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Combination of motion data and electromyography for threshold-based swallow onset detection

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Abstract

Dysphagia – difficulty in swallowing – represents a restriction for patients. Approaches like biofeedback-based training and functional electrical stimulation (FES) arise as supporting methods. Both require online swallow onset detection for triggering, whereby non-invasive measurement methods should be preferred. In this pilot work, a threshold-based approach for the detection of swallow onsets is presented, which utilizes electromyography (EMG) and motion parameters of the larynx, measured by a wearable inertial measurement unit (IMU). For data collection, a pilot study with nine subjects was conducted, in which swallows with different volumes and consistencies, movement and speech were recorded. Evaluation of the detection approach is based on a cross-validation in combination with a grid search for finding appropriate thresholds. The detection approach results in a F1 score of 0.825 ± 0.074, rated as sufficient for a first feedback mechanism. This work supports the usage of the previously named signals as non-invasive measures for onset detection.

I. Introduction

Patients, especially elderly, with dysphagia suffer from limitations due to difficulty in swallowing, which can lead to aspiration and pneumonia [1]. Additionally, dysphagia frequently occurs as a result of a stroke, with an increased risk of pneumonia and mortality [2], or as a side effect of neurodegenerative diseases, e.g., Parkinson's disease [1].

Two possible therapeutic approaches, which are currently under development, are biofeedback-based training, which utilizes the visualization of the swallowing process (e.g., [3]), and functional electrical stimulation (FES) as an assistive mechanism via focused electrical pulses. Both require an online and real-time detection of swallows, ideally with a precise detection of its onsets. Various approaches regarding the sensors and biosignals used for this task can be found in the literature. Examples include bioimpedance (BI) [4], electromyography (EMG) [3] [4] , acceleration (ACC) [3] [5] [6] and angular velocity (GYR) [6]. Additionally, combined sensor systems are often used, which can improve the detection [7].

The swallow onset detection approach presented in this paper is intended for use as a trigger mechanism. In order to maximize the usability, non-invasive measurement methods are preferred, including EMG for detection of activity in the hyoid muscles as well as changes in acceleration and angular velocity, caused by the laryngeal up- and forward movement during the pharyngeal swallowing phase. Latter are registered via an inertial measurement unit (IMU). An adaptation of this first approach could potentially be used by dysphagia patients.

II. Methods and materials

II.I. Study design

As data base for this initial investigation, a study has been carried out for data collection. This study includes nine healthy and adult subjects (2 female, 7 male, 38±12.4 years), who participated on a voluntary basis.

For the measurement, a sensor system (SensorStim Neurotechnology GmbH, Berlin, Germany) has been developed, which combines EMG and IMU hardware in a single device and allows non-invasive, wireless measurements of the muscle activity and tri-axial motion data. As shown in Figure 1, the sensor is attached to the neck via a flexible strap and a 3D-printed mount. It is placed over the cricoid cartilage for detection of laryngeal movement [6]. Two electrodes are placed bilaterally between the hyoid bone and the thyroid cartilage for a differential EMG measurement [4]. A third electrode, positioned on the clavicle, serves as patient ground.

The study protocol is comprised of five sequential steps, including two measurements of 20 swallows each time in a neutral head position, two measurements of head movement, and one measurement of speech. Each is preceded by a baseline phase of 5 s.

In detail, the swallows are divided into five saliva swallows, five swallows with 10 mL of water, five swallows with 25 mL of water and five swallows with 10 g of commercial vegan jelly. The different volumes and consistencies allow for a differentiated consideration of the influence for the detection approach. For later verification of the swallows, a button is pressed by the subjects during the conscious swallow. The third and fourth step each consist of two repetitions of head movement, including upward-downward movement, movement to the left and right, nodding and shaking. During the last measurement a text is read aloud by the subjects for around 30 s.

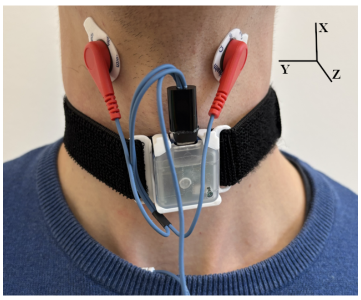

Figure 1: Sensor attached to the neck.

In the following, only the first two measurements of swallows are used as data, providing around 360 swallows, to address the basic detection ability. The remaining data will be used for future research (Section IV).

II.II. Preprocessing

The collected raw signals in form of EMG, ACC and GYR undergo a preprocessing pipeline implemented in Python, which is also suitable for online processing.

The EMG data, sampled at 2 kHz, are filtered by a Butterworth (BW) notch filter with a center frequency of 50 Hz for removal of potential power line artifacts. An additional BW band-pass filter is used for offset and movement artifacts removal via a lower cut-off frequency $f_{c,\text{lower}} = 30\,\text{Hz}$, while high frequency components, which are considered as noise, are removed by an upper frequency $f_{c,\text{upper}} = 300\,\text{Hz}$ [4]. The final calculation of the envelope EMG_{env} is achieved by filtering the rectified EMG via a BW low-pass filter with $f_c = 10\,\text{Hz}$ [4].

The IMU data are sampled at a different rate of 200 Hz. Firstly, the ACC data are filtered by a BW high-pass with $f_c = 0.1\,\text{Hz}$ to remove the offset. In the following step, the *estimated volatility* is determined, which is presented by [5] as measure for erratic and abrupt fluctuations. These prominent changes in the acceleration due to the laryngeal movement motivate the approach. The volatility estimate is calculated with a sliding window size of $w_{\text{vola}} = 0.2\,\text{s}$, whereas a size of 1 s is originally used in [5]. The three separately processed axes are combined via the L2 norm, yielding the 1D signal ACC_{vola}.

The GYR signal is filtered via a BW high-pass filter with $f_c = 3\,\text{Hz}$, which has shown to remove a relevant part of low-frequency components due to head movement while retaining the swallow part. Due to the upward and forward movement of the larynx, just one axis (Y) of the gyroscope signal, perpendicular to the axes of movement, is considered as relevant. The rectified and moving average filtered ($w_{\text{avg}} = 0.2\,\text{s}$) version GYR_{abs} of the high-pass filtered signal is used for thresholding.

All BW filters are implemented as third-order.

II.III. Timing of acceleration and bioimpedance

Only as methodical support and conceptual comparison to the previous effort of the research group [4], which includes BI and EMG for swallow onset detection, an exemplary measurement is carried out to compare the timing behavior of bioimpedance to acceleration and angular velocity, which are primarily used in this work. For the combined measurement of BI and EMG, the RehaIngest-measurement device (HASOMED GmbH, Magdeburg, Germany) is used, while the acceleration and angular velocity is measured in parallel with the previous described sensor. The BI signal is preprocessed via a BW low-pass

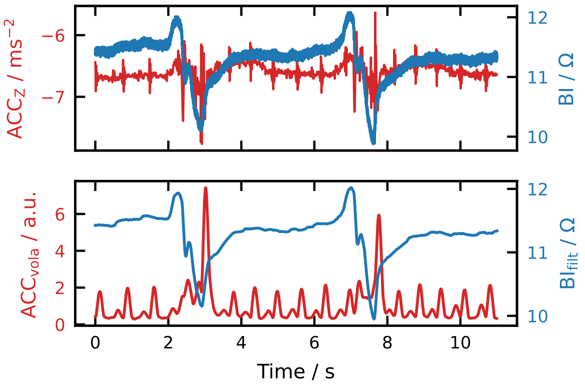

Figure 2: Visualization of the synchronized measurement of raw data ACC (z-axis) and BI (upper subplot) and processed results (lower subplot).

filter with $f_c = 15\,\text{Hz}$, yielding BI_{filt} [4]. As a synchronization mechanism, a rectangular signal with a randomly varying frequency is generated by a microcontroller and is recorded by both devices. The time shift is corrected based on the cross-correlation of the two recorded versions. The result is plotted in Figure 2 in the form of two exemplary swallows. As described in [4], the swallow onset manifests as a drop in the BI curve. The deflection of the ACC caused by the swallow, on the other hand, appears as an increase in the volatility. It is clearly visible that the event of swallow onset is present in the same time period in both approaches. This indicates and encourages the usage of acceleration and angular velocity.

II.IV. Threshold-based onset detection

The approach for swallow onset detection is based on a two-stage classification. As methodical assumption, the EMG activity is considered as a necessary condition for recognition as positive event due to the causal chain of electrical activity and muscle movement. Only when additional activity in both IMU signals, i.e., in normed volatility ACC_{vola} and rectified single-axis angular velocity GYR_{abs}, is registered, the sufficient condition is fulfilled and an onset would be marked.

Activity is registered if the signal exceeds a defined threshold, while the events in each of the three signals are detected separately. For EMG_{env} the threshold Θ_{EMG} is fixed to three standard deviations of the baseline segment, as in [3]. Before registration at time point t_{EMG}, the threshold has to be exceeded for 0.1 s. In the ACC_{vola} and GYR_{abs} signals, activity is registered at time point t_{ACC} or t_{GYR} if the respective threshold Θ_{ACC} or Θ_{GYR} is exceeded for two consecutive samples. After every detected event, the detection mechanism is suspended until the signal falls below the threshold and at least for 0.1 s. The final swallow onset is detected at $t = \max(t_{\text{ACC}}, t_{\text{GYR}})$ if both time points lie within a coincidence window $w_{\text{co}} = 0.25\,\text{s}$. After each onset pair t_{GYR} and t_{ACC} that lies in the coincidence window w_{co}, the following events within an interval of $w_{\text{skip}} = 1$ s are ignored due to the ongoing swallow and subsequent use as a trigger for FES, as in [4].

II.V. Optimization and evaluation

As ground truth, the beginning of the swallow t_{onset} is manually identified by visual inspection and set in reference to the marker created by pressing the button. A detected onset is counted as true positive event (TP) if it occurs within a defined time window $w_{\text{accept}} = 0.5\,\text{s}$ in relation to a manually set onset t_{onset} [4]. A false positive event (FP) is created if the detected onset does not fall in such a time window. If there is an EMG window, describing the interval of activity in EMG_{env}, which contains no IMU-based detections and no manual t_{onset}, this is referred to as a true negative event (TN). The amount of false negative events (FN) results from the ground truth onsets t_{onset} that are not matched while the verification.

For evaluation and optimization of the thresholds, a grid search is implemented and combined with a Leave-One-Subject-Out (LOSO) cross-validation to determine an optimal threshold pair $(\Theta_{\text{ACC,opt}}, \Theta_{\text{GYR,opt}})$ for a single subject s_{i} with $\text{i} \in \{1, \ldots, 9\}$, based on the datasets of all remaining subjects. The optimum is defined in regard to the F1 score, defined as

$$\text{F1} = (2 \cdot \text{TP})/(2 \cdot \text{TP} + \text{FP} + \text{FN}). \qquad (1)$$

While the optimization via grid search only utilizes the F1 score, the LOSO cross-validation iteratively calculates another three common scores for each subject s_{i}, namely the accuracy, precision and sensitivity. The overall evaluation of the detection algorithm is carried out on the basis of the mean of these recalculated scores over all s_{i}.

III. Results and discussion

The grid search selects threshold values of $\Theta_{\text{ACC,opt}} = \{1.625, 1.75\}$ for ACC_{vola}, close to the threshold value of 1.5 reported in [5], and $\Theta_{\text{GYR,opt}} = \{5, 5.5\}\,{}^\circ\,\text{s}^{-1}$ for GYR_{abs}.

The overall evaluation scores of the validation procedure are shown in Table 1. The precision and sensitivity

Score	**Mean**	**± Std**
Accuracy	0.916	0.042
Precision	0.819	0.065
Sensitivity	0.849	0.113
F1	0.825	0.074
Delay (s)	0.205	0.035

Table 1: Results of the LOSO cross-validation via optimized threshold pairs $(\Theta_{\text{ACC,opt}}, \Theta_{\text{GYR,opt}})$.

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scores show satisfactory results, leading to an acceptable F1 score, as it is defined as the harmonic mean of both. The fixed selection of partly experience-based parameters, that are used for the algorithm and named in Section II.IV, is thereby strengthened. In total, the validation results in 315 TP, 75 FP, 1333 TN and 57 FN events. In comparison to the findings in [4], the mean detection delay of around 0.2 s, i.e., timing difference of marker to detected onset, is rated as acceptable but slightly larger. A further reduction is necessary for precise triggering. The two exemplary detected swallows that are visualized as an example in Figure 3, are clearly recognizable in all three signals and stand out from the movement in between. The plot also illustrates the advantage of preprocessing, showing that the movement between the swallows is removed in GYR_{abs}. In relation to ACC_{vola}, where movement is visible at the same interval, the advantage of a multi-sensor approach becomes clear. The results of a methodically comparable and only EMG-based approach in [4] indicates this additionally.

Regarding the F1 score, the volatility-based swallow detection algorithm in [5] provides even better results. However, it is not suitable for real-time onset detection due to a broader calculation window size $w_{vola} = 1$ s.

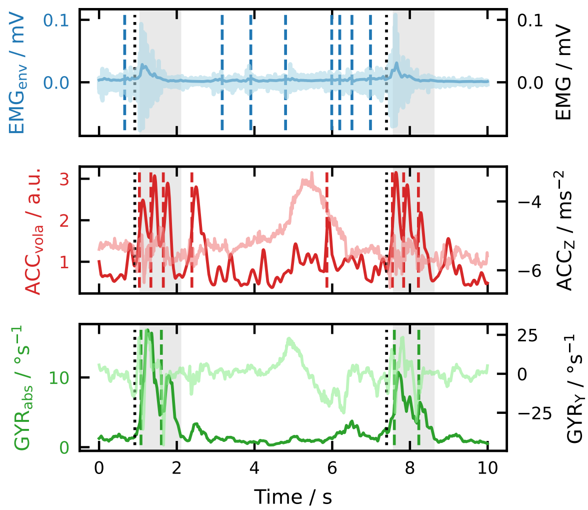

Figure 3: Exemplary representation of two water swallows. Processed and raw (light colored) signals of EMG (top), ACC (mid) and GYR (bottom). Black dotted lines highlight manually marked onsets. Colored lines mark activity in the respective signal. Gray areas mark the 1 s-sector after a detected onset.

IV. Conclusion

The approach presented in this article demonstrates the possibility of detecting the onset of swallowing using non-invasive EMG and IMU sensor technology in combination with an appropriate algorithm.

Further, the unbalanced ratio of female and male participants or the healthy population must be taken into account when continuing the study and estimating the generalizability of the results.

For everyday use, robust detection that is less sensitive to head movements and speech is particularly important. Therefore a machine learning-based approach will be trained on the data collected in the study to reduce the rate of false detections and the detection delay.

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Author's statement

Conflict of interest: T.S. and C.W. are co-founder of SensorStim Neurotechnology GmbH, which is a company developing FES stimulation devices. M.F., D.L. and B.R. are employed by that company. All other authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the Ethik-Kommission der Fakultät IV, TU Berlin (Ref.-Nr.: 311).

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