Visualizing Human Utility from Video Demonstrations for Deductive Planning in Robotics

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Introduction

We want to teach a robot how to fold shirts through human demonstrations, and have it reproduce the skill under both different articles of clothing and different sets of available actions. In this work, we focus on visualizing human utility [1] via fluents of a piece of clothing as it is being folded. We accomplish the following tasks:

1. Track relevant fluents of the shirt as it is being folded
2. Visualize utility landscape of shirt-folding and its surrounding world
3. Survey and analyze human preferences

Background

- **Fluents** are important formulations in robot learning, as they capture the change in abstract spatial and temporal concepts of an object [4]
- Fluents in an object represent the changing properties of that object. We represent the world as a state in time called $s^{(t)}$. Formally, a fluent f is a function on a state $s^{(t)}$. We assume there is a large number of fluents, namely N, and index f_i for $i \in \{1, \dots, N\}$.
- In the process of cloth-folding, the 12 fluents of a shirt drift through a 12-dimensional space.
- Figure 2 visualizes a human demonstration as a trajectory of fluents (using MDS to reduce dimensionality to 3 dimensions).

Utility Landscape Visualization

- Visualize a 3-dimensional utility landscape, where the z-axis indicates the increasing level of utility of a state
- We use Support Vector Regression (SVR) to find a model for our data
- SVR Parameters were fine-tuned during cross-validation
  - Hyperparameters: Kernel, C, gamma, epsilon
- We added some noise to the data in order to obtain a landscape that contained lower utility contours for areas that are not part of the utility desires for shirt folding.
  - We did so by generating random points that are far away Euclidean distance-wise from the current centroids.
- The utility landscape shows a global perspective of candidate goal states

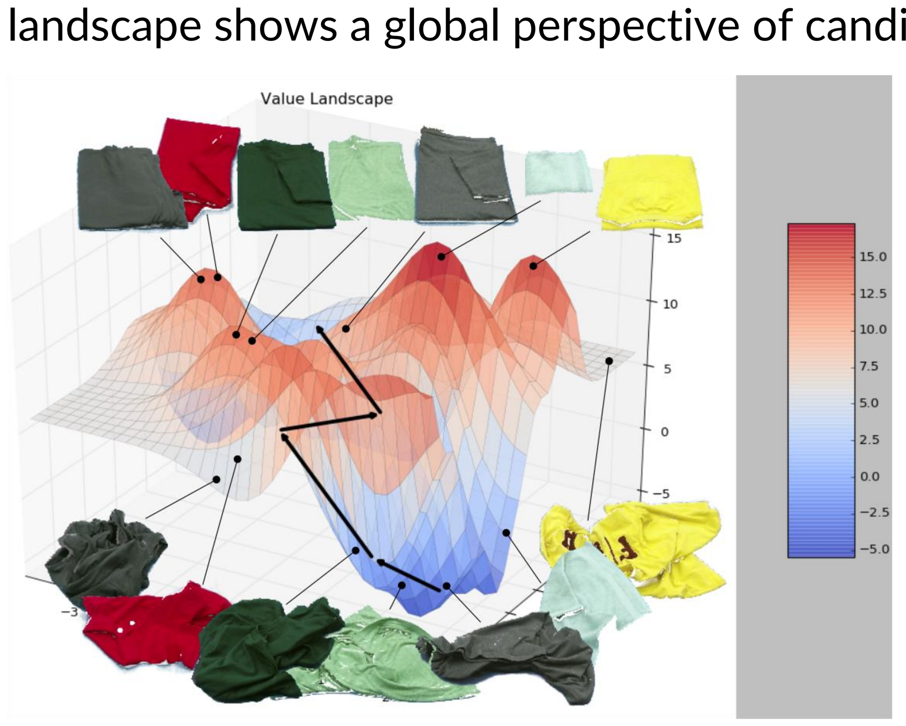

Figure 1: Visualization 3D utility landscapes of shirts in various states. We used MDS to scale our fluent data into 3 dimensions for easier visualization.

Fluent Tracking

- A bounding box is constructed around the shirt as it is being folded
- We used meanshift and GrabCut algorithm to track shirt fluents [2]
- At each frame, the vision processing step segments the cloth using graph-based techniques on the 2D RGB image
- The extracted 3D cloth point-cloud is aligned to its principal axis.
- Next, we extract fluents from the point-cloud being tracked.
  - Examples of a couple fluents include width, height, thickness, x-symmetry, y-symmetry, and the 7 moment invariants [3]

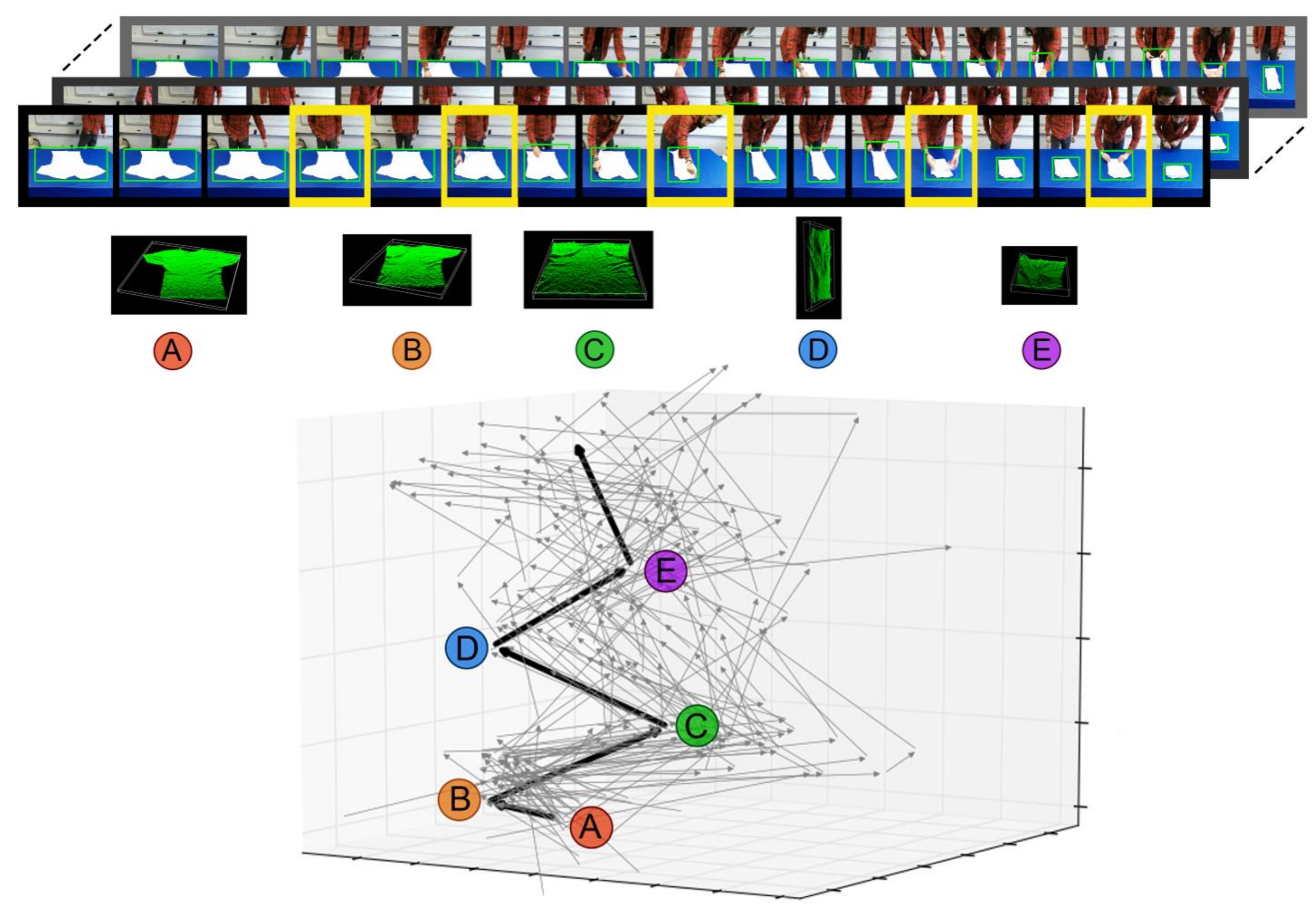

Figure 2: Fluents flow of a shirt as it transitions from one state to the next. We used MDS to scale our data into 3 dimensions for easier visualization.

Human Preferences

- The histogram of our human preference frequency is shown in Figure 3
- There is a clear preference vector that has more weight than the rest of the preference combinations; we can use this knowledge to determine if our robot's actions closely resembles that of the human preference.

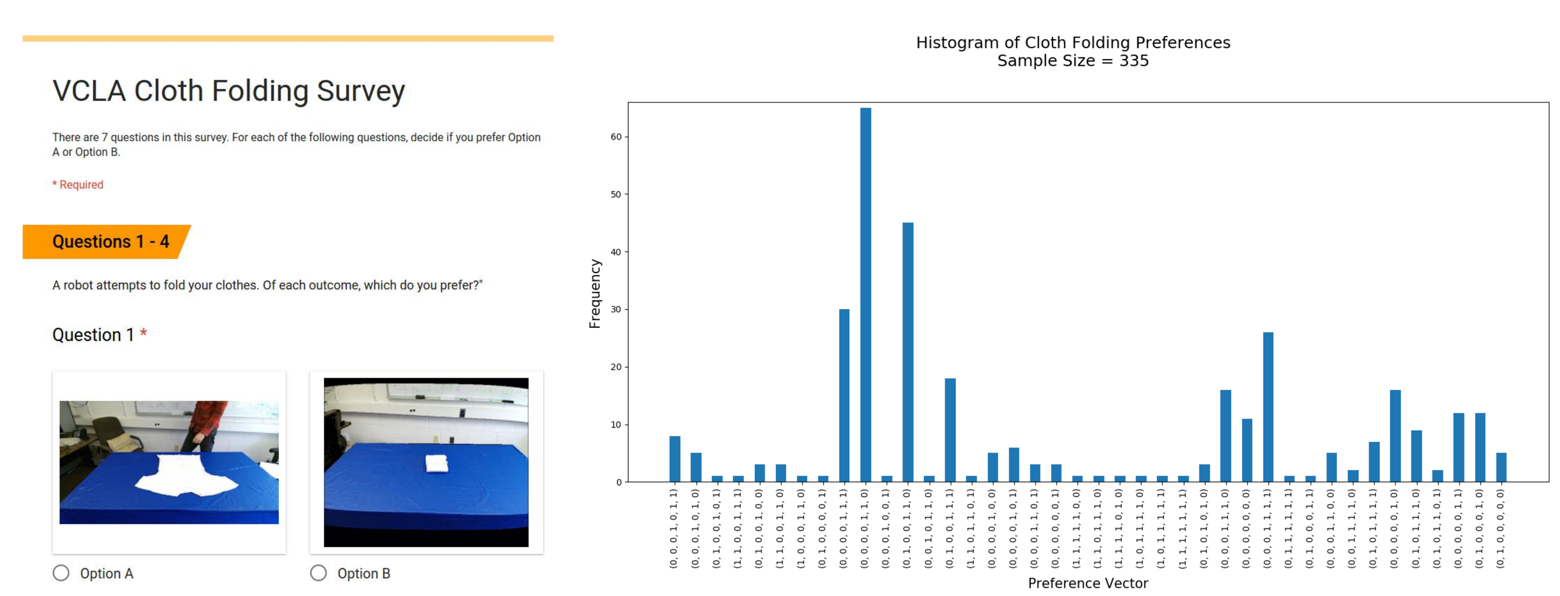

Figure 3: (left) Sample survey questions for a participant size of 335; (right) the histogram of their preferences for each scenario

Results

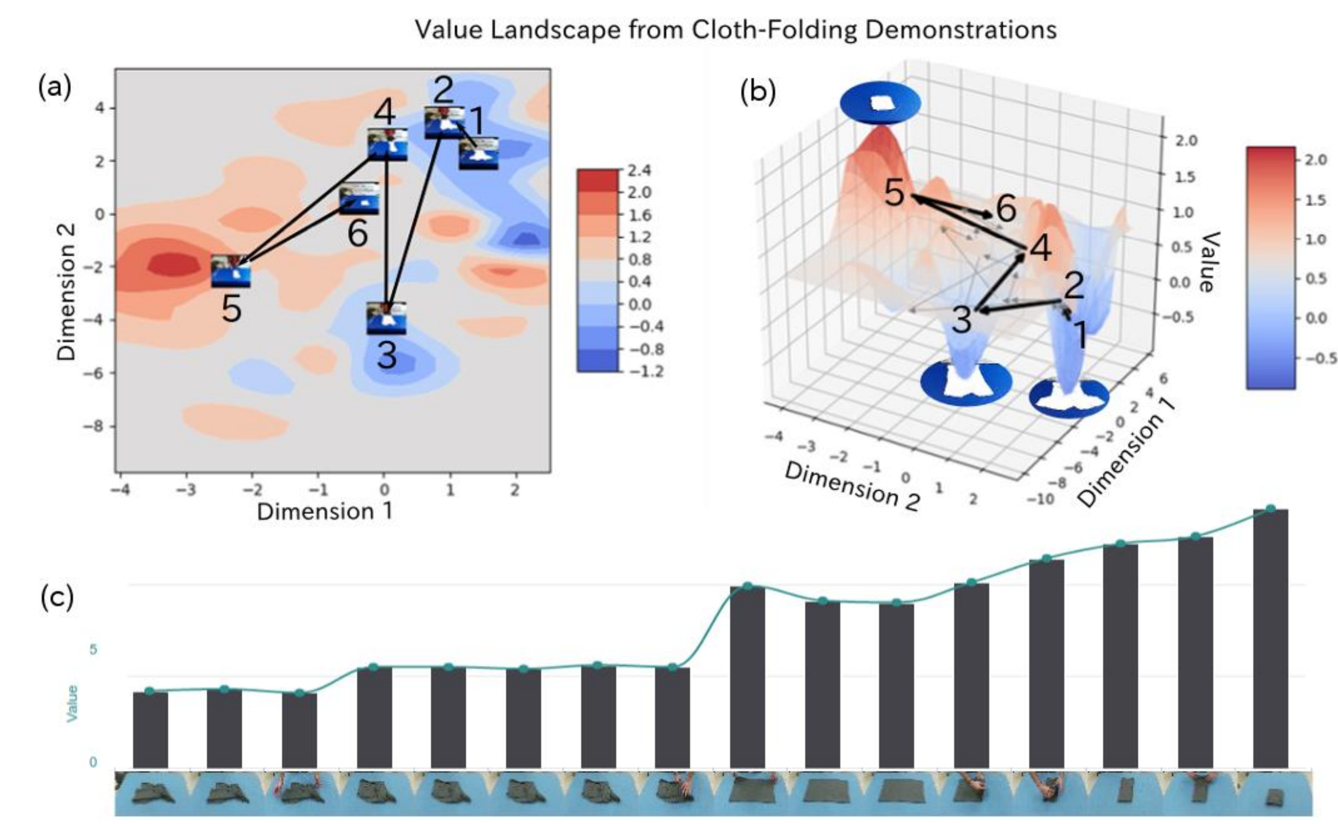

Figure 4: These landscapes are trained from 45 cloth-folding video demonstrations. (a) shows the 2D landscape; (b) shows the canyons for wrinkled clothes, and the peaks for well-folded clothes; (c) shows the gradual increase in utility of the shirt.

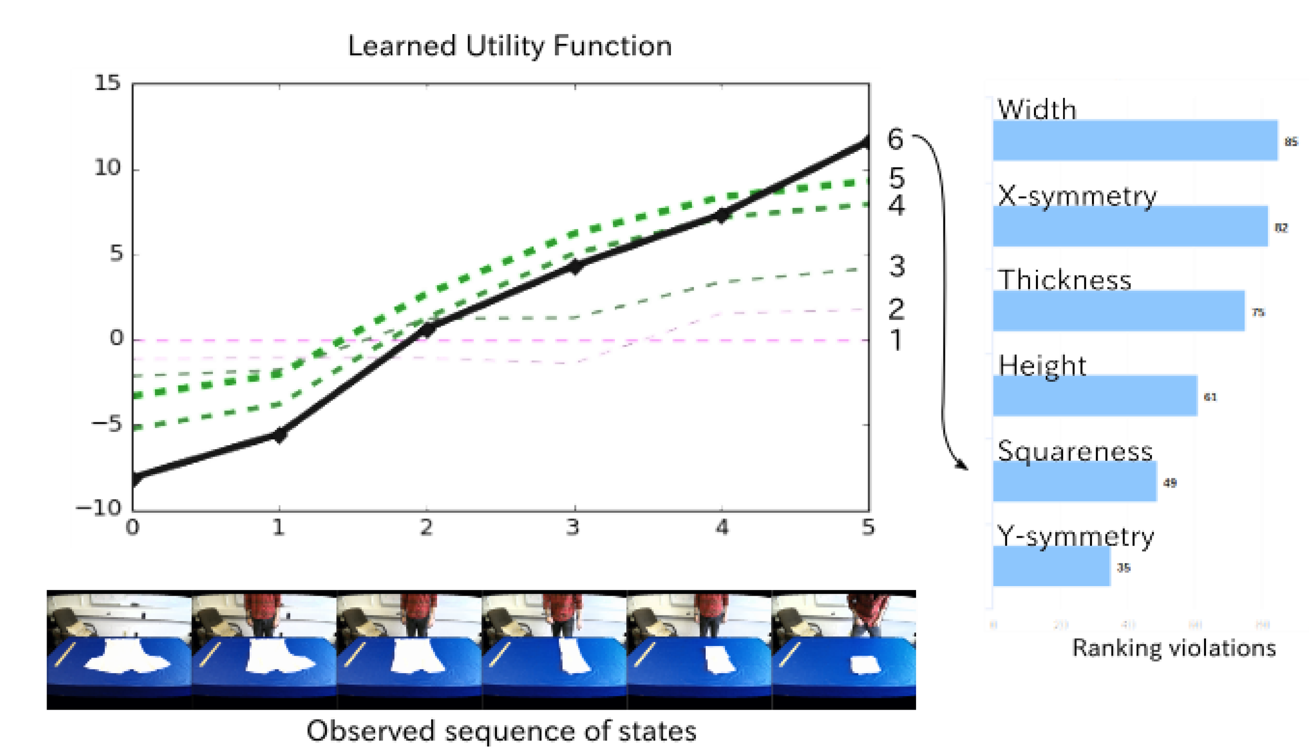

Figure 5: Value Landscape of various shirt states and learned utility function with fluent rankings

- We sampled random points and assigning lower utility values to them. After combining these "lower utility" points with the points that correspond to our own utility landscape, we generate a visualization that more closely resembles a typical utility landscape
- The bar chart in (c) shows the increasing utility from shirt-folding as the shirt is folded into a square
- Note that the sixth state seems to have lower utility than the fifth in (a) and (b). This indicates 'skepticism', as the robot may understand that the desired state is not always correct.

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Citations:

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