Wrinkle Detection and Cloth Flattening through Deep Learning and Image Analysis as Assistive Technologies for Sewing

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Robotic manipulation of fabric has potential as an enabling accessibility technology for individuals with disabilities, opening up a range of employment opportunities and helping to decrease the underemployment of this population. This research seeks to reliably characterize wrinkles and facilitate robotic removal of the wrinkles, with the focus on managing the outfeed of a sewing process, facilitating employment for individuals unable to reach behind the machine while performing sewing tasks. Outfeed management is critical in sewing to prevent bunching and maintain sewing productivity. To smooth out a fabric and eliminate wrinkles, the wrinkles need to be located and characterized, and points identified where a robotic arm can apply force on the fabric to smooth the fabric. For this purpose, we employ a deep learning technique to detect wrinkles and use corner detection of the fabric to determine an effective point for wrinkle removal.

CCS Concepts: • **Human-centered computing** → **Accessibility technologies**; • **Computing methodologies** → *Deep learning approaches*; *Computer vision.*

Additional Key Words and Phrases: Accessibility, Sewing, Cloth manipulation, Cloth Flattening, Fabric Wrinkle Detection

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1 INTRODUCTION

The Abilities-First group at Michigan State University is exploring methods to increase workforce participation for individuals with disabilities. Our approach towards disability inclusion is comprehensive, focusing on augmenting individual abilities using a range of technologies and workflow-oriented strategies. Through a partnership with Peckham, Inc. of Lansing, MI, we are specifically addressing the increased inclusion of individuals with disabilities in the garment industry. Peckham is a producer of clothing and has a corporate mandate to employ individuals with disabilities as a significant percentage of their workforce.

Individuals with disabilities represent a large and greatly underutilized workforce. While these individuals represent 11.9% of the available US workforce, their employment rate of only a little over 19% is small compared to the 65.4% employment rate for individuals without disabilities [2]. Individuals with disabilities are significantly underemployed relative to the general population and this disparity is even worse in developing countries [16]. Accessible technologies have the potential to greatly increase employment opportunities in a variety of industries. We are specifically addressing tasks related to sewing.

Industrial sewing requires training and maintenance of skills. In particular, it requires manual manipulation of fabric and hand-eye-foot coordination. Hands guide the cloth to the machine and machine operation is controlled by a foot pedal. We are exploring a range of workplace augmentations to support individuals with disabilities. This paper's research is part of a project aimed at enhancing a sewing environment with robotic support, specifically to assist in guiding the fabric. Fabric tends to bunch behind the machine in unpredictable ways. Traditionally, the worker will use their left hand to regularly reach behind the machine, manipulating the fabric to ensure a smooth outfeed from the sewing operation. This activity limits the participation of individuals who have only one hand or arm, have insufficient mobility to reach behind the machine, or experience pain when attempting to reach behind the machine.

The goal of the work described in this paper is to create a robotic assistant that can smooth the outfeed fabric. Rather than replacing a worker with a robot, our solution seeks to utilize a robot as an assistant in the task to allow a range of individuals with disabilities to be employed who would not be able to complete the sewing task in a timely manner.

Our preliminary work is focused on determining the locations of wrinkles due to fabric bunching and determining action points and the directions where a robot can manipulate the fabric to remove the wrinkle. Our system is unique in its ability to operate independently of textures, sizes, and backgrounds, addressing a gap in existing work that does not serve varying textures and cloth sizes.

2 RELATED WORK

In recent advancements, the combination of cloth detection and control in deformable object manipulation has seen significant innovation. Researchers have developed algorithms for both recognizing cloth states and executing precise control actions. Detection techniques often utilize computer vision, with methods ranging from deep learning-based image processing to extracting specific features like wrinkles or folds. Control strategies leverage these detection outputs, employing methods like reinforcement learning, path planning, or force control for effective robotic manipulation. This dual

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focus on detection and control has led to improvements in tasks like automated folding, sorting, and sewing of textiles.

2.1 Cloth and Wrinkle Detection

Research in cloth manipulation and wrinkle detection/removal has focused on two major activities: wrinkle detection and grasping point determination. In order to effectively manipulate cloth to remove wrinkling and bunching, modeling of the cloth and its intricate features, such as wrinkles, is required.

A prevalent method in many papers is image processing, which includes Gabor Filtering for wrinkle analysis [17, 30], contour detection using computer vision techniques [15], binary thresholding [10], and edge detection [7]. General image processing approaches are also employed [5, 20, 21]. Sun et al. utilize range map analysis for wrinkle detection [24]. Our early work explored this range of techniques and found them to be limited when fabric is more complex than simple smooth and evenly colored cloth. In particular, fabric with detailed patterns defeats most image processing methods.

A significant number of studies have utilized depth maps for detecting clothes and wrinkles. Features are often extracted from Red-Green-Blue-Depth (RGBD) images [11, 25, 28]. Notably, Zhengxin et al. specifically extracted 3D geometric features from fabric wrinkles using a 1/f noise function [31]. Capturing 3D point clouds is another common approach [1, 3]. Ramisa et al. describe a method using a Kinect sensor, initially capturing the depth and RGBD images of wrinkled clothes, followed by applying SIFT and GDH descriptors to these images [18]. A problem with depth-based approaches is the requirement of expensive depth camera hardware. While a Kinect sensor is not expensive, it is unlikely that it would hold up in a factory setting.

To enhance detection accuracy, several studies have incorporated deep learning techniques. Neural networks and Convolutional Neural Networks (CNNs) have been particularly effective in cloth detection tasks [19, 27]. These advanced computational methods have significantly improved the ability to detect and analyze complex fabric structures.

None of the studies reviewed have addressed problems related to textured images or developed an algorithm that operates independently of the fabric's color or texture. Our research confronts this challenge and aims to create an algorithm that is robust in a variety of content settings.

2.2 Cloth Manipulation

A popular strategy in robotic cloth manipulation is the use of reinforcement learning to adaptively refine control policies. Wu et al. introduce Maximum Value under Placing (MVP), a method enhancing the efficiency of deformable object manipulation [29]. Few-shot learning and sparse rewards to enhance control policy learning [10], Deep P-Network (DPN), and Dueling Deep P-Network (DDPN) [27] have also been utilized. Grontved et al. focus on a reinforcement learning agent for comprehensive motion planning [7], and Shehawy et al. apply the Deep Deterministic Policy Gradient (DDPG) algorithm for more nuanced control [20].

Different studies have proposed methods for the effective grasping and folding of cloth. Miller et al. utilize a g-fold mechanism, focusing on geometric reasoning for folding polygonal cloth [15]. Bersch et al. evaluate grasping actions using a score function based on geometric features [1] and Fontana et al. employ soft fingers at predefined grasping points for wrinkle flattening [5]. Williamon et al. introduce a two-phase method for cloth wrinkle and fold removal. The first phase involves preliminary smoothing without depth data, with the robot pulling at the cloth's edges. The second phase refines this by using depth data to target and rectify complex folds, optimizing the grasp points, and pulling directions [28].

Several papers have incorporated sophisticated learning algorithms for task execution such as the random-forest algorithm [11] or the VisuoSpatial Foresight (VSF) framework for predictive planning in fabric smoothing and folding [9]. Saxena et al. detect optimal grasping points using class-specific convolutional neural networks (CNNs) [19], and Sun et al. apply heuristic-based strategies for autonomously flattening wrinkles [24].

Understanding the direction and amount of force needed is crucial for successful manipulation. Qiu et al. have investigated the smoothing efficiency of a stretching direction perpendicular to the wrinkles [17]. Sun et al. utilize different poses to grasp and manipulate garments, emphasizing the geodesic distance for gentle handling [25].

3 METHODOLOGY

In the process of cloth flattening, our primary task is to identify wrinkles and, for each, a corresponding line that best represents the dominant folding of the wrinkle. Once identified, we target wrinkle elimination through strategic actions. Specifically, we select one of the cloth's corners as the *action point*, depending on the largest wrinkle position and orientation. The action point is a selected location where a robot will grasp the cloth and pull it to remove the wrinkle. The chosen corner then determines the pulling direction. In early development, we are manually performing the pulling action. We have a Fanuc LR/Mate robotic arm we are integrating it into the system, as illustrated in Figure 1. This is an iterative process, continuously focusing on the most prominent wrinkle until the cloth is smooth.

To support and refine our methodology, we compiled a comprehensive dataset comprising both captured and synthetic images of wrinkled cloth. This dataset serves as a foundation for training and testing our wrinkle detection algorithms. We utilize deep learning and a series of image-processing techniques. The deep learning approach allows the system to work for a wide variety of cloth textures, sizes, and backgrounds.

To enhance precision and flexibility, we create a binary mask of the fabric and devise an algorithm for identifying the cloth's four corners. This allows us to select the most suitable action point from these four corners.

Upon identifying the wrinkle line and corners, we calculate an orthogonal line relative to the wrinkle line and identify the closest corner to this orthogonal line. This step is crucial for understanding the spatial relationship between the wrinkle and the cloth's geometry, thereby guiding us to the optimal pulling direction for effective wrinkle removal. The subsequent action involves projecting the pulling vector onto the cloth and manually following this direction

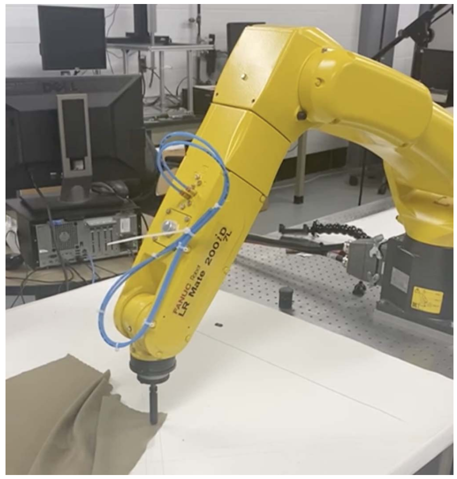


Fig. 1. Fanuc LR/Mate robot arm manipulating fabric

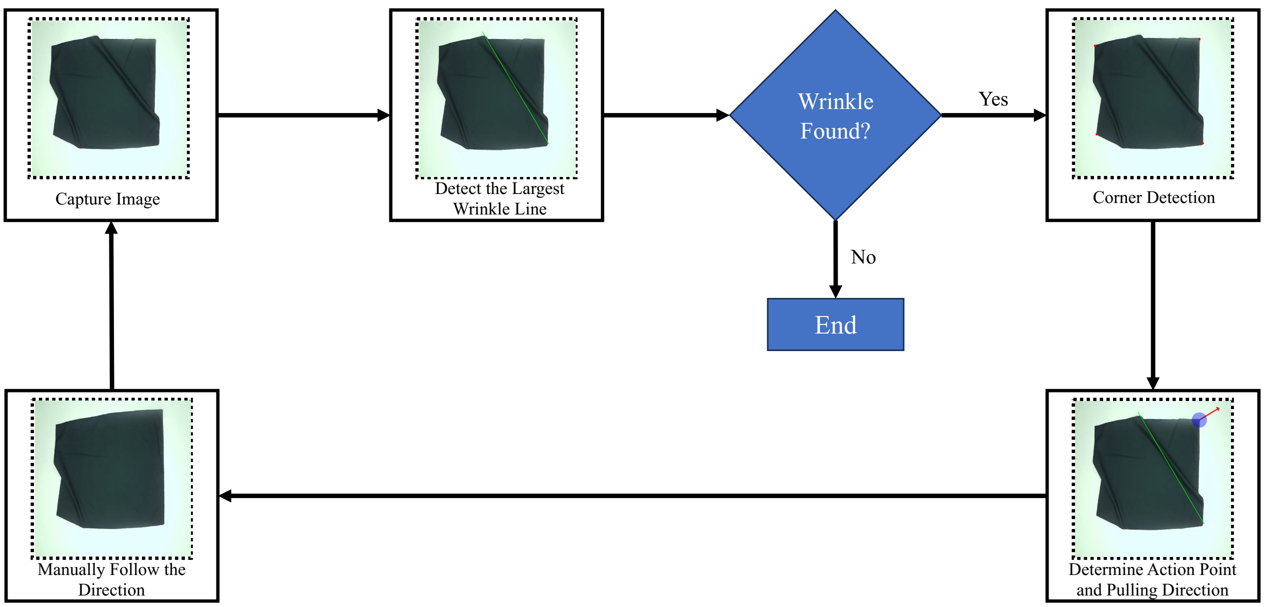
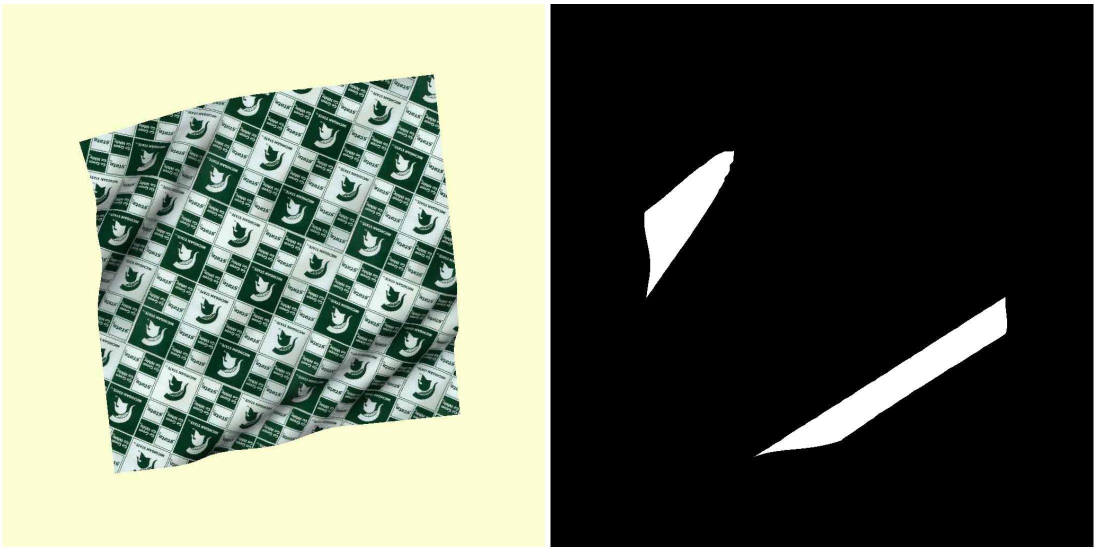


Fig. 2. The overall workflow of our proposed method to flatten a cloth

to stretch the fabric with a human operator. We repeat this process, continuously adjusting our strategy based on the cloth's changing wrinkle topology until the fabric is entirely free of wrinkles. Figure 2 illustrates the complete process flow of our proposed technique for flattening a fabric.

3.1 Dataset Preparation

Our early work on wrinkle detection focused on the application of conventional computer vision methods for detection of the wrinkles. Methods as simple as thresholding [22] or ridge detection [4] work for simple fabrics with a uniform color. However, they fail for fabrics with patterns. This naturally moved development to the application of deep learning approaches which could be trained to recognize wrinkles in a wide range of fabrics. Supporting an effective machine learning solution requires a robust and representative data set, of hundreds to thousands of images. In our work, we have captured and hand-annotated a couple hundred images for training data, but capture and annotation is a tedious process and is sensitive to the camera and lighting setup and the quality of the annotator. While we anticipate building a larger set of captured and annotated images,



(a) Wrinkled Cloth (b) Wrinkle Mask

Fig. 3. A sample of synthetic data

the bulk of the training data set we are currently using is rendered synthetic images.

A program was created that simulated cloth being dropped onto a surface with virtual obstacles that forced the cloth to wrinkle. $50cm^2$ cloth sheets were simulated by a 40 x 40 vertex triangle mesh. For each generated image, a texture is selected randomly from a library of cloth textures. The size, placement, and rotation of the texture are randomized. A modified version of Extended Position Based Dynamics (XPBD) [13] is used to simulate the physics of cloth with $16.6ms$ time integration steps and 15 sub-steps [14]. Horizontal and vertical structural springs model the limited stretch in fabrics. Crossed diagonal shear springs are applied to control shearing. Translation-based bend springs are applied horizontally and vertically over a three-vertex range to control the fabric bending characteristics.

The cloth sheets are dropped from a height of $15cm$ onto randomized obstacles and allowed to settle. The settled mesh is rendered using OpenGL and simple Gouraud shading using a custom shader that simulates an overhead light source and Lambertian illumination [6]. The camera position is randomized so that each image has some rotation applied and varies in size. Images require approximately 3 seconds to produce on an M1 Max-based Macbook Pro, allowing around 2,000 images to be produced in less than two hours. For each image, a wrinkle mask is produced based on the rendered image depth information. Example program output is presented in Figure 3.

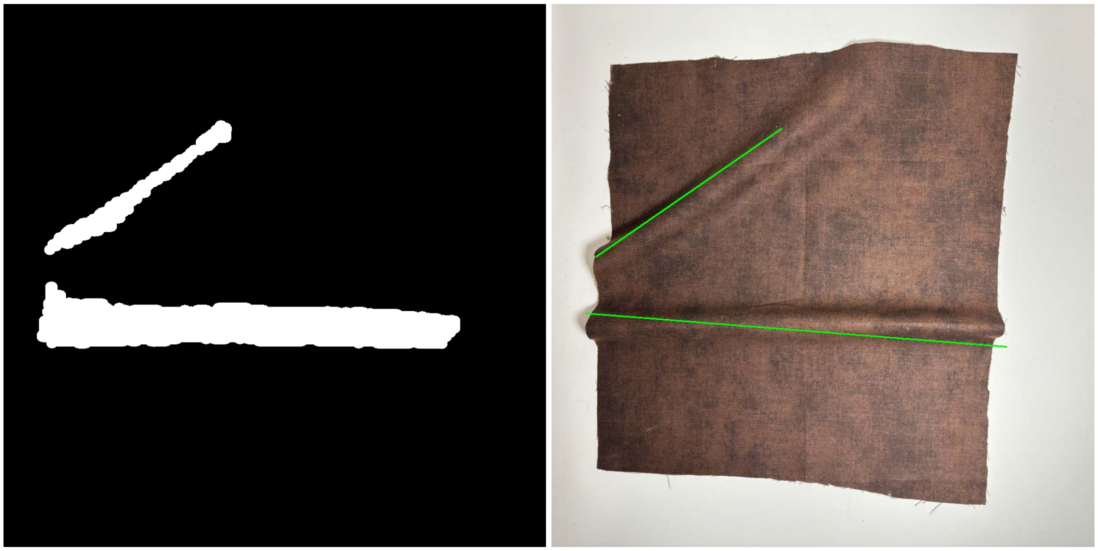
3.2 Cloth Wrinkle Detection

In our study, we address the challenge of wrinkle detection in fabrics, encompassing both textured and designed fabrics as well as plain textiles of various colors. To achieve this, we employ a deep learning approach, the Segment Anything Model (SAM) initially proposed by Meta AI [12]. This model is renowned for its robustness and versatility in segmenting a wide range of objects within images. We use this model to compute a mask of the wrinkle. The pre-trained SAM model is refined with the dataset that we prepared. The dataset is divided 90%-10% for training and testing purposes. For training, we employ Dice loss as our loss function [23], a commonly preferred option for tasks involving masking. Dice loss is a measure of the dissimilarity between the predicted segmentation and the true segmentation. It is based on the size of the intersection area in relation to the total areas of the predicted and true segmentation. The model underwent 200 epochs of training on our synthetic dataset, resulting in a reduction of the Dice loss from 0.51 to 0.084. To assess the model, we have adopted the Intersection over Union (IoU) metric. The calculation of IoU is based on Equation 1 where $A_{overlap}$ is the area of the overlap between the predicted mask and the ground truth mask and A_{union} is the area of the union between the predicted mask and the ground truth mask

$$IoU = \frac{A_{overlap}}{A_{union}} \tag{1}$$

After this fine-tuning process, the model achieved an IoU score of 64.67% over the test set. The output from this model is a binary mask, effectively highlighting the wrinkle areas against the fabric background.

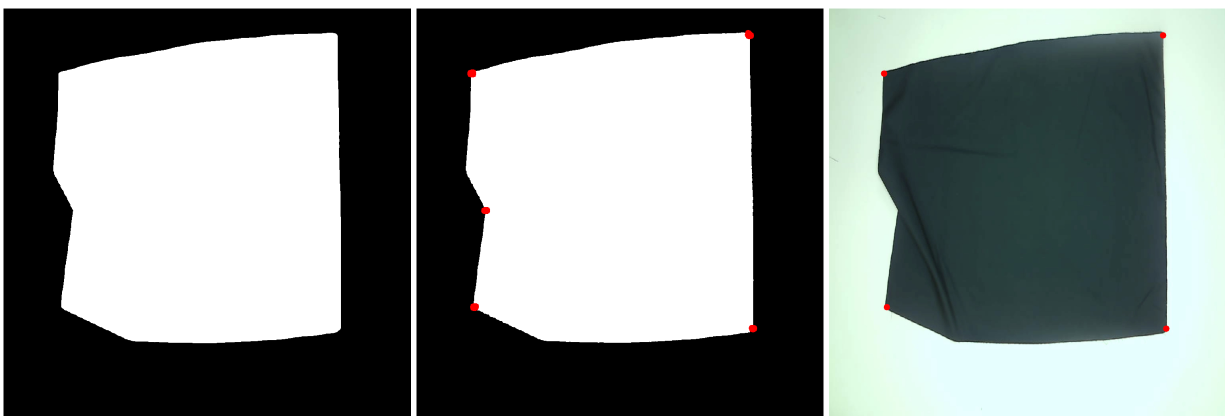
Upon obtaining the wrinkle mask, our methodology integrates advanced computer vision techniques to further refine and analyze these results. Initially, an opening operation is applied to the binary mask, which serves to remove noise and isolate significant wrinkle features. Subsequently, a contour detection algorithm is applied to identify and quantify the wrinkles present in the fabric [26]. This analysis includes the count of wrinkles, their respective magnitudes,



(a) Predicted Wrinkle Mask

(b) Wrinkle Lines

Fig. 4. (a) Initially, the wrinkle mask is identified using a deep learning technique and (b) subsequently, lines that align with the wrinkles are determined through computer vision algorithms.



(a) Cloth Mask

(b) Extra Corners Detected by the algorithm

(c) Filtered Corners of the Cloth

Fig. 5. (a) Initially, the cloth mask is identified using a deep learning method, (b) followed by the detection of corners using the Harris Corner Detector, (c) and then the four corners are pinpointed by calculating the shortest distances from the four corners of the frame.

and their orientations. Figure 4 displays the identified wrinkle mask alongside the associated wrinkle lines.

Special attention has been given to the wrinkle with the largest area, as it typically signifies the most prominent deformation in the fabric. We then pinpoint the start and end pixels of this principal wrinkle and proceed to fit a line over its span. This procedure allows us to accurately delineate the wrinkle line, providing a representation of the most significant wrinkle in each fabric sample.

3.3 Corner Detection

In our approach to corner detection, we confront the challenge posed by the variability in image conditions, particularly those caused by differences in lighting conditions, resolutions, backgrounds, and other environmental factors. Traditional image processing techniques, while effective under consistent conditions, often falter when faced with such variability. To counter this, we first generate a binary mask of the clothing item. This initial step is pivotal as it creates a controlled and uniform environment for subsequent processing, effectively mitigating the impact of inconsistent imaging conditions. To extract the cloth's mask we use a pre-trained segmentation model provided by Meta AI [12]. This model effectively generates a binary mask. To enhance the quality of the mask and decrease noise, an opening operation is applied consisting of erosion followed by dilation. This step ensures that the subsequent corner detection is not influenced by any artifacts or noise present in the original image.

Following the mask refinement, we employ a Harris Corner Detector [8], to identify potential corner points on the cloth. The Harris Corner Detector is particularly well-suited for this task due to its ability to detect corners based on local changes in intensity, which correlates well with the geometrical features of the cloth. However, as the cloth is not laid out flat, this method initially identifies numerous corners, including those with wrinkles and folds, in addition to the actual corners of the cloth. To isolate the true corners of the cloth, we implement a distance-based filtering approach. For each corner detected on the cloth, we calculate its Euclidean distance to the corners of the captured image frame. The corners of the cloth with the minimum distances to these image frame corners are then selected as the most probable actual corners of the cloth. Figure 5 illustrates the output at each stage of the corner detection process.

3.4 Action Point and Pulling Direction Determination

To flatten a cloth, the methodology involves iteratively selecting an action point and determining the optimal pulling direction. Initially, the most prominent wrinkle is identified, then one of the four corners of the cloth is designated as the suitable action point, $C_{closest}$, which, when manipulated, would most effectively remove the wrinkle. The pulling direction is then calculated as an angle pointing towards the orthogonal line of the wrinkle, ensuring that the action exerted maximally flattens the wrinkle. This process is repeated, continually reassessing the cloth's state and adjusting the action point and direction accordingly.

The most suitable action point is determined through a two-step minimization process. This task is approached by first constructing a line through the center of the wrinkle that is orthogonal to a line representing the target wrinkle. This line is characterized by the equation $a_{or}x + b_{or}y + c_{or} = 0$. The orthogonal line to a given wrinkle is determined by first calculating the slope of the wrinkle line from its start and end points. This slope is then used to derive the negative reciprocal for the orthogonal line's slope, ensuring perpendicularity. Special cases where the wrinkle line is horizontal or vertical are handled distinctly by assigning appropriate coefficients, ensuring that the orthogonal line always effectively counters the wrinkle's direction. Initially, each corner C_i of the cloth is considered, where $i = 1, 2, 3, 4$, and its perpendicular distances to the wrinkle's orthogonal line are calculated. The two corners exhibiting the minimum perpendicular distances are then identified through the minimization process using Equation 2.

$$\{C_{min1}, C_{min2}\} = \arg\min_{i \in 1,2,3,4} \left(\frac{|a_{or}C_{i,x} + b_{or}C_{i,y} + c_{or}|}{\sqrt{a_{or}^2 + b_{or}^2}} \right) \tag{2}$$

Subsequently, the focus shifts to these two selected corners. The corner from these two that is closest to the center of the wrinkle P, thereby having the minimum Euclidean distance, is determined and designated as $C_{closest}$ using Equation 3.

$$C_{closest} = \arg\min_{i \in 1,2} \left(\sqrt{(P_x - C_{min_i,x})^2 + (P_y - C_{min_i,y})^2} \right) \tag{3}$$

The pulling direction is established by constructing an orthogonal line to the wrinkle, with the start point S at $C_{closest}$ and the end point E extending a fixed distance away in the direction perpendicular to the wrinkle. Now that we have the start point s and the end point e of the wrinkle line and the start point S and the end point E of the orthogonal line, the critical intersection point I where the wrinkle line and the orthogonal line meet is determined by solving Equation 4 and Equation 5.

$$(e_y - s_y)I_x + (s_x - e_x)I_y = (e_y - s_y) * s_x + (s_x - e_x) * s_y \tag{4}$$

$$(E_y - S_y)I_x + (S_x - E_x)I_y = (E_y - S_y) * S_x + (S_x - E_x) * S_y \tag{5}$$

The subsequent analysis involves evaluating the orientation of the end point of the orthogonal line E relative to the intersection point I using two vectors $\vec{SI} = S - I$ and $\vec{EI} = E - I$. The lengths of the two vectors $||SI||$ and $||EI||$ are computed. If $||SI|| > ||EI||$, it indicates that the end point E is closer to the wrinkle, necessitating a change of 180° in direction. The end point is thus adjusted to ensure the force exerted pulls the cloth away from the wrinkle, effectively flattening it. The resulting action is visually represented by an arrow drawn from $C_{closest}$ pointing towards the newly determined pulling direction as shown in Figure 6.

4 EXPERIMENTS

4.1 Sample Trial

Figure 7 illustrates the method's iterative process. The task involves several repetitions to smooth out a cloth. Initially, an image is taken. The system then determines the largest wrinkle location, the action point, and the direction to pull. As the pull proceeds, another image is captured, and the system identifies the next most prominent wrinkle line and the direction to pull. This cycle is repeated until no wrinkles remain.

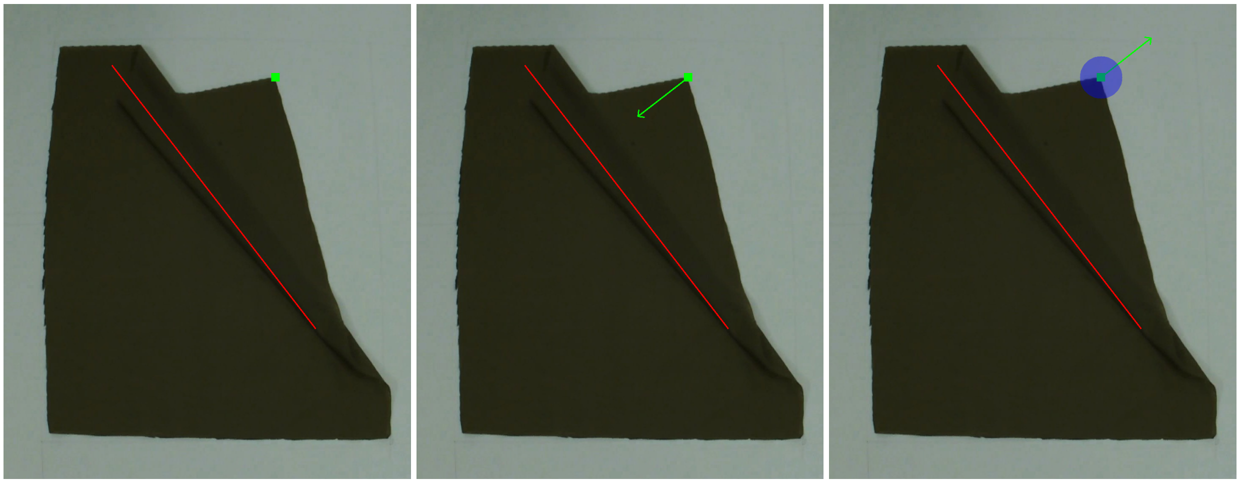
4.2 Wrinkle Detection

The algorithm for detecting wrinkles has undergone assessment on images with diverse textures. The evaluation of wrinkle detection effectiveness is based on the *Recall* metric. The calculation of *Recall* is defined by the Equation 6.

$$Recall = \frac{\text{Number of correctly predicted wrinkles}}{\text{Number of wrinkles in the ground truth}} \tag{6}$$

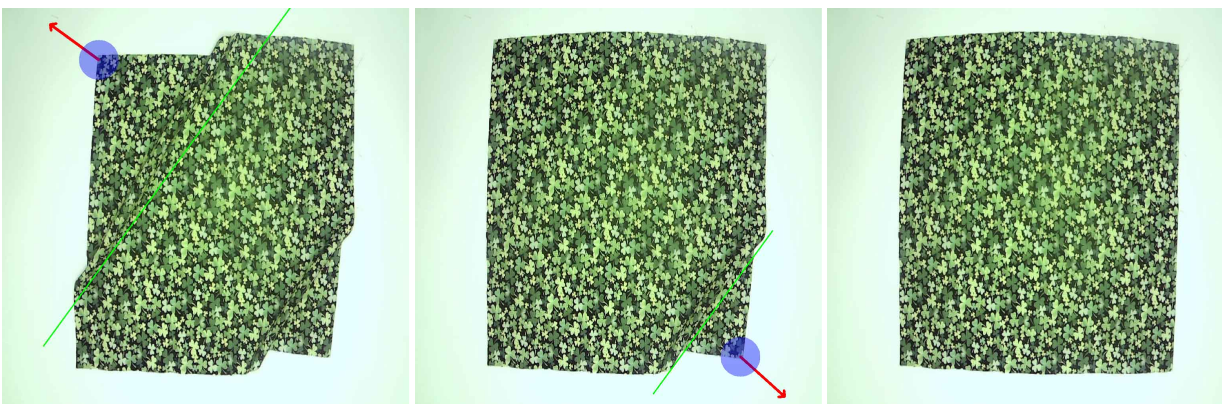
A wrinkle is correctly identified if its angle meets a specific threshold compared to the original angle. The *Recall* values for various chosen textures are shown in Table 1. It is observed that images with plain textures yield higher *Recall* scores in comparison to those with complex textures.

In this study, our primary objective is to ascertain the location and orientation of wrinkles; precise masks are not essential. Therefore, the IoU score is not vital for our objective. For instance, Figure 8 compares the original and predicted masks of an image with an IoU score of 33.75%. The figure demonstrates that our algorithm is capable of adequately detecting the position and orientation of wrinkles, which meets our requirements.



(a) Wrinkle Line and $C_{closest}$ (b) The orthogonal direction (c) The pulling direction and the action point

Fig. 6. (a) $C_{closest}$ is determined by the two-step minimization process, (b) The orthogonal direction is determined which is pointing towards the wrinkle, (c) The direction is fixed using the position of the intersection I.



(a) First Iteration (b) Second Iteration (c) Flattened Cloth

Fig. 7. (a), (b), (c) illustrate the multiple iteration process of the system

4.3 Corner Detection

To assess the corner detection algorithm, we design a metric CDR (Corner Detection Rate). A corner is considered as correctly detected if the Euclidean distance $d(true, detected)$ between a detected corner $detected$ and the nearest true corner $true$ is less than or equal to a specified $threshold$. CDR is calculated by Equation 7

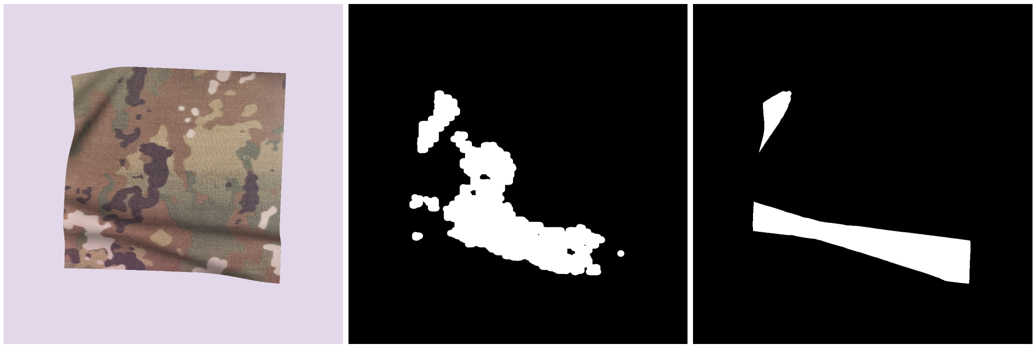
$$CDR = \frac{\sum_i^n 1(min_{detected}(d(true_i, detected)) \leq threshold)}{n} \tag{7}$$

Table 2 presents the CDR for various textures. While the majority of textures exhibit relatively uniform CDR scores, a small number of textures have resulted in marginally lower CDR scores.

4.4 Cloth Flattening

We created various types of wrinkles on clothes and conducted iterative tests. The number of iterations needed for different types of wrinkles are detailed in Table 3.

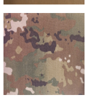
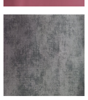
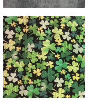
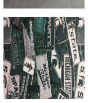
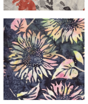
It is evident that inclined wrinkles require fewer iterations, as pulling from the cloth corners is most effective for them. However, for horizontal and vertical wrinkles, even though pulling in the direction orthogonal to the wrinkles is employed, corners alone cannot eliminate wrinkles in a single iteration. At least three iterations are necessary to remove each wrinkle. In the case of mixed wrinkles, multiple iterations are needed since pulling one corner may remove the targeted wrinkle but simultaneously create additional wrinkles in different directions on the cloth.



(a) Original Image (b) Predicted Mask (c) Original Mask

Fig. 8. The prediction and ground truth mask of an image with an IoU score of 33.75%

Table 1. Some Textures with their *Recall* Scores

Index	Texture	Number of Images	*Recall* (%)
1		9	83.33
2		14	86.90
3		13	57.69
4		10	90.00
5		11	90.90
6		7	57.14
7		11	93.94
8		13	57.69
9		12	80.56
10		13	65.38

5 DISCUSSIONS

As a work in progress, we are constantly increasing our training dataset including both real and synthetic images. Generalizing wrinkle detection requires a wide range of fabric examples. The model's performance was evaluated using both synthetic and captured data, showing enhanced effectiveness with synthetic data, primarily due to the training focus on such data. Moreover, our algorithm demonstrates superior performance on plain, single-colored images compared to textured ones, as detecting wrinkles in textured images is comparatively challenging, even for the human eye.

Detecting the four corners of a quadrilateral-shaped cloth is challenging due to the complexity introduced by wrinkles, which can significantly distort the perceived shape and boundaries of the cloth, making it hard to accurately identify the corners. We are exploring a deep learning solution to this problem to be more general, but have had good results with our variations of the Harris Corner Detection method as applied to the binary masks of the images. This method works effectively for both synthetic and real data.

Detecting action points involves complex calculations and addressing various edge cases. The system reliably determines action points and pulling directions across diverse datasets.

6 FUTURE WORK

In future iterations of our wrinkle detection and removal system, the primary focus will be on automating the process through the integration of robotics and reinforcement learning. Robotic manipulators will replace manual handling, requiring sophisticated control systems for precise fabric manipulation. Concurrently, reinforcement learning will optimize wrinkle removal strategies, enabling the system to adapt and improve over time. This approach aims to enhance efficiency, accuracy, and adaptability, facilitating broader applicability across various fabric types and settings.

7 CONCLUSION

We propose a novel approach towards cloth flattening, focusing on the development and implementation of methods using deep learning and image processing irrespective of various textured and patterned cloth. The current work lays a strong foundation for future enhancements that promise to significantly improve its efficacy.

Table 2. Some Textures with their *CDR* Scores

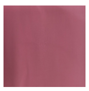
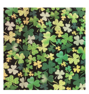
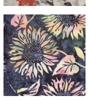
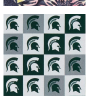
Index	Texture	*CDR* (%)
1		79.73
2		86.54
3		83.10
4		72.86
5		85.53
6		87.50
7		83.58
8		79.46
9		85.56
10		87.50
11		86.29
12		83.33

Table 3. Number of Iterations Required for the Removal of Different Types and Quantities of Wrinkles

Wrinkle Type	Number of wrinkles	Iterations
Inclined	1	1
Inclined	2	3
Horizontal	1	4
Horizontal	2	7
Vertical	1	3
Vertical	2	7
Mixed	3	11

The advancements made in this study, particularly in wrinkle detection and the wrinkle removal technique, mark critical steps in the application of these technologies in assistive environments. This has the potential to create employment opportunities for individuals with disabilities that limit their ability to engage in two-handed tasks and open a new worker population for industries currently facing a shortage of available workers.

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