Abstract—In the past decade, fashion industry and apparel manufacturing have been applying intelligent CAD technologies to operate garment panel shapes in digital form. As garment panels are being accumulated gradually, there is a growing interest in finding similar panel shapes from large collections. The retrieved panel shapes can provide recommendations for stylists to reference and re-create during the cognitive fashion design process. In this paper, we propose a novel graph modeling and matching method to facilitate the searching of panel shapes for sketch-based garment design. A panel shape is first decomposed into a sequence of connected segments and represented by the proposed bi-segment graph (BSG) model to encode its intrinsic features. A new matching metric based on weighted direct product graph and minimal spanning tree (WDPG-MST) is then proposed to compute the similarity between two BSG models of the panel shapes. Finally in the front-tier, we provide a sketching interface based on our previous work for designers to input and edit the clothing panels. The simulation of the resulting garment design is also visualized and returned to the user in 3D. Experiment results show the effectiveness and efficiency of the proposed method.

I. INTRODUCTION

For the last few decades, computer-aided design (CAD) systems for apparel manufacturing have been rapidly developed and have become the basis for textile garment production [1]. For years, a primary task in computer-aided garment design has been how to construct garment panels, i.e. strips of fabric in garment. These panels are usually produced by pattern technologists (tailors) according to the paper designs drawn by fashion stylists before they are sewn together to compose a complete dress.

As the number and variety of the designed garment panels continue to grow, these panel shapes substantially form a knowledge-base for reference in future garment design. Applications to help people manage these panel databases are attracting increasing interest. In the near future, the challenge of garment design will shift from “How to design garment panels?” to “How to manage and find the existing designs for further re-creation?”. The goal to search for similar panel shapes from large collections is shared not only by designers, technologists and professionals, but also by general users.

In this paper, we propose a new graph modeling and matching method for sketch-based panel shape design. Our goal is to return similar garment panels according to the user’s input shape. There are three main techniques in our method: (1) We first propose a new bi-segment graph (BSG) model to further formulate the bi-segment structure in our previous work [2][3] into weighted graphs. The BSG model describes the panel by a sequence of adjacent segments and the encoding features among them, which can be calculated and matched by machine. (2) In order to perform the searching task, we propose a new matching metric based on weighted direct product graph and minimal spanning tree (WDPG-MST) to compute the similarity between two BSG models. (3) Finally, in the front-end, we provide a touch sketching interface for panel shape input and edit. We also extend our previous work [4] to support 3D visual feedback for panel matching and garment simulation. Fig. 1 illustrates the working scenario of garment panel design and matching process.

Our work is the key technique for developing a cognitive recommendation system for fashion design based on accumulated knowledge, or also referred to as cognitive set. This is because, one of the best ways of creative fashion design is to constantly be paying attention to the inventory of existing ones. The previously designed garments may give ideas to today’s fashion trend. It would be meaningful to have suitable suggestions or dynamic predictions during the garment design process to complement the undergoing design subject. To make use of the available designs, it is essential to bring them to users by means of searching for the relevant information from the cognitive set. This requires effective shape representation and matching algorithms of the 2D panel shapes.

Contributions: There are three major contributions of our proposed method: (1) The BSG model can capture both geometric and topological features of the panel shapes. The panel content is represented comprehensively in this way. (2) The WDPG-MST matching algorithm effectively transforms a graph matching problem to a minimal spanning tree problem by introducing a graph product operation. It supports both global and partial matching. (3) The front-tier sketching input and 3D visualization provide a much more convenient, flexible and rapid interface for panel design. The virtual garment prototyping platform is integrated with effective panel modeling and matching functionalities.

The rest of the paper is organized as follows: Section
II presents the related work of panel shape description and matching. Section III describes the BSG modeling for panel shape representation. Section IV presents the WDPG-MST matching metric for similarity computation. Section V gives the experimental setup, performance evaluation and discussions. Finally, section VI concludes our work.

II. RELATED WORK

In this section, we look at the related work of shape modeling and matching for apparel panel design. Regarding the garment processing procedure, there are mainly three related techniques, including the garment sketching interface, shape representation and graph database matching. We will summarize the current work in these aspects as follows respectively.

Typical commercial garment design software are built towards rigid shape generation and editing which require extensive prior training. Recently, there are some systems [5][6] incorporating mouse-based sketching interface to provide design flexibility and freedom. These systems are based on virtual characters. Igarashi et.al. [7] presented free sketching interaction techniques for fitting clothes on a 3D character and then making modifications. Correspondence is built up by combining the user painted marks and that on 3D models. Turquin et.al. [8] presented a modeling system for garment creation and modification using sketch-based interactions. Special stroke symbols are designed to perform the editing operations such as breakpoint indication, corner detection and folding generation. However, most of the CAD systems require to have a complete sketch input. In order to alleviate this constraint, we proposed a garment sketching interface that dynamically returns the possible solutions along the shape drawing process in our previous work [2][3].

Shape representation and description has been well investigated in image retrieval and computer vision in the last few decades [9]. Raw input of shapes, i.e. digital images or geometries, which are also known as low-level representations are transformed into higher-level representations that are suitable for comparison. Graph-based shape descriptors [10] are widely used to represent the structural information of the shape, which view the shape as a set of segments with intrinsic structural characteristics. Liang et.al. [11][12] proposed to use topology graphs to model the topological features of the sketch shapes, and used the graph spectrum to reduce the computational complexity of the graph matching problem. Leuken et al. [13] presented a graph-based encoding of layout for trademark images, in which both directional and topological layout information is stored. However, effective and efficient graph indexing techniques need to be used to reduce the graph matching complexity.

Our work is also related to graph database, which is a relatively new area in database community. Graph databases appear in many practical applications such as biology, chemistry and social networks. Most of this work focuses either on the query processing techniques [14][15] or on the graph data indexing techniques [16][17]. Here we consider the indexing techniques to perform the matching procedure efficiently.

In our work, we mainly focus on the graph representation of the panel shapes and the similarity measurement of these graph data. The details of the proposed method are described in the following sections.

III. BSG SHAPE REPRESENTATION

In order to achieve good matching and recognition accuracy, the shape representation technique and descriptor should be robust, powerful and effective. In this paper, based on our previous work [2][3], we propose a new bi-segment graph (BSG) model to describe the content of panel shapes. In this way, both geometric and topological features of the vectorized panel shapes are characterized in the form of graph, which are comparable for computers. In section III.A, we give out the concept of bi-segment shape structures. In section III.B, we
propose the BSG model and use it as the shape descriptor for panel shapes.

A. Bi-segment shape structure

As discussed in our previous work [2][3], we model the panel shape by a “bi-segment” sequence which encodes its corresponding intrinsic characteristics. The structure of a bi-segment is given in Definition 1 as follow.

**Definition 1 (Bi-Segment Structure).** A bi-segment in a shape is the structure of a connective segment-pair and their corresponding intrinsic features. Assume $s_1$ and $s_2$ are two adjacent segments in the shape, their corresponding bi-segment structure $B_{s_1 s_2}$ is defined as:

$$B_{s_1 s_2} = s_1 \& s_2 = \text{Bi-segment Data} + \text{Bi-segment Features}$$

Note that the bi-segment structure is not simply putting the two segments together, but also extracting the features from the connected segment-pair. Both the geometric features of the segment-pair and the topological relation between them are encoded. The data of the bi-segment structure is also enriched by combining low-level machine-sensitive data and high-level human perception data together. Fig. 2 shows an example bi-segment structure of a connective segment-pair as two curves. The joint point of the two segments are shown in black. The control points of the curve are shown in blue, and the sample/re-sample points are shown on the curve in red.

![Fig. 2. Illustration of the bi-segment structure of two curves.](image)

The main advantage of the bi-segment structure is that three levels of data types contribute to the parameterization of the shape and connectivity of the bi-segments of a panel. These three levels are: the raw shape data, parametric fitting data, and perceptual attributes from machine-sensitive to human-perceptions. Original data is related to the initial input data by user sketching. It is the low-level raw data that has not been processed. This includes both static data and dynamic data. The sample points array is an example of static data, as shown in red in Fig. 2, while dynamic data includes drawing order or pen speed. Parameterized data is the middle-level data after graphics processing. The input data is computed and regularized into a standard form, such as B-spline curves and Bézier curves. In this way the original data can be parameterized by control points, as the blue control points shown in Fig. 2. Noises in the raw sketch data can also be removed by regularization. Perceptual data is the high-level data corresponding to human cognition and understanding. This includes semantics information regarding to a certain domain. Some physical attributes can also be attached.

Another advantage of the bi-segment structure is that various feature descriptors can be encoded to represent the panel shape comprehensively. The features of the bi-segment mainly fall into two categories of geometric and topological descriptors. The classification is based on whether the features of the bi-segment are extracted from its geometric characteristics, or from its topological properties. Topological descriptors which view shapes as a set of segments are essential, since garment panels have their intrinsic structural characteristics. On the other hand, geometric descriptors reflect the shape in a whole and is close to people’s visual perception. By combing both kinds of information, we can describe the panel content more comprehensively and effectively than using only one of them.

In this paper, we make use of the bi-segment structure to decompose the original panel shape. The original data is parameterized and regularized into segments of Bézier curves. For feature extraction, one type of topological descriptor and 3 types of geometric features are used to represent the panel content.

B. Bi-Segment Graph (BSG) Modeling

After the panel shape is decomposed into a set of bi-segments, it is further structured as a graph. The new form of graph representation for panel shapes is called “bi-segment graph (BSG)” in this paper. Before we define the BSG, we give out the concept of binary topological relation as follow.

**Definition 2 (Binary Topological Relation).** Assume the segment set is of type $\Sigma^T = \{\text{line}, \text{curve}\}$, then the binary topological relation $R$ between two adjacent segments $S_1$ and $S_2$ could be specified as:

$$R(S_1, S_2) = \begin{cases} 
R_{l,l}, & \text{if } S_1^T = S_2^T = \text{line} \\
R_{l,c}, & \text{if } S_1^T \neq S_2^T = \text{line} \\
R_{c,c}, & \text{if } S_1^T = S_2^T = \text{curve}
\end{cases}$$

**Definition 3 (Bi-Segment Graph (BSG)).** A BSG is defined as a 6-tuple $G = (V, E, R_E, \Theta_E, \Lambda_E, C_E)$, where

(i) $V$ is the set of graph nodes. Every node in the graph represents a single segment in the shape.

(ii) $E \subseteq V \times V$ is the set of graph edges. Edge $(v_i, v_j) \in E$ if there is a corresponding bi-segment consisting of nodes $v_i$ and $v_j$ in the shape. In other words, an edge $e_{ij} = (v_i, v_j)$ represents a bi-segment combining the two adjacent nodes/segments $v_i$ and $v_j$.

(iii) $R_E : E \rightarrow \Sigma_R$ is a function assigning topological attributes to the edges, where $\Sigma_R = \{R_{l,l}, R_{l,c}, R_{c,c}\}$ is the symbolic label set of binary topology relations in Definition 2.

(iv) $\Theta_E : E \rightarrow [0, \pi]$ is a function extracting the inner angle attribute of an edge/bi-segment. This angle is formed by the two connecting segments within the bi-segment.
Fig. 3. The BSG construction for a sleeve panel shape. (a) A regularized panel shape for the sleeve section of a dress. (b) The bi-segment decomposition of the panel shape in (a). (c) The graph representation of the corresponding BSG model for the sleeve panel shape.

(v) \( \Lambda_E : E \to \{0,1\} \) is a function to extract the segment ratio attribute of an edge/bi-segment. This is the ratio between the lengths of the two connecting segments within the bi-segment. Note that the ratio is calculated by the length of the shorter segment divided by that of the longer segment to achieve rotation invariance.

(vi) \( C_E : E \to [0,\pi] \times [0,\pi] \), and \( C_E(e_{ij}) = (\kappa_1, \kappa_2) \), where \( \kappa_1 \) and \( \kappa_2 \) are the curvatures of the segment \( i \) and \( j \) at their intersection point. Here \( \kappa_1 \) and \( \kappa_2 \) are sorted in an ascending order to achieve rotation invariance.

Fig. 3 shows the process of the construction of BSG model of a sleeve panel shape. The original panel is first regularized into segments as \( \{a, b, c, d\} \), as shown in Fig. 3(a). It is then decomposed into a bi-segment sequence of \( \{B_1, B_2, B_3, B_4\} \) (Fig. 3(b)). According to Definition 3, the features of it’s BSG representation (Fig. 3(c)) are calculated in Table I.

<table>
<thead>
<tr>
<th>V</th>
<th>E</th>
<th>R_E</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>( B_1 = (c, d) ) (a, b) ( R_{1,c} )</td>
<td>( (a, b), (0, 0) )</td>
</tr>
<tr>
<td>b</td>
<td>( B_2 = (b, c) ) (a, b) ( R_{1,b} )</td>
<td>( (b, c), (0, 0) )</td>
</tr>
<tr>
<td>c</td>
<td>( B_3 = (a, b) ) (a, c) ( R_{1,a} )</td>
<td>( (a, c), (0, 0.3198) )</td>
</tr>
<tr>
<td>d</td>
<td>( B_4 = (a, d) ) (a, d) ( R_{1,d} )</td>
<td>( (a, d), (0, 0.5873) )</td>
</tr>
</tbody>
</table>

Using the BSG shape descriptor, the panel shapes are represented in the form of weighted graphs, which characterize both geometric and topological features. In this way, the comparison of two shapes is transformed into a graph matching problem.

IV. WDPG-MST MATCHING METRIC

In this section, we propose a new matching metric based on weighted direct product graph (WDPG) to transform the graph matching problem into a minimal cost spanning tree problem. In order to give the distance measure, we first define the graph product operation to generate the product graph from two BSGs.

A. Product Graph Construction

We start with some basic notations from linear algebra and graph theory that will be used.

**Definition 4 (Modified Kronecker Product).** For two real matrices \( A \in \mathbb{R}^{m \times n} \), \( B \in \mathbb{R}^{r \times s} \), the Modified Kronecker Product \( A \otimes B \) is defined as

\[
A \otimes B = \begin{pmatrix}
    |A_{11}|r \times s & \cdots & |A_{1n}|r \times s
    
    \vdots & \ddots & \vdots
    
    |A_{m1}|r \times s & \cdots & |A_{mn}|r \times s
\end{pmatrix}
\]

where \( |A_{ij}|r \times s \) denotes a \( r \times s \) real matrix and all the elements of that matrix is \( A_{ij} \), and \( \text{abs}(A) \) is a \( r \times s \) matrix and each element of \( \text{abs}(A) \) is the absolute value of the corresponding elements of matrix \( A \).

Based on the Modified Kronecker Product, the product operation of two weighted graphs is then defined in the following.

**Definition 5 (Weighted Direct Product Graph (WDPG)).** Consider two graphs \( G_1(V_1, E_1) \), \( G_2(v_2, E_2) \) and their weighted matrices are \( W_1 \in \mathbb{R}^{m \times n} \) and \( W_2 \in \mathbb{R}^{r \times s} \) respectively, then their weighted direct product graph (WDPG) \( G_1 \otimes G_2 \) is a graph with vertex set \( V_{1 \times 2} = \{ (u_i, v_r) : u_i \in V_1, v_r \in V_2 \} \), edge set \( E_{1 \times 2} = \{ ((u_i, v_r), (u_j, v_s)) : (u_i, u_j) \in E_1 \land (v_r, v_s) \in E_2 \} \) and weighted matrix \( W_{1 \times 2} = W_1 \otimes W_2 \).

From Definition 5, the WDPG \( G_{1 \times 2} \) is a graph that each vertex involves a pair of vertices over the two graphs \( G_1 \) and \( G_2 \), an edge exists in \( G_{1 \times 2} \) if and only if the corresponding vertices in \( G_1 \) and \( G_2 \) are both connected, and the weighted matrices are determined by the Modified Kronecker Product between the weighted matrix \( W_1 \) and \( W_2 \), i.e. \( W_{1 \times 2} = W_1 \otimes W_2 \).

Fig. 4 illustrates two weighted graphs with different numbers of nodes and their corresponding WDPG. Each vertex of the WDPG is labeled with a pair of vertices, each edge is formed if and only if the corresponding vertices in both original weighted graphs are neighbors, and the weight of each
edge in WDPG is assigned by the absolute difference value of the corresponding weights of the edges in both original graphs. For example, the weight of edge \((aa', bb')\) in WDPG is 0, since the weight of edge \((a, b)\) in graph \(G_1\) (Fig. 4(a)) is equal to the weight of edge \((a', b')\) in graph \(G_2\) (Fig. 4(b)). However, the weight of edge \((aa', bd')\) is 0.2, because the weight of edge \((a, b)\) is 0.5 and the weight of edge \((a', d')\) is 0.3, hence the absolute difference of the weights between these two edges is 0.2.

B. Similarity Measurement

The graph product operation actually captures the difference between any two edges, each from one weighted graph. Each matching of the two comparing edges is built as the corresponding edge in their WDPG, and the difference of the matching is assigned as the weight of that edge. In this way, the similarity between two weighed graphs can be measured as the minimal sum of the differences of all edge-matching pairs. Therefore, the problem of matching two weighted graphs is transformed into the minimal spanning tree (MST) problem on their WDPG. To this end, we propose the “WDPG-MST matching metric” as similarity measurement and it is defined as follow.

**Definition 6** (WDPG-MST Matching Metric). Suppose the edge set of the Minimal Spanning Tree (MST) \(^1\) of the WDPG is denoted by \(\{e_{i_1}, e_{i_2}, \cdots, e_{i_{|E|}}\}\) and the corresponding weighted is \(\{w_{i_1}, w_{i_2}, \cdots, w_{i_{|E|}}\}\), then our similarity measurement between two original graphs is defined by

\[
d(G_1, G_2) = \sum_{k=1}^{||V||-1} \frac{w_{ik}}{||V|| - 1}
\]

As mentioned above, the sum of weights of MST of the WDPG captures all the minimal edge-matching pairs between two original graphs, because the weight of each edge in WDPG incorporates the difference between two corresponding weights of edges in the original graphs. Hence, the WDPG-MST measurement can capture the minimal matching cost between two weighted graphs.

When calculating the similarity between two BSGs \(G\) and \(G'\), first, we decompose each BSG into five weighted graphs \((G_1, \cdots, G_5, G'_1, \cdots, G'_5)\) in terms of different features defined in Definition 3. In particular, we can obtain a weighted graph \(G_1 = (V, E, R_E)\) according to topological feature \(R_E\). Also, we can get other four weighted graphs \((G_2 = (V, E, \Theta_E), G_3 = (V, E, \Lambda_E), G_4 = (V, E, C_E), G_5 = (V, E, C_E))\) by inner angel attribute, ratio attribute, curvatures \(\kappa_1\) and \(\kappa_2\) respectively. Second, according to the WDPG-MST metric, we compute the average similarity value among the five weighted graphs, which are induced from the BSGs. Here, we use classical Prim algorithm \([19]\) to calculate the MST, resulting in the worst-case time complexity of \(O(n m \log(n) + |E|)\), where \(n\) and \(m\) (\(m \leq n\)) denote the number of vertices of the BSG, and \(|E|\) denotes the number of edges of the direct product graph\(^2\).

It is also worth to notice that the proposed WDPG-MST matching algorithm can be used to both global matching and partial matching of the panel shapes, as the WDPG is not constrained only to graphs of the same number of nodes.

V. Experiments

In this section, we conduct experiments to verify the effectiveness and efficiency of our proposed method. Since panel retrieval is our focus in the garment design process (as shown in Fig. 1), we mainly examine the retrieval performance based on the BSG shape descriptor and WDPG-MST matching metric.

We compare our method with different panel matching approaches \([2][3][20]\) that have been proposed. We also compare the matching performance based on different feature descriptors. In section 5.1 we describe the experimental setup, including database collection, evaluation criteria and experimental environment. In section 5.2 we show the performance of different panel shape matching approaches and give out discussions.
A. Experimental Setup

We first extend our previous panel shape database [2][3]. We invite 10 experienced garment designers to draw common and standard panel shapes with traditional CAD software. A new panel database with 454 panel shapes is successfully established. Fig. 5 shows some typical panel samples in our new database.

Second, in order to perform the panel matching task, we ask designers to draw input panel shapes using our sketching interface. Our goal is to retrieve the similar panels as to the input shape from the database. To this end, we build up a corresponding feature database. As can be seen in Fig. 5, different panel shapes have different features. Here we apply our proposed BSG shape descriptor, which involves four types of different features, to extract features from the original panel shapes.

We then calculate the similarity between the input panels and the panels from the database. We return the top-$K$ panels as our retrieval results. In our experiments, we choose $K$ to be 5, 10, 15 and 20 respectively. It is worth to notice that the similarity measures used are based on the shape representation methods. Specifically, we use the proposed WDPG-MST similarity metric (Definition 6) for our proposed BSG feature descriptor. For other shape representation methods as attribute strings [20] and bi-segment descriptor [2][3], cosine similarity is used as metric. All the experimental results are averaged over all the input panel queries.

![Fig. 5. Illustration of the panel shape database.](image)

To evaluate the retrieval performance of the shape representation and similarity measure methods, we make use of two well-known criteria, i.e. the precision and recall rates [21]. They are widely used to evaluate the correctness of an information retrieval algorithm. The precision rate is defined as the ratio between the number of relevant returned shapes and the total number of returned shapes; while the recall rate is defined as the ratio between the number of relevant returned shapes and the total number of relevant shapes. Obviously, if more items are returned, the recall will be increased but the precision will be decreased. In a recall/precision graph, a higher curve signifies better retrieval performance. Besides of the precision and recall rates, we also examine the response time for the panel searching task.

All the experiments are conducted on a workstation with an Intel Core i7 2.8GHz CPU, GeForce GTX 1792 MB, 8 GB Ram using Windows 7. For interaction, a large freehand touch surface [22] is used to perform the modeling task. And all the algorithms are implemented by Visual C++.

B. Results and discussion

We compare our proposed WDPG-MST matching method with other methods, including bi-segment shape matching [2][3] and attribute strings matching [20]. We also compare the matching performance of the proposed BSG shape descriptor to the cases of using only one type of feature of the BSG model as panel shape descriptor. These descriptors include the topological feature descriptor $R_E$ (defined in Definition 2) and three geometric shape descriptors as inner angle $\Theta_E$, ratio $\Delta_E$ and curvature $C_E$ (in Definition 3). For convenience, we use abbreviations to denote different methods. Specifically, “our” denotes our proposed method, “BS” denotes bi-segment shape matching, “AS” denotes attribute strings matching, “TF” denotes topological features and “IA”, “RA” and “Cur” denote the geometric features of inner angle, ratio attribute and curvature descriptors respectively.

TABLE II

<table>
<thead>
<tr>
<th>Methods</th>
<th>Prec@5</th>
<th>Prec@10</th>
<th>Prec@15</th>
<th>Prec@20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our</td>
<td>4.75</td>
<td>8.75</td>
<td>12.25</td>
<td>15.75</td>
</tr>
<tr>
<td>BS</td>
<td>4.50</td>
<td>8.50</td>
<td>11.75</td>
<td>15.25</td>
</tr>
<tr>
<td>AS</td>
<td>3.50</td>
<td>7.25</td>
<td>10.25</td>
<td>13.25</td>
</tr>
<tr>
<td>TF</td>
<td>3.50</td>
<td>6.50</td>
<td>9.30</td>
<td>12.00</td>
</tr>
<tr>
<td>IA</td>
<td>3.65</td>
<td>6.90</td>
<td>9.75</td>
<td>12.60</td>
</tr>
<tr>
<td>RA</td>
<td>3.60</td>
<td>6.80</td>
<td>9.90</td>
<td>12.40</td>
</tr>
<tr>
<td>Cur</td>
<td>4.25</td>
<td>8.10</td>
<td>11.40</td>
<td>14.00</td>
</tr>
</tbody>
</table>

The retrieval precision among various panel shape representation and matching approaches. (in Definition 3). For convenience, we use abbreviations to denote different methods. Specifically, “our” denotes our proposed method, “BS” denotes bi-segment shape matching, “AS” denotes attribute strings matching, “TF” denotes topological features and “IA”, “RA” and “Cur” denote the geometric features of inner angle, ratio attribute and curvature descriptors respectively.

The retrieval precision among different numbers of returned samples (5, 10, 15 and 20) are shown in Table II. From Table II, we can observe that our proposed method outperforms the others. The topological feature based shape descriptor performs the worst. In particular, by a simple statistical analysis, we find out that our proposed method boosts the performance by improving the precision rates of the BS, AS, TF, IA, RA and Cur methods by 4.01%, 23.7%, 33.33%, 26.90%, 27.84% and 9.94% respectively. The average retrieval precision even reaches 0.95 under the case of $K = 5$. These results indicate that our proposed BSG representation actually captures comprehensive features of the panel shapes.
for the retrieval task. The results also imply our WDPG-MST based similarity measure is an effective metric to evaluate the similarity between two graph-based BSG representations of panel shapes.

The precision-recall graph is depicted in Fig. 6. Also, as shown in Fig. 6, the precision-recall curve of our proposed method is the highest among all the approaches, which further confirms that the proposed approach outperforms the existing methods. Generally, the precision value decreases as the recall value increases over all methods. The Cur method performs better than the TF, IA and RA methods. That is to say, the curvature descriptor is more powerful than the others to characterize the intrinsic features of the panel shapes. Moreover, the BS method outperforms the Cur method. This is because the bi-segment representation captures both the curvature and the topological features as described in [2].

We also compare these panel shape representation and matching methods according to their time costs. Our results are depicted in Fig. 7. As we can see that the average time of our proposed method is around 50ms. That is to say, the performance of the proposed method still sufficiently fulfills the time requirement of the realtime retrieval task.

VI. CONCLUSIONS

In this paper we present a novel graph modeling and matching approach for sketch-based garment panel design. We first propose a bi-segment graph (BSG) model to effectively represent the content of the panel shape. The BSG describes the panel shape as a sequence of connected segments/primitives, as well as the corresponding geometric and topological features among them. Then a new matching metric based on weighted direct product graph and minimal spanning tree (WDPG-MST) is proposed to calculate the similarity between two panel shapes. The WDPG-MST matching metric successfully transforms the graph matching problem into a spanning tree problem based on graph product operation. Moreover, both global and partial matching of the panel shapes are supported by the WDPG-MST measurement. Finally, we provide a sketching interface for panel shape input and editing. We also provide visual feedback to simulate and visualize the garment design result to users in 3D. Experiments and demonstrations show the encouraging matching accuracy of the proposed method.

For future work, we would further extend the application domains of our BSG modeling and WDPG-MST matching method, i.e. vector shape recognition and retrieval. It is also promising to further reduce the computational complexity of the matching metric to achieve higher realtime performance.

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