Computational Reconfigurable Garments

Yixuan He[1]   Haoyu Tang[1]   Kan Chen[2]   Peng Song[†1]

[1]Singapore University of Technology and Design, Singapore
[2]Singapore Institute of Technology, Singapore

Figure 1: *We present a computational approach for designing reconfigurable garments, which have two different forms (top left) sewn from a common set of fabric panels (bottom left). Our designed reconfigurable garment (right) is fabricable and wearable in the real world.*

Abstract

Reconfigurable garments consist of a common set of 2D fabric panels that can be rearranged and sewn into different 3D garment forms, promoting fabric utilization and extending clothing lifespans. However, designing reconfigurable garments is challenging since it is difficult to identify reusable regions across different garment forms. In this work, we present a computational approach for designing reconfigurable garments, taking a pair of target 3D garment shapes as the input. Our key idea is to first identify shareable 3D regions across the target garment shapes and then represent them into a common set of 2D fabric panels. To this end, we first decompose the input garment shapes into low-distortion patches and construct candidate regions by grouping neighboring patches. We then propose a seam-aware distance metric to measure compatibility between candidate regions flattened on 2D, and formulate reusable region discovery as a combinatorial optimization problem solved through integer programming. Lastly, we represent each reusable region pair using a simple polygon and optimize its shape to provide a compact approximation that can be shared across the garment forms. We demonstrate that our approach is able to design reconfigurable garments with different types and forms, and validate the usability of these garments via full-scale fabrication and wearer try-on.

CCS Concepts
• ***Computing methodologies*** → ***Shape Modeling;***

† Corresponding author.

1 Introduction

Reconfigurable garments have different forms sewn from a common set of fabric panels. In contrast to conventional garments that typically have a single form, reconfigurable garments reuse a common set of fabric panels and reconfigure them into different forms. This reconfigurability promotes fabric utlization, helps extend garment lifespans, and supports more sustainable clothing practices.

Some recent research works have explored garment design with fabric reuse. In particular, Qi et al. [QPK*25] optimizes the reuse of 2D sewing patterns between source and target garments, while Lin et al. [LLL25] promotes fabric reuse through a modular representation based on primitive 2D components. Yet, these two approaches are constrained either by reliance on predefined sewing patterns or by primitive modular representations. In this work, we aim to design reconfigurable garments by inversely modeling a common set of fabric panels that can be shared across different given garment forms.

However, designing such reconfigurable garments is nontrivial. First, reusable regions are difficult to identify from the geometry of different 3D garments. Because garments are constructed from soft 2D fabric panels, depending on how they are connected to adjacent panels and deformed over the body, the same or similar panels may deform into substantially different 3D shapes to cover different regions. Even after such reusable regions are established across garment meshes, it remains challenging to derive a compact set with a small number of reusable panels that adequately represent the regions. Furthermore, the resulting reusable panels should support complete garment reconstruction while preserving valid assembly relationships and geometry fidelity of target garment meshes. These coupled and often competing requirements make manual design difficult and motivate the need for a computational solution.

To address these challenges, we propose a computational approach for automatically designing reconfigurable garments from a pair of 3D garment meshes. Our key idea is to formulate reusable region identification as a bottom-up combinatorial optimization problem, in which garments are decomposed into fine-grained patches that are then merged with neighboring patches to form a large set of candidate regions of varying sizes and shapes. We introduce a seam-aware shape distance metric to evaluate the compatibility of regions after flattening them into 2D. Based on this, we formulate reusable region discovery as an integer programming problem to maximize the overall compatibility. Finally, we construct a compact set of shared panels to approximate the identified regions. This single panel set can then be configured to the corresponding regions to reproduce different garments. In particular, this work makes two main contributions.

- we propose a computational framework that directly constructs reconfigurable garments from a pair of 3D garment meshes, without requiring predefined sewing patterns or modular design.
- we introduce a shape distance metric for flattened 2D panels to measure reuse compatibility, together with a combinatorial optimization formulation to identify reusable regions across garments and establish cross-garment correspondences.

We demonstrate that our approach can design reconfigurable garments with diverse types and forms as well as adaptability to varying body proportions. Furthermore, we validate the effectiveness of our approach by physically fabricating the generated panels and sewing them into real garments. The code and data of this paper are available at `https://github.com/abcqmars/ReconfigGarment`.

2 Related Work

2.1 Design of Garments

Digital garment design has been an active research topic in the graphics community, with numerous studies exploring computational methods to automate the creation and modeling of 3D garments. These approaches enable users to design garments from scratch through a variety of intuitive interfaces. A common line of work focuses on sketch-based garment modeling, where users specify design cues such as folds [LSGV18], boundaries [RSW*07], or garment contours [DJW*06, RMSC11] on a digital mannequin. Another branch of research adopts data-driven strategies, leveraging existing garment datasets to synthesize new designs by learning a shared latent space [WCPM18] or by composing example models [LL14]. In addition, several works investigate the reconstruction of garments from real-world observations, including 3D scans [BKL21, PPHB17] and RGB-D imagery [CZL*15]. Beyond surface-level garment modeling, another line of work focuses on sewing-pattern-level representations. These methods support 2D–3D garment editing [UKIG11], pattern parsing [BGK*13], fit-driven pattern adjustment [Wan18, EFL*24], and pattern generation from 3D garment geometry [PDF*22]. More recent work has further explored sewing-pattern design through pattern reconstruction from 3D garments [KL22], parametric pattern programming [KS23], and automatic dart design for garment fitting [dMQP*23]. While these methods are closely related to our work, they primarily focus on creating, reconstructing, or editing garments for a single target design or body shape. In this work, we focus on designing a special kind of garment which can be reconfigured into different forms with the same set of fabric panels.

2.2 Design of Reconfigurables

In recent years, computational design of reconfigurables has attracted attention from the graphics community. Several computational methods have been developed for designing reconfigurable objects that can transform between different states. Prior work has explored reconfigurable furniture [SFJ*17], hinged kirigami tessellations [SRPS25], reconfigurable joints [MLSI24], chain-based transformations [YYL*19], and 3D dissection puzzles [TSW*19]. These methods show how computational design can help create objects with multiple configurations, but they typically rely on rigid components, explicit connectors, or predefined target configurations. Garments pose unique challenges because they are assembled from deformable fabric panels connected through sewing relationships. In this work, we focus directly on garment reuse and reconfiguration.

2.3 Reconfigurable Garments

Recent work has begun to explore garment reuse and reconfiguration from computational and modular design perspectives.

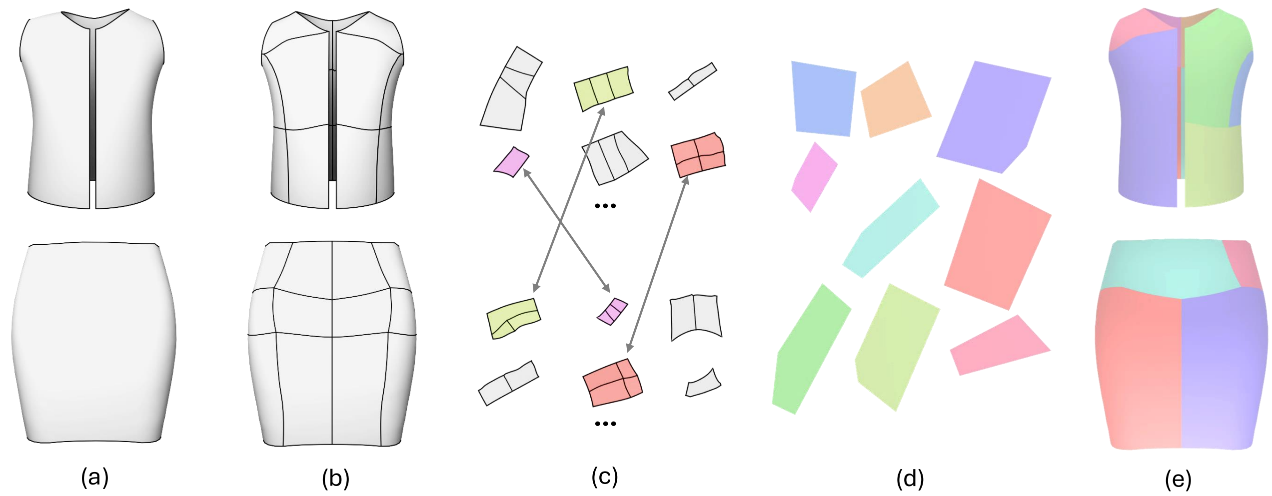

Figure 2: *Overview of our computational approach. (a) Given a pair of input garment meshes, (b) we first generate a fine-grained patch decomposition for each garment. (c) Candidate regions are obtained by merging neighboring patches. Then we identified reusable region correspondences across garments through combinatorial optimization. (d) For each matched region pair, we model and optimize a shared polygonal panel to represent both regions. (e) The resulting shared panels, together with garment-specific assembly configurations, can be used to reconstruct both target garments.*

Rags2Riches [QPK*25] formulates garment reuse as a pattern placement problem, transforming a source garment into a target design by arranging target panels over existing sewing patterns while preserving structural elements such as seams and hems. Refashion [LLL25] introduces an interactive modular garment design framework that decomposes 2D garment patterns into reusable modules via optimization, enabling users to design, resize, and restyle garments through a shared set of interchangeable building blocks. Similarly, texTile [VJY25] supports garment making and re-making through reusable crochet tiles connected by 3D-printed joints. While these methods rely on predefined 2D sewing patterns, fixed modules, or tile-based constructions, our method directly operates on 3D garment meshes to discover the set of reusable panels without being limited to primitive representations. This provides a more intuitive design workflow and enables flexible pattern sharing across garment forms, resulting in a compact set of shared panels.

3 Problem Formulation

In this section, we present the formulation of the reconfigurable garment design problem. We begin by defining the problem inputs and desired outputs, and then describe the requirements that are considered in the design process.

Input and Output. The input to our problem consists of two 3D garment meshes, G^A and G^B, each representing a fully designed garment geometry. Following [PDF*22], we assume the input garments are manifold meshes with well-shaped triangles. We further assume that they have similar total surface areas (typically within a 10% difference) and are made from the same type of soft fabric. These meshes describe the target garment shapes that our method aims to reproduce. The output of our formulation consists of two components: 1. A set of 2D fabric panels $\mathcal{P} = \{p_k\}_{k=1}^{N}$, where each panel p_k is a closed 2D discrete curve defining the boundary of a cut panel. These panels act as reusable building blocks for garment construction. 2. Two assembly configurations, where each configuration defines how the shared panels are assembled to reconstruct garments G^A and G^B. This includes the correspondence between 2D panels and garment regions, as well as the sewing topology among neighbouring panels.

Design Requirements. To ensure the resulting garments are practical and effective, the design should adhere to several key requirements. We outline these requirements below. (1) *Reconfigurability.* The shared set of fabric panels should fully represent input garments, ensuring that every subregion is represented by at least one reusable panel. Each configuration should satisfy a valid matching between panels across the two garments, specifying their correspondences. (2) *Fabrication Simplicity.* The resulting panels should have simple, regular shapes that are easy to cut and manufacture, while also keeping the total number of panels small to reduce fabrication complexity and assembly effort. (3) *Reconstruction Fidelity.* This requires that the garment geometry, after assembly, preserve the overall shape of the input garments.

4 Our Approach

In this section, we present our framework for designing reconfigurable garments from a pair of input garment meshes by computing a shared set of 2D fabric panels and their corresponding assembly configurations. We first decompose each garment into a fine-grained patch layout and construct a set of candidate reusable segments by grouping neighboring patches (Section 4.1). We then identify reusable garment regions by selecting compatible segment pairs and establishing correspondences across garments through a combinatorial optimization formulation solved via integer programming (Section 4.2). Finally, based on the optimized segment correspondences, we construct and optimize a set of shared panels that can be reconfigured to reconstruct both garments (Section 4.3). Figure 2 provides an overview of the proposed pipeline.

4.1 Generating Candidate Segments

We begin by constructing candidate reusable regions in a bottom-up manner, starting from a fine-grained patch decomposition and forming larger segments by grouping neighboring patches; see Figure 2 (b). Specifically, for each input garment mesh G, we generate an initial cutting layout using the method of [PDF*22], which places cutting seams following the principal directional field of the garment surface. This strategy produces a set of locally coherent and low-distortion patches $\mathcal{P} = \{p_i\}$ for each garment, that align with the intrinsic structure of fabric deformation and garment construction.

While these patches provide a convenient low-level decomposition, they are often too small to directly capture reusable regions across garments. In particular, meaningful garment panels are typically composed of multiple neighboring patches rather than a single patch. Therefore, we construct a richer set of candidate regions by grouping adjacent patches into larger units, which we refer to as *segments*. Each segment represents a connected 3D surface region and is flattened into a corresponding 2D shape. Operating on flattened segments allows us to directly reason about 2D panel reuse in the fabrication domain, where garment components are ultimately represented as 2D fabric panels. Also, this bottom-up representation enables the optimization to explore reusable regions with flexible scales and shapes, ranging from local regions to larger garment components, and from elongated rectangular regions to compact square-like regions; see Figure 2 (c).

To generate candidate segments, we enumerate connected groups of neighboring patches on the patch adjacency graph. Each segment s_i is therefore represented as a connected subset of patches from $\mathcal{P}$. The resulting segment set $\mathcal{S} = \{s_i\}$ serves as the search space for identifying reusable regions and establishing correspondences across garments. Enumerating all connected patch groups would lead to a combinatorial explosion in the number of candidate segments. To keep the search space tractable, we only consider connected patch groups containing two to six patches. This range was found to provide sufficient flexibility for capturing reusable garment regions while maintaining a manageable number of candidates. In addition, not all connected patch groups correspond to physically meaningful fabric regions. To ensure fabrication plausibility, we evaluate each candidate segment based on its flattening distortion and area compression. Segments exhibiting excessive distortion or compression are discarded, as they are less likely to admit a stable 2D representation. The remaining segments form the candidate set used in the subsequent optimization.

4.2 Identifying Reusable Regions

In this subsection, we identify reusable garment regions by selecting compatible segment candidates across the two garments. To this end, we formulate the problem as a combinatorial optimization problem. We first define a shape distance metric to evaluate the compatibility of candidate segment pairs across garments, and then solve for an optimal set of segment correspondences via integer programming to ensure a globally compatible decomposition. Figure 2 (c) illustrates the segment matching process within our pipeline.

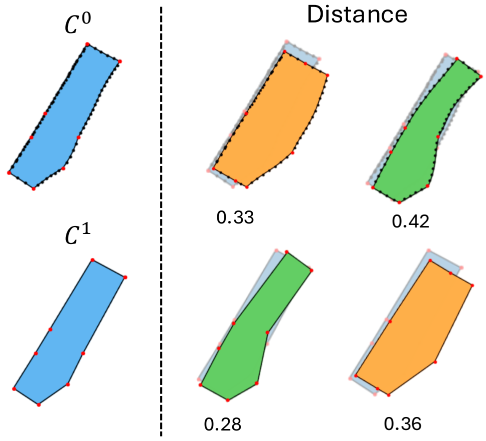

Figure 3: *Turning-function distance at different seam resolution. fine level (top) favors detailed seam alignment, whereas coarse level (bottom) emphasizes overall shape compatibility.*

4.2.1 Measuring Segments Compatibility

To identify reusable regions across garments, we first define a distance metric between candidate segments. Intuitively, two garment segments are considered replaceable if they exhibit similar boundary shapes after flattening, since the boundary geometry largely determines how a fabric panel interacts with neighboring panels through sewing. Therefore, instead of comparing geometric embeddings in 3D, we measure compatibility directly on the flattened 2D panel boundaries.

In particular, given a segment s, we represent its flattened panel by a discrete closed boundary curve. we adopt a turning-function representation to describe each flattened boundary as a cumulative turning-angle signature over the ordered boundary vertices. This representation is well-suited for discrete segment comparison, as it captures global boundary structure while remaining invariant to translation and rotation, which has been widely used for polygonal shape matching [ACH*91]. However, directly comparing the original boundary may bias the measurement toward local seam details. To mitigate this, we adopt a balanced turning-function representation that also incorporates a coarse version of the boundary, ensuring that both fine seam compatibility and overall panel shape are considered.

Specifically, for a segment s, we represent its flattened boundary as a 2D closed curve C, composed of seam edges (shared between patches) and free garment boundary edges, which capture a lot of local seam features. We construct a coarse version of C by downsampling its boundary vertices while strictly preserving the endpoints of all seam edges, to maintain the overall shape. This yields two levels of representation, C^0, C^1, where C^0 is the original boundary and C^1 is the coarsest version retaining only key structural vertices. In practice, the fine level emphasizes local seam compatibility, while the coarse level captures overall panel geometry; see Figure 3.

Given two segments s_i^A and s_j^B, we define their shape distance as a weighted combination of turning-function discrepancies at the

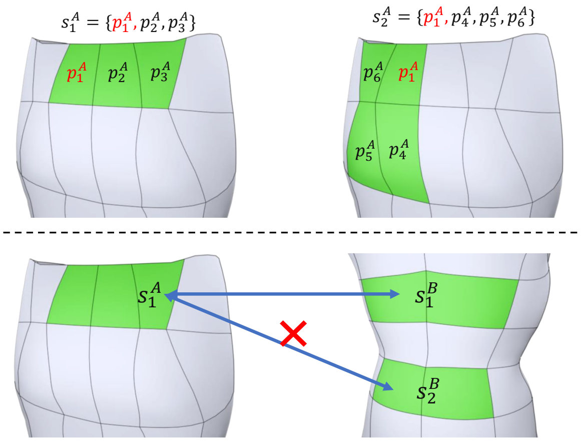

Figure 4: *Illustration of the constraints. Top: The partition constraint ensures each patch is covered once (e.g., s_1^A and s_2^A cannot both be selected). Bottom: The matching constraint enforces a one-to-one correspondence (e.g., s_1^A can be matched to either s_1^B or s_2^B).*

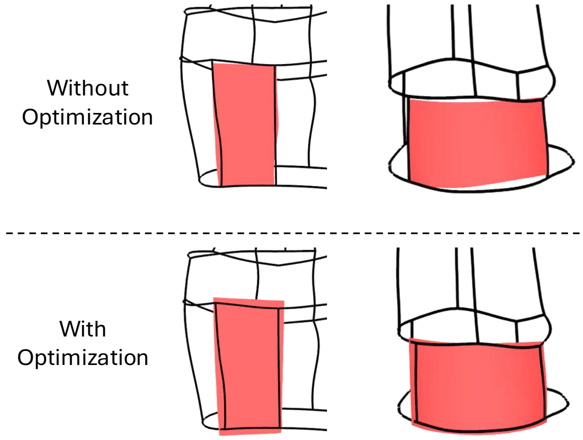

Figure 5: *Effect of shared panel optimization. Top: directly swapping matched segments across garments leads to noticeable gap. Bottom: the optimized shared panel is aligned to both regions, minimizing gaps while allowing limited excess area as seam allowance.*

two scales:

$$D_{\text{shape}}(s_i^A, s_j^B) = (1-\lambda)\, D_{\text{turn}}(C_i^{A0}, C_j^{B0}) + \lambda D_{\text{turn}}(C_i^{A1}, C_j^{B1}), \quad (1)$$

where $\lambda \in [0,1]$ controls the trade-off between fine-grained boundary compatibility and global shape consistency, and D_{turn} measures the turning-function discrepancy [ACH*91]. A lower distance indicates that the segment boundaries are more similar and therefore more compatible for reuse.

Since the turning function is scale-invariant and focuses on shape, it may match segments with similar boundaries but significantly different sizes. To avoid such mismatches, we introduce a scale penalty defined as the absolute difference of logarithmic areas:

$$D_{\text{scale}}(s_i^A, s_j^B) = \left| \log \text{Area}(s_i^A) - \log \text{Area}(s_j^B) \right|. \quad (2)$$

The final segment distance metric is then defined as

$$D(s_i^A, s_j^B) = D_{\text{shape}}(s_i^A, s_j^B) + \beta D_{\text{scale}}(s_i^A, s_j^B), \quad (3)$$

where β controls the weight of scale penalty. It is straightforward to show that the scale penalty satisfies standard metric properties [ACH*91], including non-negativity, symmetry, and the triangle inequality, as does the turning-function-based distance. As a result, the final distance metric $D(s_i^A, s_j^B)$ also defines a valid metric, which serves as the objective function for selecting shared structures in the subsequent optimization formulation.

4.2.2 Integer Programming Formulation

Next, we formulate the discovery of shareable garment regions as a combinatorial optimization problem that selects consistent segments from both garments and establishes one-to-one correspondences between them.

Variables. First, we introduce three groups of binary variables:

- Segment selection variables for garment A:

$$x_i^A \in \{0,1\}, \quad i = 1, \ldots, |\mathcal{S}^A|.$$

- Segment selection variables for garment B:

$$x_j^B \in \{0,1\}, \quad j = 1, \ldots, |\mathcal{S}^B|.$$

- Segment correspondence variables:

$$m_{i,j} \in \{0,1\}, \quad i = 1, \ldots, |\mathcal{S}^A|,\ j = 1, \ldots, |\mathcal{S}^B|,$$

where $x_i^A = 1$ indicates i_{th} segment for garment A is selected, while $m_{i,j}$ indicates segment s_i^A is matched with segment s_j^B which is considered reusable pair.

Constraints. To satisfy the reconfigurability requirements that every region of garments should be covered and no overlapping waste exists. Here, we proposed the two constraints. First, to ensure that every patch region of each garment is explained by exactly one selected segment, we impose a partition constraint using the patch-to-segment incidence matrice $I \in \mathbf{R}^{|\mathcal{P}| \times |\mathcal{S}|}$. Each row of I encodes which segments cover a given patch in each garment. This constraint can be written in a unified form as:

$$\sum_{i=1}^{|\mathcal{S}^A|} I_{k,i}^A x_i^A = 1, \quad \forall k \in \mathcal{P}^{\mathcal{A}} \qquad \sum_{i=1}^{|\mathcal{S}^B|} I_{k,i}^B x_i^B = 1, \quad \forall k \in \mathcal{P}^{\mathcal{B}}. \quad (4)$$

This ensures that each base patch belongs to exactly one selected segment, guaranteeing a valid segmentation without overlap or omission; see Figure 4 top.

Second, to ensure each segment is reused in a single consistent correspondence rather than being ambiguously matched to multiple regions. We proposed the following one-to-one matching constraint:

$$\sum_j m_{i,j} = x_i^A, \quad \forall i, \qquad \sum_i m_{i,j} = x_j^B, \quad \forall j. \quad (5)$$

It implies that when a mapping pair is selected $m_{i,j} = 1$, segment x_i^A and x_j^B should be selected ($x_i^A = x_j^B = 1$), while other entries on i_{th} row and j_{th} column of $m_{i,j}$ should be 0. These guarantees a strict one-to-one correspondence: a segment can be matched if and only

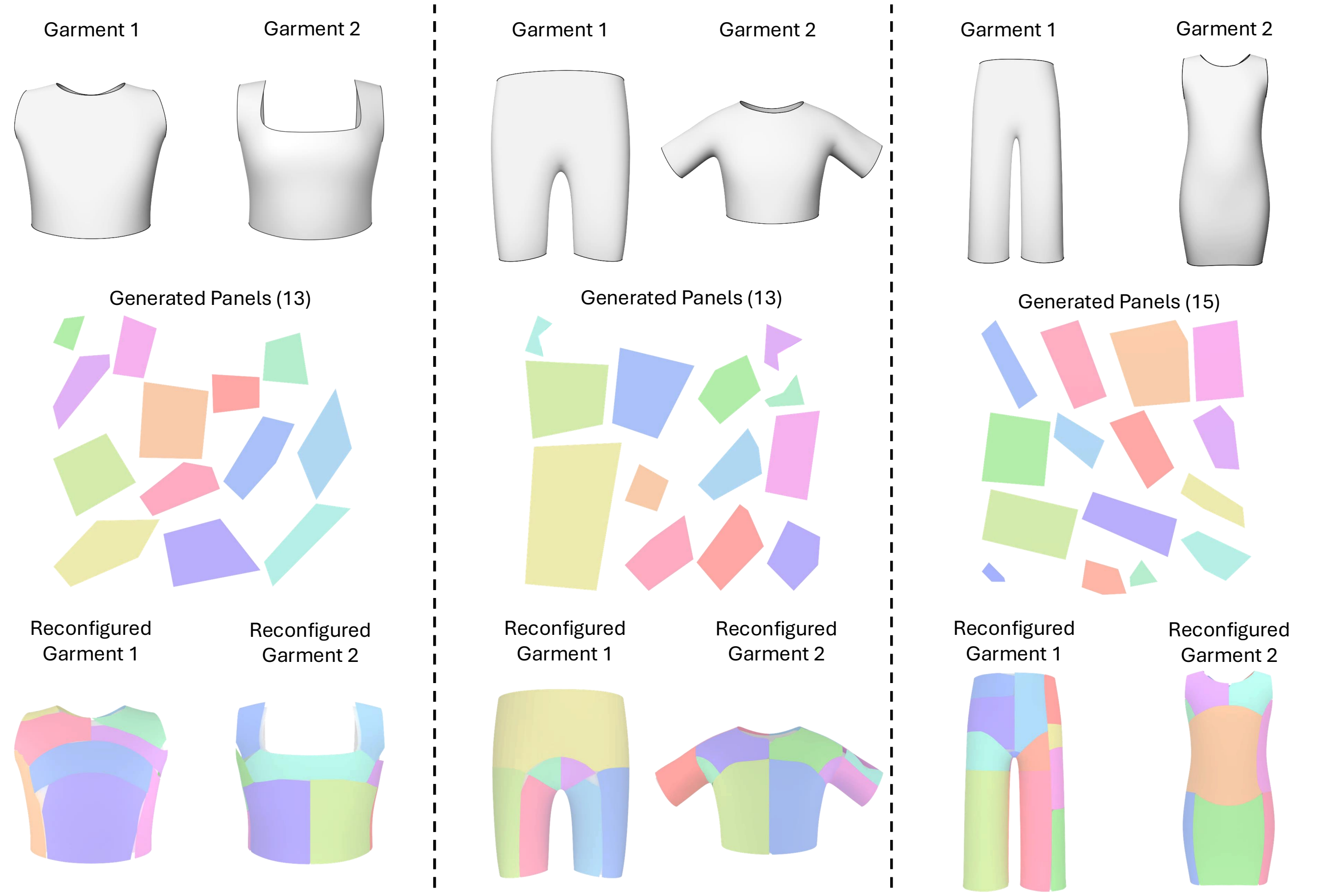

Figure 6: *Our approach enables the design of reconfigurable garments across diverse forms and uses, including topwear (e.g., vests, T-shirts) and bottomwear (e.g., shorts, pants), all constructed from a compact set of shared panels.*

if it is selected, and each selected segment is paired with exactly one counterpart in the other garment; see Figure 4 bottom.

Objective. We seek a configuration that minimizes the total dissimilarity between matched segments across the two garments. The objective is defined as:

$$\min \quad \sum_i \sum_j D(s_i^A, s_j^B)\, m_{i,j}. \tag{6}$$

This objective favors selecting correspondences with minimal turning-function distance, therefore promoting globally compatible segment matching across garments. It is worth noting that all values of $D(s_i^A, s_j^B)$ are precomputed prior to optimization. As a result, the resulting formulation is a pure integer program, allowing a globally optimal solution to be obtained whenever the feasible set is non-empty.

4.3 Generating Shared Panels

In this section, we construct a set of shared panels (Figure 2(d)) corresponding to the matched segment pairs obtained in Section 4.2. To ensure reconstruction fidelity and fabrication simplicity, each shared panel should adequately approximate both reusable regions while maintaining a shape that is practical to fabricate.

Panel Representation. We represent each shared panel as a simple quadrilateral or pentagon. In practice, we find that low-complexity polygons are sufficient to approximate most matched garment regions identified by our optimization framework, while avoiding unnecessarily complex boundary that may increase manufacturing difficulty.

Initialization. For each matched segment pair (s_i^A, s_j^B), we first align the two segments by estimating the optimal rigid transformation that maximizes their overlapping area. Specifically, we search for the flip, translation, and rotation that best aligns the flattened segment shapes in the 2D domain. After alignment, we initialize the shared panel using the oriented bounding box of the aligned segment pair. This provides a stable starting point for subsequent optimization while essentially capturing the dominant shape characteristics of both segments.

Optimization Objective. Based on the initialized polygon, we optimize the panel geometry to represent both target segments. Our objective consists of three terms.

First, we minimize the segment distance $D(\cdot,\cdot)$ introduced in Section 4.2. With a shared panel p and a matched segment pair (s_i^A, s_j^B), a shape term E_{shape} is introduced to promote that the panel

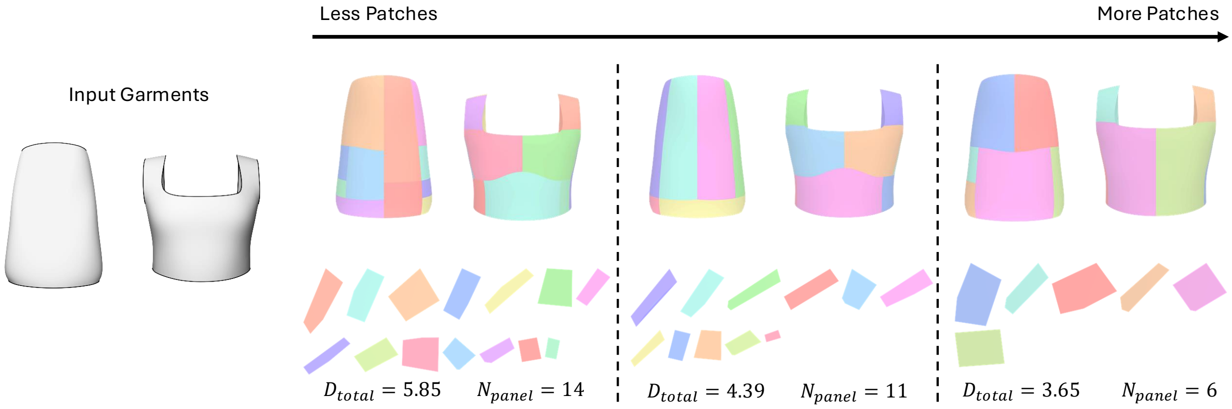

Figure 7: *Our approach allows controlling layout granularity to adjust reconfiguration quality: increasing the number of patches yields a finer structural decomposition, which reduces total segment distance D_{total} and the number of generated fabric panels N_{panel}.*

to be geometrically compatible with both segments:

$$E_{\text{shape}} = D(p, s_i^A) + D(p, s_j^B), \tag{7}$$

Second, we penalize the uncovered area between the shared panel and the target segments which leads to stretching during assembly. While we allow a small amount of excess area in the shared panel for optimization (Figure 5), this excess can be considered a form of seam allowance which is hidden from the exterior and visible only from the interior [Moo21]. We therefore define a gap-area term:

$$E_{\text{gap}} = G(p, s_i^A) + G(p, s_j^B), \tag{8}$$

where $G(\cdot,\cdot)$ measures the uncovered area of a target segment after optimal rigid alignment, computed as the segment area minus its intersection area with the shared panel.

Finally, we introduce a balance term to avoid biased solutions that fit one segment well while significantly deviating from the other. Let

$$e_A = D(p, s_i^A), \qquad e_B = D(p, s_j^B), \tag{9}$$

then the imbalance penalty is defined as:

$$E_{\text{balance}} = |e_A - e_B|. \tag{10}$$

Combining these terms, the final optimization objective becomes

$$\min \quad E_{\text{shape}} + E_{\text{balance}} + w_g E_{\text{gap}}, \tag{11}$$

where w_g control the weight of gap coverage. We iteratively optimize this objective until the relative decrease falls below a predefined threshold, and take the resulting solution as the final output. We evaluate both quadrilateral and pentagonal panel configurations and select the one with the lower final energy.

Obtained the optimized panels, we compute the optimal rigid alignment between panel and its matched segments. Combined with the segment correspondences across garments, we are able to reconstruct the target garments. More details about constructing the garment are presented in Section 5 Fabrication Results.

5 Results

Implementation. We implemented our computational design pipeline in C++ and Python on a Mac desktop with an Apple M3 CPU. Our implementation builds on the framework of [PDF*22] for patch layout generation. We use libigl [JP*18] and vcglib [CCC*08] for geometric operations, while we use OR-Tools [Goo26] for solving the combinatorial optimization problems and use Scipy [VGO*20] to implement the Nelder-Mead solver to optimize shared panels. Parameters λ and β are fixed at 0.2 and 1.0 for all instances once calibrated. Table 1 provides statistics of each result shown in the paper. In particular, reusable area ratio R_A is measured as the ratio of the garment area covered by the shared panels to the surface area of the input garment; reconstruction error $\mathcal{E}_{rec}$ is measured as Chamfer Distance between the reconstructed and input garment surfaces, normalized by the bounding-box diagonal of the input garment surface; and panel distortion D_p is measured using the average area ratio between each optimized 2D panel and the corresponding 3D garment region.

Virtual Results. We evaluate our approach on a variety of garments with diverse geometries and topologies. Figure 6 demonstrates that our framework can generate reconfigurable sewing patterns that reconstruct a wide range of garment designs using a compact set of shared panels. Small gaps can be observed between panels after reconfiguration, which arise from approximating the original garment regions with simple quadrilateral and pentagonal panels. We also observe a few small panels in some results, typically in highly curved regions of the garment surface, such as the crotch area of pants and shorts, where additional geometric complexity is required to accurately capture the local shape.

We conduct an ablation study to examine how the layout granularity affects the quality of the reconfigured garments. As shown in Figure 7, increasing the number of patches in the decomposition reduces the overall reconfiguration error. Although our objective does not explicitly penalize the number of shared panels, increasing the patch resolution enlarges the solution space for identifying compatible reusable structures, often yielding a more compact set of shared panels. We further demonstrate that our method supports

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Table 1: *Statistics of our results. Columns 3 and 4 show the numbers of patches and candidate segments for each garment, while Column 5 reports the number of resulting shared panels. R_D denotes the relative differences (in percentage) of input garments mesh in the total surface area. R_A, $\mathcal{E}_{rec}$ and D_p denotes the average reusable area ratio, reconstruction error and average panel area distortion, respectively. T_{IP} and T_{Fit} denote the running times (minutes) for the integer programe and panel fitting optimization, respectively, and T_{total} is the sum.*

Fig.	Input Garments	Patches	Segs.	Panels	R_D	R_A	$\mathcal{E}_{rec}$	D_p	T_{IP}	T_{Fit}	T_{total}
1	Skirt 1 + Crop Top 1	30+34	181+135	7	2%	0.96	0.011	1.05	1.1	1.3	2.4
2	Jacket + Skirt 2	22+30	75+140	9	1%	0.96	0.012	1.08	0.2	1.5	1.7
6	Vest + Crop Top 2	34+28	126+127	13	3%	0.92	0.014	1.21	0.8	1.3	2.1
6	Shorts + Shirts	36+40	163+176	13	6%	0.90	0.017	1.32	1.5	1.6	3.1
6	Pants + Dress	54+46	300+277	16	7%	0.91	0.015	1.25	5.6	2.5	8.1
8	Dress2 + Skirt 2	60+30	292+140	15	5%	0.95	0.012	1.06	5.6	2.5	8.1
9	Pants + Shorts	54+36	300+236	14	5%	0.93	0.013	1.41	3.1	2.1	5.2
9	Skirt 2 + Long Skirt	30+50	140+268	6	1%	0.97	0.011	1.05	3.2	1.8	5.0

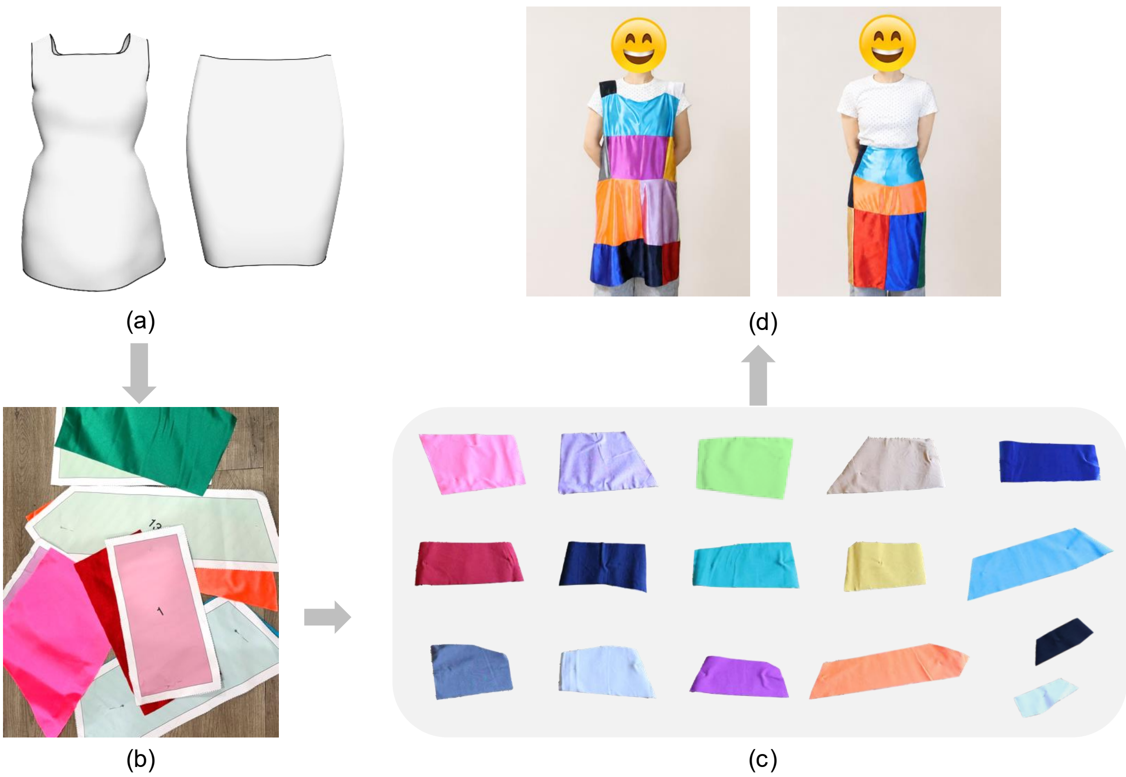

Figure 8: *Fabrication results in four steps: (a) given a pair of garment meshes as input, (b) our framework computes shared panels and prepares full-scale paper templates; (c) the fabric is then cut using the templates; (d) the fabric panels are sewn according to the generated seams and 3D assembly configurations, with the right skirt tightened at back for a better fit. The final fabricated garments are shown on the wearer.*

garment reuse across different body sizes. Figure 9 shows reconfigurable designs that maintain a similar style while adapting to different body proportions. For example, a pair of long pants designed for a 1.3 m child can be reconfigured into a pair of shorts for a 1.8 m adult from the same set of shared panels.

Fabrication Results. To validate the practicality of our approach, we fabricated two pairs of real garments based on the computed results. Given a pair of garment meshes, we first scaled them to fit a real human model and used them as input to our framework. Our approach then generated a set of shared panels on the 2D plane, along with the corresponding 3D assembly configurations. For fabrication, we printed two full-scale copies of the generated fabric panels on paper as templates for cutting in spandex fabric. To guide the sewing process, we mapped the corresponding segment boundaries onto the shared panels preserving the original sewing relationships between panels. The first example shown in Figure 1 took approximately 1 hour for cutting and 3 hours for sewing, while the second example shown in Figure 8 took approximately 2 hours for cutting and 5 hours for sewing. After cutting, the tailors assembled the garments by stitching the fabric panels according to the

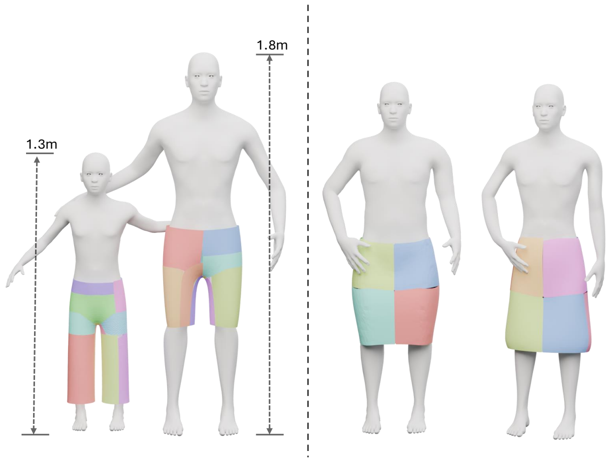

Figure 9: *Our approach enables designs of reconfigurable garments for users of varying body proportions to promote reuse. E.g., long pants for a child can be reconfigured into shorts for an adult.*

generated seams and 3D assembly configurations. The excess area is folded inward and concealed as seam allowance uing standard garment construction techniques. The final fabricated garments are shown in Figures 1 and 8. We conducted an informal user study with both tailors and wearers. Tailors reported that the reconfiguration process was easy to follow and efficient for design iteration, while wearers reported that the reconfigured garments maintained a stable fit.

6 Conclusion

This paper presents a computational approach for designing reconfigurable garments. Given a pair of 3D garment meshes, our method generates a shared set of fabric panels that can be assembled into both garments without relying on predefined sewing patterns or modular designs. The key idea is to identify reusable garment regions through a combinatorial optimization framework and then construct shared panels that approximate the matched regions across designs. We demonstrated the effectiveness of our approach on garments with diverse styles and sizes. Furthermore, we fabricated the generated designs and successfully reconstructed physical garments from the resulting shared panels which demonstrate the practical applicability and reconfigurability.

Limitations and future work. Our work has several limitations that point to future research directions. First, the quality of the results depends on the input garment meshes. Garments that do not satisfy our assumptions (e.g., noisy, scanned, or non-manifold meshes) may produce irregular segment candidates, reducing the stability of the subsequent optimization. In addition, our current shared panel representation is limited to simple polygonal shapes (e.g., quadrilateral and pentagonal panels), which may not be sufficiently expressive to represent highly irregular regions. In future work, more flexible panel representations could be explored to better handle such challenging cases. Second, our formulation is designed for a pair of garments, which limits the diversity of styles that can be jointly considered. A natural extension is to generalize our framework to garment collections, enabling a single shared panel set to support a broader design space. Third, our current model simplifies several fabrication-related constraints at the sewing layout level. Although our optimization promotes seam compatibility via panel boundary matching, we plan to explicitly model seam constraints (e.g., using a half-joint graph representation [SFJ*17]) to further improve seam compatibility. Lastly, we plan to integrate connectors (e.g., zippers) into the designed garments to facilitate the real-world garment reconfiguration process.

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