Manipulating Highly Deformable Materials Using a Visual Feedback Dictionary

Biao Jia, Zhe Hu, Jia Pan, Dinesh Manocha

Abstract—The complex physical properties of highly deformable materials like clothes pose significant challenges for autonomous robotic manipulation systems. We present a novel visual feedback dictionary-based method for manipulating deformable objects towards a desired configuration. Our approach is based on visual servoing and we use an efficient technique to extract key features from the RGB sensor stream in the form of histogram of deformable model features. These histogram features serve as high-level representations of the state of the deformable material. Next, we collect manipulation data and use a visual feedback dictionary that maps the velocity in the high-dimensional feature space to the velocity of the robotic end-effectors for manipulation. We have evaluated our approach on a set of complex manipulation tasks as well as human-robot manipulation tasks on different cloth pieces with varying material characteristics.

I. INTRODUCTION

The problem of manipulating highly deformable materials such as clothes and fabrics frequently arises in different applications. These include laundry folding [1], robot-assisted dressing or household chores [2], [3], ironing [4], coat checking [5], sewing [6], and transporting large materials like cloth, leather, and composite materials [7]. Robot manipulation has been extensively studied for decades and there is extensive work on the manipulation of rigid and deformable objects. Compared to the manipulation of a rigid object, whose state can be completely described by a six-dimensional configuration space, the manipulation of a deformable object is more challenging due to its very high configuration space dimensionality. The resulting manipulation algorithm needs to handle this dimensional complexity and maintain the tension to perform the task.

Many techniques have been proposed for the automated manipulation of flexible materials. Some of them have been designed for specific tasks, such as peg-in-hole and laying down tasks with small elastic parts [8] or wrapping a cloth around a rigid surface [9]. There is extensive work on folding laundry using pre-planned materials. One practical approach to dealing with general deformable object manipulation is based on visual servoing. [10], [11]. At a broad level, these servoing techniques use the perception data captured using cameras and formulate a control policy mapping to compute the velocities of the robotic end-effectors in realtime. However, a key issue in these methods is to automatically extract key low-dimensional features of the deformable material that can be used to compute a mapping. The simplest methods use manual or other techniques to extract features corresponding to line segments or curvature from a set of points on the surface of the deformable material. In addition, we need appropriate mapping algorithms based on appropriate low-dimensional features. Current methods may not work well while performing complex tasks or when the model undergoes large deformations. Furthermore, in many human-robot systems, the deformable material may undergo unknown perturbations and it is important to design robust manipulation strategies [3], [12].

Main Results: In this paper, we present a novel feature representation, a histogram of oriented wrinkles (HOW), to describe the shape variation of a highly deformable object like clothing. These features are computed by applying Gabor filters and extracting the high-frequency and low-frequency components. We precompute a visual feedback dictionary using an offline training phase which stores a mapping between these visual features and the velocity of the end-effector. At runtime, we automatically compute the goal configurations based on the manipulation task and use sparse linear representation to compute the velocity of the controller from the dictionary (Section III). Furthermore, we extend our approach so that it can be used in human-robot collaborative settings. Compared to prior manipulation algorithms, the novel components of our work include:

- A novel histogram feature representation of highly deformable materials (HOW-features) that are computed
directly from the streaming RGB data using Gabor filters (Section IV).

- A sparse representation framework using visual feedback dictionary, which directly correlates the histogram features to the control instructions (Section V).
- The combination of deformable feature representation, visual feedback dictionary, and sparse linear representations that enables us to perform complex manipulation tasks, including human-robot collaboration, without significant training data (Section V(C)).

We have integrated our approach with an ABB YuMi dual-arm robot and a camera for image capture and used it to manipulate different cloth materials for different tasks. We highlight the real-time performance for tasks related to stretching, folding, and placement (Section VI)).

II. RELATED WORK

In this section, we give a brief review of prior work on deformable object representation, manipulation, and visual servoing.

A. Deformable Object Representation

The recognition and detection of deformable object characteristics is essential for manipulation tasks. There is an extensive work in computer vision and related areas on tracking features of deformable models. Some of the earlier work is based on active deformable models [13]. Ramisa et al. [14] identify the grasping positions on a cloth with many wrinkles using a bag-of-features-based detector. Li et al. [15] encode the category and pose of a deformable object by collecting a large set of training data in the form of depth images from different view points using offline simulation.

B. Deformable Object Manipulation

Robotic manipulation of general deformable objects relies on a combination of different sensor measurements. The RGB images or RGB-Depth data are widely used for deformable object manipulation [1], [4], [11]. Fiducial markers can also be printed on the deformable object to improve the manipulation performance [16]. Besides visual perception, information from other sensors can also be helpful, like use of contact force sensing to maintain the tension [7]. In many cases, simulation techniques are used for manipulation planning. Clegg et al. [17] use reinforcement learning to train a controller for haptics-based manipulation. Bai et al. [18] use physically-based optimization to learn a deformable object manipulation policy for a dexterous gripper. These simulation-based approaches need accurate deformation material properties, which can be hard. Data-driven techniques have been used to design the control policies for deformable object manipulation. Yang et al. [19] propose an end-to-end framework to learn a control policy using deep learning techniques for folding clothes. Cusumano-Tooner et al. [20] learn a Hidden Markov Model (HMM) using a sequence of manipulation actions and observations.

| Symbol | Description |
|--------|-------------|
| $m$    | state of the deformable object |
| $v$    | robot’s end-effector configuration |
| $\dot{v}$ | robot’s end-effector velocity, $\dot{v} = \dot{r}$ |
| $I(w, h)$ | image from the camera, of size $(w, h)$ |
| $s(I)$ | HOW-feature vector extracted from image $I$ |
| $d_i(I)$ | the $i$-th deformation kernel filter |
| $f(t), \dot{f}(t)$ | time index |
| $\{\Delta s^{(t)}, \Delta y^{(t)}\}$ | features and labels of the visual feedback dictionary |
| $\rho(\cdot, \cdot)$ | error function between two items |
| $\lambda$ | positive feedback gain |
| $L$ | interaction matrix linking velocities of the feature space to the end-effector configuration space |
| $F$ | interaction function linking velocities of the feature space to the end-effector configuration space |
| $p_i(t)$ | histogram of value $i$ |
| $N_{dof, \text{f}, \text{r}, \text{d}}$ | number of degrees of freedom of the manipulator, images $\{I^{(t)}\}$, samples $\{r^{(t)}\}$, filters $\{d^{(t)}\}$ |
| $C_{fr}$ | constant of frame rate |
| $r^*, s^*$ | desired target |
| $\hat{r}, \hat{s}, \hat{m}$ | approximated target |

TABLE I: Symbols used in the paper

C. Visual Servoing for Deformable Objects

Visual servoing techniques [21], [22] aim at controlling a dynamic system using visual features extracted from images. They have been widely used in robotic tasks like manipulation and navigation. Recent work includes the use of histogram features for rigid objects [23]. Sullivan et al. [13] use a visual servoing technique to solve the deformable object manipulation problem using active models. Navarro-Alarcon et al. [10], [11] use an adaptive and model-free linear controller to servo-control soft objects, where the object’s deformation is modeled using a spring model [24]. Langsfeld et al. [25] perform online learning of part deformation models for robot cleaning of compliant objects. Our goal is to extend these visual servoing methods to perform complex tasks on highly deformable materials.

III. OVERVIEW

In this section, we introduce the notation used in the paper. We also present a formulation of the deformable object manipulation problem. Next, we give a brief background on visual servoing and the feedback dictionary. Finally, we give an overview of our deformable manipulation algorithm that uses a visual feedback dictionary.

A. Problem Formulation

The goal of manipulating a highly deformable material is to drive a soft object towards a given target state ($m^*$) from its current state ($m$). The state of a deformation object ($m$) can be rather complex due to its very high dimensional configuration. In our formulation, we do not represent it explicitly and treat it as a hidden variable. Instead, we keep track of the deformable object’s current state in the feature space ($s$) and its desired state ($s^*$), based on HOW-features. The visual servo-control is performed by computing an appropriate velocity ($v$) of the end-effectors. Given the visual feedback about the deformable object, the control velocity ($v$) reduces the error in the feature space ($s - s^*$). After continuously applying feedback control, the robot will manipulate the deformable object toward its goal.
configuration. In this way, the feedback controller can be formulated as computing a mapping between the velocity in the feature space of the deformable object and the velocity in the end-effector’s configuration space \( r \):

\[
\dot{r} = \arg \min_r \rho(r, r^*)
\]

where \( \dot{r} \) is the configuration of the end-effector after the optimization step and is the closest possible configuration to the desired position \( r^* \). In the optimal scenario, \( \dot{r} = r^* \).

Let \( s \) be a set of HOW-features extracted from the image. Depending on the configuration \( r \), the visual servoing task is equivalent to minimizing the Euclidean distance in the feature space and this can be expressed as:

\[
\dot{r} = \arg \min_r ((s(r) - s^*)^T (s(r) - s^*))
\]

where \( s^* = s(r^*) \) is the HOW-feature corresponding to the goal configuration \( r^* \). The visual servoing problem can be solved by iteratively updating the velocity of the end-effectors according to the visual feedback:

\[
v = -\lambda L_s^+ (s - s^*)
\]

where \( L_s^+ \) is the pseudo-inverse of the interaction matrix \( L_s = \partial s / \partial r \). It corresponds to interaction matrix that links the variation of the velocity in the feature space \( \dot{s} \) to the velocity in the end-effector’s configuration space. \( L_s^+ \) is computed offline using a non-linear minimization algorithm like Levenberg-Marquardt’s algorithm.

### C. Visual Feedback Dictionary

The visual feedback dictionary corresponds to a set of vectors with instances of visual feedback \( \{\Delta s^{(i)}\} \) and the corresponding velocities of the end-effectors \( \{\mathbf{v}^{(i)}\} \), where \( \{\Delta s^{(i)}\} = (s - s^*) \). Furthermore, we refer to each instance \( \{\Delta s^{(i)}, \mathbf{v}^{(i)}\} \) as the visual feedback word. This dictionary is computed from the recorded manipulation data. The input includes a set of images \( \{I(t)\} \) and the end-effector configurations \( \{r^{(i)}\} \). Its output is computed as \( \{\{\Delta s^{(i)}\}, \{\mathbf{v}^{(i)}\}\} \). We compute this dictionary during an offline learning phase using sampling and clustering methods (see Algorithm 2 for details), and use this dictionary at runtime to compute the velocity of the controller by computing the sparse decomposition of a feedback \( \Delta s \). More details about computing the visual feedback dictionary are give in Algorithm 2.

### D. Offline and Runtime Computations

Our approach computes the visual dictionary using an offline process (see Fig. 2). Our runtime algorithm consists of two components. Given the camera stream, we extract the HOW-features from the image \( s(I) \) and compute the corresponding velocity of the end-effector using an appropriate mapping. For the controlling procedure, we use the sparse representation method to compute the interaction matrix, as opposed to directly solving the optimization problem (Equation 2). In practice, the sparse representation method is more efficient. The runtime phase performs the actual visual servoing with the current image at time \( t \) \( I(t) \), the visual
feedback dictionary \(\{\{\Delta s^{(i)}\}, \{v^{(i)}\}\}\), and the desired goal configurations given by \((I^*)\) as the input.

IV. HISTOGRAM OF DEFORMATION MODEL FEATURE

In this section, we present our algorithm to compute the HOW-features from the camera stream. These are low-dimensional features of the highly deformable material. The pipeline of our HOW-feature computation process is shown in Figure 4. Next, we explain each of these stages in detail.

A. Foreground Segmentation

In order to find the foreground partition of a cloth, we apply the Gaussian mixture algorithm [29] on the RGB data captured by the camera. The intermediate result of segmentation is shown in Figure 4(2).

B. Deformation Enhancement

In order to model the high dimensional characteristics of the highly deformable material, we use deformation enhancement. This is based on the perceptual observation that most deformations can be modeled by shadows and shape variations. Therefore, we extract the features corresponding to shadow variations by applying a Gabor transform [30] to the RGB image. This results in the enhancement of the ridges, wrinkles, and edges (see Figure 4). We convolve the Gabor filter to our deformation model image, the choice of grids of Histogram of Oriented Gradient [33], which is computed on a dense grid of uniformly spatial and orientation cells.

We compute the grids of histogram of deformation model feature by dividing the image into small spatial regions and accumulating local histogram of different filters \((d_i)\) of the region. For each grid, we compute the histogram in the region and represent it as a matrix. We vary the grid size and compute matrix features for each size. Finally, we represent the entries of a matrix as a column feature vector. The complete feature extraction process is described in Algorithm 1.

Algorithm 1 Computing HOW-Features

Input: image \(I\) of size \((w_I, h_I)\), deformation filtering or Gabor kernels \(\{d_1 \cdots d_{N_d}\}\), grid size \(\{g_1, \cdots, g_{N_g}\}\).

Output: feature vector \(s\)

1: for \(i = 1, \cdots, N_d\) do
2: for \(j = 1, \cdots, N_g\) do
3: for \((w, h) = (1, 1), \cdots, (w_I, h_I)\) do
4: \((x, y) = (\text{TRUNC}(w/g_j), \text{TRUNC}(h/g_j))\) // compute the indices using truncation
5: 
6: end for
7: end for
8: end for
9: return \(s\)

The HOW-feature has several advantages. It captures the deformation structure that is based on the characteristics of the local shape. Moreover, it uses a local representation that is invariant to local geometric and photometric transformations. This is useful when the translations or rotations are much smaller than the local spatial or orientation grid size.

V. MANIPULATION USING VISUAL FEEDBACK DICTIONARY

In this section, we present our algorithm used to compute the visual feedback dictionary. At runtime, this dictionary is used to compute the corresponding velocity \((v)\) of the controller based on the visual feedback \((\Delta s(I))\).

A. Building Visual Feedback Dictionary

As shown in figure 2, the inputs of the offline training phase are a set of images and end-effector configurations \(\{I^{(i)}\}, \{r^{(i)}\}\) and the output is the visual feedback dictionary \(\{\{\Delta s^{(i)}\}, \{v^{(i)}\}\}\).

For the training process, the end-effector configurations, \(\{r^{(i)}\}\), are either collected by human tele-operation or generated randomly. A single configuration \(v^{(i)}\) of the robot is a column vector of length \(N_{dof}\), the number of degrees-of-freedom to be controlled. \(r \in \mathbb{R}^{N_{dof}}\) and its value is represented in the configuration space.

In order to compute the mapping \((F_{HT})\) from the visual feedback to the velocity, we need to transform the configurations \(v^{(i)}\) and image stream \(\{I^{(i)}\}\) into velocities \(v^{(i)}\) and the visual feature feedback \(\Delta s^{(i)}\). One solution is to
The visual feedback dictionary is defined by the difference between the visual features of visual feedback words computed. We show the initial and final states on the left and right, respectively. The overall algorithm to compute the dictionary is given in Algorithm 2.

At runtime, we use sparse linear representation [36] to compute the velocity of the controller from the visual feedback dictionary. These representations tend to assign zero weights to most irrelevant or redundant features and are used to find a small subset of most predictive features in the high dimensional feature space. Given a noisy observation of a feature at runtime (s) and the visual feedback dictionary constructed by features {s(i)} with labels {l(i)}. We represent s by ̂s, which is a sparse linear combination of {s(i)}, where β is the sparsity-inducing L1 term. In order to deal with noisy data, we rather use the L2 norm on the data-fitting term and formulate the resulting sparse representation as:

$$\hat{\beta} = \arg \min_{\beta} (\| \min_s (s - \sum_i \beta_i s^{(i)}) \|_2^2 + \alpha \| \beta \|_1),$$

where α is a slack variable that is used to balance the trade-off between fitting the data perfectly and using a sparse solution. The sparse coefficient β* is computed using a minimization formulation:

$$\beta^* = \arg \min_{\beta} \left( \sum_i \rho (\Delta s_i^* - \sum_j \beta_j \Delta s_j^{(j)} + \alpha \sum_j ||\beta_j||_1) \right)$$

After ̂β is computed, the observation s and the probable label ̂l can be reconstructed by the visual feedback dictionary:

$$\hat{s} = \sum_i \hat{\beta}_i s^{(i)} \quad \hat{l} = \sum_i \hat{\beta}_i l^{(i)}$$

The corresponding v* of the i-th DOF in the configuration is given as:

$$v_i^* = \sum_j \beta_j^* v^{(j)}_i,$$

where Δs(j) denotes the i-th data of j-th feature , Δs_i* denotes the value of the response, and the norm-1 regularizer \( \sum_j ||\beta_j||_1 \) typically results in a sparse solution in the feature space.

We compute the goal configuration and the corresponding HOW-features based on the underlying manipulation task at runtime. Based on the configuration, we compute the velocity of the end-effector. The different ways to compute the goal configuration are:
The human is either grasping the deformable object or applying forces. We classify the human-robot manipulation task using hidden state goal $h^*$, where we need to estimate the human’s action repeatedly. As the human intention is unknown to the robot, the resulting deformable material is assigned several goal states $\{m_1, \cdots, m_n\}$, which are determined conditionally by the action of human.

VI. IMPLEMENTATION

In this section, we describe our implementation and describe the experimental setup, including the robot and the camera. We also highlight the performance on several manipulation tasks performed by the robot only or robot-human collaboration. We also highlight the benefits of using HOW-features and the visual feedback dictionary.

### A. Robot Setup

Our algorithm was implemented on a PC and integrated with a ABB YuMi dual-arm robot with 12-DOF to capture $\{r(t)\}$ and perform manipulation tasks. We use a RealSense camera to capture the RGB videos at $(640 \times 480)$ resolution. In practice, we compute the Cartesian coordinates of the end-effectors of the ABB YuMi as the controlling configuration $r \in \mathbb{R}^6$ and use an inverse kinematics-based motion planner [37] directly. The setup is shown as Figure 7.

### B. Benchmarks

To evaluate the effectiveness of our deformable manipulation framework, we use 6 benchmarks with different clothes, having different material characteristics and shapes. Moreover, we use different initial and goal states depending the task, e.g. stretching or folding. In these tasks, we use three different forms of goal configurations for the deformable object manipulations, as discussed in Section V(B). For benchmarks 4-6, the task corresponds to manipulating the cloth without human participation and we specify the goal configurations. For benchmark 1-3, the task is to manipulate the cloth with human participation. In this the human is assistant with the task, but also introduces external perturbations. Our approach makes no assumption about the human motion, and only uses the visual feedback to guess the human behavior. In benchmark 1, robot needs to anticipate human’s
Fig. 7: **Setup for Manipulation Tasks:** We use a 12-DOF dual-arm ABB YuMi and an RGB camera to perform complex manipulation tasks using visual servoing, with and without humans.

pace and forces for grasping to fold the towel in the air. In benchmark 2, robot needs to process a complex task with several goal configurations when performing folding task. In benchmark 3, robot is asked to follow the human’s action to maintain the shape of the sheet.

C. **Benefits of HOW-feature**

There are many standard techniques known in computer vision and image processing to compute low-dimensional features of deformable models from RGB data. These include standard HOG and color histograms. We evaluated the performance of HOW-features along with the others and also explore combination of these features. The test involved measuring the success rate of the manipulator to move towards the goal configuration based on the computed velocity, as given by Equation 4. We obtain best results in our benchmarks using HOG+HOW features. The HOG features capture the edges in the image and the HOW captures the wrinkles and deformation, so their combination works well.

D. **Visual Feedback Dictionary**

The main parameter related to the visual feedback dictionary that govern the performance is its size. At runtime, it is also related to the choice of the slack variable in the sparse representation. As the size of the visual feedback dictionary grows, the velocity error tends to reduce. However, after reaching a certain size, the dictionary contributes less to the control policy mapping. That implies that there is redundancy in the visual feedback dictionary.

E. **Sparse Linear Representation**

The performance of sparse representation computation at runtime is governed by the slack variable $\alpha$ in Equation 6 and 7. This parameter provides a tradeoff between data fitting and sparse solution and governs the velocity error between the desired velocity $v^*$ and actual velocity, $\|v - v^*\|_2$. In practice, $\alpha$ affects the convergence speed. If $\alpha$ is small, the sparse computation has little or no impact and the solution tends to a common linear regression. If $\alpha$ is large, then we suffer from over-fitting.

F. **Comparisons and Benefits**

We perform two kinds of experiments to measure the precision of the algorithm on benchmarks 4-6. One is same-subject testing, which separates the same data into two parts. One data is used for training (i.e. dictionary computation) and the other is used for runtime testing. Another kind of experiment is different-subject testing, which uses different data for training and testing. The same-subject testing, which is similar to online learning method, shows faster convergence with a smaller dictionary size. The different-subject testing highlights that our visual feedback dictionary computation algorithm can be used for different environments. We highlight their performance in terms of regression results in Figure 9. We notice that the errors are comparable.

![Fig. 8: Parameter Selection for Visual Feedback Dictionary and Sparse Representation](image)

We vary the dictionary size on the X-axis and compute the velocity error for different values of $\alpha$ chosen for sparse representation for benchmark 1.

![Fig. 9: Regression Result for Different Training Methods](image)

The fitted and original data in terms of computing the controller’s velocity is shown: (a) Regression model trained same-subject data; (b) Regression model trained using different-subject data.

VII. **Conclusion, Limitations and Future Work**

We present an approach to manipulate deformable materials using visual servoing and a precomputed feedback dictionary. We present a new algorithm to compute HOW-features, which capture the shape variation and local features of the deformable material. The visual feedback dictionary is precomputed using sampling and clustering techniques and used with sparse representation to compute the velocity of the
to compute the control policy mapping. Furthermore, we could use deep learning methods for future work. Besides overcoming these limitations, we would like our approach to be more complex tasks such as human dressing. Furthermore, we could use deep learning methods to control the performance by using HOG + HOW features.

controller to perform the task. We highlight the performance on a 12-DOF ABB dual arm and perform complex tasks related to stretching, folding, and placement. Furthermore, our approach can also be used for human-robot collaborative tasks.

Our approach has some limitations. We make some assumptions about the deformable material and the movements of the end-effector. The effectiveness of the manipulation algorithm is governed by the offline training data and the sparse representation. The accuracy of HOW-feature computations can also vary based on the illumination and relative colors of the cloth. There are many avenues for future work. Besides overcoming these limitations, we would like our approach to work for more complex tasks such as human dressing. Furthermore, we could use deep learning methods to compute the control policy mapping.

REFERENCES

[1] S. Miller, J. van den Berg, M. Fritz, T. Darrell, K. Goldberg, and P. Abbeel, “A geometric approach to robotic laundry folding,” The International Journal of Robotics Research, vol. 31, no. 2, pp. 249–267, 2011.

[2] A. Kapusta, W. Yu, T. Bhattacharjee, C. K. Liu, G. Turk, and C. C. Kemp, “Data-driven haptic perception for robot-assisted dressing,” in IEEE International Symposium on Robot and Human Interactive Communication, 2016, pp. 451–458.

[3] Y. Gao, H. J. Chang, and Y. Demiris, “Iterative path optimisation for personalised dressing assistance using vision and force information,” in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2016, pp. 4398–4403.

[4] Y. Li, X. Hu, D. Xu, Y. Yue, E. Grinspun, and P. K. Allen, “Multi-sensor surface analysis for robotic ironing,” in IEEE Conference on Robotics and Automation, 2016, pp. 5670–5676.

[5] L. Twardon and H. Ritter, “Interaction skills for a coat-check robot: Identifying and handling the boundary components of clothes,” in IEEE International Conference on Robotics and Automation, 2015, pp. 3682–3688.

[6] J. Schrmpf, L. E. Wettewald, and M. Lind, “Real-time system integration in a multi-robot sewing cell,” in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2012, pp. 2724–2729.

[7] D. Kruse, R. J. Radke, and J. T. Wen, “Collaborative human-robot manipulation of highly deformable materials,” in IEEE International Conference on Robots and Automation, 2015, pp. 3782–3787.

[8] L. Bodenhausen, A. R. Fugl, A. Jort, M. Willatzen, K. A. Andersen, M. M. Olsen, R. Koch, H. G. Petersen, and N. Krüger, “An adaptable robot vision system performing manipulation actions with flexible objects,” IEEE transactions on automation science and engineering, vol. 11, no. 3, pp. 749–765, 2014.

[9] D. Berenson, “Manipulation of deformable objects without modeling and simulating deformation,” in Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on. IEEE, 2013, pp. 4525–4532.

[10] D. Navarro-Alarcon, Y. H. Liu, J. G. Romero, and P. Li, “Model-free visually servoed deformation control of elastic objects by robot manipulators,” IEEE Transactions on Robotics, vol. 29, no. 6, pp. 1457–1468, 2013.

[11] D. Navarro-Alarcon, H. M. Yip, Z. Wang, Y. H. Liu, F. Zhong, T. Zhang, and P. Li, “Automatic 3-d manipulation of soft objects by robotic arms with an adaptive deformation model,” IEEE Transactions on Robotics, vol. 32, no. 2, pp. 429–441, 2016.

[12] D. Kruse, R. J. Radke, and J. T. Wen, “Collaborative human-robot manipulation of highly deformable materials,” in IEEE International Conference on Robotics and Automation, 2015, pp. 3782–3787.

[13] M. J. Sullivan and N. P. Papanikolopoulos, “Using active-deformable models to track deformable objects in robotic visual servoing experiments,” in IEEE International Conference on Robotics and Automation, vol. 4, 1996, pp. 2829–2834.

[14] A. Ramisa, G. Alenya, F. Moreno-Noguer, and C. Torras, “Using depth and appearance features for informed robot grasping of highly wrinkled clothes,” in Robotics and Automation (ICRA). 2012 IEEE International Conference on. IEEE, 2012, pp. 1703–1708.

[15] Y. Li, C.-F. Chen, and P. K. Allen, “Recognition of deformable object category and pose,” in IEEE International Conference on Robotics and Automation, 2014, pp. 5558–5564.

[16] C. Bersch, B. Pitzer, and S. Kammel, “Bimanual robotic cloth manipulation for laundry folding,” in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2011, pp. 1413–1419.

[17] A. Clegg, W. Yu, Z. Erickson, C. K. Liu, and G. Turk, “Learning to navigate cloth using haptics,” arXiv preprint arXiv:1703.06905, 2017.

[18] Y. Bai, W. Yu, and C. K. Liu, “Dexterous manipulation of cloth,” in Computer Graphics Forum, vol. 35, no. 2, 2016, pp. 532–532.

[19] P.-C. Yang, K. Sasaki, K. Suzuki, K. Kase, S. Sugano, and T. Ogata, “Repeatable folding task by humanoid robot worker using deep learning,” IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 397–403, 2017.

[20] M. Cusumano-Towner, A. Singh, S. Miller, J. F. O’Brien, and P. Abbeel, “Bringing clothing into desired configurations with limited perception,” in IEEE International Conference on Robotics and Automation, 2011, pp. 3893–3900.

[21] F. Chaumette and S. Hutchinson, “Visual servo control i. basic approaches,” IEEE Robotics & Automation Magazine, vol. 13, no. 4, pp. 82–90, 2006.

[22] S. Hutchinson and G. D. Hager, and P. I. Corke, “A tutorial on visual servo control,” IEEE transactions on robotics and automation, vol. 12, no. 5, pp. 651–670, 1996.

[23] Q. Bateux and E. Marchand, “Histograms-based visual servoing,” IEEE Robotics and Automation Letters, vol. 2, no. 1, pp. 80–87, 2017.

[24] S. Hirai and T. Wada, “Indirect simultaneous positioning of deformable objects with multi-pinching fingers based on an uncertain model,” Robotica, vol. 18, no. 1, pp. 3–11, 2000.

[25] J. D. Langsfeld, A. M. Kabir, K. N. Kaipa, and S. K. Gupta, “Online learning of part deformation models in robotic cleaning of compliant objects,” in ASME Manufacturing Science and Engineering Conference, vol. 2, 2016.
[26] J. Van Den Berg, S. Miller, K. Goldberg, and P. Abbeel, “Gravity-based robotic cloth folding,” in Algorithmic Foundations of Robotics IX. Springer, 2010, pp. 409–424.

[27] C. Collewet and E. Marchand, “Photometric visual servoing,” IEEE Transactions on Robotics, vol. 27, no. 4, pp. 828–834, 2011.

[28] Q. Bateux and E. Marchand, “Direct visual servoing based on multiple intensity histograms,” in IEEE International Conference on Robotics and Automation, 2015, pp. 6019–6024.

[29] D.-S. Lee, “Effective gaussian mixture learning for video background subtraction,” IEEE transactions on pattern analysis and machine intelligence, vol. 27, no. 5, pp. 827–832, 2005.

[30] T. S. Lee, “Image representation using 2d gabor wavelets,” IEEE Transactions on pattern analysis and machine intelligence, vol. 18, no. 10, pp. 959–971, 1996.

[31] J. G. Daugman, “Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters,” JOSA A, vol. 2, no. 7, pp. 1160–1169, 1985.

[32] K. Yamazaki and M. Inaba, “A cloth detection method based on image wrinkle feature for daily assistive robots,” in IAPR Conference on Machine Vision Applications, 2009, pp. 366–369.

[33] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” in IEEE Conference on Computer Vision and Pattern Recognition, vol. 1, 2005, pp. 886–893.

[34] L. E. Baum, “An inequality and associated maximization technique in statistical estimation for probabilistic functions of markov process,” Inequalities, vol. 3, pp. 1–8, 1972.

[35] J. A. Hartigan and M. A. Wong, “Algorithm as 136: A k-means clustering algorithm,” Journal of the Royal Statistical Society. Series C (Applied Statistics), vol. 28, no. 1, pp. 100–108, 1979.

[36] D. L. Donoho and M. Elad, “Optimally sparse representation in general (nonorthogonal) dictionaries via 1 minimization,” Proceedings of the National Academy of Sciences, vol. 100, no. 5, pp. 2197–2202, 2003.

[37] P. Beeson and B. Ames, “Trac-ik: An open-source library for improved solving of generic inverse kinematics,” in IEEE-RAS 15th International Conference on Humanoid Robots, 2015, pp. 928–935.