Learning 2D Subspaces for User-Controlled Robot Grasping

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Human control of high degree-of-freedom robotic systems, e.g. anthropomorphic robot hands, is often difficult due to the overwhelming number of variables that need to be specified. The problem is magnified for applications to biorobotics where efforts to decode user neural activity into control signals have demonstrated success limited to 2-3 DOFs with bandwidth approximately 15 bits/sec [5]. We address this sparse control problem by learning a high-dimensional manifold of robot poses in order to provide 2D subspaces for interactive control of a high-DOF robot hand.

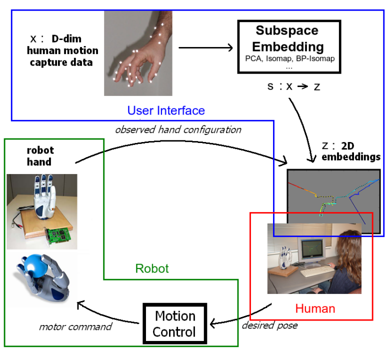
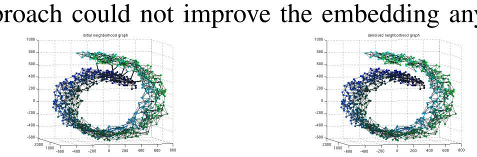


Fig. 1. **Diagram for hand control by the user using human hand motion capture data for training**

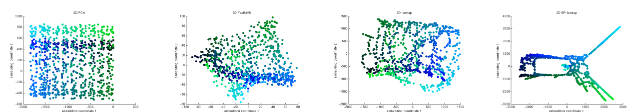
Previous attempts to control robot systems from low-dimensional user input have focused mainly on low-DOF systems. Example control applications are 2D cursor control [5], planar mobile robots [4], and discrete control of 4 DOF robot arms [3]. Bitzer and van der Smagt [1] performed high-DOF robot hand control by using kernel-based classification to index a discrete set of poses. A recent attempt in the same direction is the work in [2] where the grasping motion of a high-DOF robot hand is represented as a linear combination of 2 basis motion vectors (eigengrasps).

In our approach (Figure 1), we explore a set of current state-of-the-art dimension reduction techniques to derive a 2D control subspace from human hand motion capture data (x). This subspace is displayed on a 2D (computer) screen. Every time the user clicks on a point on the screen (z), its corresponding hand pose is sent as a motor command to the robot hand. By clicking on several points on the screen and observing the actions that the robot hand takes, the user is able to drive the hand to perform a predefined grasping task. Our approach was tested using a DLR/HIT robot hand with 13 DOF and the grasping tasks performed contained finger tapping motions, powergrasps and precision grasps example tasks (http://robotics.cs.brown.edu/projects/bpdenoising).

In addition, considering previously identified problems related to noise in manifold learning, we introduce a method for denoising neighborhood graphs in proximity-based dimension reduction techniques and combine it with Isomap [6](BP-Isomap). This method employs Belief Propagation [7] to send messsages between neighboring points in the graph to determine noisy edges. Although we were able to denoise successfully a noisy swissroll with 1000 points and 7 noisy edges (Figure 2), the motion data that we used in the previous experiments proved to have too many adjacent bad links and our approach could not improve the embedding any further.



(a) Initial neighborhood graph (b) Denoised neighborhood graph



(c) PCA (d) FastMVU (e) Isomap (f) BP-Isomap

Method	PCA	FastMVU	Isomap	**BP - Isomap**
Error	$2.00{\times}10^{12}$	$4.29{\times}10^{12}$	$1.26{\times}10^{12}$	$\mathbf{5.64 \times 10^{11}}$

(g) Embedding Error

Fig. 2. **Noisy "Swiss Roll" example (1000 points): (a) initial neighborhood graph with 7 noisy links highlighted, (b) denoised neighborhood graph, 2D embeddings of the original neighborhood graph with (c) PCA, (d) Isomap, (e) FastMVU, (f) BP-Isomap, (g) error between Euclidean distances in the noisy Swiss Roll embeddings and 2D ground truth distances.**

References

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