Real-Time Workflow Segmentation for Needle-Based Interventions

Introduction

Motivation
Patient health and safety depends vitally on the skill of clinicians. Fortunately, health and safety can be significantly improved by thorough and effective training methods. In particular, it can be promoted using computer-assisted medical training systems.

Launched computer-assisted training systems have been previously proposed for medical applications. These systems can standardize medical training regimens and make up for limited time with expert supervisors by providing automatic feedback to trainees.

Objective
We propose a computer-assisted medical training system that can provide feedback in real-time. The proposed system uses a workflow segmentation algorithm to identify what task the user is performing based on the tracked needle trajectory, and provide instruction accordingly.

The key feature of the proposed system and algorithm is its application to training for any tracked procedure. This way, a new system need not be constructed each time a new procedure is introduced.

Methods

Workflow Segmentation Algorithm
The algorithm performs workflow segmentation by this procedure [1]:
1. Filtering: Gaussian Filter
2. Feature Extraction: Legendre Transformation
3. Dimensionality Reduction: Principal Component Analysis
4. Discretization: Global k-means Clustering
5. Probabilistic Modelling: Markov Models

First, the algorithm is trained with manually segmented procedures. Then, the algorithm can automatically segment subsequent procedures.

Needle trajectories of the ultrasound-guided epidural and lumbar puncture procedures performed by medical personnel (medical students, residents, clinicians) were recorded. The algorithm’s accuracy and applicability was assessed using the leave-one-out method.

Computer-Assisted Training System
Figure 1 illustrates the proposed system setup. The system automatically provides the same valuable feedback that an expert would provide in the traditional training protocol.

![Figure 1. Illustration of computer-assisted training system setup.](image)

This system uses the PLUS (www.pluslookit.org) software library to send needle-tracking data to the workflow segmentation algorithm. The algorithm is implemented as a 3D Slicer [2] module, as part of the SlicerIGT (www.slicer.org) extension. The module provides real-time instructions to the user based on the workflow segmentation. Because it is implemented in 3D Slicer, other SlicerIGT modules can be used in complement (i.e., visualization, metric calculation).

Results

Workflow Segmentation Algorithm
The proposed algorithm segmented the ultrasound-guided epidurals with 81% accuracy and the lumbar punctures with 82% accuracy on average. Figure 2 illustrates a histogram of the workflow segmentation accuracies.

![Figure 2. Histogram of automatic workflow segmentation accuracies for the ultrasound-guided epidural (blue) and lumbar puncture (red).](image)

Based on multiple manual segmentations of the recorded ultrasound-guided epidural procedures, the manual segmentations were 84% consistent. Relative to this, the automatic workflow segmentation algorithm is 93% accurate.

Computer-Assisted Training System
Figure 3 shows the workflow segmentation algorithm as a 3D Slicer module.

![Figure 3. Screenshot of workflow segmentation module in 3D Slicer.](image)

This module can be used to train the workflow segmentation algorithm, automatically segment a procedure in real-time, and provide the corresponding instructions. The instructions may be specified by an expert clinician, depending on the application.

Conclusions

The proposed workflow segmentation algorithm is sufficiently accurate for implementation in the proposed computer-assisted medical training system. The system has been successfully implemented as a 3D Slicer module within the SlicerIGT extension that uses the PLUS library. Future work includes validation of this system as a medical training tool, and optimizing the algorithm for real-time procedures with multiple tool input.

References & Acknowledgements


M. S. Holden was supported by the NSERC Alexander Graham Bell Canada Graduate Scholarship. T. Ungi was supported by the Queen's University- Ministry of Research and Innovation Ontario Post-Doctoral Fellowship. Funding support for this project in T. M. Peters' laboratory is from the Canadian Institutes for Health Research and the Canadian Foundation for Innovation. G. Fichtinger was funded as a Cancer Care Ontario Research Chair.