

## Swallow Detection Algorithm Based on Bioimpedance and EMG Measurements

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**Abstract:** Image-based swallowing assessment tools like videofluoroscopy and endoscopy allow experts manual investigation of a few individual swallows. However, these tools are expensive and can only be used by clinicians. Systems which utilize easily attachable, inexpensive and non-invasive sensors at the throat could be a real progress for diagnosis and therapy.

This contribution investigates the use of a combined electromyography (EMG) and bioimpedance (BI) measurement at the throat to automatically detect swallowing events. The absolute value of the measured BI completely describes the swallowing process, i.e. the closure of the larynx. There is a typical reproducible drop in BI during a swallow. The muscle activity needed for the laryngeal movement during a swallow is measured using EMG. The presented algorithm involves a valley detection in order to perform a segmentation of the BI signal. Additionally, only BI valleys that coincide with EMG activity are selected for feature extraction. In the second part of the algorithm, extracted features of the BI and integrated EMG are fed into a support vector machine (SVM) which is able to separate BI valleys related to swallowing events from valleys which are not caused by swallowing.

The detection algorithm has been tested on data from nine healthy subjects. The data set contained 1370 swallows of different bolus sizes and consistency and was effected by other movements and speech. The combined BI/EMG segmentation detected 99.3% of all swallowing events. The subsequently applied classifier showed a sensitivity of 96.1% and a specificity of 97.1% for the test data.

*Keywords:* Classification, Signal processing, Medical systems, Detection algorithms, Signal-processing algorithms, Time-series analysis.

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### 1. INTRODUCTION

Swallowing is a complex vital process that takes place either consciously or subconsciously depending on the current phase of the swallowing. Controlled by cortical processes, which are coordinated in the brain stem (i.e. pattern generators), multiple muscles have to be activated in a timely manner for a swallow. Swallowing disorders (dysphagia) can lead to serious complications, including malnutrition and pneumonia, which can be lethal. The complete closure of the larynx and its timing take a central role in safe swallowing. The larynx is the bifurcation between the trachea and the oesophagus. In case of closure failure, saliva, liquid or food penetrates the airway (aspiration), which may have the consequences described above. The causes of swallowing disorders are mostly severe brain injuries and strokes. Every second stroke patient suffers from dysphagia, which is chronic in one quarter of the patients (Bath et al., 2002).

Because of the complex anatomy, the overlapping muscular processes, and the complex control, the diagnosis of swallowing disorders is extremely complex. Standard examination methods in swallowing disorders are videofluoroscopy and fiberoptic endoscopy. Both are technically complex procedures which can in most cases only be performed by clinicians.

In contrast, a system which utilizes easily attachable, inexpensive and non-invasive sensors and that contains an automatic algorithm for detection of swallows can be used for instantaneous biofeedback of the swallowing process or for continuous long-term measurements. Such a real-time measurement method should furthermore give reproducible and reliable results.

First approaches in this direction have been based on dual-axis swallowing accelerometry signals (Sejdi et al., 2009; Damouras et al., 2010), dual-axis swallowing accelerometry signals in combination with nasal respiration and submental mechanomyography signals (Lee et al., 2009), as well as swallowing sounds (Lazareck and Moussavi, 2002; Sazonov et al., 2010). Swallowing accelerometry and swallowing sounds measure the vibration and the noise which is caused by swallowing. However, vocalization which is

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caused by speech or a cough can severely disturb the measurement signal and swallow detection. These negative effects can only be partially reduced by algorithms (Sejdi et al., 2010). Therefore, it is necessary to study the performance of other real-time capable measurement methods which allow a robust detection of swallows even in presence of speech, neck or head movements.

Electromyography (EMG) can be used to measure the electrical activity of muscles and muscle groups. The EMG signal provides information about the onset and the level of muscle activation. However, EMG alone is not sufficient to evaluate swallowing (Hillel et al., 1997). Amft and Troster (2006) combined EMG measurement with swallowing sound recordings in order to detect swallowing. The results show that there is still room for improvement.

A Japanese group studied a four-electrode transcutaneous bioimpedance (BI) measurement at the throat for the assessment of swallowing (Kusuhara et al., 2004; Yamamoto et al., 1998). In a study by Yamamoto et al. (2000), the reproducibility of the curve for small changes in the electrode positions was determined. The resulting trace was interpreted as a reflection of the entire swallowing process (oral, pharyngeal, esophageal phase) caused by movement of the larynx, pharynx, throat, and oesophagus.

To our best knowledge, nobody tried to apply automatic swallowing detection based on BI. This contribution investigates the use of a combined EMG and BI measurement at the throat to automatically detect the laryngeal movement during swallowing. The presented algorithm consists of a valley detection which selects parts of the BI signal that might be related to swallows. Only valleys that coincide with EMG activity are then selected for feature extraction. In the second part of the algorithm, the extracted features are fed into a support vector machine (SVM) in order to separate swallows from non-swallows. The developed algorithm was tested on data from healthy people.

## 2. METHODS

### 2.1 Signal acquisition

The measuring system PHYSIOSENSE which allows two independent BI measurements and provides up to four channels of EMG measurement has been used. This device was developed at the Technische Universität Berlin, Control Systems Group (Nahrstaedt et al., 2010). The device has two galvanically isolated current sources. One current source generates a sinusoidal current with a frequency of 50 kHz, while the second current source is set to a frequency of 100 kHz. Thus, two independent BI measurements can be performed simultaneously. Both current sources can be used either for the four-electrode or the two-electrode measurement method (Martinsen and Grimnes, 2008). In the first case, separate electrodes are used for applying the current and measuring the voltage. In the latter case, the voltage is directly measured over the current source output. The device measures the absolute value of the BI without phase information. The sampling frequency is 4 kHz. The measurements are sent in real-time via USB to a PC. The device fulfills the following standards: IEC 60601-1:1998+A1:1991+A2:1995, IEC 60601-2-40 and IEC 60601-1-2:2007.

For the measurement of the trans-pharyngeal BI at the throat, the four-electrode method at a frequency of 50 kHz was used. Additionally, EMG was measured across both voltage measuring electrodes. The electrodes of the current source were placed on both sides of the onset of the sternocleidomastoid. The voltage measurement electrodes were placed laterally between the hyoid bone and the thyroid cartilage (Fig. 1). For this, Blue Sensor N ECG electrodes (Ambu Ltd., United Kingdom) were used.

A typical time course of the integrated EMG (after the processing described in Section 2.2 and 2.3) and BI during a swallow is shown in Fig. 5. The laryngeal closure reaches its maximum when the BI is at its local minimum.

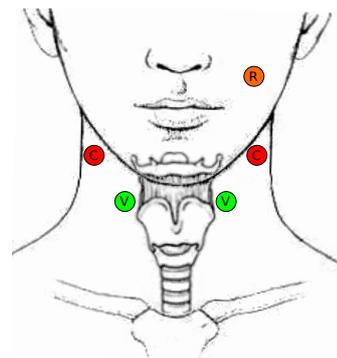


Fig. 1. Electrode positions (C - current electrodes, V - voltage measurement electrodes, R - reference electrode)

Nine adults participated in this pilot study. The exclusion criteria were: younger than 18, older than 50, pregnancy, a history of dysphagia, implanted cardiac pacemaker or defibrillator, metallic implants or central venous catheters. The participating subjects were two women (mean age 28.5) and seven men (mean age 27.4). This study was approved by the ethic board of Berlin at the Charité Berlin (EA1/160/09 and EA1/161/09). In order to examine the accuracy of the automatic detection, sensitivity and specificity were determined.

During the examination, each subject was sitting at a table, where they were connected to the measurement device through electrodes. Each subject was instructed to mark every swallow using a manual switch. Except for the consistencies of the boluses that the subject had to swallow, there were no guidelines. All subjects were allowed to talk, move their heads and place the food/liquid to their mouths on their own. Each subject was examined on two different days. In each of both sessions, the subjects first swallowed their own saliva for a period of 10 minutes. Then they drank 200 ml of water and finally ate 100 g of yogurt. In total, 1370 swallows were recorded.

### 2.2 Preprocessing

First jumps and spikes in the EMG signal are detected and removed. For this, the difference in EMG amplitude of subsequent samples is stored in a sequence. A spike/jump in the original signal is detected if the corresponding value in the difference sequence is at least eight times greater than the standard deviation of the difference sequence. Under the assumption that the sequence has a normal distribution, the probability is almost zero that a difference

of two subsequent EMG samples is greater than this threshold. All recorded spikes had always a length shorter than one second. In order to decide if a spike or jump is present, the EMG value before the detected spike/jump is stored. If the EMG signal is going back to this value within one second, a spike is assumed and all samples of the EMG signal within the spike are set to the last memorized value before the spike. Otherwise a jump is assumed, and the height of the jump is subtracted from all EMG samples after the detected jump. In the next step, a non-causal band-pass of 4th order with the frequency range of 90-230 Hz is applied. This filter removes movement artifacts and supply voltage noise at 50 Hz. However, the supply voltage also causes disturbances at the third harmonic at 150 Hz. Therefore, a non-causal band-stop filter of 3rd order with the frequency range of 140-160 Hz is additionally applied. Now, the EMG signal is downsampled to a frequency of 500 Hz. The EMG signal is then denoised using wavelet filters. This improves the signal-to-noise ratio without changing the signal amplitude in intervals where EMG activity is present. A db7 wavelet up to a level of eight is used. In all wavelet levels, the “minimax” method is used as wavelet threshold selection rule as well as the soft thresholding method for denoising. The estimated noise from the first level of wavelet coefficients is used for threshold rescaling.

Since the BI signal is mainly disturbed by noise and the crucial frequency content of the BI signal is in the range up to 100 Hz, the BI signal is filtered by a non-causal low pass of 4th order with a cut-off frequency of 125 Hz and downsampled to 250 Hz. Exemplarily, Fig. 2 shows some preprocessed BI and EMG signals together with the detected muscle activity periods.

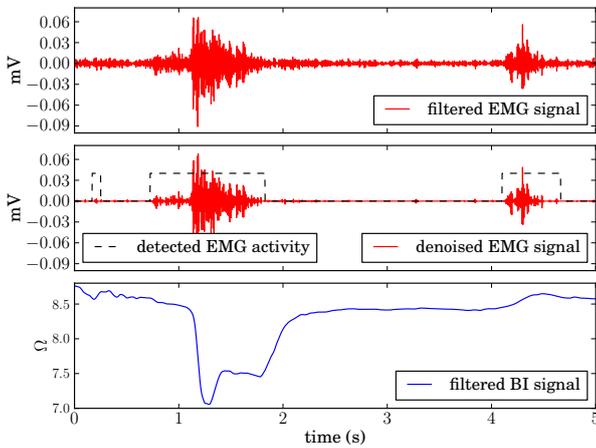


Fig. 2. EMG after filtering and denoising together with the detected muscle activity periods as well as BI after the preprocessing.

### 2.3 Segmentation of EMG activity periods

Periods of muscle activation are detected by using a double-threshold detector as described in Xu and Adler (2004). This detector is based on a previous work by Bonato et al. (1998) which is complex and requires a whitening of the signal.

The double-threshold detector consists of a sliding window of length  $m$ , a first threshold  $\zeta$  and a second threshold  $r_0$ . The sliding window moves along the auxiliary sequence

$$z(l) = x(l)^2, \quad (1)$$

where  $x(l)$  is the filtered and denoised EMG sample of time instant  $l$ . The muscle is considered active if  $r_0$  values of  $z$  are above  $\zeta$  within the sliding window. Bonato et al. (1998) have shown that  $r_0 = 1$  gives the highest detection probability. The first threshold  $\zeta$  can be calculated by a given false-alarm probability  $P_{fa} = 0.05$ , the estimated noise variance  $\sigma_n^2$  of the sequence  $x$ , and window size  $m$  according to Xu and Adler (2004). The sliding window length  $m$  should be as large as possible to increase the detection probability. However, a larger value also decreases the time resolution of the detector. In this application the window size is set to  $m = 20$  samples and  $r_0$  is set to one. The noise variance  $\sigma_n^2$  is estimated using a sliding window approach. The window length is 0.3 s (or 75 samples). This window length was chosen such that one complete EMG recordings contains at least one frame of noise without any EMG activity. The noise variance is calculated for all frames and the smallest value is taken as estimated noise variance  $\sigma_n^2$ . Finally, the detected onset/offset sequence is further analyzed to reject onset-offset-onset transitions which are shorter than 60 ms (15 samples), as supposed by Bonato et al. (1998).

For further use, the EMG signal is rectified and filtered by a non-causal low pass of 4th order with a cut-off frequency of 10 Hz. The filter parameters were chosen such that the filter output approximates the envelope of the rectified EMG signal.

### 2.4 Segmentation of BI activity

During each swallow, the measured BI decreases and then immediately increases approximately to the value before the swallow started (see Fig. 5). Thus, a valley detection algorithm seems promising for segmentation of the BI signal.

In order to fasten the segmentation, the piecewise linear approximation method (PLA) (Keogh et al., 2001) is applied to the BI signal. Using this method, the time series are approximated by straight lines of different lengths which are always an integer of the sampling time. The distance between the end and the start of two adjacent lines is the sampling time. As Keogh et al. (2001) suggest, a bottom up algorithm is used. This algorithm starts with the maximal number of segments (each segment contains only two sampling points). Then, repetitively, the merged pair of adjacent segments which would give the lowest 2-norm error with respect to the BI signal at this interval is merged. Merging means to connect the start point of the first line with the end point of the second line. This merging process is repeated until a maximal error threshold is reached. The threshold in this work is set to  $\sqrt{10}\Omega$  by trial and error.

The line segments  $P_i$ ,  $i \in \{1, \dots, N\}$  are defined by

$$P_i = [\text{length}_i, \text{start\_value}_i, \text{end\_value}_i]', \quad i = 1 \dots N. \quad (2)$$

In the next step, the vectors  $P_S \in \mathbb{R}^N$ ,  $P_I \in \mathbb{N}^{N+1}$  and  $P_C \in \mathbb{R}^{N+1}$  are calculated:

$$\begin{aligned}
 P_S(i) &= (P_i(3) - P_i(2))/P_i(1), \quad i = 1 \dots N \\
 P_I(1) &= 1, P_I(i+1) = 1 + \sum_{j=1}^i P_j(1), \quad i = 1 \dots N \\
 P_C(1) &= P_1(2), P_C(N+1) = P_N(3), \\
 P_C(i+1) &= (P_i(3) + P_{i+1}(2))/2, \quad i = 1 \dots N-1
 \end{aligned} \quad (3)$$

$P_S$  is the slope of each segment,  $P_I$  contains the position of each connection, and  $P_C$  is a vector with mean values of the end point of a line and the start point of the next line. Local minima of  $P_C$  are calculated and the positions within  $P_C$  are saved in a vector  $M$ .

**Definition 1** A valley related to a swallowing event consists of at least two segments and has to fulfill the following conditions: (i) the first line has a negative and the last line has a positive slope, (ii) the length of the valley is less than 3.6s, and (iii) the connection from the beginning to the end does not cross any other line segment in  $P$ . These conditions can be checked by using the vectors  $P_S$ ,  $P_I$  and  $P_C$ .

Within the approximated BI signal, all valleys which fulfill the conditions given in definition 1 are searched. Each valley is defined by three points: start point, minimum and end point.

In order to describe all valleys in the approximated time series, a matrix  $T \in \mathbb{Z}^{N-2 \times N-2}$  is created. A positive number in  $T(i, j)$  indicates that a valley between position  $P_I(i)$  and position  $P_I(j+2)$  exists. If the conditions for a valley are fulfilled between  $P_I(i)$  and  $P_I(j+2)$ , then the corresponding minimum in  $M$  is saved to  $T(i, j)$ ; otherwise,  $T(i, j)$  is set to  $-1$ . The lower left part of  $T$  remains untouched, as the end point  $P_I(j+2)$  has to be located behind the start point  $P_I(i)$ .

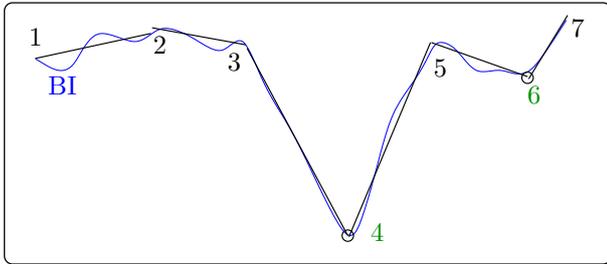


Fig. 3. Example for BI segmentation and valley detection.

Table 1. Matrix  $T$  and vector  $M$  from the example in Fig. 3.

$T$	$j+2=3$	4	5	6	7	$M$
$i=1$	-1	-1	-1	-1	-1	4
2		-1	4	-1	4	6
3			4	-1	4	
4				-1	-1	
5					6	

The definition for a valley may lead to several valleys which have the same local minimum. This can be seen easily from an example (Fig. 3 and Table 1). The sequence notation is  $V_{start}-V_{min}-V_{end}$ . For the second minimum (point 6), only one sequence of segments exists (5-6-7); whereas for the first minimum (point 4), three possible sequences of segments exist (2-4-5, 3-4-5 and 3-4-7).

Subsequently, one valley per minimum is selected by maximizing a utility function with respect to all detected valleys for the corresponding minimum. The utility function is chosen heuristically in such a way that valleys with large area and short distance between the start and end point are preferred. The utility function is given by

$$f = \frac{area}{length^{1.2}} \quad (4)$$

where  $area$  is the area enclosed by the approximated BI curve and the line between the start and end point of the valley, and  $length$  is the length of the line between start and end point of the valley.

In the previous example, the utility function will be calculated for the valleys which corresponds to the minimum at position 4. The valley giving the largest value for  $f$  will be selected and all other valleys will be neglected.

### 2.5 Combination of EMG and BI segmentation

EMG activity is a physiological prerequisite for swallowing. The laryngeal movement is caused by muscle activity. Hence, EMG activity indicates a swallow. In order to identify BI valleys which are not caused by swallowing, all valleys that do not coincide with EMG activity are neglected.

### 2.6 Adjustment of start, minimum and end of each valley

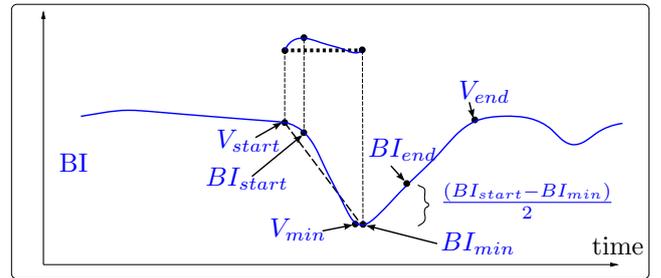


Fig. 4. Adjustment of start, minimum and end.

In order to prepare the feature extraction for a classifier, the points  $BI_{start}$ ,  $BI_{min}$  and  $BI_{end}$  of each valley have to be calculated (cf. Fig. 4). The previously found start, minimum and end points ( $V_{start}$ ,  $V_{min}$  and  $V_{end}$ ) of each valley are not accurate and reliable enough. For the recalculation of these points, the BI signal is analyzed between  $V_{start}$  and  $V_{end}$ .  $BI_{min}$  is set to the local minimum of the non-approximated BI signal.  $BI_{start}$  is set to the point where the difference between the straight line from  $V_{start}$  to  $BI_{min}$  and the BI signal in the same interval is maximal. The end point  $BI_{end}$  is located after  $BI_{min}$  and is defined as the point where the BI recovers to 50% of the swallow-related drop. The drop is defined by the BI difference between  $BI_{start}$  and  $BI_{min}$ .

### 2.7 Feature extraction

In the following, the upper index  $V$  refers to the value and the upper index  $T$  to time of a BI or EMG point of a valley (cf. Fig. 5).  $EMG_{start}$  and  $EMG_{end}$  are set to the associated EMG interval;  $EMG_{max}$  is set to

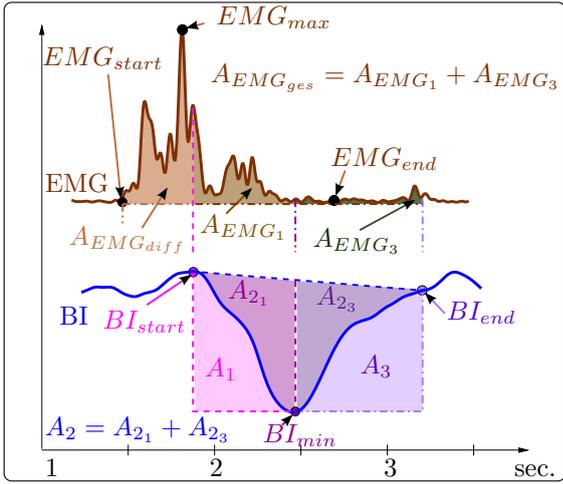


Fig. 5. Definition of area ( $A$ ) based features. The elevation of the larynx takes place between  $BI_{start}$  and  $BI_{min}$ . the maximum in this interval. Using this convention, the following features which are related to time and amplitude can be calculated:

- $t_{min} = BI_{min}^T - BI_{start}^T$ ,  $t_{end} = BI_{end}^T - BI_{start}^T$
- $t_{emgdiff} = EMG_{start}^T - BI_{start}^T$
- $t_{emgmax} = EMG_{max}^T - EMG_{start}^T$
- $t_{emgend} = EMG_{end}^T - EMG_{start}^T$
- $\Delta_{min} = BI_{min}^V - BI_{start}^V$
- $emg_{max} = EMG_{max}^V$

The slope  $S_1$  from  $BI_{start}$  to  $BI_{min}$  and the slope  $S_2$  from  $BI_{min}$  to  $BI_{end}$  are included as features.

$$S_1 = (BI_{min}^V - BI_{start}^V) / (BI_{min}^T - BI_{start}^T) \quad (5)$$

$$S_2 = (BI_{end}^V - BI_{min}^V) / (BI_{end}^T - BI_{min}^T) \quad (6)$$

Areas ( $A$ ) which are outlined by the BI and EMG signals are also used as features. Fig. 5 shows their definition.

In addition, the symbolic aggregate approximations (SAX) (Lin et al., 2003) of the BI and the EMG curves are used as features. For each possible swallow, the BI and EMG sequences are analysed within the range from 0.4s before the valley starts ( $BI_{start}$ ) to 1.6s after  $BI_{start}$ . The range was chosen such that swallow induced changes are included. Both sequences are normalized for these ranges (zero mean value, standard deviation of one). The resulting sequences are reduced in size using the piecewise aggregate approximation (PAA). Therefore, the sequence is subdivided in equally spaced segments across the time axis and each segment is approximated by its mean value. The BI sequence is reduced from 500 samples to 32 PAA coefficients, whereas the EMG sequence is reduced to 16 PAA coefficients. In a next step, the SAX method maps the PAA coefficients to SAX symbols. This step reduces the resolution across the BI/EMG-coordinate. Therefore, all PAA coefficients that are belong to the same interval across the BI/EMG-axis are mapped to the same SAX symbol. The intervals are chosen such that a signal with Gaussian distribution would produce symbols with equal probability. The number of intervals and the alphabet size is 8 for BI and 4 for EMG. The alphabet size and the number of PAA coefficients was chosen heuristically. The SAX symbol sequence are directly used as features. Fig.

6 illustratively shows the features generated by the SAX method from the normalised BI sequence.

In total the feature vector has a length of 65 entries.

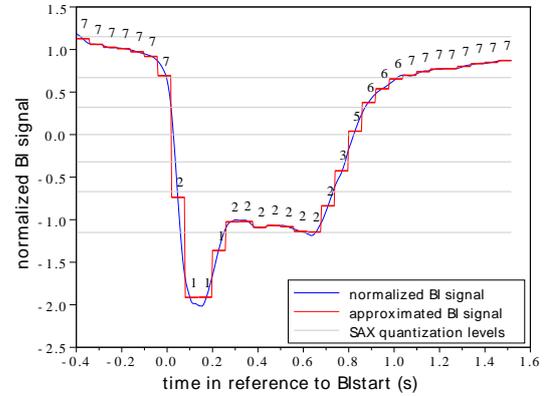


Fig. 6. Features generated by the SAX method from the normalised BI sequence.

### 2.8 Support Vector Machine

The feature vector of the training data is normalized to a range of  $[0, 1]$  such that the minimum of one feature for all training data is zero and its maximum is one. The normalization parameter are saved and later applied to the test data set. Both normalized feature vectors are used as input for a support vector machine (SVM) classifier. A group vector defines which valleys are related to swallowing events and which are not. This information is gathered from the marking of swallows by the subjects.

As implementation of the SVM, LIBSVM (Chang and Lin, 2011) with Gaussian radial basis kernel functions is used. The optimal training parameters can be found by a grid search. Therefore, the parameter  $C = 2^n$ , which is related to the cost for false classification, is varied in a range with  $n = [-1, 15]$  and the parameter  $\gamma = 2^m$ , which is the kernel width, is varied in a range with  $m = [-15, 1]$ . The parameter set with the lowest classification error according to a five-fold cross validation was used.

The measurement data sets of subject 1-5 were selected for training of the SVM classifier (703 swallows). For testing the data sets of subject 6-9 were used (667 swallows).

## 3. RESULTS

### 3.1 Segmentation

The valley detection combined with the EMG activation periods could mark 1360 of 1370 swallows correctly. This means that 99.3% of all marked swallows were detected. However, 4128 non-swallowing related valleys were also included by the segmentation algorithm.

### 3.2 Classification

The SVM-classifier was trained with the training data (698 swallows and 2433 non-swallow events). The classification results for the test data set (662 swallows and 1695 non-swallow events) are presented in Table 2.

Table 2. Performance of the classifier on the test data.

	Swallows	Non-swallows
Positive	636	49
Negative	26	1646
	Sensitivity	Specificity
	96.1%	97.1%

#### 4. DISCUSSION AND CONCLUSIONS

We have shown that an automatic detection of swallowing events is possible using BI and EMG measurements at the throat for healthy subjects. A valley detection algorithm was developed and successfully applied on the BI signal. Combined BI and EMG activity segmentation detects almost all swallowing events independent from its consistency. In contrast to other studies (e.g. Sejdi et al., 2009), subjects could eat and swallow without strict regulations in this pilot study. Thus, the segmentation algorithm includes also non-swallowing events. The selected features together with an SVM classifier were able to distinguish these non-swallows from swallows with high rates in sensitivity and specificity.

The results are very promising, until now no technical process is known which has a better performance in swallowing detection. In future studies, patient groups should be examined. Also, the feasibility of extending the classification process should be analyzed, e.g. adding classification of bolus consistency or measure of airway closure.

In order to develop a diagnosis, therapy and biofeedback system the system presented has to be improved. In future research, the presented algorithm should be enhanced towards a sliding window-based online detection algorithm. With such a system, control of a swallowing neuro-prosthesis could be feasible.

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