Garment Similarity Network (GarNet): A Continuous Perception Robotic Approach for Predicting Shapes and Visually Perceived Weights of Unseen Garments

Li Duan\(^1\) and Gerardo Aragon Camarasa\(^1\)

**Abstract**—We present in this paper a Garment Similarity Network (GarNet) that learns geometric and physical similarities between known garments by continuously observing a garment while a robot picks it up from a table. The aim is to capture and encode geometric and physical characteristics of a garment into a manifold where a decision can be carried out, such as predicting the garment’s shape class and its visually perceived weight. Our approach features an early stop strategy, which means that GarNet does not need to observe the entire video sequence to make a prediction and maintain high prediction accuracy values. In our experiments, we find that GarNet achieves prediction accuracies of 98\% for shape classification and 95\% for predicting weights. We compare our approach with state-of-art methods, and we observe that our approach advances the state-of-art methods from 70.8\% to 98\% for shape classification.

I. INTRODUCTION

Deformable objects remain an open problem for robotic perception and manipulation. This is because garments have complicated configurations such as crumpled and irregular shapes that cannot be modelled easily via simulations [1], [2] Specifically, the main challenges in deformable objects perception and manipulation are twofold. First, they usually have a complex initial configuration, which means they are wrinkled, crumpled or folded, and not in a known configuration state that can be used for manipulation tasks. Second, garments usually deform in unpredictable ways, making predictions of their deformations difficult during manipulations.

Robots manipulating deformable objects without prior knowledge about their geometric and physical properties (e.g. shapes, weights or stiffness parameters) can result in robots requiring to plan actions using a complex and high-dimensional space. This, therefore, causes failures in motion planning since robots are prone to fail due to minor variations in the deformable object’s configurations. We, therefore, propose in this paper the first step towards an online continuous perception approach that equips a robot with the ability to predict garment shapes and, consequently, allows a robot to stop a grasping or manipulation task if the prediction belief is above a threshold.

Compared to traditional research concentrating on wrinkles [3] and other local features [4], [5], we propose to learn the dynamic properties of garments from video sequences and allow a robotic system to recognize the shape and weight of a garment continuously. For this, we propose a Garment similarity Network (GarNet) that learns the physical similarity between garments to predict shapes (geometric) and visually perceived weights (physical) of unseen garments. We define a visually perceived weight in three discretized levels using an electric scale to physically weigh every garment, namely, light, medium and heavy weights. We hypothesize that GarNet can predict shapes and discretized weights in around 0.1 seconds per image frame by learning geometric and physical properties and predicting the garment’s shape and weights continuously during a robotic garment grasping task.

To test the above hypothesis, we have built a database that consists of RGBD video sequences of a robot grasping and dropping garments on a table\(^1\), see Fig. 1. We then train GarNet to learn garments’ geometric and physical similarities based on their shape and discretized weight labels. GarNet’s objective is thus to cluster garments of the same categories (shapes or discretized weights) together and pulling garments of different categories apart using a triplet loss function. These clusters are mapped into a Garment Similarity Map (GSM). To predict unseen garment shapes and weights, we introduce the concept of decision points which depend on previously mapped points in the similarity map. To introduce an early-stop strategy, we use confidence intervals for each cluster to decide whether decision points are within a statistical significant interval around a given cluster. An overview of our approach is shown in Figure 2.

---

\(^1\) This database can be downloaded from [https://liduanatglasgow.github.io/GarNet/](https://liduanatglasgow.github.io/GarNet/)
The contributions of this paper are threefold: (i) we have advanced the state-of-art by introducing GarNet that improves the prediction accuracy from 70.8% to 98% for shape classification; (ii) GarNet can visually estimate weights of unseen garments with a 95% prediction accuracy; and (iii) we propose an early stop strategy so that GarNet is faster during inference compared to the state-of-art, where a frame can be processed in 0.1 seconds.

II. RELATED WORK

Previous approaches have proposed learning geometric and physical properties of deformable objects before manipulation. Geometric characteristics of garments include shapes[4][5][3], their accessories (e.g. zips, buttons), geometric properties (lengths and heights), and physical characteristics such as weight [6], stiffness (e.g. bending, stretching and shearing)[1], damping factors and elasticity [7]. For instance, Mariolis et al. [8] proposed to use a CNN network to classify garment shapes, which are rotated by a dual-arm robot. The CNN network learns garment dynamics via depth images and achieves an accuracy rate of 89% after training. However, they train and test the network on synthetic datasets of simulated garments and tested images contain the garments that are already in the training dataset, failing to generalize for unseen garments of similar class.

Sun et al.[4] presented an approach where local (local B-spline path and locality-constrained linear coding) and global (shape index, local binary patterns, and topology spatial distances) features are extracted from single-shot images and are used to predict unseen garment shapes. This approach makes use of local and global visual characteristics of garments, such as wrinkle features. Compared to [8], their approach does not require interactions with garments, so it is faster to predict shapes and is robust while being presented with unseen samples. However, prediction accuracies are constrained by the inability of the robot to interact with the garments, and no new knowledge can be captured. For this, Sun et al. [3] proposed a Gaussian process regression classifier (GP regression classifier) to predict unseen garment shapes by accumulating knowledge after each interaction. That is, the robot in their experiment shakes or flips and then drops garments on a table to gain confidence while classifying them. This approach, therefore, demonstrated that interacting with garments and gaining prediction confidence over interactions can lead to higher prediction accuracy.

However, [3] captured the garment’s state while being static and on a table which results in making the system slow at predicting shapes. Martinez et al.[5] removed this limitation by introducing the concept of continuous perception to extract global and local features from garments. That is, they enable a robot to predict shapes by continuously observing video frames from an Xtion depth-sensing camera rather than single video frames. They showed higher accuracy in predicting unseen garment shapes compared to [3] and [4]. However, the limitation in [5] is that they let the robot to observe the entire interaction process before a decision can be made, which means that the robot takes a significant amount of time to predict a garment shape category, and this is given by the length of the video. In their work, they sample a garment for about 6 seconds.

Simulated environments [6][2] that model deformable objects, have been used in the literature to learn the physical properties of these objects and extrapolate the learned knowledge into the real world. For example, Ruina et al.[6] devised an approach where they predicted the area weights of fabrics by learning the physical similarities between simulated fabrics and real fabrics using a spectral decomposition network (SDN). Closing the gap between a simulation and the real world is effective because the physical property parameters of simulated objects are easily accessible compared to those of real objects. However, their approach is not applicable for online evaluation because it requires aligning the simulation with reality, creating an extra overhead before a prediction can be carried out. Hoque et al. [2] propose learning physical properties and dynamics of towels by a VisionSpatial Fo- sight network (VSF), which is trained on simulated towels but tested on real towels. The VSF predicts a sequence of towel deformations and corresponding robot actions based on towels’ initial and desired configurations. They used RGB plus depth images instead of RGB images in the experiment of manipulating towels and significantly improved the performance of the VSF. Using depth information helps the network(VSF) understand the dynamics characteristics of towels, which determine the deformations of manipulated towels. However, the robot implemented with the VSF takes unnecessary actions while folding a towel. Prior knowledge on understanding geometric and physical properties of deformable objects enables an effective manipulation of those objects.

This paper proposes a continuous perception approach where a robot learns the similarity between garments and predicts unseen garment shapes based on a ‘garment similarity map’. Compared with previous works (e.g. [5], and [3]), our work features an early-stop strategy, where a prediction can be halted earlier without observing the entire interaction.

III. GARNET: GARMENT SIMILARITY NETWORK

Our proposed Garment similarity Network (GarNet) consists of a Siamese network [9] which clusters garments into groups according to their shape and discretized weight categories. The objective of clustering garments is to learn common geometric and physical features of garments of the same categories. Our GarNet network comprises a residual convolutional block that extracts features from input data and a fully connected layer that maps features onto a 2D Garment Similarity Map (GSM). A garment similarity map is a 2D manifold that encodes a garment’s geometric and physical characteristics according to its shape and discretized weight categories. Garments of the same categories are clustered together, while garments of different categories are pulled apart. Figure 4 shows the generated garment similarity map in our experiment where each cluster in the map is called a Garment Cluster (GC). Our GarNet training process is expressed mathematically as:
Fig. 2. Top: Training GarNet. A positive, negative and anchor image samples from a video sequence of the training dataset are input into GarNet. Training, therefore, consists of identifying whether any two of the input triplet come from the same shape or discretized weight categories. GarNet thus maps input image frames into a Garment Similarity Map (GSM) in which input frames are mapped into clusters if they are similar; otherwise, new points are pulled apart from the cluster. Confidence intervals are computed for each cluster in the GSM as described in Section III-A. Bottom: Continuous Perception (Testing GarNet). An image from a video sequence of the testing dataset is input into a trained GarNet to get the mapping onto the garment similarity map. A video sequence of a garment in our database contains 60 frames. The plots show that GarNet gains confidence in predicting that the tested garment is a shirt. That is, as knowledge is being accumulated into the GSM, most of the decision points belong to the shirt category. In the example shown, the prediction is stopped at frame 30 because 80% of all decision points belong to the shirt category.

\[ P = F[C(I)] \]  
where \( C \) is the residual convolutional layers, \( F \), the fully connected layer, and \( I \), input images. We define \( P \) as a garment similarity point (GSP). Each frame in the video sequences of the garments is converted into one garment similarity point (GSP) by the GarNet. We also define a Garment Similarity Distance (GSD) as:

\[ GSD(x, y) = P_i - P_j \]  
where \( i \) and \( j \) are the \( i \)th and \( j \)th garment similarity point. A GSD increases between garments with different labels and decreases between garments with the same labels. Therefore, to train GarNet, we use a triplet loss [10]:

\[ PP = \left| P_{positive} - P_{anchor} \right| \]
\[ NP = \left| P_{negative} - P_{anchor} \right| \]
\[ TripletLoss = \max(0, PP - NP + margin) \]

where \( PP \) is a positive pair between positive and anchor samples and \( NP \) is a negative pair between negative and anchor samples. A positive sample is an image of a garment with the same category with respect to the anchor. A negative sample is an image of a garment that has a different category with respect to the anchor. The margin is a value that promotes the network to learn to map positive and negative samples further away from each other. In this experiment, we set this margin to 1 as suggested in [6] experiments.

Two GarNets are therefore trained separately and predict the shapes and discretized weights independently. That is, the GarNet for shape predictions is trained on the shape categories, while GarNet for discretized weight predictions is trained on discretized weight categories.

A. Garment Cluster Confidence Intervals

To decide which category (either shapes or discretized weights) a mapped garment similarity point in the similarity map belongs to, we propose to set confidence intervals
to each garment cluster in this map. That is, we define a confidence interval using a non-parametric probability density function for each garment cluster, $\mathcal{GC}$ via a kernel density estimator [11] that is defined as:

$$\hat{f}_h(\mathcal{GC}) = \frac{1}{n} \sum_{i=1}^{n} K_h(\mathcal{P} - \mathcal{P}_i)$$

$$\quad = \frac{1}{nk} \sum_{i=1}^{n} K(\mathcal{P} - \mathcal{P}_i)$$

(4)

where $\mathcal{GC}$ is the garment cluster, $K$ is a Gaussian kernel, $h > 0$ is a smoothing parameter called bandwidth which regulates the amplitude of confidence intervals, and $\hat{f}_h$ is an estimated probability density function for a garment cluster. We have conducted an ablation study on the confidence interval’s bandwidths ($h$) and results are presented in section V.C. After training a GarNet, the centroid of each garment cluster is defined as:

$$\mathcal{GC}_{mean} = \left( \frac{1}{m} \sum_{i=1}^{m} x_{\mathcal{P}_i}, \frac{1}{m} \sum_{i=1}^{m} y_{\mathcal{P}_i} \right)$$

(5)

where $\mathcal{GC}_{mean}$ is the mean value of garment similarity points mapped from one garment cluster (in Figure 4) and $m$ is the number of garment similarity points in the cluster.

We directly input unseen garments image frames as acquired by the robot to GarNet to map them into the garment similarity map. To decide the shapes and discretized weights, we define a Decision Point ($\mathcal{DP}$) that is the mean value of garment similarity points ($\mathcal{GSP}$s):

$$\mathcal{DP} = \left( \frac{1}{n} \sum_{i=1}^{n} x_{\mathcal{P}_i}, \frac{1}{n} \sum_{i=1}^{n} y_{\mathcal{P}_i} \right)$$

(6)

where $n$ is the total number of frames observed. To predict the shapes and discretized weights, we find whether a $\mathcal{DP}$ is within any confidence interval and has the minimum distance to the confidence interval’s $\mathcal{GC}_{mean}$. For this paper, we use the Euclidean distance to evaluate how close a $\mathcal{DP}$ is with respect to $\mathcal{GC}_{mean}$.

Each video sequence has 60 frames; therefore, we will have 60 decision points. To predict the shape and discretized weight, we establish that a predicted category should have at least 80% of decision points belonging to a garment cluster. If none of the categories fulfills this requirement, we denote that the observed garment does not have a known class. That is, if a decision point is outside any confidence interval, the network is not confident about which category the input garment belongs to.

By clustering garments and defining confidence intervals, it is possible to define an early-stop strategy to allow a robotic system to stop its execution if it is confident about the garment shape or weight. After observing some image frames of a garment, if any of the trained categories takes 80% of the decision points, the process is terminated, and the category is chosen as the predicted category.

### IV. Experiments

#### A. GarNet Architecture

We implement our code in Pytorch [12]. Our GarNet comprises a ResNet18 [13] as a feature extraction and fully connected networks (FC). The FC includes three linear layers, where a PReLU activation layer is placed between adjacent linear layers. The source code for GarNet and experimental scripts are available at [https://liduanatglasgow.github.io/GarNet/](https://liduanatglasgow.github.io/GarNet/)

We use an Intel-i7 equipped computer with an Nvidia GTX 1080 Ti to train the network. We use the Adam optimizer with an initial learning rate of $10^{-3}$, controlled by a learning scheduler with a decay rate of $10^{-1}$ and a step size of 8. The network is trained for 270K iterations, taking approximately 30 minutes.

#### B. Data Collection and Experiments

The database in this experiment consists of 20 garments of five different shapes, namely, pants, shirts, sweaters, towels and T-shirts. For each shape, there are four garments of different colours and materials. We used an electric scale to weigh every garment and divide their weights into three discretized levels, namely, light, medium and heavy weights. Therefore, in these experiments, we do not predict the weight values of tested garments but predict the discretized weights levels. In both shape and discretized weight experiments, we divided our garments into two groups; a training group containing 15 garments and a testing group with five garments. We ensure that garments for testing are excluded while training GarNet, which means testing garments are ‘unseen’ examples. We also ensure that both testing and training groups include all categories. (five categories for shapes and three categories for discretized weights). 80% of the training group is a training dataset used to train a GarNet, and 20% of the training group is a validating dataset used to evaluate the performance of the GarNet while it is being trained.

We have used a Baxter robot to manipulate garments. Garments are initially placed on a table. Next, they are lifted to $1m$ above the table and then dropped from this height. An Xtion depth-sensing camera is used to capture garment video sequences. Each garment is captured ten times, which means that the grasp-and-drop operation is conducted ten times. There are 200 videos in total, and each video contains 60 frames (sampling frequency is 10Hz). Therefore there are 12,000 image frames in total. Figure 1 shows the experimental setup of the robot grasping and dropping garments.

Our experiments include 50 unseen garment videos containing ten videos for each of the five categories. For each video sequence, we predict the shape and discretized weight of the garment in the video. Therefore, we have ten predictions for each category (one prediction for each video) and 50 predictions in total. The prediction accuracy for each category is defined as the percentage of correctly predicted videos in the ten videos of each category.
**TABLE I**

| Category       | Accuracy (%) | Triplet Loss |
|----------------|--------------|--------------|
| shapes         | 96.53 (93.89) | 0.0889 (0.184) |
| discretized weights | 97.79 (94.94) | 0.0577 (0.1472) |

V. RESULTS

A. GarNet Training

Table I shows training results of GarNet. We can see that the network consistently shows high accuracy results for both shape and discretized weights category experiments. Figure 4 shows the mappings of testing garments onto the similarity map, where it is possible to observe that garments of different categories are pulled apart; while garments of the same categories are clustered together.

B. Continuous Perception

Examples of testing results are shown in Figure 3. We can see that although GarNet does not recognize garments correctly from the beginning (because most of the decision points belong to an incorrect category), GarNet gradually gains confidence in predicting a correct category for each garment because more decision points are within correct categories and eventually percentages of decision points within correct categories are over 80%. The classification task is consequently stopped early, and the system does not need to observe the full video sequence to make a correct prediction of the garment class.

We conduct two ablation studies in this experiment. The first study is about comparing predictions only on local garment similarity points (GSPs) rather than on decision points (DPs). The second ablation study compares the performance of GarNet trained on RGB and depth images.

We use ‘decision points’ (DPs) (in Eq. 6) to make predictions on unseen garment shapes and discretized weights. Therefore, the position of a decision point on the garment similarity map (in Figure 4) depends on all previously observed image frames rather than on currently observed image frames. In Tables II and III, we can observe that using decision points has a better performance than by using garment similarity points (98% vs. 76% for shapes and 95% vs. 81.7% for discretized weights, respectively). This shows that GarNet benefits from using accumulated knowledge via decision points rather than local and episodic knowledge (similar to [8], [4]).

To investigate whether the type of image has an effect on the overall prediction of a garment class, we trained GarNet using RGB and depth images. Tables II and III show that a GarNet trained on depth images outperforms a GarNet trained on RGB images 98% vs 40% for shapes and 95% vs 51.7% for discretized weights. The increase in performance is because depth images captured structural and dynamic information of the garment being manipulated and are better suited to capture physical properties of garments as opposed to RGB images as proposed by [6].

C. Ablation study on the confidence intervals bandwidths

A bandwidth, as defined in section III-A, determine the size of a confidence interval. In this study, we, therefore, evaluate the effect of the bandwidth selection with respect to the performance of GarNet. A confidence interval of a garment cluster is a region in the garment similarity map of which a certain percentage of GSPs are grouped together.

A decrease in the bandwidth value denotes a decrease in the percentage of GSPs included within the garment cluster. An increase in the bandwidth means that almost all GSPs should be included, while a small portion of points are relatively far away from a garment cluster, so that a confidence interval may overlap with other confidence intervals, or even multiple confidence intervals will be generated for one garment cluster. In this case, the performance of GarNet will have an impact on the final prediction.
TABLE III  
**TABLE: PREDICTION RESULTS (DISCRETIZED WEIGHTS)**

| Category     | depth, DP | depth, GSP | RGB, DP | RGB, GSP |
|--------------|-----------|------------|---------|----------|
| lights       | 90%       | 90%        | 0%      | 0%       |
| mediums      | 95%       | 85%        | 55%     | 35%      |
| heavies      | 100%      | 70%        | 100%    | 100%     |
| Average      | 95%       | 81.7%      | 51.7%   | 45%      |

![Fig. 5. Bandwidth Ablation Study. Left: Bandwidth values versus accuracy for shape classification. Right: Bandwidth values versus accuracy for discretized weights classification.](image)

In Figure 5, we find that a bandwidth of 95% has the best performance, and we use 95% as the bandwidth for the rest of the experiments. However, at a 99% bandwidth, we can observe that the prediction accuracy drops while classifying shapes; this is because GSPs are grouped into incorrect categories.

**D. Comparison with state-of-art**

We have compared our results with the results from [4][5][3]. As observed in Table IV, our GarNet outperforms previous work on predicting unseen garment shapes. There are several reasons why our network has the best performance.

1) The use of a garment similarity map to encode knowledge of garment shapes and weights.: Inspired by [6], where the authors proposed learning the physical similarity between simulated fabrics and predicting physical properties of real fabrics, we find that the similarity network effectively predicts unseen deformable objects, such as garments and fabrics. Compared with a traditional classifier that regresses embeddings of data into labels (which is equivalent to asking which shape/discretized weight classes the data belongs to), our GarNet network learns geometric and physical characteristics that makes them the same or different (which is equivalent to asking why the data presents different/the same shapes/discretized weights). Therefore, for unseen garments, the network only needs to decide similarities of the garments for each garment cluster rather than classify them into certain classes, reducing the prediction difficulty.

2) Continuous Perception.: Traditional methods such as [4], [8] that predict shapes and weights of garments are based on static garment features such as wrinkles, outlines, creases, to name a few. Instead, we propose to carry out predictions on encoded knowledge in the GSM while learning the dynamic properties of garments.

3) Early-Stop strategy.: Compared with [3][5], where the proposed approaches involve having a robot observing the entire interaction with a garment, our approach only requires a robot to observe interactions partly if termination requirements are satisfied. Therefore, our approach has a mechanism to stop a manipulation on the fly as GarNet can process images every 0.1 seconds, taking an average of 4 seconds to generate a prediction.

**VI. CONCLUSION**

We have presented a garment similarity network (GarNet) that learns the similarity of the garments and predicts continuously their shapes and their visually perceived weights. We have also introduced a Garment Similarity Map (GSM) that encodes garment shapes and weights knowledge into clusters. These clusters were then used to decide on which cluster unseen garment samples belongs to heuristically. As observed in Fig. 3, GarNet obtains high prediction accuracies while classifying shapes (98%) and discretized weights (95%). Similarly, we have compared GarNet’s performance with the state of the art, and GarNet showed an increase of 27.2% of accuracy (Table IV).

Compared with previous work on continuous perception [5], GarNet has the advantage of an ‘early stop’ strategy. That is, a robot does not need to observe the full video sequences to make predictions which could enable robots to be more responsive and effective while manipulating garments and deformable objects. However, GarNet, in this paper, does not support online learning of unknown garment shapes. For instance, we train GarNet on five shape categories, and it can predict shapes of unseen garments from those categories. In future work, we plan to devise an online-learning approach for GarNet. Future work also includes investigating more complicated interactions, such as twisting garments, shaking garments or rotating garments. From those interactions, differences in stretching and bending characteristics of garments can be exploited to evaluate garments’ stiffness parameters, which can potentially help to develop a robot dexterous garment manipulation approach for folding [14] [15], flattening [16], to name a few, that requires fewer iterations.

**VII. ACKNOWLEDGEMENT**

We would like to thank George Killick and Nikos Pitsilos for their valuable comments while reviewing this paper.

**REFERENCES**

[1] H. Wang, J. F. O’Brien, and R. Ramamoorthi, “Data-driven elastic models for cloth: modeling and measurement,” ACM transactions on graphics (TOG), vol. 30, no. 4, pp. 1–12, 2011.
[2] R. Hoque, D. Seita, A. Balakrishna, A. Ganapathi, A. K. Tanwani, N. Jamali, K. Yamane, S. Iba, and K. Goldberg, “Visuospatial foresight for multi-step, multi-task fabric manipulation,” 2021.

[3] L. Sun, S. Rogers, G. Aragon-Camarasa, and J. P. Siebert, “Recognising the clothing categories from free-configuration using gaussian-process-based interactive perception,” in 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016, pp. 2464–2470.

[4] L. Sun, G. Aragon-Camarasa, S. Rogers, R. Stolkin, and J. P. Siebert, “Single-shot clothing category recognition in free-configurations with application to autonomous clothes sorting,” 2017.

[5] L. Martínez, J. R. del Solar, L. Sun, J. P. Siebert, and G. Aragon-Camarasa, “Continuous perception for deformable objects understanding,” Robotics and Autonomous Systems, vol. 118, pp. 220 – 230, 2019. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0921889019300417

[6] T. F. Runia, K. Gavrilýuk, C. G. Snoek, and A. W. Smeulders, “Cloth in the wind: A case study of physical measurement through simulation,” arXiv preprint arXiv:2003.05065, 2020.

[7] B. Tawbe and A. Crétu, “Acquisition and neural network prediction of 3d deformable object shape using a kinect and a force-torque sensor †,” Sensors (Basel, Switzerland), vol. 17, 2017.

[8] I. Mariolis, G. Pelekä, A. Kargakos, and S. Malassiotis, “Pose and category recognition of highly deformable objects using deep learning,” in 2015 International Conference on Advanced Robotics (ICAR). IEEE, 2015, pp. 655–662.

[9] G. Koch, R. Zemel, and R. Salakhutdinov, “Siamese neural networks for one-shot image recognition,” in ICML deep learning workshop, vol. 2. Lille, 2015.

[10] E. Hoffer and N. Ailon, “Deep metric learning using triplet network,” in International workshop on similarity-based pattern recognition. Springer, 2015, pp. 84–92.

[11] M. Rosenblatt, “Remarks on Some Nonparametric Estimates of a Density Function,” The Annals of Mathematical Statistics, vol. 27, no. 3, pp. 832 – 837, 1956. [Online]. Available: https://doi.org/10.1214/aoms/1177728190

[12] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Kopf, E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala, “Pytorch: An imperative style, high-performance deep learning library,” in Advances in Neural Information Processing Systems 32, H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alché-Buc, E. Fox, and R. Garnett, Eds. Curran Associates, Inc., 2019, pp. 8024–8035. [Online]. Available: http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf

[13] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” 2015.

[14] A. Doumanoglou, J. Stria, G. Pelekä, I. Mariolis, V. Petrik, A. Kargakos, L. Wagner, V. Hlaváč, T.-K. Kim, and S. Malassiotis, “Folding clothes autonomously: A complete pipeline,” IEEE Transactions on Robotics, vol. 32, no. 6, pp. 1461–1478, 2016.

[15] J. Stria, D. Pruša, V. Hlaváč, L. Wagner, V. Petrik, P. Krsek, and V. Smutný, “Garment perception and its folding using a dual-arm robot,” in 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014, pp. 61–67.

[16] L. Sun, G. Aragon-Camarasa, S. Rogers, and J. P. Siebert, “Accurate garment surface analysis using an active stereo robot head with application to dual-arm flattening,” in 2015 IEEE International Conference on Robotics and Automation (ICRA), 2015, pp. 185–192.