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ECE445 SPRING 2024

SENIOR DESIGN PROJECT

Smart Laundry FoldBot

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Chapter 1

Introduction

1.1 Purpose

Problem Statement
The automation of clothes folding in industrial settings presents significant challenges and opportunities for innovation. Presently, large-scale users such as dry cleaning facilities, clothing recycling centers, major retail outlets, and hotels face stringent demands for rapidly and efficiently folding a diverse array of garments. This task is predominantly performed manually, which is not only costly but also lacks efficiency.

Although there are a few products available in the market, they are limited to simple folding tasks and require garments to be perfectly flat and precisely positioned on a specific area of the workbench. This still necessitates considerable human intervention and fails to meet the needs of industrial-scale operations. Consequently, there is a notable absence of solutions that fully automate the entire garment sorting and folding process.

Solution
In view of the lack of integrated solutions for intelligent flattening and folding in the current market, we proposed a grab-flatten-fold automatic intelligent folding solution for T-shirts. Figure 1.1 shows a brief figure depicting our solution for visual aid.

1.2 Functionality

To tackle the challenges outlined, we have developed a new industrial-grade automatic clothes-folding robot. This robot seamlessly integrates into existing production lines, allowing users to input various types of disordered clothing directly.
Equipped with a mechanical gripper and a vision module, the robot accurately sorts and positions garments onto a folding board that is compatible with most clothing types. The garments are quickly folded and dispatched either to a conveyor belt or storage unit, depending on user needs. This solution boosts production efficiency, reduces labor costs, and accelerates processing speeds in the garment cleaning and recycling industries.

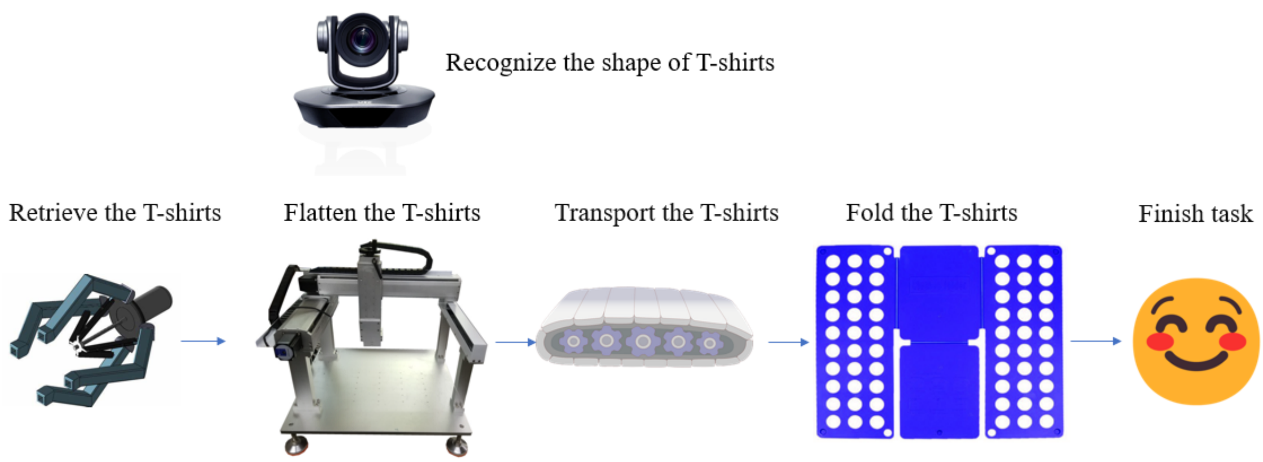

Figure 1.1: Clothes folding robot workflow chart

1.3 System Overview with Block Diagram

Smart Laundry FoldBot project has four main sub-systems, the Central Control System, the Folding System, the Grabbing System, and the Vision System.
Figure 1.2 is the high-level diagram that shows the position of each subsystem.
Figure 1.3 is the high-level diagram that shows the basic interaction mode and execution flowchart for the whole system.
Figure 1.4 is the high-level diagram that shows how sub-systems integrate and how the signal transmits.
Figure 1.5 shows the final vision of FoldBot we built in the ZJUI laboratory

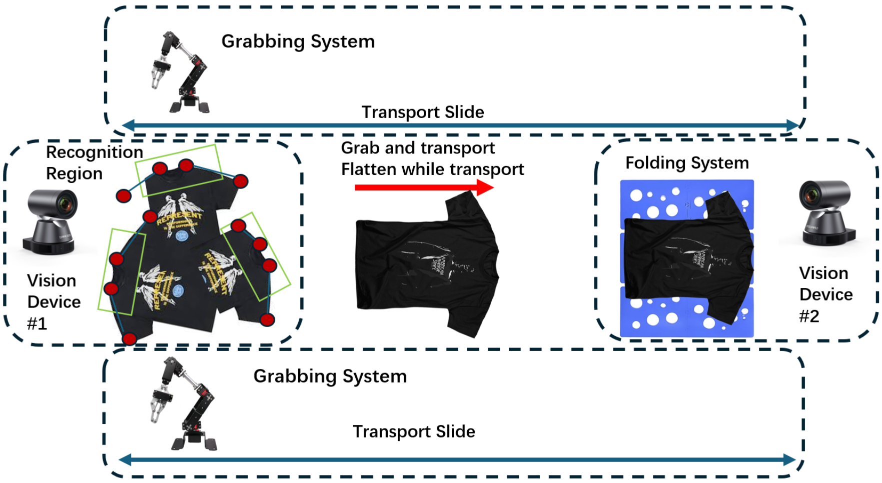

Figure 1.2: System top-level diagram (Positional)

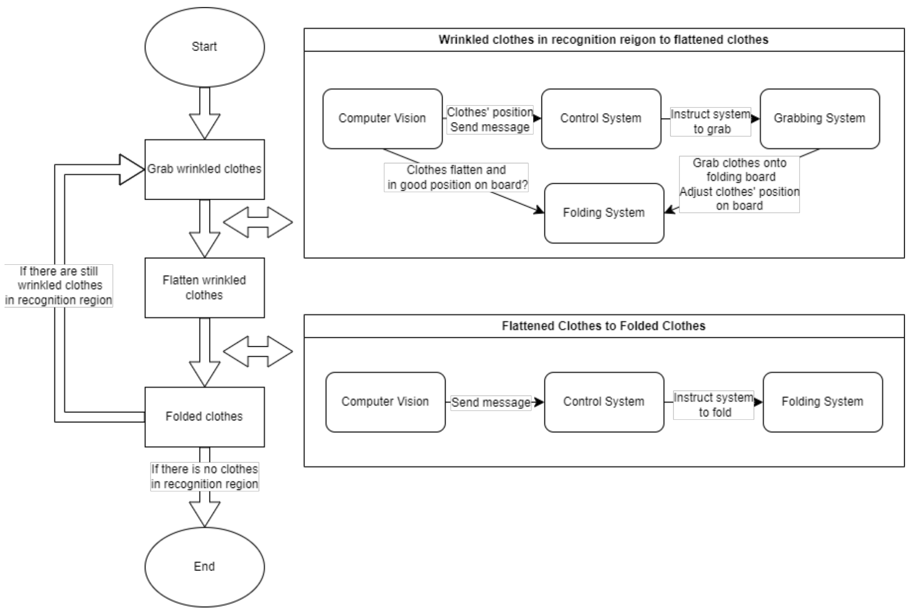

Figure 1.3: System top-level diagram (Functional)

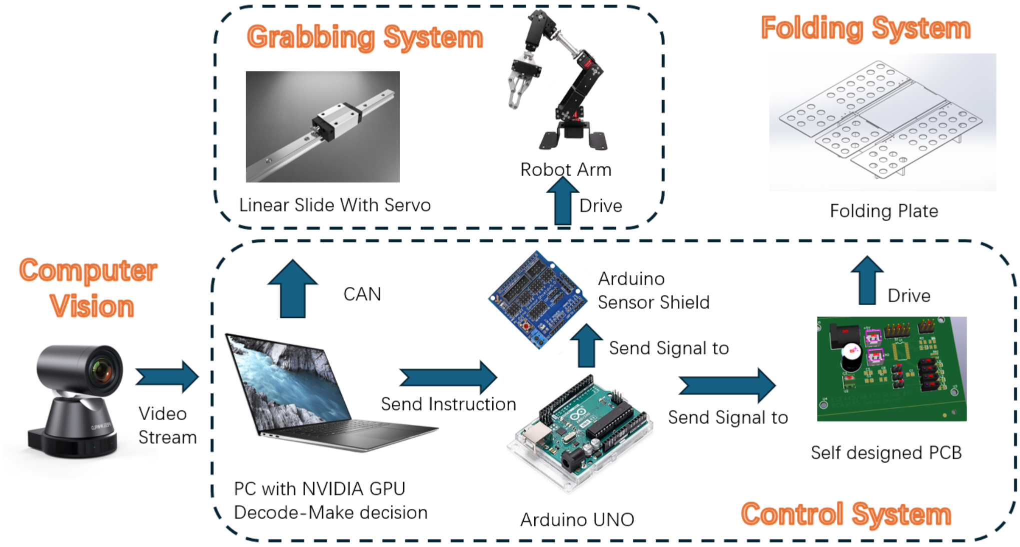

Figure 1.4: System top-level diagram (Control Signal)

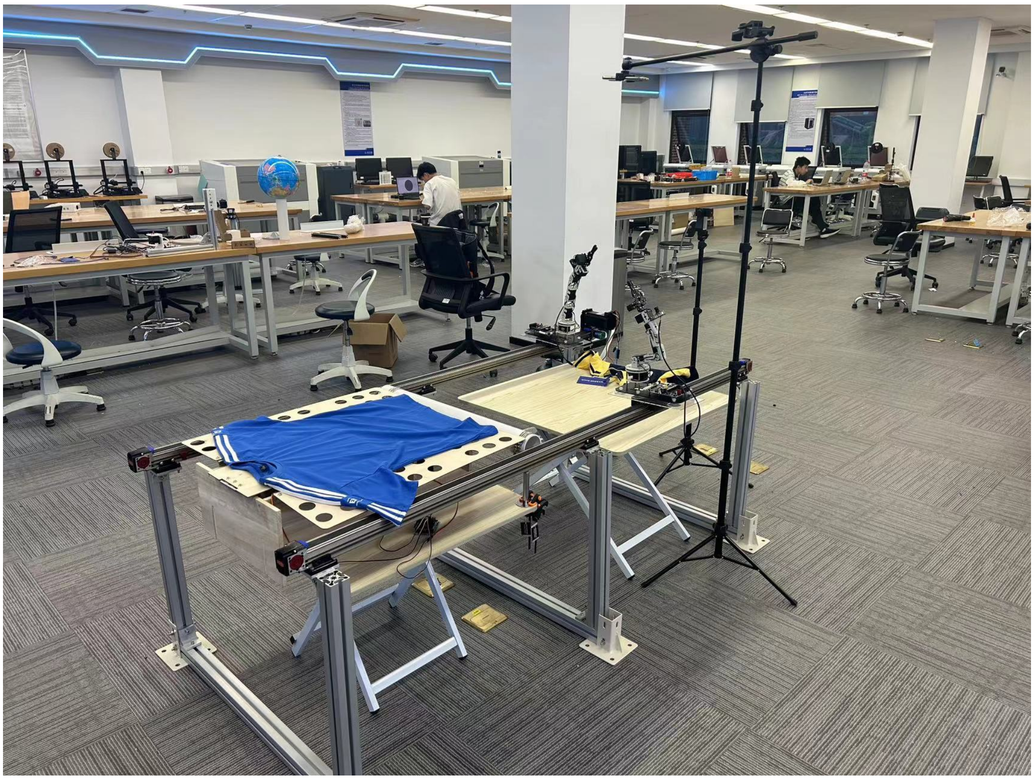

Figure 1.5: Industrial clothes folding robot

1.4 Subsystem Introduction

1.4.1 Subsystem 1: Grabbing System

The grabbing system comprises two six-axis robot arms and two transport slides. In the recognition region, vision device No.1 can automatically identify the shoulder of each piece of clothing. Subsequently, the robot arms would be able to accurately grab the clothes' shoulders and transport them to the folding system. Figure 1.7 shows the robot arm connected on the slide. Figure 1.6 shows the connected grabbing system in the laboratory.

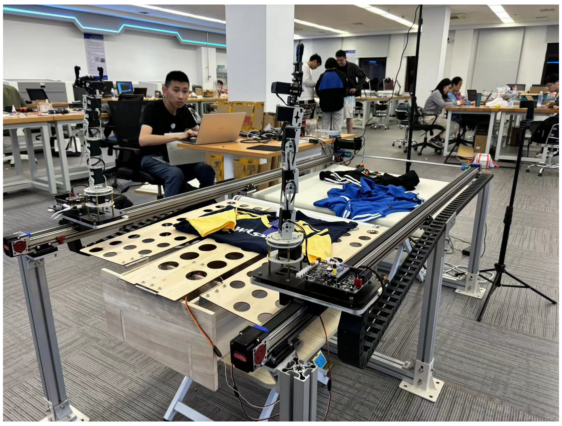

Figure 1.6: Grabbing System: Final Version

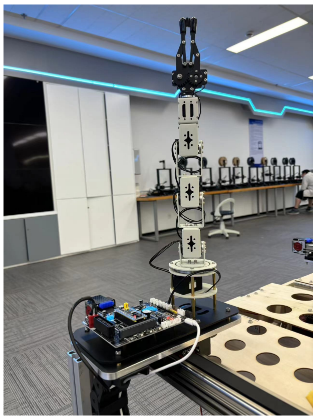

Figure 1.7: Robot Arm: Final Version

1.4.2 Subsystem 2: Folding System

The folding system consists of four folding panels. Each folding board is driven by a servo. Figure 1.8 shows the workflow of the folding system.

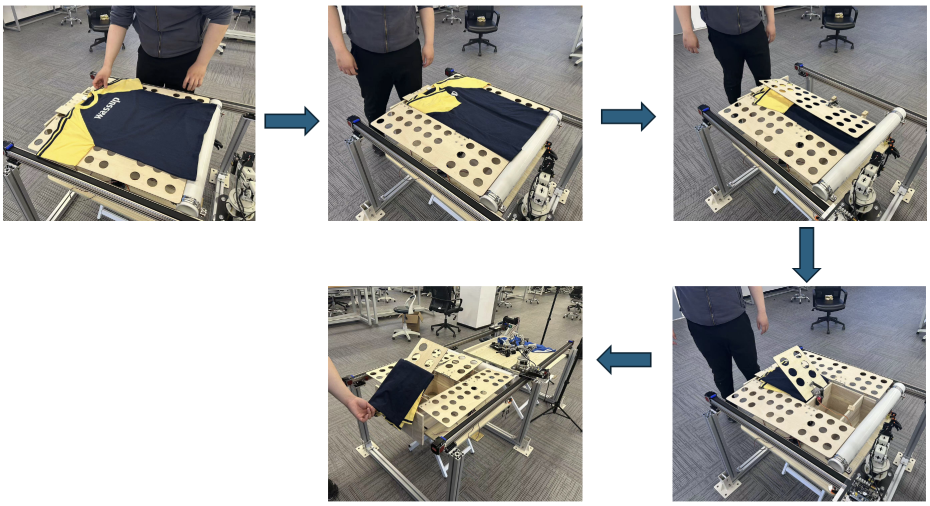

Figure 1.8: Folding system workflow chart

1.4.3 Subsystem 3: Computer Vision System

We use a camera hung on an aluminum structure to take photos and transmit the images to a PC. We use a laptop PC with NVIDIA GPU as central control and machine learning calculation. The PC will be able to run Fast-RCNN to recognize the grabbing coordinate on the shoulder of the T-shirt.

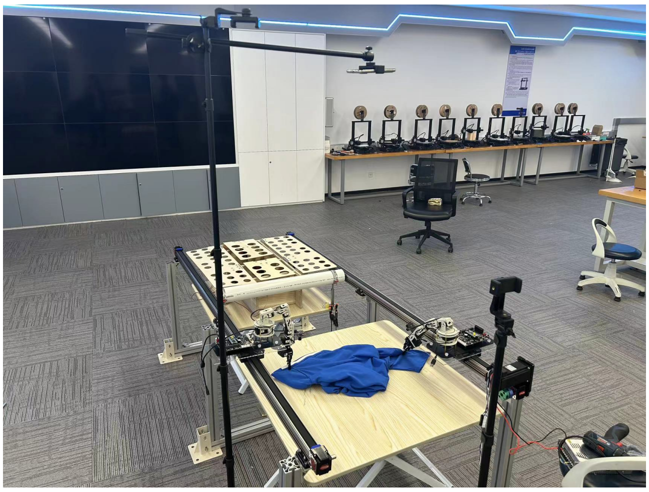

Figure 1.9: Structures of hanging camera(Two black camera stands)

1.4.4 Subsystem 4: Control System

Our purpose for the control system is that the control system can handle the video streams and calculate the kinematic variables the grabbing and folding systems need.

We use the same laptop mentioned above to transmit signals and control the components. Figure 1.10 shows how the PC connects and controls all subsystems using various extension devices.

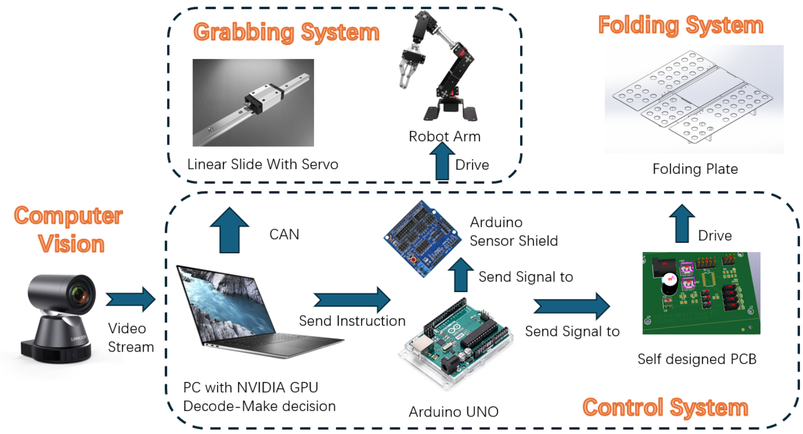

Figure 1.10: Control System Interaction

Chapter 2

Design

2.1 Design Description with Justifications

2.1.1 Subsystem 1: Grabbing System

Design Description

Purpose:
We investigated several academic researches on using Deep Reinforcement Learning and Computer Vision to classify and flatten clothes. Sun, Li (1) has shown deep reinforcement learning's promising capability for flattening Wrinkled clothes. Y Tsurumine (2) has shown deep reinforcement learning's capability for clothes smoothing. Cychnerski (3) has shown the neural network's capability for clothes detection. These researches inspired us with ideas about clothes grabbing and flattening plans.

The grabbing system is designed to grab wrinkled clothes from a clothes recognition region and transport clothes to the folding system. While transporting, the grabbing system should flatten the T-shirt through mechanical design.

Components:
The grabbing system comprises two six-axis robot arms and two transport slides. In the recognition region, vision device No.1 can automatically identify the shoulder of each piece of clothing. Subsequently, the robot arms would be able to accurately grab the clothes' shoulders and transport them to the folding system. Figure 2.2 shows the robot arm connected on the slide. Figure 2.1 shows the connected grabbing system in the laboratory.

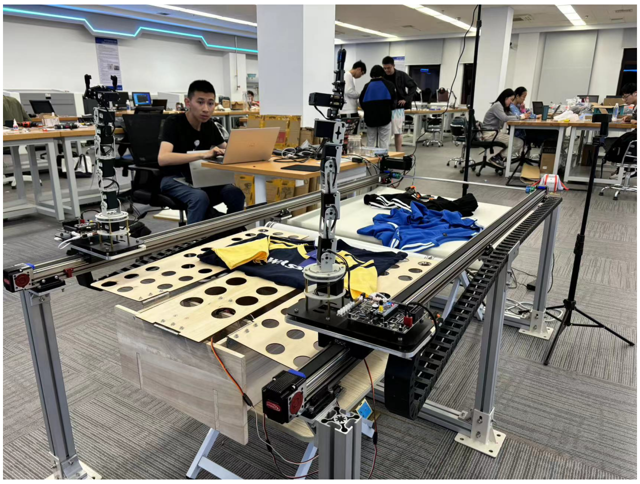

Figure 2.1: Connected Grabbing System

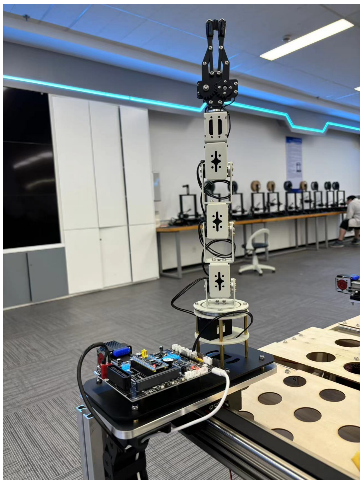

Figure 2.2: Connected Robot Arm

Figure 2.3: Connected Roller

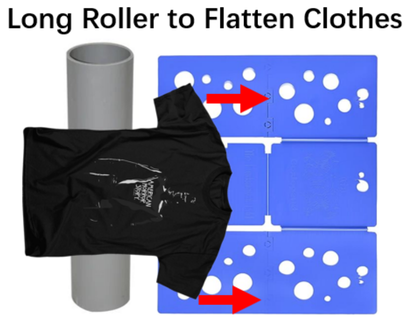

Figure 2.4: Roller Flatten Illustration

To flatten the clothes while transporting the clothes, we deploy a long roller device to flatten the T-shirt. The long roller device will ensure that when the robot arm places the clothes on the folding system. Empirically, the clothes will remain flat. Figure 2.4 shows how the long roller works during the transport process.

Operations and Interactions:

Our design uses two symmetric six-axis robot arms to grab T-shirts on their shoulders.
After robot arms grab the shoulders successfully, the transport slides will transport the entire garment to the folding system. Figure 1.2 shows how the grabbing system works to grab and transport the T-shirt to the folding system.
The clothes picked up by the robot arm will pass over a long roller device located in front of the folding system. Finally, the clothes would be flat on the folding board of the folding system.

Justification

We derives some equations to justify our design. Further more, we perform some simulations on software platform and do some tests in reality cases to justify that the grabbing system can meet with our expectation.
The main part of grabbing system is two six-axis robot arms. They're selected for their ability to transport and flatten clothes onto the folding board. The crucial parts for its tolerance analysis are its capacity to precisely grab the shoulder of T-shirts and stably carry T-shirts.
We have verified that the end effector of the robot arm can grab items with weights equal to 500g, which is enough for grabbing clothes.
Also, we want to test their capacity to locate a specific coordinate in a plane. Consequently, we derive forward kinematic and inverse kinematic method for the robot arms and compared its actual performance with simulations on software platform. 2.5 shows the actual view of the robot arm and 2.6 is the physical model of the robot arm.
1. Forward Kinematic We use product of exponentials approach to transform angles of joints to position and orientation of end effector. Product of exponentials fomula is shown below.

$$T(\theta) = e^{[s_1]\theta_1} e^{[s_2]\theta_2} ... e^{[s_n]\theta_n} M$$

In our case, we have six servos, where five servos are revolute joints and the left one servo is used to control the end effector. Formulas to calculate velocity and angular velocity for revolute joints are listed below.

Figure 2.5: Six-Axis Manipulator

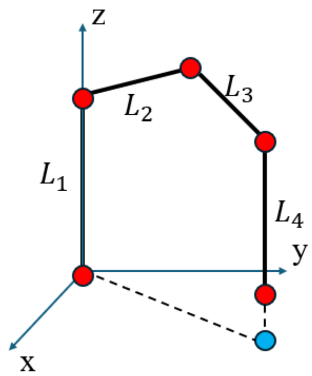

Figure 2.6: Physical model

$$\|\omega_i\| = 1$$

$$v_i = -\omega_i \times q_i$$

$$s_i = \begin{pmatrix} \omega_i \\ v_i \end{pmatrix}$$

As for our robot arms, parameters q_i and ω_i are calculated below. With all these equations we're able to test whether the robot arm can locate correct place given angles of servos using forward kinematic methods.

$$\omega_1 = \begin{pmatrix} 0 \\ 0 \\ -1 \end{pmatrix} \qquad q_1 = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\omega_2 = \begin{pmatrix} -1 \\ 0 \\ 0 \end{pmatrix} \qquad q_2 = \begin{pmatrix} 0 \\ 0 \\ L_1 \end{pmatrix}$$

$$\omega_3 = \begin{pmatrix} -1 \\ 0 \\ 0 \end{pmatrix} \qquad q_3 = \begin{pmatrix} 0 \\ 0 \\ L_1 + L_2 \end{pmatrix}$$

$$\omega_4 = \begin{pmatrix} -1 \\ 0 \\ 0 \end{pmatrix} \qquad q_4 = \begin{pmatrix} 0 \\ 0 \\ L_1 + L_2 + L_3 \end{pmatrix}$$

$$\omega_5 = \begin{pmatrix} 0 \\ 0 \\ -1 \end{pmatrix} \qquad q_5 = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

2. Inverse Kinematic

We use the inverse kinematic methods to calculate the rotation angle for each servos and compare the actual grabbing point with the correct point. The bias of the length of links, bias of length measurement, and error of computation will finally lead to the offset of the position of the end effector, so we will stimulate grabbing cases and evaluate the error. Four of the six steering engines can determine the position of the end effector. The first engine is used to determine the orientation and other three engines are used to determine the destination from the original point. We notated length of links as L_1, L_2, L_3, L_4 and rotation angles for the four steering engine as $\theta_1, \theta_2, \theta_3, \theta_4$. So given coordinate x, y and plane z, we calculate $\theta_1, \theta_2, \theta_3, \theta_4$ using equations below.

$$\theta_1 = \arctan\left(\frac{x}{y}\right)$$

$$L_1 + L_2\cos(\theta_2) + L_3\cos(\theta_2+\theta_3) + L_4\cos(\theta_2+\theta_3+\theta_4) = z$$

$$L_2\sin(\theta_2) + L_3\sin(\theta_2+\theta_3) + L_4\sin(\theta_2+\theta_3+\theta_4) = \sqrt{x^2+y^2}$$

We then write code to test whether the end effector can be able to arrive at the target position and we find that the error is within 1cm. Which is acceptable for our task. The code is listed in the appendix.
3. Stimulation
We simulate robot arm's performance on rviz platform. The figure 2.7 shows the reset state of robot arm and the figure 2.8 shows the grabbing state of robot arm.

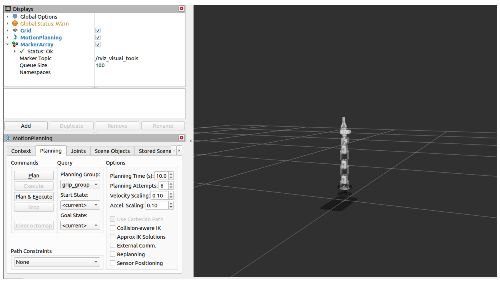

Figure 2.7: Reset Pose

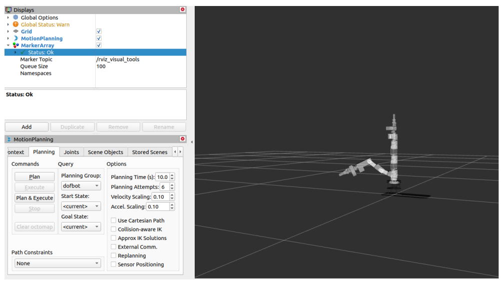

Figure 2.8: Grabbing Pose

2.1.2 Subsystem 2: Folding System

Design Description

The folding system consists of four folding panels. Each folding board is driven by a servo. Figure 2.9 shows the workflow of the folding system.

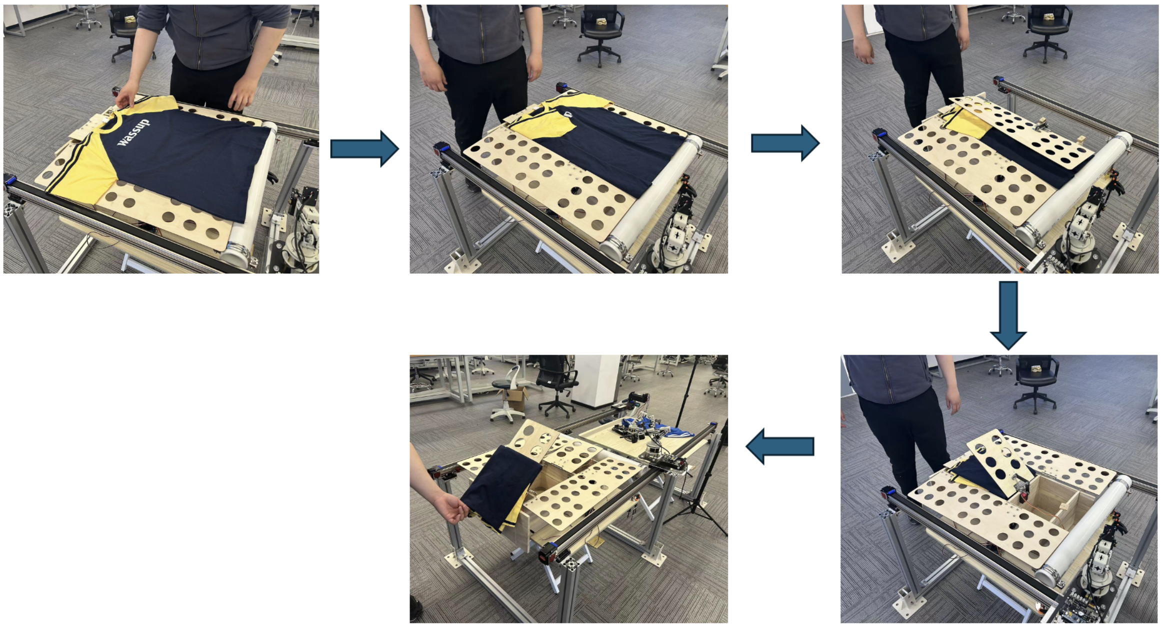

Figure 2.9: Folding system workflow chart

- **Left Board:** Positioned on the left side, folds 180 degrees to the right, folding the left portion of the clothing.
- **Right Board:** Located on the right side, it folds 180 degrees to the left, mirroring the action of the left core board.
- **Center Lower Board:** Situated below the central part of the clothing, folds upwards 180 degrees, folding the lower part of the garment.
- **Center Upper Board:** Located above the central part of the clothing, folds about 45 degrees. Rails or clothing-receiving devices will be installed behind this board (depending on the needs of the industrial user). The folded clothes will pass through a slide and slide to the conveyor belt or clothes-receiving device.

Justification

Each folding plate is powered by a servo so we'd like to justify that the servo is able to provide enough torque to raise the folding plate.

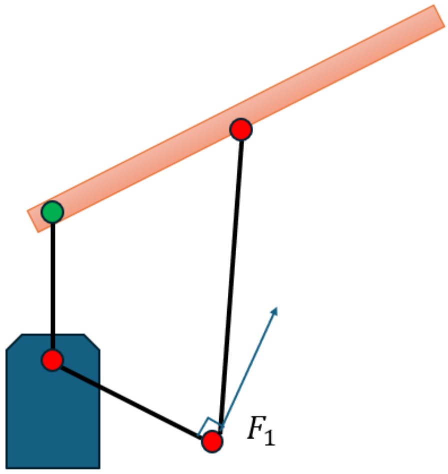

Figure 2.10: Servo structure for folding system

2.1.3 Subsystem 3: Computer Vision System

Design Description

Purpose: We consider train a Fast-RCNN model to precisely identify shoulder positions on shirts. Camera above the table will transmit the image to vision model. The vision model will identify shoulder positions on shirts and generate a (x,y) coordinate on the plate, which finally enable the robot arm to grab clothes at that position.

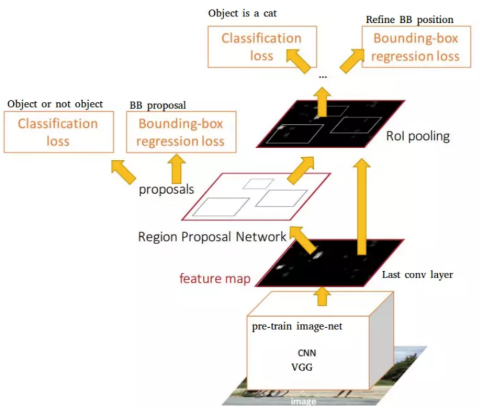

Figure 2.11: Fast RCNN structure

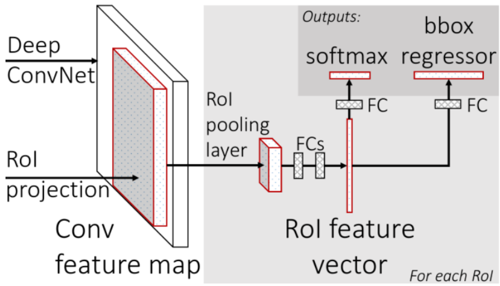

Figure 2.12: Fast RCNN structure

Components: We use a camera hung on an aluminum structure to take photos and transmit the images to a PC. We use a laptop PC with NVIDIA GPU as central control and machine learning calculation. The PC will be able to run Fast-RCNN to recognize the grabbing coordinate on the shoulder of the T-shirt.

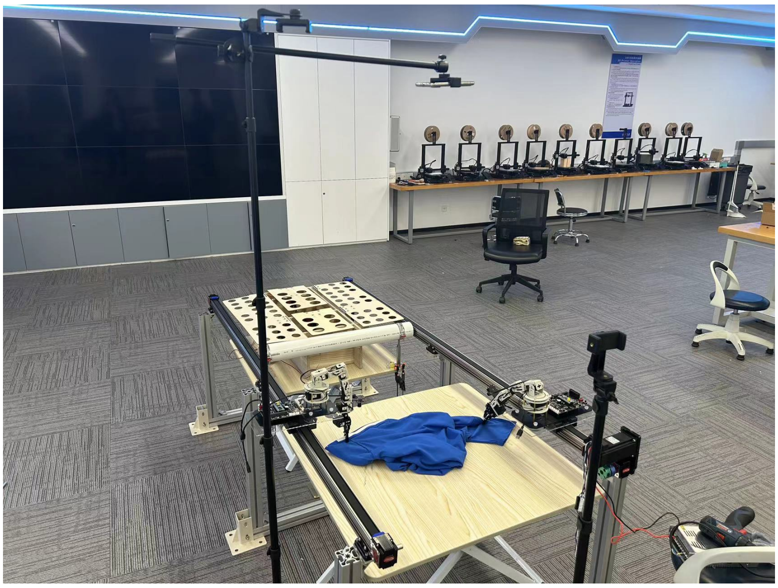

Figure 2.13: Structures of hanging camera(Two black camera stands)

Justification

In this section, we want to justify that our computer has enough resources to run Fast RCNN In this section, we compare the computing power required by computer vision models with the computing power that the GPU in current control and signal processing systems can provide. We conclude that current devices are fully sufficient to support computer vision inference tasks.
The Fast RNN framework we use is modified based on the VGG-16 computer vision model. So in fact, the computing power required by the computer vision model is determined by the computing power requirements of VGG-16. The industry already has mature literature on the computing power requirements of computer vision tasks. Vassilieva(4) from Hewlett Packard Enterprise made a clear benchmark for the mainstream computer vision models. In our vision system, we use a laptop PC with NVIDIA GPU GTX1650ti, there is also theoretical computation power throughput among different technology websites, TechPowerUp(5) made detailed GPU specs on their website.

Computer Vision Model Requirements

Figure 2.14 is from the slides made by Vassilieva(4). The figure shows the detailed computing power needed by mainstream models. The acceleration method used in the model is parallel computing of GPU, which is also the method we used in our vision model. As figure 2.14, the VGG-16 needs 15.5 GFLOPS for the forward pass inference task and needs 528 megabytes cache in GPU memory.

Popular models

Name	Type	Model size (# params)	Model size (MB)	GFLOPs (forward pass)
AlexNet	CNN	60,965,224	233 MB	0.7
GoogleNet	CNN	6,998,552	27 MB	1.6
VGG-16	CNN	138,357,544	528 MB	15.5
VGG-19	CNN	143,667,240	548 MB	19.6
ResNet50	CNN	25,610,269	98 MB	3.9
ResNet101	CNN	44,654,608	170 MB	7.6
ResNet152	CNN	60,344,387	230 MB	11.3
Eng Acoustic Model	RNN	34,678,784	132 MB	0.035
TextCNN	CNN	151,690	0.6 MB	0.009

Hewlett Packard Enterprise 10

Figure 2.14: Computer Vision Model Computing Power Benchmark

GPU Specifications

Figure 2.15 and figure 2.16 are from the website made by TechPowerUp(4). The figures show the key specifications of GPU GTX1650ti we are using for computer vision tasks. As figure 2.16 shows, the memory of GPU is 4 gigabytes, which is way larger than 512 megabytes. Figure 2.15 shows that even if we use the most precise 64-bit floating point calculation, GPU can still process 95.04 GFLOPS, which is also much larger than 15.5 GFLOPS.

Theoretical Performance	
Pixel Rate:	47.52 GPixel/s
Texture Rate:	95.04 GTexel/s
FP16 (half):	6.083 TFLOPS (2:1)
FP32 (float):	3.041 TFLOPS
FP64 (double):	95.04 GFLOPS (1:32)

Figure 2.15: GTX1650ti Computing Specs

Memory	
Memory Size:	4 GB
Memory Type:	GDDR6
Memory Bus:	128 bit
Bandwidth:	192.0 GB/s

Figure 2.16: GTX1650ti Memory Specs

In addition, it is worth mentioning that we plan to rent a more powerful server for training. So in this section, we do not consider whether the system can successfully train the model

2.1.4 Subsystem 4: Control System

Design Description

Purpose: Our purpose for the control system is that the control system can handle the video streams and calculate the kinematic variables the grabbing and folding systems need.

Components: We use the same laptop mentioned above to transmit signals and control the components. Figure 2.17 shows how the PC connects and controls all subsystems using various extension devices.

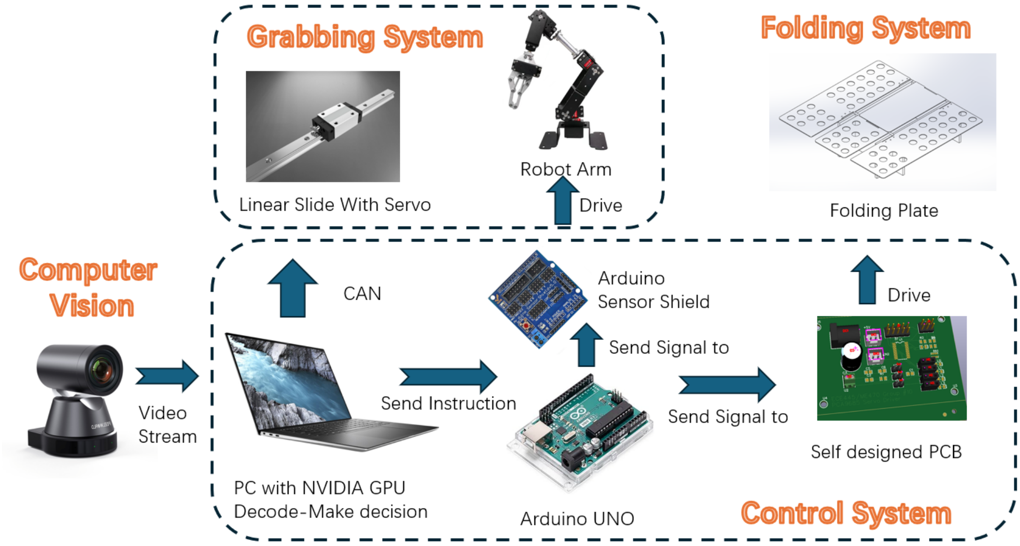

Figure 2.17: Control System Interaction

For grabbing system control, we use Arduino servo control to control robot arms and USB CAN open protocol to control the transport slide.

For folding system control, we use our self-designed PCB SoC based on PCA9685PM LED control chip to execute the motions of the folding board. Figure 2.18 is the wiring between components on the PCB and figure 2.19 is the schematic of the PCB.

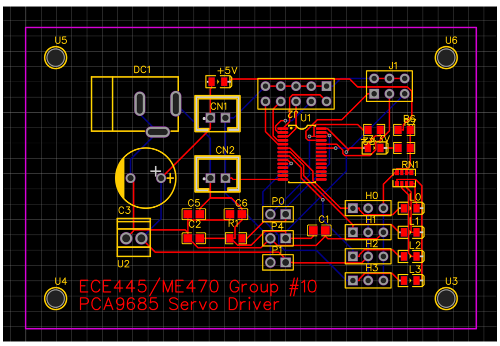

Figure 2.18: PCB Illustration

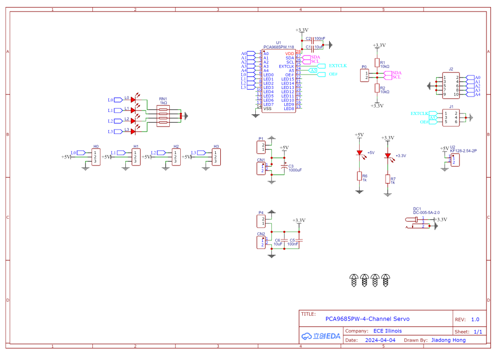

Figure 2.19: PCB Schematics

Operations and Interactions:
First, The control laptop receives and decodes the video stream, and then sends the stream to the machine-learning model.
Second, based on the result of the ML model, the laptop sends control signals and messages to Arduino and Servo PCB.
Finally, the FoldBot executes motions, vision device will monitor the motions and send feedback video streams to the laptop.
Figure 2.20 shows how the control system works abstractly.

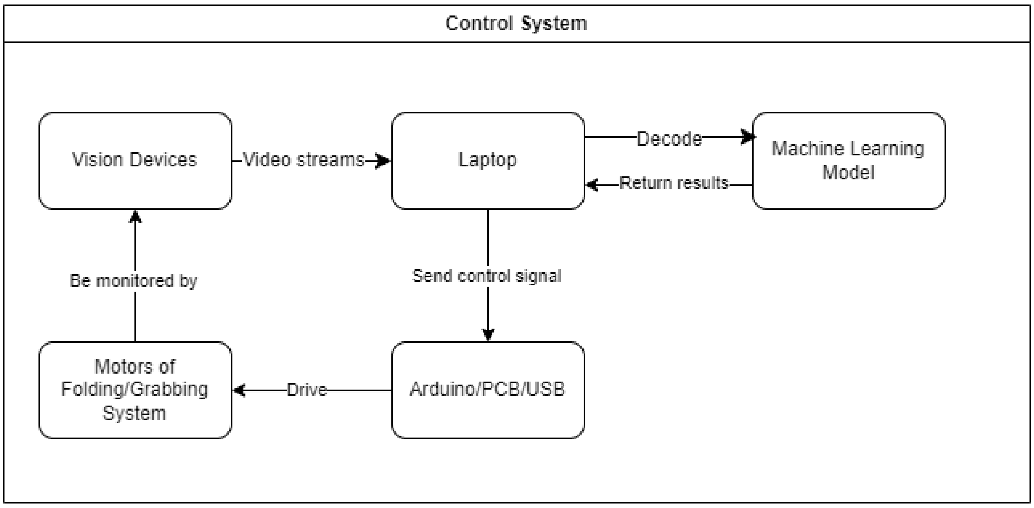

Figure 2.20: Control System Flowchart

Control system synthesizes every subsystems and justifications for those subsystems are shown above.

2.2 Design Alternatives

Issue 1: Use of Carbon Fiber for Folding Plates

Initial Choice and Problem: Carbon fiber was initially chosen for the folding plates due to its strong and lightweight properties, which were deemed essential for the mechanics of your project. However, after testing, it was found that the servos could not adequately drive the carbon fiber plates because they were still too heavy.
Corrective Actions: The material for the folding plates was switched from carbon fiber to wood. Wooden boards were chosen because they still provided sufficient sturdiness while being significantly lighter than carbon fiber. Laser cutting technology was employed to precisely shape the wooden boards into folding plates, enabling the servo to successfully drive the folding plates.

Issue 2: XYZ Three-Axis Guide Rail with a Single Manipulator

Initial Choice and Problems: The original design utilized an XYZ three-axis guide rail system combined with a manipulator, akin to a claw machine. This system faced several issues including cost overruns, operational inefficiency, and redundant design.

- **Cost Overruns:** The manufacturing cost was nearly $1,100, significantly over budget.
- **Operational Inefficiency:** The system was not effective for grasping clothes, and adding a second manipulator increased complexity and costs.
- **Redundant Design:** Extensive movement in the z-direction was unnecessary as the clothes were placed at a $z=0$ plane.

Corrective Actions: The design was modified to include two Y-axis guide rails and two 6-axis robotic arms, reducing costs by two-thirds and allowing two mechanical grippers to operate simultaneously, thereby reducing complexity.

Issue 3: Direct Folding with Mechanical Grippers

Initial Plan and Problems: The strategy to use two mechanical grippers to fold clothes directly faced multiple challenges such as high technical difficulty, inadequate speed, and high requirements for the manipulators.

- **High Technical Difficulty:** The task was too complex with the existing visual recognition technology.
- **Inadequate Speed:** The folding speed was too slow for industrial production.
- **High Requirements:** Excessive demands were placed on the manipulators in terms of cost and complexity.

Corrective Actions: Simplified the design to use only four folding plates driven by servos, significantly reducing system complexity and increasing folding speed.

Chapter 3

Requirements and Verification

3.1 Subsystem Requirements

3.1.1 Requirements for the Grabbing System

The grabbing system is tasked with the automated handling of T-shirts post-dryer, involving precise grabbing, effective flattening, and accurate placement on a folding mechanism. This system combines mechanical design and control algorithms to manage variably positioned and oriented garments.

- **Fetching Role:**
  - **Requirements:**
    - *Grasping Stability and Speed:* The claw mechanism must ensure a stable grasp on T-shirts moving at speeds up to 10 cm/s within a 2-meter square operational area. Testing conditions include a range of T-shirt sizes (S, M, L, XL) and materials (cotton, polyester, blends).
    - *Visual Recognition System:* Must accurately determine T-shirt position and orientation with a precision threshold where the deviation from the target grabbing point is less than 1 cm, achieving this accuracy within 1.5 seconds. The system should adapt to variations in lighting conditions within a luminance range of 200-800 lux.
- **Flattening and Placing Role:**
  - **Requirements:**
    - *Flattening Effectiveness:* Achieve a flattening outcome where residual wrinkles are less than 1 cm in height, and the process duration does not exceed 4 seconds per T-shirt. The mechanism must adjust its flattening strategy based on pre-identified T-shirt material characteristics.
  - **Methods:**
    - Mechanical mechanism design to incorporate adjustable pressure plates with feedback control to modulate force based on the T-shirt's fabric type and detected wrinkles. This system should self-calibrate for different garment thicknesses within 3 operational cycles.
    - Implementation of a reinforcement learning algorithm for intelligent clothing flattening, designed to optimize flattening paths and pressure application points. The algorithm requires a maximum of 5 learning iterations to adjust to a new T-shirt type, with a subsequent operation efficiency improvement target of 20%.

3.1.2 Requirements for the Folding System

The folding system encompasses an electric mechanism designed for the precision folding of T-shirts and their orderly stacking. This system leverages an electromechanical approach to ensure consistent and accurate folding, followed by stacking in a predefined arrangement.

- **Folding Clothes:**
  - Requirements:
    - *Operational Force and Speed:* The system must generate adequate force to manipulate T-shirts, with folding arm rotational speeds adjustable between 0.4 rad/s and 1.2 rad/s. The system shall achieve a folding precision where the variance from the intended fold line is less than 0.8 cm, with a consistency rate of 99% across all T-shirt sizes.
  - Mechanism: A servo-driven electro-mechanical system with integrated sensors for real-time fold quality feedback, enabling dynamic adjustment to fold parameters to maintain accuracy under varying load conditions.
- **Stacking Clothes:**
  - Requirements:
    - *Alignment Accuracy:* Stacked T-shirts must exhibit a high degree of alignment, with each subsequent layer aligning within a tolerance of 1.5 cm of the one below it, and necklines uniformly oriented, accounting for all standard T-shirt sizes.
  - Purpose: To ensure a systematic and orderly stacking process, facilitating subsequent handling, storage, or packaging activities with minimal manual adjustment requirements.

3.2 Requirements and Verification

3.2.1 Grabbing System

- **Stable Grasping Capability**
  - *Requirement:* The mechanical claw must reliably grasp garments without dropping them.
  - *Verification:* Perform a series of 100 grasp-and-lift tests with garments of varying sizes and weights. Each test involves the claw grasping a garment placed at random orientations on a flat surface, lifting it to a height of 1 meter, and holding it for 10 seconds. The success rate is recorded as the percentage of successful grasps.
- **Shoulder Identification Accuracy**
  - *Requirement:* The vision module should identify the garment's shoulder region within a tolerance of 0.3cm to 0.8cm.
  - *Verification:* Garments with marked shoulder regions will be presented to the system in various orientations. The vision module's identification accuracy is measured by comparing the detected position to the marked position using a high-precision digital caliper in 50 tests.
- **Efficient Identification Speed**
  - *Requirement:* Identification of garments by the vision module must be completed within 1.5 seconds.
  - *Verification:* Time the identification process using a stopwatch for 50 different garments, recording the time taken for each garment to ensure speed requirements are met.
- **Consistent Transport Speed**
  - *Requirement:* Garments must be transported at 10cm/s to 20cm/s over a 2m distance.
  - *Verification:* Use a motion capture system to measure the transport speed of garments over a 2m distance in 30 trials, ensuring the speed remains within the specified range.
- **Accurate Garment Placement**
  - *Requirement:* Garments must be placed accurately at the folding board's center, with collars oriented uniformly.
  - *Verification:* A grid on the folding board will be used to check the placement accuracy in 50 trials. The garment's position and collar orientation are measured using a ruler and visually inspected for uniformity.
- **Continuous Operation**

  - *Requirement:* The system must sustainably grasp multiple garments over an extended period without performance loss.
  - *Verification:* Operate the system continuously for 2 hours, grasping a garment every 30-45 seconds. The performance, including grasp success rate and identification accuracy, is monitored and recorded throughout the test duration.

- **Flattening and Smooth Transportation**
  - *Requirement:* The system must flatten garments and maintain smoothness throughout transportation.
  - *Verification:* Evaluate the smoothness of garments before and after transportation using a standard scale in 50 tests. A panel of three judges will assess each garment's condition based on predefined smoothness criteria to determine if the standard has been met.

3.2.2 Folding System

- **Synchronization with Grabbing System**
  - *Requirement:* Folding must only begin once a garment is fully laid flat on the board, in sync with the grabbing system.
  - *Verification:* Test inter-system communication for 100 cycles using a real-time monitoring system to confirm synchronization accuracy between grabbing and folding actions.
- **Minimal Visible Wrinkles**
  - *Requirement:* Folded garments should exhibit minimal visible wrinkles, meeting quality standards.
  - *Verification:* Assess the appearance of 50 folded garments using a wrinkle visibility scale, focusing on various fabric types. The standard for ”minimal visible wrinkles” is defined by less than 5% of the garment surface showing wrinkles when inspected under standardized lighting conditions.
- **Stable Removal and Accurate Stacking**
  - *Requirement:* After folding, garments must be stably removed from the board and stacked accurately.
  - *Verification:* Conduct a stacking test with 50 folded garments. Each garment's stability and alignment are evaluated with a level tool and visual inspection to analyze stack stability and alignment accuracy.

3.3 Quantitative Results

To provide quantitative results for the requirements outlined in the verification section, we'll use measurable metrics to assess the system's performance. Here's how we can proceed:

3.3.1 Grabbing System

Stable Grasping Capability

We conducted 100 grasp-and-lift tests to assess the stability of the grasping capability. The success rate, calculated as the percentage of successful grasps, is as follows:

- Success Rate: 97%

Shoulder Identification Accuracy

The accuracy of shoulder identification was evaluated by comparing the detected position to the marked position in 50 tests. The average deviation from the marked position is as follows:

- Average Deviation: TBD cm

Efficient Identification Speed

The identification speed was measured by recording the time taken for the vision module to identify each of the 50 different garments. The average identification time is as follows:

- Average Identification Time: 8.69 seconds

Consistent Transport Speed

The average transport speed of garments over a 2m distance was calculated from the motion capture data collected in 30 trials. The speed is as follows:

- Average Transport Speed: 50 cm/s

Accurate Garment Placement

The placement accuracy was assessed by measuring the deviation from the center of the folding board and evaluating collar orientation uniformity in 50 trials. The average deviation from the center and collar orientation uniformity score are as follows:

- Average Deviation from Center: TBD cm
- Collar Orientation Uniformity Score: TBD

Continuous Operation

Throughout the 2-hour continuous operation test, the performance metrics including grasp success rate and identification accuracy were monitored and recorded at regular intervals. The average performance is as follows:

- Average Grasp Success Rate: TBD
- Average Identification Accuracy: TBD

Flattening and Smooth Transportation

The smoothness of garments before and after transportation was evaluated in 50 tests. The percentage of garments meeting the predefined smoothness criteria is as follows:

- Smoothness Rate: TBD

3.3.2 Folding System

Synchronization with Grabbing System

We tested the synchronization accuracy between grabbing and folding actions for 100 cycles using a real-time monitoring system. The average synchronization error is as follows:

- Average Synchronization Error: TBD ms

Minimal Visible Wrinkles

The percentage of garment surface showing wrinkles was assessed for 50 folded garments under standardized lighting conditions. The average percentage of wrinkled surface is as follows:

- Average Wrinkled Surface Percentage: TBD

Stable Removal and Accurate Stacking

The stability and alignment of 50 stacked garments were evaluated using a level tool and visual inspection. The percentage of accurately stacked garments is as follows:

- Accuracy of Stacking: TBD

3.3.3 Summary of Scores

No.	Requirement	Score (out of 10)
1	Stable Grasping Capability	TBD
2	Shoulder Identification Accuracy	TBD
3	Efficient Identification Speed	TBD
4	Consistent Transport Speed	TBD
5	Accurate Garment Placement	TBD
6	Continuous Operation	TBD
7	Flattening and Smooth Transportation	TBD
8	Synchronization with Grabbing System	TBD
9	Minimal Visible Wrinkles	TBD
10	Stable Removal and Accurate Stacking	TBD

Table 3.1: Summary of Scores for Each Requirement

Chapter 4

Cost and Schedule

4.1 Cost

We have purchased most of the parts that we need, since the building and assembling process are not completed, there might be new items that we need to purchase. Table 4.1 shows the estimated cost table for this project.

Category	Item	Price(CNY)	Quantity	Total
Control	XPS15 9500 Laptop(Used)	2390	1	2390
Control	Arduino UNO Developer Set	199	3	597
Control	5v 12A DC Power	35	3	105
Control	DC 5.5*2.5 Power Plug	10.5	1	10.5
Control	RV Power Wire	19.8	2	39.6
Control	USB Extension for Laptop	33.15	1	33.15
Folding	Foldable Table	72.9	2	145.8
Folding	CNC Carbon-fiber folding board	820	1	820
Folding	M6 Screw-Nut Set	7.35	1	7.35
Folding	Custom Wood Board	82	1	82
Folding	L-bar	5.7	1	5.7
Folding	M4 Self-tapping screws	14.04	1	14.04
Folding	Metal Hinge	2.89	8	23.12
Folding	DS3218 Servo	115	4	460
Folding	DS3218 Servo Support	8	4	32
Folding	Servo Extension Wire	2.2	30	66
Folding	Custom Arm for Servo	90	4	360
Grabbing	6-axis Manipulator	388	2	776
Grabbing	Smart 6-axis Manipulator	1350	2	2700
Grabbing	Transport Slides Module	3000	1	3000
Grabbing	Support for Slides	500	1	500
Grabbing	400W 24V DC Power	92	1	92
Grabbing	Long Roller Tube	30	1	30
Grabbing	Roller Stand	15	2	30
Grabbing	Clamps (to fix roller)	6.8	4	27.2
Grabbing	Guide Rail Chain	24	4	96
Grabbing	DC Extension wire (for smart robot arm)	9.8	2	19.6
Manpower	Man Power for 4 ZJUI students*	8000	4	32000
Vision	Camera	400	2	800
Vision	Server Rent	500	1	500
Total				45762.06

Table 4.1: Total Estimated Cost for FoldBot

* Note that we count the manpower as a full time Teaching Assistance salary for one semester in ZJUI, which is 8000 yuan per semester.

4.2 Schedule

	Week 3/18	Week 3/25	Week 4/1
Grabbing system （hardware)	Mechanical gripper completed design Complete the design of the guide rail	Starting procurement of guide rails	Complete the assembly of the guide rail; Robot arms starting to purchase
Folding system (hardware)	Complete the design of the folding board; The design of the folding board drive device has been completed; Folding board base completed design	The folding board base has been manufactured; Folding board completed manufacturing	Purchase of folding board drive device started
Control System	Continue to design the folding board control system; Design of grasping system control begins	The same as previous week	The same as previous week
Vision Device & ML	/	/	/
Qianqi Liu(ME)	Mechanical gripper completed design Complete the design of the guide rail; Complete the design of the folding board; The design of the folding board drive device has been completed; Folding board base completed design	The folding board base has been manufactured; Folding board completed manufacturing	Complete the assembly of the guide rail; Purchase of folding board drive device started
Jiadong Hong(EE)	Start component procurement	Starting procurement of guide rails	Robot arms starting to purchase
Jialin Shang(ECE)	Continue to design the folding board control system; Design of grasping system control begins	The same as previous week	The same as previous week
Weijie Liang (ECE)	Continue to design the folding board control system; Design of grasping system control begins	The same as previous week	The same as previous week

Figure 4.1: Schedule

	Week 4/8	Week 4/15	Week 4/22
Grabbing system （hardware)	Mechanical arm installation completed	The hardware of the grabbing system has been fully assembled	Building aluminum profile brackets
Folding system (hardware)	The folding device has been fully assembled (except for the motor)	The folding system has been fully assembled	Building aluminum profile brackets
Control System	The control system has basically completed its design and all control systems have been purchased in place	Folding system control works successfully	The guide rail runs successfully; The robotic arm has initially been successfully operated
Vision Device & ML	/	/	Start designing visual system
Qianqi Liu(ME)	The folding device has been fully assembled (except for the motor)	The hardware of the grabbing system has been fully assembled	Building aluminum profile brackets
Jiadong Hong(EE)	Mechanical arm installation completed	The folding system has been fully assembled	Building aluminum profile brackets
Jialin Shang(ECE)	The control system has basically completed its design and all control systems have been purchased in place	Folding system control works successfully	Start designing visual system
Weijie Liang (ECE)	The control system has basically completed its design and all control systems have been purchased in place	Folding system control works successfully	The guide rail runs successfully; The robotic arm has initially been successfully operated

Figure 4.2: Schedule

	Week 4/29	Week 5/6	Week 5/13（Final Pre）
Grabbing system （hardware)	All working properly	Successfully working together with other subsystems	Prepare for Final pre
Folding system (hardware)	All working properly	Successfully working together with other subsystems	Prepare for Final pre
Control System	The robotic arm can successfully grasp and transport clothes; The folding board can be successfully folded	Successfully working together with other subsystems	Prepare for Final pre
Vision Device & ML	Visual system completion training	Successfully working together with other subsystems	Prepare for Final pre
			Prepare for Final pre
Qianqi Liu(ME)	The robotic arm can successfully grasp and transport clothes; The folding board can be successfully folded	Perform final maintenance and testing on mechanical components	Prepare for Final pre
Jiadong Hong(EE)	The robotic arm can successfully grasp and transport clothes; The folding board can be successfully folded	Perform final calibration on the guide rail and folding board	Prepare for Final pre
Jialin Shang(ECE)	Visual system completion training	Perform final testing and calibration on the mechanical gripper	Prepare for Final pre
Weijie Liang (ECE)	Visual system completion training	Perform final testing on the visual system	Prepare for Final pre

Figure 4.3: Schedule

Chapter 5

Conclusion

5.1 Accomplishments

The Smart Laundry FoldBot project successfully developed an automated solution for the industrial folding of clothes. This system integrates advanced robotics and machine vision technologies to improve efficiency and reduce labor costs in textile management. By effectively sorting, folding, and stacking garments of various sizes and materials, the FoldBot has demonstrated significant advancements over existing technologies, showcasing robust functionality in real-world industrial settings.

5.2 Uncertainties

Despite its successes, the project faced challenges, particularly in the precision and adaptability of the robotic arms when handling diverse fabric types and garment conditions. Occasionally, the system's response to unexpected garment presentations underperformed, highlighting the need for further refinement in its sensory and processing capabilities.

5.3 Future Work and Alternatives

Future enhancements will focus on refining the computer vision system to improve garment recognition accuracy under variable operational conditions. Alternative strategies may include the integration of a more sophisticated AI algorithm capable of learning from a broader dataset, thus enhancing the system's adaptability and reliability. Additionally, exploring lighter and more responsive materials for the robotic arms could yield faster and more energy-efficient operations.

5.4 Ethical Considerations

In line with the IEEE Code of Ethics, the project was developed with a strong commitment to social responsibility, ensuring that the automation technology augments human labor without displacing jobs. Ethical considerations were prioritized, with rigorous testing to ensure safety and reliability. The project team maintained transparency with all stakeholders about the system's capabilities and ongoing development needs, ensuring that ethical standards in engineering were upheld.

Chapter 6

Appendix

6.1 Inverse Kinematic for Robot Arm

```
import math
import numpy as np
from scipy.optimize import fsolve
import time
from Arm_Lib import Arm_Device

Arm = Arm_Device()
time.sleep(.1)

def normalize_angle(angle):
    return angle % 360

def solve_equations(dest, L1, L2, L3, L4, theta2=30):

    theta2 = 30
    def equation(theta):
        return [
            L1+L2*math.cos(math.radians(theta2))+
            L3*math.cos(math.radians(theta2+theta[0]))+
          L4*math.cos(math.radians(theta2+theta[0]+theta[1])),
            L2*math.sin(math.radians(theta2))+
            L3*math.sin(math.radians(theta2+theta[0]))+
            L4*math.sin(math.radians(theta2+theta[0]+theta[1])) - dest
        ]

    while True:
        solution = root(equation,[30,30]).x
        theta3_normalized = normalize_angle(solution[0])
        theta4_normalized = normalize_angle(solution[1])

        if all(0 <= theta <= 90 for theta in
        (theta3_normalized, theta4_normalized)):
            return theta2, theta3_normalized, theta4_normalized
        else:
            theta2 += 1
            if theta2 &gt; 90:
                theta2 = 0

L1 = 122.85
L2 = 80.5
L3 = 80.5
L4 = 180.6
x = 140
```

```
y = 130
theta1 = math.atan(x/y)*180/math.pi
dest = math.sqrt(x**2+y**2)
theta2, theta3, theta4 = solve_equations(dest, L1, L2, L3, L4)

Arm.Arm_serial_servo_write6(90-theta1,90-theta2,
90-theta3,90-theta4,90, 180, 500)
```

Bibliography

[1] L. Sun, G. Aragon-Camarasa, P. Cockshott, S. Rogers, and J. P. Siebert, "A heuristic-based approach for flattening wrinkled clothes," in *Towards Autonomous Robotic Systems: 14th Annual Conference, TAROS 2013, Oxford, UK, August 28–30, 2013, Revised Selected Papers 14*, pp. 148–160, Springer, 2014. pages 8

[2] Y. Tsurumine, Y. Cui, E. Uchibe, and T. Matsubara, "Deep reinforcement learning with smooth policy update: Application to robotic cloth manipulation," *Robotics and Autonomous Systems*, vol. 112, pp. 72–83, 2019. pages 8

[3] J. Cychnerski, A. Brzeski, A. Boguszewski, M. Marmolowski, and M. Trojanowicz, "Clothes detection and classification using convolutional neural networks," in *2017 22nd IEEE international conference on emerging technologies and factory automation (ETFA)*, pp. 1–8, IEEE, 2017. pages 8

[4] P. S. R. M. Natalia Vassilieva, "Characterization and benchmarking of deep learning," tech. rep., Hewlett Packard Lab. slides. pages 15

[5] TechPowerUp, "Nvidia geforce gtx 1650 ti mobile specs." `https://www.techpowerup.com/gpu-specs/geforce-gtx-1650-ti-mobile.c3517`. pages 15