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Synthetic Data Generation of Surgical Drills using Physics-Constrained GAN: Preliminary Results

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Extended Abstract

The efficacy of orthopaedic surgeries involving drilling into bones using a medical bone drill is dependent on the surgeon's knowledge of the drill bit's position in relation to four physiological areas: penetrating the compact (hard outer wall) bone, traversing the spongy (interior) bone, exiting the compact bone, and penetrating the soft tissue. One of the primary goals of an orthopaedic surgery is to minimize or avoid penetration of the soft tissue after exiting the compact bone.

The current approach of estimating the drill position using tactile feedback leads to increased plunge depths, resulting in incorrect screw sizes that can lead to permanent disability or life-threatening bleeding due to damage to tendons, nerves, and soft tissues [1]. If surgeons are able to determine the position of the drill bit accurately in real-time, it will lead to proper plunge depth, resulting in correct screw sizes and increased efficacy of the procedure.

To determine the position in real-time, the authors investigated the use of different deep learning models to identify the four physiological areas using a time series data sequence consisting of the distance traversed by the drill and the drill force applied by the surgeon, sampled at a constant rate [2]. This investigation demonstrated that deep learning models based on the recurrent neural network and 1-D convolution with ResNet and Inception architectures accurately determined the position of the drill bit as it penetrated the compact (hard outer wall) bone and exited the compact bone, while failing when the drill bit position was in the spongy (interior) bone or the soft tissue.

This failure can be attributed to the class-imbalanced dataset, which is caused by a low number of samples representing the spongy (interior) bone and the soft tissue physiological regions. This imbalance arises because the drill bit traverses these two regions rapidly, while sampling occurs at the same rate as it does during the slower traversal of the compact bone regions. To address this imbalance, we propose using Generative Adversarial Networks (GANs) augmented with physics-informed constraints to generate high-fidelity synthetic time series data.

A data augmentation strategy using Generative Adversarial Networks (GANs) constrained by physics-informed priors is investigated to address the imbalance issue. The approach leverages domain-specific knowledge, including force and depth boundaries as well as monotonic drilling progression, to generate synthetic time series data that adhere to real-world drilling dynamics. Specifically, the generator is modified to produce sequences with the depth component increasing monotonically, reflecting the unidirectional nature of drilling. Additionally, force values are constrained to lie within physiological limits to avoid generating unrealistic force profiles. These constraints are introduced into the composite loss function by combining adversarial loss with regularization penalties on non-monotonic depth changes and out-of-bounds force values. This results in a model increasing the representation of the underrepresented two physiological regions and also ensuring that the synthetic sequences satisfy the physical laws governing the bone drilling process. This approach builds upon existing GANs and SeriesGAN models [3, 4] and is used as a comparative baseline.

Preliminary results from 2,000 drilling sequences show improved classification performance when training with GAN-augmented data, indicating that this model effectively captures the temporal characteristics of underrepresented physiological regions and enhances model generalizability. The physics-informed GAN modifications significantly reduce the discriminative score by up to 31%, indicating improved similarity between synthetic and real data compared to the baseline. The final model, with dropouts addressing overfitting, achieves a 14.9% reduction in predictive score and a 25.9% reduction in discriminative score compared to the baseline, demonstrating the utility of this physics-constrained model for enhancing classification in class-imbalanced surgical datasets.

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