METHOD AND DEVICE FOR SWALLOWING IMPAIRMENT DETECTION

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ABSTRACT

Disclosed herein is a method and apparatus for swallowing impairment detection, whereby cervical accelerometry and nasal airflow data is acquired as a candidate executes one or more swallowing events. Upon feature extraction and classification, vibrational and airflow data acquired in respect of each swallowing event is classified as indicative of one of normal or possibly impaired swallowing. Computer-readable media comprising statements and instructions for implementation by a processing device are also described in facilitating swallowing impairment detection respective to candidate swallowing events.
FIGURE 2

SWALLOWING IMPAIRMENT SCREENING DEVICE

- COMPUTER-READABLE MEDIUM/MEDIA
  - DATA ACQUISITION AND PROCESSING
  - OPERATION PROTOCOLS
  - SCREENING TOOLS

- PROCESSOR(S)

- POWER SUPPLY

- USER INTERFACE (INTEGRATED, LOCAL AND/OR REMOTE)

- INPUT / OUTPUT
CERVICAL ACCELEROMETRY AND AIRFLOW DATA REPRESENTATIVE OF AT LEAST ONE SWALLOWING EVENT

MULTI-SENSOR FEATURE EXTRACTION FOR EACH SWALLOWING EVENT

SWALLOWING EVENT CLASSIFICATION BASED ON EXTRACTED FEATURE(S)

OUTPUT (NORMAL VS IMPAIRED)

FIGURE 3
CERVICAL ACCELEROMETRY AND AIRFLOW DATA REPRESENTATIVE OF MULTIPLE SWALLOWING EVENTS

PREPROCESSING (FILTERING, DENOISING, ARTIFACT REMOVAL)

AUTOMATIC / MANUAL SIGNAL SEGMENTATION BY SWALLOWING EVENT

MULTI-SENSOR FEATURE EXTRACTION FOR EACH SEGMENTED SWALLOWING EVENT

FEATURE REDUCTION

SWALLOWING EVENT CLASSIFICATION BASED ON EXTRACTED FEATURE(S)

OUTPUT (NORMAL VS IMPAIRED)

FIGURE 4
DUAL AXIS (A-P & S-I) ACCELEROMETRY AND NASAL AIRFLOW DATA REPRESENTATIVE OF MULTIPLE SWALLOWING EVENTS

PREPROCESSING (INVERSE FILTER, DENOISING, ARTIFACT (HEAD MOTION) REMOVAL)

AUTOMATIC / MANUAL SEGMENTATION

MULTI-SENSOR FEATURE EXTRACTION (E.G. WAVELET DECOMPOSITION)

FEATURE REDUCTION

SWALLOWING EVENT CLASSIFICATION (E.G. LDA USING MAHALANOBIS AND/OR EUCLIDIAN DISTANCES)

CLASSIFIER TRAINING

OUTPUT (NORMAL VS IMPAIRED)

FIGURE 5A
DUAL AXIS (A-P & S-I) ACCELEROMETRY AND NASAL AIRFLOW DATA REPRESENTATIVE OF MULTIPLE SWALLOWING EVENTS

PREPROCESSING (INVERSE FILTER, DENOISING, ARTIFACT (HEAD MOTION) REMOVAL)

AUTOMATIC / MANUAL SEGMENTATION

MULTI-SENSOR FEATURE EXTRACTION (E.G. WAVELET DECOMPOSITION, ETC.)

FEATURE REDUCTION (PRESELECTED FEATURE SUBSET)

SWALLOWING SAFETY CLASSIFICATION (LDA USING EUCLIDIAN DISTANCES)

SWALLOWING EFFICIENCY CLASSIFICATION (LDA USING MAHALANOBIS DISTANCES)

OUTPUT (SAFE VS UNSAFE)

OUTPUT (EFFICIENT VS INEFFICIENT)

FIGURE 5B
IDENTIFY ELIGIBLE CANDIDATE

POSITION DUAL-AXIS ACCELEROMETER AND AIRFLOW MONITOR

ACTIVATE DEVICE

START RECORDING AS CANDIDATE PERFORMS SWALLOWING EVENT (E.G. 5-CC WATER)

STOP RECORDING UPON COMPLETION OF SWALLOWING EVENT

PROCESS RECORDED ACCELEROMETRIC SIGNAL

OUTPUT RESULT

CANDIDATE COUGH?

SECOND COUGH?

THIRD EVENT?

END

OUTPUT SESSION RESULTS INDICATIVE OF SWALLOWING IMPAIRMENT?

REFER CANDIDATE FOR FURTHER ASSESSMENT

FIGURE 6
### Table 3
Best result for each classifier for the depth of airway invasion classification problem (mean ± SD).

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Adjusted accuracy (%)</th>
<th>Dimensionality</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDA Euclidean</td>
<td>1.00 ± 0.0</td>
<td>49.4 ± 5.9</td>
<td>74.7 ± 2.9</td>
<td>9</td>
</tr>
<tr>
<td>LDA Mahalanobis</td>
<td>22.5 ± 18.4</td>
<td>97.4 ± 3.5</td>
<td>59.9 ± 10.5</td>
<td>9</td>
</tr>
<tr>
<td>NN 10 HUs</td>
<td>83.3 ± 21.5</td>
<td>57.9 ± 11.1</td>
<td>76.2 ± 10.6</td>
<td>9</td>
</tr>
<tr>
<td>NN 20 HUs</td>
<td>82.5 ± 35.4</td>
<td>50.9 ± 8.1</td>
<td>69.6 ± 17.0</td>
<td>11</td>
</tr>
<tr>
<td>NN 30 HUs</td>
<td>88.3 ± 21.9</td>
<td>52.4 ± 8.7</td>
<td>70.4 ± 12.4</td>
<td>8</td>
</tr>
<tr>
<td>PNN</td>
<td>89.2 ± 14.2</td>
<td>47.8 ± 7.6</td>
<td>68.4 ± 8.0</td>
<td>11</td>
</tr>
<tr>
<td>KNN K=11</td>
<td>63.3 ± 28.4</td>
<td>72.5 ± 6.9</td>
<td>67.9 ± 16.3</td>
<td>11</td>
</tr>
<tr>
<td>KNN K=21</td>
<td>71.7 ± 27.5</td>
<td>73.2 ± 8.1</td>
<td>72.4 ± 15.5</td>
<td>11</td>
</tr>
<tr>
<td>KNN K=31</td>
<td>71.9 ± 21.9</td>
<td>71.3 ± 7.2</td>
<td>71.5 ± 11.8</td>
<td>11</td>
</tr>
</tbody>
</table>

* Best classifier overall.

### Table 4
Best result for each classifier for the bolus clearance from the valleculae classification problem (mean ± SD).

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Adjusted accuracy (%)</th>
<th>Dimensionality</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDA Euclidean</td>
<td>77.6 ± 24.3</td>
<td>86.9 ± 10.5</td>
<td>82.3 ± 16.0</td>
<td>8</td>
</tr>
<tr>
<td>LDA Mahalanobis</td>
<td>75.5 ± 15.4</td>
<td>91.9 ± 8.6</td>
<td>83.7 ± 9.7</td>
<td>11</td>
</tr>
<tr>
<td>NN 10 HUs</td>
<td>75.7 ± 20.6</td>
<td>88.6 ± 11.2</td>
<td>82.1 ± 11.0</td>
<td>6</td>
</tr>
<tr>
<td>NN 20 HUs</td>
<td>79.8 ± 14.2</td>
<td>85.2 ± 12.3</td>
<td>82.5 ± 9.8</td>
<td>7</td>
</tr>
<tr>
<td>NN 30 HUs</td>
<td>78.1 ± 14.7</td>
<td>83.8 ± 15.2</td>
<td>80.9 ± 10.7</td>
<td>7</td>
</tr>
<tr>
<td>PNN</td>
<td>77.1 ± 13.7</td>
<td>75.7 ± 12.9</td>
<td>76.4 ± 8.4</td>
<td>3</td>
</tr>
<tr>
<td>KNN K=11</td>
<td>71.2 ± 21.5</td>
<td>86.7 ± 7.0</td>
<td>78.9 ± 12.3</td>
<td>6</td>
</tr>
<tr>
<td>KNN K=21</td>
<td>70.5 ± 22.8</td>
<td>85.7 ± 15.3</td>
<td>78.6 ± 13.4</td>
<td>11</td>
</tr>
<tr>
<td>KNN K=31</td>
<td>72.1 ± 21.7</td>
<td>88.3 ± 17.7</td>
<td>80.2 ± 10.7</td>
<td>11</td>
</tr>
</tbody>
</table>

* Best classifier overall.

### Table 5
Best result for each classifier for the bolus clearance from the pyriform sinuses classification problem (mean ± SD).

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Adjusted accuracy (%)</th>
<th>Dimensionality</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDA Euclidean</td>
<td>73.3 ± 29.6</td>
<td>90.8 ± 7.9</td>
<td>82.0 ± 15.5</td>
<td>9</td>
</tr>
<tr>
<td>LDA Mahalanobis</td>
<td>81.7 ± 25.4</td>
<td>86.8 ± 7.3</td>
<td>84.2 ± 10.6</td>
<td>11</td>
</tr>
<tr>
<td>NN 10 HUs</td>
<td>78.5 ± 24.9</td>
<td>86.0 ± 8.0</td>
<td>82.2 ± 13.3</td>
<td>11</td>
</tr>
<tr>
<td>NN 20 HUs</td>
<td>83.3 ± 23.6</td>
<td>80.5 ± 11.9</td>
<td>81.9 ± 12.8</td>
<td>12</td>
</tr>
<tr>
<td>NN 30 HUs</td>
<td>83.3 ± 23.6</td>
<td>76.7 ± 9.8</td>
<td>80.0 ± 12.1</td>
<td>12</td>
</tr>
<tr>
<td>PNN</td>
<td>76.7 ± 31.6</td>
<td>80.6 ± 11.6</td>
<td>78.6 ± 16.1</td>
<td>12</td>
</tr>
<tr>
<td>KNN K=11</td>
<td>68.3 ± 42.9</td>
<td>86.0 ± 8.8</td>
<td>74.7 ± 22.2</td>
<td>11</td>
</tr>
<tr>
<td>KNN K=21</td>
<td>68.3 ± 37.2</td>
<td>84.5 ± 10.3</td>
<td>76.4 ± 20.3</td>
<td>11</td>
</tr>
<tr>
<td>KNN K=31</td>
<td>68.3 ± 37.2</td>
<td>84.5 ± 10.3</td>
<td>76.4 ± 20.3</td>
<td>11</td>
</tr>
</tbody>
</table>

* Best classifier overall.

FIGURE 7
Table 6
Features that resulted in the best mean adjusted accuracies for the 3 ratings.

<table>
<thead>
<tr>
<th>Depth of airway invasion (LDA Euclidean, Table 3)</th>
<th>Bolus clearance from valleculae (LDA Mahalanobis, Table 4)</th>
<th>Bolus clearance from pyriform sinuses (LDA Mahalanobis, Table 5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S–1 accelerometer, $ER_{0.3,1}$</td>
<td>S–1 accelerometer, $E_{44.3}$</td>
<td>S–1 accelerometer, $E_{44.3}$</td>
</tr>
<tr>
<td>S–1 accelerometer, $ER_{0.3,2}$</td>
<td>S–1 accelerometer, $E_{42.3}$</td>
<td>S–1 accelerometer, $E_{42.3}$</td>
</tr>
<tr>
<td>S–1 accelerometer, $E_{42.1}$</td>
<td>S–1 accelerometer, $ER_{47.2,1}$</td>
<td>S–1 accelerometer, $E_{49.2}$</td>
</tr>
<tr>
<td>A–P accelerometer, mean</td>
<td>A–P accelerometer, $E_{43.3}$</td>
<td>A–P accelerometer, $E_{49.2}$</td>
</tr>
<tr>
<td>A–P accelerometer, $E_{45.1}$</td>
<td>A–P accelerometer, $E_{46.1}$</td>
<td>A–P accelerometer, $E_{42.1}$</td>
</tr>
<tr>
<td>A–P accelerometer, $ER_{49.3,1}$</td>
<td>A–P accelerometer, $E_{49.3}$</td>
<td>A–P accelerometer, $E_{49.3}$</td>
</tr>
<tr>
<td>A–P accelerometer, $E_{41.3,3}$</td>
<td>A–P accelerometer, $E_{42.3}$</td>
<td>A–P accelerometer, $E_{49.3}$</td>
</tr>
<tr>
<td>Nasal airflow, $E_{47.3}$</td>
<td>A–P accelerometer, $a_5$</td>
<td>A–P accelerometer, $E_{410.3}$</td>
</tr>
<tr>
<td>Nasal airflow, $ER_{98.3,2}$</td>
<td>Nasal airflow, $E_{46.2}$</td>
<td>Nasal airflow, $ER_{98.2,3,1}$</td>
</tr>
<tr>
<td></td>
<td>Nasal airflow, $E_{46.3}$</td>
<td>Nasal airflow, $ER_{98.2,3,1}$</td>
</tr>
<tr>
<td></td>
<td>Nasal airflow, $ER_{46.3,2}$</td>
<td>Nasal airflow, $E_{46.3}$</td>
</tr>
</tbody>
</table>

FIGURE 8
METHOD AND DEVICE FOR SWALLOWING IMPAIRMENT DETECTION

CROSS-REFERENCE TO RELATED APPLICATION

[0001] This application is a continuation-in-part of International PCT Application No. PCT/CA2012/000036, filed on Jan. 18, 2012, the entire disclosure of which is incorporated herein by reference.

FIELD OF THE DISCLOSURE

[0002] The present disclosure relates to swallowing impairments, and in particular, to a method and device for swallowing impairment detection.

BACKGROUND

[0003] Dysphagia is a serious component of many neurological diseases and injuries. The incidence of dysphagia following stroke has been reported to be 37-78% across studies, with aspiration incidence estimated at 43-54% in those with dysphagia. One systematic review has concluded that stroke patients who aspirate face 11.56 times the risk of developing pneumonia, compared to those without dysphagia. Patients who are aspirate, have been shown to 10 times more likely (p<0.0001) to develop pneumonia in the ensuing 6 months than those with normal swallowing. These figures speak to the importance of identifying dysphagia and managing aspiration risk as early as possible, both in potentially avoiding numerous aspiration-related deaths, and in saving the healthcare system considerable amounts of money by providing early treatment. Over the past decade, numerous evidence-based best practice guidelines have arrived at similar conclusions, strongly endorsing the early implementation of screening protocols to identify dysphagia and aspiration in high-risk populations, such as those with stroke.

[0004] Aspiration, generally understood as the entry of foreign contents into the upper airway, is a serious concern for individuals with swallowing difficulty (dysphagia), and can lead to pneumonia, for example. For instance, prandial aspiration, or the entry of foreign material into the upper airway during swallowing, is a serious component of dysphagia.

[0005] Using known and particularly invasive techniques, such as videofluoroscopic swallowing examinations, aspiration severity may be sub-classified based on the observed depth of airway invasion. For example, transient entry of material into the laryngeal vestibule, above the vocal cords, is termed high penetration (or a score of 2 on the 5-point Penetration Aspiration Scale); scores of 3-5, termed penetration, apply when material enters the laryngeal vestibule without subsequent clearance, and aspiration is the term used when material crosses the vocal cords and enters the trachea (scores of 6-8). A major dilemma for the detection of aspiration is the fact that overt clinical signs (e.g., cough or throat clearing) are reportedly absent up to 67% of the time; this is called “silent aspiration”. The risk of developing pneumonia has been found to be 4, 10, and 13 times greater, respectively, in patients with penetration, aspiration, or silent aspiration on videofluoroscopy, compared to individuals with normal swallowing. Evidence-based best practice guidelines concur that screening protocols should be used to facilitate the prompt identification and management of aspiration risk in high-risk populations, such as stroke patients; however, currently implemented protocols to this end often fail to provide satisfactory results, or again, achieve reasonable results at the expense of requiring the application of relatively invasive procedures.

[0006] In addition to aspiration, swallowing inefficiency is a major concern in individuals with dysphagia. Swallowing inefficiency is defined as the inability to swallow the contents of a single bolus (or mouthful) in a maximum of 2 swallows. This frequently leads to the presence of residual material being left behind in the throat (pharynx) after the swallow. The presence of this leftover material is, in turn, a risk for aspiration.

[0007] The main goals of a swallow screening protocol are generally two-fold: 1) to identify risk of impaired swallowing safety, i.e. penetration (entry of material into the airway above the level of the vocal cords) and/or aspiration (entry of material into the airway below the level of the vocal cords); and 2) to identify risk of impaired swallowing efficiency, characterized either by the presence of residues in the pharynx after the swallow, and/or prolonged transit times for moving a bolus in entirety from the mouth into the esophagus. To date, the principal emphasis in health policy calls for swallow screening has been on the first of these goals, that is the identification of penetration and/or aspiration risk (henceforth, “P-A risk”). When patients are identified to have either dysphagia or P-A risk through screening, they are generally referred for comprehensive swallowing assessment.

[0008] Unfortunately, the clinical identification of impaired swallowing safety and efficiency related to dysphagia is not particularly straightforward. Under usual circumstances, healthy awake people will swallow reflexively when material penetrates the airway above the vocal cords, and will cough when this material is aspirated below the vocal cords. Current P-A risk screening tools rely heavily on the recognition of overt clinical signs that imply possible aspiration: coughing, throat clearing, changes in respiratory rate, and changes in voice quality. In those with neurologic injury, however, overt clinical signs are frequently absent or volume-dependent. As noted above, silent aspiration is reported to occur in 25%-67% of acute stroke patients, and in 28% of patients overall, according to some studies. The variable expression of overt clinical signs of impaired swallowing safety in patients with neurogenic dysphagia contributes to limited success in P-A risk detection through clinical screening, and means that screeners must be trained to be alert for signs that are subtle. Similarly, post-swallow residues, related to swallowing inefficiency, are not reliably detectable at the bedside based on the observation of clinical signs, or based on asking patients whether they feel material sticking in their throats.

[0009] For example, current clinical approaches to non-invasive screening for aspiration typically involve the swallowing of water. The clinician notes signs of difficulty, including cough, post-swallow throat clearing, or voice changes that might imply the presence of liquid around the vocal cords. However, studies differ in their conclusions regarding the validity of abnormal clinical signs for revealing aspiration, compared to blinded ratings of instrumental assessments, and screening protocols involving sips of water tend to over-identify aspiration risk with false-positive rates as high as 72%.

[0010] Furthermore, current approaches to screening frequently rely on nurses to administer/conduct screening protocols. One widely-promoted clinical screening protocol (the Tor BSST) has an accompanying training package, which
involves initial training of 8 hours for a lead clinician/champion/trainer who then delivers training of 4 hours for individuals who will administer the screening protocol. However, institutional barriers have been reported to prevent implementation of screening guidelines, even after such extensive training. Given the turnover of nursing staff, a strong institutional commitment to continuing skills training and credentialing is required on a long-term basis.

Given the variable performance of swallow screenings for detecting aspiration, and the burden that this approach involves for training and competency-maintenance, a need exists for a valid non-invasive instrumental method to reliably detect impaired swallowing safety and efficiency, for example in a clinical setting or at the bedside. While the appraisal of swallowing sounds or vibrations has been proposed as a candidate method, available studies have heretofore been unsuccessful at attaining valid identification of aspiration. Accordingly, valid, reliable tools for detecting aspiration and other related swallowing impairments are needed that overcome the variable predictive utility of known clinical screening protocols and/or reduce the substantial burden on nursing staff imposed by the implementation of such protocols.

Therefore, there remains a need for a method and device for swallowing impairment detection that overcomes some of the drawbacks of known techniques, or at least, provides a useful alternative.

This background information is provided to reveal information believed by the applicant to be of possible relevance to the invention. No admission is necessarily intended, nor should be construed, that any of the preceding information constitutes prior art against the invention.

SUMMARY

An object of the invention is to provide a method and device for swallowing impairment detection. In accordance with one embodiment, there is provided a device for use in identifying a possible swallowing impairment in a candidate during execution of a swallowing event, the device comprising: an accelerometer to be positioned in a region of the candidate's throat and configured to acquire vibrational data representative of the swallowing event; a nasal airflow monitor to be positioned in a region of the candidate's nostrils and configured to acquire airflow data representative of the swallowing event; a processing module operatively coupled to said accelerometer and nasal airflow monitor for processing said vibrational data and said airflow data to extract from each one thereof one or more features representative of the swallowing event, and classify said vibrational data and airflow data as indicative of one of normal swallowing and possibly impaired swallowing based on said extracted features.

In accordance with another embodiment, there is provided a computer readable-medium having statements and instructions stored thereon for implementation by a processor to automatically process input vibrational data and airflow data representative of a candidate swallowing event in identifying a possible swallowing impairment, by: extracting one or more preset features representative of the swallowing event for each of the vibrational data and airflow data; comparing said extracted features with preset classification criteria defined as a function of said preset features; and outputting, based on said comparing, classification of said vibrational data and airflow data as indicative of one of normal swallowing and possibly impaired swallowing.

In accordance with another embodiment, there is provided a method for identifying a possible swallowing impairment in a candidate via execution of one or more preset swallowing events, comprising: recording vibrational data and airflow data representative of the one or more swallowing events; extracting one or more swallowing-event specific features for each of the vibrational data and airflow data; and classifying said extracted features as indicative of one of normal swallowing and possibly impaired swallowing.

Other aims, objects, advantages and features of the invention will become more apparent upon reading of the following non-restrictive description of specific embodiments thereof, given by way of example only with reference to the accompanying drawings.

BRIEF DESCRIPTION OF THE FIGURES

Several embodiments of the present disclosure will be provided, by way of examples only, with reference to the appended drawings, wherein:

FIG. 1 is a schematic diagram of a swallowing impairment detection device in operation, in accordance with one embodiment of the invention;

FIG. 2 is a schematic diagram of a swallowing impairment detection device, and components thereof, in accordance with one embodiment of the invention;

FIG. 3 is a high level multi-sensor data processing flow diagram for implementation by a swallowing impairment detection device, in accordance with one embodiment of the invention;

FIG. 4 is an illustrative multi-sensor data processing flow diagram, showing optional steps in dashed-line boxes, for implementation by a swallowing impairment detection device, in accordance with one embodiment of the invention;

FIG. 5A is a detailed multi-sensor data processing flow diagram for implementation by a swallowing impairment detection device, in accordance with one embodiment of the invention;

FIG. 5B is a detailed multi-sensor data processing flow diagram for implementation by a swallowing impairment detection device in screening for both swallowing safety and efficiency, in accordance with one embodiment of the invention;

FIG. 6 is a flow chart of a candidate screening and testing protocol for implementation using a swallowing impairment screening device, in accordance with one embodiment of the invention;

FIGS. 7A, B and C are tables of classification performance results achieved for depth of airway invasion, bolus clearance from the valleculae sinuses, and bolus clearance from the pyriform sinuses, respectively, in accordance with various exemplary embodiments of the invention;

FIG. 8 is a table of feature subsets selected in achieving highest classification performances, as reported in the tables of FIG. 7.

DETAILED DESCRIPTION

As introduced above, aspiration, generally understood as the entry of foreign contents into the upper airway, is a serious concern for individuals with swallowing difficulty, for example suffering from dysphagia or other such conditions, and can lead to pneumonia, for example. Unfortunately, aspiration is not always readily identified, due to the variable expression of overt clinical signs, such as cough. Other swal-
ollowing impairments, such as the presence of residues post-swallowing, which is common in patients suffering from dysphagia, are also of concern, and the detection thereof is generally required in properly screening for and/or diagnosing a patient’s condition. The herein described swallowing impairment detection methods and devices provide a solution to the widespread need for an accurate, non-invasive instrument to detect impaired swallowing safety and/or efficiency during screening. As will be elaborated below, such methods and devices now provide for the greater ability to incorporate swallowing impairment screening into routine nursing assessments of patient vital signs, in some embodiments, with minimal training.

[0029] For instance, the methods and devices described herein provide various improvements over the state of the art that assist in the screening for, detection of, monitoring and/or diagnostic of swallowing impairment(s). It will be appreciated that while specific embodiments are described herein in the context of specific applications and implementations, the various features of the herein described methods, devices, and elements thereof, may be considered in different contexts to improve different aspects associated with swallowing impairment screening, detection, monitoring and/or diagnostics, and that, with different levels of user interaction, automation and complexity depending on the application at hand. Namely, while certain implementation protocols and operation guidelines may be considered herein with respect to specific examples, alternative or complimentary approaches may also be considered without departing from the general scope and nature of the present disclosure. Accordingly, it will be appreciated that the use herein of the term “impairment detection” is meant to be construed broadly to encompass different levels of impairment identification, be it in the context of routine screenings or diagnostics, and that, without departing from the general scope and nature of the present disclosure.

[0030] As will be discussed in greater detail below, the methods and devices described herein make use of cervical accelerometry and airflow monitoring during swallowing for detecting swallowing impairment(s), for example, in individuals with suspected dysphagia. In one example, screening for potential aspiration events in different subjects is implemented via analysis of cervical vibrations and nasal airflow during thin liquid swallows, or in executing other types of swallowing events as necessary or appropriate given a specific screening or diagnostic protocol, device programming or configuration, and other such considerations. Features extracted from acquired accelerometry and airflow signals, can be effectively and automatically classified to allow a user or operator of the disclosed device/ aspirimeter to identify individual swallowing events as one of a normal event or as one representative of a possible aspiration event. Upon applying certain screening/diagnostic protocols and/or guidelines, candidates at risk of aspiration may thus be identified as such using the disclosed methods and devices considered herein, wherein such identification may lead to further assessment, diagnostics, treatment and/or dietary restrictions, as deemed appropriate.

[0031] Similarly, screening for other swallowing impairments, such as swallowing efficiency impairments generally manifested by the presence of residues post-swallow, can also or alternatively be detected by the herein described embodiments of the invention. As will be appreciated by the skilled artisan, where the below description refers more specifically to an aspiration detection method or device (e.g. swallowing safety impairment detection/screening), a similar implementation may be considered for the detection or screening of other swallowing impairments, such as swallowing efficiency impairments, and that, without departing from the general scope and nature of the present disclosure.

[0032] For example, in some embodiments, the swallowing impairment detection device can be configured to provide indication of both impaired swallowing safety and impaired swallowing efficiency during swallow screening. Through filtering and processing of vibrational signals collected with a cervical accelerometer placed just below the thyroid cartilage, and airflow signals collected with an airflow monitor (e.g. nasal cannula), one or more classifiers, as disclosed herein, can be trained to discriminate between signals associated with penetration-aspiration and those displaying normal swallowing safety, and/or trained to discriminate between signals associated with reduced swallowing efficiencies and those displaying normal swallowing efficiencies.

[0033] As will be described in the below Example, in a study of 24 adult patients with dysphagia undergoing concurrent videofluoroscopy, a swallowing impairment detection device, configured in accordance with one embodiment of the invention, was able to accurately identify impaired swallowing safety and efficiency from the combined classification of concurrently acquired cervical accelerometry and nasal airflow data. Namely, a mean adjusted accuracy of 74.7% was achieved for depth of airway invasion classifications (i.e. safe vs. unsafe swallows), whereas mean adjusted accuracies of 83.7% and 84.2% were achieved for bolus clearance from the valleculae and pyriform sinuses, respectively (i.e. efficient vs. inefficient swallows). Based on these results, and those of similar embodiments also reported in the below Example, the combined classification of cervical accelerometry and nasal airflow data, in accordance with the various embodiments of the herein-described methods and devices, was proven effective in detecting swallowing impairments, thus validating the use of this multi-sensor fusion in accurately classifying abnormal swallows.

[0034] With reference to FIG. 1, a system for use in swallow impairment detection, generally referred to using the numeral 100, and in accordance with an illustrative embodiment of the invention, will now be described. In this example, the system 100 generally comprises a cervical accelerometer, such as dual-axis accelerometer 102, to be attached in a throat area of a candidate for acquiring dual axis accelerometry data and/or signals during swallowing (e.g. see illustrative superior-inferior axis (S-I) accelerometry signal 104 and anterior-posterior axis (A-P) accelerometry signal 106 shown in FIG. 1). A nasal airflow monitor, such as nasal cannula 108, is also provided for acquiring airflow data and/or signals during swallowing (e.g. see illustrated nasal airflow signal 110 of FIG. 1).

[0035] In one embodiment, the accelerometer is also fitted with a pressure sensor or pressure sensitive film configured to effectively measure a pressure between the accelerometer and the candidate’s throat when installed (e.g. measure a pressure applied by the accelerometer on the candidate’s throat as a function of a tension in a strap or elasticized band used to secure the accelerometer in position). Therefore, upon monitoring this pressure, for example via an indicator on the user interface associated with the device, a clinician may be better able to position the accelerometer on each candidate with reproducible accuracy, thus reducing the likelihood of
improper positioning/installation and thus, reducing data errors or improving overall performance accuracy of the device. In other embodiments, the accelerometer may rather be positioned via the application of dual-sided adhesive tape, or the like.

[0036] In some embodiments, signal quality and/or accelerometer positioning/placement may be otherwise tested and/or monitored via a testing protocol, whereby an acquired test signal, for example, may be checked for consistency with system calibration and/or preset normal operating conditions. For example, a test signal may be acquired during a non-swallowing task, such as the candidate turning its head or saying ‘ah’, and such test signal compared with one or more preset test signal ranges and/or characteristics. This and other similar testing procedures can be applied before, during and/or after different segments of the swallowing impairment detection protocol, as will be appreciated by the skilled artisan, without departing from the general scope and nature of the present disclosure. Similar nasal airflow positioning and/or calibration procedures may also be applied, in accordance with different embodiments of the invention, as will be readily appreciated by the skilled artisan.

[0037] The accelerometer 102 and airflow monitor 108 are distinctly or commonly operatively coupled to a swallowing data processing module or aspirometer 112 configured to process the acquired data for swallowing impairment detection. Note that the term “aspirometer” is used generically herein to refer not only to a device for aspiration detection, but also to similar devices also or alternatively configured for the detection of swallowing impairment, such as swallowing inefficiencies. The processing module 112 is depicted herein as a distinctly implemented device, or aspirometer, operatively coupled to accelerometer 102 and airflow monitor 108 for communication of data thereto, for example, via one or more data communication media such as wires, cables, optical fibres, and the like, and/or one or more wireless data transfer protocols, as would be readily appreciated by one of ordinary skill in the art. The processing module may, however, in accordance with another embodiment, be implemented integrally with the accelerometer/airflow monitor, for example, depending on the intended practicality of the aspirometer, and/or context within which it is to be implemented. As will be appreciated by the skilled artisan, the processing module may further be coupled to, or operated in conjunction with, an external processing and/or interfacing device, such as a local or remote computing device, or platform provided for the further processing and/or display of raw and/or processed data, or again for the interactive display of system implementation data, protocols and/or screening/diagnostic tools.

[0038] With reference to FIG. 2, the processing module, depicted herein generically as a self-contained device or aspirometer 200, generally comprises a power supply 202, such as a battery or other known power source, and various input/output port(s) 204 for the transfer of data, commands, instructions and the like with interactive and/or peripheral devices and/or components (not shown), such as for example, a distinctly operated accelerometer and/or airflow monitor (as shown in FIG. 1), external data processing module, display or the like. The device 200 further comprises one or more computer-readable media 208 having stored thereon statements and instructions, for implementation by one or more processors 206, in automatically implementing various computational tasks with respect to, for example, accelerometer and airflow data acquisition and processing, operation of the device in accordance with a given or selected impairment detection protocol (e.g. one or more clinically accepted operation protocols, testing and/or validation sequences, etc.), or again in the implementation of one or more impairment detection, monitoring, screening and/or diagnostic tools implemented on or in conjunction with the device 200. The device 200 may further comprise a user interface 210, either integral thereto, or distinctly and/or remotely operated therefrom for the input of data and/or commands (e.g. keyboard, mouse, scroll pad, touch screen, push-buttons, switches, etc.) by an operator thereof, and/or for the presentation of raw, processed and/or screening/diagnostic data with respect to swallowing impairment detection, monitoring, screening and/or diagnostic (e.g. graphical user interface such as CRT, LCD, LED screen, touchscreen, or the like, visual and/or audible signals/alerts/warnings/cues, numerical displays, etc.)

[0039] As will be appreciated by those of ordinary skill in the art, additional and/or alternative components operable in conjunction and/or in parallel with the above-described illustrative embodiment of device 200 may be considered herein without departing from the general scope and nature of the present disclosure. It will further be appreciated that device 200 may equally be implemented as a distinct and dedicated device, such as a dedicated home, clinical or bedside impairment detection device, or again implemented by a multi-purpose device, such as a multi-purpose clinical or bedside device, or again as an application operating on a conventional computing device, such as a laptop or PC, or other personal computing devices such as a PDA, smartphone, tablet or the like.

[0040] With reference to FIG. 3, an example of a data processing stream, in accordance with one embodiment of the invention, will now be described. In general terms, the processing of acquired or collected cervical accelerometry and nasal airflow data 302 representative of at least one swallowing event may be composed of two broad steps, namely a feature extraction step 304 applied for both accelerometry data and airflow data representative of each swallowing event, and a swallowing event classification step 306 based on the extracted feature(s) of step 304. In applying this approach to the combined cervical accelerometry data and nasal airflow data representative of respective swallowing events, such swallowing events may be effectively classified as one of normal swallowing events and potentially impaired swallowing events (e.g. unsafe and/or inefficient), which classification output 308 may then be utilized in screening/diagnosing the tested candidate in question and allocating thereto appropriate treatment, further testing, and/or proposing various dietary or other related restrictions thereto until further assessment and/or treatment may be applied.

[0041] As will be appreciated by the person of ordinary skill in the art upon reference to the following description of specific examples, wherein greater detail is provided in qualifying different possibilities for the implementation of these steps in accordance with different embodiments of the invention, the nature of these steps substantially remains the same in achieving swallowing event classification. As will be further appreciated by the skilled artisan, while the above and following refer to data processing steps, it will be appreciated that such processes may be implemented, in accordance with different embodiments of the invention, by various processing techniques and approaches, which may for example, be
subdivided into distinct, cooperative and/or interactive processing subroutines, modules or the like, and that, without departing from the general scope and nature of the present disclosure. For clarity, the processing steps have and will be described below as distinct processing steps or modules, however, it will be appreciated that a swallowing impairment detection device or computer-readable medium embodied therein comprising statements and instructions for implementation by a processor thereof in accomplishing a swallowing impairment detection method, in accordance with different embodiments of the invention, may be characterized by cooperative, parallel, successive and/or (distinct) processing modules that, in combination, achieve the results considered herein, without departing from the general scope and nature of the present disclosure.

[0042] With reference to FIG. 4, and in accordance with an embodiment of the invention, a further illustrative processing flow for combined cervical acceleration and nasal airflow data will be described, wherein optional steps in this embodiment are shown in dashed-line boxes. In this particular embodiment, data 402 is acquired or provided in respect of multiple swallowing events. This data is then processed via an optional preprocessing module 404 configured to condition the raw data and thus facilitate further processing thereof. For example, the raw data may be filtered, denoised and/or processed for signal artifact removal, and that via common and/or distinct pre-filtering approaches for each of accelerometer and airflow data, as necessary and/or appropriate.

[0043] The preprocessed data is then automatically or manually segmented into distinct swallowing events (step 406). For example, an automated swallowing event segmentation process may be applied to the data to segment this data by swallowing event, such as described in co-pending U.S. Patent Application Publication No. 2010/0160833, and/or such as described in the publication by Lee et al. titled Swallow segmentation with artificial neural networks and multisensor fusion and published in Medical Engineering & Physics 31 (2009) 1049-1055, the entire contents of which are incorporated herein by reference. Alternatively, manual segmentation may be applied, for example, upon visual inspection of the data (e.g. identification of the start of each swallowing event, which may be readily and systematically recognized by an operator of the device). Alternatively, the device and method, in accordance with one embodiment, may involve segmented data recordal, as will be described further with reference to the exemplary protocol depicted in FIG. 6, whereby data is explicitly recorded for each swallowing event individually. In such embodiments, it will be appreciated that swallowing event-specific data may be preprocessed individually, thus effectively applying the manual signal segmentation step 406 of FIG. 4 during acquisition of accelerometer and airflow data 402 and prior to preprocessing step 404. As will be appreciated by the skilled artisan, those and other such variations may be considered herein without departing from the general scope and nature of the present disclosure.

[0044] The event-specific data is then processed by a feature extraction module 408, and optionally, a feature reduction module 410, allowing for each swallowing event to be classified at step 412 based on these extracted features. As discussed above generally, such classification thus allows for the determination and output 414 of which swallowing event represented a normal swallowing event as compared to a potentially unsafe and/or inefficient swallowing event.

[0045] With reference to FIG. 5A, a detailed processing stream, in this example contemplating dual axis acceleration in combination with nasal airflow monitoring, will be described, showing therein specific examples of processing techniques applicable with respect to some of the general processing modules described above at a higher level. It will be appreciated that while the following provides specific examples, such examples are not intended to limit the general scope of the present disclosure, but are rather presented solely for the purpose of exemplifying certain techniques implemented for the purpose of testing and validating the various embodiments of the invention described herein.

[0046] The process of FIG. 5A is applied to dual axis acceleration and nasal airflow data 502 representative of multiple swallowing events. For example, the data may be acquired, as labeled, along the anterior-posterior and superior-inferior axes, respectively, for acceleration, and via nasal airflow monitoring during swallowing. Clearly, previously segmented and/or individually recorded data sets may also be utilized in this context, bypassing segmentation step 506 described below.

[0047] A data preprocessing step 504 is once again applied to the accelerometer and airflow data, consisting in this example, of an inverse filter, which may include various low-pass, band-pass and/or high-pass filters, followed by signal amplification (e.g. in the example below, accelerometer data was band-pass filtered 0.1 Hz to 3 kHz with 10X and 10,000X amplification for accelerometer and nasal airflow channels, respectively).

[0048] In one embodiment, a denoising subroutine is then applied to the inverse filtered data, which may consist, in one example, of processing signal wavelets and iterating to find a minimum mean square error, for example as described in co-pending application Ser. No. 12/819,216, the entire contents of which are incorporated herein by reference. It will be appreciated that various optimization schemes may be implemented to find such minimum value, as can alternative denoising subroutines to achieve similar results in accordance with different embodiments of the invention.

[0049] In one example, the preprocessing module may further comprise a subroutine for the removal of candidate movement artifacts from the data, for example, in relation to a candidate’s head movement. In one such example, a splines-based subroutine may be implemented to achieve satisfactory artifact removal; however, other techniques may also be applied to achieve similar results. Other signal artifacts, such as vocalization, blood flow, and the like, may also be removed from acquired signals as necessary or applicable, in accordance with different embodiments of the invention.

[0050] Upon completion of the data preprocessing step 504, which may involve different levels of complexity depending on the quality and reliability of acquired data, and other such parameters, the data is then manually or automatically segmented (step 506) for event-specific processing, as described above. Again, it will be appreciated that data segmentation may be implemented prior to preprocessing, or again, avoided entirely where event-specific data sets are acquired independently. In the Example described below, preprocessing steps were implemented both prior to, and after segmentation. Namely, each segmented signal was denoised by a 5-level discrete wavelet decomposition with the Daubechies-5 wavelet, and to remove low-frequency motion artifacts, each signal was then passed through a 4th-order highpass Butterworth filter with a cutoff frequency of 1 Hz. It
will be appreciated that different approaches may applied to the pre-processing of acquired data in readying such data for further processing to increase an ultimate performance accuracy of the trained classifier(s), described below.

In this embodiment, the event-specific data is processed through a feature extraction module 508, which consists of calculating one or more, time, frequency and/or time-frequency domain features for each data set. In this particular example, the feature extraction module 508 implements, amongst other possible routines, a 20-level discrete wavelet decomposition of the respective signals with the Daubechies-5 wavelet, and calculates wavelet energies and/or energy ratios thereof to be used as selected features in subsequent steps. Other features, such as selected from the time, frequency and/or time-frequency domains (e.g. mean, variance, center frequency, dispersion ratio, etc.), may also be considered jointly or distinctly to achieve similar results. It will be appreciated that different combinations of extracted features may be considered herein without departing from the general scope and nature of the present disclosure. For example, as described below, various feature combinations were tested to optimize the within described method and device, each one providing, to varying degrees, effective differentiation between healthy and potentially impaired swallowing events. Further, while some embodiments, may contemplate different extracted features for each data set (i.e. A-P axis, S-I axis and airflow), it will be appreciated that the same features may be extracted in each case, or again, that multiple features may be extracted from each set, and that, in different combinations.

Upon feature extraction, an optional feature reduction module 510 is then implemented to further process the data for effective classification. For example, the feature reduction module may be configured to select a subset of the extracted features for classification, for instance based on the previous analysis of similar extracted feature sets derived during classifier training and/or calibration. For example, in one embodiment, the most prominent features or feature components/levels extracted from the classifier training data set are retained as most likely to provide classifiable results when applied to new test data, and are thus selected to define a reduced feature set for training the classifier and ultimately enabling classification. For instance, in the context of wavelet decompositions, or other such signal decompositions, techniques such as linear discriminant analysis, principle component analysis or other such optimization techniques effectively implemented to qualify a quantity and/or quality of information available from a given decomposition level, may be used on the training data set to preselect feature components or levels most likely to provide the highest level of usable information in classifying newly acquired signals. Such preselected feature components/levels can then be used to train the classifier for subsequent classifications. Ultimately, these preselected features can be used in characterizing the classification criteria for subsequent classifications.

Accordingly, where the device has been configured to operate from a reduced feature set, such as described above, this reduced feature set will be characterized by a predefined feature subset or feature reduction criteria that resulted from the previous implementation of a feature reduction technique on the classifier training data set. Newly acquired data will thus proceed through the various pre-processing and segmentation steps described above (steps 504, 506), the various swallowing events so identified then processed for feature extraction at step 508 (e.g. full feature set), and those features corresponding with the preselected subset retained at step 510 for classification at step 512.

The features of Table 6 (FIG. 8), described below in the context of an illustrative embodiment of the invention, provides different reduced feature subsets shown to provide particularly effective means for differentiating between healthy and potentially impaired swallowing events, be it to identify possible airway invasion (i.e. unsafe swallow and/or aspiration), or post-swallow residue (e.g. inefficient swallow) for example in the valleculae and/or pyriform sinuses. Again, while different feature subsets (or reduced features) are provided in this example for each data set (i.e. axis- and sensor-specific feature subset) it will be appreciated that a same subset may be used for each axis and/or for both vibrational and airflow data sets.

As validated by the results presented in the below Example, this approach to feature extraction and reduction was effectively used to distinguish safe from potentially unsafe swallows, and efficient from potentially inefficient swallows. Namely, as evidenced by the below results and validation of the above-described technique, the extraction of these selected features from new test data can now be compared to preset classification criteria established as a function of these same selected features as previously extracted and reduced from an adequate training data set, to classify the new test data as representative of a normal vs. impaired swallow (e.g. safe vs. unsafe swallows and/or efficient vs. inefficient swallows)

While the above and below described examples contemplate a discrete selection of the most prominent features, or components thereof, other techniques may also readily apply. For example, in some embodiments, the results of the feature reduction process may rather be manifested in a weighted series or vector for association with the extracted feature set in assigning a particular weight or level of significance to each extracted feature component or level during the classification process. For example, rather than to use respective feature subsets such as listed in Table 6, a weighted sum or the like of extracted features may rather be applied to reflect the predominance of certain levels or components, while still accounting for each level, for example.

As will be appreciated by the skilled artisan, other feature sets, such as frequency, time and/or time-frequency domain features, may also be considered to provide similar results. Similarly, while the above provides one example of selected subsets of features identified via an applied feature reduction process, other feature selections based on similar feature reduction techniques (e.g. genetic algorithms, principal component analysis, etc.) and/or identified from a different training data set, may also be considered to provide similar results.

Upon feature reduction, feature classification is implemented by classification module 512, which in this embodiment, implements a discriminant analysis using Mahalanobis and/or Euclidean distances to compare the extracted features (or reduced/weighted subset thereof) of acquired swallow-specific data with pre-set classification criteria so to effectively classify each data set as representative of a normal swallowing event or a potentially impaired swallowing event. As will be appreciated by the skilled artisan, different classification techniques may be implemented in
classifying swallowing event data, which may include for example, genetic algorithms, principal component analysis, neural networks, etc.

[0059] In the Example provided below, best results were achieved via the above-described technique, wherein extracted features were ultimately evaluated as a function of their effective distance from a previously classified training data set representative of healthy and unhealthy swallows.

[0060] In one embodiment, a clinical impairment detection protocol, for example as described below with reference to FIG. 6, is implemented on a swallow-by-swallow basis, whereby a screening/diagnosis with respect to potential aspiration, and/or other such impairments, is executed for each swallowing event independently. In such embodiments, swallowing event data classification is implemented independently for each acquired data set (signal segmentation is also effectively avoided), whereby features extracted from this event-specific data set is classified upon comparison with preset classification criteria established, for example, on the basis of repeated clinical trials and/or device calibration implemented via similar data processing techniques.

[0061] For example, in one embodiment, depicted by the dashed-line boxes of FIG. 5A as an optional training/validation subroutine 516, a data set representative of multiple swallows is processed as described above such that each swallow-specific data set ultimately experiences the preprocessing, feature extraction and feature reduction modules described above. The training/validation subroutine 516 is then rigorously tested over a known training data set so to establish reliable classification criteria against which subsequent test data sets can be compared for classification. An exemplary training sequence is described in the Example below, however, one of ordinary skill in the art will appreciate that different approaches to classifier training and validation can be implemented to provide similar results, without departing from the general scope and nature of the present disclosure.

[0062] Once all events in the training data set have been classified and validated, output criteria may be generated for future classification without necessarily applying further validation to the classification criteria. Alternatively, routine validation may be implemented to either refine the statistical significance of classification criteria, or again as a measure to accommodate specific equipment and/or protocol changes (e.g. recalibration of specific equipment, for example, upon replacing accelerometers or different accelerometer type/model, changing operating conditions, new processing modules such as further preprocessing subroutines, artifact removal, additional feature extraction/reduction, etc.).

[0063] With reference to FIG. 5B, a similar process as described above with reference to FIG. 5A is presented. In this process, steps 502 to 510 are kept substantially unchanged; however, the process proceeds to distinct classification steps 512A and 512B in the classification of the acquired event-specific vibrational data and airflow data as indicative of safe vs. unsafe swallows, and as indicative of efficient vs. inefficient swallows, respectively. For example the same feature extraction and reduction techniques may be commonly applied (for the same or different preselected feature subsets) prior to the application of the distinctive classifications, which classifications may rely on distinct classification criteria previously defined as a function of respective classifier training. For instance, the same classification technique may be employed, but trained in accordance with distinct parameters, namely based on a known training data set (which may be the same for establishing both sets of classifying criteria) segregated into safe vs. unsafe swallowing events, and efficient vs. inefficient swallowing events, respectively. In such embodiments, the device may thus be configured to perform two distinct classifications in parallel or in sequence, to achieve greater screening accuracy and complexity. It will be appreciated that while the above example considers the implementation of a same feature extraction, reduction and classification technique for both intended classifications, a distinct technique may otherwise be applied to each classification problem, without departing from the general scope and nature of the present disclosure.

[0064] With reference to FIG. 6, an exemplary clinical or bedside protocol is provided in implementing a testing or screening sequence for impairment detection via dual-axis accelerometer, with candidates satisfying the following eligibility criteria:

[0065] a) patient must be alert and awake;

[0066] b) patient must be able to breathe freely on room air (those with tracheostomies or on supplemental oxygen should proceed directly to a full assessment);

[0067] c) patient should be able to sit upright with minimal support, and able to hold head upright;

[0068] d) patient should be able to follow simple instructions; and

[0069] e) patient’s mouth should be clean and free of debris before proceeding; dentures may, but do not need to be worn for this test.

[0070] As depicted in FIG. 6, upon identifying a patient as an eligible candidate (602), the testing or screening sequence proceeds as follows. At step 604, a dual-axis accelerometer is positioned on the candidates neck (e.g. by way of a strap, elasticized band and/or double-sided adhesive tape), for example in midline, anterior to the cricoid cartilage; a nasal airflow monitor is also positioned. At step 606, the device is activated (e.g. device turned on, application running on a portable screening device activated, and/or application set to initiate new screening session initiated). At step 608, and generally once the candidate has been provided with a given quantity of a substance to be swallowed as a first swallowing event (e.g. a 5-cc cup of water), recording is started, thus allowing recordal of respective accelerometric and airflow signals corresponding to the candidate’s first swallowing event (e.g. via a device push button or a virtual button rendered on a graphical user interface of the device). Upon completion of the swallowing event, or where the candidate becomes coughing, recording is stopped at step 610 (e.g. upon pushing the same or a distinct physical/virtual button), and the recorded signals automatically processed (step 612) for classification as indicative of a safe vs. unsafe swallow and/or efficient vs. inefficient swallow. In one embodiment, the graphical user interface of the device is configured to output a result at step 614 for the completed swallowing event, which may be noted manually, or tracked sequentially by the device for each subsequent event. Exemplary outputs may include, but are not limited to, a message such as “No aspiration/residue detected” or “Possible aspiration/residue detected”, a colour coded light or indicia to identify a safe swallowing event (e.g. green), possibly unsafe swallowing event (e.g. red), or possibly inefficient swallowing event (e.g. orange), and/or other such display mechanisms. Note that such results may alternatively be recorded automatically by the device to
render a consolidated/overall report at the end of the protocol/session, thus further reducing reliability on user intervention.

In this exemplary embodiment, the above steps are repeated for 3 swallowing events, unless coughing is identified during the first two events, at which point, the session is ended after two events at step 616 and the candidate automatically referred to further assessment (e.g., via VFSS) at step 618. Otherwise, overall results may be output at step 620 (e.g., upon pressing an "end session button" or again automatically output upon the device acknowledging at step 622 the completion of the session's prescribed three swallowing events) and, where results are indicative that the candidate may be exhibiting a swallowing impairment (e.g., detection of at least one possibly unsafe or inefficient swallowing event), the candidate is again referred for further assessment at step 618.

It will be appreciated that different embodiments may be configured to provide different levels of information, consistent with the classification techniques employed and level of training implemented in configuring the device. For example, in one embodiment, the device is configured to output an indication as to potential swallowing safety impairment (e.g., healthy swallow vs. possible penetration/aspiration). In another embodiment, the device may be further configured to also output an indication as to potential swallowing efficiency impairment (e.g., absence vs. presence of residue post-swallow). In such embodiments, the device would effectively process the recorded signal based on a dual classification process, namely one trained to identify aspiration risk, and the other to identify swallowing inefficiencies, the combined results thus providing for a more complete dysphagia screening and characterization process, for example.

From the above, it is appreciated that limited training and intervention is required for implementation of the above protocol in assessing aspiration and/or swallowing efficiency risks. Namely, the device considered herein in accordance with different embodiments of the invention allows for the ready assessment, or pre-assessment (e.g., screening) of potential aspiration/dysphagia candidates, without significant operator intervention, contrary to traditional swallowing impairment detection techniques. Furthermore, and as validated by the results of the specific example described below, the reliability of the results output using this approach, as compared to other approaches, makes for a greater candidate assessment tool resulting in fewer misdiagnoses and/or fewer referrals of otherwise healthy patients to further and generally more invasive treatment/testing procedures.

The following provides an example of a swallowing impairment detection system, method and device, in accordance with an embodiment of the invention, validated by the parallel implementation of videofluoroscopic examinations. It will be appreciated by the person of ordinary skill in the art that the following describes an exemplary embodiment of the invention, and is not intended as a limiting disclosure, but rather merely illustrative of one of different possible embodiments of the inventive impairment detection method, system and devices considered within the context of the present disclosure.

**EXAMPLE**

In this example, dual-axis accelerometry and nasal airflow signals were acquired from 24 (22 males) adult patients with dysphagia during routine VFSS sessions. All patients had suffered either stroke or acquired brain injury and underwent VFSS to investigate their swallowing function. The average age of the patients was 64.8±18.6 years. Corresponding X-ray videos were recorded as well. The preceding speech-language pathologists determined the number of swallows and stimulus types for each patient, although a standardized approach, beginning with a thin liquid 40% weight per volume barium suspension and progressing through nectar and spoon-thick liquids to solid stimuli, was used. The mean number of swallows per patient was 17.8±8.8.

Dual-axis accelerometry signals were acquired via a dual-axis accelerometer (ADX1322, Analog Devices) placed on the neck just below the thyroid cartilage, with the axes oriented in the A-P and SI directions. The sensor was attached to the neck with a double-sided electrode collar (650455, Viasys Healthcare). Nasal airflow signals were recorded with a nasal cannula (Pro-Flow Cannula Model 1259, Grass Technologies) placed at the nares, connected to a pressure transducer (PAF510TE, Grass Technologies), e.g., as shown in FIG. 1. Each signal channel was sampled at 10 kHz by a custom LabVIEW application. A pre-amplifier with a bandpass filter (Model P55, Grass Technologies) was utilized for each channel, with the cutoff frequencies set at 0.1 Hz and 3 kHz. Amplification was set at 10 and 10,000 for the two accelerometry channels and nasal airflow, respectively.

The signal acquisition hardware was comprised of two separate components: one for the acquisition of the accelerometry and nasal airflow signals and the other for videofluoroscopy recording. The two components were synchronized by resetting the time-code generator (Time Code Master Model 5010, Evertz Microsystems), which inserted time stamps on the X-ray videos, when signal acquisition started immediately prior to the beginning of the VFSS session. Signal acquisition and video recording were stopped immediately after the end of the session.

The X-ray video of each swallow was analyzed and rated by a speech-language pathologist. First, individual swallows were located in the videos. Swallow onset was defined as the moment when the leading edge of the bolus crossed the inferior margin of the shadow of the ramus of the mandible. The corresponding offset was defined as the moment when the hyoid bone returned to a resting position following the passage of material from the pharynx into the esophagus.

Each swallow was then rated in terms of the depth of airway invasion and bolus clearance from the valleculae and pyriform sinuses. A 4-point scale was utilized for each rating. Tables 1 and 2, below, tabulate the scale descriptions for the depth of airway invasion and bolus clearance, respectively. Bolus clearance from the valleculae and pyriform sinuses followed the same scale. In Table 1, note that levels 1 and 2 correspond to penetration, whereas level 3 refers to aspiration.

<table>
<thead>
<tr>
<th>TABLE 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
</tbody>
</table>
TABLE 1-continued

<table>
<thead>
<tr>
<th>Level</th>
<th>Clinical Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Material enters airway, and contacts true vocal folds but does not pass below</td>
</tr>
<tr>
<td>3</td>
<td>Material enters airway, and passes below true vocal folds</td>
</tr>
</tbody>
</table>

TABLE 2

<table>
<thead>
<tr>
<th>Level</th>
<th>Clinical Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Material does not enter airway</td>
</tr>
<tr>
<td>1</td>
<td>Material enters supraglottic space, but does not reach true vocal folds</td>
</tr>
<tr>
<td>2</td>
<td>Material enters airway, and contacts true vocal folds but does not pass below</td>
</tr>
<tr>
<td>3</td>
<td>Material enters airway, and passes below true vocal folds</td>
</tr>
</tbody>
</table>

In this example, a binary system was implemented for each scenario whereby classification of acquired signals was implemented to distinguish those associated with a level 0 from those associated with a level 3, for each rating. Clinically, the automatic discrimination between a level 0 and level 3 rating may serve as a useful decision support or screening tool. Levels 0 and 3 represented healthy and abnormal swallows, respectively, and a separate binary classification was considered for each rating scheme. In the end, there were 265 level-0 and 39 level-3 swallows with a depth of airway invasion rating, 61 level-0 and 64 level-3 swallows with a bolus clearance from the valleculae rating, and 129 level-0 and 25 level-3 swallows with a bolus clearance from the pyriform sinuses rating. The total number of swallows was not constant across the three rating schemes because visual obstruction (e.g., the shoulder) or image quality issues prevented several swallows from receiving all three ratings. Hence, the clinical ratings provided up to three labels for each swallow, a depth of airway invasion label and two bolus clearance labels (clearance from the valleculae and pyriform sinuses). These labels served as the true classification of the swallow.

All signals were first down-sampled to 1 kHz from a 10 kHz sampling frequency, which was initially selected to account for the potential for high frequency content in the signals. Since the majority of the signal power in cervical accelerometry is expected to lie below 100 Hz, and since respiration completes only 10 to 12 cycles per minute at rest in adults, this down-sampling was expected to result in minimal signal information removal, while greatly reducing computational burden for subsequent analyses.

Individual swallows were then segmented according to the swallow onsets and offsets determined from the X-ray videos. The time stamps on the videos identified the corresponding onsets and offsets in the signals, and the same onsets and offsets were applied to all signal channels. Each segmented signal was then denoised by a 5-level discrete wavelet decomposition with the Daubechies-5 wavelet. To remove low-frequency motion artifacts, each signal was then passed through a 4th-order highpass Butterworth filter with a cutoff frequency of 1 Hz. FIG. 1 shows sample signals from one particular swallow after all the pre-processing steps applied in this example. It will be appreciated that these sample signals portray just one swallow, and that substantial variability among the signals in terms of length and visual characteristics is to be expected between swallowing events.

For each segmented swallow, a variety of features were extracted from the pre-processed accelerometry and nasal airflow signals in the time, frequency, and time-frequency domains. A large number of features, 444 in total, were first extracted from each swallow to maximize the possibility of finding discriminatory features in the subsequent feature selection step.

Specifically, the mean, variance, skewness, kurtosis, interquartile range, number of zero-crossings, maximum hyolaryngeal excursion (estimated via dual integration of accelerometry), air volume (estimated via integration of airflow), normality, stationarity (via the reverse arrangement test), dispersion ratio, peak Fast Fourier Transform (FFT) magnitude, frequency at spectral peak, and 10th order linear prediction coefficients (LPC) were computed for each signal.

In addition, wavelet energies extracted from the beginning, middle, and end of the swallow were also considered using a 20-level discrete wavelet decomposition with the Daubechies-5 wavelet. Each of the approximation and detail signals were divided into three equal segments, and the average of the coefficients in each segment became a feature. Moreover, all 21 possible ratios between the energies in two segments for each approximation or detail signal were used as features. For instance, for the 1st-level detail signal whose ith data point is denoted as d1, i=1, 2, . . . , [n/2], the energy of the jth segment, E_{ij}, where j=1, 2, 3, was computed as follows:

\[ E_{ij} = \sum_{i=1}^{[n/2]} d_{1,j} \]

Again for the 1st-level detail signal, the energy ratio of the ith to jth segment, ER_{i,j}, was computed as follows:

\[ ER_{i,j} = \frac{E_{i,j}}{E_{d,j}}, \quad i > j \]

Each feature was also linearly normalized to the range [-1, 1].

From the large feature pool, the most discriminatory feature combinations were selected by a genetic algorithm, which can efficiently identify discriminatory feature subsets from massive feature spaces without the need for a priori knowledge about the discriminability of individual features. In this particular example, the target dimensionality of the reduced feature space, D_f, was varied such that 3\leq D_f \leq 12, D_f \leq 7. It will be appreciated that different target feature space dimensionalities may be selected depending on the quality and efficiency of results desired or required, which can also vary depending on the types of features selected, signal quality, and other such parameters as will be readily appreciated by the skilled artisan. In this particular case, a lower limit of 3 was selected in seeking to achieve a certain minimum degree of classification efficiency, whereas a higher limit of 12 was selected to, amongst other reasons, manage computational load. With these limits and given that 444 features were originally sampled, the number of possible combinations ranged from \( \binom{444}{3} = 1.45 \times 10^7 \) for 3 features to \( \binom{444}{12} = 1.05 \times 10^{12} \) for 12 features. As it would have been computationally prohibitive to try all possible combinations, a genetic algorithm was used and deemed particularly helpful. Namely, as stochastic optimization routines, genetic algorithms are capable of finding locally optimal solutions in
high-dimensional feature spaces by considering only a finite tractable subset of solutions at any given time. In this example, chromosomes were defined as feature combinations represented as vectors of length equal to $D_r$. Each chromosome was comprised of a sequence of $D_r$ genes, each ranging in value from 1 to 444 to indicate the selection of one of the 444 features. In each generation, the two elite chromosomes that resulted in the minimum error rates were guaranteed to survive to the next generation. Half of the population in the next generation, not including the elite children, were created via a scattered crossover function. In this crossover scheme, each gene of a newly generated chromosome was randomly selected between the parental genes at the same genetic locus with equal probabilities. In addition, uniform mutation was employed, in which each gene of a chromosome had a probability of 0.01 of being replaced by a random gene uniformly selected from all possible genes.

To avoid local minima, random initialization was utilized by running the genetic algorithm 10 times for each target dimensionality, while limiting the population size to 2000. The fitness function of the genetic algorithm employed a linear discriminant classifier and 10-fold cross-validation for the estimation of error rate. All swallows from the 24 patients were conglomerated and randomly partitioned into training and test sets; this partitioning scheme was repeated throughout this example. The linear discriminant classifier fitted a separate multivariate normal density for each class and utilized the Euclidean distance measure. Due to the prominent imbalance between the two classes in the data set, the output of the fitness function was set to be the average of false positive and negative rates, so that the classifier would not be trained to favor the majority class.

Each of the 10 random initializations of the genetic algorithm yielded 10 feature combinations, one for each of the 10 $D_r$ values. For each $D_r$ value, the best among the 10 feature combinations from the random initializations was further selected after a more rigorous evaluation of classification performance with resampling. The resampling step served two objectives: (1) to eliminate the imbalance between the two classes by generating the same number of samples for each class, and (2) to resolve the curse of dimensionality by generating a large number of training samples.

For each feature and for each class, a univariate density estimate was constructed with a Gaussian kernel based on the original training data points. The following is a mathematical representation of the probability density estimation:

$$f_h(y) = \frac{1}{N h} \sum_{i=1}^{N} K\left(\frac{y - y_i}{h}\right)$$

where $N$ is the number of original training data points in the given class, $h$ is the bandwidth, and $y_i$ is the feature value of the $i$th training data point. $K$ is a Gaussian kernel with zero mean and unit variance.

The density estimates were then used to resample 5000 examples for the training data of each class. This technique is equivalent to the smoothed bootstrap, in which resampled examples are not exact replicas of the original data, unlike the typical bootstrap methodology. Each feature was resampled independently from its univariate density estimate; correlations among features were ignored.

The validity of resampling from such univariate density estimates was evaluated by reporting classification performance on test data that had been excluded from density estimation. Ten-fold cross-validation and linear discriminant classifiers with the Euclidean distance were employed. In order to compensate for the imbalance between the two classes in test data, which had not been subjected to the resampling, adjusted accuracy was computed as follows to serve as the criterion to select the best feature combination for each $D_r$:

$$\text{Adjusted accuracy} = \frac{\text{sensitivity} + \text{specificity}}{2}$$

At this point, 10 feature combinations, one for each of the 10 $D_r$ values, remained for each of the 3 rating schemes. The efficacy of different classifier models on the final feature combinations was explored by training several different classifiers with a larger resampled data set. The same resampling methodology described above was repeated to generate 10,000 examples per class. Also, the same 10-fold cross-validation scheme was utilized so that density estimation and resampling were solely based on training data. Four classifier models were deployed: linear discriminant analysis (LDA), neural network (NN), probabilistic neural network (PNN), and k-nearest-neighbor (KNN). These choices covered linear (LDA), non-linear (NN), and nonparametric (PNN and KNN) classification paradigms.

As in the previous feature selection steps, LDA classifiers were trained by fitting separate multivariate Gaussian densities for the two classes. Two variants were trained: one with the Euclidean and the other with the Mahalanobis distance measure.

Feed-forward NN classifiers with one hidden layer were trained with three different numbers of hidden units (HU’s): 10, 20, and 30. Hyperbolic tangent sigmoids were the activation functions in both the hidden and output units. Each training data set was randomly split 80-20 for training and validation; early stopping based on validation data ensured regularization. The networks with 30 HUs and 12 features (inputs) were the largest networks and possessed 421 free parameters (360 input weights+30 hidden biases+30 hidden weights+1 output bias). To avoid overfitting, the number of free parameters should generally be limited to roughly 10% of the number of training samples. In this example, the number of free parameters was less than or equal to 421 while the number of training samples was 20,000 (10,000 from each class). Therefore, accompanied by the early stopping during training, overfitting was mitigated.

PNN classifiers were trained as two-layer networks. The first layer had radial basis neurons with a spread value of 0.1, which was 5% of the normalized feature value range [-1,1]. The neurons in the second layer employed the competitive transfer function, which yielded the output vector, $Y=[y_1, y_2, \ldots]$, given an input vector, $X=[x_1, x_2, \ldots]$, according to the following:
KNN classifiers were evaluated with three K values: 11, 21, and 31. Classification performance on test data was reported in terms of sensitivity, specificity, and adjusted accuracy. For each classifier, the best result across different D, was selected with respect to mean adjusted accuracy.

Tables 3 to 5 (FIGS. 7A to C) tabulate the best classification results of each classifier model for the depth of airway invasion, bolus clearance from the valleculae, and bolus clearance from the pyriform sinuses, respectively. The corresponding feature space dimensionality is also reported. All LDA and NN classifiers for bolus clearance ratings (Tables 4 and 5) show mean adjusted accuracies greater than 80%, whereas mean adjusted accuracies for depth of airway invasion ratings (Table 3) were found as high as approximately 75%. The Euclidean LDA and Mahalanobis LDA classifiers are associated with the best mean adjusted accuracy for depth of airway invasion and both bolus clearance ratings, respectively. In particular, the mean adjusted accuracy of 84.2% by the Mahalanobis LDA for bolus clearance from the pyriform sinuses is the highest of all rating schemes.

Table 6 (FIG. 8) lists the feature combinations that resulted in the best mean adjusted accuracies for each of the 3 rating schemes. The first, second, and third columns correspond to the classification performance scores shown in the first row of Table 3, the second row of Table 4, and the second row of Table 5, respectively. The majority of the selected features are from wavelet analysis.

For all three rating schemes, the outcome of the feature selection steps included features from all three signal channels, demonstrating the improvements brought forth by the herein proposed approach to swallowing impairment detection via multi-sensor classification, whereby information made available via cervical accelerometry can be enhanced by information hereby shown available in nasal airflow data.

In this particular example, most of the features in Table 6 stemmed from wavelet analysis. In particular, two levels of wavelet decomposition were repeatedly selected across all three ratings: 3rd level A-P accelerometry and 7th level S-I accelerometry, corresponding to approximate frequency bands of 6.25-125 Hz and 3.9-7.8 Hz, respectively. It will be appreciated that while these particular wavelet features were deemed most useful in the present example, other features and feature subsets may be readily applied and relied upon to achieve similar results, and that, without departing from the general scope and nature of the present disclosure.

While certain results have been demonstrated above to provide useful results in classifying data related to swallowing activity, it will be appreciated that other techniques or feature selection may yield similar results. Namely, since genetic algorithms are susceptible to yield results at local minima, repeated random initialization, as contemplated above, can allow for greater optimization, and thus, further attempts at feature selection and classifier training may provide alternative solutions, which, as will be appreciated by the skilled artisan, should be construed to fall within the scope of the present disclosure.

The current data demonstrates that the combination of cervical accelerometry and nasal airflow can be useful in discriminating swallows with poor hyolaryngeal excursion and associated pharyngeal residues from healthy swallows in individuals with dysphagia. A device and method as described herein thus provides a valuable contribution to the clinical swallowing assessment toolkit, because the presence of residues is something that cannot be determined with confidence without instrumental confirmation. Furthermore, because reductions in hyolaryngeal excursion are known to be common in those with dysphagia, they commonly constitute a major focus in rehabilitative intervention. The current analysis thus also supports the use of a combined accelerometry and airflow data classifier in monitoring progress and improvement in hyolaryngeal excursion across treatment.

The above also demonstrates the usability of a combined classifier for cervical accelerometry and nasal airflow data in detecting the occurrence of aspiration in swallowing.

This example shows that cervical accelerometry, in combination with nasal airflow, as discussed and considered in accordance with different embodiments of the invention, provides a reasonable alternative to known techniques in providing a substantially noninvasive technique for accurately detecting swallowing impairments, as evidenced by the results of the above-described Example.

While the present disclosure describes various exemplary embodiments, the disclosure is not so limited. To the contrary, the disclosure is intended to cover various modifications and equivalent arrangements included within the spirit and scope of the appended claims. The scope of the following claims is to be accorded the broadest interpretation so as to encompass all such modifications and equivalent structures and functions.

What is claimed is:

1. A device for use in identifying a possible swallowing impairment in a candidate during execution of a swallowing event, the device comprising:
an accelerometer to be positioned in a region of the candidate’s throat and configured to acquire vibrational data representative of the swallowing event;
a nasal airflow monitor to be positioned in a region of the candidate’s nostrils and configured to acquire airflow data representative of the swallowing event;
a processing module operatively coupled to said accelerometer and nasal airflow monitor for processing said vibrational data and said airflow data to extract from each one thereof one or more features representative of the swallowing event, and classify said vibrational data and airflow data as indicative of one of normal swallowing and possibly impaired swallowing based on said extracted features.

2. The device of claim 1, the possible swallowing impairment comprising at least one of a swallowing safety impairment and a swallowing efficiency impairment.
3. The device of claim 1, said accelerometer comprising a dual-axis accelerometer configured to acquire axis-specific data, said processing module for processing said axis-specific data to extract from each axis one or more features respective thereto representative of the swallowing event.

4. The device of claim 3, wherein said features extracted from said axis-specific data comprise distinct axis-specific features.

5. The device of claim 3, said dual-axis accelerometer configured for alignment along an anterior-posterior axis (A-P) and a superior-inferior axis (S-I) of the candidate’s throat.

6. The device of claim 1, wherein said extracted features comprise at least one vibrational data feature distinct from at least one airflow data feature.

7. The device of claim 1, said processing module configured to classify the swallowing event by comparing said extracted features with preset classification criteria defined by features previously extracted and classified from a known training data set.

8. The device of claim 8, wherein said extracted features are classified as a function of a distance of said extracted features from said classification criteria.

9. The device of claim 8, wherein said extracted features are classified via discriminant analysis using one of Mahalanobis distances and Euclidian distances.

10. The device of claim 1, said processing module comprising a feature extraction module for extracting said one or more features from each of said vibrational data and said airflow data, a feature reduction module for identifying, based on preset feature reduction parameters, predominant components of said extracted features, and a classifier configured to classify said vibrational data and said airflow data based on said extracted features and said predominant components thereof.

11. The device of claim 1, for identifying the possible swallowing impairment during execution of multiple successive swallowing events, said processing module configured to classify vibrational data and airflow data acquired in respect of each of said successive swallowing events as indicative of one of normal swallowing and possibly impaired swallowing.

12. The device of claim 11, further comprising an event segmentation module for automatically segmenting vibrational data and airflow data acquired in respect of each of said successive events for independent processing and classification.

13. The device of claim 11, further comprising a user interface for selectively segmenting vibrational data and airflow data acquired in respect of each of said successive events for independent processing and classification.

14. The device of claim 11, further comprising an output, said processing module further configured to process said vibrational and airflow data acquired in respect of each of said successive events, and output results thereof in accordance with a preset swallowing impairment assessment protocol.

15. The device of claim 1, wherein at least one of said extracted features comprises a value derived from at least one signal wavelet decomposition level.

16. The device of claim 15, wherein said value comprises at least one of an energy and an energy ratio associated with said level, or one or more segments thereof.

17. A computer readable-medium having statements and instructions stored thereon for implementation by a processor to automatically process input vibrational data and airflow data representative of a candidate swallowing event in identifying a possible swallowing impairment, by:

extracting one or more preset features representative of the swallowing event for each of the vibrational data and airflow data;

comparing said extracted features with preset classification criteria defined as a function of said preset features; and

outputting, based on said comparing, classification of said vibrational data and airflow data as indicative of one of normal swallowing and possibly impaired swallowing.

18. The computer readable-medium of claim 17, said possibly impaired swallowing comprising one or more of unsafe swallowing and inefficient swallowing.

19. The computer readable-medium of claim 17, said possibly impaired swallowing comprising identification of substantial post-swell residual material in one or more of valleculae and pyriform sinuses.

20. The computer readable-medium of claim 17, the vibrational data comprising dual-axis accelerometry data representative of the swallowing event, said extracting comprising extracting one or more features for each axis of said axis-specific data.

21. The computer readable-medium of claim 1, said comparing comprising calculating a distance of said extracted features from said classification criteria and selecting a most likely classification as a function of said distance.

22. The computer readable-medium of claim 21, said calculating comprising performing a linear discriminant analysis of said extracted features using at least one of Euclidian and Mahalanobis distances.

23. The computer readable-medium of claim 17, the vibrational data and airflow data representative of successive swallowing events, further comprising statements and instructions for automatically segmenting the vibrational data and airflow data into event-specific data, and repeating said extracting and classifying for each said event-specific data.

24. A method for identifying a possible swallowing impairment in a candidate via execution of one or more preset swallowing events, comprising:

recording vibrational data and airflow data representative of the one or more swallowing events;

extracting one or more swallowing-event specific features for each of the vibrational data and airflow data;

and classifying said extracted features as indicative of one of normal swallowing and possibly impaired swallowing.

25. The method of claim 24, comprising, for execution of two or more preset swallowing events, selectively recording said vibrational data and airflow data for each event independently to provide event-specific data, and implementing said extracting and classifying on said event-specific data for each of said events.

26. The method of claim 24, comprising, for execution of two or more preset swallowing events, successively recording said vibrational data and airflow data for each of said events, and further comprising automatically segmenting said successively recorded data to provide event-specific data, and implementing said extracting and classifying on said event-specific data for each of said events.

27. The method of claim 24, the swallowing impairment comprising at least one of penetration, aspiration, unsafe swallowing, inefficient swallowing, and post-swell residue material in one or more of valleculae and pyriform sinuses.