Cognitive Garment Design Interface Using User Behavior Tree Model

Shuang Liang, Eddie C.L. Chan, George Baciu, Rong-Hua Li
Department of Computing
The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong
{cssliang, csclchan, csgeorge, csrhli}@comp.polyu.edu.hk

Abstract

An effective user interface helps to hinge on ideas and imagination from fashion designers and most importantly express their artworks with their flair. Shape, material, color, movement and flow—all these qualities give a piece of clothing its uniqueness, and the designer uses drawings to communicate his intentions. Sketches of various views of the garment provide the preliminary clues needed for bulk manufacturing. However, it is very difficult to develop a common user interface platform even as intuitive as sketching interface, since different designers have different senses and habits to work on their drawings. In this paper, we focus on this sketching issues and propose a user behavior tree (UBT) model that helps to return the corresponding shapes according to the preference of user. Also, in the front-tier, we provide a 3D user interface for editing the clothing panels, adjusting the sewing lines and simulating the garment design. Experiment results show the effectiveness and efficiency of the proposed model.

1. Introduction

In traditional manufacturing and textile garment production, pattern technologists (tailors) design the 2D garment panels according to the stylists’ design concepts before they are sewn together to form a complete dress [1]. Garment computer-aided design systems have been rapidly developed in recent years and have become the basis for the clothing design process. Typical commercial design platforms are built towards rigid shape generation and editing. There are also some systems [5][11][13] incorporate sketching interface to provide designing flexibility and freedom. However, operating a CAD system requires extensive prior training, and it’s neither flexible to operate nor efficient to carry out validity assessment based on prior domain knowledge. It is mainly because current CAD technology for garment design is mainly conceived for 2D geometric modeling for cloth shapes, but generally does not provide high-level interactive environment with aesthetic and functional features. Most of CAD systems require to have a complete sketch input. It would be better to have a dynamic predictions or suitable suggestions during the partial sketch process.

In this paper, we propose a user behavior tree (UBT) model that capture all of the drawing procedures (habits) for hundreds of standard panel shapes from designers. Second, we develop a partial matching algorithm from the proposed UBT model. We make use of UBT model and the partial matching algorithm to dynamically return the possible predictions and suggestions along with the shape drawing process. Finally, in the front-tier, we provide a 3D user interface for modifying the clothing panels, adjusting the sewing lines and simulating the final garment design.

There are three major contributions of our proposed model. First, the proposed model effectively gives a proactive user interface to speed up the garment design progress. Second, the suggestions are tailor-made derived from a corresponding designer which fits more exactly the flair of every designer. Third, the 3D user interface helps to visualize the garment design and it is much more convenient and cheaper to view the appearance of 3D simulation design rather than a real final garment.

The rest of paper is organized as follows: Section 2 presents the related work of partial shape matching. Section 3 describes the derived process of UBT. Section 4 presents the partial matching algorithm from UBT model. Section 5 describes the experiment design and setup. Section 6 discusses the performance evaluation of UBT model. Finally, Section 7 offers our conclusion and future work.

2. Related Work

In this section, we summarize current research works of shape matching. Shape matching has been well investigated in computer vision in the last few decades [2], [3], [6], [8], [9], [10], [12] and [16]. There are three types of
shape matching algorithms including complete-to-complete matching (CCM), partial-to-partial matching (PPM), and partial-to-complete matching (PCM).

As our work focuses on partial matching. We only discuss PPM and PCM in following subsections.

2.1. Partial-to-Partial Matching (PPM)

PPM copes with the occlusion when comparing two shapes, i.e., matching some part of shape \( B \) as fit as some part of shape \( A \).

Chen et al. [3] applied the smith-waterman algorithm to find local alignments between two shapes. The matching procedure is solved by dynamic programming, which suffers from high computational complexities.

Lateck et al. [6] proposed to transform shapes into sequences and used an algorithm that determines the best matched subsequence to the query. They mapped the problem of determining the best-matched subsequence to the problem of finding a path in a directed acyclic graph with lowest cost.

Saber et al. [9] presented a partial shape recognition algorithm by sub-matrix matching using a proximity-based shape representation. They selected the points with maximum curvature along the shape as feature points to compute distance matrices for each candidate shape region and sample template. A sub-matrix matching algorithm is then used to determine correspondences for evaluation of partial similarity between a sample template and a candidate object region.

Partial-partial matching is usually transformed into a sub-graph/sub-matrix matching problem. However, these algorithms are generally computational-expensive.

2.2. Partial-to-Complete Matching (PCM)

PCM refers to finding the shapes which contain a part that is similar to the query shape, i.e., matching some part of shape \( B \) as fit as possible to the complete shape \( A \). Many local shape descriptors were presented to deal with PCM problems.

Ozcan et al. [8] used genetic algorithm to perform partial matching based on attributed strings. Their approach claimed to be fast, but they cannot guarantee to obtain the optimal result.

Berretti et al. [2] proposed a local shape descriptor which partitions a shape into tokens and represents each token by a set of perceptually salient attributes with orientation and curvature information. But the above method only considered geometric features while neglected topological features.

Tanase et al. [10] used turning function of two polylines to represent local shape information. Chen et al. [2] improved it by applying features of both turning angle and distance across the shape (DAS). Local shape descriptor based on turning angle is invariant to scaling, translation, and rotation. Due to the limitation of turning function, it only works well with polygons, and may not be suitable for garment panel shapes.

Chi et al. [4] proposed a primitive based descriptor according to the law of Gestalt theory. The law of focal point, proximity, continuity, similarity and symmetry are adopted to construct a local shape descriptor, which is effective and efficient in partial object retrieval in cluttered environment. However, their method only considers two types of primitives of arc and line and could not represent complex shapes. Finally, these PCM algorithms are mostly based on static geometric information, but fail making use of the dynamic features from shape generation process.

![Figure 1. Garment panel shape](image)

3. User Behavior Tree Model

There are basically four observations of user behaviors of dynamic garment design process: 1) Informal activity. Informal drawing is usually involved with sketching interactions which allows for quick drafting and creative design. 2) Partial matching. Partial matching with dynamic feedback is used to predict user’s intention to the rest of drawing. This could save user effort in further process. 3) Closed Shape. Typically, panel shapes are closed-shapes that could be decomposed into lines and curves [1], such as the cuff of a sleeve and collar, as shown in Figure 1. 4) Spatial connectivity. The behavior when users drawing a panel shape, they tend to divide shapes into several strokes connecting one with another in the sketching process.

Based on observation 4 that users tend to draw panel shapes connectively to achieve a continuous design process, we propose a tree-based user behavior model, which is called user behavior tree (UBT) in this paper, to capture all of the drawing procedures for a given panel shape.

Figure 2 illustrates the construction of UBT from a sleeve panel shape. The panel shape in Figure 2(a) can be represented with four bi-segments by our bi-segment model, which represents a connective segment-pair in the shape and was proposed in our previous work [7]. Figure 2(b) shows the UBT of the whole drawing space. The corresponding
user behavior of panel drawing in Figure 2(a) can be modeled by a UBT path in the Figure 2(c). It is important to notice that a designing sequence can be represented by a bi-segment sequence readily according to our bi-segment panel shape descriptor. The detailed tree constructing procedure is described in the following.

In the UBT model, the first bi-segment in a bi-segment-driven drawing sequence may be either $B_1, B_2, B_3$ or $B_4$. To this end, we introduce a dummy node as root node of the tree and each bi-segment of the panel shape as its children nodes. Recall that, in our bi-segment-based shape descriptor, a bi-segment involves two connective segments. Without loss of generality, assume the first bi-segment in a drawing sequence is $B_2$. Then, the second bi-segment is either $B_1$ or $B_3$ based on observation 4. Thereby $B_1$ and $B_3$ will be constructed as children nodes of $B_2$. Suppose the second bi-segment in the drawing sequence is $B_3$, then the next bi-segment could be either $B_1$ or $B_2$, which form the children nodes of $B_3$. The remainder branches of the tree are constructed by drawing sequences starting with other probable bi-segment ($B_1, B_3$ and $B_2$) in the same way.

According to our UBT model construction procedure, each path from the root, or more specifically a secondary node, to a leaf node of the tree denotes a different drawing sequence to complete a whole panel shape. Obviously, the number of various user behavior sequences is $n \times 2^{n-2}$. This makes the optimal partial matching between two shapes of exponential computational complexities.

### 4. UBT-Driven Partial Matching Algorithm

In order to reduce the complexity of optimal partial matching, we propose a greedy algorithm to match the input partial shape with the reference shape in the database based on both the local similarity measure between bi-segments [7] and the user behavior model UBT. In our algorithm, the partial matching problem is transformed into a problem of determining a sub-path with maximum similarity in the UBT.

Suppose the input shape is given by $I = (i_1, i_2, \ldots, i_m)$ and the reference shape is represented by $R = (r_1, r_2, \ldots, r_n)$, where $i_k (1 \leq k \leq m)$, $r_j (1 \leq j \leq n)$ stand for the bi-segment descriptor of the input shape and that of the reference shape respectively. According to UBT, the partial matching between shape $I$ and $R$ can be converted to finding a sub-path of $m$-length that has the maximum similarities in the UBT of shape $R$. Here we present a greedy algorithm to avoid exponential complexity of optimal matching, and the detailed description of the UBT-

![Figure 2. Illustration of user behavior tree (UBT) model](image)

**Algorithm 1. Partial matching algorithm**

**Input:** A input shape $I = (i_1, i_2, \ldots, i_m)$ and the reference shape $R = (r_1, r_2, \ldots, r_n)$, where $i_k (1 \leq k \leq m)$, $r_j (1 \leq j \leq n)$ stand for the bi-segment descriptor of the input shape and that of the reference shape respectively.

**Output:** The matching results $(r_{i_1}, \ldots, r_{i_m})$

**Step1:**

Construct the UBT model for shape $R$ represented as $UBT(R)$.

**Step2:**

for $j \leftarrow 1$ to $n$

compute $sim(i_1, r_j)$

end for

**Step3:**

$(r_{h_1}, \ldots, r_{h_k}) \leftarrow TOP_k\{sim(i_1, r_j), j = 1, \ldots, n\}$

where $TOP_k\{A\}$ denotes a operator to choose the top $k$ maximum elements of set $A$.

**Step4:**

for $l \leftarrow 1$ to $k$

$r_{c_l} \leftarrow r_{h_l}$

for $u \leftarrow 2$ to $m$

$r_{c_u} \leftarrow \max\{sim(i_u, r_{temp})$, where $r_{temp}$ is a child node of $r_{c_{u-1}}$ in $UBT(R)\}$

end for

$Sim \leftarrow \sum\{sim(i_u, r_{c_u}), 1 \leq u \leq m\}$

where $\sum\{A\}$ is a operator to sum all the element of set $A$.

if $Sim > Max$

$Max \leftarrow Sim$

$(r_{t_1}, \ldots, r_{t_m}) \leftarrow (r_{c_1}, \ldots, r_{c_m})$

end if

end for
driven partial matching algorithm is given as algorithm 1.

5. Experimental Setup

In this section, we describe a partial matching experiment to verify the effectiveness and efficiency of our proposed method. We conducted our experiment with 200 panel shapes, which are collected by ten experienced panel designers. The machine we used in our experiment was a HP TouchSmart with AMD Turion X2 RM-74(2.2GHz) CPU, 2GB memory.

We build up a feature database based on panel database. We extract features from panel shapes. We sample 5 points on each segment in our experiment, and get a 13-dimension numerical vector for each bi-segment. Finally, we evaluate the effectiveness of our proposed partial matching with attributed strings method [8]. We compare the matching result based on two drawing sets of front panel and skirt panel. Figure 3 shows different samples in panel shape database.

6.1. Result for 3D Garment Simulation

In this subsection we implement our model in a freehand, pen-centric, sketch-based tablet PC. We extend our previous work of an interactive 3D visualization system for assembling garment panels and producing 3D garments based on material characteristics and geometric constraints. The comments from designers show that our model helps to have fast prototyping of 2D panels and garment design. Figure 4 and 5 show the interactive draping and fitting visualization functionalities in our system.

6.2. Result for Panel Matching

Figure 6 and Figure 7 show the partial matching results of both the proposed approach and the attributed strings method based on two drawing sets of front panel and skirt panel. We arrange the best matching result first and the worst result at last. The top 10 matched results indicate two major achievements. First, our proposed bi-segment descriptor outperforms attributed strings descriptor. This result further confirms our bi-segment descriptor could enhance the representation power of shape descriptors and thus get a higher partial matching accuracy. Second, our proposed descriptor improves the matching accuracy gradually according to steps along with the completion of the input panel drawing, while attribute strings descriptor cannot reveal this capability.

7. Conclusions

In this paper, we propose a user behavior tree (UBT) to model the designer’s drawing styles based on mild observations. Secondly, we develop a partial matching algorithm from the proposed UBT model. We make use of UBT
model and the partial matching algorithm to dynamically return the possible predictions and suggestions along with the shape drawing process. Finally, in the front-tier, we provide a 3D user interface for modifying the clothing panels, adjusting the sewing lines and simulating the final garment design. Experiments and demonstrations show the encouraging matching accuracy of the proposed model and friendliness of our 3D sketching interface.

We would further extend our work to mechanical drawing and optimize our model that guarantees low bound result of matching.

8. Acknowledgement

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References