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Generative Adversarial Networks (GANs) for Simulating Human Behaviors during Bone Registration to Improve Registration Algorithms

THINK Surgical, Inc.

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Introduction

A robotic surgical system generally includes: a pre-operative planning software program to generate a surgical plan having a desired position for an implant relative to a bone; and a surgical robot to prepare the patient's bone to receive the implant as planned. One such robotic surgical system is the TSOLUTION ONE® Surgical System manufactured by THINK Surgical, Inc., which assists surgeons in total hip and total knee arthroplasty. The TSOLUTION ONE can accurately mill the bone to receive an implant as planned with minimal error, with overall good clinical outcomes. In order for the surgical robot to accurately mill the bone, the surgical plan needs to be accurately registered to the bone in the operating room. The final surgical plan generally includes a 3-D model of the patient's bone to assist with the registration, as well as a set of instructions for the surgical robot to accurately mill the bone in the planned location for the implants. Methods of registration are well-known in the art, such as the registration techniques described in U.S. Patent No. 6,033,415. In general, registration requires the collection of a plurality of points on the bone with a digitizer, where those points are matched with corresponding points or surfaces on the 3-D model of the bone using iterative closest point (ICP) algorithms. Since the registration accuracy has a direct influence on the resulting cut and implant fit, various registration algorithms have been proposed and improved upon to increase the registration accuracy. One method to assist with improving or developing the registration algorithms may involve the use of simulations. These simulations introduce error and random noise to the 'point collection' process to better mimic how a surgeon might collect points on the bone in the OR. The registration algorithms are then executed using points with random error and noise to determine a theoretical registration accuracy. While these simulations are helpful, the results are only sufficient enough to veto an algorithm change but not sufficient enough to approve an algorithm change. In addition, there is a room to improve the simulations to more accurately simulate real-world registration processes or scenarios.

Methods

To better simulate real-world registration processes (e.g., the registration point collection process), the use of generative adversarial networks (GANs) is proposed. GANs consist of two neural networks (Discriminative Network and Generative Network) that compete against each other to solve structural learning problems. GANs are widely used in deep learning applications. For example, GANs can generate pictures of human faces that are indistinguishable from real human photographs. The proposed method seeks to generate registration simulations that closely match real experimental data. By using historical registration data from previous clinical procedures and/or experiments performed on cadavers, the registration simulations can be incrementally improved and eventually mimic that of real experimental data. The GANs network for accomplishing this goal is as follows.

A discriminative network is setup to judge whether the simulated registration data (e.g., the random error and noise in the collected points) is close to experimental data (e.g., errors in the actual points collected by a surgeon on a cadaver bone). A generative network is setup to generate simulated registration data that best matches with historical experimental data to fool the discriminative network. The historical experimental data is used as initial rough estimates and derived from experimental data previously collected during cadaver experiments or on previous patient cases. Auto encoding, or a generator method like a GMM (Gaussian Mixture Model) may be used to help with providing these initial estimates. As the training progresses, both the discriminative network and generative network improves. The training cost function of the GANs minimizes the success rate of the discriminative network in identifying whether the simulation data is not real experimental data as the training progresses. After enough training, the generative network is able to generate simulation data that is nearly the same as real experimental data and is not discriminated against by the discriminative network. This simulation data can then be used to improve or develop new registration algorithms, and can be particularly useful in approving or vetoing changes to the registration algorithms.

Advantages

With a well-trained generative network, there is high confidence that generated simulation data will match or behave almost the same as real experimental data. This can minimize the need to collect additional experimental data on cadaver bones or through costly clinical trials.

With a well-trained discriminative network, it is possible to perform real-time guidance in the operating room to differentiate whether a "collected" point is a normal registration point or an outlier. This can provide real-time feedback to the user to re-collect certain points to reduce any errors, which will increase the registration success rate significantly. This can also help train new users with the registration process.