Application

2015-03-31

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Information about application

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Project title (english): Goal-oriented Grasping and Manipulation based on Learning and Multisensory Perception

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Classification code: 10207. Datorseende och robotik (autonoma system)

Keywords: Robotics, Machine Learning, Computer Vision

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Amount:	1,116,000	1,177,000	1,263,000	1,360,000

Descriptive data

Project info

Project title (Swedish)*

Målorienterade grepp och manipulationsfärdigheter baserat på inlärning och mutlisensorisk perception

Project title (English)*

Goal-oriented Grasping and Manipulation based on Learning and Multisensory Perception

Abstract (English)*

Our aim is to enable autonomous task-oriented grasping of novel objects based on multisensory perception (tactile, visual and proprioceptive) and learning manipulation capabilities through exploration both from successful and unsuccessful grasping trials. It is a core challenge in robotics to equip agents with the ability to intelligently interact with the world. To achieve this, a robot needs to gather and interpret sensory information in new, unforeseen situations with minimal prior knowledge. However, a man-made environment is challenging for a robot due to the constant change in type and placement of objects it needs to interact with. To develop cognitive and behavioural capabilities in such a context, the robot needs to learn useful representations for objects and manipulation tasks by being actively engaged in the environment.

To deal with uncertainties, we work on probabilistic methods for object representations and modeling of robot grasping tasks. Our robot will learn its low-level sensorimotor ability by exploration to fulfil high-level task requirements, be able to interpret outcomes of its actions and apply corrective movements if needed to successfully complete its task. Our approach is based on adaptive exploration and enables the agent to update its knowledge based on both successful and unsuccessful experiences. After an initial discovery phase, the system will be able to transfer its grasping knowledge obtained from training to novel objects and correct its actions when failure is predicted, e.g., place the robotic gripper in a different position if the achieved position is estimated to lead to failure based on acquired sensory data. The project focuses on addressing three fundamental robotics challenges, grasp hypotheses generation, learning from experience and grasp success monitoring and correction using sensory data.

We believe, the proposed research in task-oriented grasp planning, execution and grasp adaptation will pave an important pathway towards the development of autonomous artificial agents that can interact with their environments.

Popular scientific description (Swedish)*

För att robotar skall kunna ta steget ut från fabriker, laboratorier och in i våra hem krävs att de kan handskas med den osäkerhet som finns i omgivningen. Roboten måste kunna samla in och bearbeta osäker sensorinformation i nya och oplanerade situationer med begränsad initial kunskap. Robotarna måste också kunna lära sig om sina egna förmågor och miljön de verkar i. De måste kunna lära sig om objekten och representationer för dessa genom interaktion med dem. Utöver att kunna detektera och känna igen objekt måste roboten kunna gripa tag i objekten och manipulera dem. Det kan vara för att vända på ett objekt för att få en mer komplett bild av det eller för att flytta det från en plats till en annan. Dessa förmågor begränsas till viss del av den mängd sensorinformation som finns tillgänglig samt mekaniska och dynamiska egenskaper hos roboten. Att lära sig dessa egenskaper och begränsningar är mycket utmanande för ett artificiellt system. Ett exempel som visar hur komplicerad denna process är ett nyfött barns utveckling. Det tar ett år innan de kan ta de första stegen och långt mycket längre än så innan de kan cykla och hålla kolla på trafiken runt omkring sig.

I detta projekt kommer vi att skapa ett artificiellt autonomt system som kan interagera med omgivningen. Systemet måste kunna resonera kring vad som krävs för en given uppgift och relatera detta till sin egen sensor motoriska förmåga. Mer specifikt kommer vi att fokusera på att utveckla matematiska modeller för att möjliggöra för robotar att förstå objektspecifika egenskaper som är viktiga för att kunna gripa tag i olika, tidigare okända, objekt och sedan lära sig hur dessa kan användas för att uppnå manipuleringsuppgifter genom återkoppling från multipla sensorer så som taktila och visuella sensorer. Vår metod baseras på att roboten själv skall lära sig att utforska sin omgivning och kunna lära sig både från lyckade och misslyckade försök.

Project period

Number of project years*

4

Calculated project time*

2016-01-01 - 2019-12-31

Deductible time

Deductible time

Cause	Months
Career age: 28	

Career age is a description of the time from your first doctoral degree until the last day of the call. Your career age change if you have deductible time. Your career age is shown in months. For some calls there are restrictions in the career age.

Classifications

Select a minimum of one and a maximum of three SCB-codes in order of priority.

Select the SCB-code in three levels and then click the lower plus-button to save your selection.

SCB-codes*	1. Naturvetenskap > 102. Data- och informationsvetenskap (Datateknik) > 10207. Datorseende och robotik (autonoma system)

Enter a minimum of three, and up to five, short keywords that describe your project.

Keyword 1*

Robotics

Keyword 2*

Machine Learning

Keyword 3*

Computer Vision

Keyword 4

Keyword 5

Ethical considerations

Specify any ethical issues that the project (or equivalent) raises, and describe how they will be addressed in your research. Also indicate the specific considerations that might be relevant to your application.

Reporting of ethical considerations*

The project does not raise any ethical issues.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

Goal-oriented Grasping and Manipulation based on Learning and Multisensory Perception

Yasemin Bekiroglu

1 Purpose and Aims

Robotic systems providing advanced service will be integrated into many aspects of daily life in the future driven by both industrial and societal needs.[1] There are areas where robotic applications have already been deployed, such as industrial and service sectors. One area of interest with the potential to have a very positive impact supported by many trials is developing robotic helpers for the elderly.

One of the key skills for a robot is to physically interact with the environment in order to achieve basic tasks such as pick-and-place, sorting, carrying, opening doors/drawers etc. For physical interaction, object grasping and manipulation capabilities along with dexterity (e.g. to use objects/tools successfully) and high-level reasoning (e.g. to decide about which object/tool to use) are crucial.

Industrial robotics where operations that are rule based, in environments that are static (unchanging) and structured (e.g. on fixed known routes) are considered has become a mature research field and the focus shifted towards autonomous robots and robots in unstructured environments where unlimited combination of shapes, sizes, appearance, and positions of objects need to be taken into consideration.

Despite many studies and significant progress over the last decades regarding different steps in grasping and manipulation[2,3,4,5] (see Figure 1.1), a robust and general approach to grasping for wide variety of tasks and objects encountered in dynamic and unstructured environments and novel situations, which is close to human grasping skills does not exist yet. Current systems have severe limitations in terms of dealing with novelty, uncertainty and unforeseen situations.

In this project, we will focus on grasping with multiple sensory modalities (vision, haptics, proprioception) and investigate a learning approach to encode grasping knowledge acquired from experience. The aim is to provide robots with means of reasoning about object grasps and their probability of success, taking into account the information provided by complementary sensory channels. We consider vision and touch sensing which can complement each other when in contact with the object, while exploring and manipulating it with the hands.

The main objective in this project is to build a robotic system than can learn to grasp and manipulate objects to accomplish a given everyday manipulation task based on exploration and multisensory modalities, i.e., vision, touch and proprioception. We will follow a probabilistic learning approach in order to deal with imperfect real sensory data and to have an adaptive system that can update its knowledge based on its both successful and unsuccessful experiences. After an exploration phase, the system will be able to transfer its grasping knowledge obtained from training to novel objects and to correct its actions when failure is predicted, e.g., place the robotic gripper in a different position if the achieved position is estimated to lead to failure based on acquired sensory data.

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[1] http://www.robotcompanions.eu and http://www.robotics-platform.eu

[2] A. Bicchi and V. Kumar. "Robotic grasping and contact: a review". In: *IEEE Int. Conf. on Robotics and Automation*. 2000.

[3] J.M. Romano et al. "Human-inspired robotic grasp control with tactile sensing". In: *IEEE Transactions on Robotics* 27.99 (2011), pp. 1–13.

[4] R. B. Rusu et al. "Fast 3D Recognition and Pose Using the Viewpoint Feature Histogram". In: *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*. 2010.

[5] Ashutosh Saxena, Justin Driemeyer, and Andrew Y. Ng. "Robotic Grasping of Novel Objects using Vision". In: *The International Journal of Robotics Research* 27.2 (2008), pp. 157–173.

1.1 Basic Idea and Scientific Challenges

There are main issues which make grasping difficult for robots: Unknown information required to plan grasps such as object shape and pose need to be extracted from the environment through sensors. However, sensory measurements are noisy and associated with a degree of uncertainty. Therefore, grasp planning is based on noisy data. Even if perfectly accurate information is obtained, planning a suitable grasp is still a challenge. There are a huge number of possibilities to choose from and the parameter space cannot be searched exhaustively.

A good planning strategy should take important factors into account such as frictional properties, obstacles or the kinematics of the robot. The task that the robot needs to accomplish is another important factor that greatly influences the decision on grasp selection, namely how to place the hand on an object. Each task has its own requirements on the geometry and the robustness of the grasp. Thus, objects are grasped differently according to the tasks, e.g., if a mug is to be placed somewhere else, grasping from the top without applying much force might be suitable. However to pour water with a mug, the grasp should not block the top or to hand someone an object it should leave enough free volume.

Since the perceptual observations on which the planner bases its reasoning are noisy, It is unlikely that the robot's fingers will come in contact with the object at the exact intended points. The object will generally move while fingers are being closed, and the final object-gripper configuration, even if geometrically similar to the intended one, may present a prohibitively different force configuration and thus failures might occur. Thus, executing grasping actions in an open-loop system is unlikely to prove viable in in real-world environments and a closed-loop system in which perceptual feedback is constantly monitored and triggers plan corrections is often required.

In our work we will address these problems, i.e., how to construct grasp hypothesis from sensory data, how to learn from experience and how to monitor success and recover from failures, and provide contributions regarding learning manipulation capabilities through exploration and based on multi-sensory perception, e.g., visual, tactile and proprioceptive. We will use probabilistic approaches to deal with uncertainties and exploratory strategies to let the robot discover low-level information it needs to execute its task. We will construct suitable object representations from sensory data for grasping purposes and evaluate techniques for successful grasp and task completion. In summary, our main objectives are:

- to learn grasp-related parameters from sensory data so that the robot will be able to transfer its knowledge to new situations and execute grasps on previously unseen objects in a task-oriented way,
- to learn both from failures and successful trials, and
- to monitor the state (success/failure) during grasp execution and apply the obtained knowledge from experience to correct actions if failure is estimated.

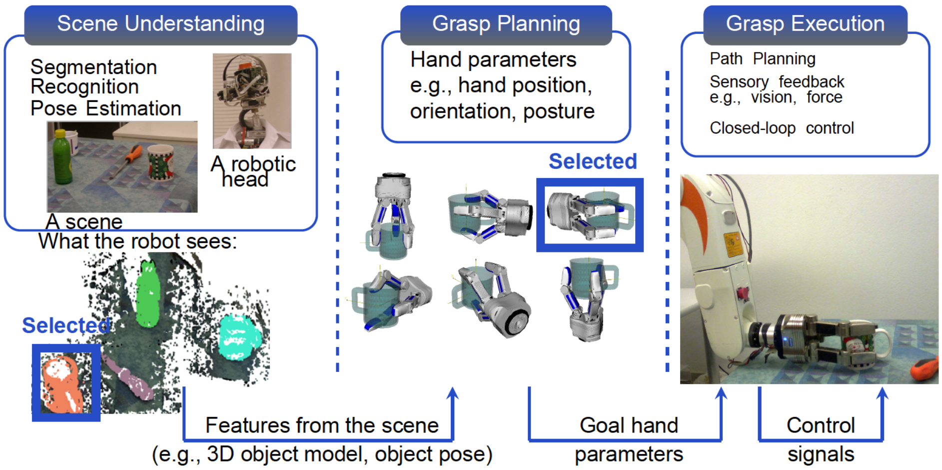


Figure 1: Grasping process: Scene understanding where visual input is use to extract descriptors to obtain hand parameters, Grasp Planning where descriptors along with other parameters of interest such as task requirements are used to decide hand pose and configuration, Grasp Execution where planned grasp is realized and success is monitored based on sensory data.

2 Survey of the Field and Progress Beyond the State of the Art

Grasping is a key building block of autonomous robots and as a result it has received much attention in the last three decades[6,7,8,9,].[10] Different approaches have been studied, e.g., analytic[11,12] and data-driven[13,14,].[15] Morevoer, different subproblems have been addressed, e.g., grasp planning ,[16] force control ,[17] stability estimation from sensory data after grasp execution[18] or grasp adaptation .[19] However, current robotic systems still have severe limitations in terms of dealing with novelty, uncertainty and unforeseen situations. Limitations arise from multiple sources: noisy and incomplete perceptual data, insufficient experience and high dimensionality of the problem involving variables with complex relations.

[6] V.-D. Nguyen. "Constructing force-closure grasps". In: *IEEE Int. Conf. Robotics and Automation (ICRA)*. vol. 3. Apr. 1986, pp. 1368–1373.

[7] C. Ferrari and J. Canny. "Planning Optimal Grasps". In: *IEEE Int. Conf. on Robotics and Automation*. Vol. 3. 1992, pp. 2290–2295.

[8] A. Bicchi and V. Kumar. "Robotic Grasping and Contact: A Review." In: *IEEE Int. Conf. on Robotics and Automation*. 2000, pp. 348–353.

[9] A. Sahbani, S. El-Khoury, and P. Bidaud. "An overview of 3D object grasp synthesis algorithms". In: *Robotics and Autonomous Systems* 60.3 (2012), pp. 326–336.

[10] J. Bohg et al. "Data-Driven Grasp Synthesis – A Survey". In: *Robotics, IEEE Transactions on* 30.2 (Apr. 2014), pp. 289–309.

[11] K.B. Shimoga. "Robot grasp synthesis algorithms: A survey". In: *The Int. Journal of Robotics Research* 15.3 (1996), p. 230.

[12] Bicchi and Kumar, "Robotic grasping and contact: a review".

[13] Saxena, Driemeyer, and Ng, "Robotic Grasping of Novel Objects using Vision".

[14] L. Montesano and M. Lopes. "Learning Grasping Affordances from Local Visual Descriptors". In: *IEEE Int. Conf. on Development and Learning*. 2009.

[15] Bohg et al., "Data-Driven Grasp Synthesis – A Survey".

[16] T. Asfour M. Przybylski and R. Dillmann. "Planning Grasps for Robotic Hands using a Novel Object Representation based on the Medial Axis Transform". In: *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. 2011, pp. 1781–1788.

[17] Romano et al., "Human-inspired robotic grasp control with tactile sensing".

[18] Y. Bekiroglu, R. Detry, and D. Kragic. "Learning tactile characterizations of object- and pose-specific grasps". In: *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*. 2011, pp. 1554–1560.

[19] E. L. Sauser et al. "Iterative learning of grasp adaptation through human corrections". In: *Robotics and Autonomous Systems* 60.1 (Jan. 2012), pp. 55–71.

Vision is one of the modalities which contribute substantially to grasp control and stability .[20] Touch is another one, as supported by numerous studies which show the influence of tactile feedback on different grasp sub-processes[21,22]

In robotics, vision-driven grasping and manipulation have been extensively studied .[23] Vision has typically been used to plan grasping actions, and to update action parameters as objects move to compensate for manipulator positioning inaccuracies and sensor noise. However, most vision based approaches have been used only for objects known to the robot prior to task execution, since they commonly need a desired pose with respect to the object to be defined beforehand, which is not easy for unknown objects. Touch-based grasp controllers have also been studied, with emphasis on designing programs for controlling finger forces to avoid slippage and to prevent crushing objects .[24]

Various approaches for avoiding or recovering unsuitable or potentially failing grasps have been proposed in the literature. An example is to correct grasps by adapting to local geometry using the force-closure criterion.[25] Contact positions are transferred between objects of the same functional class by surface geometry warping. Grasps are adapted by moving finger contacts onto the object's surface to reach force-closure, or reject the grasp. Compared to our work, this system does not integrate experience from training data or feedback from grasp execution. Another way is to include an off-line training phase based on examples demonstrated by a teacher[26,27,28] The teacher shows the robot a set of grasps, and the robot autonomously explores more grasps in the neighborhood of those demonstrated by the teacher. The learning process is thus data-driven, based on self-exploration without human intervention. Grasp corrections can be synthesized by matching to a database of stable grasps based on similarity in tactile measurements.[29] If a match similar enough to the current tactile measurements is found in the database, the current grasp was adjusted accordingly. An unsuccessful look-up initiates tactile-based reconstruction of local surface geometry and re-planning to adapt the grasps to the actual local object shape. The assumption is that the recorded stable grasp that resulted in the most similar tactile reading is the best correction of the current grasp. As a statistical modeling of grasp correction is not employed, novel grasps cannot be synthesised due to lacking a continuous mapping within a probabilistic framework. Another method for grasp adaptation is to learn a statistical model to adapt the hand posture based on perceived contacts.[30] Kinesthetic demonstration learning is used to train a Gaussian mixture model (GMM) for prediction of desired joint values and finger pressure from contact signatures. For this a human teacher improves robot grasps while the robot

[20] R.S. Woodworth. "The accuracy of voluntary movement". In: *The Journal of Nervous and Mental Disease* 26.12 (1899), p. 743.

[21] R Johansson and G. Westling. "Roles of glabrous skin receptors and sensorimotor memory in automatic control of precision grip when lifting rougher or more slippery objects". In: *Experimental Brain Research* 56.3 (1984), pp. 550–564.

[22] R. Johansson. "Sensory input and control of grip". In: *Novartis Foundation Symposium*. 1998, pp. 45–59.

[23] Danica Kragic, Andrew T. Miller, and Peter K. Allen. "Real-time Tracking Meets Online Grasp Planning". In: *IEEE International Conference on Robotics and Automation*. 2001, pp. 2460–2465.

[24] Romano et al., "Human-inspired robotic grasp control with tactile sensing".

[25] U. Hillenbrand and M.A. Roa. "Transferring functional grasps through contact warping and local replanning". In: *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*. 2012, pp. 2963–2970.

[26] J. Tegin et al. "Experience based Learning and Control of Robotic Grasping". In: *2006 IEEE-RAS Workshop on Towards Cognitive Humanoid Robots*. 2006.

[27] J. Tegin et al. "Demonstration-based learning and control for automatic grasping". In: *Intelligent Service Robotics* 2.1 (2009), pp. 23–30.

[28] Sauser et al., "Iterative learning of grasp adaptation through human corrections".

[29] P.K. Allen and P. Michelman. "Acquisition and interpretation of 3-D sensor data from touch". In: *Robotics and Automation, IEEE Transactions on* 6.4 (Aug), pp. 397–404.

[30] Sauser et al., "Iterative learning of grasp adaptation through human corrections".

generates a database of poses and contacts. Examples of failed grasps are not explicitly included.

It has been shown that learning how to grasp from grasping examples is viable. A Bayesian approach has been proposed to learn local visual descriptors of good grasping points from images based on a set of trials performed by a robot.[31] Grasp densities defined on the space of 6D object-relative gripper poses has been learned from experience with an importance-sampling algorithm.[32] It has also been showed that task parameters can be included in the learning process, e.g., learning that grasping from the top of an object is not good for pouring task.[33] GMM models have been learned from grasping examples generated offline in simulation for a given object.[34] Compared to these approaches, this study focuses on modelling uncertainty for predictions and learning from both successful and failed grasp examples capturing common properties and relations between them.

Learning models of grasping-related parameters has also been targeted.[35] Generative models have been trained allowing for inference of any variables involved in the learning problem. However, compared to our approach the differences are that, in those approaches a large set of training data is needed to learn the parameters of the model, learning explicitly from negative examples is not addressed and an independent preprocessing step with variable selection, which is not inferred from data, or dimensionality reduction, which changes the data space possibly leading to a loss of information, is needed.

Progress beyond the state of the art:

Problems such as *selecting* the relevant information from the environment, *merging* different sources of information to reduce uncertainty and, making use of experience (even from failures) by relating sensor data to *previous knowledge* remain open. There is no system addressing all these problems in a principled manner in one framework. These three aspects of reasoning will be addressed based on a probabilistic learning approach in this project. In our approach, we will show that learning can be achieved with smaller amount of training data, we make use of failed grasps during training, and we use a latent space which acts as a feature extractor, an automatic view consolidation and an intermediate low dimensional space for regression. In addition, within the same model feature selection is performed which allows for testing the influence of different grasp-related parameters without deterioration in learning performance and also confidence in predictions can be provided.

3 Project Description: Workplan and Milestones

In this project, we will address problems related to three steps of the grasping process. Firstly, we will perform segmentation of the given scene and extract object models based on sensory measurements. Based on these models we will construct grasp hypotheses to achieve a given task. As a final step of the grasping system, we will study how to evaluate achieved grasps based on sensory data and trigger plan corrections if needed. In all these steps, we will follow an exploration based learning strategy.

Grasp Hypotheses Generation (month 12): In order to learn an empirical representation of stable and unstable grasps, the robot will explore objects and execute grasps planned based on their models. This way it is possible to learn which configurations lead to successful task

[31] Montesano and Lopes, "Learning Grasping Affordances from Local Visual Descriptors".

[32] R. Detry et al. "Refining Grasp Affordance Models by Experience". In: *IEEE Int. Conf. on Robotics and Automation (ICRA)*. 2010, pp. 2287–2293.

[33] D. Song et al. "Learning Task Constraints for Robot Grasping using Graphical Models". In: *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*. 2010.

[34] B. Huang et al. "Learning a real time grasping strategy". In: *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. May 2013, pp. 593–600.

[35] Song et al., "Learning Task Constraints for Robot Grasping using Graphical Models".

completion so that later it can plan suitable grasps. The robot will execute multiple grasps in a region of objects. The aim is to make experiments feasible and also let the robot learn the relations between perceptions and the stability outcomes in a region of an object. The sensor signals issued during the execution of grasps, either suggested by a human or generated from low-level visual descriptors, will be observed with the aim of learning what it feels like to grasp an object from a specific side, and learn which grasping configurations lead to a stable grasp. This is important because on real platforms it cannot be guaranteed that the robot will always be able to grasp an object exactly at the same place. We would like to allow part-based grasps which are important for task-oriented grasping. Different tasks may require different parts of the objects to be grasped. Example task, object and grasp requirements can be seen in Fig. 2.

Measure of Success: The first stage scenario will involve demonstration of a robot that can use visual data extracted from a given scene and be able to generate reachable grasps on different parts of the objects.

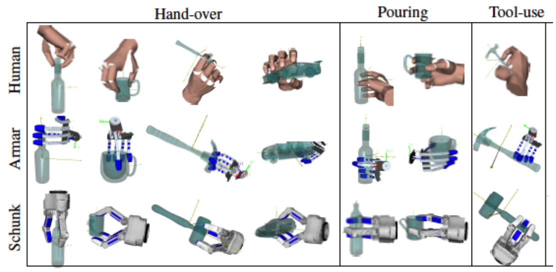
Learning from Experience (month 30): We will look at using object segmentation that will identify different parts of the object, e.g., handle, container. This way, we can associate task requirements with object parts, e.g., grasping an object from its handle for a certain task.

We will study modeling techniques to encode high-level task knowledge from humans and low-level planning to meet the task and stability requirements. We will develop a probabilistic model for joint representation of several sensory modalities and action parameters for goal-oriented grasping. The model will allow us to answer different grasping-related questions within the same framework. We will initially use a latent variable model referred to as Manifold Relevance Determination (MRD)[36] that learns a structured representation of all available sensor modalities, and of robot action parameters, and extend the approach later for online learning (Figure 3). We will study the effects of different parameters in terms of generalization properties and choose the most efficient ones leading to best results, e.g., how the object shape should be represented taking segmented parts into consideration.

We will focus on multiple sensor modalities, aiming to automatically learn which modalities contain information that correlates with another modality or with action parameters, and how to learn the structure of these relationships. The model will provide a conditional structure which allows for feature selection and merging. The structure of the model will be learned from data which means that it encodes previous knowledge. We will compare this model with a more traditional discriminative approach which does not address *selecting* the relevant information from the environment, *merging* different sources of information to reduce uncertainty or, making use of experience by relating sensor data to *previous knowledge*. The MRD model will learn a single latent representation consolidating several observation modalities or views through the use of Gaussian process priors. Views and modalities will be general vector valued observations and in our specific application, firstly, they will consist of the hand pose and the tactile sensing for both the successful and the unsuccessful grasp, the object orientation and the object type, resulting in six different views in total. *Measure of Success: The second stage scenario will demonstrate that the robot can choose the right objects and suitable grasps for the task.*

Grasp Success Monitoring and Correction (month 48): We will focus on how perceptual feedback (e.g., visual and tactile and proprioceptive) available to a robot, before attempting to manipulate an object, can be utilized to predict grasp stability during grasp execution. This enables a robot to be aware of the outcome of its grasping action and allows it to trigger plan corrections. We will demonstrate the applicability of the trained models to correcting unstable grasps, when a grasp is estimated to lead to a failure based on the available sensory data after

[36] Andreas C Damianou et al. "Manifold Relevance Determination". In: *International Conference on Machine Learning*. June 2012, pp. 145–152.



Tasks	The object	The grasp should
Hand-over	can be of any kind (all 4 object classes)	leave enough uncovered surface or handle for safe regrasp
Pouring	should be pourable (bottle, mug)	not cover opening part for pouring out the liquid
Tool-use	should be a tool (hammer)	be on the handle for applying the function of the tools

Figure 2: Task-oriented grasping: Task-constrained grasp examples using different hand models on the left and example task requirements on objects and grasps.

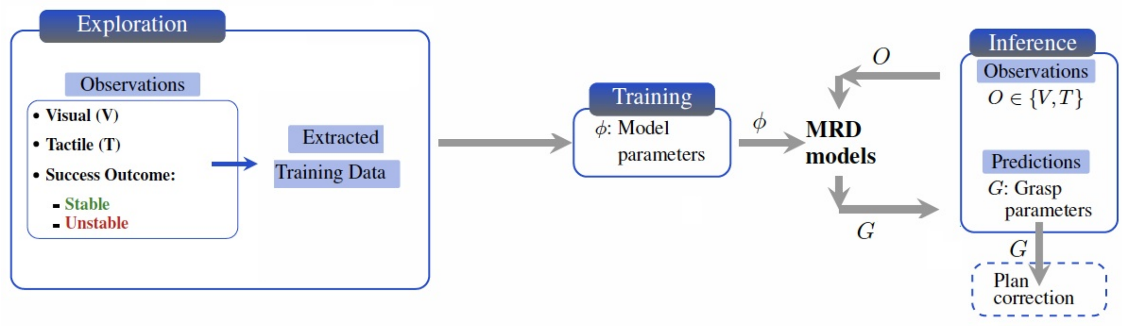


Figure 3: The system overview: Our approach involves exploration, training and inference steps in order to answer grasp-related questions. During grasping trials, the robot gathers visual and tactile observations as well as success outcomes of each grasp, i.e., whether or not lifting leads to slippage or rotation. The extracted data from these observations are used to train MRD models and obtain model parameters,ϕ. These MRD models are then used to infer grasp parameters, G, given a set of observations, O, based on the obtained models with the aim of using those parameters for grasping and potentially plan corrections.

grasp execution before lifting. Our approach will learn associations between stable and unstable grasps that the robot experienced during the exploration phase. During inference our models will produce stable grasps that reflect the characteristics of the unstable grasps. We will use a Gaussian process prior to model a functional relationship between unstable and stable grasps. The model will also be able to handle scenarios where an unstable grasp can be corrected in several different ways due to its multi-modal structure. This is not possible in a regression model which is unimodal and will model the response by the mean of the stable grasps for which there is no guarantee that it will be stable.

Measure of Success: The third stage scenario will demonstrate that the robot can estimate if the grasp it executed is likely to lead to a failure (e.g., prediction of success given grasp configuration and obtained tactile readings) and apply corrections (e.g., synthesize a grasp configuration that is likely to lead to success, given the current grasp configuration and object features).

4 Significance

To our best knowledge, very few works have engaged in developing a comprehensive embodied-cognitive system for object grasping and manipulation in real-world settings. In such situations, robots need to engage in a large collection of sensorimotor modalities such as visual recognition of objects and actions, visuomotor transformations for grasp planning, and low-level sensorimotor coordination for stable, robust grasping and manipulation under any task requirements. Our proposed work is dedicated to constructing such a comprehensive system. We will show how sensory information, e.g., visual and tactile, can be used to extract object attributes, how these attributes will be used for grasp planning under the guidance of high-level task requirements, and when combined with haptic (tactile) cues, how the grasp execution can be adapted on-line to enable successful, goal-oriented object manipulation to assist the human users in their everyday lives. We believe, the proposed research in task-oriented grasp planning, execution and grasp adaptation will pave an important pathway towards the development of autonomous artificial agents that can interact with their environments.

5 Preliminary Results

Regarding the first part of the project, we have previously studied how to generate[37] and transfer[38] grasps between objects given 3D data, how to explore a given scene to understand if there are one or multiple objects[39] and construct approximate object models[40] from visual and tactile measurements. In this part of the project we will build upon the experiences gained through these works and prepare the tools to obtain suitable data to learn how to grasp from sensory data.

We presented preliminary results regarding grasp success evaluation[41,42,43] where we had constrained settings with limited grasp configurations on a limited set of objects. We will extend that method to deal with more objects, more variant grasping configurations. We will study learning models that characterize only a part of an object which would be applicable to novel objects that share the same part.

We proposed a probabilistic framework[44] for grasp modeling and stability assessment. The framework facilitated assessment of grasp success in a goal-oriented way, taking into account both geometric constraints for task affordances and stability requirements specific for a task. We integrated high-level task information introduced by a teacher in a supervised setting with low-level stability requirements acquired through a robot's self-exploration. The conditional relations between tasks and multiple sensory streams (vision, proprioception and tactile) were modeled using Bayesian networks. In that we assumed that object models and the class they belong to were given. A human teacher was labelling each grasp hypothesis as being suitable for the defined tasks. This inspection was being done by checking the geometry of the grasps, i.e., visually. Then, the robot was exploring each grasp hypothesis by executing the tasks to further eliminate unsuitable hypothesis.

The trained models were generative allowing for inference of any variables involved in the

[37] Yasemin Bekiroglu, K. Huebner, and D. Kragic. "Integrating grasp planning with online stability assessment using tactile sensing". In: *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. May 2011, pp. 4750–4755.

[38] F.T. Pokorny, Y. Bekiroglu, and D. Kragic. "Grasp moduli spaces and spherical harmonics". In: *Robotics and Automation (ICRA), 2014 IEEE International Conference on*. May 2014, pp. 389–396.

[39] Marten Bjorkman and Yasemin Bekiroglu. "Learning to disambiguate object hypotheses through self-exploration". In: *Humanoid Robots (Humanoids), 2014 14th IEEE-RAS International Conference on*. Nov. 2014, pp. 560–565.

[40] M. Bjorkman et al. "Enhancing visual perception of shape through tactile glances". In: *Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on*. Nov. 2013, **(CoTeSys Cognitive Robotics Best Paper Award Finalist)**, pp. 3180–3186.

[41] Yasemin Bekiroglu et al. "Assessing Grasp Stability Based on Learning and Haptic Data". In: *Robotics, IEEE Transactions on* 27.3 (June 2011), pp. 616–629.

[42] Yasemin Bekiroglu, D. Kragic, and V. Kyrki. "Learning grasp stability based on tactile data and HMMs". In: *RO-MAN, 2010 IEEE*. Sept. 2010, pp. 132–137.

[43] Yasemin Bekiroglu, R. Detry, and D. Kragic. "Learning tactile characterizations of object- and pose-specific grasps". In: *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*. Sept. 2011, pp. 1554–1560.

[44] Y. Bekiroglu et al. "A probabilistic framework for task-oriented grasp stability assessment". In: *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. May 2013, **(Best Manipulation Paper Award)**, pp. 3040–3047.

learning problem. We will build upon that work and extend it so that: we can learn from limited data, learn both from successful and unsuccessful examples, test the influence of different grasp-related parameters without deterioration in learning performance, perform grasp correction based on experience, provide confidence in estimates, involve object features obtained from segmented parts to associate them with task parameters and to deal with novel objects.

We have tested an initial implementation of the proposed system[45] regarding encoding grasping knowledge from sensory data and have submitted a journal paper based on the findings. We have shown that the chosen visual and tactile parameters can be successfully learned and obtained models can be used for goals such as correcting grasps given object type and failing grasp configurations (Figure 4). Other goals such as predicting expected tactile readings given grasp configuration, or object recognition given tactile readings could also be achieved.

The initial results are promising, however further evaluations on different objects of varying shapes and sizes and also tasks need to be performed. This requires involving more task parameters and object related paramaters encoding object shape. Regarding grasp correction/adaptation strategies, we have also studied different approaches[46,47] and plan to investigate the feasibility of merging crucial findings from those with the current research.

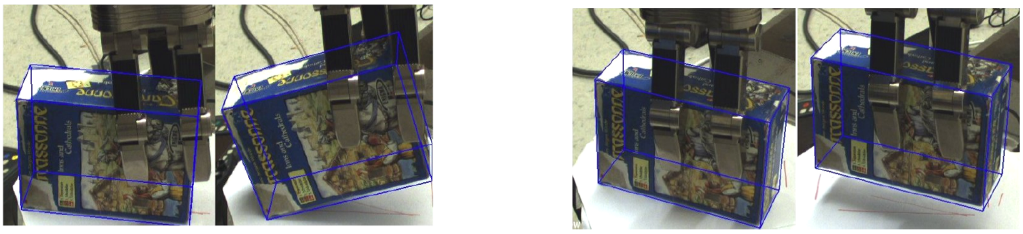


Figure 4: An application of our MRD model: Our method enables inference of better grasping poses (right) given that the current pose (left) is predicted to lead to failure (rotation during lifting).

6 Independent line of research

In this project, a novel scientific area will be explored by the PI independently and a new approach that no other researcher in CVAP is addressing will be followed. This work is substantially different from the PI's previous research. This project will enable the PI to conduct research by supervising more closely a PhD student and explore the proposed methodology in depth independently from her main supervisor. This project relates to the other projects in the group as it will provide important tools to support systems with manipulation needs. The research findings in this project will be complementary to the ongoing project that finances the PI's postdoctoral research currently.

7 Form of employment

The PI will be employed for four years as a researcher. It is also planned that one doctoral student will be funded through this project who will also take part in another project in CVAP. This way the student will be able to collaborate with other researchers and gain more experience.

[45] Yasemin Bekiroglu et al. "Probabilistic Consolidation of Grasp Experience". In: *The International Journal of Robotics Research, under review* ().

[46] Kaiyu Hang et al. "Hierarchical Fingertip Space for Synthesizing Adaptable Fingertip Grasps". In: *IEEE International Conference on Robotics and Automation, ICRA 2014 Workshop: Autonomous Grasping and Manipulation: An Open Challenge*. 2014.

[47] Miao Li et al. "Learning of grasp adaptation through experience and tactile sensing". In: *Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on*. Sept. 2014, pp. 3339–3346.

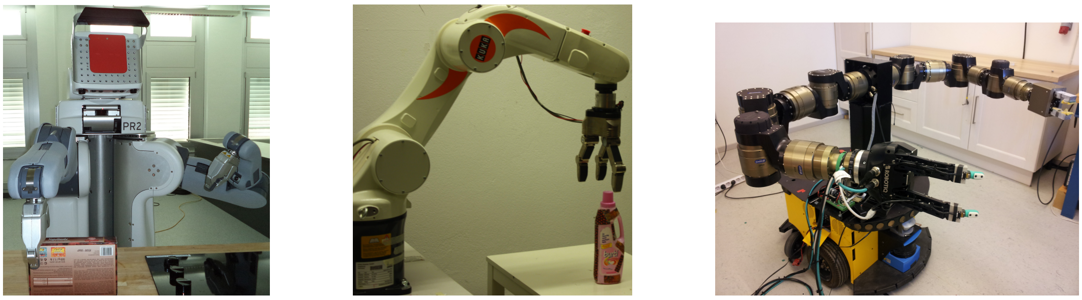


Figure 5: Robots PR2, Kuka arm and Schunk Hand, the dual arm platform with the two-finger gripper and the Robotiq hand.

The student will have background in: machine learning and robotics, will be involved in all stages of the project and will work closely with the PI. There are several ongoing projects in CVAP and the student will benefit from the direct interaction with these. The PI also plans to invest a significant amount of her research time on the project.

8 International and national collaboration

Currently the PI is involved in the EU project RoboHow with the vision of a cognitive robot that autonomously performs complex everyday manipulation tasks and extends its repertoire of such by acquiring new skills using web-enabled and experience-based learning as well as by observing humans. Collaboration with the RoboHow project can lead to efficient progress as RoboHow focuses on comprehensive knowledge-enabled robot control models for complex manipulation tasks. During the project, it is also planned to visit several research laboratories where similar goals are pursued and the PI is already in contact with, Robot Learning Group at Max-Planck Institute for Intelligent Systems in Germany, Learning Algorithms and Systems Laboratory at EPFL in Switzerland.

9 Equipment

There are several state-of-the-art robot equipments in CVAP, Fig. 9: a mobile dual arm robot with 7 DOF Schunk arms, ATI Mini45 6DOF force/torque sensors at the wrists, a two-finger gripper and a three-finger Robotiq hand with self-adaptive fingers; a 6 DOF industrial KUKA arm with a three-finger 7 DOF Schunk hand; and a PR2 which is a mobile humanoid robot with two backdrivable arms, two-finger grippers, stereo head cameras and fore-arm cameras. In those setups, there are also calibrated Kinect cameras that deliver RGBD Images, i.e., a combination of three color channels (red, green and blue) and another for the depth data. As for the touch sensors, the Schunk hand is equipped with six pressure-sensitive tactile array sensors, the PR2 has similar pressure sensors with lower resolution on its grippers and there are three BioTac sensors attached to the Robotiq hand. Among these, the BioTac sensors provide the richest information. They are capable of detecting the full range of sensory information that human fingers can detect: forces, microvibrations, and thermal gradients.

Interdisciplinarity

My application is interdisciplinary

☐

An interdisciplinary research project is defined in this call for proposals as a project that can not be completed without knowledge, methods, terminology, data and researchers from more than one of the Swedish Research Councils subject areas; Medicine and health, Natural and engineering sciences, Humanities and social sciences and Educational sciences. If your research project is interdisciplinary according to this definition, you indicate and explain this here.

Click here for more information

Scientific report

Scientific report/Account for scientific activities of previous project

Budget and research resources

Project staff

Describe the staff that will be working in the project and the salary that is applied for in the project budget. Enter the full amount, not in thousands SEK.

Participating researchers that accept an invitation to participate in the application will be displayed automatically under Dedicated time for this project. Note that it will take a few minutes before the information is updated, and that it might be necessary for the project leader to close and reopen the form.

Dedicated time for this project*

	Role in the project	Name	Percent of full time
1	Applicant	Yasemin Bekiroglu	30
2	Other personnel without doctoral degree	Phd Student A	80

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	2018	2019	Total
1	Applicant	Yasemin Bekiroglu	30	204,000	209,000	214,000	219,000	846,000
2	Other personnel without doctoral degree	Phd Student A	80	440,000	484,000	532,000	586,000	2,042,000
	Total			644,000	693,000	746,000	805,000	2,888,000

Other costs

Describe the other project costs for which you apply from the Swedish Research Council. Enter the full amount, not in thousands SEK.

Premises

	Type of premises	2016	2017	2018	2019	Total
1	Offices	78,000	84,000	90,000	97,000	349,000
	Total	78,000	84,000	90,000	97,000	349,000

Running Costs

	Running Cost	Description	2016	2017	2018	2019	Total
1	Travel costs	Conferences and Research Visits	40,000	40,000	40,000	40,000	160,000
2	Material	Computers	20,000				20,000
	Total		60,000	40,000	40,000	40,000	180,000

Depreciation costs

Depreciation cost	Description	2016	2017	2018	2019

Total project cost

Below you can see a summary of the costs in your budget, which are the costs that you apply for from the Swedish Research Council. Indirect costs are entered separately into the table.

Under Other costs you can enter which costs, aside from the ones you apply for from the Swedish Research Council, that the project includes. Add the full amounts, not in thousands of SEK.

The subtotal plus indirect costs are the total per year that you apply for.

Total budget

Specified costs	2016	2017	2018	2019	Total, applied	Other costs	Total cost
Salaries including social fees	644,000	693,000	746,000	805,000	2,888,000		2,888,000
Running costs	60,000	40,000	40,000	40,000	180,000		180,000
Depreciation costs					0		0
Premises	78,000	84,000	90,000	97,000	349,000		349,000
Subtotal	782,000	817,000	876,000	942,000	3,417,000	0	3,417,000
Indirect costs	334,000	360,000	387,000	418,000	1,499,000		1,499,000
Total project cost	1,116,000	1,177,000	1,263,000	1,360,000	4,916,000	0	4,916,000

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

It is planned to hire a PhD student. The remaining salary of the student will be financed through another project in CVAP.

Other funding

Describe your other project funding for the project period (applied for or granted) aside from that which you apply for from the Swedish Research Council. Write the whole sum, not thousands of SEK.

Other funding for this project

Funder	Applicant/project leader	Type of grant	Reg no or equiv.	2016	2017	2018	2019

CV and publications

CV

Curriculum Vitae-Yasemin Bekiroglu

1. Higher Education Qualifications

- Ph.D., November 2012, Computer Science, Royal Institute of Technology KTH, Sweden
- M.S., 2008, Applied Artificial Intelligence, Dalarna University, Sweden, *Non-Stationary Feature Extraction Techniques for Automatic Classification of Impact Acoustic Signals*
- M.S., 2007, Computer Engineering, Karadeniz Technical University, Turkey, *Evaluation of Similarity Between Human Faces with Principal Component Analysis*
- B.S., 2005, Computer Engineering, Karadeniz Technical University, Turkey
  2004-2005, Computer Science, Erasmus Student, Roskilde University, Denmark

2. Doctoral Degree

- 2012, November, Computer Science, KTH, Sweden, Thesis: Learning to Assess Grasp Stability from Vision, Touch and Proprioception, Supervisor: Prof. Danica Kragic

3. Postdoctoral Position

- 2012, December - Present Computer Science., Computational Vision and Active Perception Lab (CVAP/CAS), KTH, Sweden,

4. Qualification required for appointments as a docent

- The applicant plans to file the application during 2016

5. Current Position

- Postdoctoral Researcher, CVAP/CAS, KTH, Full-time research (100%) on grasping and manipulation, computer vision and machine learning, December 2012 - Present

6. Previous Positions and Periods of Appointment

- Ph.D. Student, KTH, CVAP/CAS, Sweden, September 2008-November 2012
- Research Assistant, Karadeniz Technical University, Department of Computer Engineering, Turkey, September 2005-August 2008

7. Interruption in research

- None

8. Supervision

- None in the capacity of main supervisor, but co-supervising 3 PhD students:
  - Kaiyu Hang, Ph.D. studies on grasping and manipulation
  - Puren Guler, Ph.D. studies on tracking deformable objects
  - Johannes Stork, Ph.D. studies on in-hand manipulation

9. Other Merits of Relevance to the Application:

Project Involvement

- RoboHow.Cog Web-enabled and experience-based cognitive robots (FP7-ICT-288533), 2012-Present
- eSMCs: Extending Sensorimotor Contingencies to Cognition (FP7-IST-270212), 2012-2014
- CogX: Cognitive Systems that Self-Understand and Self-Extend (FP7-ICT-215181), 2008-2012

Awards and Scholarships

- KTH Innovation Competition 2014 Prototyping and user testing
- IEEE/RSJ IEEE/RSJ International Conference on Intelligent Robots and Systems IROS CoTeSys Cognitive Robotics Best Paper Award Finalist Tokyo, Japan, 2014
- Best Manipulation Paper Award, IEEE International Conference on Robotics and Automation (ICRA) ICRA, Karlsruhe, Germany, 2013
- Best presentation among PhD students at CogX project, 2011
- Scholarship by The Scientific and Technological Research Council of Turkey, 2005-2007
- Erasmus Scholarship for Exchange Studies, 2004-2005

Teaching

- Supervision, KTH, 2010 - Present
  Judith Butepage, intern on grasping and manipulation, ongoing, main supervision
  Francisco Vina, Ph.D. studies on grasping and manipulation, co-supervision, 2012-2014
  Johannes Exner, intern on shape modeling, main supervision, 2014
  Mateusz Herczka, intern on robotic software, main supervision, 2014
  Lu Wang, "Learning Task-Based Robotic Grasping, with Vision, Haptics and Proprioception", M.S., 2012, co-supervision
  Claudio Giovanoli, "Potential Field Based Tactile Exploration", M.S., 2011
  Maren Leithe, "Use of tactile sensors for object modelling", Intern, 2010
  Anaïs Peyrucq, "Learning grasp stability based on tactile data", Intern, 2010
- Lecturer, KTH, 2014-2015: Scientific Programming
- Lab examiner, KTH, 2014: Image Analysis and Computer Vision
- Teaching Assistant, KTH, 2012: Image Analysis and Computer Vision; Karadeniz Technical University 2005-2007: Microprocessors, Computer Systems, Data Structures, Artificial Intelligence

Journal and Conference Reviewer

- Member of the Program Committee of the International Conference on Computer Vision Systems (ICVS) 2015, reviewer for Advanced Robotics 2015, International Conference on Advanced Robotics (ICAR) 2015, IEEE-RAS International Conference on Humanoid Robots (Humanoids) 2014, IEEE Transactions on Robotics 2014 - current, Journal of Intelligent and Robotic Systems 2013 - current, IEEE Transactions on Haptics 2013 - current, IEEE IROS 2011 - current, IEEE ICRA 2009 - current

Research Visits

- University of Bremen, May, 2013, building a ROS package for grasp stability assessment
- University of Bremen, March, 2014, integrating the package with CRAM, a Cognitive Robot Abstract Machine

Conference Talks

- Humanoids 2014, IROS 2014, ICRA 2014, ICRA 2013, IROS 2012, IROS 2011, ICRA 2011, Ro-Man 2010, Workshop organizer at 2015 Robotics: Science and Systems (RSS)

International Co-authors in Publications

- Prof. Ville Kyrki, Aalto University; Dr. Renaud Detry, University of Liége; Prof. Aude Billard, École Polytechnique Fédérale De Lausanne; Miao Li École Polytechnique Fédérale De Lausanne;Dr. Jimmy Alison Jørgensen, University of Southern Denmark; Dr. Florian T. Pokorny UC Berkeley

Journal Publications in Preparation and Submission

- Bekiroglu, Y., Detry, R., Ek., C. H. (2015), Learning grasp stability from vision and touch, *to be submitted to IEEE Robotics and Automation Magazine*.
- Bekiroglu, Y., Exner, J., Bjorkman, M. (2015), Object Shape from Vision and Touch, *to be submitted to IEEE Transactions on Haptics, Special Issue on Active Touch Sensing in Robots, Humans and Other Animals*.
- Bekiroglu, Y., Detry, R., Damianou, A., Stork, J. A., Ek, C.H. (2015), Probabilistic Consolidation of Grasp Experience, International Journal of Robotics Research *under review*.
- Bekiroglu, Y., Pokorny, F. T., Pauwels, K. (2015), A collaborative grasping and manipulation database, *to be submitted to International Journal of Robotics Research*.

Publication list

Publication List – Yasemin Bekiroglu

1 Peer-reviewed Original Articles

(*) **Bekiroglu**, Y., Laaksonen, J., Jørgensen, J. A., Kyrki, V. & Kragic, D. (2011), Assessing grasp stability based on learning and haptic data. ***IEEE Transactions on Robotics***, Vol.27, No.3, 616–629, **(Impact Factor: 2.649)**, [47].

2 Peer-reviewed Conference Papers

Stork, J. A., Ek, C. H., **Bekiroglu**, Y., & Kragic, D., Learning Predictive State Representation for In-Hand Manipulation. *IEEE International Conference on Robotics and Automation (ICRA)*, 2015, Seattle, Washington, USA, *accepted*.

Bjorkman, M., **Bekiroglu**, Y., & Kragic, D., Learning to Disambiguate Object Hypotheses through Self-Exploration. *IEEE-RAS International Conference on Humanoids Robots (HUMANOIDS)*, 2014, Madrid, Spain.

Guler, P., **Bekiroglu**, Y., Gratal, X., Pauwels, K., & Kragic, D., What is in the Container? Classifying Object Contents from Vision and Touch. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2014, Chicago, USA, [2].

(*) Li, M., **Bekiroglu**, Y., Kragic, D., and Billard, A., Learning of Grasp Adaptation through Experience and Tactile Sensing. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2014, Chicago, USA, [1].

Pokorny, F. T., **Bekiroglu**, Y., Bjorkman, M., Exner, J., and Kragic, D., Grasp Moduli Spaces, Gaussian Processes and Multimodal Sensor Data. *RSS 2014 Workshop: Information-based Grasp and Manipulation Planning, Berkeley, USA.*

Hang, K., Li, M., Stork, J. A., **Bekiroglu**, Y., Billard, A., and Kragic, D., Hierarchical Fingertip Space for Synthesizing Adaptable Fingertip Grasps. *ICRA 2014 Workshop: Autonomous Grasping and Manipulation: An Open Challenge, Hong Kong, China.*

Pokorny, F. T., **Bekiroglu**, Y., & Kragic, D., Grasp Moduli Spaces and Spherical Harmonics. *IEEE International Conference on Robotics and Automation (ICRA)*, 2014, Hong Kong, China, [1].

Vina, F., **Bekiroglu**, Y., Smith, C., Karayiannidis, Y. & Kragic, D., Predicting Slippage and Learning Manipulation Affordances through Gaussian Process Regression. *IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, 2013.

Bjorkman, M., **Bekiroglu**, Y., Hogman, V., Kragic & D., Enhancing Visual Perception of Shape through Tactile Glances. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2013, **IROS CoTeSys Cognitive Robotics Best Paper Award Finalist**, [4].

(*) **Bekiroglu**, Y., Song, D., Wang, L., & Kragic, D., A Probabilistic Framework for Task-Oriented Grasp Stability Assessment. *IEEE International Conference on Robotics and Automation (ICRA)*, 2013, **Best Manipulation Paper Award**, [9].

(*) **Bekiroglu**, Y., Detry, R., & Kragic, D., Learning Tactile Characterizations of Object-And Pose-specific Grasps. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2011, [14].

(*) **Bekiroglu**, Y., Hübner, K., & Kragic, D., Integrating Grasp Planning with Online Stability Assessment using Tactile Sensing. *IEEE International Conference on Robotics and Automation (ICRA)*, 2011, [14].

Bekiroglu, Y., Kyrki, V., & Kragic, D., Learning grasp stability with tactile data and HMMs. *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 2010, [11].

Bekiroglu, Y., Detry, R., & Kragic, D., Grasp Stability from Vision and Touch. *IEEE IROS 2012 Workshop: Advances in Tactile Sensing and Touch-based Human-Robot Interaction*, [2].

Bekiroglu, Y., Song, D., Wang, L. & Kragic, D., Learning Task- and Touch-based Grasping, *IEEE IROS 2012 Workshop: Beyond Robot Grasping - Modern Approaches for Dynamic Manipulation*.

Bekiroglu, Y., Detry, R. & Kragic, D., Joint Observation of Object Pose and Tactile Imprints for Online Grasp Stability Assessment, *IEEE ICRA 2011 workshop: Manipulation Under Uncertainty*, [2].

Bekiroglu, Y., Laaksonen, J., Jørgensen, J. A., Kyrki, V. & Kragic, D., Learning grasp stability based on haptic data, *Robotics: Science and Systems (RSS) 2010 workshop: Representations for object grasping and manipulation in single and dual arm tasks*, [11].

3 Monographs

Bekiroglu, Y., Learning to Assess Grasp Stability from Vision, Touch and Proprioception, 2012, *PhD Thesis*, ISBN 978-91-7501-522-4.

Bekiroglu, Y., Elementary grasping actions for grasping polyflaps, 2009, *technical report*, Skolan för datavetenskap och kommunikation, Kungliga Tekniska högskolan, TRITA-CSC-CV, 1653-6622 ; 2009:4, Stockholm.

4 Research Review Articles

None

5 Books and Book Chapters

None

6 Patents

None

7 Open Access Databases

Real and simulated tactile data from grasping experiments with the Schunk Dexterous hand, *url:* `http://www.csc.kth.se/~yaseminb/`

8 Popular Science Articles/Presentations

None

Summary

The conferences listed are the leading international conferences in the robotics field. IEEE Transactions on Robotics is with the impact factor 2.649 and the rank: 1/21-Q1 in 2013. The five publications that are the most relevant to the project are marked with an asterisk (*). The number of citations is indicated at the end of the references. Citation statistics is provided from Google Scholar on the 30th of March 2015. The total number of citations and the h-index are 118 and 6 respectively.

CV

Name: Yasemin Bekiroglu	**Doctorial degree:** 2012-11-14
Birthdate: 19820124	**Academic title:** Doktor
Gender: Female	**Employer:** Kungliga Tekniska högskolan

Research education

Dissertation title (swe)
Inlärning av manipulationsförmågor från syn, känsel och proprioception för att förstå grepp stabilitet

Dissertation title (en)
Learning to Assess Grasp Stability from Vision, Touch and Proprioception

Organisation	Unit	Supervisor
Kungliga Tekniska Högskolan, Sweden Sweden - Higher education Institutes	CVAP, Datorseende och robotik	Danica Kragic

Subject doctors degree	ISSN/ISBN-number	Date doctoral exam
10201. Datavetenskap (datalogi)	ISSN 1653-5723 ISBN: 978-91-7501-522-4	2012-11-14

Publications

Name: Yasemin Bekiroglu	**Doctorial degree:** 2012-11-14
Birthdate: 19820124	**Academic title:** Doktor
Gender: Female	**Employer:** Kungliga Tekniska högskolan

Bekiroglu, Yasemin has not added any publications to the application.

Register

Terms and conditions

The application must be signed by the applicant as well as the authorised representative of the administrating organisation. The representative is normally the department head of the institution where the research is to be conducted, but may in some instances be e.g. the vice-chancellor. This is specified in the call for proposals.

The signature*from the applicant*confirms that:

- the information in the application is correct and according to the instructions form the Swedish Research Council
- any additional professional activities or commercial ties have been reported to the administrating organisation, and that no conflicts have arisen that would conflict with good research practice
- that the necessary permits and approvals are in place at the start of the project e.g. regarding ethical review.

The signature *from the administrating organisation* confirms that:

- the research, employment and equipment indicated will be accommodated in the institution during the time, and to the extent, described in the application
- the institution approves the cost-estimate in the application
- the research is conducted according to Swedish legislation.

The above-mentioned points must have been discussed between the parties before the representative of the administrating organisation approves and signs the application.

Project out lines are not signed by the administrating organisation. The administrating organisation only sign the application if the project outline is accepted for step two.

Applications with an organisation as applicant is automatically signed when the application is registered.