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A System for Affordance Based learning of Object Grasping in a Robot

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***Abstract*— A system is described which takes synergies extracted from human grasp experiments and maps these onto a robot vision and hand-arm platform to facilitate the transfer of skills [1]. This system forms part of a framework which is extended by adding a self organizing map based affordance learning system. This affordance system learns the correlations between perceived object features and relevant motor outputs expressed in the form of synergies, and comes to guide grasping of an object by predicting the appropriate synergy outputs for a given object. It does so online and autonomously. Preliminary results test its effectiveness in this role and show that it is capable of learning fast and in spite of noise.**

I. Introduction

Humans have an unmatched ability to learn about their environment and generalise this knowledge to novel situations. Despite the sheer volume of information entering our brains at any given point in time, we are able to spot correlations and associate together relevant information in a fast and online way, allowing us to gain an awareness of the control we have over both our own body, and by proxy the environment surrounding it. This paper describes a system which models human grasping skills in a flexible way by extracting relevant synergies and mapping them to a robot system, which can then learn and improve these motor skills online and autonomously through exploration and imitation.

From birth, humans begin to acquire and improve upon basic motor skills. It is not long before these motor skills can outperform robots on many tasks. Typical robot controllers are endowed with a high degree of precision, able to replicate the same movement time and time again. However, when faced with a dynamic environment requiring novel movements, it is often the case that a long and costly search needs to be employed to find the most suitable one.

Rather than employing often complex and costly search algorithms to compute suitable motor outputs, humans learn by trial and error, progressively building up more detailed correlations between input, action and outcome. When we wish to grasp an object, rather than using an algorithm to run through input data and calculate a suitable set of motor values, we simply access our memory and use prior learning to shape our grasp, basing it on similar successful grasps in the past. Initially, we will have very limited prior knowledge, leading to more random and unsuccessful movements, but eventually we begin to learn which of these movements leads to a given set of outcomes, and thus over time we build up a more detailed knowledge base to draw from.

Mapping human skills directly to a robot system is one way of giving it the necessary prior knowledge to base its actions on. Under this paradigm, the robot system can very quickly be taught to become effective in a variety of different motor tasks. In order to transfer human motor skills to a robot, we have to solve two problems. First, we need to extract or model the human skill to be transferred. Then, we need to figure out how to implement or map this skill to a robot platform whose joint configurations and sensorimotor systems are likely very different from those of a human.

Different methods have been employed in the past in an attempt to map various human skills to robots in different environments. Cortesao and Koeppe [2] transferred the human skill in the peg-in-hole task to a robot. When a human performed this task, the forces, torques and velocities of the peg were recorded as a function of its pose. Next, a neural network trained with this data was used to control the robot in the same task. In another study [3], the human expertise in a manipulative task was modelled as an associative mapping in a neural network and implemented on a direct-drive robot. Yang and Chen [4] represented human skills in tele-operating as a parametric model using a hidden Markov model. Unlike these more specific approaches, the more general framework proposed by Oztop and Lin [5] integrated a 16-DOF robotic hand into the experimenter's body schema and used the dexterity then exhibited by the experimenter to design a robot controller.

Rather than directly mapping a human skill to a robot, skill transfer has also been achieved by imitation, whereby the robot watches a skill being performed and used the information gathered to reproduce it. In [6], a robot imitated the grasping and placing of a human model. Skill transfer was realized when the robot learned a goal-directed sequences of motor primitives. In [7], a continuous hidden Markov model was trained with characteristic features of the perceived human movements and used in a simulated robot to reproduce the human movements. Rather than using robots to observe or imitate human movements, [8] developed a communication language for transferring grasping skills from a nontechnical user to a robot during human-robot interaction.

While this transfer of skill can help endow robots with the knowledge required to complete a task, it is often the case that this knowledge can not be generalised to novel events or scenarios. In order to refine and generalise existing skills to new tasks, the acquisition of skills must continue as novel events are encountered. To achieve this, the mapping used to transfer skills must allow continued learning to take place after the skill transfer has been completed. For this reason, synergies are used to map from human to robot.

A. Synergies

A synergy refers to a subgroup of muscles or joints that are activated together in a stereotyped pattern [9], in contrast to the decoupled control of individual joints commonly used in robot systems. As a simple example, flexing your biceps muscle naturally relaxes the opposing triceps muscle. Synergies are biologies way of dealing with the high dimensionality of joints and therefore large problem space encountered when deciding which movements to make. It has been found for example that a small number of muscle synergies in frogs accounts for a large fraction of the variation in the muscle patterns observed while jumping, swimming and walking [9]. In addition, the human hand had more than 20 degrees of freedom, but two synergies can account for 84% of human grasping [10]. In addition, synergies have also been noted in hand reaching movements prior to grasping [11] [12].

Some robot controllers also make use of synergies [13] [14] [15], as they are capable of reducing the dimensionality of the problem space, while still allowing novel movements based around the kind of movements the synergies were based on. The system described here uses human grasp data to extract useful grasp synergies, and a neural network to map these onto a robot arm and hand system. This skill transfer endows the robot platform with a human-like grasping ability, while at the same time reducing the problem space significantly and keeping the door open for continued learning and novel grasping movements.

In order to enable online learning once grasp synergies have been extracted and mapped in the system described, we propose here an affordance based learning system. The concept of affordances dates back to 1972 when Gibson argued that properties in the environment could influence the organisms goals [16]. Gibson saw affordances as relations between properties of objects registered directly by our perceptual system, and the actions that could be performed on them. More recent research defines affordances more as relations between objects, their context, and the organism itself. Under this definition, affordances can be seen as the associative structures formed from various sensory and motor information for given objects. A typical object affordance for an apple might link the name apple with the features commonly associated with apples, the grasp used to hold it and an action (eg. eat) that can be performed on it.

Several experiments have demonstrated such a link between names or features of an object, and associated motor actions [17] [18] [19]. In addition, research tends to support the idea that affordances are associative structures formed from links between different related information. [20] asked participants to read a sentence composed by an action or observation verb, and an object name. Next, an image was shown and participants had to decide whether it was the same object referred too in the sentence. Action verbs increased RT's, as did objects presented in canonical viewpoints. Viewing affordances as associative structures, it appears obvious that motor predictions elicited from action verbs in tandem with object names will prime those objects more than just their name, especially if the object presented is in a canonical orientation which better matches the primed motor information.

B. Affordances

By using affordances, we are essentially learning relevant associations between information. This allows us to recall object features typically linked with a name, or motor commands typically linked with a set of features. By endowing a robotic platform with an affordance learning system, we give it a model into which associations between various sensory and motor information can constantly be refined and improved as it continues to explore its environment, while at the same time using these associations to guide it.

Self organizing maps form the foundation for the modelling of affordances in the system described here. First described by Kohonen [21], self organizing maps (SOMs) map input data down onto a low dimensional input space (typically just 2) in a topology preserving way, clustering similar inputs together. This allows for easy visualisation of data, and as such they are most often used for the clustering and subsequent visualisation of high dimensional data sets [22] [23]. However, the learning algorithm of the SOM lends itself well to associating inputs in different dimensions together and generalising to novel input patterns. One could see a SOM as building a map of the average input patterns it expects to see across the input space, making it naturally resilient to noise and artefacts. In addition, generalisation from known input patterns to novel ones is made possible by the neighbourhood learning approach, as the space between two known input patterns will be occupied with input patterns that are the average of the two. As such, applying the SOM to a system which requires robustness, generalisation to novel inputs and correlation between multiple dimensions seems natural.

Next, we describe the methods by which grasping is learned in the form of synergies and mapped from human to robot, but then expand on this by showing how a self organizing map based affordance learning system can be used to drive the learning of grasps using synergies effectively, online and fast, while being robust to noise.

II. System Overview

A. Hardware

The robot platform used for grasping comprises a two camera active vision system and a robot hand and arm system. The vision system integrates two cameras (each providing RGB image data at a maximum resolution of 1032x778 at 25 frames per second) mounted on a pan-tilt-verge unit. Currently, this system is not interested with moving the cameras and simply uses one camera at a fixed position to provide input images. The robot arm and hand systems (SCHUNK GmbH Co. KG) have 7 DOF each (see Fig. 1). The hand system has 3 fingers. All fingers have 2 segments each equipped with a pressure sensitive sensor pad.

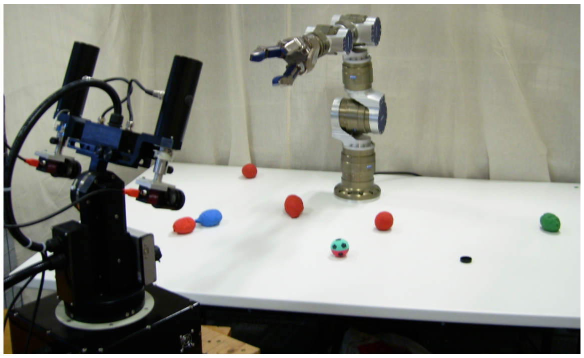

Fig. 1: The hardware that is used for grasp synthesis, including the 7DoF arm with attached 7DoF Gripper, and twin pan-tilt-verge camera system.

B. Extracting Synergies from Grasp Data

Synergies are essentially correlations between muscle movements. A simple example would be opposing muscle synergies; in the case of arm flexing, as the biceps muscle contracts, the opposing triceps muscle relaxes. Synergies can be more complex however. In the case of grasping for example, several fingers close simultaneously to achieve the grasp. In this system, synergies are used to model both reaching and grasping. Using synergies allows the dimensionality of the problem space to be significantly reduced, while retaining the key elements required for successful reaching and grasping.

In order to find and extract the synergies most relevant to grasping, human grasping experiments were carried out. To extract grasp synergies from human grasp data, a subject made 60 two or three finger grasps of various different objects (see Fig. 2). The positions of the hand joints in the grasping postures were recorded with a Shapehand data glove, while the positions and orientations of the wrist in a fixed world frame were recorded with a Polhemus Patriot magnetic sensor. The data acquired is processed using Principal Component Analysis, and the principal components are found which are responsible for most of the variance in the grasping and reaching data. The first three principal components account for 90% of the reaching data and 82% of the grasp data (see Fig. 3), and are therefore chosen as synergies [1]. This reduces the dimensionality of the reaching space from 6 to 3, and the grasping space from 7 to 3. With respect to the grasp data, this dimensionality reduction makes it far more likely that selecting random grasp values will produce sensible grasps rather than just random nonsensical motor movements, which helps to increase the systems robustness.

C. Mapping Synergies from Human to Robot

Before applying these synergies to the robot arm-hand system as a basis for grasping objects, They first need to be mapped from the human to the robot hand. A novel method is used to map between human and robot hand [1]. Ordinarily, a fixed frame of reference between human and robot hand is decided on prior to experimentation (eg.

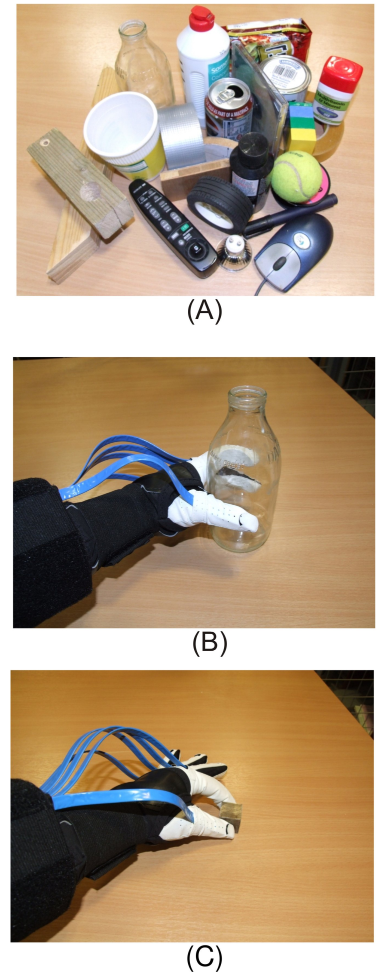

Fig. 2: Here we see (A) the selection of objects used in grasping experiments in order to extract grasp synergies,(B) a three finger grasp and (C) a two finger grasp.

[24] and [25]). However, given the mechanical constraints of our robot hand, a genetic algorithm is used to select the transformation between human and robot frame of reference which minimises the error between fingertip position online before each grasp is carried out. After about 1 second and 45 generations, error is reduced to below 2mm.

Given the mapping from human to robot hand, an inverse kinematics model is used to drive the 7DOF arm system to reach the desired position. While some approaches are not suitable for our 7DOF hand, neural networks have been successfully trained to calculate the inverse kinematics of high DOF manipulators. Given a dataset of 50000 points and associated joint angled, four separate MLP neural networks are trained on 12500 points each. To minimise the error when asking for joint positions from the network, the minimum error is taken from each of the 4 networks each time, significantly reducing the average error rates.

Given that the inverse kinematics can now be calculated, and the synergies effectively mapped from human grasping trials to the robot hand, it is now a trivial matter to ensure

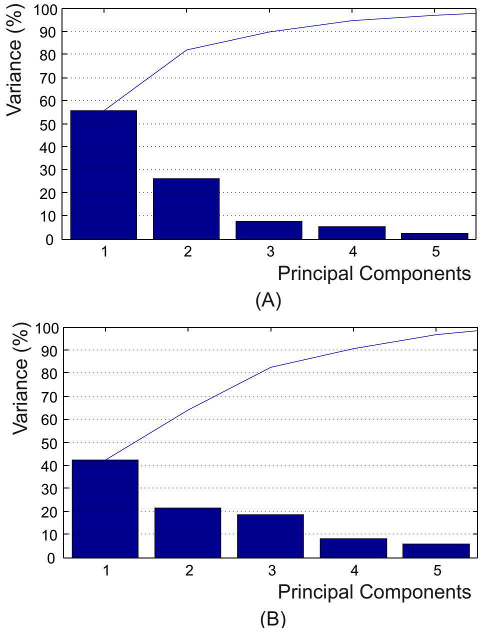

Fig. 3: The principle components extracted (A) from human reaching data, and (B) from human grasp data.

a good grasp results. First, the arm is moved into position using the aforementioned inverse kinematics. Next, the grasp described by the synergy values is made by closing one finger joint at a time. Finally, each finger makes use of the tactile pads on its end by closing until contact pressure is over a certain threshold. While this contact pressure is low, the rubberised pads allow the grasp to successfully grasp and lift objects up to 2kg in weight [1].

D. The Affordance Learning System

Given a system that can produce grasps by using appropriate synergy values, we now introduce a method of quickly and reliably learning the correlations between relevant object feature values and those synergies required to successfully grasp the object.

Affordances, as described earlier, can be seen as associative structures linking various related sensory and motor information together. In this case, we are interested in the association between various feature information and the required synergy values necessary to grasp the object with those features. To model this correlation, we use a modified SOM (Self Organizing Map) to cluster and consequently correlate the feature and synergy inputs. Essentially, a SOM is a grid of nodes (usually 2 dimensional), each representing a random input pattern. Each time an input is presented, the node most closely matching the input pattern, and those around it, have their values moved closer towards the input pattern (Fig. 4 gives an example of this). The effect is that more similar inputs will tend to end up closer to eachother. Ordinarily, SOM's have a decreasing neighbourhood range as a function of time. This means that each iteration, the amount by which input patterns can alter the structure of the network decreases, until eventually only fine tuning occurs. To make the SOM work over an undefined length of time, we instead decrease the neighbourhood range as a function of input error at each iteration. As such, the network can learn as normal, but is also capable of dynamically restructuring itself as required over time, and as novel inputs are presented. In addition, this gives the SOM the potential to learn faster, as it does not have to wait for any predefined length of time to settle down and fine tune its winning nodes.

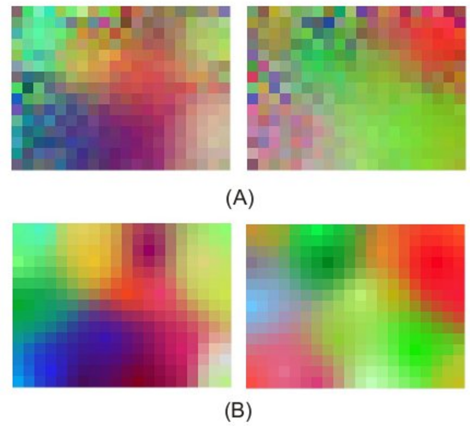

Fig. 4: Image showing the correlations formed in a single SOM between 3 feature dimensions (left) and synergy dimensions (right) soon after training commences (A), and as learning has peaked (B). Notice the similarities in the structure of the feature and synergy correlations, as a result of the correlation between feature and synergy values.

We make use of the associations formed between dimensions in the SOM by presenting partial inputs to the network. The remaining values from the node which comes closest to this partial input are output, essentially returning the closest matching complete input present in the SOM. There is no limit to which or how many inputs one can provide to the network in order to get complete outputs, giving it a degree of flexibility not present in standard neural network models. That said, providing more values as part of a partial input pattern will result in a more accurate complete output, as is to be expected. In addition, the discrimination between predicting and learning is made simple; The SOM is automatically trained on complete patterns, whereas it will only predict from partial ones.

In order to speed up learning, we also implement a simple STM (Short Term Memory) alongside the SOM. This works as follows. Depending on its predefined size N, the STM stores N previous trained inputs, and each time a new input is presented to the SOM for training, all previous inputs in the STM are also trained. By training a selection of prior inputs, rather than increasing the learning rate for each individual input, we have ensured that input to the network is diverse enough for learning to take place, while also dramatically decreasing the amount of presentations required to learn below a given error threshold.

E. System Summary

The complete system aims to integrate the use of synergies extracted from human grasp experiments, and the affordance learning system for the online learning of synergy-feature correlations. The operational procedure is as follows. A set of features is perceived by the camera system. The features are sent to the affordance memory and a set of synergies is retrieved. These synergies are mapped to the robot hand and executed. If a grasp is successful, the resulting values are sent back to the affordance memory for learning. Otherwise, exploration mode is entered. In exploration mode, random synergy values are generated and tested until a successful grasp is achieved, at which point, the affordance memory learns the resulting feature and synergy values. In addition to this, the system will incorporate an imitation mode, by which a human hand using the dataglove and patriot magnetic sensor grasps an object, and the resulting synergies and object features can be immediately learnt and later replicated.

Essentially, the system described combines the use of synergies as a robust model of human grasping, with a SOM based affordance learning system and an exploration mode to learn and refine grasping of novel objects online and efficiently.

III. Experimentation and Results

The experimentation focuses on the ability of the proposed affordance learning system to learn the necessary correlations between feature information extracted from objects and the associated motor synergy values used to drive grasping of them. In addition, we test its ability to learn fast with the help of the proposed STM addition, and learn in spite of noisy input data. Both qualities are necessary if this system is to be effective at learning online using data from a camera and synergies extracted live.

To perform these experiments, a selection of 27 silhouetted images of objects picked from the original training set were used (see Fig. 5). 8 objects from the original set of 35 were discarded on account of having grasp synergies based on details which could not be picked up during feature extraction. First, basic features - orientation sine and cosine, size, and shape (the proportion of minor axis to major axis length) - were extracted from each of these objects and normalised to values between 0 and 1. Next, each set of feature values and their associated synergy values were fed, in a random order, into the affordance learning system for training. Testing was carried out by feeding just the object features into the system after a given number of training cycles. The system then outputs its best prediction of the synergy values. Error rates in terms of the euclidean distance between expected and obtained synergies were recorded. Each experiment was ran 5 times and average results taken.

First, to test noise in the system, each input value (ranging from 0 to 1) had noise added to it prior to learning. A noise level of 0.05 for example, indicates that each input value was shifted a random amount from 0-5% up or down from its original value, prior to being learned. Noise levels of 0.02, 0.05, 0.1, 0.12 and 0.15 were tested. Performance is shown in Fig. 6. Next, maintaining a constant noise level of 0.05, the performance of the STM was tested by comparing various sizes of STM against each other and observing effects on learning rate. Recall that the STM size is simply the number of prior inputs stored in it that are trained each time a new input is trained. As the STM size increases, as does learning rate (see Fig. 7), although this effect diminishes and further size increases have a diminishing effect.

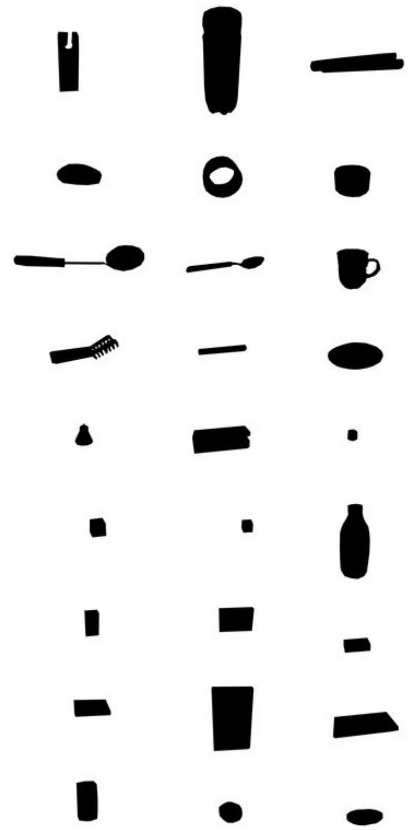

Fig. 5: The selection of object images used to train the affordance learning memory with. These were taken from human grasp experiments and therefore each come with the accompanying synergy values required to grasp them.

Overall, results show that the affordance learning system is robust to noise and can still learn effectively with around 10% noise added. In addition, learning rate can be dramatically increased with the help of a simple STM module. Taken together, these preliminary results suggest that the affordance learning system described is well suited to the online learning and prediction of object grasping.

IV. Conclusion

In summary, the grasp modelling system described can successfully map from human grasps to robot grasps using robust dimension reducing synergies to model the problem space. To enable the online and autonomous learning of grasps in this system, we have proposed an affordance learning system which can successfully learn the correlations

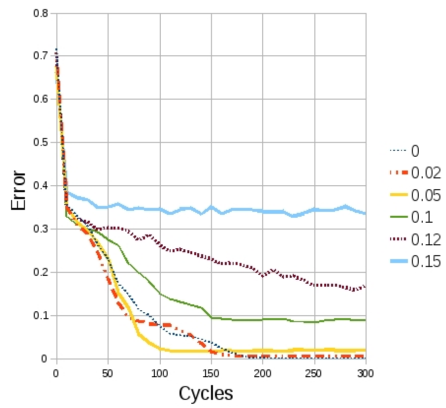

Fig. 6: Graph showing the error rate when predicting the correct grasp to apply to a given object decreasing over time, despite various amounts of noise ranging from 2% to 15% noise (see the legend). It can be seen that more noise leads to a decreased reduction in error rates over the number of cycles shown.

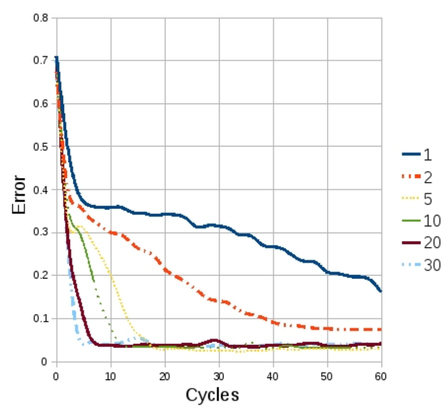

Fig. 7: Graph showing the error rate after a given number of cycles with various different sizes of STM ranging from 2 to 30 prior inputs. It can be seen that increasing the number of inputs in the STM, we significantly decrease learning times. That said, increasing the size beyond 30 leads to little benefit and greater cost.

between object features and grasp synergies online, fast, and autonomously through exploration of the environment. Preliminary results have been presented, and support this assumption. We are now in the process of integrating these systems together in our general framework, with the aim to create a system that models grasping in terms of synergies extracted from human grasp data, and learns to correlate these grasps with appropriate objects online and through exploration of the environment by using the affordance learning system proposed here.

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