Statistical Methods for Haptics-enhanced Skill Transfer

Notes

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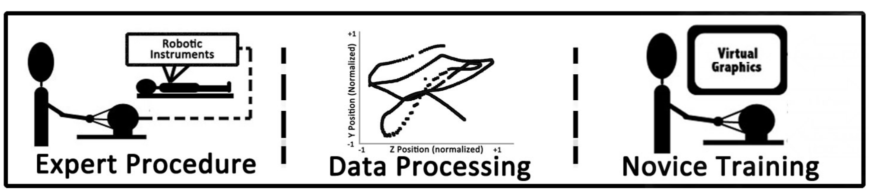
Overview and broader scope

Background: Haptics has the potential for enormous benefits in the scientific and medical communities that will result in safer surgical operations and new techniques capable of minimizing patient complications. Haptics refers to the use of robotic mechanisms capable of recording human motion and giving physical feedback. It has been shown that haptic simulation combined with visuals can have a significant benefit on user training [1, 7, 8]. While industrial solutions such as Intuitive Surgical's Da Vinci system have helped bring the idea of haptics into practice, there is a large amount of work necessary to create realistic control in both the simulation and real world domains. This work seeks to evaluate and develop methods for skill transference that use haptics to teach procedures to new users based on training from professionals. Skill transference includes the stages of: (1) having an expert perform a procedure, (2) using algorithms to process the data, and (3) teaching a novice using haptic guidance. Results will be compared to standard training techniques for determining effectiveness in a real-world environment.

Studies show that teaching robotic surgery skills in residencies increases the quality of performance for standard laproscopic procedures [2]. Thus, further research into this area will likely show benefits in future medical school training. There has been recent concern from residency directors claiming students don't have enough time for sufficient training, so by using haptics it is possible to teach the same amount of material in fewer hours. Furthermore, techniques developed in this research will allow for tracking of student progress to show quantitative assessment of skill.



Prior work in haptics-based skill transference shows promising results. Howard et al. evaluated Support Vector Regressions (SVR) and Artificial Neural Networks (ANN) for generalizing an experts handwriting using haptics and found 88% and 66% success measures respectively [1]. Goodrich et al. employ Q-learning, a reinforcement technique, for haptics-enhanced driving which shows increasedafety with fewer near-automobile collisions [3]. Schmidhuber et al. evaluated a Recurrent Neural Network (RNN) technique used for teaching a robot surgical knot-tying that shows a 23% decrease in time over a conventional robotic procedure [4].

Research: The plan is divided into three main areas: (1) implementation of a framework to incorporate skill transfer into a haptics platform, (2) evaluation of reduction and transference algorithms, and (3) deployment for medical procedures. Challenges come in the data processing and novice training stages. It is necessary to generalize the expert's movements due to inaccuracies and variability in the data. Other complications include teaching speed; when guiding a novice it may not be suitable for them to go at the same pace as the expert. High-dimensional data including position, velocity, time, and resisting forces captured from the expert need to be reduced to determine the output for the novice.

A principal component in this work is guiding the user's motion, therefore control methods will be necessary to determine the force outputs for the system. Significant work over the past decade in haptic rendering has shown success using rigid body simulations, potential-based force con- trol, and a variety of other methods as outlined by Otaduy and Lin [5]. Fundamental techniques such as using linear spring and damper models have been explored in my previous work on haptic rendering of virtual mechanisms [6] and my prior research on virtual fixtures and haptic rendering methods may also contribute to success in carrying out these experiments. The problem of generalizing the data will be tackled through non-linear component analysis and other statistical methods. Component analysis is used to reduce the dimensionality of the data and discover the most useful information. For example, it is still not apparent whether position or velocity measurements are most useful for training.

This work will answer important questions including: (1) what techniques are best at generalizing the expert's motion, (2) are current methods of constraining user motion adequate for complex procedures, and (3) how effective is haptic skill transference over standard learning methods. Quantitative analysis will be performed using a variety of metrics such as time of procedure, average mean error of the end effector position, and similarity measures.

See references at the bottom of this document

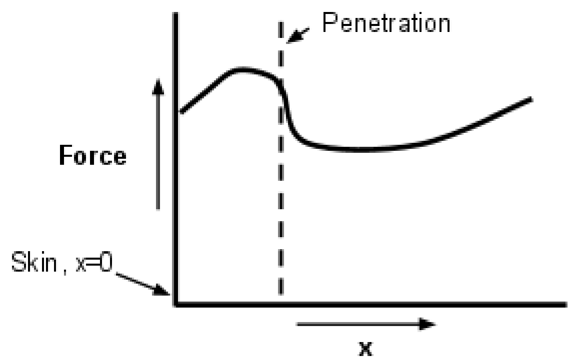
What has been done thus far

Thus far our research has focused on learning how to do a basic task such as drawing shapes and symbols. This is used as an example analogous to related work by Howard [1] and Goodrich [3]. An “expert” performs the task on a Novint Falcon or Phantom Omni device and in our case draws a line, circle, triangle, and complex shape. This is used as a training set for the learning algorithms. A model is extracted that generalizes the action and eliminates extraneous movements. Many input parameters need to be considered including position, velocity, and orientation. So far we have started to examine: nonlinear principle component analysis, moving least squares, and support vector regressions. The output of these algorithms is used to generate forces to teach a new user. We have gotten data from nPCA and LS but ultimately had problems with SVR, talked about below.

Data from the output of our algorithms is be used to compare each method’s ability to smooth the experts path while retaining fidelity. For the experiment to be effective it must be able to enhance the users ability to learn a new task. Therefore evaluation of a novice’s ability to complete a task post haptic-guidance is also important. Metrics such as Longest Common Subsequence (LCSS) have been used to compare paths in others studies such as [5] and are considered for this application. Ultimately a measure based on euclidean distance is evaluated. We have generated preliminary results which are discussed in the following documentation.

What should be done for continuation

We are looking at developing automated parametric models for use in haptic simulation. Doctors will be brought in to perform a needle insertion task using a Novint Falcon. The device will be placed upwards and the users will try to push through virtual skin. A model will be implemented using a look up table based on realistic skin forces. As the hand penetrates the virtual wall, the force increases until it starts to break through. At that point the force decreases.



Open Source Haptics Platform

H3D is an open source haptic software developed in part by Sensegraphics. It provides a framework for haptic and visual simulations. Models can be created using X3D, a graphic modeling standard (similar to VRML) which uses XML. Additional force generation can be implemented using Python and C++.

Primary H3D site: http://www.h3dapi.org

In spring 2010 I developed a set of ten tutorials on how to get started with haptics. The goal of these tutorials is to get a user started with H3D beginning with a basic introduction to X3D and progressively getting more in depth with the introduction of Python integration and ending with the creation of force effects with C++. The target demographic is anyone interested in haptics with some programming experience.

Tutorials: http://sites.google.com/site/h3dtutorials/

There are other components for H3D that allow for medical simulation (DICOM files), physics simulations, and other utilities. Some of these are discussed and linked to in the following document including H3D vs HAPI, H3DUtil, H3DUI, MedX3D, and Rigid Body Physics. Some other useful modules

https://docs.google.com/Doc?docid=0AWEDVAtaGbOtZGY2bjZwMmtfMzAyZGI1bmtncmg&hl=en

Other useful toolkits:
http://www.h3dapi.org/modules/mediawiki/index.php/Candy

- Fake haptics device

http://www.h3dapi.org/modules/mediawiki/index.php/Various_useful_nodes

- Paintable texture

References

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