Optical force and distance sensing in intraoral devices for stroke rehabilitation: a distance calibration and force classification approach

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Abstract

Stroke survivors often suffer from oro-facial impairments, affecting swallowing function and speech production. Measuring tongue pressure and position intraorally can help to improve therapy for both symptoms, but space inside the oral cavity is extremely limited and such devices can easily be prohibitively large and obstructive if too many sensors are needed. In this work, we present our efforts to sense the force of the tongue exerted against the hard palate and the tongue-palate distance, using only optical proximity sensors. To explore the feasibility and accuracy of this approach and to evaluate the selected sensor, we conducted a study with 10 subjects and measured the sensor's response to 10 discrete distances ranging from 0 mm to 30 mm between tongue and sensor, and to a continuously increasing tongue force against the sensor from 0.1 N to 8 N. For distance measurements, an existing in-situ calibration method was applied and verified that yielded errors of less than 2 mm for the estimated distances in nearly every case. For force measurements, a Bayesian classification approach was adopted to map sensor data to two force regions (below and above a certain boundary value), where up to 84.1% (average: 71.7 %) of ADC values were classified correctly within-sample.

1 Introduction

Stroke remains one of the major causes of death worldwide. Statistically, every sixth person at the age between 55 to 75 suffers a stroke [1]. As three out of four stroke victims survive, an even bigger number of stroke survivors remain, most of which are left with various disabilities [2]. Due to the nature of stroke affecting certain motor areas in the brain, two very common complications are dysphagia (i.e., the difficulty in swallowing) [3] and dysarthria (the inability to properly articulate) [4]. Rehabilitation measures include strengthening [5–7] and articulatory exercises [4] for the tongue. Strengthening exercises are rather simple in the sense that the patient simply has to press his or her tongue against the hard palate and the only concern is the magnitude of force applied. Articulatory exercises are more complex, need to be chosen individually and depend on how the patients speech is affected [8]. Although strength plays a role in proper articulation, there has not been any evidence that strengthening exercises alone help to improve acquired speech disorders [9] and as such, additional exercises are necessary. Several devices exist that can measure tongue pressure against the hard palate or track the tongue position inside the oral cavity. One way to measure tongue position is to use optical distance sensors [10–13] and this concept has also been used as an input modality for so called serious games in therapy [14]. As dysphagia and dysarthria often coexist, they could potentially be treated simultaneously, however current pressure sensing devices are unable to track the tongue during articulation, and optical devices are not designed to measure tongue pressure. Our recent results [15] show, however, that due to the subsurface scattering property of the tongue tissue (or soft tissue in general), optical pressure sensing seems possible to a certain extend. Other authors have exploited this subsurface scattering effect in a similar fashion but different fields of application to measure pressure optically [16, 17].

Combining the measurement of both pressure (or force) and distance using a single sensor type within a single device is extremely beneficial for intraoral applications, not only because of the advantages mentioned above for combined therapy, but also because space inside the oral cavity is extremely limited and every sensor saved directly equates to a less obstructive device for the patient. Using optical sensors poses several challenges for user-friendly devices. Most optical proximity sensors measure the intensity of reflected light and as such depend on the surface reflectance. Since tongue reflectance spectra differ slightly from person to person, the sensors have to be calibrated. Preuß et al. [18] developed a calibration technique, where the measured sensor value at zero distance (with the tongue held directly against the sensor) is taken to predict the sensor values greater than 0 mm in a multiple linear regression approach, based on distance characteristics from different subjects. This approach consequently relies on sensor data from several subjects to effectively train the prediction parameters.

The intent of this paper is two-fold: Firstly, we wanted to confirm the proposed method from [18] and its applicability for a different optical sensor (see Section 2.1) with newly recorded data from a study with 10 subjects, and secondly present results for optical force measurements for different tongues along with a first approach to map sensor values to force levels in a probabilistic manner.

2 Methods

2.1 Sensor

The sensor under test was the optical infrared proximity sensor sfh7779 (wavelength 940 nm, OSRAM, Munich) with dimensions 2 mm × 4 mm × 1.4 mm (length × width × height), 12 bit ADC, adjustable emitter current up to 200 mA and an I2C interface. The current was set to the maximum of 200 mA for all measurements to account for the rather poor reflectance of the tongue. As the emitter LED was pulsed (200 µs per pulse), the mean current consumption was around 4 mA. The sensor was coated with a thin layer (18 µm) of parylene (Heicks Parylen Coating GmbH, Geseke), to seal it against saliva, and encapsulated in silicone to avoid sharp edges (Figure 1b).

2.2 Measurement setup and procedure

The study was conducted with 10 subjects (2 female, 8 male, age 27 to 67). For distance and force measurements,

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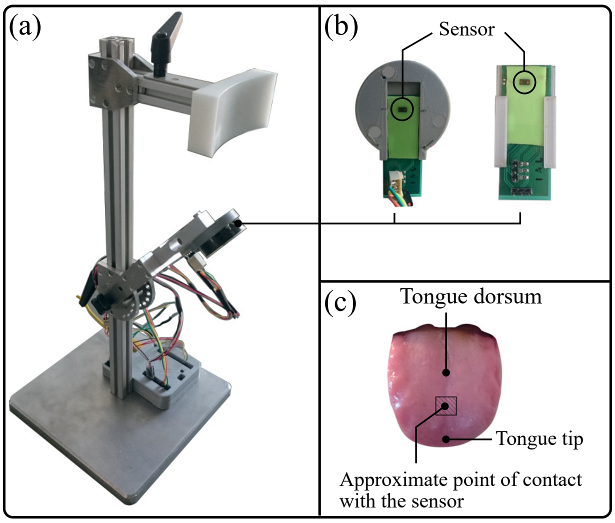

Figure 1: (a) Test station for measurements [15], (b) clips to hold the sensor in place during distance and force measurements, (c) approximate tongue contact point during force measurements.

our earlier developed test station [15] was used (Figure 1a). The sensor was placed in a 3D-printed clip (Ultimaker 3, Figure 1b), which itself was attached to the strain gauge. A sampling rate of 50 Hz was used. For distance measurements, several spacers as in [19] with lengths of {0, 2, 5, 10, 15, 20, 25, 30} mm were magnetically attached one after another to the sensor clip to provide a fixed distance between tongue and sensor. Before each use, the sensor clip, strain gauge, encapsulated sensor and every spacer were sanitized using Helipur H plus N (BBraun AG, Melsungen) according to the standard protocol. For each distance measurement, 150 samples were taken and the mean was calculated. The measurements were force-activated, i.e., if the subject lost contact to the spacer, the measurements would halt to avoid reading wrong distances. To get an accurate distance measurement at $d = 0$ mm without already applying too much force, the threshold for activation was set to within a narrow range of 0.1 N to 0.2 N. For force measurements, the spacers were removed and the tongue was directly pressed against the sensor with increasing force over 0.1 N to 8 N and within a time interval of around 2 s to 3 s [15]. The point of contact with the sensor was approximately 1 cm from the tongue tip (see Figure 1c). Each subject performed 10 repetitions of increasing his or her tongue force against the sensor. Measurements were recorded using a custom Matlab program.

2.3 Distance calibration

For distance calibration, the method proposed in [18] was used. The basic idea behind this method is that the measured sensor value (converted to a digital value, i.e., its ADC value), when the tongue barely touches the sensor, contains enough information a- bout the general reflectance behavior of the tongue to estimate the rest of the distance characteristic of the tongue. Each ADC value x_i at distance $d_i > 0$ mm is related to the ADC value x_0 at distance $d_0 = 0$ mm by a second order polynomial:

$$x_i = a_{i,0} + a_{i,1} \cdot x_0 + a_{i,2} \cdot x_0^2 \qquad (1)$$

Given a number of tupels $\{x_0, x_i\}$, this results in N equations ($i = 1 \ldots N$, with N = number of discrete distances) with the unknown parameters $\mathbf{a_i} = [a_{i,0}, a_{i,1}, a_{i,2}]^T$ and can be written in matrix form as $\mathbf{x_i} = \mathbf{X_0} \cdot \mathbf{a_i}$, with the $M \times 3$ matrix $\mathbf{X_0} = [1, \mathbf{x_0}, \mathbf{x_0^2}]$ ($\mathbf{x_0}$ being a column vector containing the ADC values at $d = 0$ mm from all M subject) and $\mathbf{x_i}$ as a column vector, containing all measured ADC values for this specific distance. Solving this yields the result

$$\mathbf{a_i} = (\mathbf{X_0^T} \cdot \mathbf{X_0})^{-1} \cdot \mathbf{X_0^T} \cdot \mathbf{x_i} \, . \qquad (2)$$

With the calculated parameters $\mathbf{a_i}$ for every distance d_i, the 8 distances of each of the ten sets were estimated in ADC values and converted to millimeter (assuming linear interpolation between fixed distances). The calibration technique was evaluated using leave-one-subject-out cross validation.

2.4 Force measurement

Due to the random nature of subsurface scattering of light in tissue, mapping ADC values to force values is challenging and can be almost completely ambiguous in extreme cases (i.e., for ADC values around 400, Figure 5a). As such, a conventional regression approach that predicts a force value given a measured sensor value would yield poor results. However, there exists a general trend that higher forces do result in higher ADC values. Therefore, it should at least be possible to find specific force values (boundaries) that divide the measurements into several intervals or regions. New ADC values could then be classified/mapped into one of these intervals that they most likely belong to. In this study, a binary classifier with two regions was tested. The ADC values were split into two groups at a chosen force value and the histogram was computed (with the number of bins $k = \sqrt{n}$, n = number of samples). The boundary value was then systematically varied and the overlap between both histograms recalculated. Because the overlap would tend to be lower when split close to the minimum and maximum recorded force, splitting the ADC values was done in an interval of 2 N to 6 N. The force value that divided the measurements with minimal overlap was taken as the optimal force boundary. Figure 2 visualizes this procedure. In the following classification process, every ADC value was classified as either above or below this boundary value.

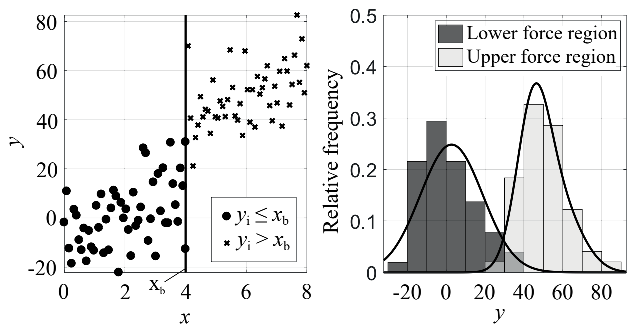

Figure 2: Showcase of the procedure of splitting data into two regions with minimal overlap. Left: scatterplot with boundary value (x_b, vertical line). Right: histogram of the two regions along with a GMM fitted to the data.

To approximate the distribution of ADC values in each force region with a continuous probability density function, the histograms were fitted to a Gaussian mixture model (GMM), using Matlabs fitgmdist() function and choosing the fit with the lowest AIC score. The maximum possible order was set to 8. Based on the found GMMs and using Bayes' theorem, the decision to which class c a new ADC value y_i was assigned to, was based on the maximum *a posteriori* probability $P(c|y_i)$ as follows:

$$c^* = \arg\max_c \frac{P(y_i|c)\cdot P(c)}{P(y_i)} = \arg\max_c P(y_i|c)\cdot P(c), \quad (3)$$

where c^* is the selected class, $c \in \{L, H\}$ and $P(y_i|c)$ is the likelihood of y_i given class c. The *a priori* probability $P(c)$ was set to $[0.5, 0.5]$. The classification error was calculated as

$$e_{cl} = \frac{\text{Incorrectly classified ADC values}}{\text{Total number of classified ADC values}} \cdot 100\% \,. \quad (4)$$

3 Results

3.1 Distance calibration

Figure 3 shows the boxplots for the out-of-sample distance error between measured and estimated distances for all d_i following cross-validation.

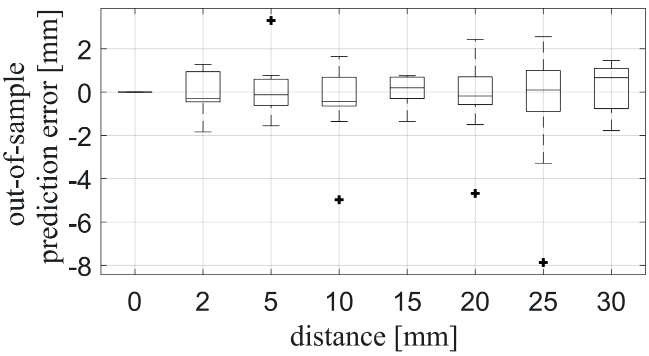

Figure 3: Boxplots of the distance error between predefined (by the spacers) and estimated distance $\hat{d}_i$. Outliers are marked with a plus (+).

Figure 4 displays two examples of very good (left) and rather poor (right) distance estimation and reveals the importance of sufficient training data to estimate new distance characteristics. In the latter case (Figure 4, right), the ADC value of d_0 was significantly higher than any of the d_0 values from other data sets. When left out during cross-validation, the parameters $\mathbf{a_i}$ could not reflect this deviation, as they were trained without this particular d_0. This approximation was also responsible for the three outliers for 10, 20 and 25 mm in Figure 3. However, if the shape and magnitude of the distance curve, that had to be estimated, was sufficiently represented in the training data, the estimation was very accurate (Figure 4, left).

3.2 Force measurements

Figure 5 shows the recorded force measurement results for all 10 subjects along with the calculated force boundary values for minimal overlap, which are also summarized in Table 1. Figure 6 serves as an example to display the *a*

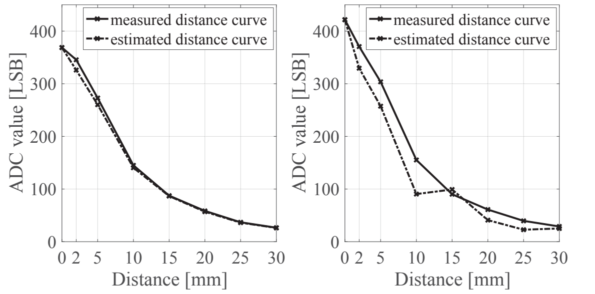

Figure 4: Left: example of a very good distance estimation. Right: example of poor distance estimation due to the test data not being sufficiently represented in the training data.

posteriori probabilities for the ADC values and the classification result (class L or H), using equation (3), for data set 2. Figure 7 shows the results of the within-sample classification and labelling of every measured ADC value into either of the two force regions, exemplary for data set 2, as well.

data set	1	2	3	4	5	6	7	8	9	10
f_b [N]	4.1	5.4	2.01	2.6	4.1	3.84	2.01	2.83	2.69	4.17
e_{cl}[%]	29.5	15.9	23.5	24.5	28.2	20.9	25.9	46.3	28.1	26.4

Table 1: Classification error e_{cl} and force boundary values f_b where the overlap is minimal for every data set 1 to 10.

4 Discussion and Outlook

The results for the proposed distance calibration technique confirm that this method is very well suited to overcome differences in tongue reflectance and to accurately predict the distance characteristics with minimal input data (only one measurement) for different tongues, *given* that measured data is available beforehand, and that the training data is sufficient. Furthermore, the calibration accuracy improves as more data is available. This data is, however, sensor specific and a new sensor with a different light source or detector would require new measurements. Our study also showed that the accuracy of measured values (at a given distance) is quite high, i.e., consecutive measurements of the same distance yield similar results. Similarly, the general *shape* of the distance curve and the magnitude of the sensor values to different distances are within a certain (predictable) range, i.e., a distance of 15 mm will be at around 90 ADC values (for this sensor) and not suddenly twice as much. Insufficient generalization of the predictive model as in Figure 4 (right) could furthermore be addressed by adding a regularization term.

With the spatial heterogeneity of tongue muscle tissue with respect to its optical properties, force measurements were much less predictable. Because of the random nature of scattering processes, a probabilistic approach for force measurements seems natural and the error rates for the presented binary classifier show that this type of classification method can partly counter the enormous variance in the measurements (except for data set 8, where the error was only slightly below 50%, which is only marginally better than guessing).

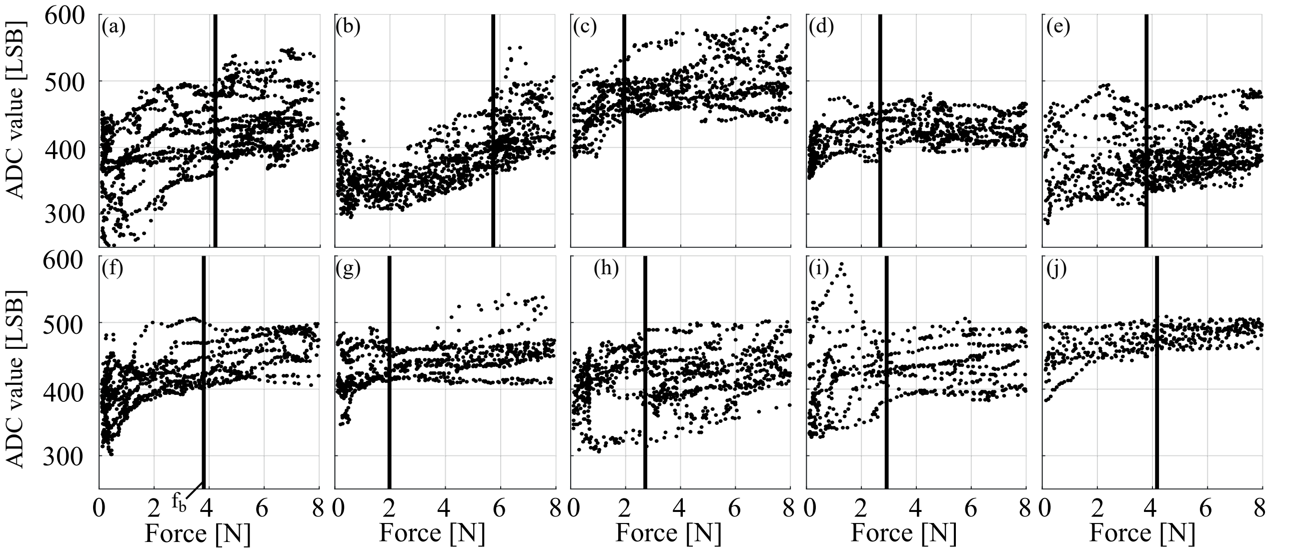

Figure 5: Scatterplots of force measurements for subject (data set) 1 to 10, (a) to (j). Vertical lines mark the boundary value f_b that splits the data into two force regions with minimal overlap.

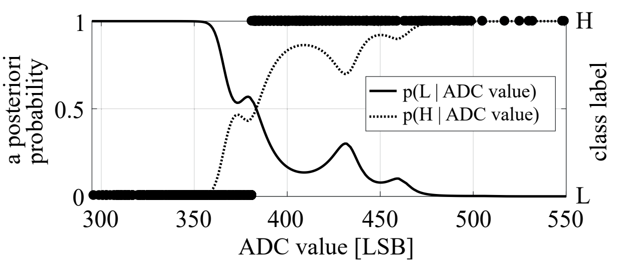

Figure 6: Results for the *a posteriori* probabilities of ADC values coming from either distribution and classification into class L or H. Exemplary for subject 2.

Since speech therapists are often interested in whether the patient's tongue strength has increases over the course of therapy, relative to his or her starting condition, a binary classifier is most likely not sufficient to catch subtle improvements. However, this is only the first step into the direction of making optical force measurements possible and several improvements will be addressed in future work to increase its sensitivity: Instead of splitting the data into just two regions where overlap is minimal, several regions could be predefined which would increase the resolution of the classifier. As for any data driven approach, additional measurements would also increase the confidence of the predicted force levels, as they serve as the ground truth. One could also assume that - due to the general trend of sensor values increasing with force - the classified value is more likely to stay within its current class, rather than to switch to another one. This would make the *a priori* probability a parameter for optimization. Furthermore, with actual intraoral tests, the maximum force value of 8 N could turn out to be unnecessarily high (especially for stroke patients, where tongue strength is already rather low) which in turn would very likely increase the classification accuracy, because the sensor value increase is higher for lower forces. Pre-processing the sensor data with suitable filters could also reduce some of the variance before classification even starts and will be a major focus in future work. Additionally, more insights into the scattering behavior of tongue tissue is needed to better predict, how the measurements will behave for certain force levels (similar to knowing the general shape of the distance curve in advance). Lastly, some form of patient specific calibration process could be necessary to increase the robustness of force measurements, as the tongue effectively becomes part of the sensor, and its optical properties vary between patients.

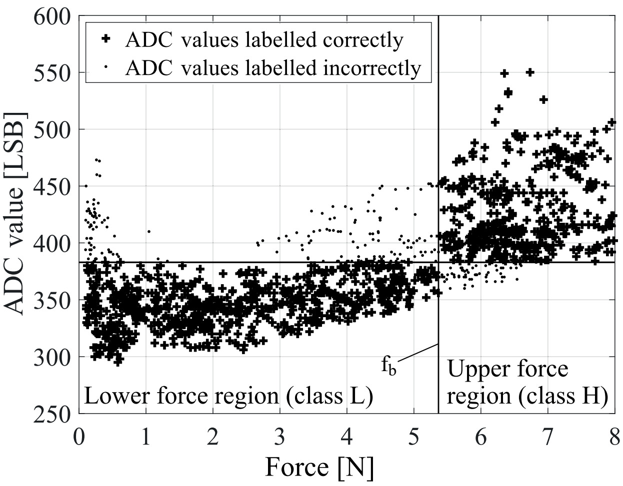

Figure 7: Classification results for every measured ADC value in data set 2. Plus signs (+) mark correctly classified ADC values into the lower or upper force region, dots (·) mark incorrectly classified values. The resulting e_{cl} is 15.9 %. Horizontal line: ADC value of the classification boundary. Vertical line: force boundary value f_b.

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