Benjamin Riebold*, Holger Nahrstaedt, Thomas Schauer, and Rainer O. Seidl

Self-adapting Classification System for Swallow Intention Detection in Dysphagia Therapy

<https://doi.org/10.1515/cdbme-2019-0013>

Abstract: In dysphagia the ability of elevating the larynx and hyoid is usually impaired. Electromyography (EMG) and Bioimpedance (BI) measurements at the neck can be used to trigger functional electrical stimulation (FES) of swallowing related muscles. The height and speed of larynx elevation can be assessed by evaluating the BI during a swallow. For the triggering of an supporting FES and for biofeedback online detection of swallow onsets is required. Patients can practice by a gamified biofeedback to swallow harder, swallow in a timely manner or to maintain the larynx elevation for a longer time period (Mendelson maneuver). The success of the stimulation and biofeedback therapy as well as the acceptance by the patient strongly depends on the precise detection of swallow onsets. We have introduced a classification algorithm based on a random forest classifier to trigger FES in phase with voluntary swallowing based on EMG and BI. Although the classification is successful in healthy subjects, difficulties appear in the utilization on some patients. The reason for this can be found in a strongly varying residual swallow activity. Usually the activity of EMG and change in BI are smaller in patients compared to healthy subjects. Thus an adaption procedure is needed, that can be easily applied. In this paper we introduce an algorithm that is capable to find an optimal classifier for a patient in terms of sensitivity. The adaption algorithm uses a small number of recorded swallow onsets of a patient at the beginning of a therapy session to evaluate different classifiers and to pick the most suitable for the treatment. The set of random forest classifiers has been trained with data from healthy subjects by step wise shifting the class weights of swallows and non-swallows, yielding classifiers with different sensitivities. The evaluation is done using data from 41 patients. It showed that the sensitivity of the classification can be increased by 4 to 6 % in average compared to fixed classifiers, but up to 66 % for individual patients. Finally, we studied the effect this adaptive classifier in triggered stimulation therapy in a single dysphagia patient.

Swallowing performance was measurements during one week of therapy consisting of eleven therapy session. An improvement of 40 and 63 % in larynx elevation and speed could be observed, respectively.

Keywords: dysphagia, biofeedback, classification

1 Introduction

EMG and BI measurements at the throat can be used to detect and evaluate swallows [1, 2]. These measurements show a valley-like shape in the absolute value of BI signal at 50 kHz and a distinct activity of EMG at the beginning of the swallow. The change of BI correlates to the movement of larynx. This is a clear advantage compared to methods that use only EMG or accelerometers for biofeedback of swallowing. In [3] we showed that BI and EMG patterns can be used to trigger FES in phase with voluntary swallow onset. This classification system was built on data of healthy subjects, for that reason it is not always sufficient for patients who have decreased EMG activity and a smaller change in BI. To achieve a suitable sensitivity of the classifier for a patient either additional sensor technology [3] must be employed or an adaptive classification system must be realized. The system proposed in this paper follows the second approach and is based on a set of classifiers with increasing sensitivity trained on data from healthy subjects. After a small number of swallows is recorded, the most suitable classifier for the patient is selected. In the following we explain the classification of swallow onsets and show the automatic adaption to the patient's swallow activity. Afterwards the system is evaluated on a set of measurements recorded in 41 patients. Finally, we present the therapy progress of a patient, who was treated with the system.

2 Swallow Onset Detection

EMG and BI measurements at the throat, both sampled with 4000 Hz, show typical patterns. In Figure 1 the most right vertical marker indicates the decrease of BI and the inherent activity of EMG at the beginning of a swallow.

*Corresponding author: Benjamin Riebold, TU Berlin, Control Systems Group, Einsteinufer 17, Berlin, Germany, e-mail: riebold@control.tu-berlin.de

Holger Nahrstaedt, Hasomed GmbH, Magdeburg, Germany

Thomas Schauer, TU Berlin, Control Systems Group Berlin, Germany

Rainer O. Seidl, Unfallkrankenhaus Berlin, Berlin, Germany

Fig. 1: EMG/BI signals of a healthy persons swallow.

This pattern has to be detected as fast as possible, to give the patient an effective biofeedback or FES support. Since the swallow is not finished at this time, we call the algorithm swallow onset detection. The detection consists of four parts: 1st) Signal Pre-Processing, 2nd) Segmentation, 3rd) Feature Calculation and 4th) Classification.

2.1 Signal Pre-Processing

EMG and BI signals are sampled with 4 kHz using the devices PhysioSense (TU Berlin, Germany) [2] or RehaIngest (Hasomed GmbH, Germany). The EMG is high-pass filter with a cutoff frequency of 30 Hz. Disturbances originating from the power grid with 50Hz and integer harmonics are removed with a harmonic band stop starting at 50 Hz and ending at 250 Hz. To reduce the costs of the segmentation and slope calculation, the BI signal is downsampled by a factor of 100 from 4000 Hz to 40 Hz by taking the mean of 100 successive samples, yielding a sufficient noise reduction.

2.2 Segmentation

The online segmentation algorithm performs a piece wise linear approximation [4] of the down-sampled BI signal. A new line segment is completed whenever a maximum mean squared error ($1.5 \Omega^2$) between the line segment and signal is exceeded or time duration or absolute value difference of the line segment are above defined maximal values (1.5 s and 0.5Ω , respectively). After every completion a feature vector is calculated and the classification is executed. The feature extraction uses the pre-processed EMG and BI data from the last 1.5 s before the end time of the currently completed line segment. This corresponds to the current sample time.

2.3 Feature Calculation

To assess the EMG activity we calculate the variance of the EMG signal 0.1 s before the current sample time. Important features are the first time derivative of the BI signal, because a negative slope indicates a potential start of a swallow. The time derivative is calculated in four overlapping windows of length 0.1 seconds with an overlap of 50 percent by taking the average of the differences between all successive samples in each time window. We use as features the difference between the maximum and the minimum value of the BI signal and its time derivatives in a time windows of 0.25 seconds before the current sample time.

Symbolic Aggregate Approximation (SAX) is an effective method to obtain an approximation of signal behavior, while achieving a suitable data reduction [5].

The signal duration for EMG and BI SAX-features is 0.5 s before the current sample time. For each signal a SAX word with 10 symbols and word depth of 16 steps are calculated. These SAX words are used to approximate the specific patterns in BI and EMG signal before a swallow. In addition, a SAX word with a length of 4 symbols is build from the BI signal in a time window from 1.5 to 0.5 s before the current sample time. This SAX word is intended to model movements that belong to swallow preparation. All SAX words are included in the feature vector. A visualization of the time intervals used for feature calculation is given in Figure 1.

The foundation of the training data is a set of EMG and BI measurements of healthy subjects, where all swallow onsets were manually marked by experts. To calculate the features we apply the segmentation algorithm to the BI signal of all recordings. Every time a segmentation point is found, the features are calculated and labeled as swallows or non-swallow using the manually set swallow onset marks. Finally we obtain a data set of 66887 samples (feature vectors) containing 3837 swallows.

2.4 Classification

For the classification of the swallow onsets, we use a random forest classifier. This classifier is part of the scikit-learn package for Python [6] and provides the best results for our data. Random forest belongs to the class of ensemble classifiers and consists of multiple single decision tree classifier. The result of a single tree is a probability for the classes (swallow or non-swallow) that are averaged to form the final classification result. We use a random forest that consists of 40 single trees with a maximum depth of seven nodes, a minimum number of six samples per leaf, a minimum of 18 samples at a node to create a split and Gini-gain cost function to calculate the

impurity of split in a node. The scikit-learn package allows the user to set weights for the classes manually. This option can be used to create classifiers with different sensitivities. To achieve a reliable evaluation we apply the leave-one-subject-out validation. Setting the class weights balanced yields a **sensitivity** of 91.0%, a **precision** of 43.4% and an **accuracy** of 92.6% for healthy subjects.

Remark: The swallow onset detection is paused for 1 s after a swallow onset has been detected to avoid unwanted re-triggering during biofeedback or stimulation.

3 Adaptive Classifier

Sensitivity is the most important measure of a classifier in our application, because we want to enable the patient to reliably trigger the stimulation or biofeedback. The amount of false positives has only a subordinate priority and is given by the precision. Dysphagia patients usually have decreased EMG activity and a smaller decay of BI compared to healthy subjects. This leads to a generally decreased classification accuracy for patients. The sensitivity of a random forest classifier can be adjusted by tuning of the class weights. We created a set of seven classifiers with increasing sensitivity from 78.5% to 96.7%. The training was based on data of healthy subjects.

To determine the best classifier for swallow onsets, we deploy as reference the swallow classification algorithm introduced by Nahrstaedt et al. [2], which is capable of detecting completed swallows (not onsets!) with a high accuracy. The adaption process can be summarized as follows:

1. Calculate the features for each segmentation point until four swallows are found with the swallow detection.
2. Find time points of swallow onset (drop of BI) by using the swallow detection.
3. Predict the swallow onsets for feature vectors with every of the seven swallow onset classifiers in the set.
4. Calculate the sensitivity for every onset classifier with respect to the results from the swallow classification.
5. Pick the onset classifier with the highest observed sensitivity. If several onset classifiers possess the same sensitivity then choose the one with the highest precision for healthy subjects.

After this procedure the treatment is executed with the optimal swallow onset classifier to trigger stimulation or biofeedback.

Remark: There is the additional possibility for the therapist to adjust the sensitivity of the used swallow onset classifier by a slider via a graphical user interface.

4 Evaluation

To evaluate the proposed adaptive classification algorithm, we use a data set containing measurements of 41 patients. The evaluation algorithm applies the five adaption steps described in Section 3 to the first four swallows of every measurement file. The remaining data in each file is used to find swallow onsets by applying the automatically selected classifier and the following fixed classifiers: with lowest sensitivity (#1), with highest sensitivity (#7), and with balanced class weights (#3). The classification results of all classifiers are presented in Table 1. The reference was the swallow classification algorithm by Nahrstaedt et al. [2], the result of which was validated by an expert. The adaptive classifier shows a slight improvement in sensitivity and precision compared to the fixed classifiers in terms of mean values and standard deviations. However, observed individual improvements in sensitivity were up to 66 % for some patients.

5 Therapy Example

The swallow classification algorithm can be used to assess the quality of a swallow [2]. To accomplish that, the slope and maximum difference of the valley shaped BI signal can be calculated and interpreted as a measure for elevation speed and elevation height of the larynx. We use these measures to trace the progress of a patient, who was treated with transcutaneous functional electrical stimulation of the submental muscles in eleven therapy session during a week. The patient underwent standard dysphagia therapy before the FES treatment which did not cause any improvement in swallowing function. For the evaluation we first removed the stimulation artifacts and then calculated the average of the absolute values of the slope and the maximum difference for all swallows in each session. A linear function was fitted to the data points of all sessions as shown in Figure 2 and 3. The average progress of larynx elevation and elevation speed is calculated using the offset and slope of the linear function. An improvement of larynx elevation speed by 63% and elevation by 40% can be observed.

6 Discussion and Outlook

We introduced an adaptive classification algorithm for swallow onsets, that is capable of choosing a classifier with the highest sensitivity for an individual patient while maintaining the best performance in terms of precision. Yet, the precision of the classifier is not satisfying and requires discussion and

Tab. 1: Performance of fixed and adaptive classifier approaches.

Classifier	#1		#3		#7		Adaptive	
	Mean	Standard dev.	Mean	Standard dev.	Mean	Standard dev.	Mean	Standard dev.
Precision	25.4%	22.2%	27.3%	22.6%	25.4%	31.9%	28.9%	24.6%
Sensitivity	54.8%	34.0%	57.3%	31.5%	54.8%	33.6%	61.1%	29.6%

Fig. 2: Progress of larynx elevation speed across therapy sessions. **Fig. 3:** Progress of larynx elevation across therapy sessions.

further work. It is important to keep in mind that the statistic measures represents an average over all patients in the test data set. Huge improvements have been observed in some patients. It is interesting to note that the fixed classifier with the highest sensitivity did not yield the highest sensitivity for the patients on average. A possible explanation for this behavior is the pausing of 1 s after a swallow onset detection – the higher risk of false positives increases the probability of missing true swallow onsets that fall in the detection pauses (cf. Section 2).

In general, there is a difference in patients' behavior in treatment sessions without stimulation and with stimulation. In a treatment session with stimulation, patients are usually more concentrated on their swallowing and perform a smaller

number of head movements in order to prevent unnecessary stimulation. We could observe that the patients adapt their behavior to improve the swallow onset detection. In future, a further reduction of the amount of false positives is desired. Since most false positives arise from head and jaw movements of the patient, one or two inertial measurement units might be involved to predict and eliminate movement artifacts in the EMG and BI signals.

Author Statement

Research funding: This research was funded by the DFG under sign SE 2882/1. **Conflict of interest:** Holger Nahrstaedt is employee of the company HASOMED GmbH that develops a BI and EMG measurement system for diagnostic and treatment of swallowing disorders. **Informed consent:** Informed consent has been obtained from all individuals included in this study. **Ethical approval:** The research has been approved by the authors' institutional review board (Charité Berlin (EA1/019/10)).

References

- [1] Schultheiss C, Schauer T, Nahrstaedt H, Seidl RO. Automated Detection and Evaluation of Swallowing Using a Combined EMG/Bioimpedance Measurement System. *The Scientific World Journal* 2014.
- [2] Nahrstaedt H. Automatic detection and assessment of swallowing based on bioimpedance and electromyography measurements. Dissertation TU Berlin <http://dx.doi.org/10.14279/depositonce-6427> 2017
- [3] Riebold B, Nahrstaedt H, Schultheiss C, Schauer T, Seidl RO. Multisensor Classification System for Triggering FES in Order to Support Voluntary Swallowing. *Eur J Transl Myol* 26 2016.
- [4] Keogh E, Chu S, Hart D, Pazzani M. An online algorithm for segmenting time series. *Proceedings 2001 IEEE International Conference on Data Mining: IEEE*; 2001:289–96.
- [5] Lin J, Keogh E, Lonardi S, Chiu B. A symbolic representation of time series, with implications for streaming algorithms. *Proceedings of the 8th ACM SIGMOD workshop on Research issues in data mining and knowledge discovery: ACM* 2003:2.
- [6] Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* 2011;12:2825–30.