Force Prediction using OCT Sensor Data by Linear Regression, CNN and RNN

Felix Wege, Yuria Konda, and Lakshamanan Chockalingam

Intelligent Systems in Medicine, Institute of Medical Technology,
Am Schwarzenberg-Campus 3, 21073 Hamburg
{felix.wege,yuria.konda,lakshamanan.chockalingam}@tuhh.de

Abstract. Content of this student project is to develop a model that gives information about the force acting at a needle tip while plunging it against a tissue. The purpose is to give the operator some kind of force feedback without measuring it explicitly. Input of this model is an optical coherence tomography (OCT) signal that is measured at the needle tip. Three models which are linear regression, convolutional neural network and recursive neural network are considered and tested with real data.

Keywords: Machine learning, linear regression, CNN, RNN, optical coherence tomography

1 Introduction

In medical approaches OCT scans are used to image the uppermost layer of biological tissues non-invasive. For the purpose of being able to investigate internal areas of the body with this technique, researchers have developed OCT needles. By that, inner organs can be scanned directly and for example, tumors can be classified as malignant or not. One main reason for this attempt was that large surgical interventions can be avoided in many cases what results in smaller physical damages and faster healing processes of the patients. However a large disadvantage of this procedure is that no feedback for the acting force of the needle is given. This can lead to complications and injuries in surgical treatments and makes the handling unintuitive for the operator. To address this problem, force needs to be measured in some way without expanding the clinical set up spatially and financially. Both aspects oppose the attachment of a force sensor directly on the tip of the needle and a force sensor somewhere outside the treated area tends to measure additional lateral forces of the environment. (Stick slip effect) By estimating the force with OCT scans, no further equipment is required and data is already accessible.

Therefore, in this paper three different models are developed to output a force estimation based on the oct data. These consists of a linear regression model, a convolutional neural network and a recursive neural network.

2 Data Acquisition

As stated in the introduction 1, models are build to estimate the force at the needle tip using the OCT data as input.

2.1 Data

To gather ground thruth data for modelling and supervised learning a force sensor is integrated into the OCT system by placing it at the tip of the needle.

PICTURE

Data is collected by poking the needle against a metal plate back and forth in linear or stepwise motions. The OCT sensor detects the deformation of the transparent material at the tip of the needle that leads to a faster reflection of the light and thus changes the depth of the maximal reflection in the B-scan. Therefore, only frontal forces without any ditributing factors are measured. The transparent material of the OCT needle deforms up to 0.35mm and one A-scan is represented by 512 pixels. The acting forces are up to ...(???) Newton by only considering the force in needle direction. (z direction)

In total we measured data for poking against the metal plate 29 times and 9 times for poking against gelatin phantoms. The type of motion as well as the amount of needle displacemet was varied.

2.2 Preprocessing

The measurement setup did not contain any mechanism for synchronization between the data; the synchronization was part of the preprocessin. In addition to determining the start and end points of both the raw OCT and force data the sampling frequencies had to be matched. The force data was interpolated to ensure that the data contained the same number of samples, i. e. there is a force datum for each depth scan. The size of the OCT image is reduced to 50 pixels above and below the mean position of the maximum intensities due to computational reasons. Consequently, the reflection of the repetitive light is neglected. fig. 2 illustrates the reduced depth. The force sensor was highly noise sensitive. Therefore, a low-pass filter was used to smooth the measurements. An example of synchronized and truncated data is shown in fig. 1.

2.3 Feature Extraction

By comparison of the preprocessed OCT depth scans and the low-pass filtered force data it is evident that there is a relationship between the depth at the maximum intensity and the force at each point in time. Thus, the depth at which the OCT intenity is at its maximum was used as a predictor in the models. In fig. 1 one can observe distortions and artifact in the measured depth scans which threaten to impair the feature extraction if one solely consideres the single depth of the maximum intensity.

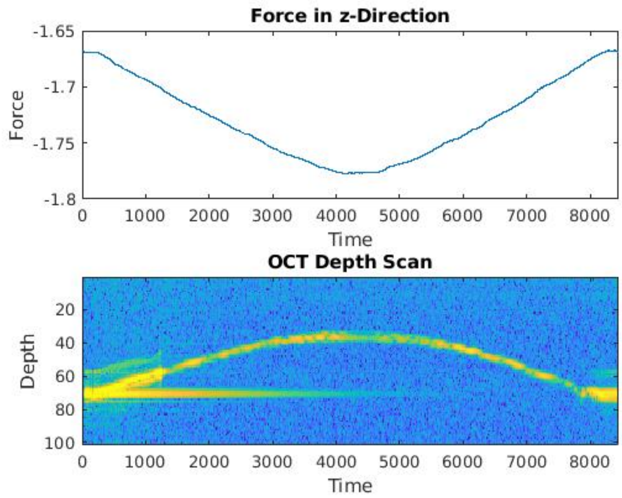

Fig. 1. Preprocessed metal data showing both the force and the OCT scan.

These effects were circumvented by considerung multiple depth indices in process of feature extraction. For each point in time only pixels with an intensity larger than a threshold value were considered. Pixels at a lower depth were given a preference. Hence, the constant stripe visible in fig. 1 was avoided. Additionally, an outlier replacement based on the moving mean of the previous depth was performed. An exemplary feature extraction for data from poking against the metal plate and poking against gelatin are depicted in fig. 2 and fig. 3, respectively.

3 Models

Three models were trained and evaluated. Firstly, simple linear regression was used to describe the relationship between the depth at maximum intensity and force. Secondly, a CNN was employed with the advantage of not relying on the feature extraction. The third model was an RNN, which, by having a 'memory', are able to model dynamic behaviour.

3.1 Linear Resgression

In section 2.3 a correlation between depth at maximum intensity and force was noticed. The scatter plot in fig. 4 further supports this assumption. Hence, linear regression is supposed to explain the relation well. A simple linear regression with the feature 'depth at maximum intensity' as the sole predictor was used. The model fitted by ordinary least squares approach is depicted in fig. 4

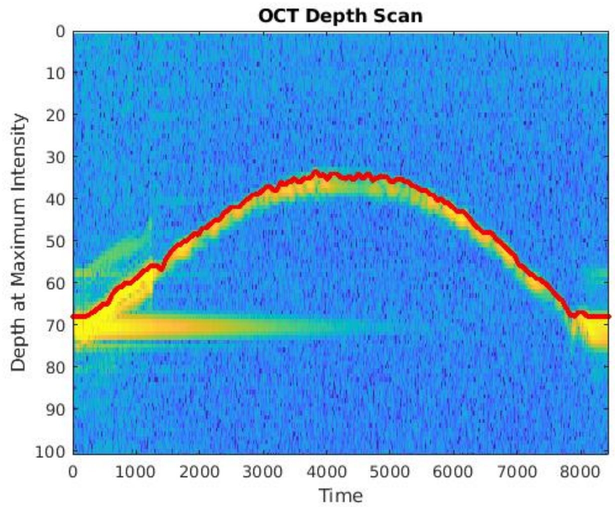

Fig. 2. Preprocessed metal depth scan. The detected depth at the maximum intensity is shown as a red line.

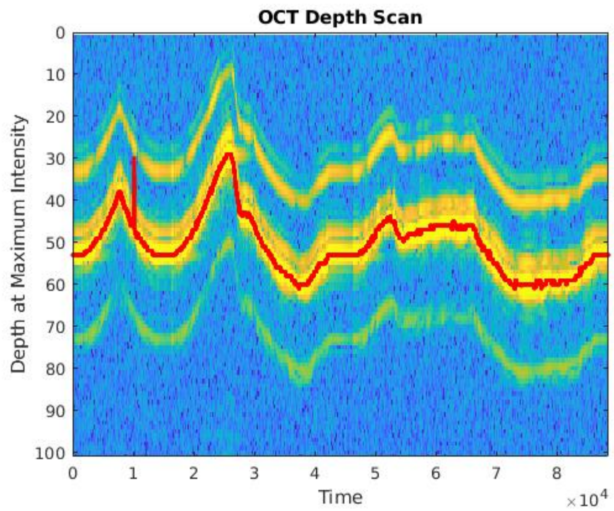

Fig. 3. Preprocessed phantom depth scan. The detected depth at the maximum intensity is shown as a red line.

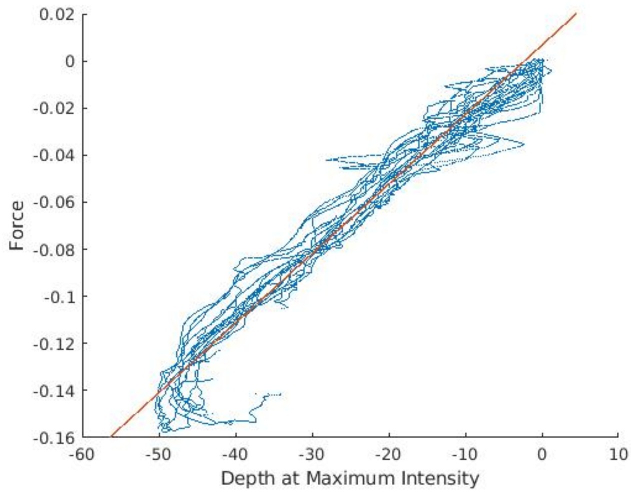

Fig. 4. asdf

3.2 CNN

We set up a convolutional neural network with the preprocessed oct images as input. The main idea is, that force acts continuously on the tissue and therefore its value depends on the past. By considering several A-scans for force estimation at one timestamp, outliers are weakened and local connectivity between actual measurement data and past data is created.

Architecture The image size of the oct is defined by the number of A-scans, whereby one A-scan contains data of 101 pixels. To obtain a desired input image size HxW for the model, the whole B-scan HxW' is splitted by windowing it with a stride of 1. Thus, a dimension of $D = W' - W - 1$ of the input image arises. The architecture of our CNN is adapted to paper gel force estimation . Due to the small amount of data, we use one convolutional layer followed by a rectified linear units layer and one 2x2 max pooling layer with a stride of two. The convolutional layer has 32 filter with size of 3x6 and a stride of one.

3.3 RNN

4 Results

The results of the different models are presented individually and compared by the mean squared error to emphasize large errors over small ones.

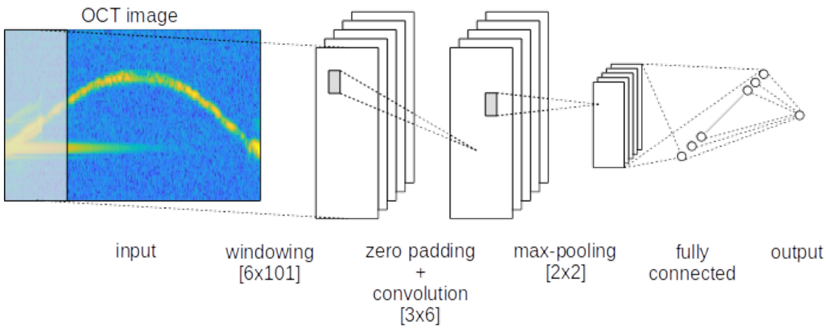

Fig. 5. Architecture of the CNN

4.1 Linear Regression

4.2 CNN

4.3 RNN

4.4 Comparison

5 Conclusion

References