Chapter 5 - Recognition of grasping primitives using tactile sensory data

Chapter 5

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5.1 Introduction

Over the past few years, several research fields (e.g. human-computer interface sciences, crowd behaviour, medical rehabilitation, robotics, surveillance, and sport performance analysis) have focused some of their attention on the understanding and analysis of human behaviour and human motions [Aggarwal and Ryoo, 2011]. In robotics, the analysis of human movements has been applied (among others) in research areas concerning the task of learning by imitation of human demonstrations [Billard et al., 2008]. This approach was motivated by principles described in several studies from human developmental sciences, which propose that humans learn most of their skills by observing and analysing others performing those tasks (observational learning) [Magill and Anderson, 2007].

Robot learning by human demonstration consists of using examples (successful and failed) of a task performed by humans, to extract key-points and other types of constraints (e.g. velocities, contact intensity, and trajectories) and statistics (e.g. causal dependencies, alternative redundancies, and contextual preferences). The data extracted from the demonstrations is used to estimate several parameters of the model of the task being learned.

The diversity of the demonstrations is essential to provide the robotic system with a robust model of the task. The robustness of the model establishes the capability to deal autonomously with (partially) new contexts (generalization capability). The approaches based on the robot learning by human demonstration try to implement generalizable models of the tasks, in contrast to the traditional approaches consisting of the full analytic formulation and specification of the models.

The work presented in this chapter of the thesis intends to contribute to the development of autonomous robotic hands by modelling the strategies used by humans to manipulate objects using the intrinsic movements of the hand (fingers, palm), which is

Table 5.1: Comparison between the contributions of this work and the related works

Study	Task Model [a]	Approach [b]	Features [c]	Application [d]
This Work	SL	P	T	HMA
[Delson and West, 1996]	TL	D	F, M	RPD
[Tso and Liu, 1996]	TL	P	M	RPD
[Calinon et al., 2007]	TL	P	M	RPD
[Kondo et al., 2011]	SL	D	T	RPD
[Bernardin et al., 2005]	SL	P	T, M	HMA
[Kruger et al., 2010]	SL	P	M	RPD

[a] SL- symbolic level; TL- trajectory level.
[b] P- probabilistic; D- deterministic.
[c] T- tactile based; F- force based; M- movement trajectories based;
[d] HMA- Human movement analysis; RPD- robotic platform development;

known as in-hand manipulation. This type of movements requires the complex coordinated action of the fingers and palm. The temporal characteristics and sequence of the contact between the object, fingers, and palm plays a crucial role in the stabilization of the object being manipulated and consequently in the success of the manipulation task.

This work intends to contribute with the definition of a set of primitives to represent in-hand manipulation movements, as well as the statistical relations between them, in order to model different tasks of this class performed by humans; this is termed generalization capability.

5.2 Related work

In the robotics research field, several approaches to solve the motion learning problem from human demonstrations have been proposed [Billard et al., 2008]. Typically, the proposed approaches can be grouped in two main categories.

One approach represents the movements at the trajectory level and generalizes the representation of the movements through the extraction of statistical regularities from several human demonstrations of the movements. Researchers [Tso and Liu, 1996] applied Hidden Markov Models to encode a training dataset built from a set of human demonstrations. Given a human demonstration as input, the system reproduces the trajectory of the training dataset with the highest likelihood. A simple approach was also presented by [Delson and West, 1996] . The authors simply made a statistical analysis of human demonstrations of a pick-and-place task and defined the range of Cartesian trajectories that can be performed to achieve that task. Calinon [Calinon et al., 2007] proposes to extract continuous constraints from a set of demonstrations, using different initial positions of the object. The Cartesian trajectories of these demonstrations are projected using Principal Component Analysis, and then the constraints are represented through Gaussian Mixture Models. To reproduce the task, the constraints are reprojected on the original data space, and the generalized version of the Cartesian trajectory is found

Figure 5.1: Schematic representation of the typical contact signatures of different grasps. Adapted from [Bernardin et al., 2005]. The boxes highlighted with orange border show different demonstrations of the grasp. The green border highlights the regions of the hand recruited to perform that type of grasp.

by estimating the trajectory that satisfies all the constraints. The approaches described previously propose the learning and encoding of movements at the trajectory level.

This work follows an alternative class of approaches defined using a symbolic learning and encoding of manipulation movements, performing the supervised segmentation and labelling of the primitives during the learning stage. Several works use Support Vector Machines (SVM) to extract sequences of primitives from human demonstrations. The output of the SVM, temporal sequences of labelled data, is combined with Hidden Markov Models (HMM), which provides the most probable temporal sequence of primitives [Vicente, 2007]. The HMM complements the initial sequence of primitives estimated by SVM, which does not consider the temporal relations and dependencies between the data elements.

[Kondo et al., 2011] proposes a method to describe in-hand manipulation movements by recognizing a sequence of contact state transitions between the human hand and the manipulated object. The recognition algorithm is based on a Dynamic Programming approach by comparing the similarity of the contact state transition between an input sequence and templates of manipulation primitives.

[Bernardin et al., 2005] describes a technique to recognize continuous human grasping sequences using HMM. Twelve different grasp primitives are recognized, combining data from palm tactile sensors and hand joint flexure levels from a data glove.

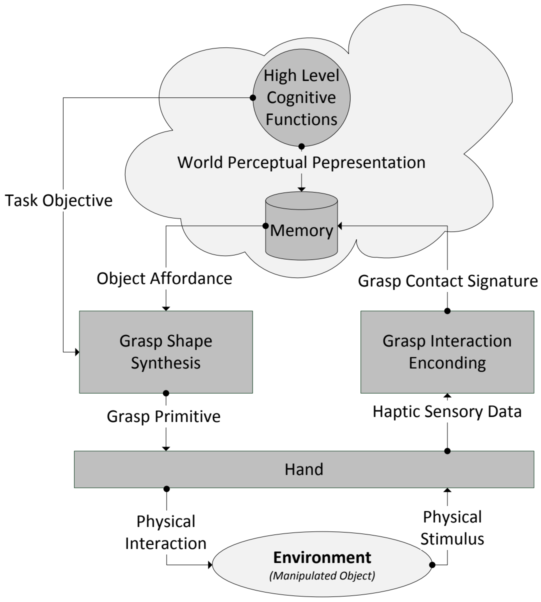


Figure 5.2: Modular representation of the processes involved in the planning and execution of a manipulation task. The representation is simplified to highlight the mechanisms (grasping primitives based on contact signatures) supporting the approach proposed in this chapter, Figure 5.3.

The work by [Kruger et al., 2010] presents the automatic extraction of action primitives (without the necessity of presegmentation and manual labelling) and the corresponding grammar from continuous movements of several human demonstrations of grasping tasks. The approach considers that all the actions can be described by a set of elementary building blocks (action primitives). A grammar (set of rules) defines how the action primitives can be combined. The action primitives are represented by parametric HMM (an extension of HMM). The extraction of the motion primitives from the movements also considers the changes in object state.

Matsuo proposed a segmentation method of human manipulation task that measures the contact force imposed by a human hand on the grasped object [Matsuo et al., 2009]. The work proposes a metric, whose values are used for segmenting a manipulation movement into primitives. The temporal evolution of the metric is calculated from the contact forces sensed at different regions of the hand, as long as the manipulation task progresses.

5.3 Approach overview

This work presents an approach to model the strategies underlying the in-hand manipulation tasks performed by humans. The main contributions of this chapter are summarized in Figure 5.3 and are detailed throughout the next sections of the manuscript.

Several studies [Johansson and Flanagan, 2009], [Castiello, 2005] concluded that a general human manipulation movement can be decomposed on different stages such as reach, load, lift, hold, replace, and unload. The manipulation movements can be segmented and represented as a sequence of primitives, which can be thought of as the elementary building blocks of the task model. The temporal transition between different primitives is made by specific events such as the variation of the intensity and extension of the hand-object contact areas, variation of grip aperture, and type of grasp.

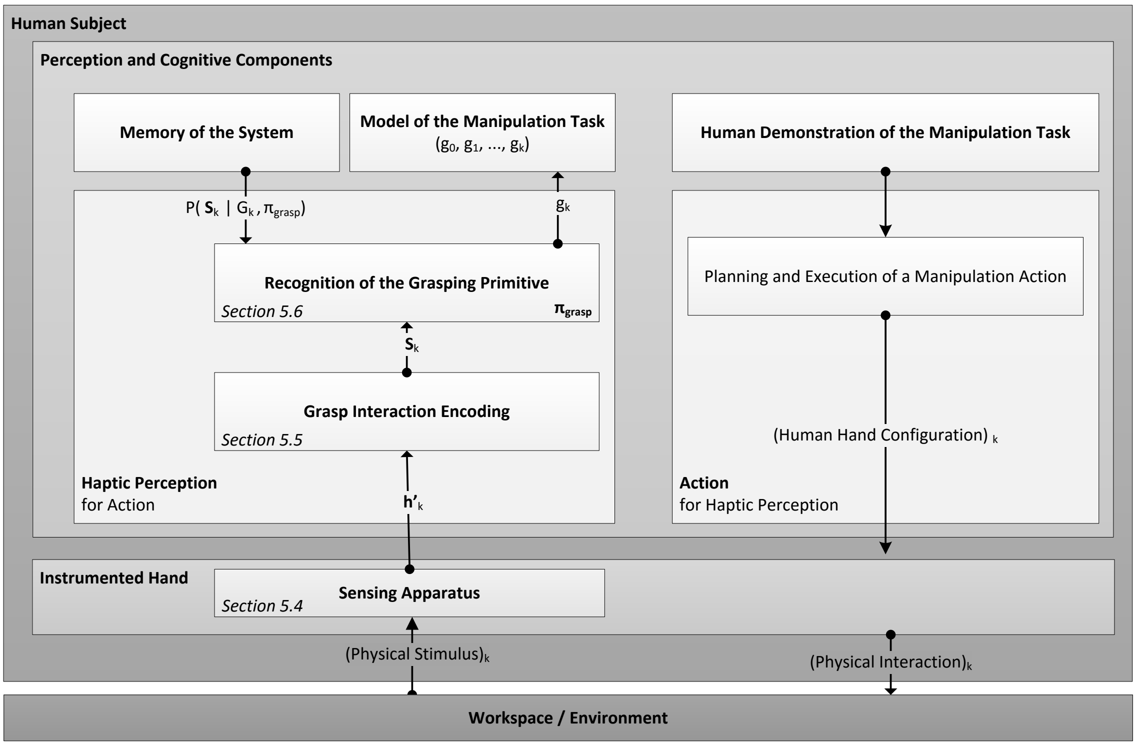


Figure 5.3: Global architecture of the approach proposed in this chapter. The main contributions (description of the sensing apparatus, grasp interaction encoding, and inference of grasping primitives) are highlighted in bold and presented in sections 5.4, 5.5, and 5.6, respectively. The variables representing the flow of the data are detailed in Table 5.2.

Table 5.2: Summary of the relevant variables used in this chapter

Variable	Description	Domain
k	Time iteration	$\mathbb{N}^0$
$\mathbf{h}_k$	Tactile sensing output of the instrumented hand. (360 elements)	$\mathbb{R}^{360}$, $h^i \in [0, 255]$
$\mathbf{h}_k^{'i}$	Tactile sensing output of the instrumented hand (15 cluster regions)	$\mathbb{R}^{15}$, $h^{'i} \in [0, 255]$
G_k	Category of the grasping primitive	$\{Primitive_1, \ldots, Primitive_7\}$
$\mathbf{S}_k$	Tactile activation descriptor of the instrumented hand.	$S^i \in \{"NotActive", "LowActive", "HighActive"\}$

The approach described in Figure 5.3 models the in-hand manipulation tasks by a temporal sequence of primitives. The in-hand manipulation movements are performed to reorient and to repost the manipulated object, which require the change of the type of grasp applied to the object and a precise contact interaction between the object and the hand.

Each type of grasp can be characterized by a specific hand-object contact signature (Figure 5.1), resulting from the interaction of the hand and the object during that period of the task. Thus, the in-hand manipulation task can be described by a temporal sequence of the contact signatures corresponding to different types of hand configurations interacting with the object. The primitives used to model the in-hand manipulation task are defined on the tactile sensing domain.

For each primitive, the spatial configuration of the contact signatures is stored, as well as the force intensities for each region of the hand. These parameters characterizing each primitive can then be used as control states, described by the tactile intensity and hand locations, during the transfer of these skills to a robotic platform with manipulation capabilities.

The flow of the data is summarized in Figure 5.3. The human demonstrator performs an in-hand manipulation task using an instrumented data glove equipped with tactile sensors distributed on the hand palm and finger surface region. The haptic sensory data output is presented in section 5.4. The descriptor used to encode the grasping interaction is detailed in section 5.5. During the execution of the task, a sequence of the elementary primitives, selected among the set of pre-defined primitives, is extracted from the raw data provided by the data glove. The detection of primitives is performed by a Bayesian model detailed in section 5.6. The set of pre-defined primitives is shown in Figure 5.5. The set of task primitives is defined and learned *a-priori* from human demonstrations.

The diversity of the demonstrations promotes the exploration of the variability of the strategies used by humans to perform the same task. The essential primitives of those strategies will emerge as permanent elements. Then, it is possible to build the temporal and functional relations between those elements to find a canonical representation of those strategies. This canonical representation of different in-hand manipulation tasks and the learned parameters describing each of the primitives can be transferred to robotic platforms (not addressed in this thesis).

5.4 Haptic sensory data

This work considers that the hand of the participant manipulating the object is instrumented with a data glove, which is equipped with a distributed tactile sensing array throughout the hand surface (palm and fingers). The methods presented in this work were formulated considering the *Tekscan Grip* (Tekscan Inc, Boston, MA, U.S.) tactile sensing array (Figure 5.4). However, the proposed approach can be adapted easily to other types of tactile sensing devices.

During a manipulation task, at each time interaction k , the instrumented hand interacts with the object, producing the haptic sensory output presented in equation 5.1.

$$\begin{gathered}\mathbf{h}_k = (h^1, h^2, \ldots, h^{360}) \\ h^1, h^2, \ldots, h^N \in [0, 255]\end{gathered} \tag{5.1}$$

The variables $h^1, h^2, \ldots, h^{360}$ represent the raw tactile sensing outputs of each of the 360 elements of the tactile sensing array. The output of each of the *Tekscan Grip* sensing elements is an eight-bit integer (equation 5.1).

The sensing outputs are used to encode (section 5.5) and categorize (section 5.6.2) different classes of grasping primitives.

Figure 5.4: Representation of the fifteen spatial segments $Region_i$ and their correspondence with the sensing elements of the instrumented glove.

5.5 Encoding of the grasping interaction

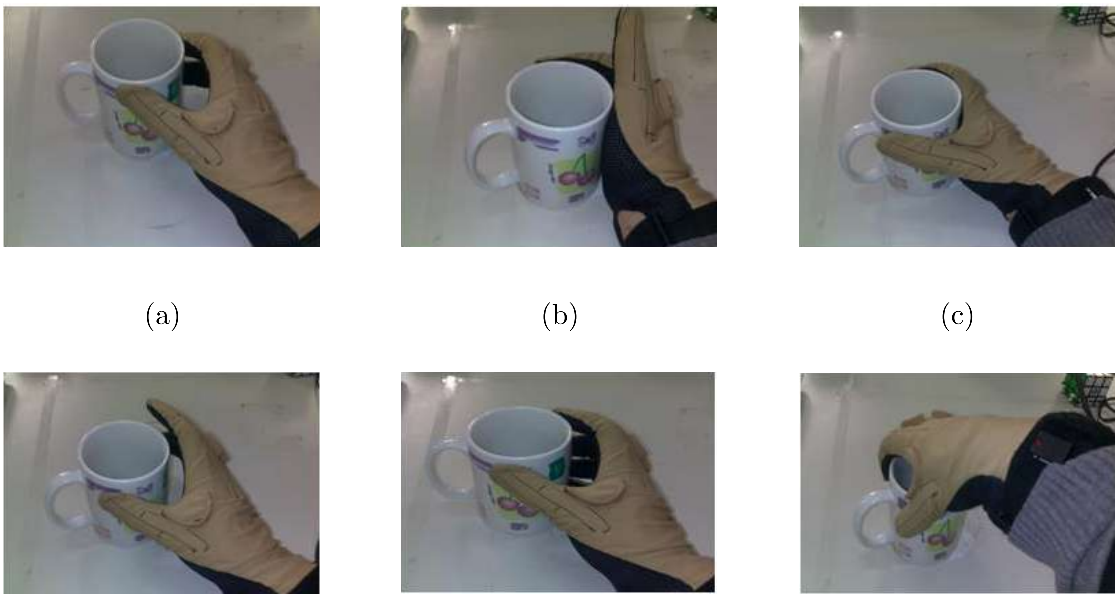
This section proposes the descriptor used to model the tactile sensing signatures produced during the interaction between the instrumented hand and the manipulated object. The tactile sensing device *Tekscan Grip* consists of 360 sensing elements distributed by the hand palm and finger surface, as presented in Figure 5.4. This work groups the 360 sensing elements in 15 regions (highlighted in red, Figure 5.4).

The contact sensing output of each of these 15 regions $Region_i$ of the hand is described by the variable presented in equation 5.2 .

$$\mathbf{h}'_k = (h'^1, h'^2, \ldots, h'^{15}) \\ h'^1, h'^2, \ldots, h'^{15} \in [0, 255] \tag{5.2}$$

The variable h'^i (equation 5.3) represent the mean output of the tactile sensing elements h^j belonging to the $Region_i$ of the instrumented hand shown in Figure 5.4.

$$h'^i = mean(\quad \{\forall_{j \in Region_i} \quad h^j\} \quad) \tag{5.3}$$



(a) (b) (c)

(d) (e) (f)

Figure 5.5: Human demonstration of the grasping primitives: a) $Primitive_1$, b) $Primitive_2$, c) $Primitive_3$, d) $Primitive_4$, e) $Primitive_5$, f) $Primitive_6$. $Primitive_7$ corresponds to a grasp in which the hand does not contact the object.

5.6 Recognition of the grasping primitive

5.6.1 Random variables of the model

The Bayesian model π_{grasp} presented in this section is used to discriminate different types of grasp primitives during a manipulation task. A grasping primitive recognized by the system, at time iteration k, is represented by the discrete random variable G_k, described in equation 6.8.

$$\begin{aligned} G_k - \text{"Category of the grasping primitive."} \\ G_k \in \{"Primitive_1", \ldots, "Primitive_7"\} \end{aligned} \tag{5.4}$$

This work considers that the system is able to recognize seven different grasping primitives (equation 5.4). Six of these grasping primitives are demonstrated in Figure 5.5. The remaining one, $"Primitive_7"$, corresponds to the situation when there is no contact between the hand and the object.

The subset of seven grasping primitives was selected from an extended set of grasping primitives presented in chapter 3. This subset was considered representative for the type of manipulation tasks proposed in this work.

During each time iteration k, the interaction of the instrumented hand equipped with the tactile sensing array and the manipulated object is described by the sensory output $\mathbf{h}'_k$ presented in equation 5.2. The level of tactile activation of each of those 15 regions h'^i during the manipulation task is described by the discrete random variable S^i presented in equation 5.5.

$$\begin{aligned} \mathbf{S}_k - \text{"Tactile activation descriptor of the instrumented hand at instant } k\text{."} \\ \mathbf{S}_k = (S^1, S^2, \ldots, S^{15}) \\ S_k^i \in \{"NotActive", "LowActive", "HighActive"\} \end{aligned} \tag{5.5}$$

The tactile activation levels $NotActive$, $LowActive$, and $HighActive$ are defined as proposed in equation 5.6.

$$
\begin{aligned}
"NotActive" &: h^{'i} \in [0, 10] \\
"LowActive" &: h^{'i} \in [11, 190] \\
"HighActive" &: h^{'i} \in [191, 255]
\end{aligned}
\tag{5.6}
$$

The 3 levels of discretization of the contact intensity are considered appropriate to characterize and distinguish the fundamental functional levels of mobilization of the different regions of the hand. The proposed contact activation levels are used to distinguish different stages of the interaction between the hand and object. Regions of the hand corresponding to $NotActive$ are involved in pre-grasp segments of the manipulation task and in transitions between consecutive re-grasp. $LowActive$ regions participate in initial contact with the object and are partially involved in a stage of the manipulation task. $HighActive$ regions are highly involved in stabilization of the object.

5.6.2 Inference of the category of grasping primitive

The inference of the category of the grasping primitive G_k at each time iteration step k is performed by the Bayesian model π_{grasp} presented in Figure 5.6a.

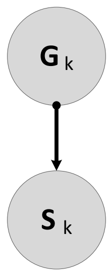
Based on the statistical independence relations between the random variables G_k and $\mathbf{S}_k$ described in Figure 5.6a, the joint probability distribution function $P(G_k, \mathbf{S}_k|\pi_{grasp})$ is decomposed as summarized in Figure 5.6b and presented in equation 5.7.

$$
P(G_k, \mathbf{S}_k|\pi_{grasp}) = P(\mathbf{S}_k|G_k, \pi_{grasp})P(G_k|\pi_{grasp}) \tag{5.7}
$$

The factor $P(\mathbf{S}_k|G_k, \pi_{grasp})$ expresses the likelihood of a specific grasping contact profile, given a category of grasping primitive. This probability distribution function is modelled by a histogram function as described in detail in section 5.6.3. The factor $P(G_k|\pi_{grasp})$ expresses the *a-priori* probability distribution function of the category of the grasping primitive. In this work, $P(G_k|\pi_{grasp})$ is modelled by a uniform probability distribution function.

The category of grasping primitive G_k is inferred by running the Bayesian program described in Figure 5.6b with the question proposed in equation 5.8.

$$
P(G_k|\mathbf{s}_k, \pi_{grasp}) = \frac{P(\mathbf{s}_k|G_k, \pi_{grasp})P(G_k|\pi_{grasp})}{\sum\limits_{G_k} P(\mathbf{s}_k|G_k, \pi_{grasp})P(G_k|\pi_{grasp})} \tag{5.8}
$$



(a)

Bayesian Program

Description

Specification

Relevant variables:

$\mathbf{S}_k, G_k$

Decomposition:

$P(\mathbf{S}_k, G_k|\pi_{grasp}) = P(\mathbf{S}_k|G_k, \pi_{grasp}).P(G_k|\pi_{grasp})$

Parametric forms:

$P(\mathbf{S}_k|G_k, \pi_{grasp}) \equiv \mathit{Histogram}$

$P(G_k|\pi_{grasp}) \equiv \mathit{Uniform}$

Identification:

Histogram learned during the training sessions: Human demonstrations.

Question:

$P(G_k|\mathbf{S}_k, \pi_{grasp})$

(b)

Figure 5.6: Description of the Bayesian model π_{grasp} "Recognition of the grasping primitive". a) Graphical representation. b) Bayesian program.

The estimated category of the grasping primitive $\hat{g}_k$ is given by equation 5.9 via *Maximum a-Posteriori* decision rule (MAP).

$$\hat{g}_k = \arg\max_{G_k} P(G_k|\mathbf{s}_k, \pi_{grasp}) = \arg\max_{G_k} P(\mathbf{s}_k|G_k, \pi_{grasp})P(G_k|\pi_{grasp}) \tag{5.9}$$

5.6.3 Determination of $P(\mathbf{S}_k|G_k, \pi_{grasp})$

The parameters of the histogram function modelling the probability distribution function $P(\mathbf{S}_k|G_k, \pi_{grasp})$ are learned during a training period. Each of the grasping primitives G_k is demonstrated for a pre-defined number of training runs. For each training run, the corresponding contact signature of the instrumented hand $\mathbf{S}_k$ is acquired. After completing the training runs, the parameters of the histogram function are statistically estimated.

This methodology is demonstrated during the presentation of the experimental results (section 5.7.2).

5.7 Experimental results

5.7.1 Experimental setup

During the Human demonstrations of the in-hand manipulation tasks, the subject wears in the right hand an instrumented glove (*Cyberglove II*) with a tactile sensing array (*Tekscan Grip System*) attached to the palm and fingers.

The objects that are placed on the top of a table are manipulated only with one hand (right hand). The subject is seated during the demonstration of in-hand manipulation tasks. The data from the tactile sensing array is sampled at 500 Hz. The configuration of the tactile sensing array, as well as the typical configuration of the experimental area during the task demonstration, are shown in Figure 5.8.

5.7.2 Learning of the grasping primitives $P(\mathbf{S}_k|G_k, \pi_{grasp})$

During the training period, a participant performs five runs demonstrating each of the seven grasping primitives, illustrated previously in section 5.6. The data acquired from the demonstrations is used to estimate the parameters of the probability distribution function $P(\mathbf{S}_k|G_k, \pi_{grasp})$ for each primitive G_k. The results of the learning stage of the grasping primitives are shown in Figure 5.7.

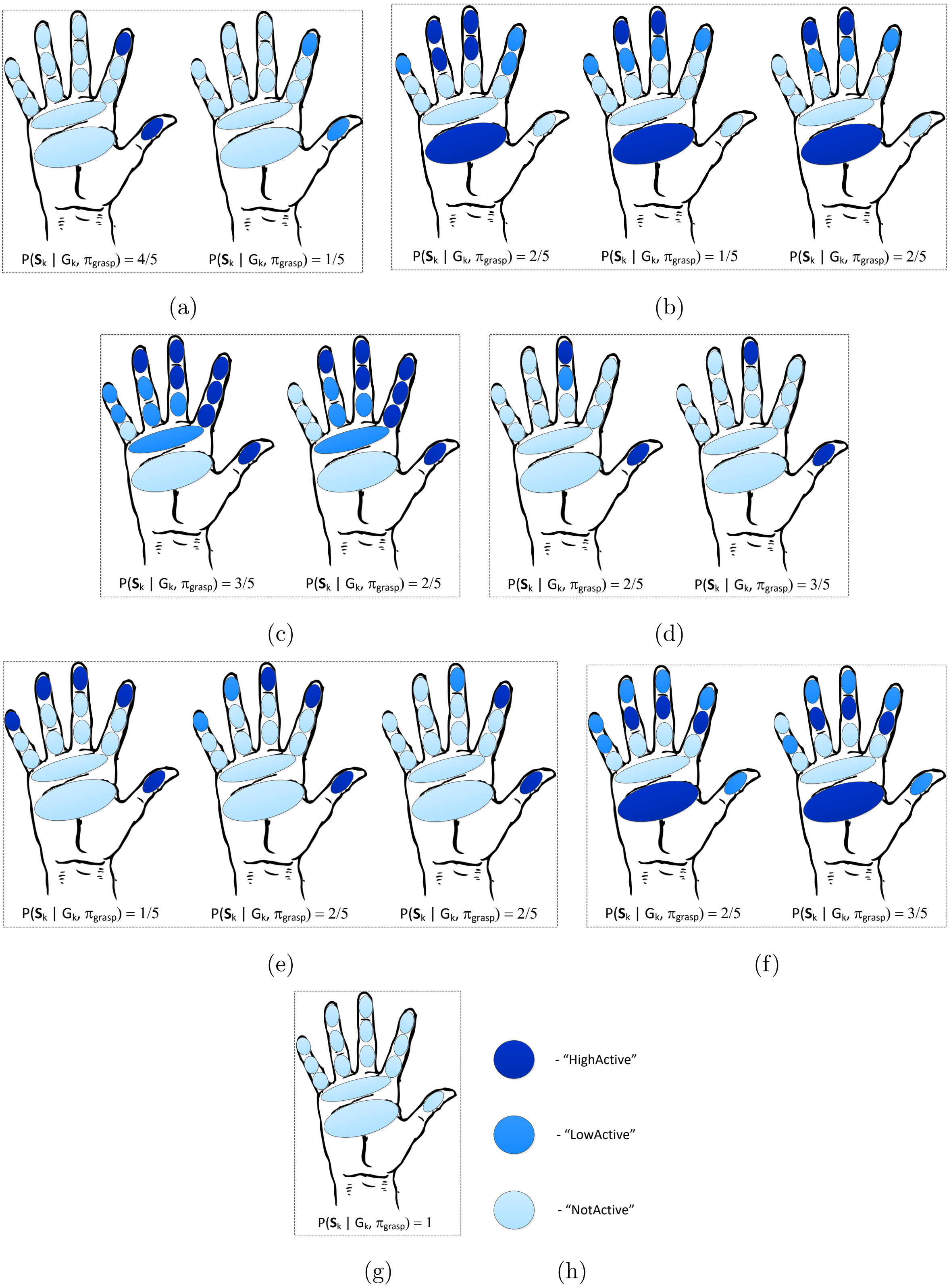


Figure 5.7: Illustration of the probability distribution function $P(\mathbf{S}_k|G_k, \pi_{grasp})$ learned from the human demonstration data (training period). a) $Primitive_1$. b)$Primitive_2$. c)$Primitive_3$. d)$Primitive_4$. e)$Primitive_5$. f)$Primitive_6$. g)$Primitive_7$. h) Colormap

5.7.3 Detection of grasp primitives in manipulation tasks

The approach proposed in section 5.6, to segment a human manipulation task as a sequence of grasping primitives, was tested for two different tasks, as shown in Figure 5.8.

(a)

(b)

Figure 5.8: Human demonstration of the tasks. a) *Task I: "Mug reorientation"*. b) *Task II: "Mug displacement/elevation"*.

During the execution of both tasks, the participant is seated comfortably in front of a table. A mug is placed on top of the table in its initial configuration.

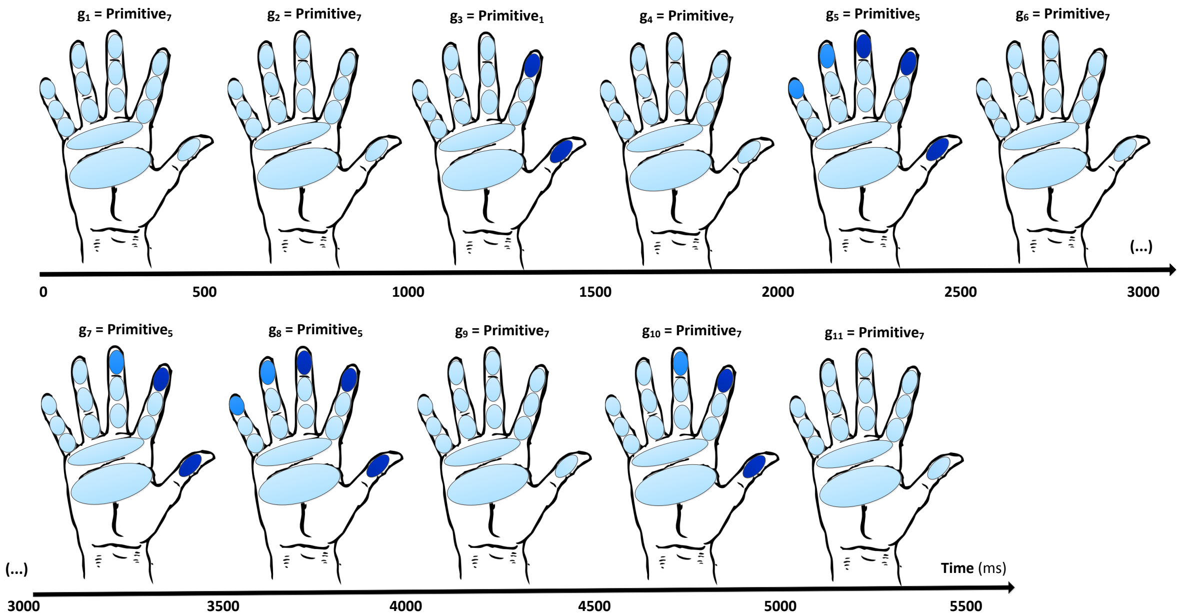
In *Task I: "Mug reorientation",* the participant rotates the mug around the longitudinal axis. This rotation moves the the handle of the mug to a pose suitable to be grasped by the right hand of the participant (Figure 5.8a).

In *Task II: "Mug displacement/elevation",* the participant grasps the mug and elevates it along the direction of the longitudinal axis. The participant finishes the task by placing the mug back on the table (Figure 5.8b).

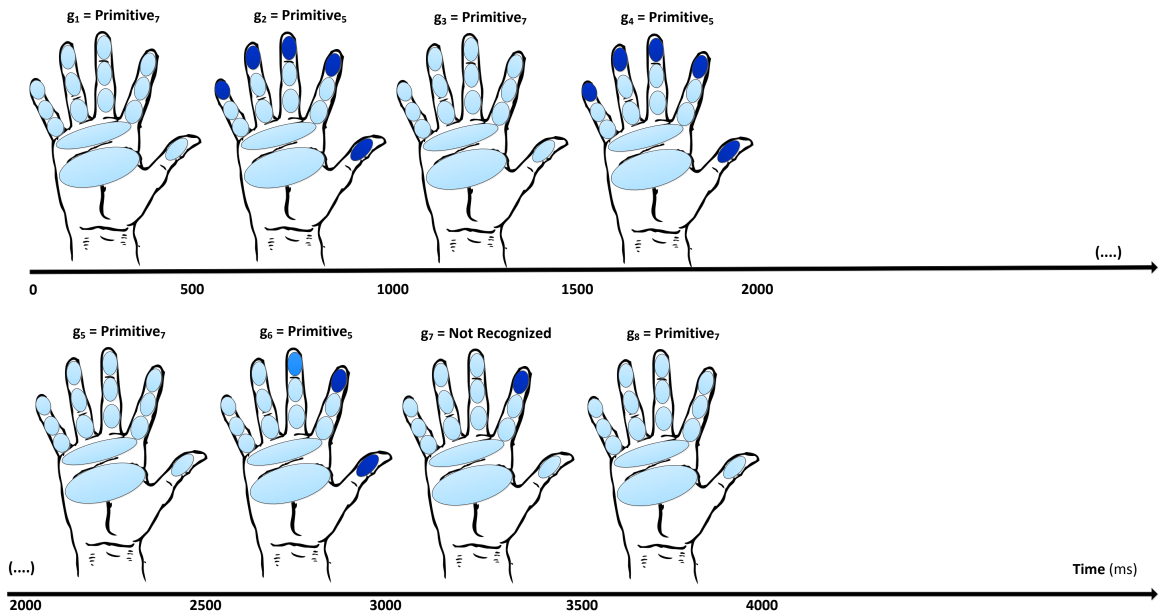
The data acquired during the demonstrations of the two tasks was segmented and time-averaged using a time window of 500 ms. Each time iteration k corresponds to a temporal segment of the sensory data.

The results of the segmentation of the data and recognition of grasping primitives are presented in Figure 5.9 (*Task I: "Mug reorientation"*) and Figure 5.10b (*Task II: "Mug displacement/elevation"*). In both tasks, the first segments are categorized as $Primitive_7$. The human hand is not contacting the object yet. The segments correspond to the reach-to-grasp stage, when the hand moves toward the object which will be manipulated.

The runs of *Task I: "Mug reorientation"* (figure 5.9) were segmented, by the Bayesian model π_{grasp}, on a cyclic sequence of grasping ($Primitive_1$, $Primitive_5$) and releasing ($Primitive_7$) the object. The sequence was used to reorient the mug placed on top of

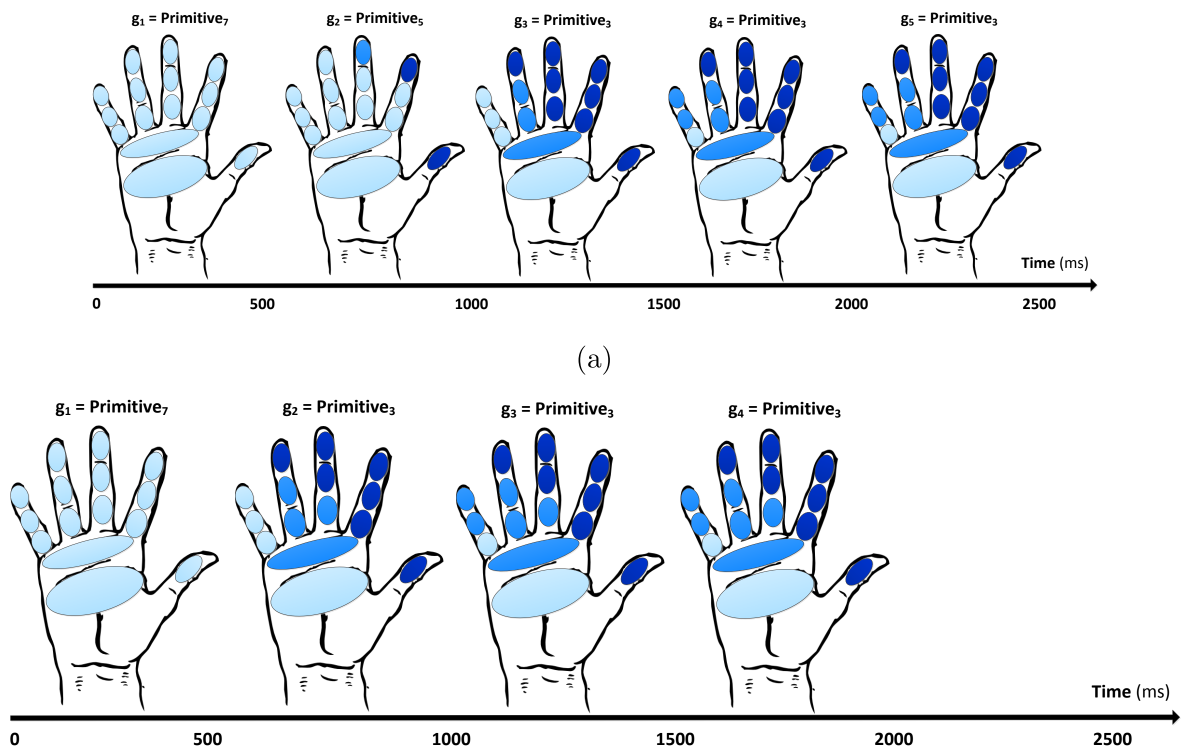


(a)



(b)

Figure 5.9: Grasping primitives $\hat{g}_k$ inferred from the data acquired during the execution of *Task I: "Mug reorientation"*. a) Run 1. b) Run 2. Colormap represented in figure 5.7h.



(b)

Figure 5.10: Grasping primitives $\hat{g}_k$ inferred from the data acquired during the execution of *Task II: "Mug displacement/elevation"*. a) Run 1. b) Run 2. Colormap represented in figure 5.7h.

the table. The sequence of grasp-release allows the participant to reposition the hand on the object, adapting the grasp configuration to the new pose of the object. This strategy promotes the maximization of the effect of the subsequent grasp primitive actuating the object. The regions of the fingers recruited during the reorientation of the mug are predominantly the distal segments of the index, thumb, and middle fingers. These grasping primitives are involved in actions requiring the fine and precise control of the movements of the object: precision grasps.

The runs of *Task II: "Mug displacement/elevation"* (Figure 5.10) were segmented, by the Bayesian model π_{grasp}, on a continuous sequence of grasping primitives ($Primitive_3$, $Primitive_5$). Due to the objective of the task (object displacement), the object was not reoriented. The grasping primitives modelling the strategy are characterized by the recruitment of larger extensions and with more intensity of the palm and surface of the fingers. These primitives provide powerful grasps, contributing to the stability of the execution of the task: power grasps.

5.8 Conclusions

This work presents an approach to modeling the mechanisms underlying the strategies performed by humans to perform manipulation tasks requiring the in-hand manipulation (reorientation and repositioning) of objects. The description and representation of the tasks is made symbolically by using a set of primitives defined on the tactile domain. Each primitive represents a specific spatial distribution of tactile force intensities across the palm and fingers.

The Bayesian model π_{grasp} was able to categorize different types of grasping primitives using as input only the hand-object contact interaction signature. The sequence of primitives modelling two different manipulation tasks was inferred by the Bayesian model π_{grasp}. *Task I* required regrasping and precision grasps. *Task II* was demonstrated using power grasps.

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