded use of an object materially promotes or prevents goal-success. This conception of affordance applies not only to features of the environment, but to features of the individual as well. An opposable thumb affords grasping a pool cue. The ability to reason geometrically and to hit the cue ball accurately affords the likelihood of causing the balls to drop into their planned holes. The ability to assess an opponent's strengths and weakness affords the opportunity to plan side-effects that create an inopportune lay of the balls for one's opponent. None of these affordances are available to direct perception. All must be imputed in the context of having the goal of winning a game of pool.

Approaches to robotic machine learning have typically focused, not on affordances per se, but rather on exploring an environment in an attempt to formalize the system’s underlying behavior selection model. This involves learning to predict the outcomes of behaviors, behavior reliability (i.e., likelihood of success), as well as necessary and/or sufficient conditions for behavior selection. One question that traditional learning techniques leave open is how to link behaviors, percepts, and goals in such a way as to identify which perceptual features indicated affordances that can be leveraged by behaviors in the robot's repertoire, so as to promote system goals. While little work has been done to answer the question, the work that has been done adds important insights.

In research that demonstrates the basic utility for robotics of the concept of affordance, Cos-Aguilera et al. [36] investigated the acquisition of affordances for behavior selection and the satisfaction of internal drives, in order to enable a mobile robot to exist autonomously within its environment. In order to accomplish this, the robot is endowed with an internal homeostatic system. This system measures quantities such as battery power and movement and links these quantities with the concepts of hunger and fatigue. An internal drive system monitors the homeostatic system and arbitrates behavior selection. Over time, the robot attempts to learn correlations between behavior execution, percepts, and the satisfaction of internal drives. These correlations are modeled as learned affordances and used to guide behavior selection in the future.

In an ambitious effort, Stoytchev [37] adds Piaget's developmental theories [38] to Gibson's notion of affordance, to take a developmental approach to learning affordances. The simulated robot ('simbot') begins with an internal representation of itself, as well as a means of identifying visual signatures of both its bodily parts and environmental objects. The simbot then explores various behaviors using a "motor-babbling" technique. This technique is similar to what happens when infants explore their own motor capacities and biomechanical constraints, and discover the possible contingencies between their movements and accompanying sensory effects.

The process of motor-babbling results in a sequence of behaviors that are then recorded and linked with the system's corresponding visual inputs. Once a behavioral sequence/visual signature list has been obtained, numerical techniques search for invariants among the visual signatures and attempt to correlate these invariants with subsets from the behavioral sequence. Finally, the identified behavioral subsets are performed once more, and if the invariant(s) persist, an affordance is created between the environmental objects used by the behaviors, the behavioral subset, and the known invariants [37]. While a powerful demonstration, Stoytchev [37] also reveals how lengthy and laborious a developmental approach is, as the simbot is preprogrammed to start at

Piaget's Stage II of sensory-motor operations, and advances through its experiences to Stage III. We have shown that a part of his approach could be applied to a humanoid robot, ISAC (Intelligent Soft Arm Control), to make ISAC learn traversability affordances. In Erdemir [39] , we considered the following reaching task for ISAC: Given an environment of unfamiliar objects, one of which is a goal object, ISAC should be able correctly to traverse the environment with its arm and reach the designated goal object, or else refuse to traverse an environment in which collision with non-goal objects is unavoidable.

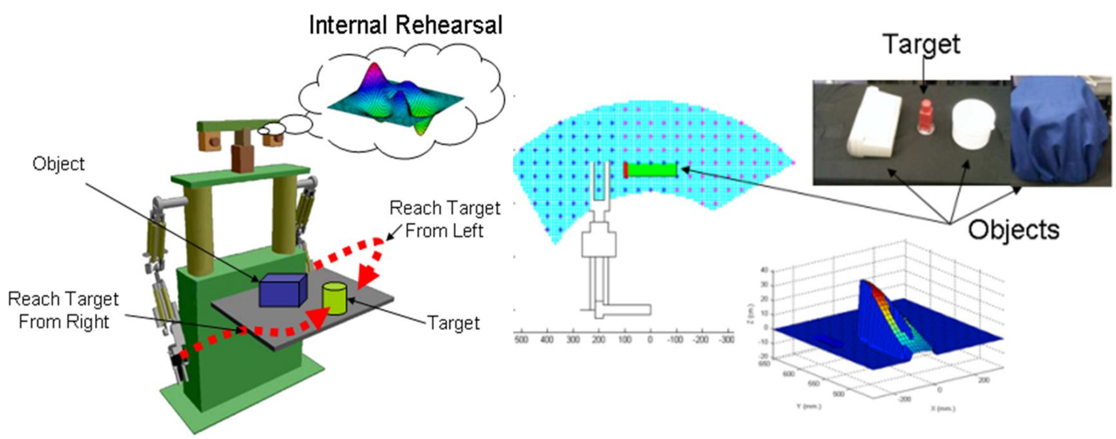


Figure 5. ISAC Simulator and Internal Rehearsal

Instead of recognizing objects and learning affordances to be attributes of specific objects, as was done in Erdemir et al. [39] we used the edge features as the basis of a traversability affordance relation. Then, instead of interpreting human behaviors and mimicking these, we allowed ISAC to rehearse its behaviors internally to estimate general affordance relations and how best to leverage these for any given task. ISAC acquired knowledge of affordance relations in two stages, a babbling stage followed by a learning stage. In the first stage, ISAC's Central Executive Agent (CEA), as shown in Figure 6, primed the Internal Rehearsal Subsystem (IRS), by having ISAC engage in random behavior, "motor babbling" [40], in order to accrue a baseline of experiences and consequences from which to generalize. In the first part of this stage, ISAC reached to the goal-object in an obstacle-free environment. Every time it reached the goal, it got a reward. In the second part of this stage, an impediment object was put between ISAC and the goal object. Every time ISAC's end-effector hit the impediment object, ISAC got a punishment and noted the position where its end-effector hit the object. These rewards and punishments were tracked in order to structure ISAC's motivational processing to be congruent with the demand to reach only into traversable spaces.

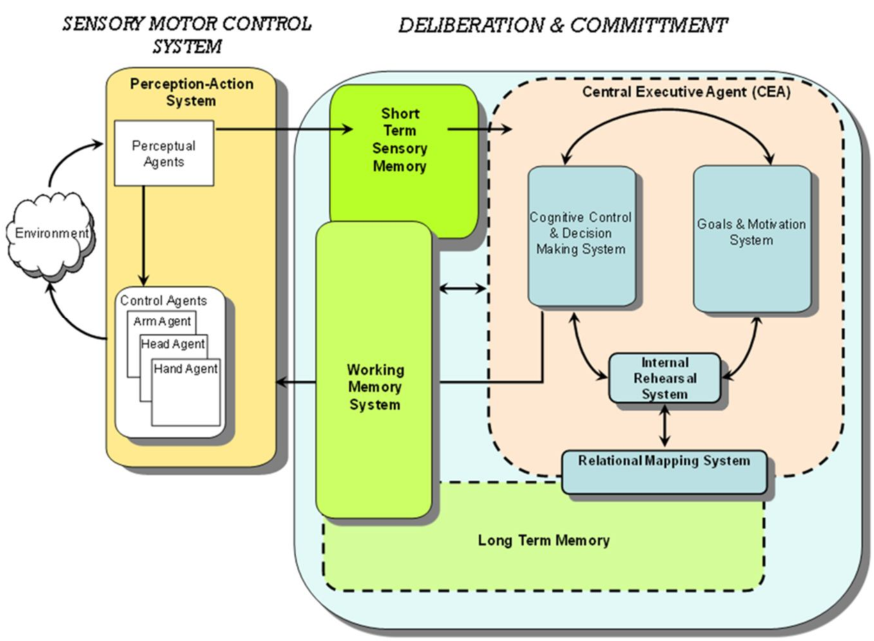


Figure 6. ISAC Cognitive Architecture [41]

In the learning stage, ISAC's IRS created and optimized a Gaussian Mixture Model (GMM) to represent its accrued experiences. GMMs comprise a weighted sum of Gaussian probability density functions. GMMs are one of the more widely used methods for unsupervised clustering of data, where clusters are approximated by Gaussian distributions and fitted on the provided data.

An interesting result we discovered from our experiment was the impact of the shape of the gripper on collision probability and the formation of impedance surfaces as shown in Figure 7. In simulation, the shape of the gripper was an intrinsic part of the simulation and it had no effect on experiment. In the real-world experiment, we found that since we did not predefine the exact gripper shape for each arm, additional collision data was generated near the edges of the obstacles. This data was found to follow a Gaussian distribution. We therefore added an additional term to the collision probability to represent different grippers used. This in turn yielded the result that ISAC was willing to move the arm with the smaller gripper closer to an obstacle than the other arm. This shows that ISAC is beginning to learn how to use each gripper distinctively.

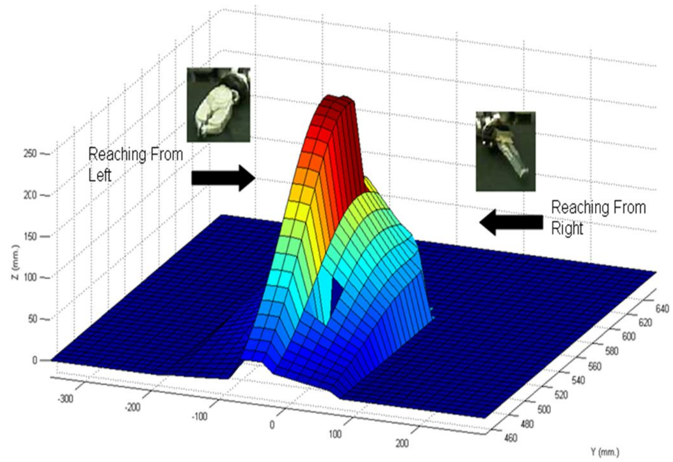


Figure 7. The Impedance Surface Created for an Object Located at (0, 550). The impedance surface does not allow left hand to reach the object, but ISAC can reach the object using its right hand [39].

Additional exploratory research has utilized back-propagation of reinforcement learning signals to enable affordance cueing [42], combined imitation learning with a world model developed through learned affordances [43], and function-based object recognition [44]. Moving beyond Gibson's original formulation, as we also propose, [45] reviews the affordance formalizations of [46] [47] [48] [49] and suggests that for robot control there are three different perspectives from which to view affordances: agent, observer, and entity [45]. For example, the human-robot interface research of [50] takes an observer perspective, inasmuch as a human operator perceives and subsequently utilizes affordances for the robot in a given environment. Herein we take an agent perspective, in which the robot-agent learns about affordances by imitation learning.

Sensory-motor Coupling

How perception and action are linked together and act as a coordinated system is one of the most fundamental problems autonomous robots are faced with. Traditionally robots depended on theoretical models designed by people, however new approaches based on sensori-motor contingencies need to be developed. Laflaqui`ere et al. [51] uses a multi-modal integration method to equip a robot with action-perception performance without any a priori knowledge about itself nor the outside environment. The robot learns about its own interation with the environment and extracts this information bu using its sensori-motor flow. The idea that perception is independent of action has long been challenged, and the dominant view that action and perception are closely linked and are in constant interaction throughout development. In line with this idea, and as suggested by sensorimotor contingencies theory O'Regan and Noe [52] argues that perception is not passive phenomenon where the outside world leads to the activation of some internal representations, but it is active in the sense that it leads to some sort of interaction with the environment.

Similarly, Philipona et al. [53] suggests that in biological organisms the perception of our bodies, other agents and objects is a consequence of the interplay between sensory inflow and motor outflow. An agent's movements are accompanied by a sensory change inflow emerging from the environment. Sensori-motor contingencies (the spatio-temporal link between motor movement and resulting sensory consequences) allow one to infer the outside physical space, because any change in movement leads to a predictable change in the physical space as well, which also makes it possible to differenciate between movements of the agents and movement of the outside environment only. Another related is work by Philipona and O'Regan [54] who described an algorithm that discovers the structure of the outside environment by analyzing the interplay between its motor outputs and resultant sensory inflow without relying on the body its linked to. Through simulations they show that the algorithm can discover the info about its relation to the outside world and learn to move in a desired way by comparing its motor outflow to their accompanying sensory inflow, and thus by forming sensori-motor contingencies. Another approach that focuses on Sensory-Motor mapping is offered by Chalodhorn et al. [55] who tested the methodology on both a dynamic simulator and a humanoid robot learning a complex set of motion dynamics by imitation. Their approach was based on optimization of motion dynamics by mapping motor commands in the low dimensional subspace onto expected sensory feedback, so that in the task phase the robot could select appropriate motor commands based on the sensori-motor match and learned kinematic constraints.

Imitation Learning in Robots

Imitation learning has been receiving broad attention in the robotics community as a powerful tool for rapid transfer of skills from demonstrators to robots [56] [57] [58]. The objectives of imitation learning include efficient motor learning, connecting action and perception, dimension reduction, capability of copying novel cognitive rules and transferring information/knowledge from a mentor. Imitation learning also offers a promising direction to gain insight into faster affordance learning [59] and a perceptual-motor control mechanism, which can ultimately lead to developing autonomous robots. In particular, imitation learning in robots offers great promise for the realm of humanoid robots that aims to look and behave like human beings. In our lab, we have used a dynamic motor primitive method [56] and a potential filed method for imitation learning for object avoidance behavior in simulation [60]. Imitation learning also offers a promising direction to gain insight into faster affordance learning [59] and perceptual-motor control mechanism which can ultimately lead to developing autonomous robots.

Most of the robotics research that implements imitation learning in robots actually uses mimicry in their tasks. There is a significant difference between mimicry and imitation; however most of the robotics community seems to be unaware of that distinction. Mimicry involves superficially copying the modeled behavior without understanding it [25]. A good example would be of how parrots mimic words that they hear automatically without comprehension. Imitation, on the other hand, is much more sophisticated and deliberate in terms of recreating the action. It involves consciously attempting to copy the behavior. Most robotics studies refer to imitation as the behavior of robots as they replicate an action that is already in their motor repertoire; in psychological studies, on the other hand, the stress is on the "learning" aspect of imitation. Cognitive psychologists often define true imitation as the capacity to acquire a motor behavior previously not present in the observer's motor repertoire [61]. According to Thorndike's [26] definition of imitation, which is also adopted by Rizzolatti, "imitation is learning to do an act from seeing it done". Thereby, according to Thorndike's definition, in true imitation the observer not only truthfully transforms an observed action into an executed action; also acquires a new motor behavior. Therefore, imitation implies learning.

In line with this premise, the self-exploratory stages described in this study, which focus on discovery of motoric capacities, biomechanical constraints, limb affordances and skill learning set the stage for a much more advanced action reproduction mechanism, which resembles more the mechanism of imitation observed in human beings than pure mimicry. Imitation ability requires understanding and encoding an observed task first and then translating that information onto one's own motor representation. It is built upon the ability to form action-effect relations within one's own perceptual-motor system first. The ability to form associations between actions and their perceptual effects is mainly maintained through an active self-exploration stage analogous to the one in which an infant discovers the cross-modal contingencies from body movement. Similarly, in our studies the developmental stages (such as motor babbling and self-exploration) that the robot goes through would lead to a complex and true imitation ability which is biologically grounded.

Observational learning and learning by imitating human performance is one of the most fundamental problems addressed by developmental cognitive robotics [62] [63]. The underlying mechanism that gives rise to imitation ability attracts a lot of attention from the field of not only neuroscience and psychology but also robotics. One of the long cherished goals of cognitive robotics is to implement a robot with the ability to learn and generalize motor behaviors from observing human demonstrators. Imitation is a complex skill that requires perception (vision) and action (motor system) to be coupled and combined with memory and action representations in a meaningful way. Imitation requires self-learning and social interaction, and it plays a fundamental role in getting in contact with physical objects as well interacting with other beings [64]. Imitation learning is also a very powerful tool for acquiring new complex behaviors, ranging from tool use to different forms of social interaction which are passed from generation to generation. The social aspect of imitation learning where individuals learn to interact with objects and other beings plays an important role in cognitive development starting very early in life. Given the complexity of the imitation ability and tasks to be imitated, it is extremely difficult and inconvenient to program robots manually. Also, imitation ability requires rapid behavior acquisition which makes manual programming with a large set of trial-and-errors an undesirable approach. Moreover, humanoid robots are designed to be in interaction with human beings and the environment. Therefore robots need to be able to learn new tasks on their own, and generalize their ability to different contexts.

Early studies in cognitive robotics modeled imitation ability using neural networks, which consists of learning, vision and motor modules, and successfully imitated various oscillation and reaching behaviors [65]. Fitzpatrick et al. [66] went further and proposed that a robot uses target information and simple experimentation with action consequences to learn to imitate. According to the authors robots can be implemented with active observational strategies which allow them to experiment with their motion primitives and thereby manipulate the visual target, and then to understand the causal relation between their actions and the resultant visuals in the environment. Like current study, they underline the importance of experimentation with motor primitives for action learning in humans as well as in robots.

Schaal et al. [67] defined complex movements as combination of movement primitives, and outlined the use of non-linear dynamic equations derived from these motion primitves which are then used to build up the complex patterns. Ilg et al. [68] proposed that robots can learn complex human behaviors through a reinforcement learning algorithm which goes beyond standard imitation, and one that involves parsing complex movement patterns into meaningful movement subsequences; and then use of dynamic programming to combine matched segments and build up a complete morphable motion trajectory. The authors selected the points of zero velocity as the dividing criterion between movement segments. Another reinforcement method has been proposed by Guenter et al [69] in order to cut down on the number of demos trials shown to the robot. They proposed a reinforcement strategy which was used combine with the knowledge acquired during action observation.

Some approaches to generate imitation in robots rely on using nonlinear dynamical systems [70] while others take inspiration from biological algorithms [65]. Programming by Demonstration (PbD) takes inspiration by the way human beings learn new skills through imitation and implement robots with these kinds of skills [71]. One such example is the work by Calinon et al. [72] who developed a PbH framework which requires generalizing a learned knowledge to different contexts. They conducted a series of experiments where humanoid robots learn simple manipulation tasks by observing human demonstrators. They suggested a probabilistic relevance estimation using Principal Component Analysis (PCA), where the resultant signals are encoded by Gaussian/Bernoulli distributions (GMM/BMM). This approach allowed for spatial and temporal correlations across modalities to be gathered from the robot, and then be generalized to different contexts using Gaussian Mixture Regression (GMR).

However one disadvantage of general PbD approaches is that is depends on a large amount of predefined prior knowledge. Most of prior approaches have required large number of training trials and an additional smoothing process. The robust probabilistic method of Hidden Markov Model (HMM) [73] and spatio-temporal Isomap [74] alike have been proposed as possible solutions to the problem. Kulic et. al [75] modeled imitation by focusing on the intrinsic dynamic features of the motion, using Hidden Markov Model (HMM) which is designed to deal with spatio-temporal variability in human motion across different demonstrations. This is advantageous in situations where the robot could perform in any workspace provided actions with similar trajectory dynamics are produced.

Another probabilistic approach is proposed by Grimes et al. [76] who used probabilistic interference and Gaussian processes to implement the robot with ability to lift objects of varying weights from human demonstration. The robot learns by sensori-motor feedback control, and infers a stable action plan for use in imitation. The fixed action plan could be used with various tasks since it does not require any knowledge of the environment. Similarly, a probabilistic encoding method with Gaussian Mixture Models was applied to a humanoid robot so that it can learn the important features of observed object trajectories, and develop new bimanual motor skills [77].

Having taken inspiration from recent discoveries in humans about action observation/execution Erlhagena et al. [78] propose control architecture for use in robots learning by observation and imitating goal-directed actions. Their approach is based on findings of human studies which state that imitation is different from mimicking, and is aimed at reproducing the end goal (intention) of an action rather than the means that lead to the goal. Similarly Guenter at al. [69] emphasizes the importance of being able create new solutions when learning a task from a demonstrator, such that the robot need to be able to imitate even in unexpected situations, so the demonstrator does not need to perform all possibilities during the training phase. Moreover human studies suggest that the motor intention of other agents is understood by internally simulating the observed action within one's own motor repertoire. Erlhagena et al. [78] base their control architecture on human findings and validate the model by showing robots can learn to imitate grasping and sequencing actions performed by a human model in a goal-directed manner. The control framework is based on the work on dynamic fields [79] and implements goal-directed imitation by combining contextual reference, sensory input and mapping of the observed action onto robots internal motor system. Similarly, Calinon et al. [80] taking inspiration from developmental psychology, present a strategy where the robot infers the goal of an observed task and determines the best method to reach the goal itself through use of a robust discriminant controller.

Some of the other biologically inspired robotic studies include Metta et al. [81] who used neurophysiological findings about the mirror neuron system to develop a model for action understanding and imitation by taking into consideration object affordances. The authors first recorded actions with accompanying multi-sensory information from humans and then used this info to train an action-recognition system. Second, they implemented this model on a humanoid robot which was trained to imitate simple object oriented actions performed by a human being. Their model correctly predicted a mirror-like motor representation in the motor system of the robot. A similar work by Maistros et al. [82] proposed an imitation system which was modeled based on the functional role of premotor brain areas with mirror-like properties. Mirror neurons are activated with both action observation and action execution and the imitation system is thought to rely on the mirror neuron system. Another biologically inspired model is proposed by Billard [83]. The model was implemented in humanoid avatars when they learned repetitive arm/leg movements, oscillatory shoulder/elbow movements as well as grasping and reaching movements by observing the video of a human demonstrator. Their model consisted of modules that are inspired from the motor control regions of the brain, including spinal cord, Cerebellum, Primary Motor Area (M1) and Premotor Cortex (PM). DRAMA neural architecture was used to model the neural network in PM and cerebellum, which are responsible for decoding visual information from observed actions (PM) and generate corresponding motor commands (cerebellum) so that new action representations could be formed.

Similarly, Berthouze [84] developed adaptive agents that can learn by imitation by use of a neural mirror similar to those found in biological systems. The systems is these agents included perceptual-motor coupling which enables replication of observed actions within one's own motor system.

Some past studies bear similarities to the current work in terms of their developmental approach to investigate the imitation mechanism. For instance, Lopes [85] implemented a robot with skills developed through various developmental stages until imitation ability is successfully acquired. Then stages included sensory-motor coordination, interaction with the outside world, and finally imitation. Specifically the robot started with an emphasis on its own body and then to physical objects and eventually to human beings. The implemented modules included teaching sensory-motor maps, methods for grasping objects, and a framework to learn by observation. Another work in developmental robotics is that of Rajesh [86] who proposed a probabilistic model of imitation learning based on Meltzoff and Moore's four-stage imitation progression. Their model was based on the developmental stages of babbling, imitation of body movements, imitation of object-oriented actions, and the most advanced version of imitation with inferring other's intentions. The model was focused on the role of internal sensori-motor control and Bayesian inference techniques which have the advantage of more accurate performance in noisy environments. Another developmental perspective was offered by Montesano [87] who proposed an affordance learning which was focused on learning about the statistical relations between actions, and their effects on object properties. Their approach suggests affordance learning as a building block of sensori-motor coordination and a prerequisite for simple imitation tasks with action planning capabilities. Billard et al. [88] developed another probabilistic approach to model the imitation process in a humanoid robot, which involves discovering different strategies for different tasks.

Similar to the current work, study by Wanitchaikit et al. [89] focused on the visual information and used a self-organizing neural network module to test on robots approaching a target and avoiding an obstacle. The visual system captured the movement of the demonstrator, and the movement features were extracted from the vision and embedded into a self-organizing neural network which was then supplemented with a simple action selection algorithm. The visual information needed for robot imitation could be gathered through use of high-resolution motion capture systems which are used to record high quality human movements. In line with this, the approach by Kuli´c et al [90] emphasizes the advantage of observing human demonstrators rather than other robots in terms of the success of learning by imitation. Observing and imitating a human demonstrator rather than a another robot, has the advantage that the robot can use the structural similarity between human and robot bodies, without having need to program complex robot actions. Their approach was based on recording human movements using motion capture, and then partitioning the action into motion segments, and them clustering and organizing those segments into basic human motion primitives.

Cognitive Architecture for Imitation Learning

"Cognition" is a term referring to the mental processes involved in gaining knowledge and comprehension, including thinking, knowing, remembering, judging and problem solving. These are higher-level functions of the brain and encompass language, imagination, perception and planning. Due to this broad definition, the task of developing a general cognitive architecture and subsequent computational models is extremely difficult. Nevertheless, cognitive architectures and computational neuroscience systems are designed to capture key cognitive processes that exist in biological cognitive systems such as humans.

Neuroscience and computational neuroscience has recently made major advances, especially in understanding the neural control of behaviors [91] [92] [93] [94] uncovering features of learning [94, 93] memory [95] [96]. They also deal with how we perceive and interact with the external world [97] [98] giving some initial purchase on how human experience and human biology influence each other. Similarly, robotics research has reached out to neuroscience to inform the design of increasingly more complex robots, to address high-dimensional problems of motor control [99] [100] perception [101] [102] and decision-making [103] [104].

Artificial implementation of neurobiological control of sensori-motor processes is being markedly advanced by the design of neuroscience-based theoretical models and the creation of physical devices, known as Brain-Based Devices which are controlled by simulated nervous systems [104]. This research tests theories of the nervous system, so as to provide a basis for robotic design and practical applications. Advances from this research include the construction of devices based on principles of nervous systems, experience-dependent categorization and learning [93] and implementation of a value system [104] which informs individuals about the situations that can bring pleasure and pain, one of the most basic rudiments of emotion. These studies provide important steps toward embodying an artificial nervous system which appraises the salience and value of environmental cues from the real world in order to modulate its own operation.

Work in the CIS laboratory has yielded an operational cognitive robot that implements of crucial features of the neurobiology of human working memory (ITR: A Biologically Inspired Adaptive Working Memory System for Efficient Robot Control and Learning, NSF grant # EIA0325641). In this implementation (ISAC—Intelligent Soft Arm Control humanoid robot [http://eecs.vanderbilt.edu/CIS]) learning how to respond to novel tasks is accomplished using an untrained long-term memory model, in conjunction with a working memory system that is grounded in computational neuroscience models of the working memory circuits of the prefrontal cortex [104]. This work shows how to provide robotic systems with a means of maintaining task-related information during task execution, in a manner similar to human task execution. When a novel stimulus is present, this system explores different responses and, over time, learns on which information to focus, in both working and long-term memory, in order to best execute the novel task. Offline, the robot reviews its experiences and uses Internal Rehearsal of alternatives to its actually exhibited behavior, in order to estimate likely consequences of behavioral alternatives, thereby to learn how to improve its performance, when similar situations arise in the future. The robot thereby learns from its experiences in a way that goes beyond the associative learning of which simple creatures with but a handful of neurons are capable. This research demonstrated the utility for robot learning of embedding a neurobiologically faithful working memory in a robot.

It is expected that these kinds of close, mutually informing interchanges between neuroscience and robotics will lead to more complex, realistic robotic systems involving perceptual systems, actuators, attention, emotion, working and long-term memory structures, reasoning and learning that go beyond associative learning. Indeed, an adaptive control substrate that is faithful to the neurobiology of emotion holds promise for facilitating a robot, with neurobiologically faithful working memory, to learn more quickly and robustly that knowledge which is important for its adequate functioning, and then to apply that knowledge adequately during real-time task performance.

Motion Capture for Robotics Research

Some recent studies emphasize the use of motion capture and gathering 3D motion data from the movement of human demonstrators for humanoid robot imitation learning. This method allows recording the motion trajectories of the human movements and partitioning the movement patterns into motion segments, which then can be used as a learning tool. For instance, Kuli´c et al. [90] propose an approach where human actions gathered from motion analysis are segregated into motion segments using stochastic segmentation, and then are organized into motion primitives of which the sequential relationship is learned by the system. Another study by Suleiman et al. [105] tested the idea whether imitated motions in a dynamic humanoid robot simulator matched those of the original human captured data. In order to achieve a good replica they used an optimization approach which involved an efficient dynamics algorithm to control parameters and considered the physical limits of the robot as constraints.

Tang and Leung [106] propose a motion retrieval method called Adaptive Feature Selection (AFS) which allows for selection of different movement features depending on the relative distance among joints. The method, if used in robot imitation tasks, could be advantageous over other methods. Another approach proposed by Ott et al. [107] is a Cartesian control approach in which a humanoid robot is connected to measured marker points, which allows the robot to follow marker positions from the motion data rather than computing inverse kinematics, in order to recognize and imitate human action. Moreover, they integrated marker control with hidden Markov models (HMMs), which, together with the Cartesian control method, allowed for action learning, action recognition and action imitation involving object manipulations tasks.

Another work by Yamane at al. [108] defined a control framework for robots, which tracts data from motion capture using all of its joints (tracking controller), while trying to maintain balance (balance controller). Using joint pressure information as the input, and by computing joint torques that are as close as possible to the motion capture data (tracking controller) the authors demonstrate the efficiency of their system to produce dynamics simulations.

IV. EXPERIMENTAL SET-UP

Imitation Learning of Affordances on a Humanoid Robot

Having recently shown the use of biologically inspired cognitive mechanisms such as affordance relations, internal rehearsal [40] [39] and working memory [41] [109] on a humanoid robot, ISAC, we demonstrate affordance learning by imitation using a simple and small humanoid robot based on the Bioloid Humanoid Robot (BHR) as shown in Figure 8 [6]. The BHR platform consists of the following components, a CM-5 circuit board, designed by Robotis, and small, modular servomechanisms called Dynamixels, which have their own Atmel MEGA8 microcontrollers and can be used in a daisy-chained fashion to construct robots of various configurations, such as wheeled, legged, or humanoid robots. The structure of the B-type humanoid robot, shown in Figure 8, was used in this dissertation for learning crawling affordances.

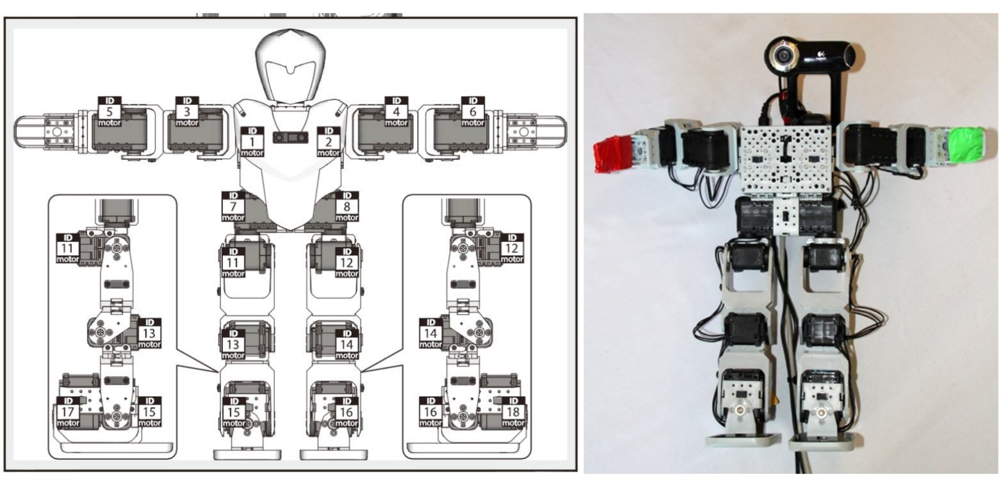


Figure 8 Bioloid Humanoid Robot (BHR) [6].

The microcontroller mounted on the back of the BHR was bypassed and we directly connected the Bioloid servo network to the laptop via Dynamixel single cable network connection. A camera with a resolution of 640x480 pixels was mounted to the head of this robot. The camera was connected to the USB Port of the laptop to enable the robot to process the environment and accomplish the task accordingly. The overall system is shown in Figure 9.

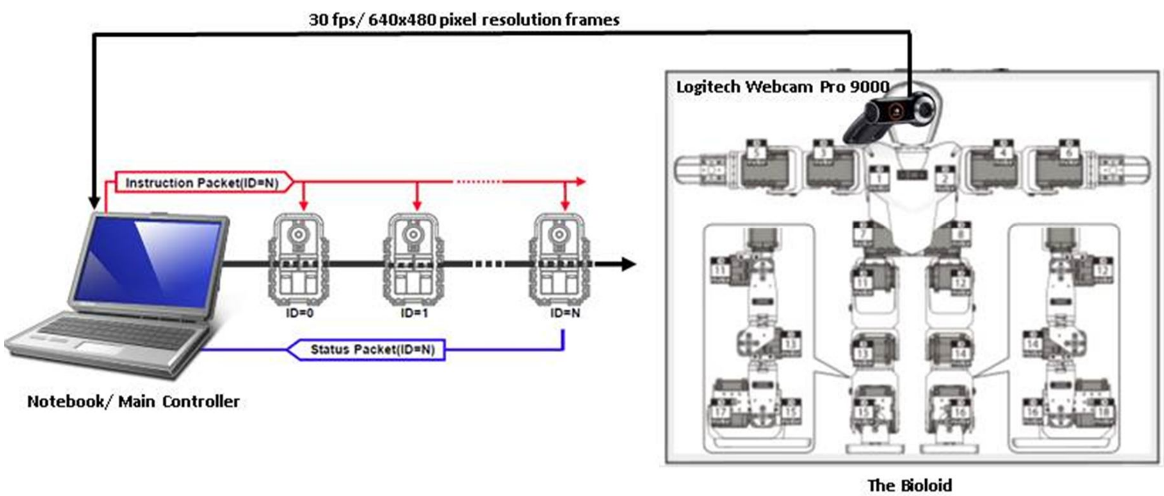


Figure 9. The Bioloid and Overall Control System

General Approach

Considering the complexity, intricacy and cost of a robot capable of learning by imitation, it is of fundamental importance to be able to first build a prototype and simulate the overall robotic system on this prototype. In this dissertation, we plan to show how imitation learning of affordances can be done by using an educational robot kit that ultimately could lead to important improvements in the autonomy of humanoid robots.

The Bioloid robot came with a set of preprogrammed behaviors such as walking, kicking, and lifting. However, instead of using these behaviors, the robot explored, learned and created its behaviors and its motion primitives by itself in the babbling or virtual exploration stage. We attached a camera on the top of the robot to use as an external sensor and find relevant virtual features for the affordances. We chose a simple behavior, a crawling behavior, to demonstrate how the robot learned body affordances to change its position by way of a crawl-like behavior.

General Summary

In **STAGE 1** called LIMB AFFORDANCE LEARNING THROUGH MOTOR BABBLING, our humanoid robot provisionally learned a set of basic affordance relations by exploring ways of crawling and discovering the outcomes of its actions. After having classified the arms, then in **STAGE 2**, called IMPROVING LEARNED LIMB AFFORDANCES THROUGH SELF-EXPLORATION, the robot will provisionally learn a set of basic motion primitives, its own motor limits, biomechanical constraints and skills by performing random arm movements and discovering the associations between those movements and their spatial effects in the visual space. And having learned the perceptual-motor coupling between arm movements and their resultant visual effects, lastly in **STAGE 3**, called IMITATION LEARNING FROM MOTION CAPTURE, the robot will learn to imitate a novel object-oriented action such as lifting/pushing/pulling an object.

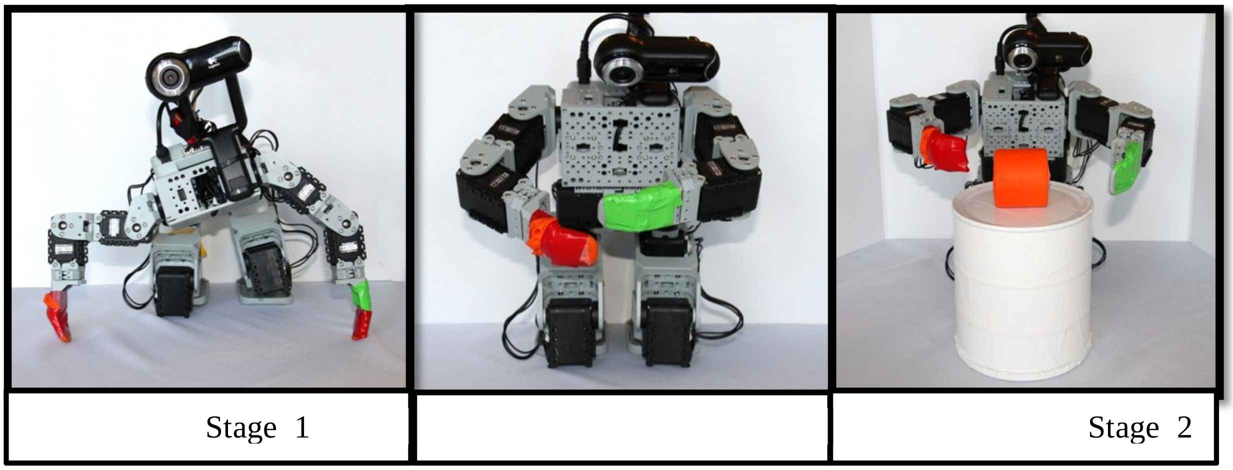


Figure 10. Schematic Summary of the Experimental Stages. In Stage 1, the robot learns affordance relations through motor babbling, in Stage 2 the robot improves affordance relations though self-exploration, and in Stage 2 the robot learn to imitate a novel action.

V. STAGE 1: LIMB AFFORDANCE LEARNING THROUGH MOTOR BABBLING

Self-Reflection in Human Infants & in a Bioloid Robot

Self-exploration observed in human infants is the basic building block for all kinds of action based learning including imitation learning. Infants first need to discover their own bodies, and their motor capacities, which mainly involve learning action-effect relations, i.e., learning to associate actions with corresponding sensory effects. Starting at birth infants engage in active exploration of their own body by touching it, moving it and investigating the cross-modal contingencies of their action effects [7]. Self-exploration helps infants to close the action-perception loop and learn the relationship between motor commands and resultant sensory feedback (i.e., visual, proprioceptive, auditory, etc.) so that they can act accordingly to bring about the desired action effects. Moreover, during most of the actions the infant's exploration of the action is organized around a goal, which might be an object. Affordances encode the relationships between actions, objects, and their effects in the environment, and they play an essential role for discovering perceptual-motor contingencies in object oriented actions. Thus, infants also guide their actions and perceive affordances by exploring and learning action-effect relations [22].

Like infants, the BHR is not pre-programmed with knowledge of affordances and action-effect relations, and thereby it requires a great deal of self-experience from which to extract progressively more abstractly represented knowledge so it can learn to imitate. Thus, the robot needs to go through a set of self-exploration stages in which it learns affordance and action-effect relations. In this first stage, similar to a young infant who moves his/her arms in order to explore the cross modal match between specific proprioceptive cues from the movement of particular limbs and the accompanied visual cues from the spatio-temporal characteristics of the arm, our robot moves its arms randomly and forms specific associations between its arm movements and the kind of change in the visual space, thereby learning to classify certain motor units as belonging to the left and right arm as shown in Figure 11.

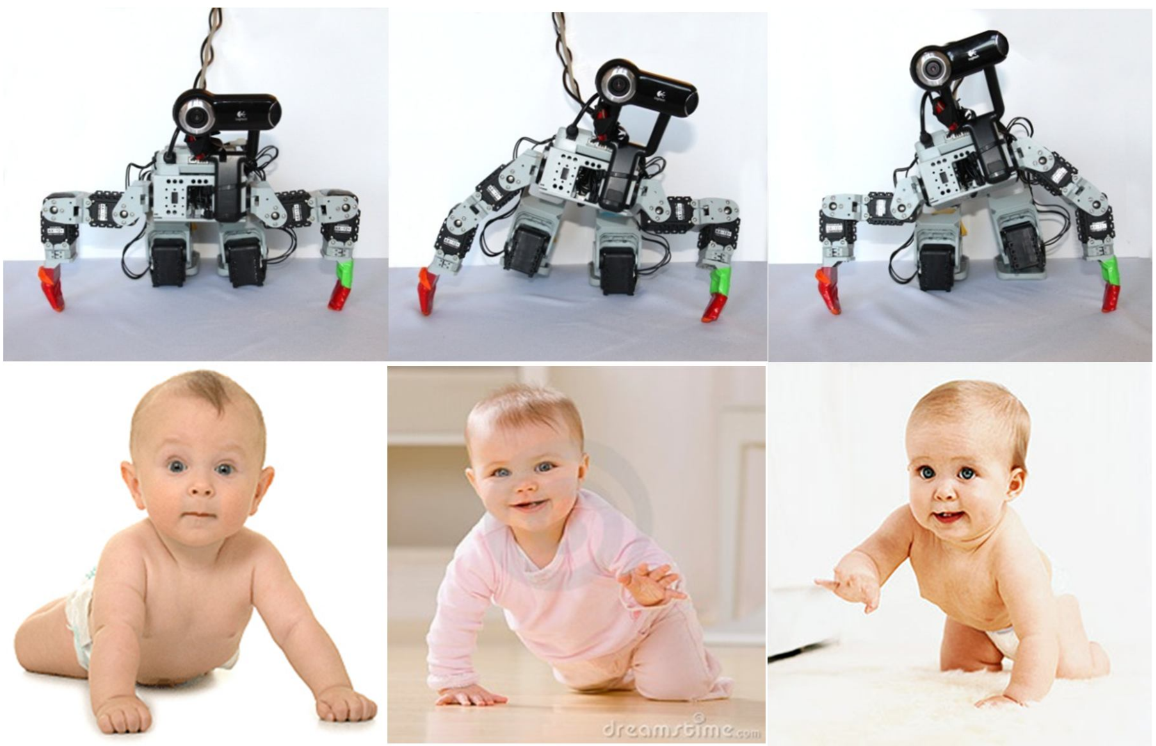


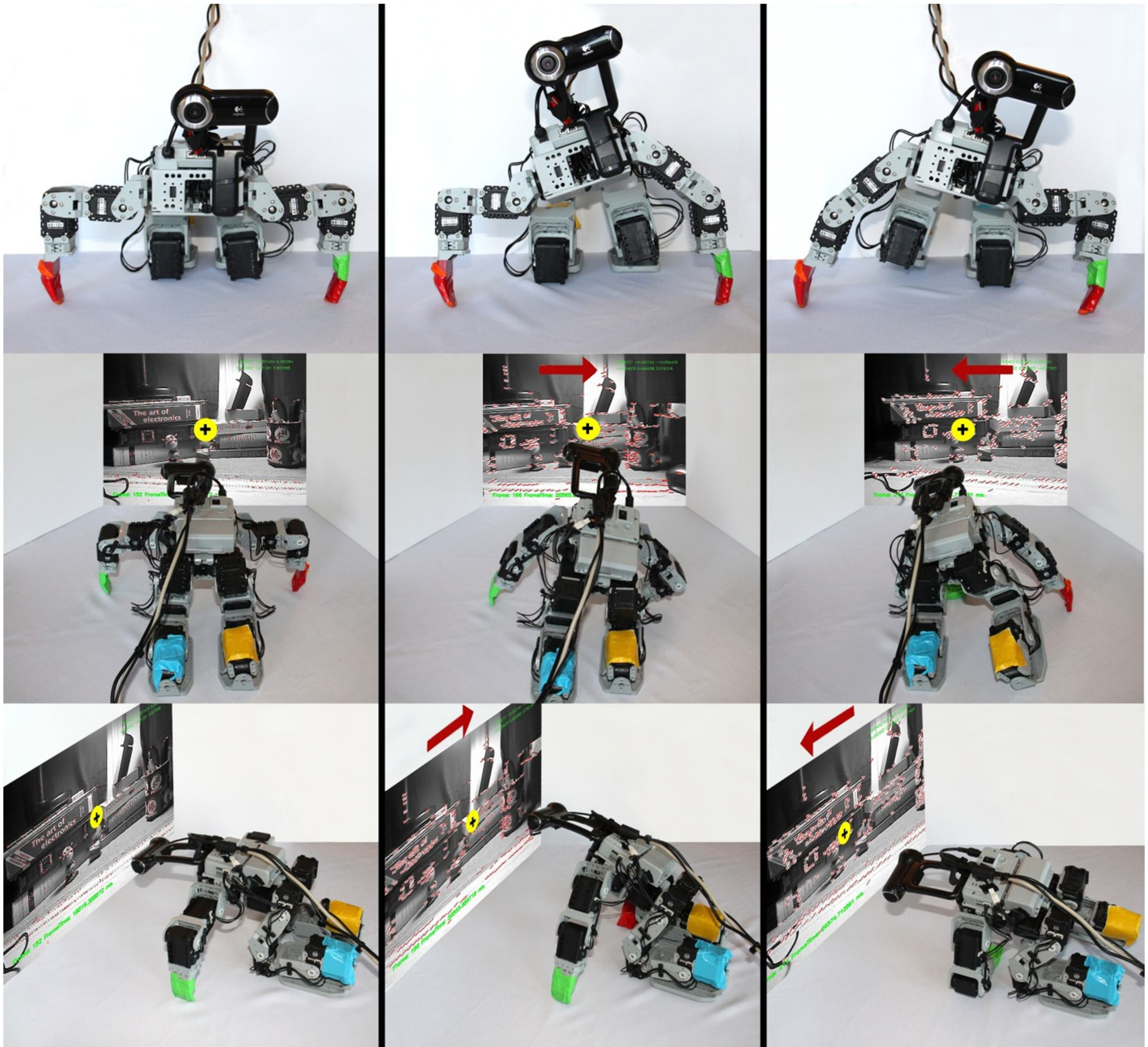
Figure 11. Developmental and Computational Similarities in Stage 1. BHR goes through a set of self-exploration stages, similar to an infant.

Methods

Similarly to how a human baby discovers action-effect relations of his arm movements, BHR provisionally discovered affordance relations between certain arm limb movements and corresponding motor unit numbers by exploring the outcomes of its random arm movements while in a crawling position. The robot has three motor units at the joints for each arm. The task was to execute a random arm movement which happened as a result of random limb angle assignments for each of the three motor units in a certain arm. Each arm movement resulted in a particular shift in the visual field of view of the robot (ego motion). Then, by evaluating those resultant action effects (visual feedback or ego motion) and their link to specific joint angles, the robot learned limb affordances: learned to classify which motors belong to the right or the left arm, and what right and left arm motion affords to.

Motor babbling was used to speed up the process of learning motion primitives by randomly executing, analyzing and gathering the outcomes of actions. These actions are based on the most primitive motor actions, i.e., the positions of its servomotors, rather than higher level actions such as walking. This would take a long time if all these were done in a real environment by a real humanoid robot, but it can be done more quickly and safely by this prototype.

Figure 12 shows the experimental set-up while the robot is crawling and trying to discover cross correlations between motor units and the accompanying arms. In a stable position the focus of the vision is on a certain object (a). As the robot bends its right arm (using various motor unit angles), there is shift in the visual focus to the right (b). As the robot bends its left arm (using various motor unit angles), there is shift in the visual focus to the left (c). By exploring the cross modal associations between certain arm movements and corresponding shifts in the visual fixation point, then the robot learns to classify its left and right arm. Figure 13 shows the view from the robot's camera as a function of the movement of the robot as it bends its arms. Note the shift in visual fixation point as a function of movement.



a) Stable position	*b) Right arm bended*	*c) Left arm bended*

Figure 12. Experimental Set-Up for Stage 1. Markers attached to the hands of the robot while robot is crawling and trying to discover cross correlations between motor units and the accompanying arms.

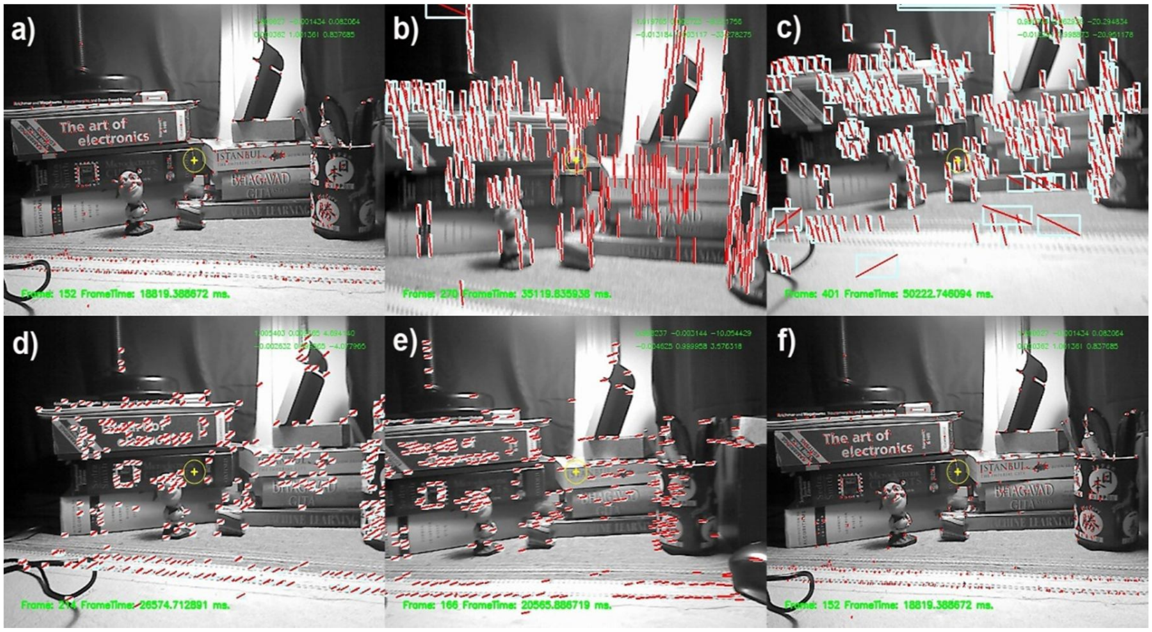


Figure 13. The Shift in the Field of View from the Robot's Camera as a Function of Movement. The columns represent: a) stable position b) moving up c) moving down d) moving left e) moving right, and f) stable position. Note the shift in visual fixation point as the robot bends its arms.

Assumptions

- It is assumed that the robot knows its joint limits and programmed the babbling with these limits, unlike Brooks' approach [110]. The robot could have learned its limits by watching the torques at its servo motors during babbling and if the torque values came to a maximum point it could record these points and limit the babbling between these maximum points.
- In the babbling stage, we let the robot babble using smooth approximately sinusoidal actions instead of white noise to discover the babbling space. Giving a white noise sequence and watching the outcomes of the motors may damage the coils of the

motors, so we avoid these kinds of babbling sequences by forcing the robot to create random sinusoidal sequences and execute them.

Motor Babbling

Sensori-motor learning based on motor-babbling has been shown to be effective for autonomous humanoid robots for developing an internal representation of the relationship between the self and the surrounding environment [111].

During this stage, the m number of actuators of BHR were given sinusoidal angle references, denoted by $\theta_{i0} \pm d_i^N(NT)$ where N is the number of babbling trials, T is the sampling time of, n is the step number where the sinusoidal cycle was divided into n *parts*, $i = 1 \dots m$ is the joint number, θ_{i0} is the initial angle of the *ith* joint angle and the sign of the $d_i^N(NT)$ changes randomly to let BHR try different sequences of angle combinations. When the angle references were given to the joint actuators, the Dynamixel Motors' controllers move joints to these reference angles, as an example is shown in Figure 12, and the outcomes of these actions are recorded as raw encoder readings as $d_i^N(NT)$ at each time step. At the same time, the position of BHR fixation point locations,$\{x^N(nT), y^N(nT)\}$, *where* x and y values were pixel-wise displacements in horizontal and vertical displacements respectively, as shown in Figure 13. The calculation of the fixation point locations are shown in section Egomotion Estimation.

Egomotion Estimation

The egomotion of the BHR was determined by the use a camera attached to the head of the BHR and the use of a kind of visual odometry technique on a sequence of the images taken from that camera. Optical flow was constructed by using The Kanade-Lucas-Tomasi (KLT) feature tracker [112] from two image frames in a sequence. The good features that were tracked in the KLT were found by Shi-Tomasi's method [113]. Finally, affine transformations were calculated and the change in the position of the fixation point from the egomotion was estimated from these transformations.

The egomotion estimation contains the feature point extraction, optical flow detection, global parametric motion model estimation, affine transformation estimation and estimating the position of the fixation point.

Feature Point Extraction

Transforming the image data into the set of useful set of features, mostly corners, is called feature extraction and a special form of dimensionality reduction. Usually the image data is too large to be processed and it is suspected to be noisy, redundant and full of poor information so the image data should be analyzed and transformed into a reduced representation set of features. There are many feature extraction algorithms like Harris corner detector, Shi-Tomasi's corner detector, SUSAN, SIFT, SURF, and FAST and around all Shi-Tomasi is considered to be the fastest and most reliable [114]. Shi-Tomasi [113] feature extraction algorithm estimates the quality (called them good features) of image features during tracking by using a measure of feature dissimilarity function that quantifies the change of appearance of features between the consecutive frames. They indicated that a good feature extraction algorithm should take the motion of points in consecutive frames into account to find the best features to track. So they modeled the motion of points, indicated as $p = [p_x \quad p_y]$ where p_x and p_y are the pixel-wise locations of the point is the horizontal and vertical directions respectively, as both pure translational and affine transformed motion. They showed in both cases the best corners/features were located where the gradient matrices, as shown in Equation 1, calculated around the pixels have two large eigenvalues. A matrix of gradients, g_{px} , g_{py} , at each point $p = [p_x \quad p_y]$ was generated by using the image derivatives in the x and y directions , as shown in Equation 2.

$$\boldsymbol{Z} = \begin{bmatrix} \boldsymbol{g_{p_x}^2} & \boldsymbol{g_{p_x} g_{p_y}} \\ \boldsymbol{g_{p_x} g_{p_y}} & \boldsymbol{g_{p_y}^2} \end{bmatrix} \quad \textbf{(1)}$$

The eigenvalues of the Z matrix were calculated for each point and these points were ranked in descending order according to their eigenvalues. Then, a certain number of top points that were greater than a given minimum threshold were selected as “good features to track”. The OpenCV cvGoodFeaturesToTrack() funtion implements the Shi and Tomasi [113] approach and is used to find the good features.

Optical Flow Detection

Bouguet’s [115] Pyramidal Implementation of the Lucas Kanade Feature Tracker was indicated to be one of the best ego-motion estimation algorithms in Yao et.al.’s paper

[114]. This approach was used to match good corner features, which were found in the feature extraction section, between adjacent pairs of video frames to obtain a sparse estimate of the optical flow field.

Let I_t be a 2D grayscale image and I_{t+dt} represents a consecutive image that comes afterI_t. Let a point $p = [p_x \quad p_y]$ in these frames have grayscale values of $I_t\,(p)$ and $I_{t+dt}(p)$. The vector $d = [d_{px} \quad d_{py}]$ is the image velocity at p, also known as the optical flow at p. The goal of this feature tracking is to find the location of $p + d$ in the image $I_{t+\Delta t}$ such as $I_t(p)$ and $I_{t+\Delta t}(p + d)$have some "similarity". Let w_x and w_y be two integers indicating the window sizes or image neighborhood sizes. The definition of velocity flow, d that minimizes the residual function shown in Equation 2 [115].

$$\boldsymbol{\varepsilon(d)} = \sum_{x=p_x-w_x}^{p_x+w_x} \sum_{y=p_y-w_y}^{p_y+w_y} \left(\boldsymbol{I_t(x,y)} - \boldsymbol{I_{t+\Delta t}}\left(\boldsymbol{x} + \boldsymbol{d_x}, \boldsymbol{y} + \boldsymbol{d_y}\right)\right)^2. \quad \textbf{(2)}$$

For each corner feature found in the subsection feature extraction, Equation 2 was solved for a sub-pixel translational displacement vector that minimized the sum of squared intensity differences between an image patch centered at the corner and a patch in the subsequent frame centered at the estimated translated position.

Affine Transformation Estimation

Ego-motion was found by fitting a global six parameter affine motion model to sparse optic flow vectors found in subsection Optical Flow Detection. Affine transformation, which preserves collinearity (maps parallel lines to parallel lines) and ratios of distances, is a parametric and geometric transformation. Affine transformations can be constructed by any combination of translations, scales, flips and sequences of rotations.

Six-parameter affine transformation model is given in Equation 3.

$$\begin{pmatrix} p_x^{\boldsymbol{t+\Delta t}} \\ p_y^{\boldsymbol{t+\Delta t}} \end{pmatrix} = \begin{bmatrix} a_{11}^t & a_{12}^t \\ a_{21}^t & a_{22}^t \end{bmatrix} \begin{pmatrix} p_x^{\boldsymbol{t}} \\ p_y^{\boldsymbol{t}} \end{pmatrix} + \begin{pmatrix} b_1^t \\ b_2^t \end{pmatrix} \qquad (3)$$

where $p_x^{\boldsymbol{t+\Delta t}}$ and $p_y^{\boldsymbol{t+\Delta t}}$ are the corner features in frame $\boldsymbol{I_{t+\Delta t}}$, $p_x^{\boldsymbol{t}}$ and $p_y^{\boldsymbol{t}}$ are the corner features in frame $\boldsymbol{I_t}$ from the optical flow calculations,$\{a_{11}^t\ a_{12}^t\ a_{21}^t\ a_{22}^t\ b_1^t\ b_2^t\}$ are the affine transform parameters, which are account for the deformations and translations. The $\{a_{11}^t\ a_{12}^t\ a_{21}^t\ a_{22}^t\ \}$parameters account for the deformations while the $\{b_1^t\ \ b_2^t\}$ parameters are account for the translations. This over-determined system was solved using the pseudo-inverse, which used SVD methods to find the least-squares solution for these affine parameters.

Estimating the Position of the Fixation Point

The fixation point,$f^{\boldsymbol{t}} = \{\, x^{\boldsymbol{t}} \,, y^{\boldsymbol{t}} \,\}$, of the BHR was assumed to be at center of the image, when BHR started moving, $f^{\boldsymbol{0}} = \{\, 0 \,, 0 \,\}$. The location of the fixation point changed due to the movement of arms in each time step and the location of the fixation point was updated by the affine transformation as show in Equation 4.

$$\begin{pmatrix} x^{\boldsymbol{t+\Delta t}} \\ y^{\boldsymbol{t+\Delta t}} \end{pmatrix} = \begin{bmatrix} a_{11}^t & a_{12}^t \\ a_{21}^t & a_{22}^t \end{bmatrix} \begin{pmatrix} x^{\boldsymbol{t}} \\ y^{\boldsymbol{t}} \end{pmatrix} + \begin{pmatrix} b_1^t \\ b_2^t \end{pmatrix} \qquad (4)$$

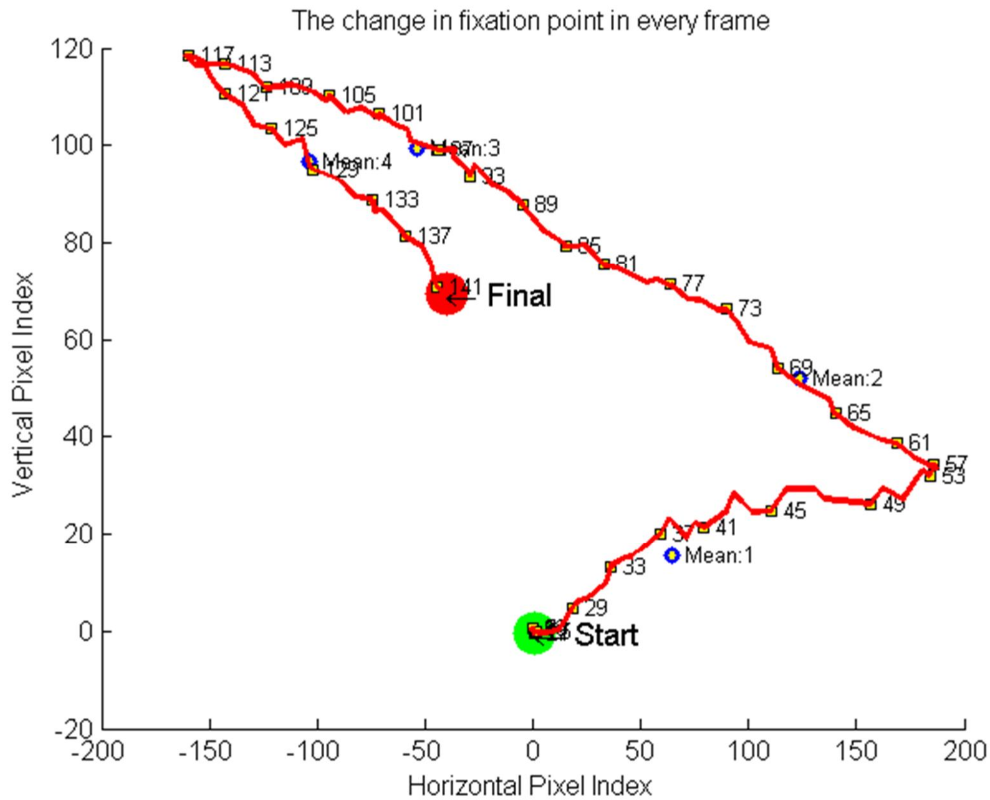


Figure 14 The change in fixation point during the motor babbling stage. Numbers on the red line indicates the frame number.

Self-Organizing Maps

In this stage, Self-Organizing Maps [1] were used to extract the affordance relations between its crawling motion and its motor actions. The SOM is an unsupervised algorithm which forms a nonlinear regression of the ordered set of reference vectors into the input space, and is a special tool which can be used at the same time both to reduce the amount of data by clustering, and for projecting the data nonlinearly onto a lower-dimensional display [1]. This combination of vector quantization and dimension reduction allows the SOM to visualize large bodies of high-dimensional data and help researchers to create a model like affordance learning from imitation learning.

The self-organizing map is an unsupervised neural network that projects a high dimensional input space onto a group of neurons organized on a regular low-dimensional grid. Each neuron in this grid has a d dimensional weight vector, w_d, which gets updated such that neighboring neurons on this grid get similar weight vectors during training. In this way, these neurons learn to recognize groups of similar input vectors and respond to similar input vectors. Samples (one row at a time, as shown in Equation 5) from the samples data, $\mathbb{X}$, are presented to the map one at a time as input vectors, and the algorithm gradually moves the weight vectors towards them, as shown in Figure 15 using the Equation 6.

$$\mathbb{X}(nT,:) = \{q_1^N(nT), \ldots, q_m^N(nT), x^N(nT), y^N(nT)\} \quad (5)$$

$$W_{ij}(nT+1) = W_{ij}(nT) + \alpha\left(\mathbb{X}(nT,:) - W_{ij}(nT)\right) \quad (6)$$

where $W_{ij}(nT+1)$ is the updated weight vector, i and j are the neuron indices in the spatial neighborhood of the winning neuron and α is the learning coefficient. In this way, neurons, the weight vectors of which are closest to the input vector, are updated to be even closer. Next time, the winning neuron is more likely to win the competition when a similar vector is presented, and less likely to win when a very different input vector is presented. As more and more samples/input vectors from $\mathbb{X}$ are presented, each neuron in the layer closest to a group of input vectors soon adjusts its weight vector toward those input vectors.

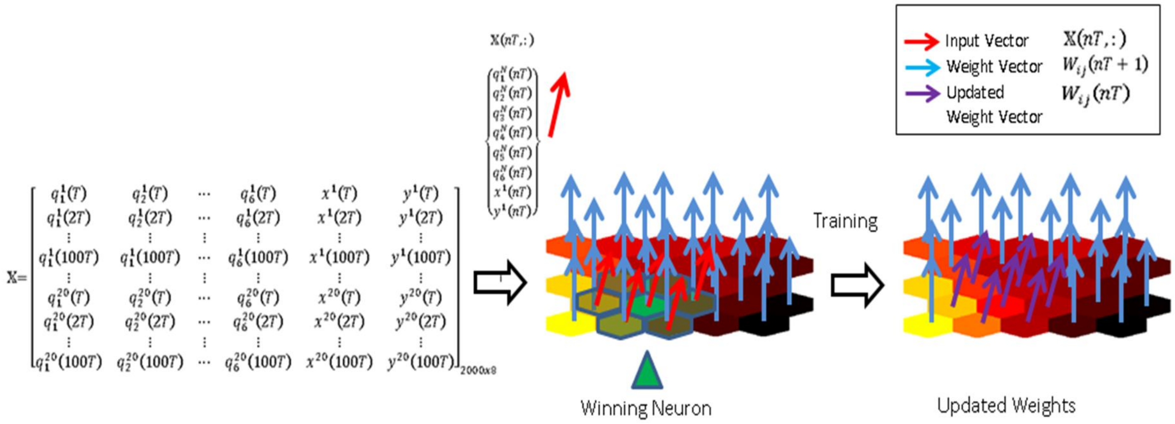


Figure 15. A 5x5 SOM training illustration.

Since SOM is an unsupervised learning method and does not have target vectors, the target vectors, the pixel-wise location of the fixation points $\{x^N(nT), y^N(nT)\}$, were included in the input vector to force SOM to divide the input vectors into clusters that give some information about the correlation between the arm motors of BHR. The results are discussed in the Conclusion section in detail.

Learning Vector Quantization

A Learning Vector Quantization (LVQ) network has a first competitive layer, which learns to classify input vectors in the same way as the competitive layers of SOM, and a second linear layer, which transforms the competitive layer's classes into target classifications given by the user.

The second layer of the LVQ network compares the output of the competitive layer output with the given target vector and updates the weight function as shown in Figure 16 and Equation 7.

$$\begin{aligned} W_{ij}(nT+1) &= W_{ij}(nT) + \alpha\left(\mathbb{X}(nT,:) - W_{ij}(nT)\right)\ \mathit{if\ the\ output} = \mathit{target\ class} \\ W_{ij}(nT+1) &= W_{ij}(nT) - \alpha\left(\mathbb{X}(nT,:) - W_{ij}(nT)\right)\ \mathit{if\ the\ output} \neq \mathit{target\ class} \end{aligned} \tag{7}$$

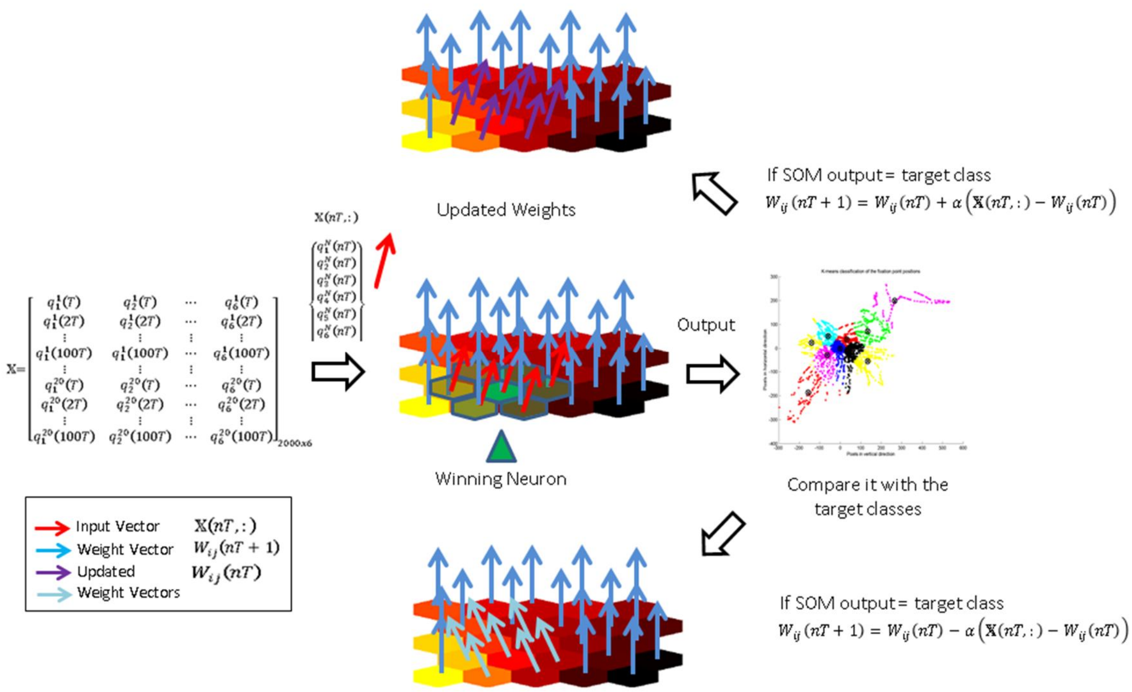


Figure 16 LVQ training illustration.

K-Means Clustering and Validation of Clusters of Data

The target vector was prepared for the LVQ network by using a k-means clustering. k-means clustering divided the fixation points,$\{x^N(nT), y^N(nT)\}$ found by the egomotion calculations, into k number of clusters in which each fixation point belonged to the cluster with the nearest mean. The number of clusters is an important parameter and wrong choice of this number may yield poor results so this number is chosen after running silhouette validation method. It is known that good clusters have the property that cluster members are close/similarity to each member and far from/dissimilarity to the members of the other clusters. Silhouette is the relation between a member's dissimilarity to its own cluster and the dissimilarity with its neighboring cluster. The ratio between the average distances to the members in its own to the distance of the closest member in the neighbor cluster gives the silhouette value of this member, as shown in Equation 8. The silhouette score is the average of these silhouette values for entire cluster members, as shown in Equation 10.

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \qquad (8)$$

$$S = \frac{\sum_{i=1}^{n} s(i)}{n} \qquad (9)$$

where $a(i)$ is the average dissimilarity of i^{th} member to all other members in the same cluster and $b(i)$ is the minimum of average dissimilarity of i^{th} member to all members in the neighbor cluster, which is the closest cluster to the member and , n is the number of members in the cluster.

Intuitively, if silhouette value is close to 1, it means that member in the cluster is appropriately clustered. If silhouette value is about zero, it means that this member can be assigned to other group and equally far away from both clusters. If silhouette value is close to –1, it means that it would be more appropriate if the member was clustered in its neighboring cluster.

To find the best number of clusters, the data is clustered into different number of clusters using k-means algorithm and the largest overall average silhouette score indicates the best clustering number. Consequently, the number of cluster with maximum overall average silhouette score is taken as the optimal number of the clusters.

Design Problem

Let $\{M_i\}_{i=1}^{m}$ be m even number actuators of a robot. Assume M_1 and M_2 are sub groups of $\{M_i\}_{i=1}^{m}$ which has the same number, $m/2$ of independently controllable motors. Let $\{\, x^N(nT), y^N(nT)\}$ be the absolute change of the fixation point in image plane after n random actuation signals for N, number of babbling trials, at time $n\mathsf{T}$ are applied for each motor. Let $\{C_i\}_{i=1}^{k}$ is the target classes used for the LVQ network where the number of clusters k is found after clustering the fixation points using k- means and silhouette validation method. Let $\mathbb{X} = \{q_1^N, \dots q_m^N\}$ is the *N-by-m* input matrix which has N angular position samples of m actuators. Use target classes and input matrix to train an LVQ network and find the *m-by-m* autocorrelation matrix, $A_{i,j}$ of weight vector. Find the column number of the highest correlation value in the ith row. Group these indices and show that the highly correlated indices are physically connected actuators and construct the M_1 and M_2 subgroups.

VI. STAGE 2: IMPROVING LEARNED LIMB AFFORDANCES THROUGH SELF-EXPLORATION

Motor Skill Learning in Human Infants and in BHR

Self-exploration promotes cross-modal calibration which is necessary for the emergence of complex action forms. However in order to be able to interpret the relationships between actions, objects, and their effects in the environment infants need to discover their own bodies, and their motor capacities, which is mainly based on self-exploration of action-effect relations, where they actively get involved in random acts repeatedly and observe the accompanying changes in the perceptual world, so they start forming associations between their action commands and accompanying perceptual effects. Infants routinely improve their performance by revisiting their experiences, taking them apart and putting them back together in alternative ways, to explore changes in behavior that are likely to make performance better or worse. Imitation ability is built upon the ability to form perceptual-motor contingencies, and self-awareness of one's own body's limitations and biomechanical constraints.

Like infants, the Bioloid robot is not pre-programmed with knowledge of its own motor limits and the motor skill of lifting/pushing/pulling objects. Thereby the robot needs to go through a great deal of self-experience which involves a trial by trial method with possible erroneous attempts. Thus, the robot needs to go through a set of self-exploration stages in which it learns limb affordance and action-effect relations. In this second stage similar to a young infant who moves his/her arms systematically in an aim to explore the resultant perceptual effects (i.e. visual feedback from the arm in space); BHR moves its arms repeatedly and explores the kinds of changes in its own visual perspective, which are then linked back to the particular motor unit codes the robot assigned Figure 17.

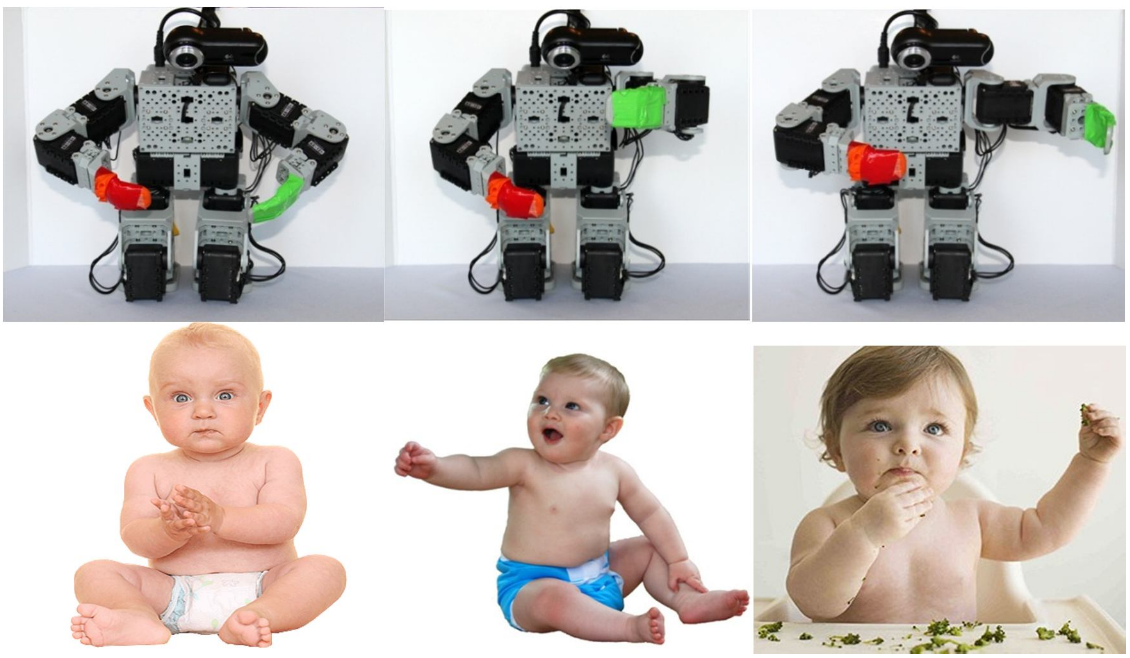


Figure 17. Developmental and Computational Similarities in Stage 2. The Bioloid Robot goes through a set of self-exploration stages using its arms, similar to an infant.

Methods

This stage is comprised of accomplishing two tasks: learning the biomechanical limits, and learning the motor skill through repeated trials. In this stage by randomly assigning angles to the arm motor units the robot will act in a certain way Figure 18, and then explore the resultant action effects: the final position of the hands in robot's visual perspective. Each motor unit has a torque power, so the torque sensors notify the robot when there is high pressure thereby classifying the action as mechanically impossible. Using a neural network, the robot learns the biomechanically possible work space, and explores its biomechanical limits. Also, through repeated assignment of joint angles, and by observing the resultant hand location in the visual space, the robot learns to associate particular arm movements with particular coordinates of the hands. The robot tracks the hands with its camera as it performs. In this stage the robot will learn which muscles to contract (which joint angles to assign) so as to bring about desired action effects: desired Cartesian coordinates of the hands in the visual workspace.

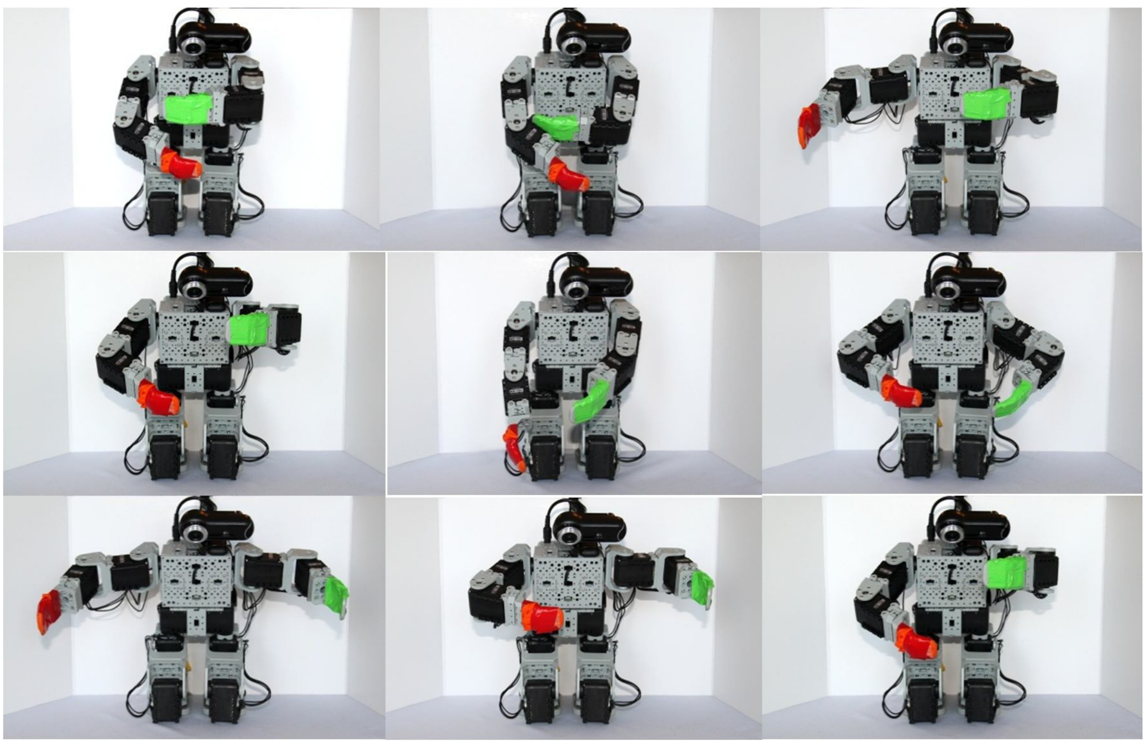


Figure 18. Experimental Set-Up for Stage 2. By randomly assigning angles to the arm motor units the robot will explore the associations between its actions, and the resultant action effects: the final position of the hands in robot's visual perspective.

Assumptions

- The robot learned its limits by watching the torques at its servo motors during babbling and if the torque values came to a maximum point it could record these points and limit the babbling between these maximum points. Applying the white noise of approach is not recommended, because this method can damage the robot while it tries to discover its limits. The robot worked and improved its skills only in these limits.
- In the babbling stage, we let the robot babble using smooth approximately random prerecorded actions instead of white noise to learn the skill workspace. Giving a white noise sequence and watching the outcomes of the motors may damage the coils of the motors, so these kinds of babbling sequences are avoided by forcing the robot to track prerecorded sequences and execute them.

The Artificial Neural Networks

Artificial Neural Networks (ANNs) are inspired from the structure and functions of biological neural networks. They are typically designed to perform high dimensional nonlinear mapping from a set of inputs to a set of outputs. ANNs are developed to model complex relationships between inputs and outputs or to find patterns in data using a dense interconnection of simple processing elements analogous to biological neurons. ANNs learn from experience and generalize a model from previous examples. They modify their behavior and structural variables in response to the environment, and are ideal in cases where the required mapping algorithm is not known and tolerance to faulty input or inconsistent information is required [116]. ANNs contain electronic processing elements

(PEs) connected in a particular fashion. The behavior of the trained ANN depends on the weights, which are also referred to as strengths of the connections between the PEs.

ANNs offer certain advantages over conventional electronic processing techniques. These advantages are the generalization capability, parallelism, distributed memory, redundancy, and learning [116].

The Backpropagation Neural Network

Backpropagation is a common method of training multilayer interconnected artificial neural networks so as to minimize the cost using gradient descent method. The layered structure of the backpropagation network deals with the linear separability limitation making it a much more powerful tool for nonlinear complex systems. The backpropagation neural network is not limited to only to binary outputs; but also it can create any number of outputs whose values fall within a continuous range. The backpropagation neural network is ideal for problems involving classification, projection, interpretation, and generalization, finding complex relationships between inputs and outputs [117]. A simple backpropagation neural network contains three layers, input, output and middle layers. Figure 19 shows a sample backpropagation neural network with middle layer, n input layer nodes and m output layer nodes. Backpropagation neural network training involves three stages

- Feedforward of the input training pattern,
- Calculation and backpropagation of the associated error,
- Adjustment of the weights.

In the application of the network involves only the computations of the feedforward phase after training with new weights. The training process is slow; however the trained network can produce its output very rapidly [118]. A sample training algorithm of the backpropagation is [117] [118]:

Step 0. Initialize weights.

Step 1. Until all examples classified correctly or stopping criterion satisfied do Steps 2-9.

Step 2. For each training pair, do Steps 3-8.

Step 3. Each input unit $\{X_i\}_{i=1}^{n}$ broadcasts this signal to all units in the hidden layer.

Step 4. Each hidden unit $\{Z_j\}_{j=1}^{p}$ accumulates its weighted input signals, and applies activation function to create the output. Later it broadcasts this output to other layers and if there is only one hidden layer, it sends the output directly to the output layer of the neural network.

$$z_j = f\left(v_{oj} + \sum_{i=1}^{n} x_i v_{ij}\right) \qquad (10)$$

Step 5. Each output unit $\{Y_k\}_{k=1}^{m}$ accumulates its weighted input signals, and applies activation function to compute the output.

$$y_k = f\left(w_{ok} + \sum_{k=1}^{m} z_i w_{jk}\right) \qquad (11)$$

Step 6. Each output unit $\{Y_k\}_{k=1}^{m}$ receives a target pattern corresponding to the input training pattern, computes its error information term,

$$\delta_k = (t_h - y_k)\dot{f}\left(w_{ok} + \sum_{k=1}^{m} z_\iota w_{jk}\right) \qquad (12)$$

The weight correction term

$$\Delta w_{jk} = \sigma \delta_k z_j \qquad (13)$$

where σ is the learning rate.

Step 7. Each hidden unit $\{Z_j\}_{j=1}^{p}$ sums its delta inputs from units in the layer

$$\delta_j = \sum_{k=1}^{m} \sigma_k w_{jk} \,.\, \dot{f}\left(v_{oj} + \sum_{\iota=1}^{n} x_\iota v_{\iota j}\right) \qquad (14)$$

The weight correction term is,

$$\Delta v_{ij} = \sigma \delta_k x_i \qquad (15)$$

Step 8. Each output unit $\{Y_k\}_{k=1}^{m}$ updates its bias and weights,

$$w_{jk}^{new} = w_{jk}^{old} + \Delta w_{jk} \qquad (16)$$

Each hidden unit $\{Z_j\}_{j=1}^{p}$ updates its bias and weights,

$$v_{ij}^{new} = v_{ij}^{old} + \Delta v_{ij} \qquad (17)$$

Step 9. Test stopping condition [117] [118]

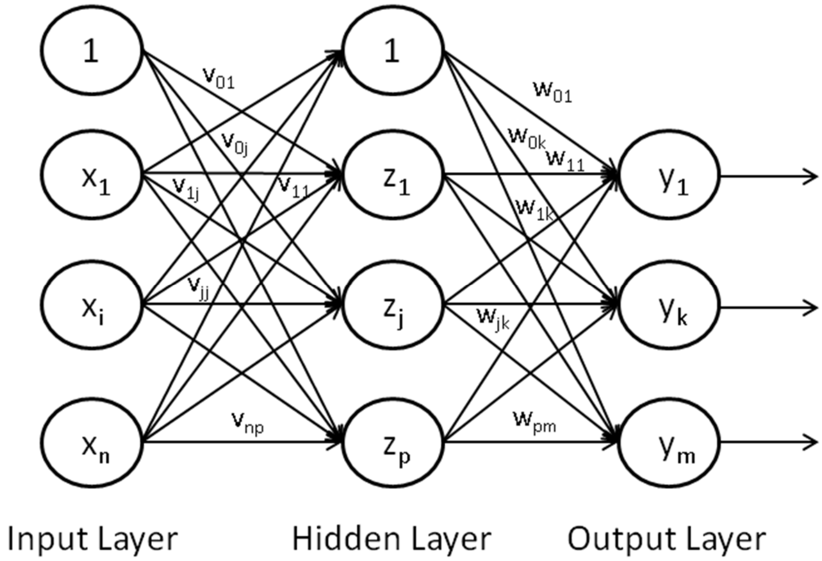


Figure 19 Backpropagation Neural network structure with one hidden layer [118].

The PONNET

To construct the position control neural network (PONNET) based on the relation between the joint angles and the pixel-wise position and the size of the markers which are attached on the arms of the robot, a three layer backpropagation neural network with a simple structure with an input layer, a hidden layer and an output layer is used. The back-propagation neural network with the generalized delta rule is employed as the learning mechanism. The main motivation of using PONNET in learning limb affordances is its capability of learning and mapping the joint position-marker size and position, which is nonlinear and involves inconsistency.

Like infants, BHR needs to go through a great deal of self-experience which involves a trial by trial method with possible erroneous and inconsistent data. Thus, the robot needs to go through a set of self-exploration stages in which it learns limb affordance and action-effect relations. In this second experiment and as shown in Figure 20, similar to a young infant who moves his/her arms systematically in an aim to explore the resultant perceptual effects (i.e. visual feedback from the arm in space); BHR moves its arms repeatedly and explores the change in the markers positions and the size in its own visual perspective, which are linked to the particular joint positions.

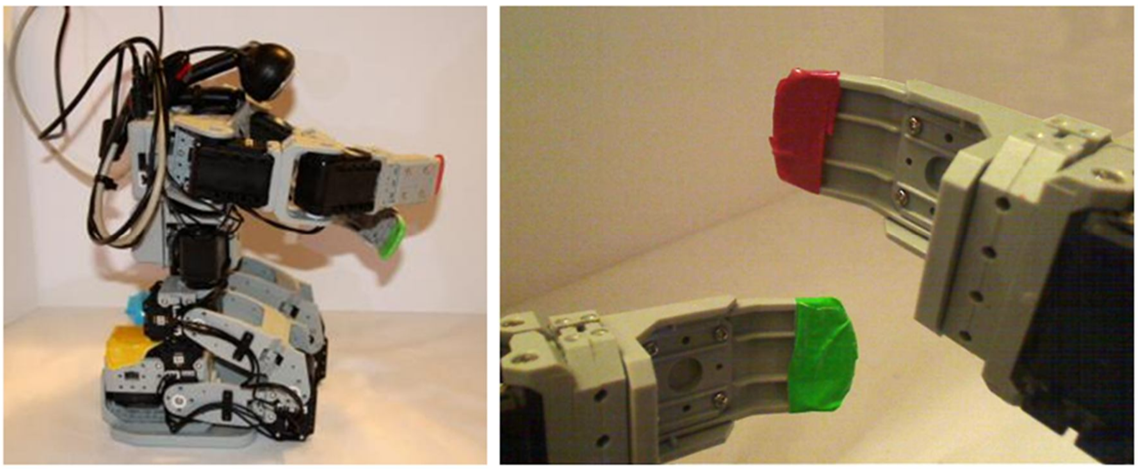


Figure 20 BHR moves his arms systematically and explores the resultant perceptual effects

Design Problem

Let $\{M_i\}_{i=1}^{m}$ be m even number actuators of a robot. Assume M_1 and M_2 are sub groups of $\{M_i\}_{i=1}^{m}$ which has the same number, $m/2$ of independently controllable motors and these are known from the experiment 1. Let $\{x_{red}(nT) \quad y_{red}(nT) \quad s_{red}(nT)\}$ be the pixel-wise positions (horizontal and vertical) and size of the red marker and $\{x_{green}(nT) \quad y_{green}(nT) \quad s_{green}(nT)\}$ be the pixel-wise positions (horizontal and vertical) and size of the blue marker, in image plane found at the nth step of the prerecorded actuation. Let $\mathbb{X} = \{q_1(nT) \ldots q_m(nT)\}$ is the *N-by-m* input matrix which has N angular position samples of m actuators. Use and train multilayer backpropagation neural network to create the mapping between the marker features and the angular position samples of m actuators.

VII. STAGE 3: IMITATION LEARNING FROM MOTION CAPTURE

Imitation Learning in Human Beings & in BHR

An Infant's ability to form action-effect relations further develops into the ability to transfer an observed action onto one's own motor system. Infants go through active self-explanatory stages where they form contingencies between self-performed actions and their resultant sensory effects, and then this leads to advanced imitation abilities where they can translate observed action-effect relations into their own perceptual-motor systems.

Similarly, the self-exploratory stages described in the previous stages, which focus on discovery of motor capacities, biomechanical constraints, limb affordances and skill learning set the stage for a much more advanced action reproduction mechanism in our robot, which resembles the mechanism of imitation observed in human beings. In this stage, the robot performs the goal task, which is to imitate a novel object-oriented action by observing a human being through motion capture. In this final stage the robot builds upon its skill on limb affordance relations, and action-effect associations, and by bringing the perceptual-motor system a step further now it can imitate a novel action Figure 21.

Figure 21. Developmental and Computational Similarities in Stage 3. The Bioloid Robot trying to imitate a novel object-oriented action, similar to an infant.

Methods

In this final stage the robot imitates a novel object-oriented action after having analyzed the motion capture data of a human being performing lift/push/pull actions oriented towards certain objects in a motion capture suit Figure 22. The robot analyzes the motion capture data; identify the markers using the sequence of the markers. By analyzing the data the robot identifies the affine transformation and so the Cartesian coordinates of the final position of the hands from the visual perspective of the actor. Then the robot correlates what it learned from the first two stages (self-exploration) and finds the relevant joint positions from PONNET to bring its own arms to the corresponding target spatial location within its own visual perspective. In other words, the robot identifies corresponding movement sequences in its own motor system that is suited for the spatio-visual effect being observed. The robot takes the perspective of the human actor and discovers the relevant joint angle combinations that would result in corresponding visual effects (particular spatial location of the robot arms) in its own visual perspective through affine transformations. This phase requires a direct mapping of the perceived sensory effects to the robot's own action system so it can choose the right joint angle combinations so as to bring about the perceived effect. The complete set of actions that the robot will need to perform can be seen in Figure 23.

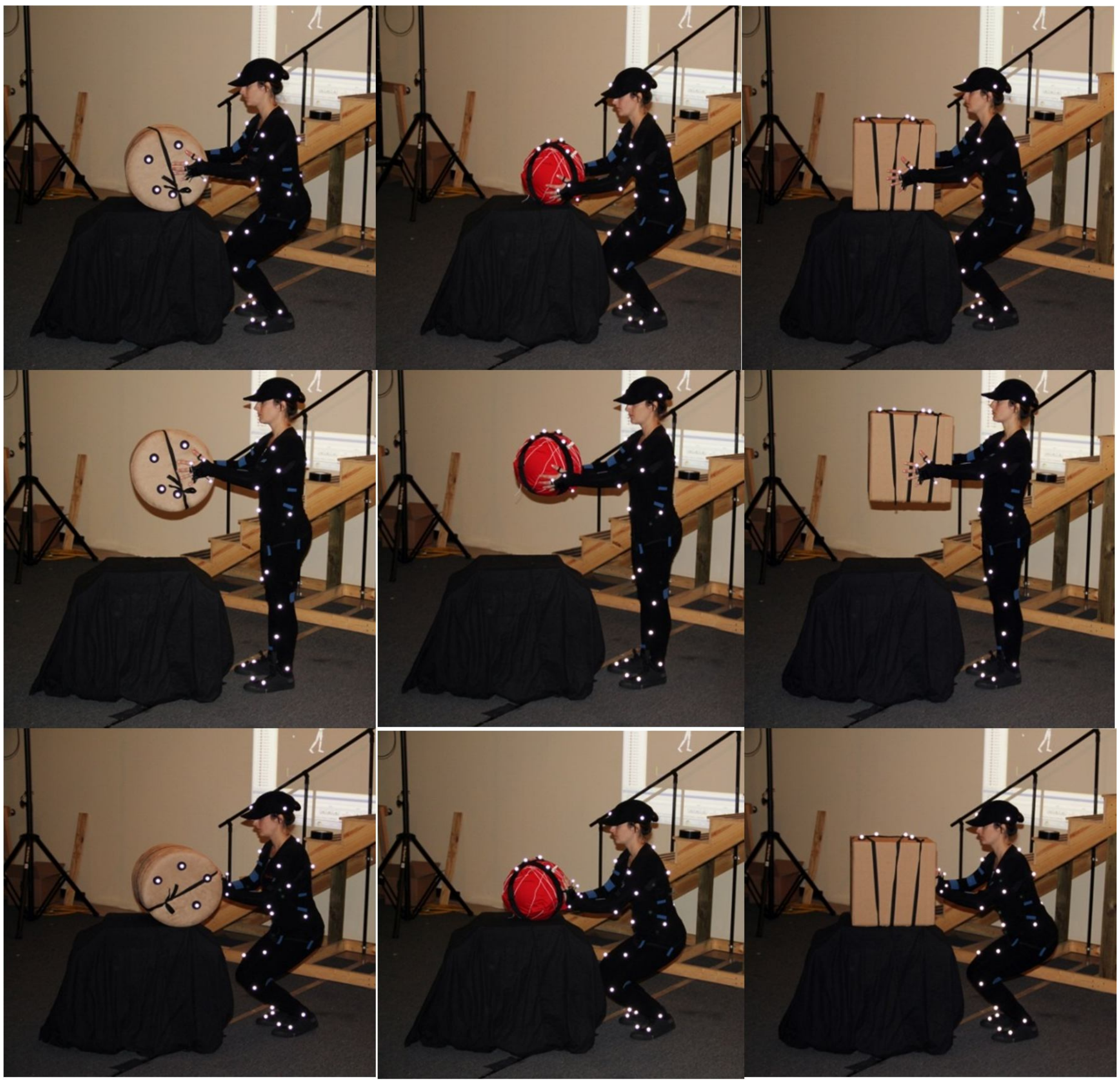


Figure 22. To-be-Imitated Actions Performed by a Human Actor and Recorded via Motion Capture System.

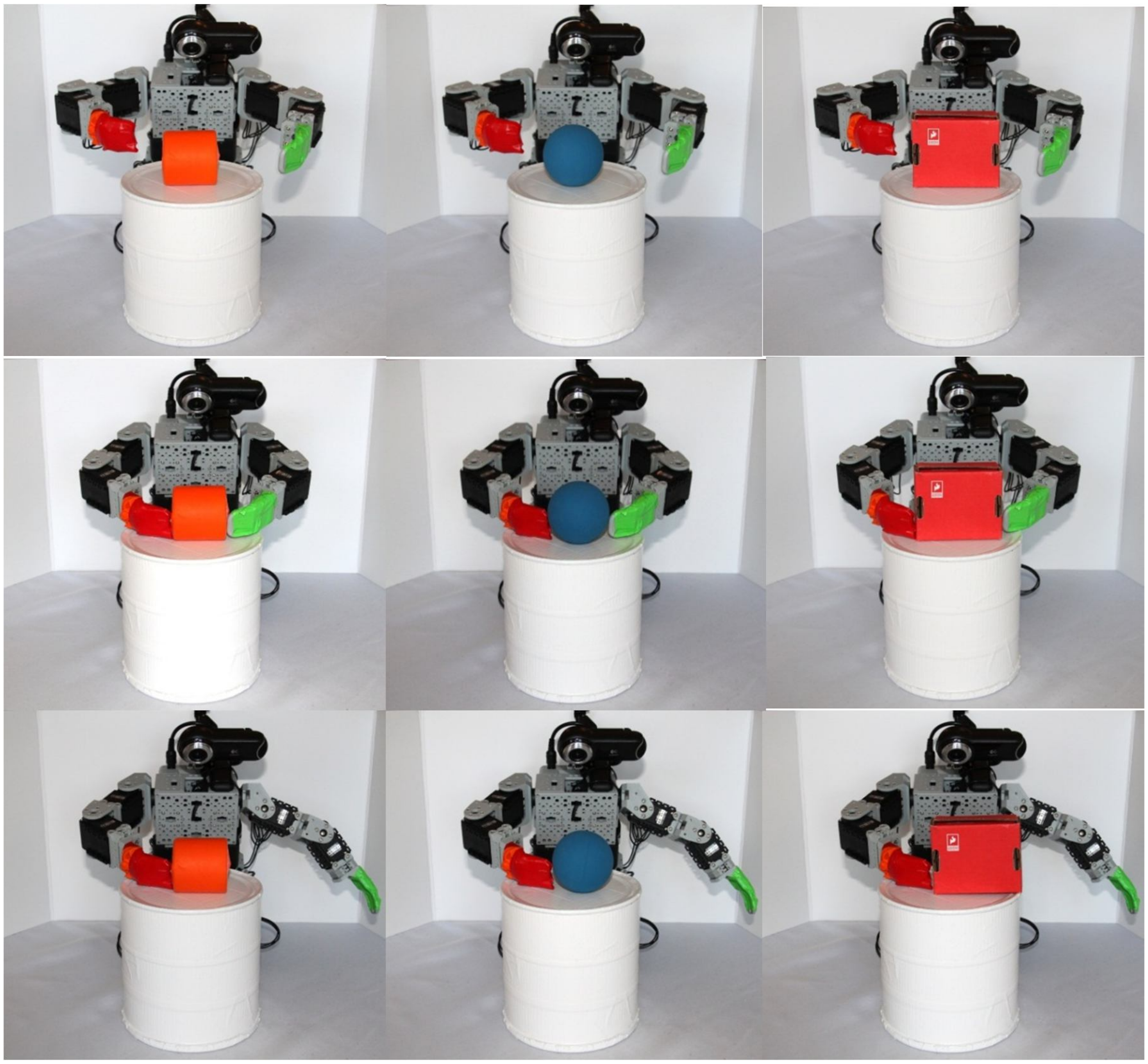


Figure 23. The Experimental Set-Up for Stage 3. Having gone through set of self-exploratory stages, now the robot imitates novel object-oriented actions, which are performed by a human being and recorded via motion capture.

The Motion Capture System

The recordings for the human actor performing lift/push/pull actions were made at The Center for Intelligent Mechatronics, Vanderbilt University, which is comprised of 800 square foot motion capture laboratory, shown in Figure 24. The lab is used for subject preparation, warm-up, motion recording, data processing, and data analysis. The system is equipped with a 12-camera Optitrack optical motion capture system tracking at a frame rate of 250 fps with real-time capability. The lab also holds a treadmill, biomechanical experimentation stairs with hand rails, a high speed video camera (Sony), and two single axis Vernier analog force plates. Moreover, a full safety harness system is installed with adjustable attachment points and a re-configurable unistrut rail for support during gait. A PC computer runs the data collection and analysis software and is linked to a password protected remote server for data storage. Skeletal models can be fit to the actors using NaturalPoint's ARENA software environment, along with the custom definition of rigid body models. Tracked motion can be exported in a number of standard formats including C3D, which stores 3D coordinate information of the markers, and BVH which provides skeleton hierarchy information in addition to the 3-D motion data.

For the purposes of our study, the actor was equipped with 21 reflective markers, the locations of which were tracked during data recording. And then a highly accurate 3-dimentional representation of the performed action was formed. The data was exported to BVH file formats, Biovision hierarchical data, which is the standard optical marker-based file format that includes skeletal data in addition to the markers. The anterior view of the location of these 21 joints/markers in a sample exported BVH file is depicted in Figure 27.

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Figure 24 The Motion Capture System

Affine Transformation Estimation

Affine transformation, which preserves collinearity (maps parallel lines to parallel lines) and ratios of distances, is a parametric and geometric transformation. Affine transformations can be constructed by any combination of translations, scales, flips and sequences of rotations.

Six-parameter affine transformation model is given in Equation 18.

$$\begin{pmatrix} p_x^{\boldsymbol{robot}} \\ p_y^{\boldsymbol{robot}} \end{pmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{pmatrix} p_x^{\boldsymbol{human}} \\ p_y^{\boldsymbol{human}} \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \qquad (18)$$

where $p_x^{\boldsymbol{robot}}$ and $p_y^{\boldsymbol{robot}}$ are the eight limit point features found in experiment 2 and $p_x^{\boldsymbol{human}}$ and $p_y^{\boldsymbol{human}}$ are the eight limit point features from the motion capture data, $\{a_{11} \quad a_{12} \quad a_{21} \quad a_{22} \quad b_1 \quad b_2\}$ are the affine transform parameters, which are account for the deformations and translations. The $\{a_{11} \quad a_{12} \quad a_{21} \quad a_{22}\}$ parameters account for the deformations while the $\{b_1 \quad b_2\}$ parameters are account for the translations. This over-determined system was solved using the pseudo-inverse, which used SVD methods to find the least-squares solution for these affine parameters.

Motion Capture Data, Affine Transformation and PONNET

In order to transform the motion from the recorded motion capture data to the BHR, first the recorded data is transformed into BHR perspective and then feed into PONNET. PONNET gives the joint positions at each time step and the controller actuates to the motors, which brings the joints to the desired position.

Dynamic Time Warping

Dynamic Time Warping (DTW) is a distance measurement technique that creates a non-linear mapping of one time sequence to another by minimizing the distance between the two and maintaining the important features [119]. This technique is very similar to how humans compare curves by finding the most important features of curves such as sudden turns, starting points and end points and comparing these features in two sequences. In recent years, it has been accepted as an important tool for clustering [120], bioinformatics [121], indexing time series [122] and classification [119].

Despite the time complexity of DTW, DTW is superior to other distance measurement techniques such as the Euclidean distance metric, Minkowski distance, Chebyshev distance and Manhattan distance which have been widely used, despite their known weakness of sensitivity to distortion in time axis [119] [123] .

The matching path between two sequences is the most important part of the comparison of two sequences. The matching techniques determine which points match and are to be used to calculate the distance between the two sequences. The graphical comparison of two matching techniques, one-to-one and DTW is shown in Figure 25. The DTW technique is able to compare two sequences by matching the important features such as sudden turns, starting points and end points in two sequences [7].

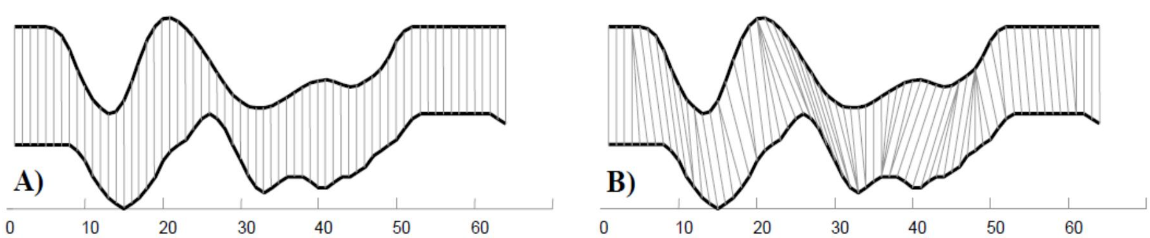

Figure 25. Comparison of two sequences a) one-to-one, b) DTW [124].

The Dynamic Time Warping Algorithm

Suppose that we have two sequences, H (sequence from the motion capture data) and R (sequence from the execution of behaviors of BHR).

$$H = h_1, h_2 \dots h_i \dots h_n$$
$$R = r_1, r_2 \dots r_j \dots r_m \qquad (19)$$

The n-by-m distance matrix contains the norm-2 Euclidean distances $d(h_i, r_j)$ between the two points h_i and r_j. Each matrix element (i, j) corresponds to the distance between the points h_i and r_j. A warping path W, is an adjacent set of matrix elements that defines a mapping between H and R, and the k^{th} element is defined as $w_k = (i, j)_k$ as shown in Figure 26 [124].

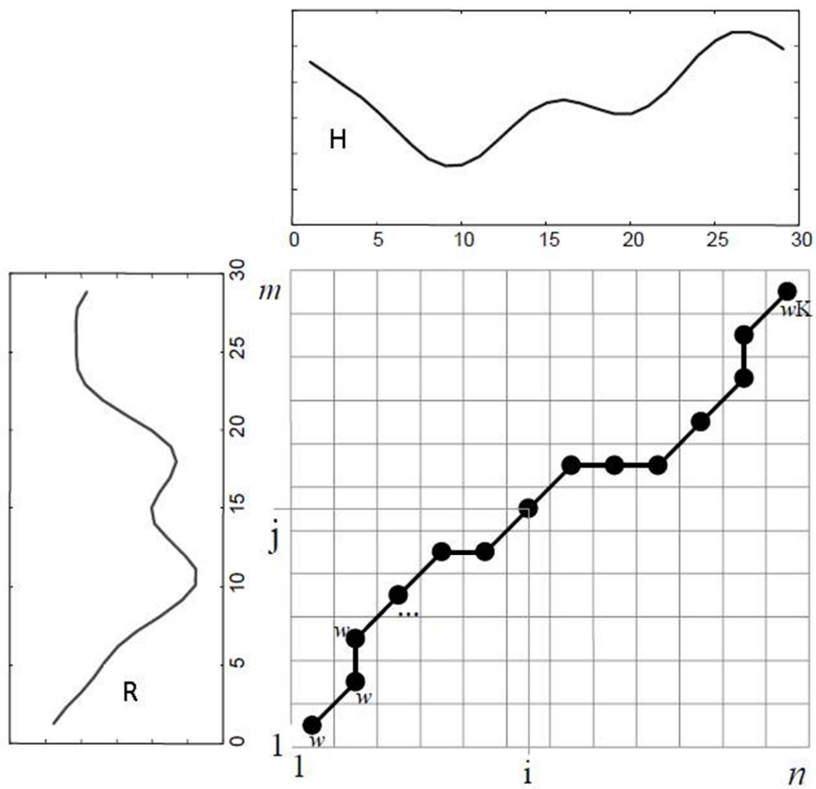

Figure 26. An example warping path [125]

$$W = w_1, w_2 \dots w_k \dots w_K \qquad where\ \max(m, n) \leq K \leq m + n - 1$$

There are three constraints that are applied to DTW.

- The warping path should start and finish in diagonally opposite corner cells, given by $w_1 = (1,1)$ and $w_K = (m, n)$ of the matrix.
- Given the location of the path at w_k then the next location w_{k+1} should be one of the adjacent cells to w_k, which implies continuity.
- The path should be monotonically increasing.

The path that gives the minimum of the cumulative distances of the adjacent elements is found by using a search tree in dynamic programming. This path is used to calculate the DTW of motion capture data sequence and robot motion sequence, as shown in Equation XXX.

$$DTW(H, R) = min\left\{\sqrt{\sum_{k=1}^{K} w_k}\Big/K\right\} \qquad (20)\backslash$$

Design Problem

Let $\{x_{left}^{human}(nT) \quad y_{left}^{human}(nT) \quad s_{human}^{human}(nT)\}$ be the positions (horizontal and vertical) and size of the virtual lefthand and$\{x_{right}^{human}(nT) \quad y_{right}^{human}(nT) \quad s_{right}^{human}(nT)\}$ be the positions (horizontal and vertical) and size of the virtual right hand, at the nth step of the recorded motion capture data. Use found affine transformation to find $\{x_{red}^{robot}(nT) \quad y_{red}^{robot}(nT) \quad s_{red}^{robot}(nT)\} and \{x_{green}^{robot}(nT) \quad y_{green}^{robot}(nT) \quad s_{green}^{robot}(nT)\}$ Use PONNET and use the result of the affine transformation as input to create the sequence of desired joint positions. Examine how efficient the controller moves the joints to these desired references using dynamic time warping method.

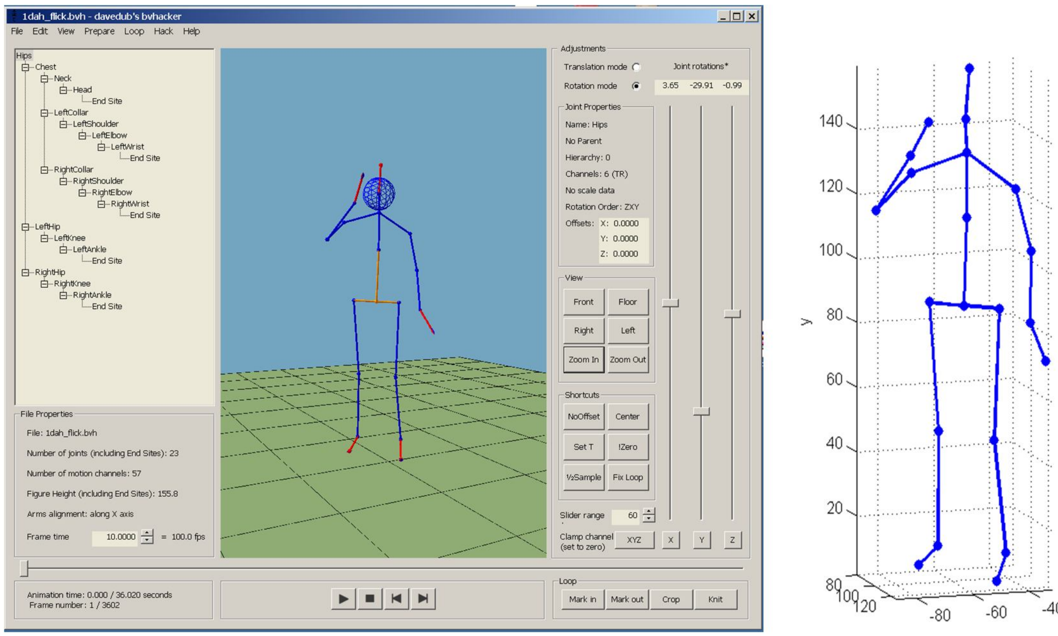

Figure 27. Sample Exported BVH File. The stick figures depict the location of markers/joints.

VIII. EXPERIMENT RESULTS AND CONCLUSION

Results

Supervised learning vector quantization (LVQ), learning vector quantization with silhouette validation (LVQS) and unsupervised learning (SOM) methods were used to find the limb affordances of BHR. The performance of the methods depends on how they correlated the motors with the arms. The number of actuators m is six because only the upper body motors were used. From Figure 8, the subgroups, M_1 and M_2, can be clearly shown that motors 1, 3 and 5 are the actuators of the right arm, M_1 subgroup and motors 2, 4 and 6 are the actuators of the left arm, M_2 subgroup.

In the first babbling stage, random sinusoidal angle references, for 20 babbling trials, the sampling time, T, of *125* milliseconds, 100 for n steps for a full sinusoidal cycle were given to the six actuators of BHR The changes in the position of the fixation point were recorded and created the matrix in Equation 19. This data was used to train SOM, LVQ and LVQs networks. The size of the data,$\mathbb{X}$, collected was 16000 data points = 20 (*N*, total number of babbling trials) x 6 (total number of motors) x 100 (total time steps) + 20 (*N*, total number of trials) x 2 (total number of fixation point directions) x 100 (total time steps). The recorded matrix is shown in Equation 21.

$$X=\begin{bmatrix} q_1^1(T) & q_2^1(T) & \cdots & q_6^1(T) & x^1(T) & y^1(T) \\ q_1^1(2T) & q_2^1(2T) & \cdots & q_6^1(2T) & x^1(2T) & y^1(2T) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ q_1^1(100T) & q_1^1(100T) & \cdots & q_6^1(100T) & x^1(100T) & y^1(100T) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ q_1^{20}(T) & q_2^{20}(T) & \cdots & q_6^{20}(T) & x^{20}(T) & y^{20}(T) \\ q_1^{20}(2T) & q_2^{20}(2T) & \cdots & q_6^{20}(2T) & x^{20}(2T) & y^{20}(2T) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ q_1^{20}(100T) & q_2^{20}(100T) & \cdots & q_6^{20}(100T) & x^{20}(100T) & y^{20}(100T) \end{bmatrix}_{2000x8} \quad (21)$$

SOM networks with 5x5, 7x7, 15x15, 20x20 and 30x30 neurons were created and trained for 100 epochs, an example of the weight matrix is shown in Figure 28. Due to the problem of stacking in local minimum, this process was repeated 50 times with different network initialization and each time the performance of the network was recorded and the results were shown in Figure 28.

It is hard to figure out how SOM weights correlated with the other from Figure 28 so the autocorrelation of weights are given in Table 1.The calculation of the performance depends on the autocorrelation of the weights in the network. In each row, the two number of columns, which have the biggest values (one of them is always 1), show the highest correlation of two motors. If this pair is in one of the subgroups M_1 or M_2, it is assumed that the algorithm succeeds for this row. If all the rows have a pair which belongs to one of these subgroup, the performance criteria is %100 successful. For example, at the first row in Table 1, the column numbers 1 and 5 are the highest correlated pair and belong toM_1 .

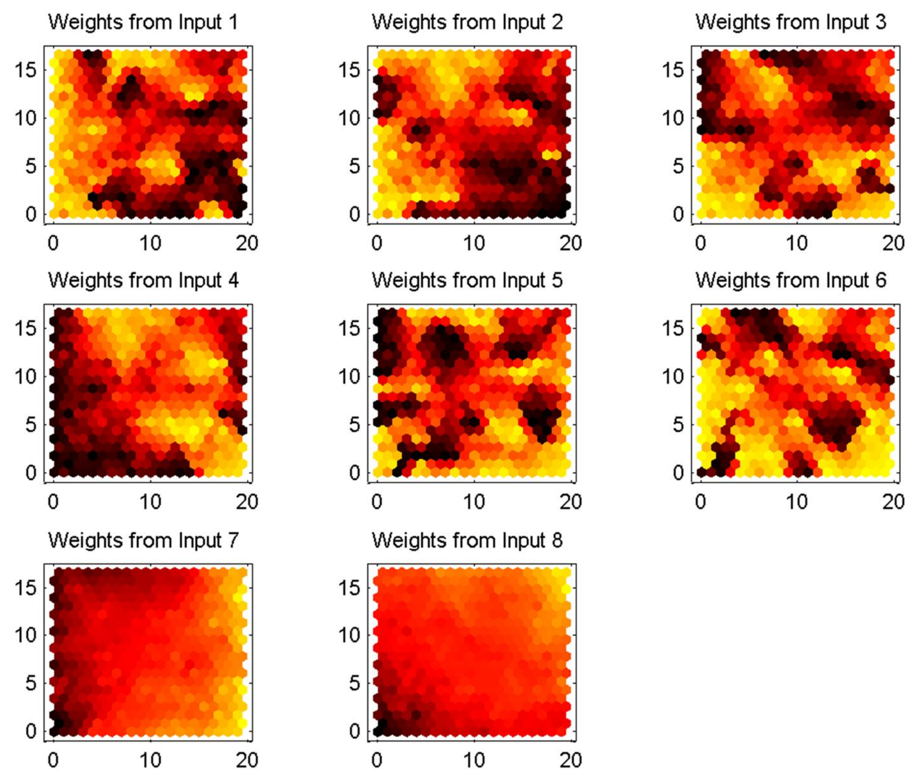

Figure 28. The visualization of the SOM weights after training. Dark colored regions mean that the weight distances are far apart from each other in this region.

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Table 1 Autocorrelation calculations of SOM weight vector

Autocorrelation	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
Weight 1	1	0.2096	-0.2179	-0.0436	-0.0925	0.0376
Weight 2	0.2096	1	0.1432	-0.232	-0.2139	0.0959
Weight 3	-0.2179	0.1432	1	-0.0084	0.2323	-0.0549
Weight 4	-0.0436	-0.232	-0.0084	1	0.1177	-0.299
Weight 5	-0.0925	-0.2139	0.2323	0.1177	1	0.0385
Weight 6	0.0376	0.0959	-0.0549	-0.299	0.0385	1

LVQ networks with 5x5, 7x7, 15x15, 20x20 and 30x30 neurons were created and trained for 100 epochs, an example of the weight matrix is shown in Figure 33. Due to the problem of stacking in local minimum, this process was repeated 50 times with different network initialization and each time the performance of the network was recorded and the results were shown in Figure 34.

The target vector was prepared for the LVQ network by using a k-means clustering to divide the fixation points into k number of clusters in which each fixation point belonged to the cluster with the nearest mean. The number of clusters is an important parameter and wrong choice of this number may yield poor results so in order to show the importance of this parameter, two groups of LVQ networks, one with a random number between 5-15 of target classes and the other with a number of target classes determined the silhouette validation method were trained and the performance of them are shown in Figure 34.

To find the number of clusters using the silhouette validation method, the data is clustered into various numbers of clusters using k-means algorithm and the largest overall average silhouette score indicates the best clustering number. Consequently, the number of cluster with maximum overall average silhouette score is taken as the optimal number of the clusters. Figure 29 shows the means of these silhouette scores of the clusters and 10 is the highest score.

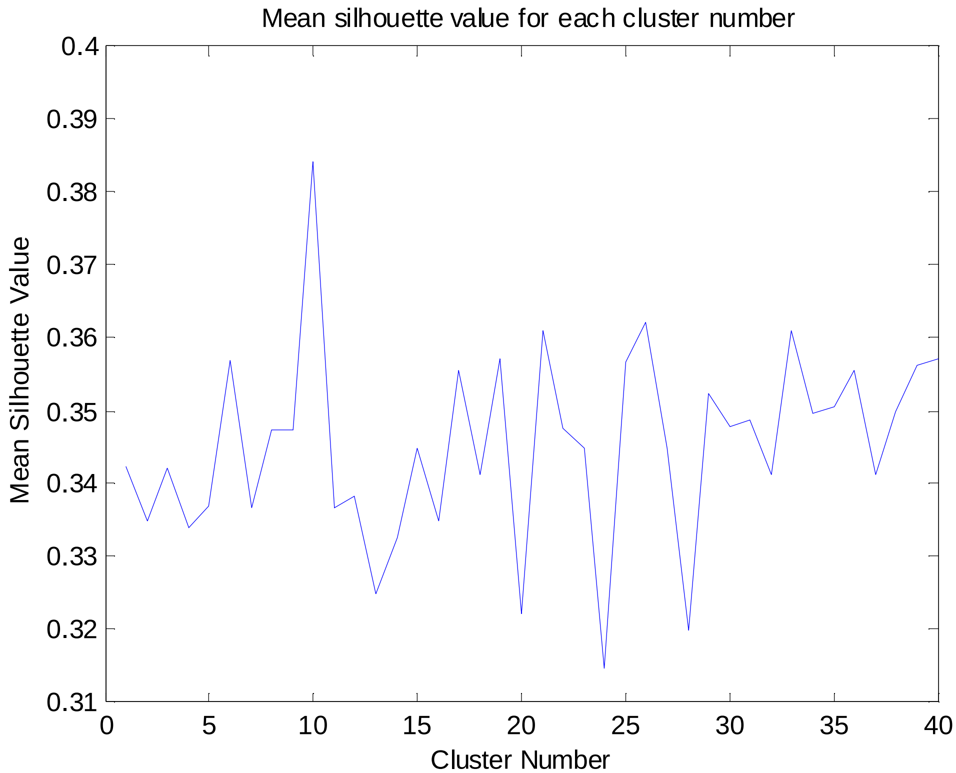
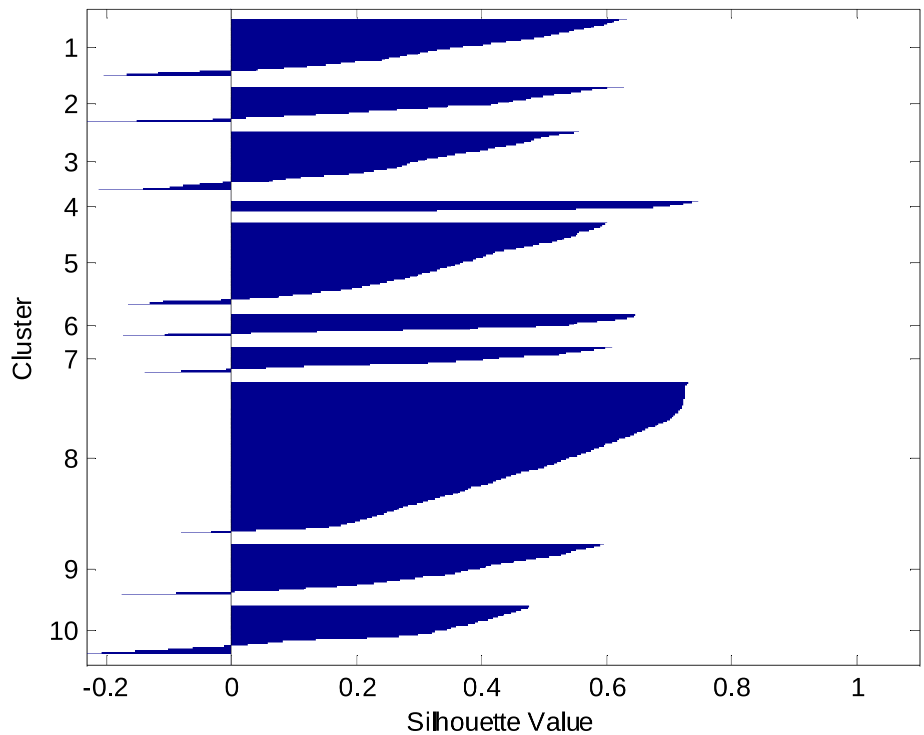


Figure 29 Mean silhouette scores for various cluster numbers. The maximum silhouette score is 0.386 for the cluster number 10.

The target data after dividing into 10 clusters by the k-means algorithm for the LVQS is shown in Figure 31. In order to compare the performance of the cluster numbers for the given data set, the silhouette values for the best cluster number, 10, and the worst cluster number are shown in Figure 30.



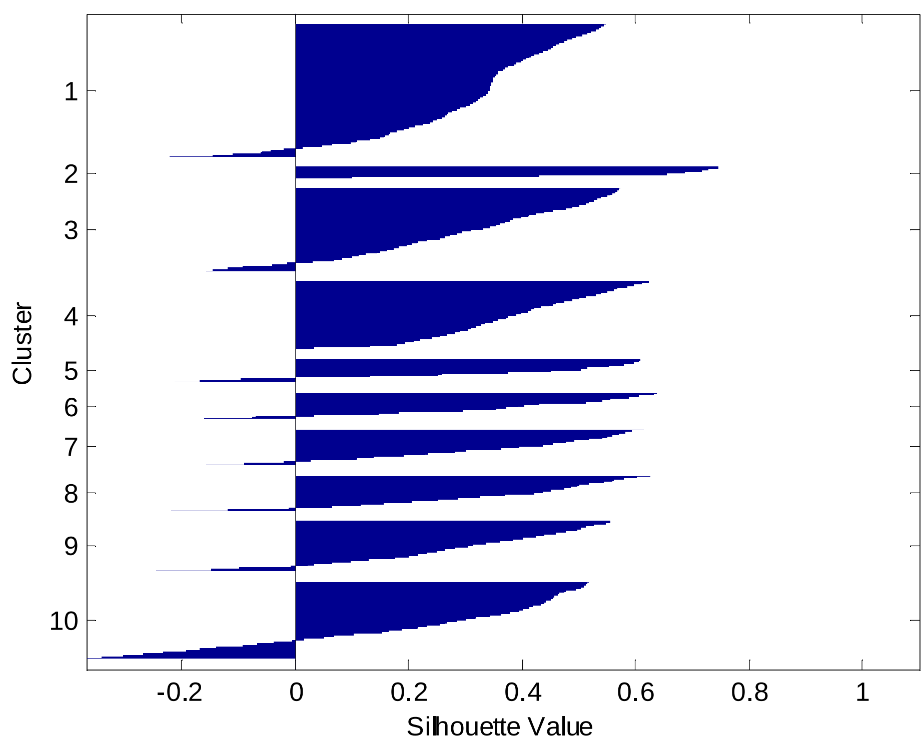


Figure 30 Silhouette values for the cluster number 10 (up) and the cluster number 24.

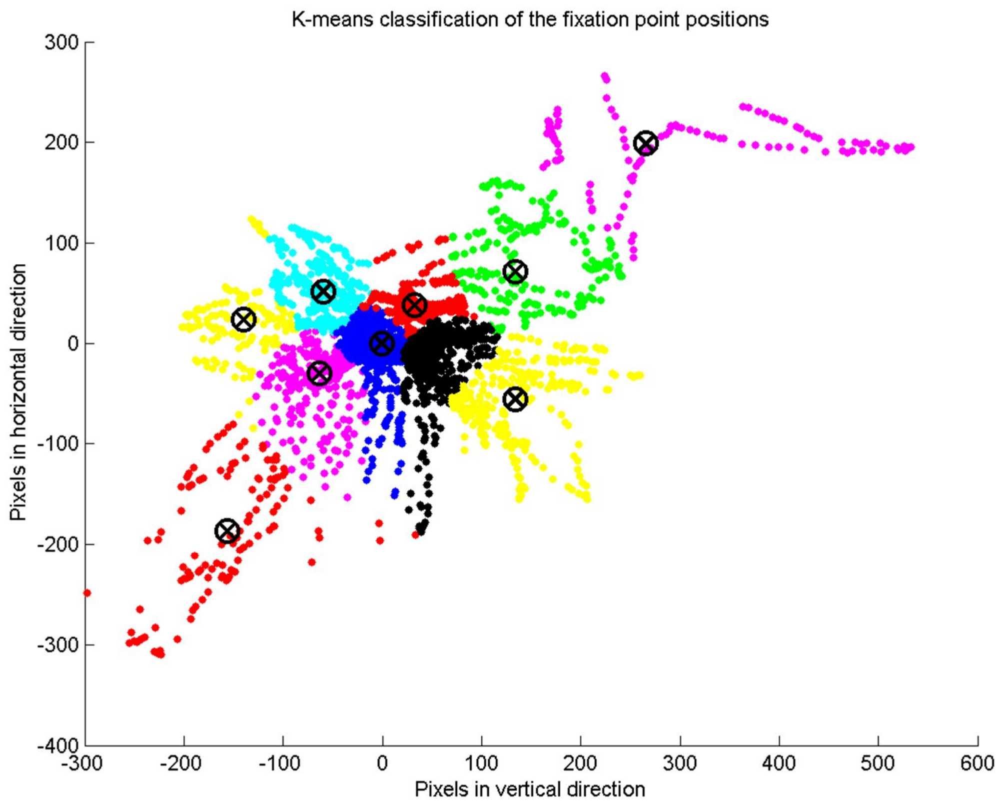


Figure 31 K-means clustering of the fixation point positions into 10 classes.

There is an another way to find a good estimate for the number of the clusters for the clustering of the recorded fixation points, first a distance matrix is created and using this matrix a similarity matrix created. After the singular value decomposition of this similarity matrix, the diagonal matrix gave us a good estimate of the numbers of clusters that should be used for LVQ and it was shown that this number also holds the good choice of number of clusters found in the silhouette validation method.

Suppose that we have the data of recorded m number of fixation point samples, in 2D pixel coordinates, F, which is a 2-by-m matrix.

$$F = \begin{Bmatrix} (x_1, y_1) \\ \vdots \\ (x_i, y_i) \\ \vdots \\ (x_j, y_j) \\ \vdots \\ (x_m, y_m) \end{Bmatrix} \qquad (22)$$

The m-by-m distance matrix contains the norm-2 Euclidean distances $d((x_i, y_i), (x_j, y_j))$ between the two points (x_i, y_i) and (x_j, y_j) .Each matrix element (i, j) corresponds to the distance between the points(x_i, y_i) and (x_j, y_j) . The similarity matrix is an m-by-m matrix, the elements of which are found by using the Equation 23 for every element in the distance matrix.

$$\boldsymbol{s(i,j)} = \boldsymbol{e}^{-(\frac{\boldsymbol{d(i,j)^2}}{\boldsymbol{2}})} \qquad (23)$$

The result of the diagonal matrix found by the singular value decomposition of this similarity matrix is shown in Figure 32. The diagonal values after the SVD decomposition..

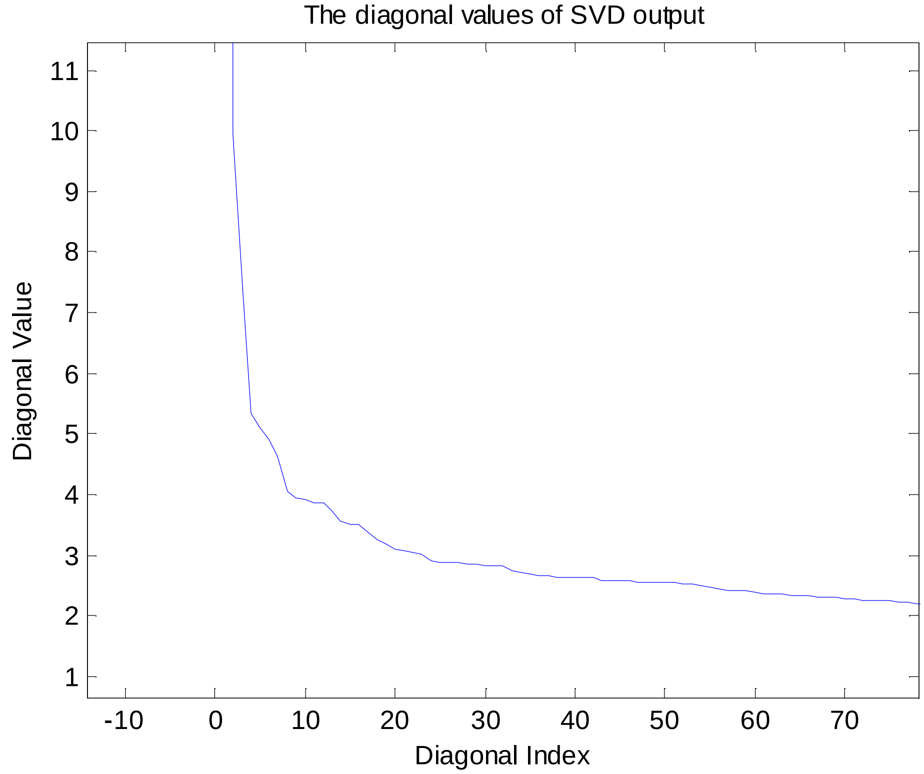


Figure 32. The diagonal values after the SVD decomposition.

As it is shown in Figure 32, there is a sharp jump between 8 and 12, which is also very close to the cluster number found that fits to this data from the silhouette validation method.

After finding the number of clusters for LVQ networks, an example LVQS network with 7x7 neurons was created and trained for 2000 epochs with a learning rate of 0.01 and target vector that had 10 classes. The weights of this LVQS are shown in Figure 33.

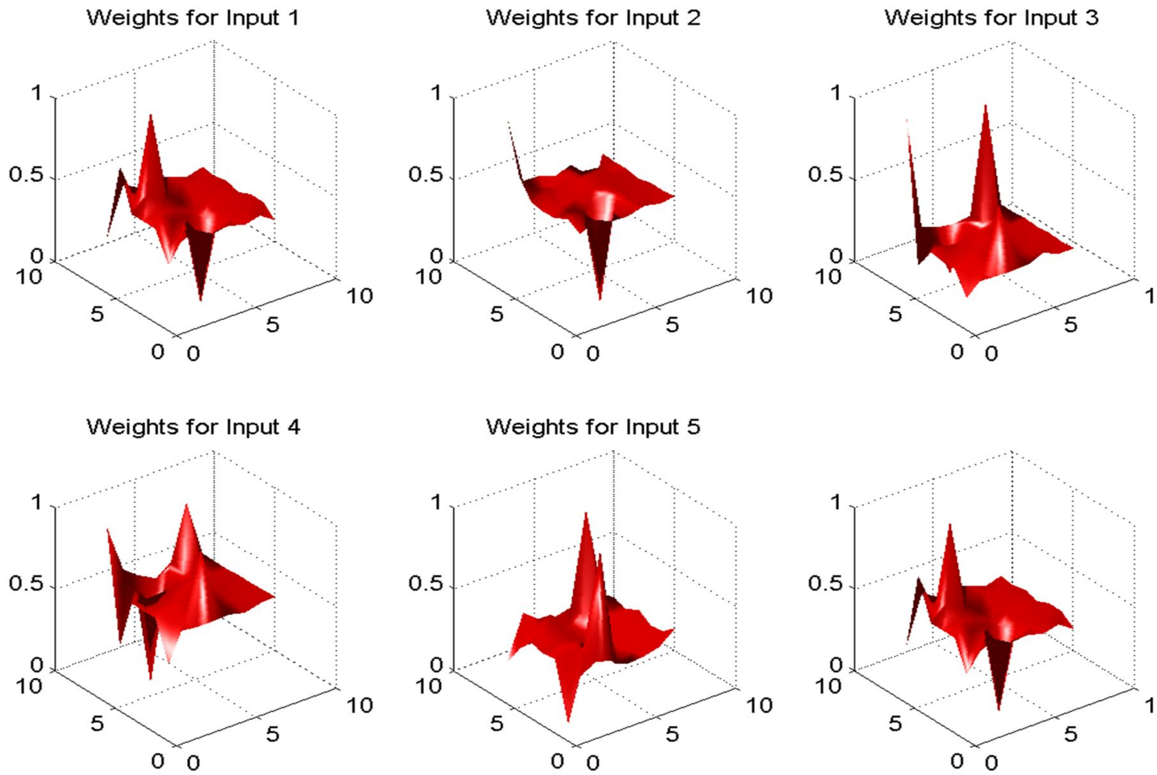


Figure 33. The visualization of the LVQS weights after training.

Table 2. Autocorrelation calculations of LVQS weight vector

Autocorrelation	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
Weight 1	1	0.0611	-0.5776	-0.1104	-0.7584	-0.195
Weight 2	0.0611	1	-0.2113	0.3484	0.1812	0.3156
Weight 3	-0.5776	-0.2113	1	0.5051	0.5604	-0.0065
Weight 4	-0.1104	0.3484	0.5051	1	0.3352	0.6168
Weight 5	-0.7584	0.1812	0.5604	0.3352	1	0.1304
Weight 6	-0.195	0.3156	-0.0065	0.6168	0.1304	1

The same performance test was used as the one for SOMS to show the performance of LVQ and LVQS methods. To show the performance of all these methods two babbling data sets were gathered and these methods were applied on them. The results were shown in Figure 34.

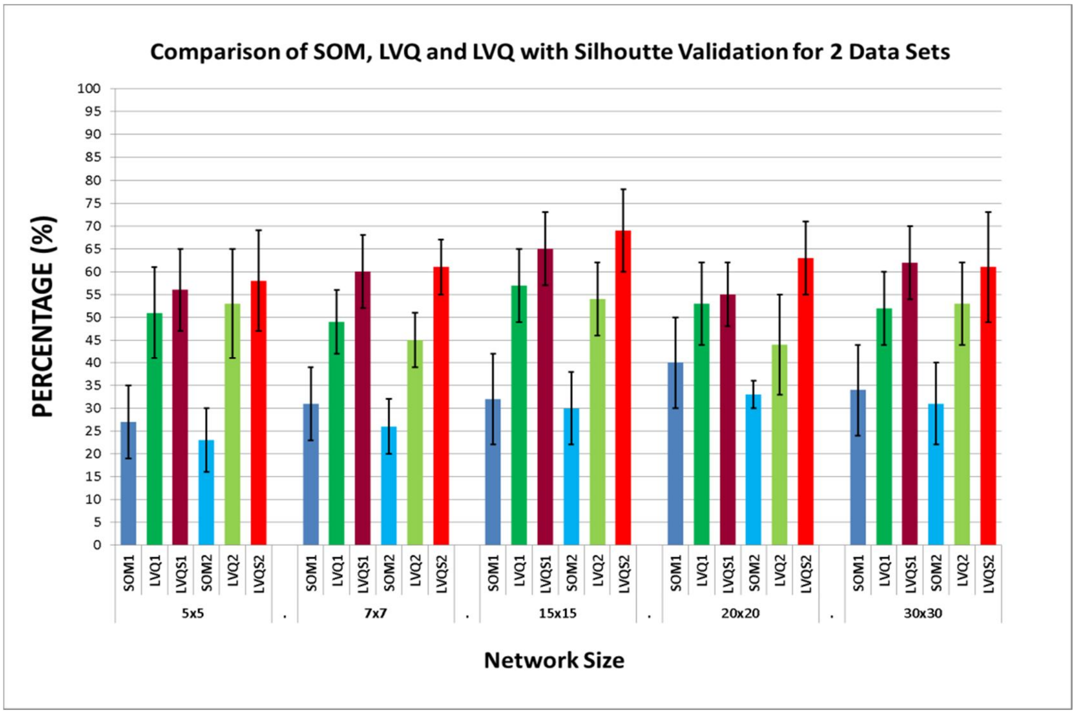


Figure 34 The performance of SOM, LVQ and LVQS methods.

Figure 34 shows that supervised learning techniques are superior to unsupervised SOMs. All the methods gave similar result for different babbling trails. The performance difference between the LVQ and LVQS training is not significantly different than each other, so the effect of selecting the best cluster number for clustering the target class has no or a little effect on the performance of the learning.

In stage 2, the position control neural network (PONNET) which finds the relation between the joint angles and the pixel-wise position and the size of the markers which are attached on the arms of the robot, a three layer, 100 neurons backpropagation neural network was used and trained for 1000 epochs.

In stage 3, after finding the affine transformations, the BVH files for different behaviors were transformed into the BHR perspective and the trajectory were fed into the

PONNET. The results of the PONNET controller for different behaviors, pull/push/lift are shown in Figure 35, Figure 36 and Figure 37.

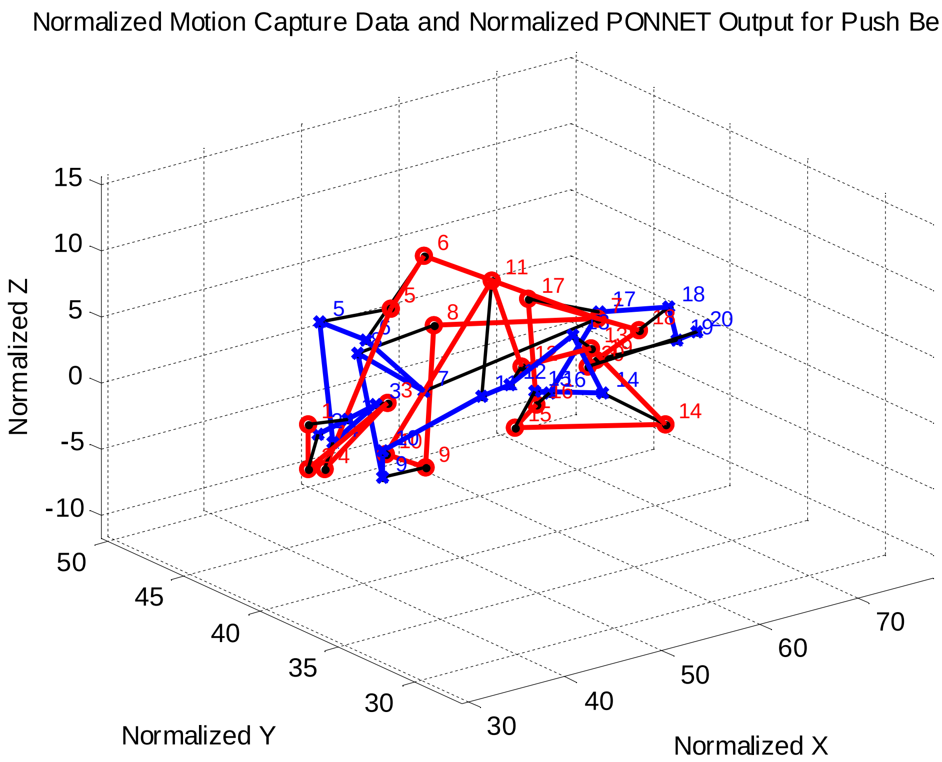


Figure 35 PONNET output for push behavior. The red marker is the output of PONNET and the blue marker is the normalized motion from the motion capture system. . The black lines show the DTW distances.

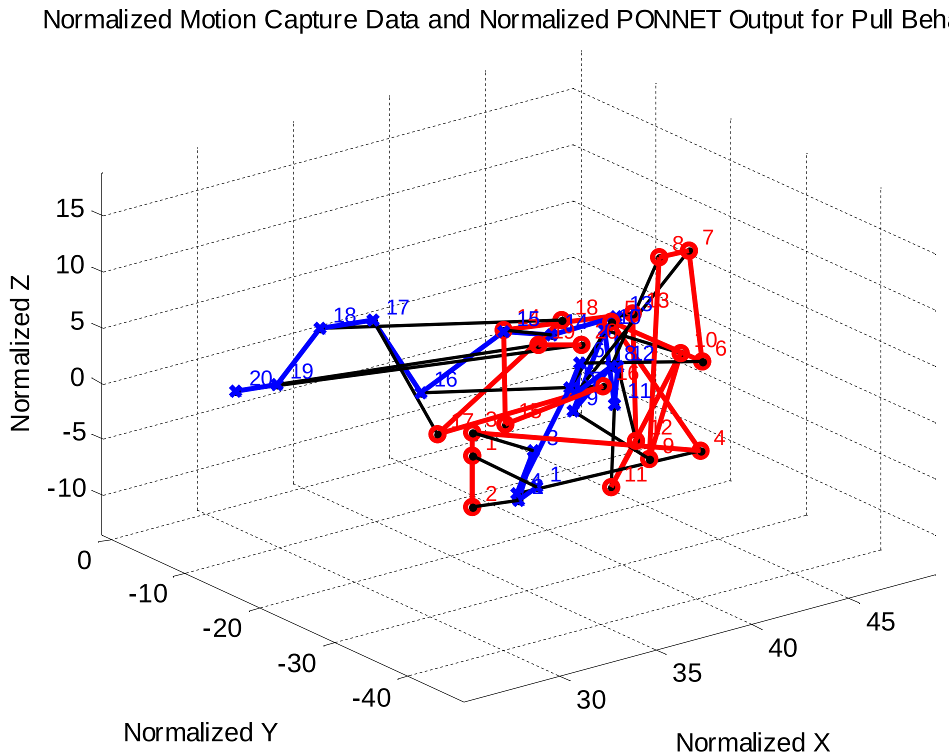


Figure 36 PONNET output for pull behavior. The red marker is the output of PONNET and the blue marker is the normalized motion from the motion capture system. The black lines show the DTW distances.

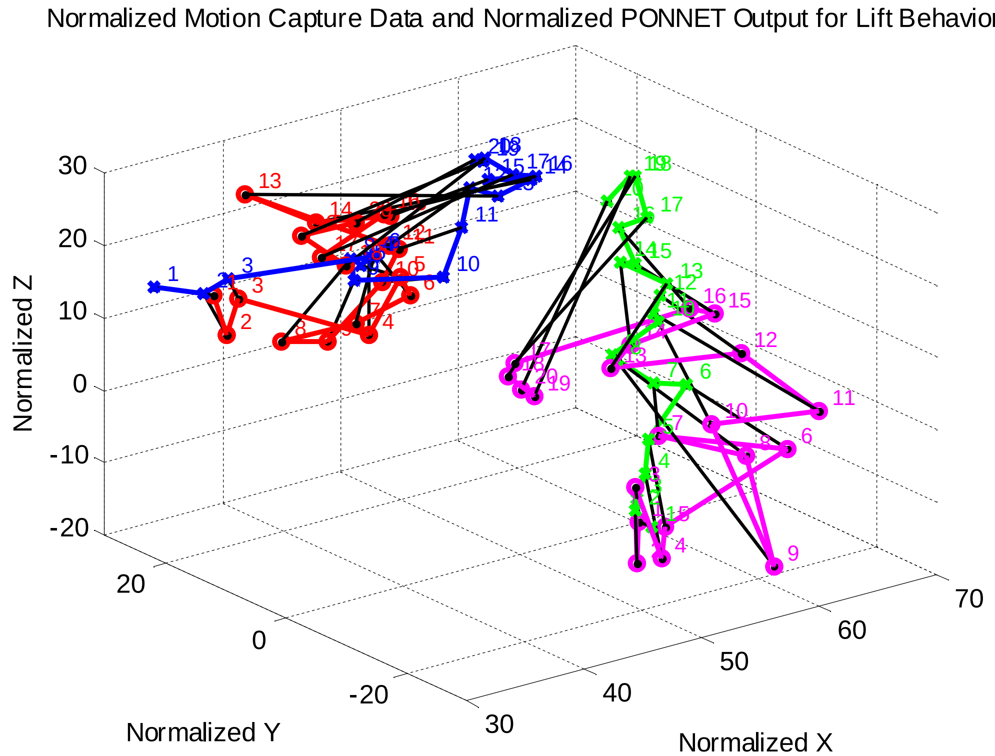


Figure 37 PONNET output for lift behavior. The red markers are the output of PONNET for the left arm, the cyan markers are the output of the PONNET for the left arm, the blue markers are the normalized motion for left arm from the motion capture system and the purple markers are the normalized motion for the right arm from the motion capture system. The black lines show the DTW distances.

In order to show the performance of the approach the DTW distances of the motion capture data and the robot motion data are calculated and show in Table 3.

Table 3. DTW distances between human and robot motion sequences.

DTW		Motion Capture Sequences			
Distances		Push	Pull	Lift-Left	Lift-Right
Robot Motion Sequences	Push	1.22	6.37	3.8	6.3
	Pull	5.47	1.6	6.19	3.28
	Lift-Left	4.51	9.12	1.62	8.59
	Lift-Right	6.45	4.94	7.29	2.69

The distances on the diagonal shows that the robot motion and human motions sequences for the specific behavior are noticeably close to each other than other behavior sequences.

Conclusion

Recently the idea of imitation learning – designing robots that can learn from imitation – has started to attract increasing attention in the field of robotics as it offers a promising method to automate the tedious manual programming of robots.

Implementation of imitation mechanisms is offered as a possible solution for problems created by sophisticated software systems, control of human programmers and task specificity used in robots. In this way, robots can learn to execute an action or task by merely observing someone else, without any knowledge of complicated programming languages.

Imitation learning also offers promising directions to gain insight into faster affordance learning and perceptual-motor control mechanism which can ultimately lead to developing of autonomous humanoid robots. Imitation learning offers promise for the realm of humanoid robots and robots that look and behave like human beings.

In this research, how a robot could babble to get data to build limb affordances by processing it using LVQs was demonstrated. LVQ, LVQS and SOM methods were compared and it was shown that LVQ and LVQS could find the relations, whereas SOM couldn't find any clear relation between motors.

These results can be considered as the first steps towards allowing robots to systematically learn how to integrate perception, action, tasks and goal information from a relatively small number of experiences much like a human being does, so as to generate adaptive behaviors efficiently and flexibly.

Future Work

In this dissertation, a developmental approach for affordance and imitation learning was discussed, and was demonstrated using a humanoid robot BHR kit. The approach could be expanded to address other aspects of this approach, which can be:

Using stereo camera

At birth vision is not very accurate and it is not fully developed until about several years after birth. Depth perception, which is crucial for acting, develops gradually after birth, and it is not until even 6-7 months of age that infants are capable of perceiving a three-dimensional shape. This ability further develops as infants enter the crawling age, which enables them to act upon the world using eye-hand-body coordination, then depth perception develops significantly. In a classic study, called "the visual cliff experiment" by Gibson and Walk [117], it was shown that when placed on a glass topped table that creates the impression of a cliff, infants with developed 3D views of their surroundings usually show signs of fear and avoid the deep side of a cliff. Most babies at crawling age show signs of depth perception, but this ability continues to improve and fine-tuned as they get more practice with crawling to reach out objects at different distances. Therefore the more experienced the babies are with crawling; the better they are in depth perception. Because binocular vision and full depth perception is not present very early in life, in our study we used a single camera to mimic monocular vision and simple perception. Using more complicated stereo image processing will allow the processing of spatial images and create more features that can be used to train the neural networks with more features.

Motion capture from infants

The approach in this paper was inspired from the developmental learning of infants from imitation. The BHR robot used the approach of an infant's imitation learning to imitate an adult's body movements from the motion capture data. According to Simulation Theory, which states that we understand others' actions (and thus able to imitate) by using our own internal motor system as an emulator, an adult can learn or imitate more efficiently from another adult whose size is similar to his/her size [29] [30].

On the other hand, according to the Meltzoff and Moore's research, newborns were shown to display facial gestures that matched those performed by an adult model [27]is a remarkable indication that infants as young as a few months old seem to be capable of replicating actions despite the differences in body size, perspective of view and lack of conception of self-other distinction. A follow-up study in which the observed data was captured using an infant's actions rather than an adult would contribute to the findings of this research.

Online training vs. offline training

All the neural networks were trained by using offline gathered data because of that, both systems could not achieve high learning performance or low learning errors satisfactorily or stuck at a local minimum that is worse than the global one. In the future, using an online learning systems or an adopting online training ability for the neural networks, can overcome these problems. As discussed in [116], using a better online learning approach ensures that small learning rates will be sufficient to increase the learning performance of the neural networks.

IX. REFERENCES

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