NAIST-IS-DD1461210

Doctoral Dissertation

Data-efficient Learning of Robotic Clothing Assistance using Bayesian Nonparametric Latent Variable Models

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September 6, 2017

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A Doctoral Dissertation
submitted to Graduate School of Information Science,
Nara Institute of Science and Technology
in partial fulfillment of the requirements for the degree of
Doctor of ENGINEERING

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Abstract

Assistance with dressing is an essential care-giving task that could be performed by robots and improve the independence of the elderly. However, robotic clothing assistance is considered a highly challenging problem involving close interaction of the robot with non-rigid clothing articles and with the assisted person whose posture can vary. Design of an efficient clothing assistance framework involves reliable state estimation and efficient motor skills learning.

In this thesis, Bayesian nonparametric latent variable models are applied to tackle two problems of robotic clothing assistance. Firstly, the problem of reliable cloth state estimation is addressed. Manifold Relevance Determination (MRD) is used to learn a shared latent space for observations from a noisy depth sensor and accurate motion capture system. This latent space is used to infer the accurate cloth state given only the noisy depth sensor readings in a real-world setting. In the second part, the problem of data-efficient motor skills learning for clothing assistance is addressed. Bayesian Gaussian Process Latent Variable Model (BG-PLVM) is used to learn a low dimensional latent space that can encode the task specific motor skills for clothing assistance. It is demonstrated that performing policy search reinforcement learning in this latent space outperforms learning in the high-dimensional joint configuration space of the robot. Furthermore, this framework is demonstrated as a user-friendly tool that can impart novel motor skills to bulky humanoid robots.

*Doctoral Dissertation, Department of Information Science, Graduate School of Information Science, Nara Institute of Science and Technology, NAIST-IS-DD1461210, September 6, 2017.

Keywords:

Assistive Robotics, Bayesian Nonparametrics, Reinforcement Learning, Robotic Clothing Assistance, Depth Sensor

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1. Introduction

In the recent years, there has been a tremendous increase in the elderly population of the world. This has been seen especially in industrialized nations such as Japan. These demographic trends have also been accompanied by a decreasing work force which has caused a severe shortage in trained caregivers that can assist the elderly. Assistive robots are a promising solution and are already playing an increasing role in improving the living standards and independence of the elderly and disabled. The long term goal for the robotics community is the realization of caregiving robots that not only provide companionship but also physical assistance with everyday activities. The major requirements for such a caregiving robot includes safe and reliable human interaction and the ability to manipulate a wide array of household items. Assistance with dressing is one such basic caregiving task in the daily life of the elderly and disabled that could be performed by assistive robots. Automating this task could greatly improve the independence of the elderly as they would not have to rely on another person and also alleviate the burden on caregivers. However, this task is highly challenging as there are many factors that the robot needs to consider to ensure safe and reliable execution. It remains an open problem with active ongoing research.

1.1. Research Motivation

Japan has the highest percentage of elderly population in the world. In 2011, 23.1% of the population were 65 and above, while 11.4% were already 75 and above [8]. On the other hand, the Japanese Health Ministry estimates that Japan's total population will fall by 25% from 127.8 million in 2005, to 95.2 million by 2050 [9]. With the growing elderly population, there are two main concerns that need to be addressed. First, it is expected that there will be a tremendous shortage of qualified healthcare personnel in the near future. Second, people would prefer to live in their own homes instead of being institutionalized in nursing facilities. To address these issues, we need a greater presence and appliance of ICT-technology and robotics. In the recent years, many robotic applications have been designed to assist the elderly and disabled people in their daily life.

Broekens *et al.* [10] have conducted a comprehensive survey on some of these developments and their impact on the lives of the elderly. Assistive robots are broadly divided into three categories, i.e. social robots, rehabilitation robots and service robots. The first category are systems that can communicate with the user and provide companionship. The second category provides assistance to improve physical well-being which need not be social. The third category includes projects that have both assistive as well as social aspects such as service robots.

Service robots, provide functionalities that accommodate independent living to users by supporting basic activities and providing household maintenance. One of the earliest service robot is the nurse bot Pearl [11] which had two main functions 1) reminding the user about routine activities such as eating and drinking and 2) guiding the user through the household. This robot was successfully deployed in retirement homes and has been effective in improving the quality of life for its users. A similar but more recent project is the German Care-o-bot [12]. This robot is similar to Pearl along with having a manipulator arm that can be used to grasp household items and a sophisticated vision system to recognize specific items in a cluttered household environment. It can be used for standard transport tasks such as getting food or medicines and providing assistance to the user while drinking water by holding the bottle.

Meanwhile, one of the major problems is the loss of motor functions to perform highly dexterous tasks such as putting on clothes. Patients with bone and muscle related diseases find it difficult to move their arms beyond a certain range and are not able to wear clothes by themselves. Similarly patients with conditions like Alzheimer's disease face difficulty in performing fine movements such as putting on buttons and are dependent on the caregiver. Although in most cases, the patient is not entirely dependent on the caregiver and can perform the tasks requiring some assistance. This task could ideally be performed by service robots as discussed above.

The long term goal for our research group is in the development of a framework for clothing assistance that can address this need. The service robot needs to interact with the users, understand their needs and provide “assistance-as-needed”. The emphasis is on enabling generic humanoid robots to extract the important information from the environment and acquire the required motor skills to perform the task.

1.2. Problem Overview

Robotic clothing assistance is considered an open problem by the robotics community. The challenges involved are the close interaction of the robot with non-rigid clothing materials which are usually represented in a high dimensional space and adaptation of robot’s trajectory to changes in posture of assisted person. A promising approach is to treat it as a learning problem where an efficient formulation enables the robot to learn the desired motor skills by itself.

In the recent years, there have been several studies that addressed robotic clothing assistance as presented in Section 2.4. These studies considered various subproblems such as human pose estimation, cloth state estimation and motor-skills learning. However, they handled clothing tasks where there isn’t significant coupling between the human and cloth. In tasks with tight coupling such clothing a human with a T-shirt as shown in Figure 1.1, the problem becomes much more challenging. The clothing article undergoes large changes in its shape and there can also be occlusion from the human making state estimation challenging. The robot needs to ensure safe human-robot interaction as it will operate in close contact with the human. Furthermore, there can be significant variability in the motor-skills required depending on the environmental settings such as the human subject and clothing article used.

To ensure a real-world implementation of robotic clothing assistance, these problems need to be addressed. Firstly, state estimation i.e. the relationship between the human and cloth is crucial for efficient motor-skills learning. There has been significant research on human pose estimation and the challenge lies with cloth state estimation. On the other hand, existing learning frameworks for

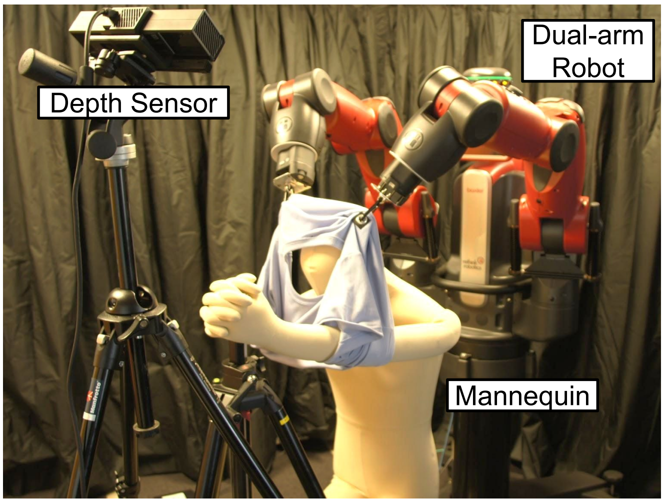


Figure 1.1.: Task setting for performing robotic clothing assistance.

robotics either require large number of interactions or rely on an accurate modeling of the environment. Both these constraints are not applicable for clothing assistance as it involves interaction with an elderly human and accurate modeling of human-cloth interaction is challenging. There needs to be a learning framework that is fast and can generalize to various settings using little or no expert supervision.

1.3. Research Contribution

This thesis aims towards a practical implementation of a learning framework for robotic clothing assistance building upon the work by Tamei *et al.* [1]. The main contributions are as follows: (1) develop a framework for real-time estimation of human-cloth relationship with an emphasis on reliable cloth state estimation and (2) formulate a motor skills learning framework that is data-efficient as well as flexible to adapt to various environmental conditions. These research problems are addressed through the use of Bayesian nonparametric latent variable models as it has several desired features. Dimensionality reduction is used to reduce the high dimensionality and model the problems in a low dimensional space that efficiently capture the underlying task. These models rely on the use of Gaussian Processes [3] which leads to handling the inherent non-linearity and also perform model learning in a data-efficient manner.

In (1), the problem of reliable cloth state estimation is addressed by using a depth sensor to overcome the problems faced with the motion capture system. This thesis proposes the use of Manifold Relevance Determination (MRD) to learn a shared latent space for observations from a noisy depth sensor and accurate motion capture system. This latent space is used to infer the accurate cloth state given only the noisy depth sensor readings in a real-world setting. In (2), the problem of data-efficient motor skills learning for clothing assistance is addressed. This thesis proposes the use of Bayesian Gaussian Process Latent Variable Model (BGPLVM) to learn a low dimensional latent space, encoding the task specific motor skills for clothing assistance. It is demonstrated that performing policy search reinforcement learning in the latent space outperforms learning in the high-dimensional joint configuration space of the robot. Furthermore, this framework is also demonstrated as a user-friendly tool to impart novel motor skills to the robot. The proposed frameworks are demonstrated for a T-shirt clothing task performed by a Dual-arm robot with a soft mannequin used as the assisted person.

1.4. Thesis Overview

This thesis is organized and divided into six chapters. Chapter 2 gives an overview of all the related works. Chapter 3 summarizes the theory of Bayesian nonparametric latent variable models used for the modeling of the research problems in this thesis. Chapter 4 describes the proposed framework for real-time cloth state estimation. Chapter 5 describes the proposed framework on data-efficient motor skills learning. Lastly, Chapter 6 concludes the thesis with directions for future research and a road map to realize a practical implementation of robotic clothing assistance.

2. Related Works

This chapter summarizes studies related to the research problems addressed in this thesis. The key challenge for robotic clothing assistance is with clothing articles. There has been significant research related to state estimation and robotic manipulation for rigid objects. However, clothing articles are inherently non-rigid and difficult to model. In the recent years, there has been a lot of attention on developing frameworks for robotic cloth manipulation. The studies tackle different aspects of the problem and are presented here in two sections. Section 2.1 has studies on cloth state estimation which is related to the first problem handled in this thesis. Section 2.2 includes frameworks for motor-skills learning and its specific application to cloth manipulation related to the second problem.

In this thesis, Bayesian nonparametric latent variables are proposed to address the research problems. Section 2.3 includes a literature survey on the use of latent manifold learning in the domain of robotics and computer vision. Section 2.4 presents studies that specifically tackled the problem of robotic clothing assistance. Finally Section 2.5 describes the studies which form the basis of this thesis and further elaborates upon the research motivation.

2.1. Cloth State Estimation

One of the popular approaches for robotic cloth handling is to rely on efficient cloth state estimation and to perform static planning of the robot. Ramisa *et al.* [37,38] designed efficient feature descriptors for detection and parts segmentation of clothing articles that relied on both appearance and depth features. They proposed novel depth descriptors that performed well for clothing articles and used Bag of Visual Words (BoVW) to efficiently encode the feature information. Cusumano-Towner *et al.* [35] tackled the problem of bringing clothes to a desired

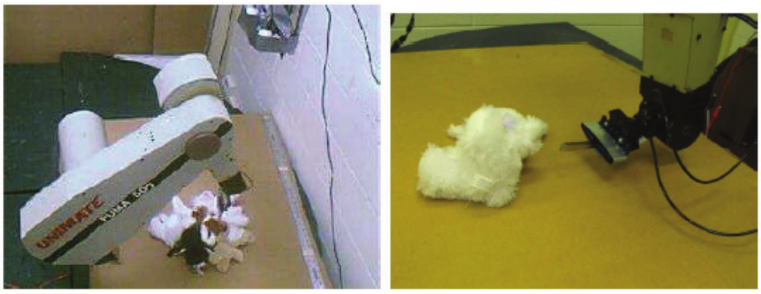


Figure 2.1.: Robot performing interactive perception for efficient state estimation [41].

task-specific configuration using HMM to model the state transitions. The state of clothing article was approximated using a triangulated mesh model which is estimated by comparison of simulated and observed contour shapes.

Wang *et al.* [39] handled the problem of sock configuration detection for manipulation and classification. They extracted texture- and shape-based local features to estimate a global sock configuration which was used for planning robotic manipulation tasks. Willimon *et al.* [40, 41] relied on the concept of interactive perception, where the goal of the robot is to classify non-rigid objects in a cluttered environment through perception and interaction with the objects. An example of interactive perception on a non-rigid object is shown in Figure 2.1. The data obtained from robotic interaction was used to construct a skeleton representation of both rigid and non-rigid objects with which the objects could be efficiently classified.

Another approach to cloth handling is to construct high-dimensional models of clothing articles using depth sensors. Kita *et al.* [43, 44] proposed a framework for cloth state estimation using multiple observations of the cloth through rotation along a vertical axis. A mesh-model was fit through optimization to the observations and was used for informed cloth manipulation as shown in Figure 2.2. Li *et al.* [69], performed construction of 3D mesh models of clothing articles using depth image segmentation and volumetric fusion. They proposed an efficient approach to estimate the 3D mesh model by relying on an offline database of mesh models and computationally efficient feature representations for searching within the database.

Maitin-Shepard *et al.* [36] proposed an end-to-end cloth folding system that

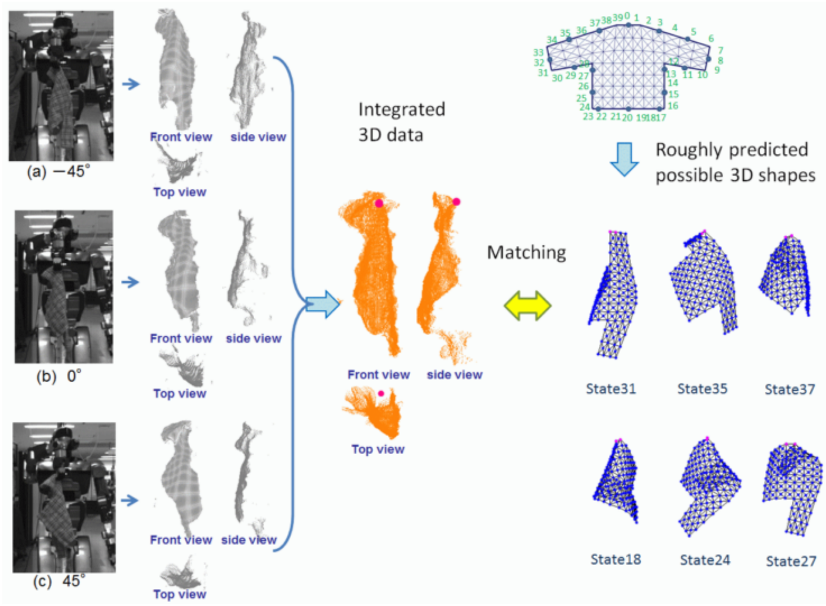


Figure 2.2.: Dense cloth state representation for state estimation from depth sensor [44].

uses geometric cues to complete the folding task through a predefined sequence. The framework relied on border geometry information to detect grasping points that are most suitable for performing the folding task. Bersch *et al.* [42] proposed a cloth folding framework starting from a crumpled state. The task was performed using a T-shirt that was patterned with fiducial markers. These markers were tracked to provide an accurate estimate of the cloth state which was used to plan the next grasp motion of the robot. They also relied on a computationally complex mesh-model to represent the cloth state.

Recently, there have been several studies that rely on the use of deep learning for cloth state estimation. Tangseng *et al.* [47] proposed the use of fully convolutional networks (FCN) for cloth parsing task. They designed a novel architecture along with a conditional random field (CRF) that can explicitly encode clothing semantics to disambiguate between similar looking clothing articles. Liu *et al.* [48] released a comprehensive dataset of clothing articles along with their semantic and landmark annotation. They also proposed a novel deep model that could simultaneously estimate global appearance, local features and landmarks. This model could be used for several commercial purposes such as searching for

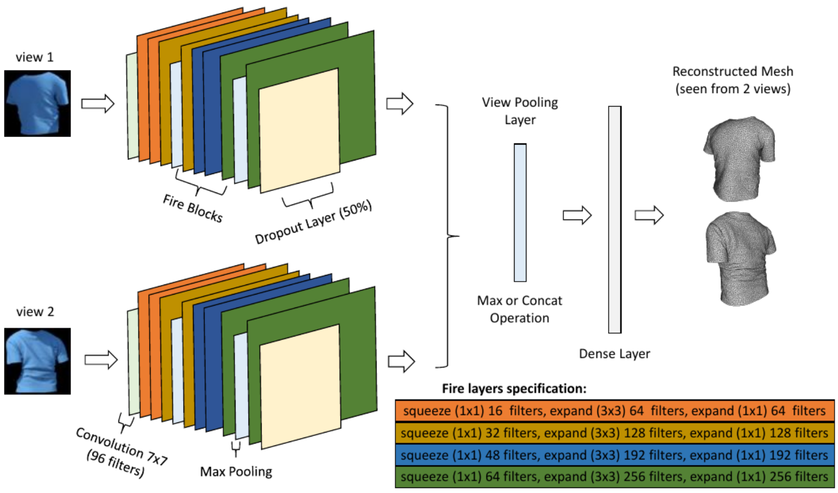


Figure 2.3.: 3D garment shape estimation from single images using fully convolutional networks (FCN) [49].

similar clothes within a database.

Danerek *et al.* [49] proposed a framework to predict the 3D shape of a garment given a single image under various occlusions and lighting conditions. A synthetic dataset was generated through physically based simulations between humans and clothing articles which was used to train the model. This framework was applied to predict the 3D shape in real-world examples with promising results. Gabas *et al.* [50] performed classification of clothing articles using only depth images and convolutional neural networks (CNN). They generated a dataset for five categories of clothing articles while being manipulated by a robot arm. This comprehensive dataset was used to train the model used for classification. The proposed framework was able to obtain an accuracy of 80% even from a single observation of the clothing article and with monotonic increase as more observations were provided.

The studies presented thus far have several limitations in the context of robotic clothing assistance. These tasks rely on the use of high-dimensional cloth state models and sometimes optimization-based techniques for fitting these models to sensory observations. In most of the studies, planar assumption is taken for clothing articles to constrain state estimation. However, clothing assistance can not use such assumptions and would require computationally efficient representations to ensure real-time state estimation. There is also a significant effort in designing efficient features suitable for performing the task and these features usually do not generalize to other related tasks.

Meanwhile, deep learning based studies avoid the need for feature design and have provided promising results in this domain. However, the studies presented here either rely on large datasets or generation of synthetic datasets. Data augmentation for robotic clothing assistance is challenging as it is difficult to model the human-cloth-robot interaction efficiently in a simulator. On the whole, these studies also do not specifically handle the interaction between clothing articles and human-subjects required for clothing assistance.

2.2. Motor Skills Learning

One of the major challenges in robotics is acquiring motor skills to perform complex behaviors. This can be achieved using methods such as Imitation Learning (IL) [51] where the robot mimics expert demonstrations of the task and reinforcement learning (RL) [55] where the robot learns the behavior through a trial-and-error process. These methods usually rely on using statistical machine learning and the representation used to encode the robot's motor skills play a crucial role. Motor skills, usually a trajectory or a robot controller, are encoded using representations such as Dynamic Movement Primitives (DMP) [32], Linear Quadratic Regulator (LQR) and Neural Networks (NN). Over the past few years, there have been several studies that applied these methods to various robotic applications.

Imitation Learning (IL) or Learning from Demonstration (LfD) is often used in robotics to enable fast learning of complex behaviors. Schaal [51] provide an introduction to the topic and its application towards autonomous humanoid robots. He has drawn parallels between computational approaches and biological basis of imitation learning in the human brain. Argall *et al.* [52] provide a comprehensive survey of applying LfD to robotics. The robot usually extracts information from expert demonstrations to reproduce the behavior. The extracted information can either be the motor skills itself that directly mimics the expert [53] or it can be a model of the environment using which the motor skills can be learned [54]. Usually LfD tends to overfit to the expert demonstrations and is used as an initialization to reinforcement learning for generalization to novel settings.

(a)

(b)

Figure 2.4.: Examples of reinforcement learning in robotics: a) Helicopter learning controller for inverted flight [57], b) Four legged little dog robot learning controller for climbing stairs [59].

Reinforcement learning (RL) is a branch of machine learning wherein an agent learns to interact with its environment so as to maximize its long-term rewards [55]. Kober *et al.* [56] provides a detailed survey on application of RL to robotics. The challenges involved in applying RL to robotics is that the agent needs to handle a continuous action space and usually has a partially observable setting with noisy sensory data. RL is typically used when manual-coding or tele-operation of the robot is infeasible. Some of the example applications are autonomous helicopter flight [57], robot soccer [58], legged locomotion [59] and robotic table tennis [60] as shown in Figure 2.4.

Data-efficiency is crucial for robotics applications as it is time consuming and expensive to perform real-world experiments. This has been handled using two approaches. Firstly, policy search methods have been proposed where the robot directly searches for an optimal policy and usally does not rely on a value function. Deisenroth *et al.* [61] have provided a survey on various policy search methods. These methods firstly parametrize the motor skills of robot and directly optimize the policy parameters for efficiently performing the task. Another approach are model-based methods where a model of the environment is used to avoid unnecessary exploration in RL. Nguyen *et al.* [62] present some of the approaches used for model learning and its application to robotics.

The representation used for motor skills play a crucial role in the efficiency

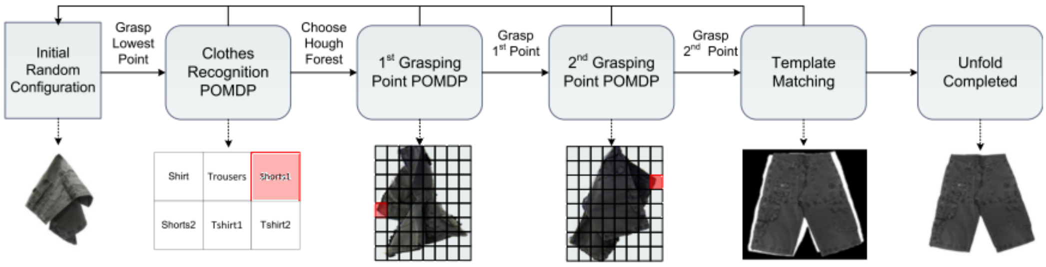


Figure 2.5.: POMDP formulation to sort clothing articles [70].

of LfD and RL algorithms. The representation can either be applied to an entire trajectory or it can be in the form of a controller i.e. a mapping from state space to robot's action space. Several representations have been applied for robot trajectories such as Via-points, Gaussian Mixture Models (GMM) and Dynamic Movement Primitives (DMP) [32]. DMPs are nonlinear dynamical systems capable of movement generation. They are most commonly used in robotics [64, 65] as they have several desired properties such as efficient teaching, task generalization [66] and sensory feedback [67]. Paraschos *et al.* [68] have also proposed a probabilistic extension to DMP called ProMP where the motor primitive now captures a distribution of trajectories.

Several studies have proposed motor skills learning specifically for cloth manipulation to handle the inherent non-rigidity. Doumanoglou *et al.* [70] formulated a Partially Observable Markov Decision Process (POMDP) framework for cloth unfolding along with the use of random forests for cloth classification as shown in Figure 2.5. Huang *at al.* [71] used depth and appearance features for detecting graspable regions and generated trajectories through a warp function to bring clothes to a desired configuration.

Lakshmanan *et al.* [72] used movement primitives to parametrize motion planning for performing robotic cloth folding. The planning algorithm can explicitly handle robot constraints and it generates a sequence of motions for folding a given clothing article. They evaluated the proposed framework in both simulation and real-world experiments. Monso *et al.* [73] proposed a probabilistic motion planning framework for cloth separation by formulating the problem as a POMDP to handle uncertainty during manipulation. They defined a low-dimensional state

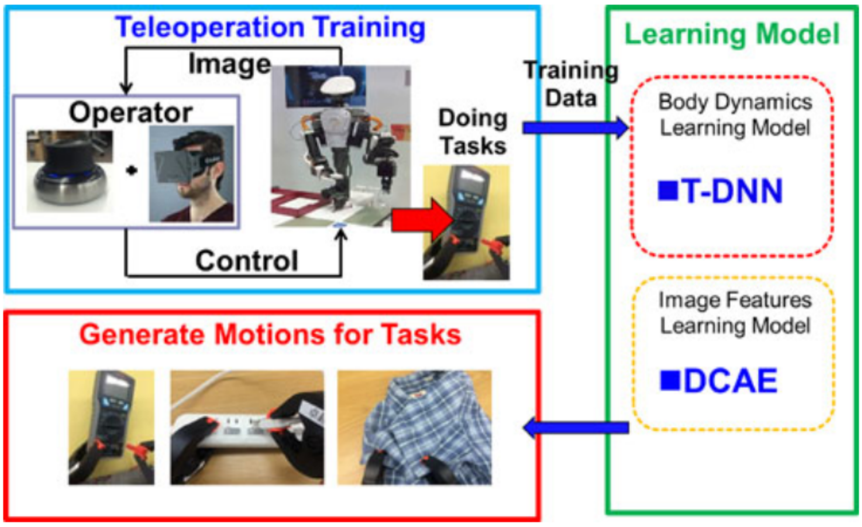


Figure 2.6.: Deep learning framework for robotic cloth folding [76].

representation to ensure fast and efficient learning of the task. Real-world evaluation demonstrated that the partially observable setting has the best performance as it could explicitly model the occlusion of clothing articles when present in a heap.

Miller *et al.* [74, 75] performed robust robotic cloth folding for a wide variety of clothing articles by generating motion trajectories for a 2D polygon approximation of the clothing article. They parametrized the shape of clothing articles using skeletal models and performed parameter optimization to detect the category as well as state of clothing article on being manipulated by a robot. Yang *et al.* [76] proposed a deep learning based framework for autonomous cloth folding shown in Figure 2.6. They relied on a convolutional autoencoder for task specific feature extraction from raw images and a time delayed neural network to learn the dynamics of cloth folding. Teleoperation was used to collect sequences of cloth manipulation that were used as training data for the deep learning models.

The non-rigidity of clothing articles increases drastically for high dynamics tasks. There have also been studies that proposed frameworks for handling such complex dynamics. Balaguer *et al.* [77] proposed a reinforcement learning framework that exploits the dynamics of clothing articles to perform a high momentum folding task. They used a motion capture system for real-time cloth state estimation as the clothing article did not undergo much occlusion. Yamakawa *et al.* [78] developed a high frequency visual-feedback control mechanism to control a dual-arm setup to perform a towel folding task. The clothing article was modeled using a linear flexible object model which is specified through an algebraic equation.

There several problems to apply existing motor skill learning frameworks to robotic clothing assistance. One of the major challenges is data-efficiency. The existing policy-search methods do not scale well to high dimensional state spaces and take prohibitively long time. Existing model-based studies rely on learning an accurate model. However, it is very difficult to capture the human-cloth interaction and model the nonlinear dynamics of clothing articles. DMP is a promising policy representation for performing the task but the parameters for DMP increase with dimensionality thereby increasing the learning time.

The frameworks presented for cloth manipulation mainly handle tasks that require point-to-point planning based on one-shot cloth state estimation decisions. There are also studies that handle dynamical tasks, but the clothing articles do not undergo severe occlusions and the cloth state was represented by tracking specific positions of clothing articles such as the corners. However clothing assistance tasks are highly dynamical requiring efficient cloth state estimation to handle cloth occlusions and constraints due to coupling with the human.

2.3. Manifold Learning in Robotics

Robotics applications require learning motor skills with high-dimensional observations obtained using noisy sensors. Usually the inherent dimensionality of the task is much lower and is nonlinearly related to the observation space. One approach is to use dimensionality reduction and obtain a low-dimensional manifold that efficiently captures the task representation as well as variability in different settings. This section is a survey of studies that employ manifold learning for various robotics related applications.

A common approach is to use Principal Component Analysis (PCA) [15] as a preprocessing step to extract a low dimensional manifold from the high dimensional observations and use this manifold to achieve the task. PCA is a

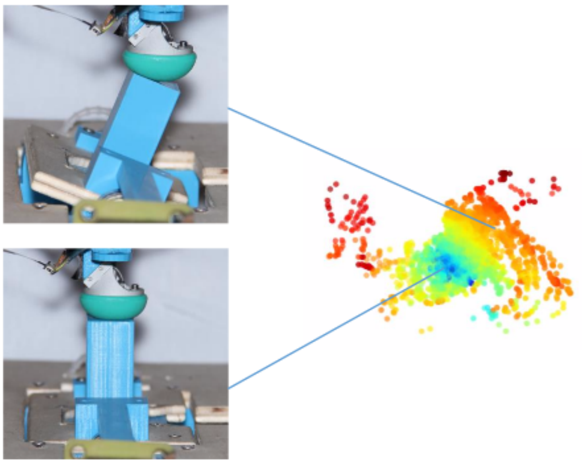


Figure 2.7.: High dimensional sensory data mapped to low dimensional space using VAE for manipulation of 5 DoF robot [87].

dimensionality reduction technique that performs an orthogonal transformation and projects high dimensional data onto a subset of linearly uncorrelated variables called *principal components*. Some of the applications include robot localization [79], learning from demonstration in humanoid robots [80], robotic hand grasp planing [81] and EMG-based robot arm control [82].

One of the major problems with reinforcement learning (RL) is the curse of dimensionality. This is further amplified in robotics applications where conducting real-world experiments can be time consuming. There have been some studies that combined RL with PCA. Luck *et al.* [83, 84] proposed a policy search framework that inherently combines dimensionality reduction with RL through an expectation-maximization (EM) formulation. They applied this framework to various robotic applications and demonstrated sample efficiency in comparison to traditional policy search algorithms. Curran *et al.* [85] used PCA as a preprocessing step to efficiently represent expert demonstrations of various robotic tasks. This latent manifold was used with existing value-based RL algorithms and showed faster learning rates.

With the increasing popularity of deep learning, there have been several studies that use neural network based autoencoders to learn low-dimensional manifolds in various robotics applications. Watter *et al.* [86] used variational autoencoders and a locally linear approximation of nonlinear dynamical systems to generate high-dimensional image trajectories given current observations. They applied this framework to various motor learning tasks such as balancing of a cart-pole. Hoof *et al.* [87] proposed the use of autoencoders to learn a low dimensional feature space of high dimensional tactile and visual information. This feature space was used as the state space for performing reinforcement learning where a 5 DoF robot learned to manipulate a pole as shown in Figure 2.7.

Veres *et al.* [88] trained a conditional variational autoencoder (CVAE) using a synthetic dataset and learned object-action representations to generate grasps for unseen objects. They demonstrated that CVAE was able to learn a complex nonlinear mapping and model multi-modal distributions that represent the variability of grasp configurations. Chen *et al.* [89, 90] proposed the combination of variational autoencoder (VAE) with dynamic movement primitives (DMP) by embedding it into the latent space learned by VAE. They applied this approach to complex human movements and demonstrated generalization ability as well as the capability to switch between various tasks using the latent space.

There have been several studies that use Gaussian process latent variable model (GPLVM) and their extensions to perform dimensionality reduction in various settings. The use of Gaussian process leads to data-efficient learning and nonlinear covariance functions enables the learning of nonlinear mappings. Shon et al. [91] formulated a shared Gaussian process latent variable model (SGPLVM) for multiple observation spaces. They applied this model to learn a nonlinear mapping from human degrees of freedom to a humanoid robot and performed robotic imitation of human motion capture data. They demonstrated that the proposed model is data-efficient and also robust to noisy observations.

Gupta et al. [92] proposed a framework for monocular human pose estimation using GPLVM. They proposed the use of a back constraint to infer the human pose using not just the image data but also information from other contextual features. Ko et al. [94] formulated a generic framework for Bayes filters in settings with incomplete ground truth data where a state sequence is generated using GPLVM. They demonstrated the proposed framework to a wide range of robotics task where obtaining ground truth information is difficult.

GPLVM has also been used in reinforcement learning to overcome the curse of

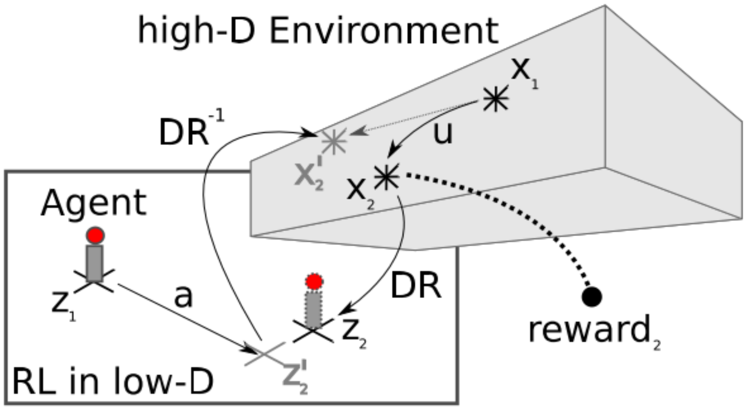


Figure 2.8.: Latent space reinforcement learning performed using GPLVM [93].

dimensionality where the policy learning is done in a low-dimensional latent space that captures task space constraints [93] as shown in Figure 2.8. Wang et al. [95] proposed a dynamics extension to GPLVM that can infer the intention of a human subject given task demonstrations in a human-robot interaction setting. They further developed an online inference algorithm to overcome the computational complexity of Gaussian process to perform real-time inference of human intention.

The studies presented in this section use various manifold learning techniques depending on the application. For robotic clothing assistance, the robot has to handle a non-rigid clothing article and the motor-skills vary largely depending on the environmental setting. Linear models such as PCA are not suitable to handle the nonlinear dynamics of clothing articles. On the otherhand, methods such as variational autoencoders are capable of learning complex non-linear mappings but are not very sample efficient. The studies using VAE that are presented in this section rely on large training datasets which could be challenging in the domain of assistive robotics.

The later part of this section covered studies that used GPLVM in complex settings to perform data-efficient learning. Gaussian process mapping leads to uncertainity estimates while performing test inference which was used as a measure of model uncertainity. Furthermore, various constraints and prior information were placed on the latent space which depended on the application. These studies demonstrate the applicability of GPLVM to robotic clothing assistance.

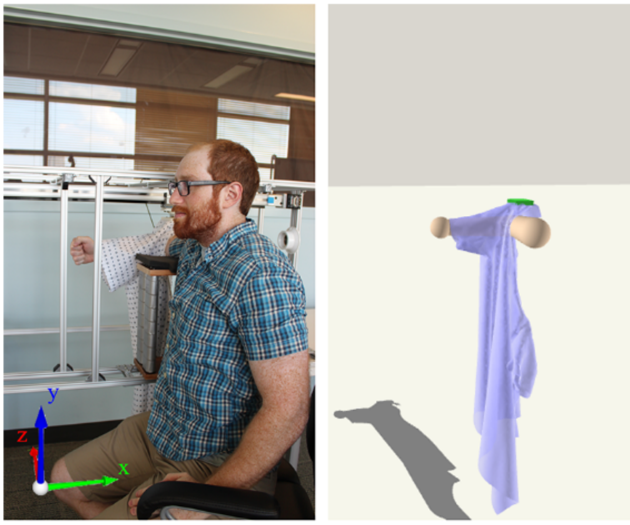


Figure 2.9.: Use of haptic simulation for failure detection in real-world implementation [102].

2.4. Robotic Clothing Assistance

Recently, there have been several studies that tackle the problem of clothing assistance and it is considered an open problem by the robotics community. Assistance with dressing involves several subproblems such as human pose estimation, cloth state estimation and robot control for the actual assistance. The studies presented here tackle one or several of these subproblems.

For people with cognitive impairments, dressing assistance mainly involves providing social cues to wear the appropriate clothes rather than physical assistance. There have been several studies that tackled this problem. Burleson *et al.* [98] proposed a framework to detect abnormal dressing states by tracking clothing articles that have fiducial markers. The abnormal states examples such as wearing clothes inside-out and wearing the backside front. The system could be used by patients with cognitive disabilities but healthy physical state.

Orr *et al.* [99] developed a multi-agent system that relied on information from various sensors to provide recommendations for clothing when the users were about to leave their house. Klee *et al.* [97] proposed a clothing assistance framework to communicate and coordinate with a human to complete clothing tasks. They emphasized on human motion tracking and performed tasks such as putting

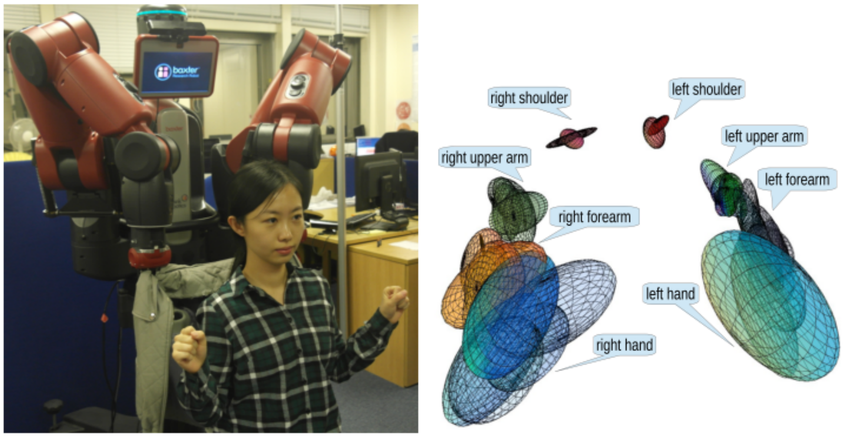


Figure 2.10.: User modeling for constraint-aware motion planning of clothing assistance [105].

on a cap or a backpack onto the human. The motion planning was done through a predefined sequence of poses.

Conducting clothing assistance experiments with human subjects is difficult and eventual real-world implementations need to be safe and efficient. One approach to sidestep this problem is to develop a realistic simulator of the process and use this as a testbed for implementing various strategies. Clegg *et al.* [100] developed a framework to synthesize dressing motion performed by animated human characters. They extracted a set of primitive actions that could be combined to generalize motion across different clothing articles. Erickson *et al.* [101] relied on simulations of dressing a human hand with a shirt to infer the forces felt by the human from the end effector forces of the robot. They generated large amounts of data and used it to train deep neural networks for force estimation. Yu *et al.* [102] used haptic information obtained from a simulation of dressing assistance to train a classifier that could predict failure scenarios in a real-world implementation of the same task as shown in Figure 2.9.

Dressing assistance is meant for users who have impaired motor functions and it is crucial to perform human pose estimation while providing assistance with the robot. Gao *et al.* [105, 106] tackled the problem through user-specific body constraints calibration to perform reliable motion planning for clothing assistance as shown in Figure 2.10. They have considered the task of clothing a human with a sleeve-less jacket and have modeled the human constraints using randomized de-

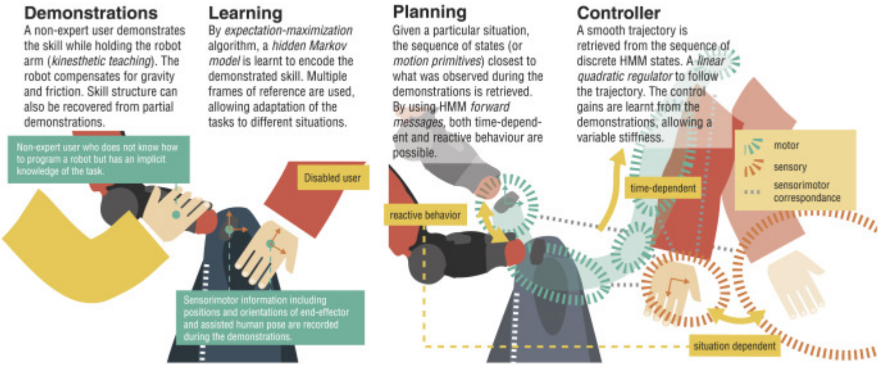


Figure 2.11.: OVerview of Learning from Demonstration framework for dressing assistance [110].

cision forests. Twardon *et al.* [107] handled the problem of cloth state estimation during dressing assistance. They relied on the use of active boundary components to track the extremities of clothing articles and model the human-cloth interaction using topology coordinate representation.

The main challenge towards implementing robotic clothing assistance is motor-skills learning and generalization to novel settings. There have been some studies which handled this problem. Colome *et al.* [109] performed clothing of a mannequin with a scarf using reinforcement learning. They relied on an accurate inverse dynamics model and force feedback for reliable motion planning. Pignat *et al.* [110] developed a learning from demonstration (LfD) framework to obtain the desired motor-skills from a human performing clothing assistance tasks as shown in Figure 2.11. They learned a joint distribution of human sensory information and robot control commands and encoded each of these sensorimotor pattern as a state of hidden semi-Markov model (HSMM).

There have been several studies that simultaneously achieved several problems and proposed end-to-end framework towards dressing assistance. Yamazaki *et al.* [103, 104] have proposed a framework for clothing of subjects with pants. In their framework, they relied on the use of optical flow and an offline database of image streams to detect the current state of clothing task. Force-based information along with dynamic state matching was used to detect failure and success states. Chance *et al.* [108] relied on sensor-fusion for human tracking, proprioceptive information for failure detection and human-robot interaction to recover from failure scenarios. They applied this framework to cloth a mannequin with a clothing article.

The studies presented here tackle various aspects of dressing assistance moving towards a real-world implementation. However, there are several aspects that haven't been handled thus far. Most of these studies do not handle tasks that have tight coupling between the human and clothing article. For such tasks, clothing articles undergo severe deformations and cloth state estimation becomes challenging. Furthermore, offline motion planning of the robot would not suffice to achieve the task and the dynamics of performing the task also need to be considered. They do not specifically handle reliable cloth state estimation and address other aspects of clothing assistance such as human-pose modeling, robot dynamics handling.

2.5. Proposed Framework

In this thesis, we address the challenge where there is significant coupling between the clothing article and the human such as the clothing with a T-shirt involving severe cloth deformation and occlusion by the mannequin. This thesis builds upon the clothing assistance frameworks proposed by Tamei *et al.* [1] and Matsubara *et al.* [2], that treat the task as a learning problem.

Tamei *et al.* [1] developed a reinforcement learning-based clothing assistance framework that addressed the challenges discussed above. In this framework, a dual-arm robot learns the necessary motor skills to perform clothing tasks by adapting to changes in the posture of the subject. They considered the task of clothing a soft mannequin with a T-shirt that is initially resting on the mannequin's arms as shown in Figure 1.1. The robot performs several clothing trials before it successfully learned a suitable trajectory to perform clothing tasks. However, this framework has several limitations which need to be addressed towards realizing a practical implementation in a real-world scenario.

In the framework by Tamei *et al.* [1], the human-cloth relationship is observed using the motion capture (Mo-cap) system with optical markers placed on the mannequin and T-shirt. Mo-cap system has a complex and expensive setup using multiple infrared cameras and can provide location information of discrete markers in the environment. Furthermore, this system is not suitable for real-time

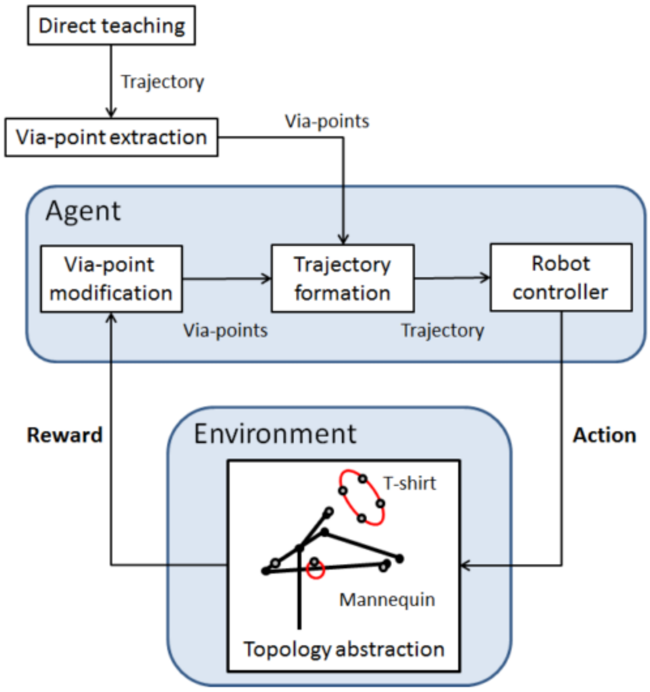


Figure 2.12.: Reinforcement learning framework for clothing assistance [1].

tracking of markers on non-rigid objects such as clothes. Due to these limitations, only the final state of a clothing trial could be used forcing the robot to perform multiple trials.

Another limitation is the policy representation used. The robot's trajectory is parametrized using Via-points [34] which represents the key points that encode the trajectory. The humanoid robot has two arms with 7 joints/degrees of freedom (DoF) each. To ensure fast learning time, only one Via-point of one particular joint is used as a policy parameter that is optimized. Due to the inherent variability of the task, such a constrained policy representation severely limits the generalizability to different environmental conditions.

The common difficulties for both the research problems are the inherent nonlinearity and complexity in the task. Clothing articles are non-rigid objects that lie in a high dimensional configuration space. The task of clothing assistance follows non-linear dynamics with large variabilities between various environmental conditions. Another difficulty is the inherent high dimensionality of the problems.

The humanoid robot has 14 DoFs and skill learning in such high dimensional continuous search space is a challenging problem. Another common constraint is the emphasis on fast learning time due to its application in a health-care setting wherein the robot needs to model the task using few observations in a data-efficient manner.

In this thesis, we propose the use of Bayesian nonparametric latent variable models to handle the high-dimensionality and perform data-efficient learning. Firstly, we propose a framework for real-time cloth state estimation that relies on the offline fusion of a depth sensor and a motion capture system. We use Manifold Relevance Determination [7] to perform the shared manifold learning and handle the non-rigid dynamics of clothing articles. We demonstrate the proposed cloth state model can generalize to unseen environmental settings.

Second, we propose a framework for data-efficient motor-skills learning. We use Bayesian Gaussian Process Latent Variable Model to learn a task-specific latent space that efficiently encodes the required motor-skills using few or even one demonstration. This latent space is used as a user-friendly interface for imparting novel motor skills and as a search space for reinforcement learning. The proposed frameworks are evaluated for the clothing task wherein a dual-arm robot clothes a soft mannequin with a T-shirt which is initially resting on the mannequin's arms. These frameworks can also be extended to other related cloth manipulation and assistive tasks.

3. Bayesian Nonparametric Latent Variable Models

The difficulties faced with robotic clothing assistance are its inherent non-linearity and high dimensionality. Clothing articles are non-rigid objects that lie in a high dimensional configuration space. The task of clothing assistance follows non-linear dynamics with large variabilities between various environmental conditions. Furthermore, it is necessary to have fast learning due to its application in a health-care setting and the robot needs to efficiently model the task in a data-efficient manner.

This thesis proposes the use of Gaussian Process (GP) [3] non-linear latent variable models [5, 7] to address these difficulties. Dimensionality reduction is used to reduce the high dimensionality and model the problems in low dimensional spaces that efficiently capture the underlying task. These models rely on the use of Gaussian Processes [3] which leads to handling the inherent non-linearity and also perform model learning in a data-efficient manner. This chapter provides the mathematical formulation of the models and discuss the applicability of these models for robotic clothing assistance.

These models can extract the underlying latent space from high dimensional and noisy observations. An intuitive understanding is provided in Figure 3.1 wherein high-dimensional observations lie on a complex non-linear manifold which can be mapped from a planar latent space. These models are capable of extracting the underlying latent space as well as learn a non linear mapping to the high dimensional observation space.

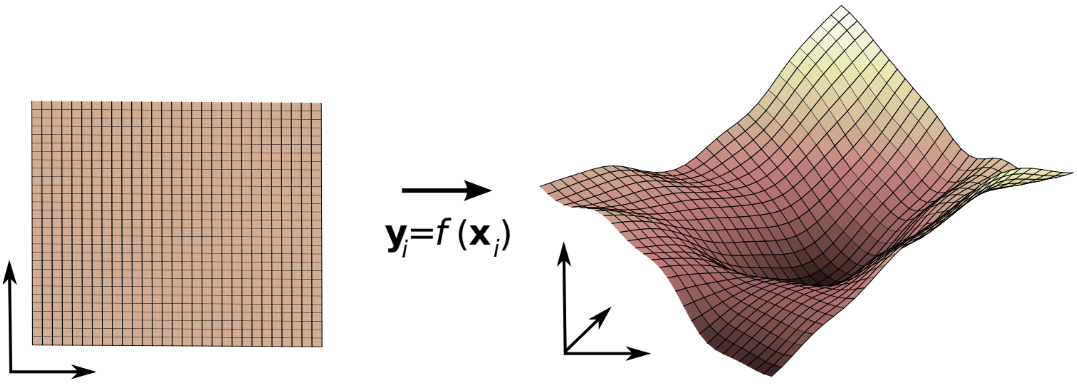


Figure 3.1.: Intuitive understanding of BGPLVM [5]

3.1. Bayesian Gaussian Process Latent Variable Model

Bayesian Gaussian Process Latent Variable Model (BGPLVM) is a non-linear dimensionality reduction technique proposed by Titsias *et al.* [5]. It is derived from the generative model shown in Figure 3.2 where the observations, $\mathbf{Y} = \{\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_N\},\ \mathbf{y}_n \in \mathbb{R}^D$, are assumed to be generated through a noisy process from latent variables $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\},\ \mathbf{x}_n \in \mathbb{R}^L$,

$$\begin{aligned} \mathbf{y}_n &= f(\mathbf{x}_n) + \epsilon_n,\ \ \epsilon_n \sim \mathcal{N}(\mathbf{0}, \beta^{-1}\mathbf{I}), \\ p(\mathbf{y}_n|\mathbf{x}_n, f, \beta) &= \mathcal{N}(f(\mathbf{x}_n), \beta^{-1}\mathbf{I}) \end{aligned} \tag{3.1}$$

where β denotes the inverse variance for the noise random variable ϵ and the conditional distribution for an observation sample can be derived as a Gaussian distribution. In this model, a prior on the mapping function f is placed using a Gaussian Process ($\mathcal{GP}$) [3] $f(x) \sim \mathcal{GP}(\mathbf{0}, k(\mathbf{x}, \mathbf{x}'))$, where $k(\mathbf{x}, \mathbf{x}')$ is the covariance function. For performing automatic model selection of the latent space dimensionality, the Automatic Relevance Detection (ARD) kernel [3] can be used,

$$k_{\text{ARD}}(\mathbf{x}_i, \mathbf{x}_j) = \sigma^2_{\text{ARD}} \exp\left(-\frac{1}{2}\sum_{l=1}^{L} \alpha_l (x_{i,l} - x_{j,l})^2\right) \tag{3.2}$$

The ARD weights $\{\alpha_l\}_{l=1}^{L}$ describe the relevance of each dimension and σ_{ARD} describes the scale of the GP mapping function. The relevance is usually determined using a heuristic threshold such that dimensions with weights below the threshold have insignificant contribution to reconstructing the observations [5, 7].

The objective is to infer the unknown latent variables $\mathbf{X}$ and the model parameters $\Phi = \{\beta, \sigma^2_{ARD}, \{\alpha_l\}_{l=1}^{L}\}$ of the mapping function. The conditional likelihood is derived by assuming D independent GP mappings evaluated on the latent variables $\mathbf{X}$,

$$\begin{aligned} p(\mathbf{Y}_{:,d}|\mathbf{X}, \Phi) &= \mathcal{N}(\mathbf{Y}_{:,d}|\mathbf{0}, \mathbf{K}), \\ p(\mathbf{Y}|\mathbf{X}, \Phi) &= \prod_{d=1}^{D} p(\mathbf{Y}_{:,d}|\mathbf{X}, \Phi), \\ = \frac{1}{(2\pi)^{\frac{DN}{2}}|\mathbf{K}|^{\frac{D}{2}}} &\exp\left(-\frac{1}{2}\mathrm{tr}((\mathbf{K})^{-1}\mathbf{Y}\mathbf{Y}^T)\right) \end{aligned} \tag{3.3}$$

where $\mathbf{K}$ is the $N \times N$ covariance matrix obtained from the covariance function $k_{\mathrm{ARD}}(\mathbf{x}, \mathbf{x}')$ and observation noise β, $\mathbf{Y}_{:,d}$ represent columns of the observation samples. A prior can be placed on the latent variables $\mathbf{X}$ and marginalization w.r.t $\mathbf{X}$ leads to a full Bayesian treatment,

$$\begin{aligned} p(\mathbf{X}) &= \prod_{n=1}^{N} \mathcal{N}(\mathbf{x}_n|\mathbf{0}, \mathbf{I}), \\ p(\mathbf{Y}|\Phi) &= \int p(\mathbf{Y}|\mathbf{X}, \Phi)p(\mathbf{X})d\mathbf{X} \end{aligned} \tag{3.4}$$

However, the integral for marginalization becomes intractable as $\mathbf{X}$ appears non-linearly in the inverse of the kernel covariance matrix $\mathbf{K}$ as shown in Eqn. (3.2,3.3). To make the marginalization tractable, approximate variational inference can be applied wherein a variational distribution $q(\mathbf{X})$ is used to approximate the true posterior distribution $p(\mathbf{X}|\mathbf{Y})$ given by,

$$q(\mathbf{X}) = \prod_{n=1}^{N} \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_n, \mathbf{S}_n) \tag{3.5}$$

where $\{\mu_n, S_n\}_{n=1}^{N}$ are the variational parameters. A Jensen's lower bound on the log marginal likelihood log $p(\mathbf{Y})$ can be derived as follows:

$$F(q) = \int q(\mathbf{X})\log \frac{p(\mathbf{Y}|\mathbf{X})p(\mathbf{X})}{q(\mathbf{X})}d\mathbf{X} \tag{3.6}$$

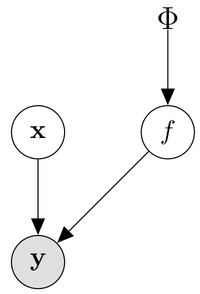


Figure 3.2.: Graphical model of Bayesian Gaussian Process Latent Variable Model (BG-PLVM) [5]

The hyper parameters Φ are dropped for notational simplicity. The lower bound still remains intractable as the latent variables appear non-linearly in the conditional likelihood term $p(\mathbf{Y}|\mathbf{X})$.

Titsias *et al.* [5] resolved this problem by introducing data augmentation which is commonly used in sparse GP regression. Data augmentation involves adding M extra observations $\mathbf{U} = \{\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_M\},\ \mathbf{u}_m \in \mathbb{R}^D$ known as inducing variables. These are evaluated at a set of pseudo inputs $\hat{\mathbf{X}} \in \mathbb{R}^{M \times L}$ through the same GP Prior as the latent variables, $\mathbf{X}$. The joint probability density and the variational distribution under this augmentation are modified as follows,

$$\begin{aligned} p(\mathbf{Y}, \mathbf{U}, \mathbf{X}, \hat{\mathbf{X}}) &= p(\mathbf{Y}|\mathbf{U}, \mathbf{X})p(\mathbf{U}|\hat{\mathbf{X}})p(\mathbf{X}), \\ q(\boldsymbol{\Theta}) &= p(\mathbf{Y}|\mathbf{U}, \mathbf{X})q(\mathbf{U})q(\mathbf{X}) \end{aligned} \tag{3.7}$$

where $q(\mathbf{X})$ takes the form of Eqn. (3.5), $q(\mathbf{U})$ is a variational distribution on the inducing variables whose form needs to be optimized and $p(\mathbf{Y}|\mathbf{U}, \mathbf{X})$ is the GP likelihood constrained by the latent variables as well as the inducing variables. This augmented probability model leads to a tractable Jensen's lower bound $\hat{F}(q)$ through the removal of the non-linear factor $p(\mathbf{Y}|\mathbf{X})$ thereby making the approximation tractable. Detailed derivations of the model are further presented in [5].

The prediction of unseen test data $\mathbf{y}^*$ is performed by evaluating $p(\mathbf{y}^*|\mathbf{Y})$,

$$p(\mathbf{y}^*|\mathbf{Y}) = \frac{\int p(\mathbf{y}^*, \mathbf{Y}|\mathbf{x}^*, \mathbf{X})p(\mathbf{x}^*, \mathbf{X})d\mathbf{X}d\mathbf{x}^*}{\int p(\mathbf{Y}|\mathbf{X})p(\mathbf{X})d\mathbf{X}} \tag{3.8}$$

The predictive distribution is given by the ratio of two marginal likelihoods, both of which can be approximated using the augmented probability model i.e.

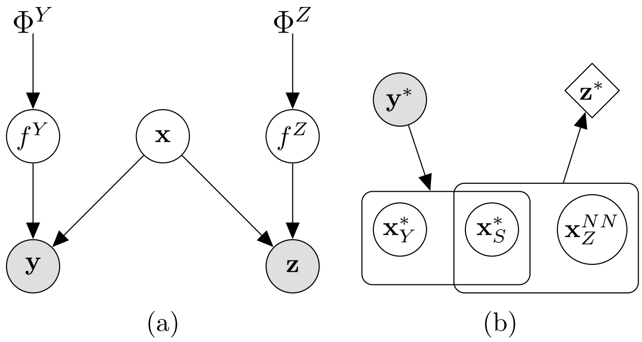


Figure 3.3.: a) Graphical model of Manifold Relevance Determination (MRD) [7], c) Overview of test inference for MRD

$\exp(\hat{F}(q, \mathbf{X}, \mathbf{x}^*))$, $\exp(\hat{F}(q, \mathbf{X}))$. Efficient computations to handle test data are further described in [5].

3.2. Manifold Relevance Determination

Damianou *et al.* [7] proposed an extension to BGPLVM for learning a shared latent space among multiple observation spaces called Manifold Relevance Determination (MRD). In this section, the formulation of MRD for two observation spaces is presented as shown in Figure 3.3(a) i.e. $\mathbf{Y} \in \mathbb{R}^{N \times D_Y}$, $\mathbf{Z} \in \mathbb{R}^{N \times D_Z}$ assumed to be generated from a single latent variable $\mathbf{X} \in \mathbb{R}^{N \times L}$ through the GP mappings $f^Y : X \to Y$, $f^Z : X \to Z$,

$$\begin{aligned} \mathbf{y}_n &= f^Y(\mathbf{x}_n) + \epsilon_n^Y, \;\; \epsilon_n^Y \in \mathcal{N}(\mathbf{0}, \beta_Y^{-1}\mathbf{I}), \\ \mathbf{z}_n &= f^Z(\mathbf{x}_n) + \epsilon_n^Z, \;\; \epsilon_n^Z \in \mathcal{N}(\mathbf{0}, \beta_Z^{-1}\mathbf{I}) \end{aligned} \tag{3.9}$$

where $\epsilon_n^Y, \epsilon_n^Z$ are the noise random variables parametrized by the inverse variance parameters β_Y, β_Z. The GP mappings for the Y observation space can be modeled using the ARD kernel,

$$k_Y(\mathbf{x}_i, \mathbf{x}_j) = \sigma_Y^2 \exp\left(-\frac{1}{2}\sum_{l=1}^{L} \alpha_k^Y (x_{i,l} - x_{j,l})^2\right) \tag{3.10}$$

and similarly for the Z observation space. Learning the ARD weights $\{\alpha_l^Y, \alpha_i^Z\}$ results in not only inferring the latent space dimensionality but also partitioning of the latent space into shared ($\mathbf{X}_S$) and private spaces ($\mathbf{X}_Y, \mathbf{X}_Z$). This is done using a heuristically set threshold δ on the normalized ARD weights to determine a latent dimension's relevance to each observation space,

$$\begin{aligned} \mathbf{X}_S &= \{\mathbf{x}_l\}_{l=1}^{L} : \mathbf{x}_l \in \mathbf{X}, \alpha_Y > \delta, \alpha_Z > \delta, \\ \mathbf{X}_Y &= \{\mathbf{x}_l\}_{l=1}^{L} : \mathbf{x}_l \in \mathbf{X}, \alpha_Y > \delta, \alpha_Z < \delta, \\ \mathbf{X}_Z &= \{\mathbf{x}_l\}_{l=1}^{L} : \mathbf{x}_l \in \mathbf{X}, \alpha_Y < \delta, \alpha_Z > \delta \end{aligned} \tag{3.11}$$

The objective is to evaluate the shared latent variables as well as the GP mapping hyper parameters for each observation space $\Phi^{\{\mathbf{Y},\mathbf{Z}\}}$. The joint conditional likelihood is obtained by factorizing each observation space as follows,

$$p(\mathbf{Y}, \mathbf{Z}|\mathbf{X}, \Phi_Y, \Phi_Z) = \prod_{\Gamma=\{\mathbf{Y},\mathbf{Z}\}} p(\Gamma|\mathbf{X}, \Phi_\Gamma) \tag{3.12}$$

Marginalization of the latent variables, similar to BGPLVM, is intractable due to its non-linear appearance in the kernel covariance matrix. Damianou *et. al.* [7] proposed an approximate variational inference formulation that relies on the use of an augmented probability model similar to BGPLVM (Eqn. (3.7)),

$$q(\boldsymbol{\Theta}) = q(\mathbf{X}) \prod_{\Gamma=\{\mathbf{Y},\mathbf{Z}\}} q(\mathbf{U}^\Gamma) p(f^\Gamma|\mathbf{U}^\Gamma, \mathbf{X}), \tag{3.13}$$

$$\tag{3.14}$$

where $\mathbf{U}^{\{Y,Z\}}$ are the inducing variables for each observation space similar to the BGPLVM formulation. The Bayesian formulation further enables test inference in the form of $p(\mathbf{z}^*|\mathbf{y}^*)$ i.e. inference of test sample in Z observation space ($\mathbf{z}_*$) given the Y observation space $\mathbf{y}^*$. This inference is done by first estimating the latent sample $\mathbf{x}^*$ similar to test inference given in Eqn. (3.8) and using this estimate through the GP mapping f^Z.

The inference for a test sample follows a sequence as shown in Figure 3.3(b). Firstly, the latent state x_Y^*, x_S^* corresponding to test sample y^*. The shared latent state x_S^* is then used to find nearest neighbors among the latent points corresponding to the training data and obtain the private dimensions information for Z i.e. x_Z^{NN}. Finally, the full latent state x_S^*, x_Z^{NN} is used to infer the test pose state i.e. z^*. In this sequence, the computationally expensive operation is inference of x_Y^*, x_S^* as it involves optimization of marginal likelihoods similar to the

MRD model training. This makes real-time inference difficult and so alternative strategies for the test inference are explored as presented in Section 4.1.3.

The latent variable models presented in this section are a powerful class of models that can be used in a wide range of settings. The use of GP mappings leads to data-efficient learning of complex mappings. Approximate Bayesian inference along with ARD kernels avoids overfitting and enables automatic dimensionality reduction.

4. Real-time Cloth State Estimation

Clothing articles inherently lie in a high dimensional configuration space and feature extraction becomes a challenging task as the clothing article could have large shape variations and occlusions. However, clothing articles follow consistent deformations for a particular task thereby constrained to a low-dimensional manifold which is task-specific. A possible approach for reliable cloth state estimation is to constrain the search space within task-specific latent cloth models.

In this chapter, we propose to learn an offline cloth model that is used to perform informed cloth state estimation in real-time as shown in Figure 4.1. This model is learned using the non-linear dimensionality reduction technique Manifold Relevance Determination (MRD) [7] to handle the non-rigidity of clothing articles and learn the cloth latent features in a Bayesian manner avoiding the problem of over-fitting. MRD is used to learn an offline low-dimensional latent manifold for data from simultaneous observation of clothing article using a motion capture system and a depth sensor. Both sensory systems have complimentary capabilities, when combined provide the most informative observation of clothing articles. The motion capture system can provide accurate location information of discrete markers in the environment, however, it is an expensive and complex system that requires precise calibration and can not be used in real-time. On the other hand, depth sensors are low-cost and calibration free, however, they provide noisy point cloud information of the whole environment.

MRD provides a principled probabilistic framework for inferring the accurate motion capture state when only the noisy depth sensor state is available in real-time. In this chapter, we demonstrate that MRD is capable of learning task specific latent features which can be interpretable. We show that MRD has

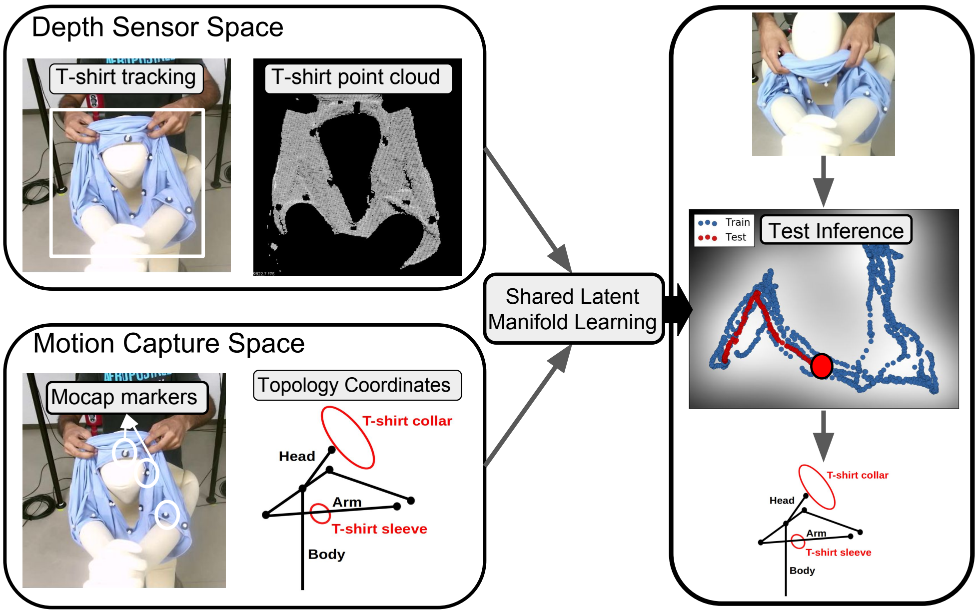


Figure 4.1.: Proposed framework for cloth state modeling using MRD. Observations from a depth sensor and the motion capture system are used to train a latent manifold used in real-time to infer human-cloth relationship information.

the best predictive performance for accurate cloth state estimation. We further investigate the effect of factors such as feature representations on the predictive performance of the trained cloth state model.

4.1. Methods

Clothing articles are highly non-rigid and can undergo large deformations. The deformations occurring during a cloth folding task can be significantly different when compared to wearing the same clothing article. This makes general-purpose modeling and state estimation of clothing articles not only difficult but also impractical. Poor feature extraction could also lead to model inaccuracies for motor skills learning thereby restricting the learning rate for robotic applications to cloth handling. To address this problem, we propose the use of Bayesian nonparametric latent variable models described in Chapter 3. This leads to task-specific feature extraction in a purely data driven manner.

Our framework is applied for the real-time tracking of human-cloth relationship using a depth sensor. A depth sensor is a low-cost solution to capture 3D shape information without requiring any elaborate setup or calibration of the sensor. These features are crucial to develop a real-world implementation of clothing assistance wherein end-users and caregivers can easily setup the system. However, depth sensors provide noisy information and there is also the problem of cloth occlusion in our task setting. We tackle these problems by assuming that clothing articles are constrained to a low-dimensional latent manifold specific to clothing assistance tasks forming a task-specific cloth model.

We consider clothing assistance tasks for demonstrating our proposed method. A mannequin was used as the subject and the clothing task is to cloth the mannequin with a T-shirt that is initially lying on its hands. We are interested in real-time estimation of the relationship between the assisted subject and cloth using a low-cost depth sensor for the implementation of a practical and efficient robotic clothing assistance framework. However, this is a challenging task as there are significant changes in the cloth state during clothing tasks along with self-occlusions and occlusion by the mannequin. To address this problem, we propose the learning of an offline cloth state model using information from both the depth sensor and motion capture system.

The purpose of the cloth model is to learn a latent representation $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_N]^T$ corresponding to an aligned data set of clothing article observations from the depth sensor $\mathbf{Y} = [\mathbf{y}_1, \ldots, \mathbf{y}_N]^T$ and motion capture system $\mathbf{Z} = [\mathbf{z}_1, \ldots, \mathbf{z}_N]^T$. The motivation behind this modeling approach is that the motion capture system can provide precise location information of markers placed on the cloth where as the depth sensor can provide a generalized shape description. By learning a shared latent structure, we are indirectly learning a mapping from the generic depth sensor information to the more detailed motion capture information, which can be used for constrained cloth state estimation in real-time using noisy depth sensor observations. The predictive performance of the learned latent structure further depends on several factors such as the representations used for the observation spaces and the inference technique used. In the following subsections we describe the approach used in handling these factors.

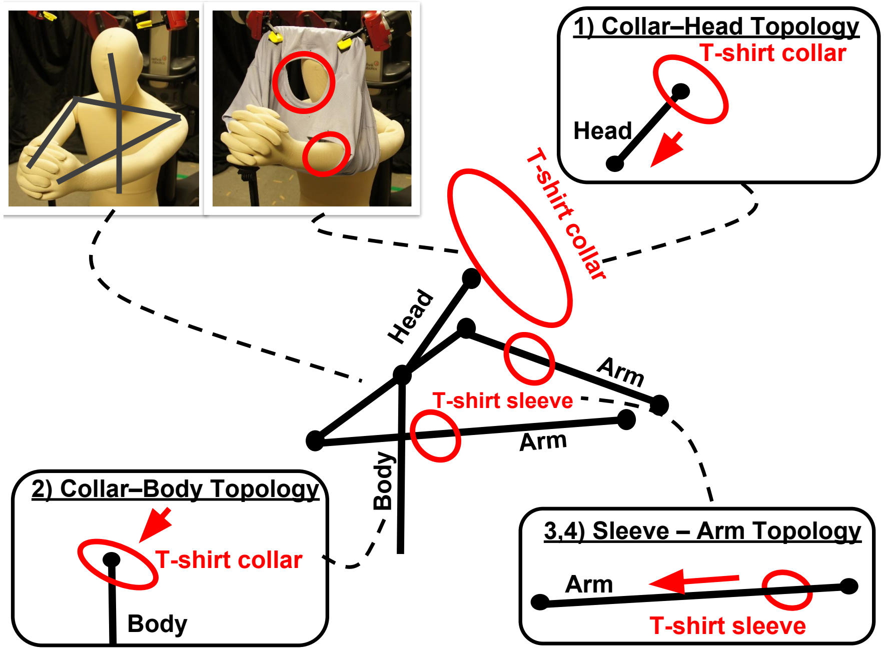


Figure 4.2.: Topology Coordinate representation used for the Human-Cloth Relationship as Pose Space Representation

4.1.1. Motion Capture Representations

The purpose of using motion capture system is to capture precise cloth state information which is required for efficient motor skills learning. We consider the clothing task where the robot has to cloth a mannequin with a T-shirt which is initially on the mannequin's hands. We assume that the details of clothes such as wrinkles are not important to achieve clothing assistance tasks and hence used low-dimensional topology coordinates [13] to capture the relationship between human subject and clothing article. Furthermore, we have previously demonstrated that topology coordinates are robust to noise in the motion capture observations and can efficiently capture the human-cloth interaction in a practical setting [113].

Topology coordinates [13] were formulated for synthesizing human-like motions that involve close interactions. Topology coordinates compactly define the relationship between two curves in the Cartesian space using three different attributes, i.e. writhe w, center of twist $\mathbf{c} = [c_1 \; c_2]$ and density d. Writhe w measures the total twisting between two curves γ_1, γ_2 by using an approximation of the Gauss Linking Integral (GLI) [14]:

$$\mathrm{GLI}(\gamma_1, \gamma_2) = \frac{1}{4\pi} \int_{\gamma_1} \int_{\gamma_2} \frac{(\gamma_1 - \gamma_2) \cdot (d\gamma_1 \times d\gamma_2)}{\|\gamma_1 - \gamma_2\|^3} \tag{4.1}$$

The center of twist $\mathbf{c}$, composed of two scalars explains the relative position of twist with respect to each of these lines. The density d represents the relative twisting between the two lines, i.e. which line is twisting around the other. These parameters can be analytically computed by dividing the given curves into chains of small line segments. The details for analytical computation of these parameters along with examples are presented in Appendix A.

The motor skills required for the robot to complete the clothing task are 1) to pull the T-shirt collar over the mannequin's head and onto the mannequin's body, 2) to pull the T-shirt sleeves along the mannequin's arm towards its shoulder. To achieve these motor skills, the following needs to be estimated and tracked by the depth sensor: T-shirt collar, T-shirt sleeves and the mannequin's posture. In this chapter, the focus is on the cloth state estimation and therefore the mannequin's posture remains fixed during the task. The human-cloth relationship is given by considering the writhe and center of twist of the T-shirt w.r.t the mannequin for 4 different topologies as shown in Figure 4.2: 1) T-shirt Collar - Mannequin's Head Topology, 2) Collar - Body, 3) Left Sleeve - Left Arm, 4) Right Sleeve - Right Arm thereby forming a eight-dimensional representation $\mathbf{Z} \in \mathbb{R}^8$. The density parameter is not considered as the T-shirt will always twist around the mannequin and this topology is never reversed for clothing assistance tasks.

The topology coordinate values were computed using the observations from motion capture system. The setup had eight infrared (IR) cameras placed carefully around the experimental setting to maximally avoid occlusion of markers. Six IR markers were attached on the T-shirt collar, three markers on each T-shirt sleeve and five markers on the mannequin respectively to estimate the human-cloth topological relationship. These markers were used to obtain approximate curves of the T-shirt collar and sleeves which were used in the computation of topology coordinates. The computation of topology coordinates for the T-shirt clothing task are presented in the Appendix A.

To evaluate the effect of pose space representation on the predictive performance of the cloth model, we considered two alternative representations along

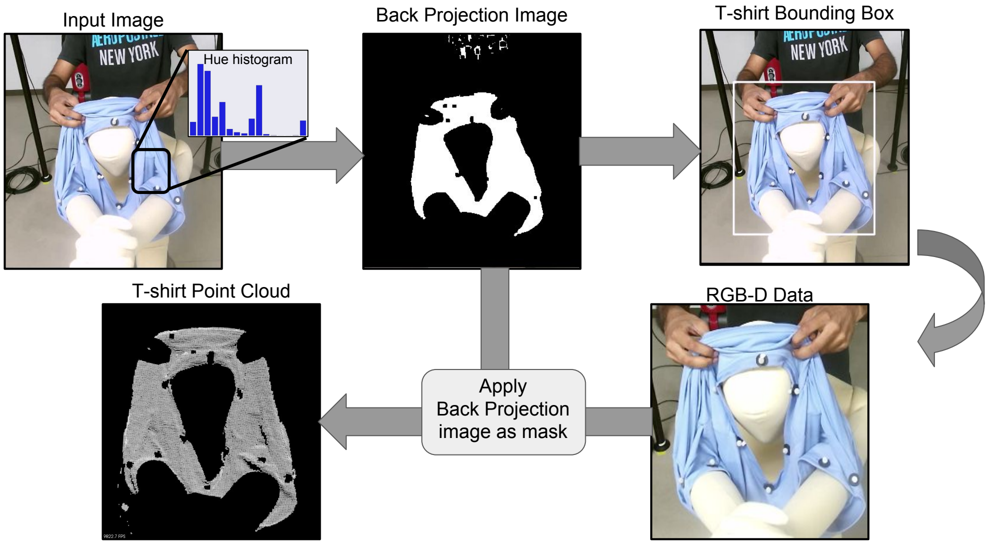


Figure 4.3.: Overview of the algorithm used to extract the point cloud corresponding to the T-shirt from raw RGB-D data from depth sensor.

with topology coordinates:

- *Marker Representation*: given by the Cartesian position of each of the 12 markers placed on the collar and sleeves of the T-shirt forming a 36 dimensional space.

- *Circle Approximation*: given by the parameters of a circle approximation to the T-shirt collar and the sleeves obtained from the marker positions. Each circle is parametrized by $[C\ r\ \vec{n}] \in \mathbb{R}^7$ i.e. its center ($C \in \mathbb{R}^3$), radius ($r \in \mathbb{R}$) and normal ($\vec{n} \in \mathbb{R}^3$) thereby forming a 21 dimensional feature representation.

4.1.2. Depth Sensor Representations

A depth sensor is capable of capturing shape information of clothing articles. The purpose of the feature space representation is to capture the global cloth shape. For this, we consider the point cloud representation of the clothing article. The point cloud data can be used in real-time along with the proposed cloth modeling approach to infer precise human-cloth relationship information. In this section we present the method used to preprocess the RGB-D data and obtain the point cloud corresponding to the clothing article.

For the real-time estimation of human-cloth relationship, we need to track the overall cloth shape during the clothing task. There have been several studies that can reliably locate clothing articles within a cluttered environment [45, 46]. We assume that it is possible to obtain a seed bounding box for clothing articles through the existing methods. In this framework, to simplify the process, we have used clothing articles that are of a single color to reliably localize the clothing article in an input frame.

The depth sensor provides a pair of RGB and depth images as each observation. The RGB image is used to locate the clothing article and the depth image is used to construct the cloth point cloud. Prior to the tracking, we perform hue-saturation color calibration where in a histogram of hue and saturation values is constructed from a region of interest (ROI) that corresponds to the T-shirt. This histogram can be used to find pixels corresponding to the T-shirt in an input image. For tracking of clothing article, we use the following approach as illustrated in Figure 4.3:

- T-shirt hue-saturation histogram is applied to the input frame to obtain a back projection image. The back projection image is computed using the T-shirt histogram where the intensity of each pixel in the back-projection image corresponds to the probability of belonging to the T-shirt.

- Back-projection image along with a seed T-shirt bounding box is provided as input to the standard CAMshift algorithm [16] where the shift and scaling of the bounding box between frames is estimated.

- To ensure feature consistency across multiple demonstrations, a bounding box of fixed size (250×250 in this case) is computed with a center corresponding to the bounding box obtained from the CAMshift algorithm.

- Back projection image within the bounding box represents the probability of belonging to the T-shirt and is applied as a mask to both the RGB and depth images and obtain the region corresponding to the T-shirt.

- Point cloud from the T-shirt depth image pixels is constructed using the intrinsic parameters of the sensor. This point cloud is further processed by applying statistical outliers removal techniques.

The image processing functions were implemented using the OpenCV library [17] and the point cloud processing was done using the Point Cloud Library (PCL) [18]. The point cloud constructed through preprocessing is down sampled to 50×50 forming a 7500 dimensional space ($Y_{\text{depth}} \in \mathbb{R}^{7500}$) with a triplet of 3 dimensions capturing the Cartesian position of a point in the T-shirt point cloud.

We also considered two alternate representations for the RGB-D data to evaluate the effect of feature space representation. Each representation for the feature space captures different physical aspect of shape information.

- *Color Pixel Data*: The color pixel data from the bounding box of the T-shirt is evenly down sampled to 50×50 and converted to single channel thereby forming a 2500 dimensional space ($Y_{\text{color}} \in \mathbb{R}^{2500}$) with each dimension representing the intensity of a pixel.

- *Ensemble of Shape Functions*: ESF is a global feature descriptor proposed by Wohlkinger *et al.* [19] that is primarily used to represent the underlying shape of a 3D point cloud. ESF is a fixed 640 dimensional feature histogram ($Y_{\text{ESF}} \in \mathbb{R}^{640}$), consisting of a concatenation of 10 histograms with 64 bins each in them. These histograms are generated by repeated random sampling of pairs or triplets of points from the point cloud and computing various parameters of the resultant triangles and lines.

4.1.3. Real-time Implementation

The latent manifold learned by the MRD model includes two sets of ARD kernel weight parameters. These parameters describe the relevance of each latent dimension with respect to the corresponding observation space as described in Section 3.2. The latent space is partitioned into three subspaces $\mathbf{X}_S, \mathbf{X}_Y, \mathbf{X}_Z$ where $\mathbf{X}_S$ are the shared latent dimensions and $\mathbf{X}_Y, \mathbf{X}_Z$ are the private latent dimensions. The partitioning is done by placing manually set thresholds on the ARD weights as shown in Eqn. 3.11.

The objective of trained cloth models is to infer accurate pose state (motion capture space) given an unseen feature state (depth sensor space) in real-time. The inference of pose state z^* for an unseen feature state y^* involves a sequence of several steps as presented in Section 3.2. As this inference approach is not suitable for real-time implementation, we considered two alternate strategies with improved computational efficiency.

Optimization Approach: This is the standard strategy where optimization is performed for each test sample y^* to obtain the test latent state x^*_Y, x^*_S. This is the most computationally expensive approach and is expected to have the best predictive performance. *Nearest Neighbor Regression*: This is a naive strategy where we obtain the nearest neighbors y^{NN} to the test data y^* in the training set and approximate x^*_Y, x^*_S with mean of nearest neighbor latent points x^{NN}_Y, x^{NN}_S. This is the most computationally efficient approach and is expected to have the least predictive performance.

Hybrid Approach: This strategy can be considered as a trade-off between the two strategies presented above. The latent states obtained using the optimization approach were found to have strong temporal correlation. This insight was used to propose a hybrid inference strategy where an Unscented Kalman Filter (UKF) [20] is applied to latent states predicted using the nearest neighbor strategy. Furthermore, for every fixed number of observations, the internal state of UKF is updated using the optimization inference technique. This approach provides more reliable estimates compared to the nearest neighbor approach with similar computational efficiency and can be considered as a trade-off between accuracy and time complexity.

4.1.4. Experimental Setup

Experimental setup includes the clothing assistance framework with Kinect V2 depth sensor and MAC3D motion capture system for cloth state estimation. We designed a framework using Robot Operating System (ROS) [21] and socket programming to integrate both devices and for synchronous data recording. Each sensor device has a program or node running on the control PC to perform data collection. We collected clothing trials with simultaneous observation of the T-shirt state using both the depth sensor and motion capture system. The node for

(a) (b) (c) (d)

Figure 4.4.: Four T-shirts were used for collecting clothing trials: a) T-shirt 1: Polyester and V-neck, b) T-shirt 2: Polyester and round neck, c) T-shirt 3: Cotton and V-neck, d) T-shirt 4: Cotton and round neck

motion capture system is designated as the master and other node as slave. Synchronization for data collection was performed by the master node which sends messages to the slave nodes for starting and stopping data collection.

The observations were temporally aligned ensuring point-to-point correspondences in the training phase. Cloth state is observed using both the sensors at a rate of 30 frames per second (FPS) during the clothing assistance tasks. The observations were also spatially aligned by performing an absolute orientation calibration between the motion capture system and the depth sensor. The method proposed by Umeyama [22] was used to compute the transformation between the two reference frames. The source code for this framework is published online as a ROS package for further reference [28].

The efficiency of MRD to learn cloth state models was evaluated for clothing assistance tasks. Ideally, the learned cloth state model needs to be task specific such as for clothing tasks and should generalize to various environmental settings. For the case of robotic clothing assistance, the model needs to generalize to unseen postures of mannequin and different clothing materials. To evaluate the generalization capability, we used four T-shirts with different features as shown in Figure 4.4. For each T-shirt, we collected several clothing trials for six different postures of the mannequin obtained by varying the head inclination ($\{30^o, 45^o\}$) and the shoulder elevation ($\{100^o, 105^o, 110^o\}$) angles. The head inclination and shoulder elevation angles were measured with respect to the positive and negative Z-axis normal to the ground plane as shown in Figure 4.5. A clothing demonstration

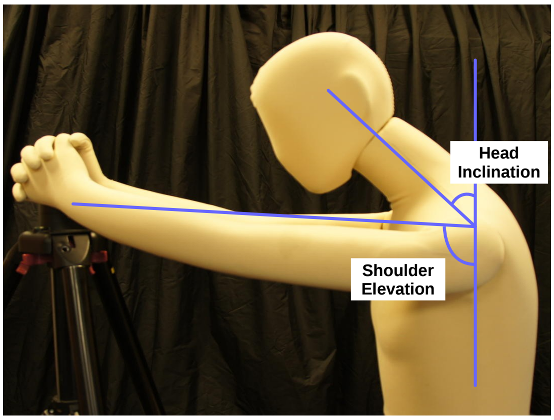


Figure 4.5.: Clothing trials were collected by varying the head inclination and shoulder elevation angles of the mannequin.

along with the extracted feature representations and test inference for MRD is shown in the video demonstration available at `https://youtu.be/UuJGzhKb9KM`.

The clothing trials in the dataset were collected through human demonstrations to ensure subtle variations which can not be induced by a robot in the demonstrations so that the dataset includes observations for different shapes of clothing articles. The motivation behind creating such a dataset was that the force applied by the robot changes largely for different T-shirts and different postures thereby imparting significant variations in the observed cloth state transitions across the clothing trials. The performance of using BGPLVM and MRD were evaluated using three metrics in all the experiments i.e. the Pearson correlation coefficient, root mean square error (RMSE) and normalized root mean square error (NRMSE). Given two univariate random variables x, y with samples $x_n, y_n : n \in \{1, \cdots, N\}$ having means $\bar{x}, \bar{y}$, the metrics can be evaluated as follows:

$$\begin{aligned} \text{RMSE} &= \sqrt{\frac{\sum_{n=1}^{N}(x_n - y_n)^2}{N}} \\ \text{NRMSE} &= \frac{RMSE}{\max(\{x_n\}) - \min(\{x_n\})} \\ \text{Corr} &= \frac{\sum_{n=1}^{N}(x_n - \bar{x})(y_n - \bar{y})}{\sqrt{\sum_{n=1}^{N}(x_n - y_n)}\sqrt{\sum_{n=1}^{N}(x_n - y_n)}} \end{aligned} \tag{4.2}$$

Statistical significance was evaluated for all the experiments by using the one-sided Wilcoxon signed rank sum test [27].

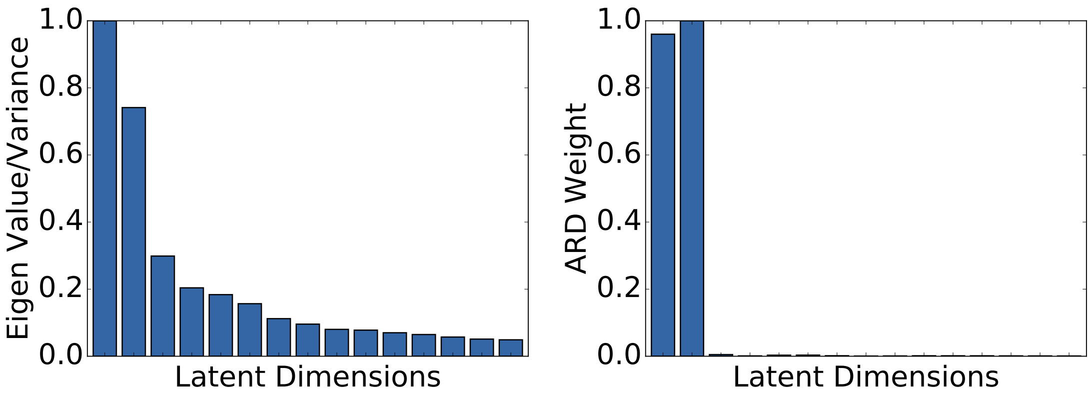
The training of an MRD model is a computationally expensive task which scales with the size of the training dataset as it is a kernel-based method. The computational complexity of the model scales as $O(NM^2)$ where N is the size of the training dataset and M are the number of inducing points used for the variational approximation. For all our experiments we have set the number of inducing points $M = 100$. We have conducted our experiments on a desktop machine with an Intel i7 3.5 GHz processor. The training time for an MRD model with 1275 observations took 3 hrs and 25 minutes for the model to converge. The BGPLVM and MRD models were trained using the GPy python library [25] along with the implementations for real-time inference. The source code to generate all the presented results are published online for further reference [29].

4.2. Results

In this section, we describe the experiments conducted to evaluate the performance of our proposed framework. Section 4.2.1 demonstrates the effectivity of using Bayesian nonparametrics in handling the non-rigidity of clothing articles. Section 4.2.2 shows the predictive performance of the trained cloth models for various environmental settings. The computational complexity for the algorithm along with real-time implementation for test inference is demonstrated in Section 4.2.3. Finally, Section 4.2.4 demonstrates the generalization ability of MRD cloth models to unseen environmental settings.

4.2.1. Latent Features Learned

In this section, we investigate the effectivity of using Bayesian nonparametrics and non-linear modeling for cloth state estimation. We evaluated the effectivity by only considering the depth sensor observation and by comparing the performance of BGPLVM with a linear latent variable model, Principal Component Analysis (PCA). We performed dimensionality reduction using both BGPLVM and PCA on the point cloud observation space and inspected the learned latent structures for both models. The BGPLVM model was optimized until there was negligible increments in the likelihood function and the variational distribution



(a) (b)

Figure 4.6.: Comparison of Latent Dimension relevance learned by PCA and BGPLVM: a) PCA relevance given by Eigen values, b) BGPLVM relevance given by ARD kernel weights

Table 4.1.: Reconstruction Error for PCA and BGPLVM Models

Data	RMSE			Correlation		
	PCA	**BGPLVM**	p-Val	PCA	**BGPLVM**	p-Val
Train	0.016	**0.012**	0.05	0.646	**0.800**	0.05
Test	0.024	**0.023**	0.01	0.559	**0.593**	0.01

for the latent space was initialized using the positions of training data in the latent space obtained from PCA.

For the observed data, we considered the point cloud representation from depth sensor as presented in Section 4.1.2 which is a 7500 dimensional observation space. The training data for the models was obtained from 5 clothing trials performed over 5 different postures with T-shirt 1 from Figure 4.4. The test data for the model was given by 1 clothing trial for an unseen posture with T-shirt 1 and 3 clothing trials each using T-shirt 2,3 forming a total of 7 test clothing trials. Each clothing trajectory has about 100 samples measured at a frequency of 8 FPS, leading to 638 observations in the training data and 803 observations in the

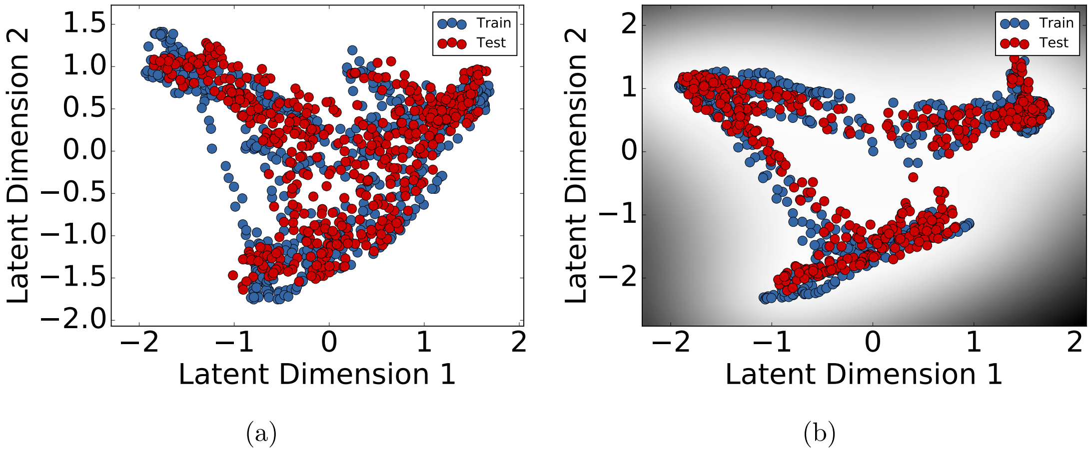


Figure 4.7.: Comparison of latent spaces learned by a) PCA and b) BGPLVM for the 1^{st}, 2^{nd} significant latent dimensions. Blue dots indicate training data, red dots indicate test data. Gray scale gradient for BGPLVM indicates the predictive variance obtained from the GP mapping.

test data.

Figure 4.6 demonstrate the relevance of each dimension in the latent space after training. The relevance for PCA is given by Eigen values and by the ARD kernel weight parameters for BGPLVM (Eqn. 3.2). The relevance parameters for both models are normalized such that the most significant dimension has a weight of 1.0 to demonstrate the relative importance between the dimensions. The relevance weights indicate that PCA takes all 15 dimensions to capture cloth transitions through the linear mapping, where as BGPLVM captures the underlying features within 2 dimensions using the non-linear GP mapping.

Figure 4.7 shows the latent spaces for two most significant dimensions. The latent space learned by BGPLVM is constrained to a task-specific manifold in comparison to PCA. For BGPLVM, the samples from each clothing trial seem to follow a two dimensional latent trajectory which is consistent across the clothing trials with various environmental settings. The latent features explained by each dimension were inspected by reconstructing the high dimensional data for latent point variations only along that corresponding dimension. These dimensions explain the horizontal motion of the T-shirt collar and sleeves along the mannequin's hands and the vertical motion on the T-shirt collar onto the mannequin's head.

An inspection of the latent space is included as a video demonstration available at `https://youtu.be/A-EeXtpPLvA` wherein BGPLVM was applied to motion capture marker data and the latent feature represented by each dimension was evaluated by generating the high-dimensional marker space for changes along a single latent dimension.

To evaluate generalization capability, we compared reconstruction error between PCA and BGPLVM as shown in Table 4.1. Reconstruction error is given by comparing the input data point and the reconstructed data point from the latent point corresponding to the input,

$$\begin{aligned} \mathrm{Err} &= \|y_{\mathrm{org}} - y_{\mathrm{pred}}\|, \\ y_{\mathrm{pred}} &= f_{\mathrm{model}}(f^{-1}_{\mathrm{model}}(y_{\mathrm{org}})) \end{aligned} \tag{4.3}$$

where y_{org} is an input sample from dataset, y_{pred} is the predicted value after reconstruction and f_{model} is the forward mapping from latent space to observation space. We evaluated Root Mean Square Error (RMSE) and Pearson correlation as the metrics. The Wilcoxon signed rank sum test [27] was used to evaluate statistical significance and the p-value was evaluated for a one-sided test. We used an exact distribution over the W-statistic as the number of clothing trajectories were few (5 for training and 7 for test). For the training data, BGPLVM has much better performance as it is a kernel method and stores the complete training data unlike PCA. However, BGPLVM also has significantly better performance (p-value: 0.01) for the test data demonstrating its superior generalization capability for high dimensional and noisy point cloud data.

The latent space learned by BGPLVM captures clothing demonstrations as consistent low-dimensional trajectories which could correspond to the task-specific dynamics. This indicates that the latent space could be a suitable state space representation for reinforcement learning, thereby removing the need to estimate topology coordinates. To evaluate this, we designed a reward function for reinforcement learning with different state representations as follows,

$$\begin{gathered} r(s_t^{\mathrm{state}}) = \|s_T^{\mathrm{state}} - s_t^{\mathrm{state}}\|, \\ \mathrm{state} \in \{\mathrm{Top.\ Coord}, \mathrm{BGPLVM}\} \end{gathered}$$

where s_T^{state} corresponds to a desired target state and the state representation can either be the topology coordinate values estimated from the motion capture

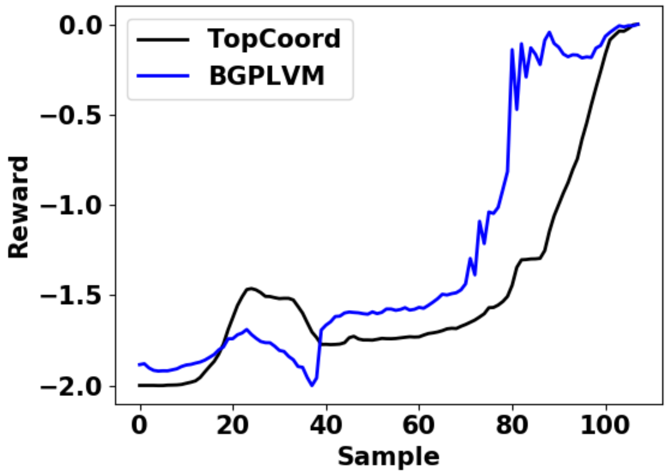


Figure 4.8.: Reward values for sample clothing demonstrated evaluated using different state representations.

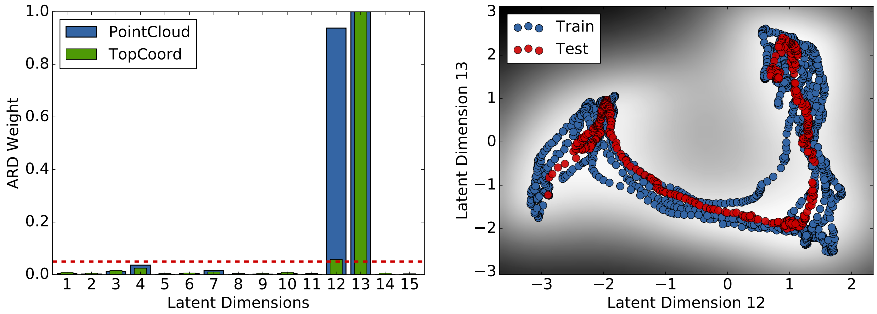
data or the BGPLVM latent state obtained from the noisy depth sensor readings. The reward values were computed for the test clothing demonstrations using both state representations with a sample demonstration shown in Figure 4.8. By considering the rewards obtained using topology coordinates as the ground truth, the error in estimated rewards was evaluated with Pearson correlation ρ and normalized RMS error used as the metrics and summarized in Table 4.2

Table 4.2.: Reconstruction Error for PCA and BGPLVM Models

Metric	BGPLVM
Correlation (ρ)	0.82±0.03
NRMSE	0.22±0.02

4.2.2. Predictive Performance of Cloth Models

Reliable cloth state estimation is a challenging problem due to the inherent ambiguity when observing from a single view point along with occlusion. We propose

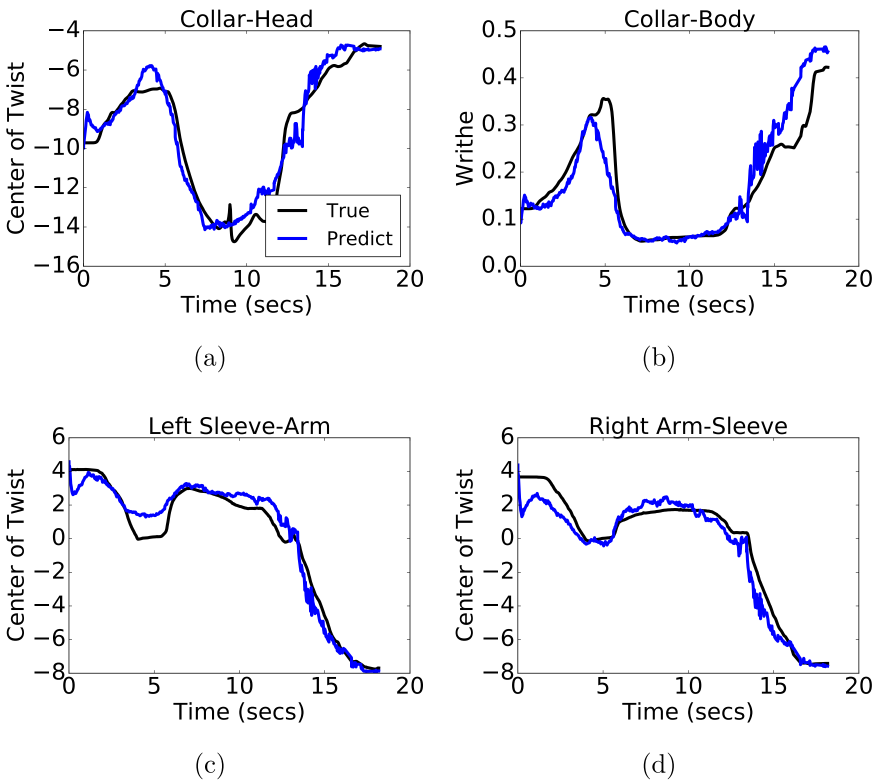


(a) (b)

Figure 4.9.: Example MRD Model: a) ARD Kernel weights, b) Latent space for two significant dimensions.

the learning of a shared latent manifold using Bayesian nonparametrics to disambiguate and solve the problem. In this section, we demonstrate the effectivity of using MRD for modeling cloth state. An MRD model is trained over observations from a depth sensor (feature space) and motion capture system (pose space). The trained model is then used to infer the human-cloth relationship information given a test point cloud. Firstly, we present the latent features learned and the predictive performance of an example cloth model. We further present comparison of MRD with standard regression techniques to investigate the advantage of using a shared latent manifold for inferring cloth state.

Figure **??** illustrates an MRD model between the topology coordinate and point cloud representations trained over five clothing trials for five different postures with T-shirt 1 of Figure 4.4. A clothing trial on an unseen posture is used as the test data. Figure 4.9(a) shows the sets of ARD kernel weights that are learned. The threshold on ARD weights was set to 0.05 as shown by the red line leading to two shared dimensions between the observation spaces and no private dimensions for either observation space. However, this structure of the latent space, especially the private space dimensionality, was found to vary depending on the training data used. Figure 4.9(b) shows the latent manifold for the two most significant dimensions. It can be seen that the model captures the dynamics of performing clothing tasks through the well-formed trajectories in the latent space. Figure 4.10(a)-(d) show the prediction of topology coordinate values for the test



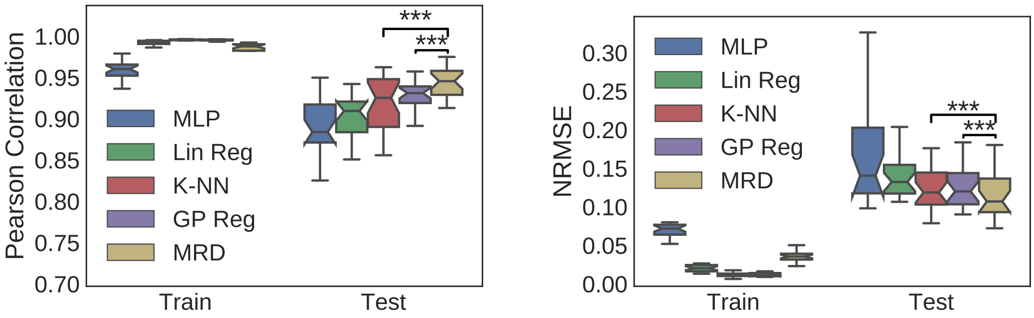
(a) (b) (c) (d)

Figure 4.10.: Example MRD model: Test inference of four topology coordinates.

data where each figure indicates a particular topology presented in Section 4.1.1 demonstrating the predictive performance of MRD.

To validate the effectivity of using a shared latent manifold, we further compared the predictive performance of MRD with standard regression techniques. We considered four regression candidates i.e. linear regression, K nearest neighbor regression, multi-layer perceptron and Gaussian process regression. For nearest neighbor regression, we used five nearest neighbors for predictions. For neural networks, we used a single hidden layer with 200 hidden nodes and Rectified Linear Unit (ReLU) activation function in the network. GP regression was performed using the Radial Basis Function (RBF) kernel. All the models were trained until there were insignificant changes in the objective function for optimization.

The models were evaluated over a dataset of 24 clothing trials collected for six different postures of the mannequin using four T-shirts as described in Sec-



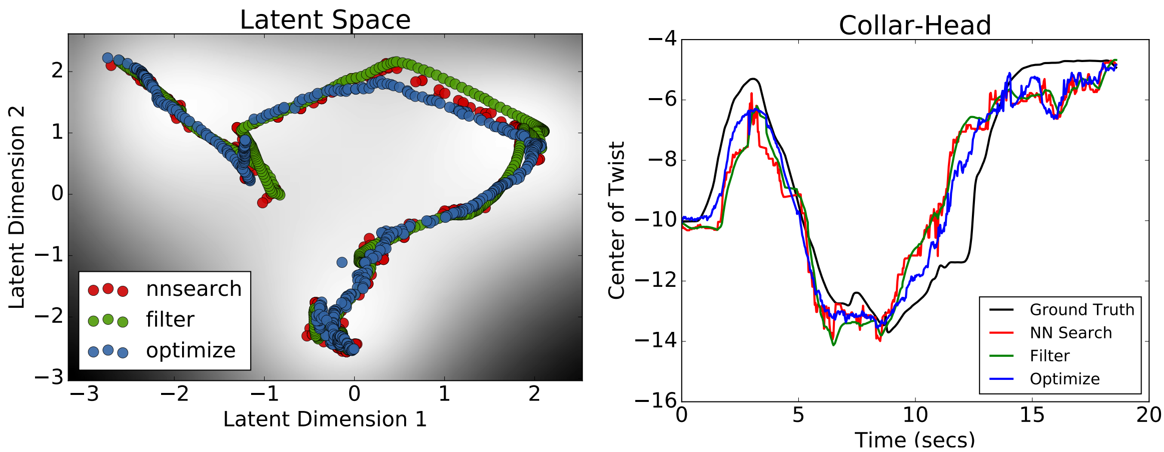
(a) (b)

Figure 4.11.: Comparison of predictive performance between MRD and standard regression techniques. Evaluation on two metrics, a) Pearson correlation and b) Normalized RMS error. $***$ indicates $p < 0.001$ for one-sided Wilcoxon signed rank sum test [27].

tion 4.1.4. A set of six cloth models were trained for each T-shirt (total of 24 models) using leave-one-out cross validation wherein one clothing trial was used as test data and remaining five were used as training data. Figure 4.11 shows the comparison of MRD with regression techniques. Normalized RMS error and Pearson correlation were used as the metrics for evaluation. Statistical significance was evaluated using the one-sided Wilcoxon signed rank sum test [27]. An approximate distribution over the W-statistic was used as the number of trials was relatively large ($N = 24$). It can be seen that MRD has the best predictive performance being significantly better ($p < 0.001$) over other regression techniques.

4.2.3. Comparison of Inference Methods

The inference for test data is a computationally expensive task that involves the optimization of a ratio of two marginal likelihoods similar to the training of the MRD model. To ensure real-time estimation of the human-cloth relationship, we considered two alternative strategies as presented in Section 4.1.3. In this section, we present the relative predictive performance and computational complexity for these strategies. Our experimental setup was implemented such that, we could

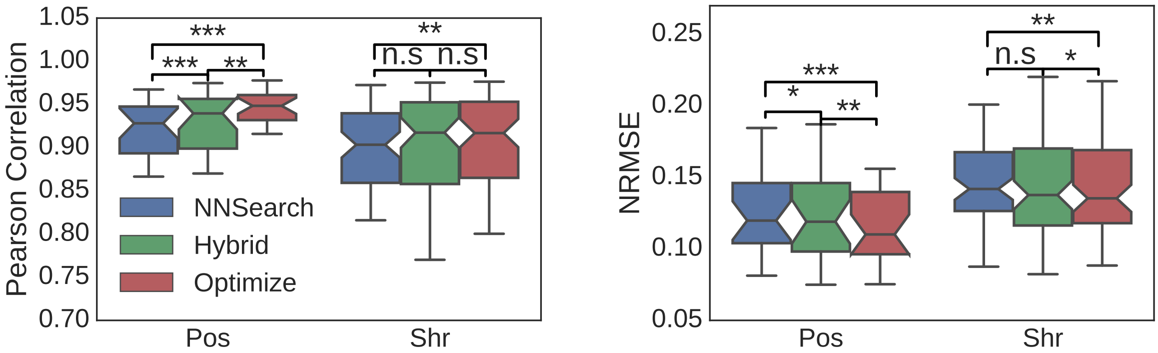


(a) (b)

Figure 4.12.: a) Estimates for shared latent dimensions of MRD model evaluated for three inference strategies. b) Topology coordinate estimates from MRD model evaluated for three different inference strategies compared with the ground truth values

obtain raw T-shirt point cloud from the depth sensor and broadcast at a rate of 30 frames per second (fps) using the ROS framework. A separate program subscribes to the point cloud streams and infers the human-cloth relationship using one of the presented inference strategies.

The implementation details for each inference strategy is as follows. For the nearest neighbor search, the number of neighbors was set to five and a KD-tree [26] was used to search through the high dimensional training dataset. The optimization strategy was implemented as described in Section 3.2 with the initialization for latent point given by the nearest neighbor search. The hybrid strategy was applied by using an unscented Kalman filter to handle the non-linear transitions in the latent points obtained using the nearest neighbor strategy. The filter was only applied to the shared latent dimensions which vary from two to four depending on the latent manifold learned for different datasets. The state transition function was given by a constant velocity model with only the position used as observation variables. The internal state of UKF was updated every 15 observations which ensures a considerably good computational complexity. The parameters for the filter such as the process and measurement noise covariances were manually tuned minimizing the predictive error of the model.

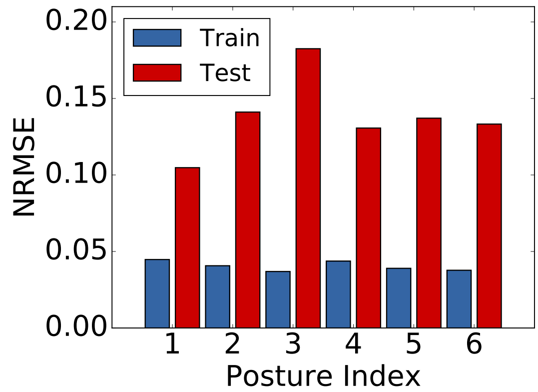


(a) (b)

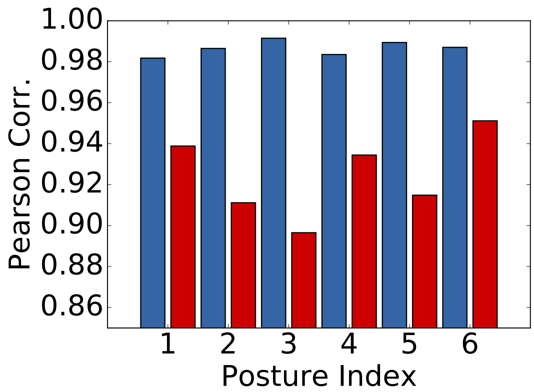
Figure 4.13.: Comparison of different inference strategies with MRD. Evaluation on two metrics, a) Pearson correlation and b) Normalized RMS error. $n.s$: not significant, $*$: $p < 0.05$, $**$: $p < 0.01$, $***$: $p < 0.001$ for one-sided Wilcoxon signed rank sum test [27].

We considered the performance of inference strategies for two different scenarios i.e. an unseen mannequin posture and for an unseen T-shirt. The MRD models were trained between the point cloud (feature space) and topology coordinate (pose space) representations. The evaluation dataset had 24 clothing trials as described in Section 4.1.4. For the unseen posture scenario, we performed leave one out cross-validation for each T-shirt with one posture as test data and the remaining five postures used for training. For the unseen T-shirt scenario, we used six clothing trials from three T-shirts as the training data and clothing trials for the unseen T-shirt as the test data. The state estimated for the shared latent dimensions along with the inferred topology coordinate values for an unseen T-shirt clothing trial is presented for the three inference strategies in Figure 4.12(a),(b).

The performance of the inference strategies was evaluated using three metrics, i.e. normalized RMS error, Pearson correlation and the computational complexity as presented in Figure 4.13. The nearest neighbor strategy has an average time complexity of processing 30 frames per second (fps), the hybrid method with a complexity of 10 fps and the optimization method with about one fps. The results averaged over the test clothing trials have an intuitive trend, with nearest



(a)



(b)

Figure 4.14.: Generalization capability of cloth model to unseen postures evaluated through 6-fold cross validation given by a) Normalized RMSE and b) Pearson Correlation values

neighbor search having the least predictive performance and best computational complexity and the optimization-based approach having the opposite trends. The hybrid approach is a good trade-off as it has a computational complexity suitable for a practical setting but with considerable improvements in the predictive performance. However, for the unseen T-shirt setting, the problem becomes quite difficult and there is no longer a significant improvement for the hybrid approach. This indicates the requirement for stronger temporal constraints such as placing a dynamics prior on the latent space as presented by Damianou *et al.* [6].

4.2.4. Generalizability of Cloth Models

In this section, we evaluate the generalizability of cloth models trained using MRD for various environmental settings. Ideally, we would want the cloth model to learn clothing task specific latent features and generalize to unseen postures of the mannequin and unseen clothing articles. To evaluate the generalization capability, we conducted two sets of experiments. In the first experiment, we evaluated the generalization to unseen postures. For this we considered four sets of six clothing trials corresponding to four T-shirts and six postures respectively. We performed six-fold cross validation across postures for each T-shirt and evaluated

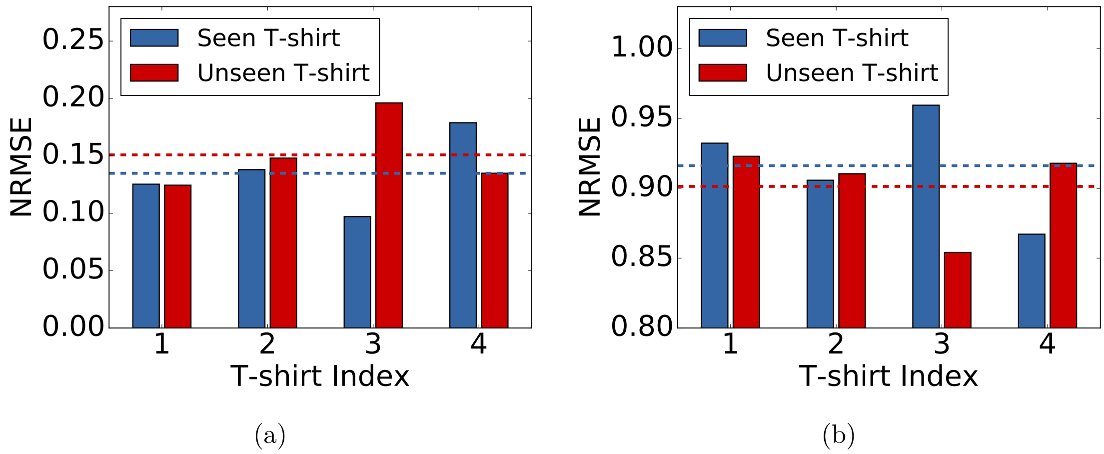


Figure 4.15.: Generalization to clothing trials for seen and unseen T-shirts given by a) Normalized RMSE and b) Pearson Correlation values. Horizontal dotted lines indicate the mean values across the T-shirts.

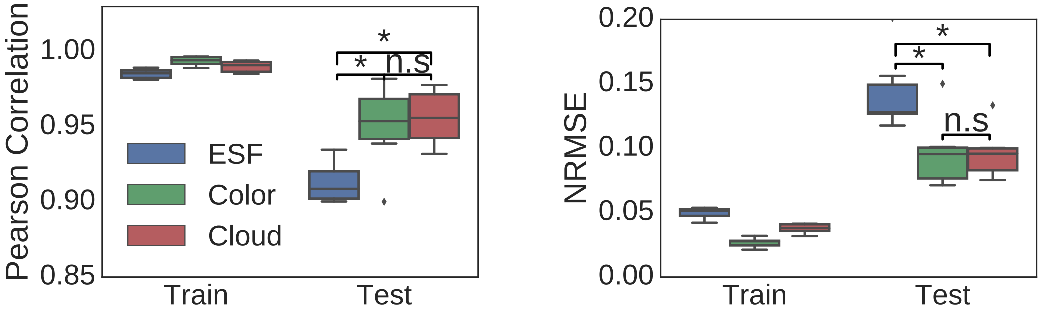
the predictive performance as shown in Figure 4.14. The results show that the trained cloth models can generalize well to unseen mannequin postures with mean normalized RMSE 0.134 and mean Pearson correlation 0.925.

In the second experiment, we evaluated generalization to unseen T-shirts. We considered a similar dataset as the posture experiment, however we performed four-fold cross validation across the T-shirts and evaluated the predictive performance to unseen T-shirts as shown in Figure 4.15. For each cross-validation, we included six clothing trials from three T-shirts and trained an MRD model. The predictive performance was evaluated for unseen clothing trials of both seen and unseen T-shirts. The results indicate that the performance is slightly better for seen T-shirts however the performance is also good for unseen T-shirts.

4.2.5. Comparison of Feature Representations

The latent features and predictive performance of MRD depends on the feature representations used for the observation spaces. In this section, we consider several representations for each observation space that are relevant to the clothing assistance framework and evaluate their relative performance.

The feature representations used for an observation space capture different in-

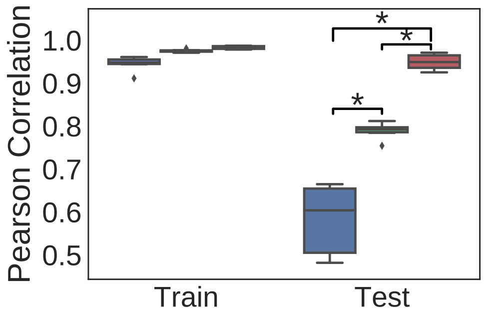


(a) (b)

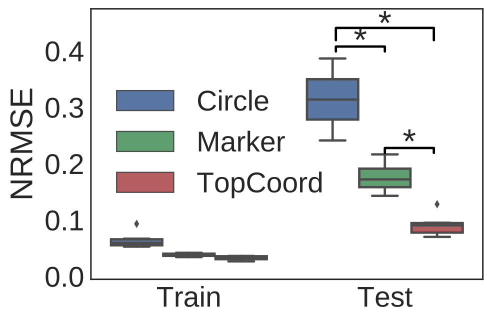
Figure 4.16.: Comparison of different feature representations for depth sensor observation space. Evaluation on two metrics, a) Pearson correlation and b) Normalized RMS error. $n.s$: not significant, $*$: $p = 0.025$ for one-sided Wilcoxon signed rank sum test [27].

formation about clothing articles thereby leading to different latent features on training. For this purpose, we used several representations for each observation space as presented in Sections 4.1.2 and 4.1.1. We compared the predictive performance for each of the representation to evaluate the best representation in each observation space for clothing assistance tasks. The representations for the feature space were trained along with topology coordinate representation for comparison and the pose space representations were trained along with the point cloud representation. Observations from six clothing trials for six different postures of the mannequin with T-shirt 1 were used as the evaluation dataset. We performed six-fold cross-validation on the dataset with a single clothing trial taken as test data and the remaining five trials used as training data.

The results for comparison between the representations is shown in Figures 4.16 and 4.17 given by the mean values of normalized RMS error and Pearson correlation across the six folds. Figure 4.16 indicates that the point cloud representation and the color representations have almost similar performance and are significantly better than the ESF representation. This indicates that both color or point cloud representations are suitable for the task of clothing assistance. However, the ESF representation being a feature histogram seems to drop some crucial shape information that is necessary for reliable cloth state estima-



(a)



(b)

Figure 4.17.: Comparison of different feature representations for motion capture observation space. Evaluation on two metrics, a) Pearson correlation and b) Normalized RMS error. *n.s*: not significant, $*$: $p = 0.025$ for one-sided Wilcoxon signed rank sum test [27].

tion. Figure 4.17 indicates that the topology coordinate representation has the best predictive performance. The marker and circle approximation representations have significantly lower performance ($p = 0.025$) as the variation between clothing trials for specific marker positions is significantly higher in comparison to topology coordinates which mainly captures the relationship between human and cloth rather than specific cloth state.

4.3. Discussion

The experimental results presented in Section 4.2 demonstrate the effectivity of using Bayesian nonparametrics to model cloth state and learn task-specific latent features such as for clothing assistance. Section 4.2.1 presents results that demonstrate the effectivity of using a non-linear dimensionality reduction technique i.e. BGPLVM in comparison to a linear model such as principal component analysis (PCA). Figure 4.7 demonstrates that the latent features learned in BGPLVM were found to be consistent across various environmental settings and is much more informative in comparison to PCA even without any information from the motion capture system. This indicates that BGPLVM can be used to learn a task specific representation and the latent state can itself replace topology coordinates as state representation for motor-skills learning.

Section 4.2.2 presents the predictive performance of learning a shared latent manifold using Manifold Relevance Determination (MRD) between data obtained from a depth sensor and a motion capture system. Firstly, the effect of the state representation used for each observation space is demonstrated. The results indicate the point cloud for depth sensor and topology coordinate representation for motion capture system provide the most relevant features that are shared between both the observation spaces. We further demonstrated the generalization capability of MRD for unseen postures of the mannequin and unseen clothing articles. The results indicate good predictive performance with some reduction for drastic changes in the environmental settings. Finally, the predictive performance was compared with standard regression techniques and MRD was found to have the best predictive performance demonstrating the effectivity of learning a shared latent manifold.

The predictive performance of MRD has been evaluated by comparison with standard regression techniques and it was demonstrated that MRD has the best performance using Pearson correlation and normalized root mean square error as metrics. However, the performance by MRD was slightly better. One of the reasons for this is that the current task setting does not include much variations in cloth shape and are limited by the interaction with clothing articles. As the task complexity increases, MRD could have better performance over other regression techniques as it can effectively handle the non-linearity.

Section 4.2.3 provides details for real-time implementation of the proposed method. The method relies on the use of MRD which is a kernel-based method and therefore the computational complexity for both training and test inference increases with the size of the training data. To handle this issue for real-time implementation we proposed two alternate strategies for test inference and compared the relative performance of the inference strategies. The filtering inference strategy was found to be a good trade-off and suitable for real-time estimation of human-cloth relationship from noisy point cloud observations. The computations for all the experiments were performed on a CPU of average computing power. The predictive performance can further be improved by implementing the inference algorithm on a Graphical Processing Unit (GPU).

5. Data-efficient Motor Skills Learning

Enabling robots to learn motor skills for performing complex tasks is a major goal of the AI community. However, existing methods require large number of interactions to learn optimal behavior which is not suitable in practical scenarios such as in the field of assistive robotics. Clothing assistance is one such task which is a necessity in the daily life of the elderly and disabled people. Design of a practical framework involves reliable cloth state estimation in real-time and a motor skills learning framework that can detect and adapt to various failure scenarios. A possible approach is to formulate robotic clothing assistance as a reinforcement learning problem wherein the robot learns to recover from failure scenarios and adapt to new settings from experience.

In this chapter, we propose an efficient representation of motor skills that relies on the use of Bayesian Gaussian Process Latent Variable Model (BGPLVM) [5]. BGPLVM is capable of learning a data-efficient latent space for clothing tasks performed by a dual-arm robot. Representation of clothing skills in a low dimensional space enables the use of expressive policy update rules for generalization to very different settings. We apply our proposed method in a practical setting of robotic clothing assistance framework as shown in Figure 5.1. We demonstrate that the learned space generates robot trajectories that maintain task space constraints required for clothing tasks. We further present the design of a real-time controller from the BGPLVM latent space that can be used as a tool for Learning from Demonstration (LfD). The experimental results indicate a promising policy representation with reinforcement learning that can be used for robotic clothing assistance.

The rest of the chapter is structured as follows. Section 5.1 introduces the

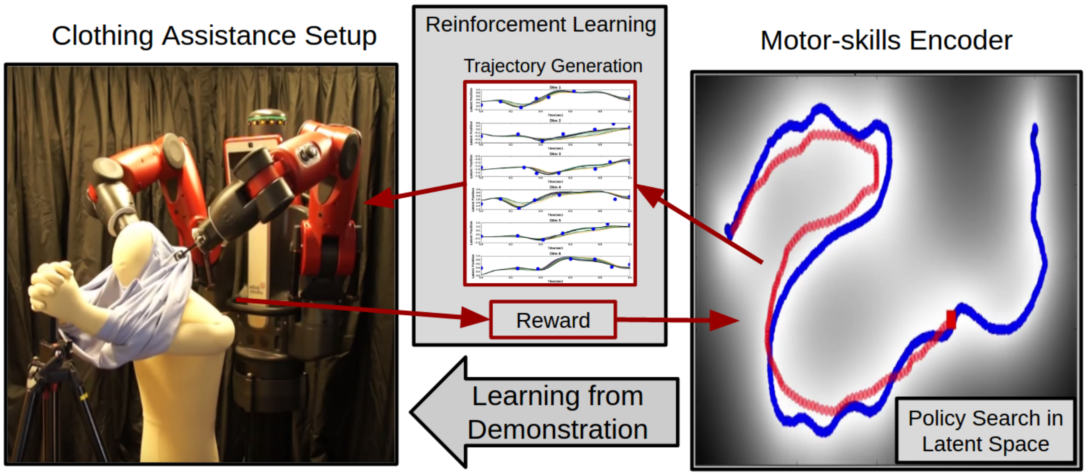


Figure 5.1.: Overview of proposed framework for motor skills learning. Figure on the left shows the setup for clothing assistance and the figure on the right shows the latent space encoding the motor skills.

proposed framework. Section 5.2 includes experimental results and Section 5.3 provides discussion on the results.

5.1. Methods

Learning motor skills in a data-efficient manner is crucial for domains such as assistive robotics where the robot needs to quickly adapt and reliably perform the desired task. Tamei *et al.* [1] have proposed a reinforcement learning (RL) framework for clothing assistance with a dual-arm robot as the agent and a mannequin as the subject. A limitation of this framework is that policy search is performed in kinematic space which is considerably high dimensional for a seven degrees of freedom (DoF) dual-arm robot. For tractable learning time, policy update was done using finite difference policy gradient applied to a single via-point of a single joint in each robot arm. This severely constrained the generalization capability to very different environmental settings such as major changes in the mannequin's posture or using different clothing articles.

Motor skills for clothing assistance are given by high dimensional joint angle trajectories of the dual-arm robot. Furthermore, the robot also has to maintain several task space constraints such as coupling with a clothing article along with safe human-robot interaction as shown in Figure 5.1. In this thesis, we consider an alternate representation that is more flexible and suitable for robust learning of motor skills. We propose the use of dimensionality reduction (DR) to learn a low-dimensional latent space that encodes clothing skills without losing any generalization capability.

Reinforcement learning (RL) usually suffer from the curse of dimensionality especially for continuous action spaces and a possible solution is the use of dimensionality reduction (DR). Some studies use DR as a preprocessing step and perform RL in the reduced search space [93]. Others inherently combine DR and RL wherein the dimensionality reduction is motivated by the rewards obtained during the learning phase [83,96]. However, these studies either use linear models for DR limiting the modeling capability or rely on a MAP estimate of the latent space which tends to overfit to the training data.

We propose the use of Bayesian Gaussian Process Latent Variable Model (BGPLVM) [5] for learning a low dimensional latent space through a non-linear mapping to the kinematic space. The advantage of BGPLVM is that it relies on variational inference to learn a posterior distribution on the latent space rather than a MAP estimate as in GPLVM. This avoids over fitting to the training data, thereby, improving the generalization capability of the model to unseen environmental settings. We further explore various representations to the learning of BGPLVM model specific to clothing assistance tasks. We implement our framework on a practical setting of clothing assistance as formulated by Tamei *et al.* [1] that involves tight coupling between human and the clothing article along with high variability in policy depending on the task settings.

5.1.1. Motor Skills Representation using BGPLVM

In this section, we present the formulation used to apply BGPLVM to clothing assistance skills. We consider the clothing task where a dual-arm robot dresses a soft mannequin with a T-shirt which is initially resting on the mannequin's arms. The training dataset is given by human demonstration through kinesthetic movement while controlling the robot under gravity compensation mode. The BGPLVM model learns a mapping from the low dimensional latent space to the robot kinematic space such that a trajectory of points in the latent space generates a trajectory on the dual-arm robot. The Gaussian process mapping leads to data-efficient learning, thereby requiring few demonstrations, possibly one, for task generalization.

The latent features learned by BGPLVM depend on the input dataset provided. We consider two alternate representations i.e. 1) kinematic representation (JA) given by joint angles of 6 DoF for each arm of a dual-arm robot $D_K = 12$ and 2) task space representation (EE) given by the end-effector pose of both arms with Cartesian position $P_X, P_Y, P_Z \in \mathbb{R}^3$ and orientation $O_X, O_Y, O_Z, O_\omega \in \mathbb{R}^4$ forming a 14-dimensional space $D_T = 14$. We set the dimension of the latent space as $q = 6$ for all our experiments. However, the dimensionality is eventually inferred through the training of the ARD kernel weights as explained in Section 3.1.

5.1.2. Real-time Controller for Skill Transfer

There can be several types of failure scenarios when the robot performs clothing tasks. To recover from these failures, not only is the trajectory of the robot important, but also the speed of execution. Imparting these skills through kinesthetic movement of the arms can be difficult for inexperienced users and could lead to noisy demonstrations. To address this problem, we have implemented a real-time controller as shown in Figure 5.2 that gets an input signal from the BGPLVM latent space to control the robot. This interface can be used as a tool for Learning from Demonstration (LfD) where the necessary clothing skills are imparted to the robot by using cursor control over the latent space.

Real-time implementation of the controller was designed using Robot Operating System (ROS) software framework. A pipeline was formed where cursor coordinates in the latent space were mapped through BGPLVM to generate a robot joint angle pose which was provided as input to the low-level controllers of the robot. Using this interface, a path traced in the latent space converts to a trajectory performed on the dual-arm robot in real-time. An example scenario for this interface is care-givers imparting motor skills to assistive robots in a real-world health care facility.

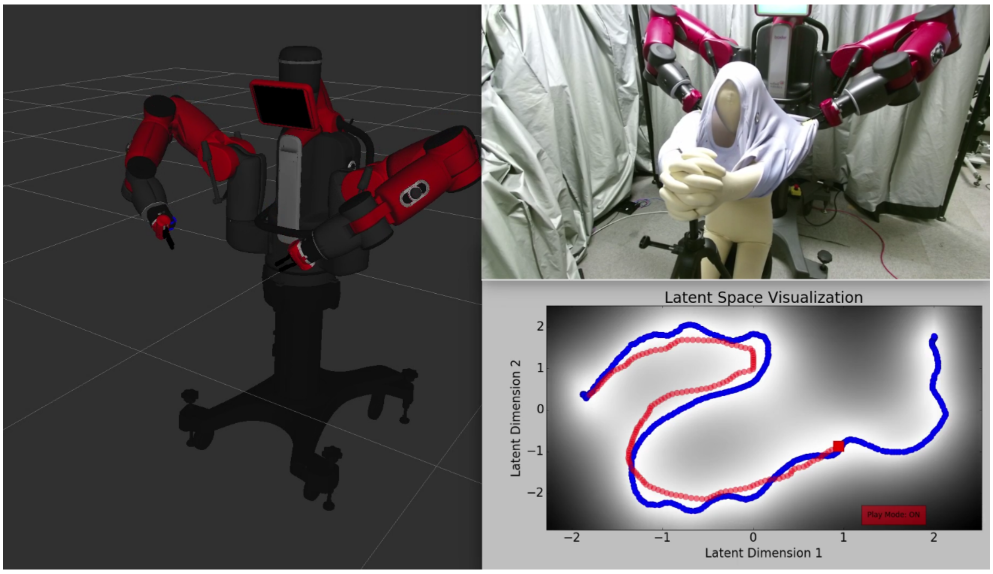


Figure 5.2.: Interface for imparting motor skills. Left: Simulator to plan trajectory, Right Top: Robot performing trajectory. Right Bottom: BGPLVM latent space to control robot.

5.1.3. Latent Space Reinforcement Learning

In this section, we formulate a policy search framework in the BGPLVM latent space. The objective is to learn a high-dimensional robot trajectory for performing the clothing task on an unseen posture of the mannequin by searching within this latent space. Firstly, a dataset of successful clothing assistance trajectories is used to train a latent space that encodes the motor skills. Each of the trajectory is now transformed into a sequence of points in the latent space forming latent space trajectories. The policy search is performed using Policy learning by Weighted Exploration with Returns (PoWER) [30] which is a commonly used policy search algorithm. It has been widely used in robotics to learn controllers for performing various tasks.

We consider Dynamic Movement Primitives (DMP) [32] as policy representation. It is the combination of a point attractor dynamical system and a non-linear forcing term ($f(s)$) learned using Locally Weighted Regression (LWR) [33]:

$$\begin{aligned} \tau\ddot{x} &= K(g-x) - D\dot{x} + (g-x_0)f \\ f(s) &= \frac{\sum_i w_i \psi_i(s) s}{\sum_i \psi_i(s)}, \text{ where } \tau\dot{s} = -\alpha s \end{aligned} \tag{5.1}$$

We train a DMP on the latent points corresponding to one of the training trajectory and the LWR weight coefficients are used as policy parameters which are modified to generalize to unseen environmental settings. The cost function for policy improvement is designed in the high-dimensional action space. In the current setting, we obtain a demonstration for the unseen posture and consider this as the optimized trajectory to be achieved. The optimized trajectory is efficiently encoded by via-points extracted using the minimum jerk criterion [34] that the robot needs to pass through. The cost function is given by the sum of all errors between the reconstructed robot trajectory and the desired via-points:

$$R(\tau) = \sum_{i=1}^{n_{\text{dims}}} \sum_{j=1}^{n_{\text{via}}} \|V_{i,j} - x_i^{recons}(t_{i,j})\|^2 \tag{5.2}$$

where $R(\tau)$ is the total reward for trajectory τ, $V_{i,j}$ is the j^{th} via point of i^{th} dimension and $x_i^{recons}(t)$ is the value at time t for i^{th} dimension of reconstructed trajectory.

5.1.4. Experimental Setup

Experimental setup includes the clothing assistance framework with Kinect V2 depth sensor for state estimation and Baxter research robot used to perform the clothing tasks. We designed a framework using Robot Operating System (ROS) [21] to control the robot and for providing demonstrations. To impart the motor skills for clothing task, the robot is controlled under gravity compensation mode during which the demonstrator can provide a kinesthetic demonstration. The robot is further controlled in a *puppet* mode wherein one of the arms (slave)mimics the motion of the other arm (master) and the demonstrator interacts with master arm as shown in Figure 5.3. This strategy is necessary as the robot is too bulky and usually leads to noisy demonstrations when each arm is controlled independently. The source code for this framework is published online as a ROS package for further reference [28].

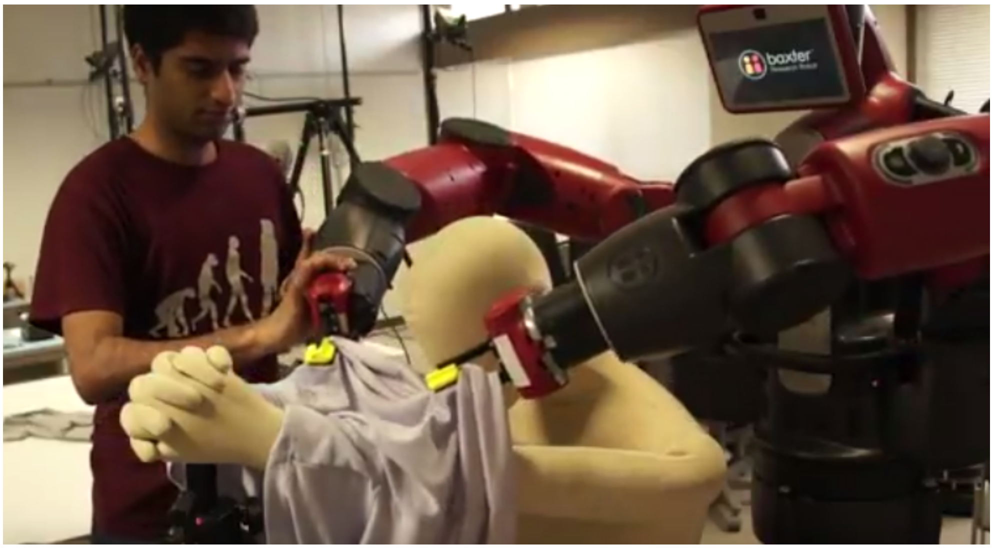


Figure 5.3.: Human demonstrator imparting motor skills under puppet mode.

The efficiency of BGPLVM to encode motor skills is evaluated for clothing assistance tasks. Ideally, the learned model needs to be task specific such as for clothing tasks and should generalize to various environmental settings. Furthermore, the model needs to generalize to unseen postures of mannequin and to an unseen demonstrator performing the task. The evaluation dataset contains kinesthetic demonstrations performed by 3 experienced users i.e. graduate students who have varying experience {2 years, 1 year, 6 months} interacting with Baxter robot. For each demonstrator, clothing and unclothing demonstrations were recorded for 6 different postures of the mannequin wherein the shoulder elevation $\{65^o, 70^o, 75^o, 80^o\}$ and head elevation $\{30^o, 45^o\}$ were varied. These postures cover the entire range for which the robot can successfully perform clothing tasks thereby spanning all feasible postures. The head inclination and shoulder elevation angles were measured with respect to the positive and negative Z-axis normal to the ground plane as shown in Figure 4.5.

We consider the performance for the clothing and unclothing tasks of the T-shirt. Each task follows different dynamics and need to be modeled independently. Usually running a clothing demonstration backwards for unclothing leads to failure. The performance of using BGPLVM was evaluated using two metrics in all the experiments i.e. the Pearson correlation coefficient and normalized root mean square error (NRMSE). Given two univariate random variables x, y with samples $x_n, y_n : n \in \{1, \cdots, N\}$ having means $\bar{x}, \bar{y}$, the metrics can be evaluated as follows:

$$\begin{aligned} \text{NRMSE} &= \frac{RMSE}{\max(\{x_n\}) - \min(\{x_n\})} \\ \text{Corr} &= \frac{\sum_{n=1}^{N}(x_n - \bar{x})(y_n - \bar{y})}{\sqrt{\sum_{n=1}^{N}(x_n - y_n)}\sqrt{\sum_{n=1}^{N}(x_n - y_n)}} \end{aligned} \tag{5.3}$$

Statistical significance was evaluated for all the experiments by using the one-sided Wilcoxon signed rank sum test [27].

5.2. Results

In this section, we present the performance of the proposed framework in a practical setting of robotic clothing assistance. Section 5.2.1 demonstrates the predictive performance of using BGPLVM to encode motor skills in comparison to other latent variable models (LVMs). Section 5.2.2 provides an evaluation of the real-time controller for imparting motor skills to the robot. Finally, Section 5.2.3 shows the effectivity of using BGPLVM as a search space in policy search reinforcement learning.

5.2.1. Comparison of Latent Variable Models

In this experiment, we inspect the motor skills i.e. latent features learned by BGPLVM and evaluate the predictive performance in comparison to other latent variable models (LVM) i.e. Principal Component Analysis (PCA) [15] and Gaussian Process Latent Variable Model (GPLVM) [4]. Firstly, we consider the dataset of demonstrations from the evaluation dataset for both clothing and unclothing tasks. For each task, demonstrations for four postures were used as training data and for two postures were used as test data. BGPLVM models were trained for both the kinematic space (JA) and task space (EE) representations. The ARD weights on training resulted in varying number of active latent dimensions for different scenarios. For the clothing task, the JA representation resulted in three

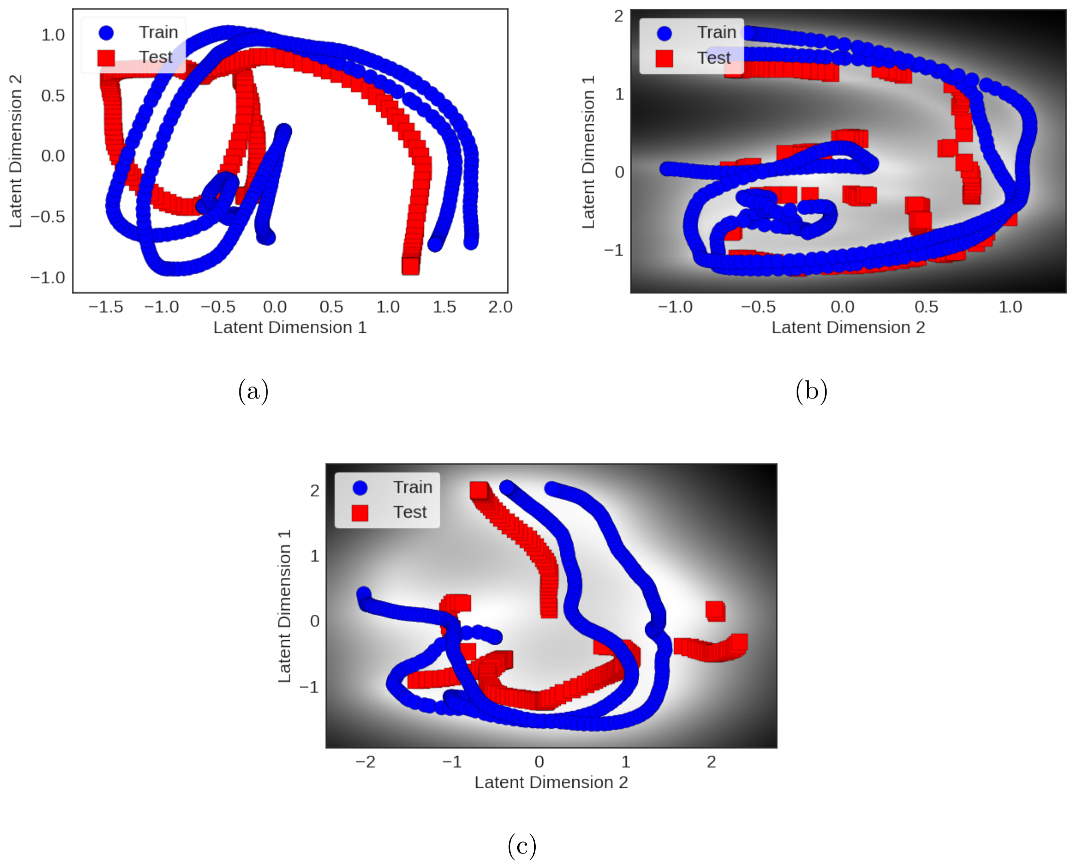
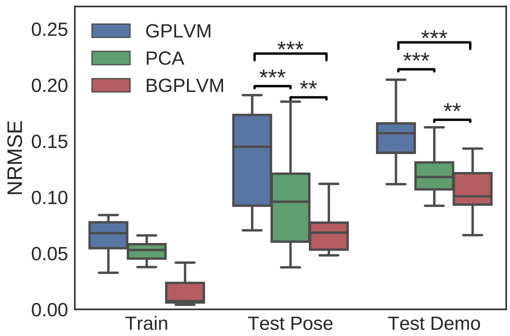


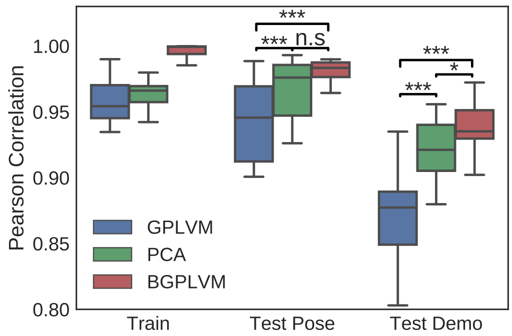
Figure 5.4.: Comparison of latent spaces learned by LVMs: a) PCA, b) GPLVM and c) BGPLVM

latent dimensions and two latent dimensions for the EE representation. This implies that the encoded motor skills varies depending on the input observations.

It was observed that the latent space varied for different latent variable models (LVMs). Latent spaces learned for the clothing task and JA representation is shown in Figure 5.4. In general, all the LVMs resulted in latent trajectories for the training data which correspond to the demonstrations. However, the variability between demonstrations is larger for BGPLVM which implies it can capture the posture specific variation efficiently. Furthermore, BGPLVM was able to obtain a smooth latent trajectory for the test data as well where as GPLVM leads to a fragmented trajectory which could indicate overfitting in the case of GPLVM.



(a)



(b)

Figure 5.5.: Comparison of generalizability by LVMs over evaluation dataset a) Normalized RMS error, b) Pearson Correlation

The predictive performance of BGPLVM was evaluated by comparing the reconstruction error with two other latent variable models (LVM) i.e. Principal Component Analysis (PCA) [15] and Gaussian Process Latent Variable Model (GPLVM) [4]. For each demonstrator, six-fold cross validation was performed where four demonstrations were used as training data. The remaining two demonstrations (Test Pose) along with demonstrations from an unseen demonstrator (Test Demo) were used as test data. To evaluate generalization capability, we evaluated reconstruction error given by comparing the input data and the reconstructed data from the latent points corresponding to the input,

$$\begin{aligned} \mathrm{Err} &= \|y_{\mathrm{org}} - y_{\mathrm{pred}}\|, \\ y_{\mathrm{pred}} &= f_{\mathrm{model}}(f_{\mathrm{model}}^{-1}(y_{\mathrm{org}})) \end{aligned} \tag{5.4}$$

where y_{org} is an input sample from dataset, y_{pred} is the predicted value after reconstruction and f_{model} is the forward mapping from latent space to observation space.

The results for reconstruction error are provided in Figure 5.5. We evaluated Normalized Root Mean Square Error (NRMSE) and Pearson correlation as the metrics. The Wilcoxon signed rank sum test [27] was used to evaluate statistical significance and the p-value was evaluated for a one-sided test. It can be seen that BGPLVM has the best predictive performance which can be considered

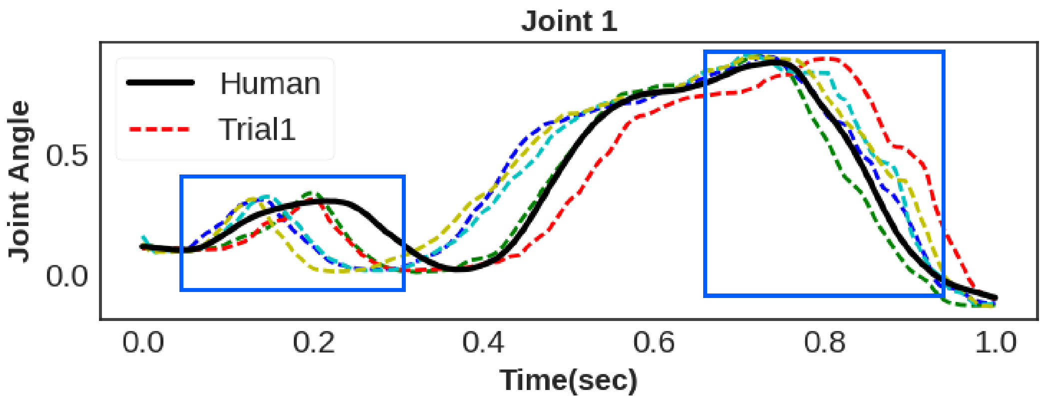


Figure 5.6.: Variation in dynamics of performing clothing task using latent space controller.

as a measure of generalization capability of BGPLVM latent space to unseen environmental settings.

5.2.2. Evaluation of Latent Space Controller

In this experiment, we evaluate the latent space controller for imparting motor skills to the robot. For the evaluation, BGPLVM models were trained on kinesthetic demonstrations of performing clothing and unclothing task for a given posture of the mannequin. The model is used as an interface to control the robot and reproduce the task by performing cursor control on the latent space of the demonstration.

The latent dimensions learned by BGPLVM capture a specific aspect of the clothing motor skills. For the joint angle scenario, the most significant dimension captured the horizontal motion of the arms along the mannequin while maintaining the constraints for clothing. The second dimension captured various vertical motions of pulling up the T-shirt in the beginning and pulling it down along the torso at the end. The third dimension captured variations in joint configurations across the demonstrations and could explain the constraint of safe human-robot interaction. A video demonstration with the exploration of the latent dimensions is available at `https://youtu.be/2TCZnt_qBHU`. This makes the interface intuitive to the users for planning a desired alteration to the robot trajectory.

Five subjects without prior experience of interacting with the robot were asked

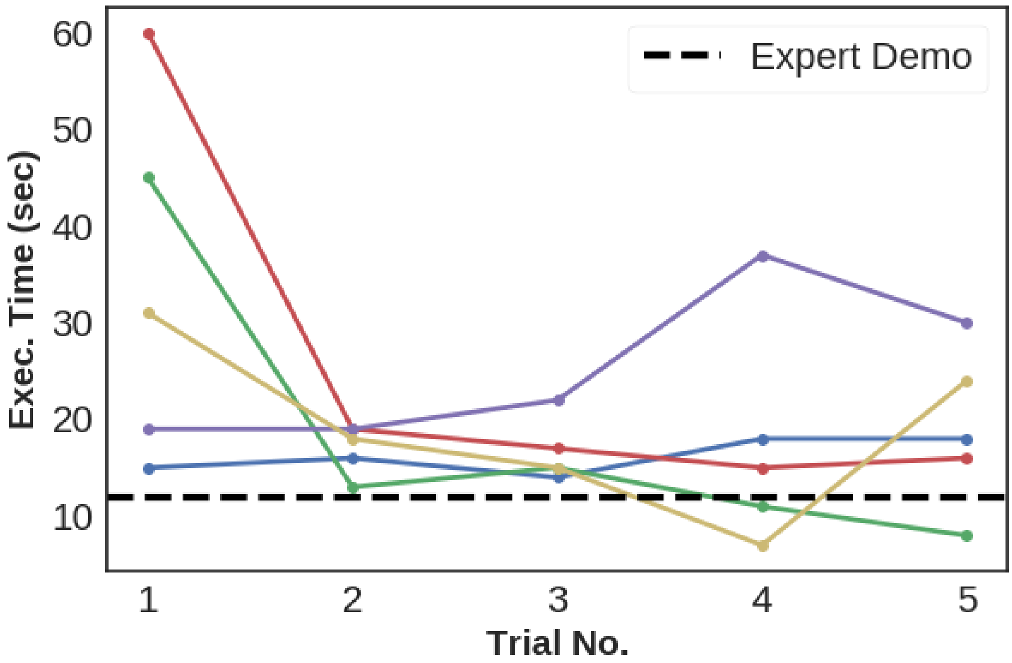


Figure 5.7.: Execution time of five novice users interacting with the latent space controller over five trials.

to use the interface to reproduce the tasks. The joint angles along with proprioceptive information were recorded while the interface was used. In general, the subjects were able to reproduce the clothing demonstration even when the latent trajectory was different from the training latent points. The subjects had fast learning curves with the execution time for performing the demonstration decreasing drastically within five trials of using the interface as shown in Figure 5.7. A video demonstration of an inexperienced subject interacting with the real-time controller is available at `https://youtu.be/2TCZnt_qBHU`.

The subjects also learned to modulate the dynamics of performing the task wherein crucial parts were performed slowly and parts without much human-cloth interaction being performed quickly. Figure 5.6 shows the modulation in the dynamics of performing the task for one of the subjects. The time normalized trajectories for a single joint of the robot is shown for five trials of using the interface along with the original kinesthetic demonstration. For the regions indicated

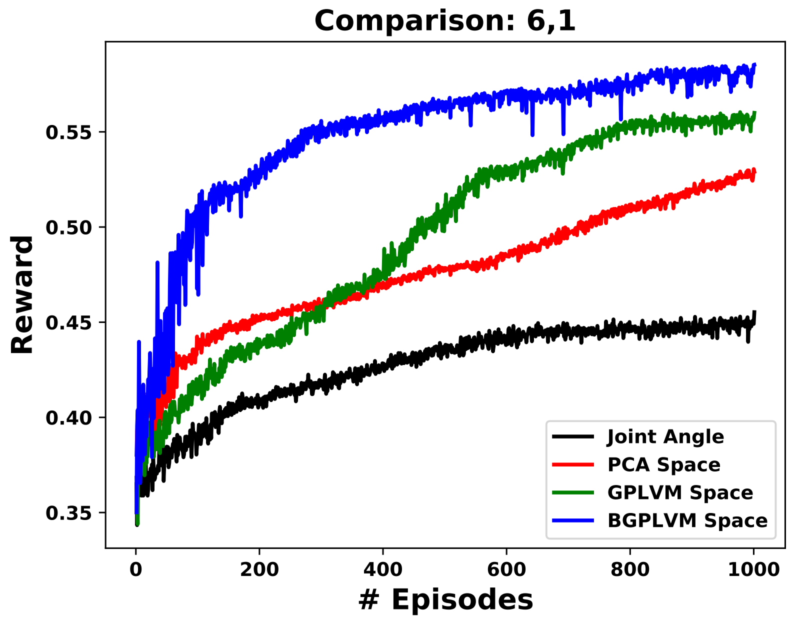
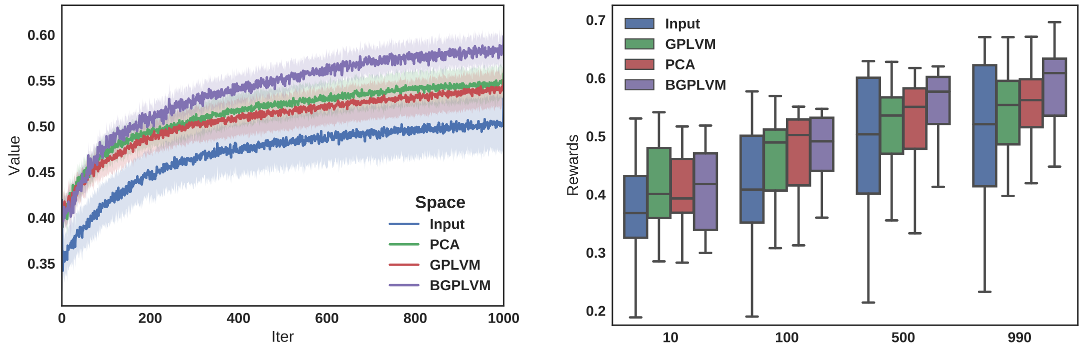


Figure 5.8.: Learning curves with various policy search spaces for JA scenario.

in the red squares, it can be seen that the trajectories through the interface vary drastically from the original demonstration. This indicates that novel motor skills for performing complex tasks can be imparted by inexperienced users as well.

5.2.3. Latent Space Reinforcement Learning

In this section, we demonstrate the effectivity of performing policy search in the BGPLVM latent space by comparison with search in the high-dimensional action space and in latent spaces learned using PCA and GPLVM. PoWER algorithm was implemented with the same state and reward representations and only the policy search space varied depending on the scenario. For each demonstrator, six-fold cross validation was performed where three demonstrations of the clothing task were used as training data for learning latent spaces. The latent space of each LVM was used as a search space for reinforcement learning to learn the policy corresponding to the remaining three unseen demonstrations. Policy search was run for 1000 iterations where 20 rollouts with the best overall rewards were used to update the policy in each iteration. The initial policy was generated from



(a) (b)

Figure 5.9.: Comparison of different search spaces for policy search: a) Average learning curves over the evaluation dataset, b) Rewards obtained at different stages of learning.

DMP that is fit on a latent space trajectory of one of the human demonstrations used to train the latent space.

Figure 5.8 shows the learning curves for an example clothing task and JA scenario. It can be seen that BGPLVM scenario outperforms all other search spaces. The performance was exhaustively evaluated by considering the complete dataset. The average learning curves over the entire dataset is shown in Figure 5.9. This indicates that BGPLVM captures the necessary motor skills most efficiently and also has the best generalizability in comparison to other LVMs.

5.3. Discussion

We presented the use of Bayesian Gaussian Process Latent Variable Model (BGPLVM) as a representation for encoding motor skills to perform clothing assistance task. The experimental results indicate our method as a promising approach for learning in combination with reinforcement learning. We further demonstrated its applicability as an intuitive and user-friendly tool for Learning from Demonstration (LfD).

The results in Section 5.2.1 indicate that non-linear mapping and Bayesian inference are necessary for the most efficient encoding of motor skills. PCA relies on a linear model thereby constraining its capability. GPLVM has the worst performance among the latent spaces as it relies on a MAP estimate of the latent space and it is overfitting to the training data. This validates our hypothesis that encoding motor skills using Bayesian nonparametric latent variable models is an effective parametrization for learning.

The computational complexity of the proposed framework depends on the forward mapping from the BGPLVM latent space to joint angle space which scales with the size of the training dataset (n) and the number of inducing points used to approximate the dataset (m) i.e. $O(nm^2)$ [5]. During test inference, the training dataset remains fixed and so precomputed values of the kernel matrix can be used to reduce time-complexity to $O(1)$ which makes it suitable for real-time implementation.

5.3.1. Real-world Implementation

The long-term research goal is a real-world implementation of motor-skills learning that could be used in health-care settings. This would require efficient and real-time state estimation and its integration along with the framework proposed in this chapter. This can be achieved by designing a state space that incorporates the human-cloth relationship obtained from a depth sensor as well as the proprioceptive information from the robot arms. BGPLVM is capable of learning task-specific state models using few observations as shown in Section 4.2.1. The latent space learned by BGPLVM can be used as a low-dimensional approximation of human-cloth relationship.

The next challenge would be to design a reward function from the state space that enables fast learning. This can be a replacement to the reward function used in Section 5.1.3. An expert demonstration of the robot performing the clothing assistance task can be used to initialize the latent space. This latent space can be used for policy search reinforcement learning as presented in Section 5.1.3. The current formulation leads to an episodic implementation. However, this can also be extended to be more reactive by replacing DMP with a controller such as Linear Quadratic Regulator (LQR) as the policy representation.

6. Conclusion

Recent demographic trends has led to a tremendous shortage of care-givers for the elderly. Assistive robots are playing an increasing role in alleviating this need. Assistance with clothing can greatly improve the quality of life as well as independence of the elderly and disabled. However, robotic assistance is still considered an open problem with several challenges involved. The robot has close interaction with non-rigid clothing articles and with the assisted person whose posture can vary during the task. A promising approach is to treat it as a learning problem where the robot is enabled to learn the desired motor skills by itself.

Tamei *et al.* [1] have developed a reinforcement learning-based clothing assistance robot that addressed the challenges discussed above. In this framework, a dual-arm robot learns the necessary motor skills to perform clothing tasks by adapting to changes in the posture of the subject. However, this framework has several limitations towards a practical real-world implementation. The environment i.e. human-cloth relationship is observed using the motion capture (Mo-cap) system which has a complex setup and is not suitable for real-time tracking of markers on non-rigid objects such as clothes. The policy representation is highly constrained reducing its generalizability to large variations in the environmental setting.

This thesis addressed these problems moving towards a practical implementation of robotic clothing assistance. The main contributions were as follows: 1) framework for real-time estimation of human-cloth relationship with an emphasis on reliable cloth state estimation and 2) formulation of a motor skills learning framework that is data-efficient as well as flexible to adapt to various environmental conditions. These research problems are addressed through the use of Bayesian nonparametric latent variable models as it has several desired features. Dimensionality reduction is used to model the problems in low dimensional spaces that efficiently capture the underlying task and Gaussian Processes [3] lead to handling the non-linearity and performing model learning in a data-efficient manner.

Clothing articles are non-rigid and lie in a high dimensional configuration space. We hypothesize that clothing articles undergo consistent deformations which vary from task to task and thereby lie in a lower dimensional task specific latent space. In this thesis, Manifold Relevance Determination (MRD) [7] is used to learn the underlying latent features from high dimensional observations. A low-cost depth sensor and the motion capture system are used to learn a shared latent manifold that captures complementary latent features from both systems in an offline manner. This shared model is incorporated to reliably infer cloth state in real-time given high dimensional and noisy depth sensor observations. The predictive performance and generalization capability of MRD was demonstrated for estimating the human-cloth relationship from noisy depth sensor readings.

Similarly, the humanoid robot has two arms with seven degrees of freedom (DoF) each. Fast learning of motor skills is challenging in such high dimensional continuous action spaces. This thesis proposed the use of Bayesian Gaussian Process Latent Variable Model (BGPLVM) to learn a low dimensional latent space, encoding the task specific motor skills for clothing assistance. It was demonstrated that performing policy search reinforcement learning in the latent space outperforms learning in the high-dimensional joint configuration space of the robot. Furthermore, this framework was also demonstrated as a user-friendly tool to impart novel motor skills to the robot.

6.1. Future Work

This section provides directions for future work to the frameworks proposed in this thesis. Section 6.1.1 provides some theoretical considerations that can be addressed related to robotic clothing assistance. Section 6.1.2 provides a tentative road map in realizing an end-to-end clothing assistance framework.

The advantage of using MRD is that a corresponding latent space manifold can be learned for any observation space of the same underlying phenomenon. Based on this flexibility, future work will be to learn models that incorporates T-shirt state as well as the assisted subject's posture and mainly the proprioceptive information of the robot. This is from the insight that while humans are performing clothing tasks they rely more on the forces experienced from the clothing article rather than the visual appearance of clothing articles. Furthermore, the framework currently relies on using the motion capture system to obtain the ground truth data. This need can be removed by using a cloth simulator to generate the desired training data for the models. Finally, the proposed framework can be applied to other cloth manipulation tasks which can have potential industrial applications such as putting on seat covers for car seats.

For the second framework on data-efficient motor skills learning there can be several promising extensions. The framework relies in expert demonstrations to initialize the latent space. An interesting future work will be strategies to incorporate prior information such as the garment used and human safety constraints. This will further reduce the exploration space in the latent space leading to faster learning of control policies. The current experimental evaluation demonstrates the effectivity of using BGPLVM as a preprocessing step to encode motor skills in low dimensional spaces. It would be interesting to develop a framework that can inherently combine policy search with dimensionality reduction where the learning of the latent space is motivated by the rewards observed during the policy search. This derives from the framework by Luck *et al.* [83] wherein an EM-formulation is proposed that treats the parameters for dimensionality reduction as the latent variables.

6.1.1. Theoretical Considerations

There remain several open problems which need to be addressed before moving towards a practical implementation. This thesis treats clothing assistance as a learning problem. However, the current formulation requires a lot of human oversight to initialize the learning framework. There can be two solutions to avoid this where in the robot can 1) learn from humans performing the task and 2) learn from its own prior experience. This section provides some insight on how these can be achieved.

For reinforcement learning, one of the most crucial component is the reward function which requires significant amount of human engineering. When humans perform clothing assistance, they have a rich internal reward structure which relies on forces being applied on the finger tips, visual features of the cloth state and an estimate of the comfort felt by the assisted person. Inverse Reinforcement Learning (IRL) is a promising future work wherein these reward structures can be extracted based on observing human demonstrations and used in forward reinforcement learning.

In the current setting, the robot initializes the learning framework from a human kinesthetic demonstration which is adapted to various environmental settings. A first step to remove this need for initialization is to build a database of successful policies learned by the robot. This database can be used for a better initialization of the initial policy based on the current environmental setting and its similarity to previously seen settings. This could also be extended to share the sensorimotor experience across multiple robots for even faster learning [111].

It would also be promising to implement a simulator for clothing assistance that can capture the human-cloth-robot interaction reliably. This simulator can be used for the robot to explore the search space and learn controllers in the simulator that could potentially generalize to various settings. There has been several studies recently that have addressed this issue. These studies were able to model the complex interaction between human and cloth during clothing tasks [100,101] and the experience gained in the simulator could be transferred to a real-world implementation [102].

In Chapter 2, several studies were presented that used deep learning towards cloth state estimation and robotic manipulation demonstrating their strength as universal function approximators. However, existing methods in deep learning are very sample inefficient and require large datasets to train the models which motivated us to rely on Bayesian nonparametric models. This problem could be handled by either generating datasets from a realistic simulator or with more recent deep learning techniques such as transfer learning, generative modeling. A promising future work is to explore the applicability of deep learning towards robotic clothing assistance.

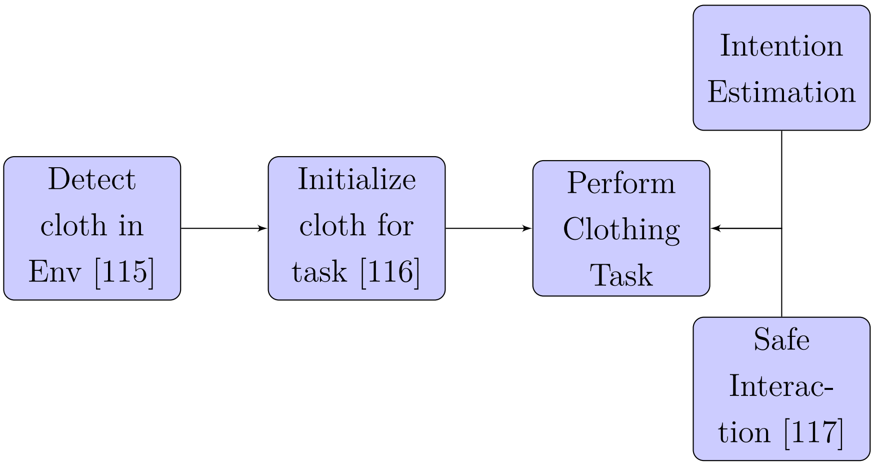


Figure 6.1.: Flowchart for end-to-end implementation of clothing assistance

6.1.2. Towards Real-world Implementation

The ultimate goal remains the practical implementation of robotic clothing assistance. For this, there needs to be an end-to-end implementation which involves the following steps as shown in Figure 6.1. The robot needs to locate a desired clothing article in a house-hold environment and differentiate it from other garments. This involves recognizing clothing articles when present in a clutter or in a shelf. It then needs to manipulate the cloth and bring it to a desired initial state with which the clothing assistance can be initialized. This involves fine manipulation skills such as rolling up the sleeves of a sweater. Finally, the robot needs to actually perform the clothing task by keeping track of several constraints such as:

- Tracking the progress of the task by observing the human-cloth relationship.
- Estimating the pose of the human and ensuring safe human robot interaction.
- Communicating with the human and estimating the intention of the human.

The last constraint is provide a social component to the assistance where assistance is provided as needed.

Our research group is already tackling some of these problems. For the recognition of clothing articles, Gaurav *et al.* [115] proposed a framework to sort clothing articles from a pile by detecting the extremities. This relies on the use of BG-PLVM [5] to learn a latent space that captures the shape variations in the cloth extremities and classification is performed in this latent space to detect cloth extremities. For initialization of the clothing task, Joshi *et al.* [116] investigate the applicability of using Dynamic Movement Primitives (DMP) [32] to parametrized the motor skills required to put a T-shirt on the mannequin's arms. This framework can also be extended to real human subjects whose posture can vary during the task. To ensure safe human-robot interaction, Yamaguchi *et al.* [117] proposed the use of Support Vector Machine to detect failure scenarios based on the proprioceptive information observed by the robot while performing clothing assistance tasks.

Progress on each of these sub problems will be made and eventually integrated to form an end-to-end framework of clothing assistance. The emphasis will be on implementing a low-cost flexible framework that can be used in a care-home or household environment.

Appendices

A. Computation of Topology Coordinates

This appendix summarizes the computation of topology coordinates, as presented in [13]. Given two continuous curves γ_1 and γ_2 in the euclidean space, the topology coordinates are computed by approximating the Gaussian Linking Integral(GLI). Firstly the curves need to be divided into a number of small line-segments. These segments are used for constructing a writhe matrix $T \in \mathbb{R}^{N_1 \times N_2}$ where N_1, N_2 are the number of line segments in the curves.

Let r_{ab}, r_{cd} be two segments (one from each curve), where $a, b, c, d \in \mathbb{R}^3$ are the end points of the segments. Firstly the following vectors are calculated:

$$\begin{aligned} n_a &= \frac{r_{ac} \times r_{ad}}{\|r_{ac} \times r_{ad}\|},\ n_b = \frac{r_{ad} \times r_{bd}}{\|r_{ad} \times r_{bd}\|} \\ n_c &= \frac{r_{bd} \times r_{bc}}{\|r_{bd} \times r_{bc}\|},\ n_d = \frac{r_{bc} \times r_{ac}}{\|r_{bc} \times r_{ac}\|} \end{aligned} \tag{A.1}$$

Using these vectors, the writhe between the line segments is given by:

$$T_{i,j} = \arcsin(n_a^T n_b) + \arcsin(n_b^T n_c) + \arcsin(n_c^T n_d) + \arcsin(n_d^T n_a) \tag{A.2}$$

where $T_{i,j}$ is the (i, j)th element in the writhe matrix. Now the

- Writhe w of the two curves is given by summation over the writhe matrix as a measure of the total amount of twisting between the curves: topology coordinates are computed from the writhe matrix as follows:

$$w = \text{GLI}(\gamma_1, \gamma_2) = \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} T_{i,j} \tag{A.3}$$

where N_1,N_2 are the number of segments for curves γ_1 and γ_2 respectively.

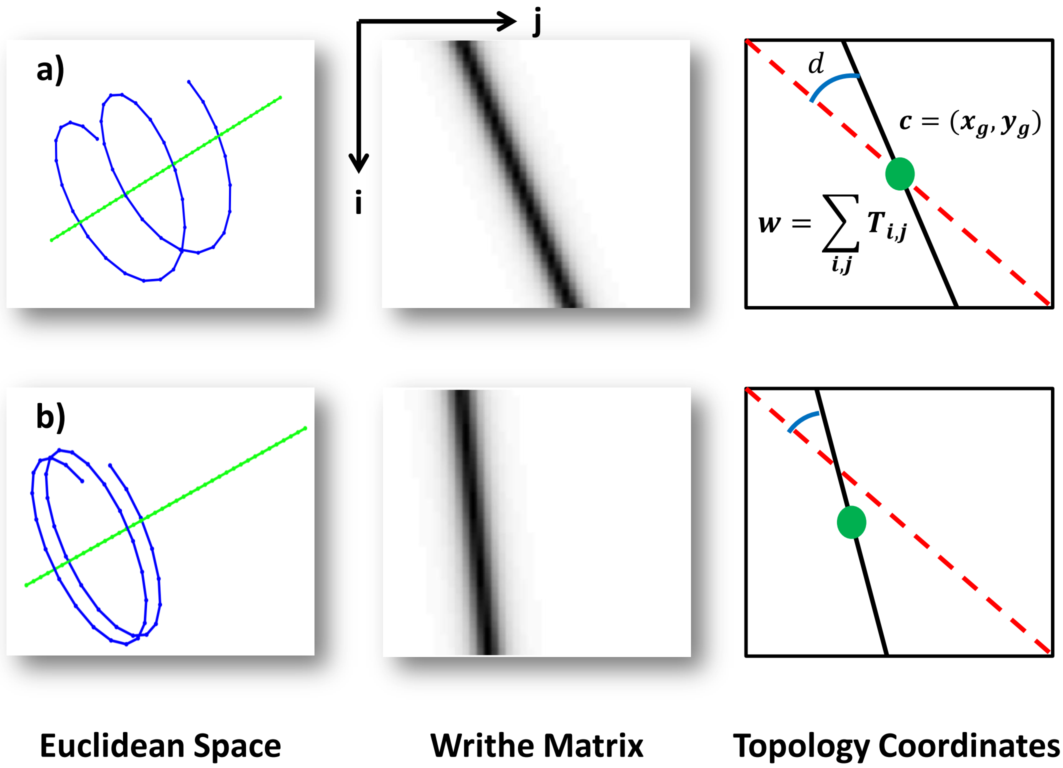


Figure A.1.: Example showing the computation of topology coordinates for two configurations of Cartesian curves shown in Fig. 14 (a) and (b): (Left) Curves in Euclidean Space (Center) Writhe Matrix computed for both cases (Right) Topology coordinates computed from writhe matrix.

- The center of twist **c** is given by two scalar values which indicate the center of twist for each curve about the other curve. These values are given by weighted summations of the writhe matrix:

$$\begin{aligned} \mathbf{c} &= (x_g, y_g) \\ &= \left(\frac{\sum_i^{N_1} \sum_j^{N_2} i T_{i,j}}{w} - \frac{N_2}{2}, \frac{\sum_i^{N_1} \sum_j^{n_2} j T_{i,j}}{w} - \frac{N_1}{2} \right) \end{aligned} \tag{A.4}$$

- The density d is given by computing the angle between the principal axis of the writhe matrix and the diagonal line of the matrix.

An example of computing the topology coordinates is shown in Fig. A.1. The pane on the left shows two examples of curves in the euclidean space, the pane in the center shows the writhe matrix computed for each case and the pane on the right shows the computation of topology coordinates from the writhe matrix thereby forming the topology space. It can be seen from this example that the parameters change based on the topological relationship between the curves thereby capturing the complex relationship using few scalar parameters.

For clothing assistance tasks, the motion capture system was used to obtain the Cartesian position of markers placed on the mannequin and T-shirt. The markers placed on the mannequin were used to approximate its posture using a stick figure. For example, the left arm of the mannequin was approximated by a line segment joining two markers placed on its wrist and shoulder joint. Each line segment for the mannequin were divided into 20 segments $N_{mannequin} = 20$. The markers placed on the T-shirt were used to obtain circle approximations of its collar and sleeve shapes. The T-shirt collar curve was approximated using 40 segments and each of the sleeves were approximated with 20 segments i.e. $N_{collar} = 40, N_{sleeves} = 20$. This data was then used to compute the topology coordinates given by the equations presented above.

Acknowledgements

The path leading to obtaining my PhD degree was a challenging one, whose obstacles I would not have overcome alone.

First of all, I would like to sincerely thank my advisers, Professor Kazushi Ikeda and Professor Tomohiro Shibata. To Professor Ikeda, for accepting me as a PhD student in his laboratory and the support to complete my study in Japan. He has been very flexible and supportive with my research. I am honored to be a member of the Mathematical Informatics Laboratory at NAIST. To Professor Shibata, I will be forever grateful for inviting me to Japan and for constantly supporting me over the past five years. His words of encouragement have inspired me to strive harder and to never give up when faced with difficulties. I am very grateful to Assistant Professor Tomoya Tamei who has been the adviser working closely with me. I have learned many practical skills needed for research work through his teaching and in some cases just by watching him work.

The members of the Mathematical Informatics laboratory and Shibata Laboratory welcomed me like a family. Thank you for the fruitful conversations, the good advice, and the companionship. I would like to thank all my NAIST and Kyutech friends. I met many colorful characters during my stay here. I wish everyone the best of luck in research and life. Big thanks goes to my family especially my brother Rahul Koganti, who has gone beyond the call of duty to support me.

Finally, I would like to thank the MEXT Scholarship Program for the support in my education and research. Without this scholarship, my dream of studying in Japan would never have come true. Thank you for this valuable opportunity.

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