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How closely do machine ratings of duration of UES opening during videofluoroscopy approximate clinician ratings using temporal kinematic analyses and the MBSImP?

Cara Donohue, MA CCC-SLP[1], Yassin Khalifa, MS[2], Subashan Perera, PhD[3], Ervin Sejdić, PhD[2,4,5,6], James L. Coyle, PhD[1]

1Department of Communication Science and Disorders, School of Health and Rehabilitation Sciences, University of Pittsburgh, Pittsburgh, PA 15260, USA
2Department of Electrical and Computer Engineering, Swanson School of Engineering, University of Pittsburgh, Pittsburgh, PA 15260, USA
3Division of Geriatrics, Department of Medicine, University of Pittsburgh, Pittsburgh, PA 15261, USA
4Department of Bioengineering, Swanson School of Engineering, University of Pittsburgh, Pittsburgh, PA 15260, USA
5Department of Biomedical Informatics, School of Medicine, University of Pittsburgh, Pittsburgh, PA 15260, USA
6Intelligent Systems Program, School of Computing and Information, University of Pittsburgh, Pittsburgh, PA 15260, USA

Reprint address:

Dr. James L. Coyle
Department of Communication Science and Disorders
School of Health and Rehabilitation Sciences
6035 Forbes Tower
University of Pittsburgh
Pittsburgh, PA 15260

E-mail: jcoyle@pitt.edu
Phone number: (412)-383-6608

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Abstract:

Clinicians evaluate swallow kinematic events by analyzing videofluoroscopy (VF) images for dysphagia management. The duration of upper esophageal sphincter opening (DUESO) is one important temporal swallow event, because reduced DUESO can result in pharyngeal residue and penetration/aspiration. VF is frequently used for evaluating swallowing but exposes patients to radiation and is not always feasible/readily available. High resolution cervical auscultation (HRCA) is a non-invasive, sensor-based dysphagia screening method that uses signal processing and machine learning to characterize swallowing. We investigated HRCA's ability to annotate DUESO and predict Modified Barium Swallow Impairment Profile (MBSImP) scores (component #14). We hypothesized that HRCA and machine learning techniques would detect DUESO with similar accuracy as human judges. Trained judges completed temporal kinematic measurements of DUESO on 719 swallows (116 patients) and 50 swallows (15 age-matched healthy adults). An MBSImP certified clinician completed MBSImP ratings on 100 swallows. A multi-layer convolutional recurrent neural network (CRNN) using HRCA signal features for input was used to detect DUESO. Generalized estimating equations models were used to determine statistically significant HRCA signal features for predicting DUESO MBSImP scores. A support vector machine (SVM) classifier and a leave-one-out procedure was used to predict DUESO MBSImP scores. The CRNN detected UES opening within a 3-frame tolerance for 82.6% of patient and 86% of healthy swallows and UES closure for 72.3% of patient and 64% of healthy swallows. The SVM classifier predicted DUESO MBSImP scores with 85.7% accuracy. This study provides evidence of HRCA's feasibility in detecting DUESO without VF images.

Key words: dysphagia, upper esophageal sphincter, videofluoroscopy, machine learning, cervical auscultation, swallow screening, deglutition, deglutition disorders

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Introduction

Within clinical and research settings, a variety of temporal and spatial swallow kinematic measurements are conducted by analyzing videofluoroscopy (VF) images to identify impairments warranting intervention for patients with dysphagia [1]. There are a variety of important biomechanical events that occur during swallowing that facilitate safe and efficient transport of the bolus from the mouth to the stomach including the duration of upper esophageal sphincter opening (DUESO) [2-7~~3~~]. Upper esophageal sphincter (UES) opening consists of five stages: relaxation, opening, distention, collapse, and closure [2-7]. At rest, the UES remains closed. Relaxation of the UES occurs due to vagal inhibition leading to reduction of the tonic activity of the cricopharyngeus and inferior pharyngeal constrictor muscles. As this decrease in UES intraluminal pressure occurs, ~~occurs during swallowing when~~ the suprahyoid muscles contract ~~and is facilitated by "relaxation" of the UES~~ to produce traction forces that facilitate UES opening and anterior and superior hyolaryngeal excursion [2-7~~3~~]. These events along with simultaneous propulsion of the bolus and shortening of the pharyngeal elevator muscles (e.g. stylopharyngeus) result in distention of the UES due to net traction forces which are applied to the anterior wall of the UES. Following UES distention and passage of the bolus, the UES collapses due to decreased intrabolus pressure. UES closure occurs when the hyolaryngeal complex descends and is facilitated by passive elastic forces and resumption of tonic contraction of the cricopharyngeus and inferior pharyngeal constrictor muscles [2-7]. DUESO is an important temporal swallow kinematic event, because reduced DUESO can lead to pharyngeal residue and/or increased risk of postprandial ~~/or~~ penetration or ~~/~~aspiration of retained food and liquids [8~~4~~-11~~8~~]~~., although~~ However, there is ~~some~~ disagreement in the literature about whether DUESO independently contributes to an increased risk of penetration/aspiration [12~~9~~].

Due to the relationship between DUESO, pharyngeal residue, and penetration/aspiration, DUESO is one important biomechanical event of swallowing that can be objectively measured to determine impaired swallow function (e.g. dysphagia diagnostics) and to measure treatment progress since improving DUESO is a frequent target in compensatory (e.g., swallow maneuvers) and restorative dysphagia (e.g., exercises) treatments that target the suprahyoid muscles [13~~0~~-17~~4~~]. To objectively evaluate UES functioning within clinical and research settings, videofluoroscopic swallow studies (VFSSs) and high-resolution pharyngeal manometry (HRM) are most frequently used [18~~4~~], yet there are limitations to both evaluation methods. VFSSs expose patients to radiation and are not always feasible or readily available with some patients, within some clinical settings, when demand exceeds availability, or in underserved regions of the world. While clinicians can measure DUESO by analyzing VF images using frame-by-frame analyses, this is a time-consuming process and few clinicians are trained in accurately performing these measurements. Additionally, specialized image processing software is required to make these measurements and a recent study revealed that few clinicians perform frame-by-frame temporal kinematic analyses at all [19~~5~~]. In an attempt to standardize VFSS procedures and analyses, the Modified Barium Swallow Impairment Profile (MBSImP) was developed. The MBSImP is a multidimensional clinical, ordinal/categorical rating scale that can be used to rate 17 physiological aspects of swallowing in the oral, pharyngeal, and esophageal phase [20~~16~~]. Compared to temporal swallow kinematic measurements, the MBSImP is a more efficient rating tool within fast-paced clinical settings. However, the initial training to become certified is time-consuming (20-25 hours according to the training website) and the rating scales for pharyngoesophageal segment opening are limited and somewhat subjective (0-complete distention and duration; no obstruction of flow, 1- partial distention and duration; partial obstruction of flow, 2- minimal distention and duration; marked obstruction of flow, and 3-no distention with total obstruction of flow). Likewise, HRM is a relatively invasive procedure and cannot independently provide insight into certain aspects of swallowing such as the presence of pharyngeal residue, the occurrence of penetration/aspiration, and hyolaryngeal excursion that must be visualized with imaging. Furthermore, while efforts are being made to deploy HRM within clinical settings, few clinicians are trained in conducting and interpreting HRM and have access to the appropriate equipment [21~~17~~].

In lieu of instrumental swallowing methods, clinical bedside swallow evaluations or dysphagia screening tools are often implemented within medical settings to determine whether or not a patient has swallowing impairments and to infer the nature of those impairments. While these methods do not provide much insight into pharyngeal swallowing physiology (such as DUESO) and have poor specificity, they have relatively high sensitivity for several measures and are inexpensive, non-invasive, easy to deploy evaluation methods [22~~18~~-24~~0~~]. Due to the limitations of current dysphagia screening and instrumental swallowing evaluation methods, there is a high demand for an inexpensive, non-invasive dysphagia screening method that provides insight into swallowing physiology that may help guide dysphagia diagnostics and rehabilitation in the future and when VFSSs are not readily available.

High resolution cervical auscultation (HRCA) is a novel, non-invasive dysphagia screening method that uses sensor-based technology to characterize swallow function. During data collection, a contact microphone and a

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tri-axial accelerometer are attached to the anterior laryngeal framework to obtain acoustic and vibratory signals, which are time-linked with videofluoroscopy (VF) images. To characterize swallow function with HRCA signals, signal feature extraction is performed and combined with advanced statistical models and machine learning techniques [25~~1~~-33~~27~~]. To date, research findings comparing HRCA and manual kinematic analyses of VFSS ~~video~~ data have demonstrated HRCA's ability to accurately detect a variety of swallow kinematic events with similar accuracy as trained human judges and to differentiate between safe and unsafe swallows (as determined by the penetration-aspiration scale) with a high degree of accuracy [25~~1~~-34~~27~~]. HRCA signals are strongly associated with hyoid bone displacement, and hyoid bone displacement signal features have demonstrated the ability to predict penetration and aspiration [35~~28~~-38~~31~~]. Expanding upon this work, HRCA signal features combined with machine learning techniques have demonstrated the ability to track ≥50% of the body of the hyoid bone on each frame of a VFSS without human supervision or VFSS images [39~~2~~-40~~33~~]. In addition to HRCA's ability to track hyoid bone movement non-invasively, preliminary evidence demonstrates that HRCA can detect laryngeal vestibular closure and DUESO with similar accuracy as human judges [41~~34~~-42~~35~~] and that HRCA signal features are associated with MBSImP component scores #9 (anterior hyoid bone movement) and #16 (pharyngeal residue) [40~~33~~, 43~~36~~-~~37~~44]. Likewise, preliminary studies have demonstrated the ability of HRCA to characterize swallow function in specific patient populations including patients with post-stroke dysphagia and patients with neurodegenerative diseases [~~35~~45~~-,~~ 46~~38~~].

Therefore, the current study will expand upon prior work by examining the ability of HRCA signals combined with machine learning techniques to independently annotate temporal swallow kinematic measurements of UES opening and UES closure (DUESO) and to predict clinical MBSImP ratings of DUESO (component #14). We hypothesized that 1. HRCA signal features combined with machine learning techniques would annotate UES opening and UES closure (DUESO) with a similar error-tolerance as human judges (3-frame, 0.1 second) and 2. HRCA signal features combined with machine learning techniques would predict MBSImP DUESO component scores as "normal" or "impaired" with a high degree of accuracy. It's important to note that the main purpose of this study was not to characterize swallowing physiology based on participant age, diagnosis, posture in the sagittal plane during swallowing (i.e. flexion, extension), bolus characteristics, or any other variable, but rather to determine the accuracy of annotating temporal swallow kinematic measurements and MBSImP ratings of DUESO with HRCA signal features and machine learning algorithms regardless of participant or bolus characteristics~~.~~.

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Methods

Participants and study procedures:

This research study was approved by the University of Pittsburgh Institutional Review Board and all participants provided written informed consent prior to study enrollment. For data analyses, two different data sets were used (patient data and healthy community dweller data). Data collection for both data sets occurred in a similar fashion at two different timepoints. The first data set included 719 swallows from 116 patients (72 males, 44 females, age 62.7±15.5) who underwent VF at the University of Pittsburgh Medical Center Presbyterian hospital due to suspected or confirmed dysphagia. The swallows included for data analyses from the patient data set consisted of a variety of bolus conditions (volume, texture, mode of administration, head position, etc.), because the VF procedures were conducted by speech-language pathologists (SLPs) as a part of standard clinical care rather than for research purposes alone. Bolus characteristics for the patient data set can be viewed in Table 1, however it should be underscored that the aim of the study was to determine the accuracy of the HRCA system of performing DUESO measurements and MBSImP ratings regardless of any variable that may affect DUESO.

The second data set included 50 swallows from 15 age-matched adults (8 males, 7 females, age 63.7±6.2) from an ongoing HRCA clinical experiment with healthy community dwelling adults. Participants reported no history of swallowing disorders, neurological disorders, surgery to the head or neck region, or chance of being pregnant. To minimize radiation exposure for healthy community dwelling adults during data collection, bolus administration procedures were standardized (average fluoro time= .66 minutes). Participants swallowed ten, thin liquid boluses in a randomized order (5 at 3mL by spoon, 5 self-selected volume cup sips). For presentations by spoon, researchers instructed participants to, “Hold the liquid in your mouth and wait until I tell you to swallow it” and for presentations by cup, researchers instructed participants to, “Take a comfortable sip of liquid and swallow it whenever you’re ready.” Bolus characteristics for the healthy community dweller data set can be viewed in Table 2.

During data collection, VF images and HRCA signals were collected concurrently. To obtain swallowing video segments, a standard fluoroscopy system (Precision 500D system, GE Healthcare, LLC, Waukesha, WI) was used and set at a pulse rate of 30 PPS. To capture raw videos at a rate of 60 frames per second directly from the x-ray apparatus without compression or processing, a frame grabber module (AccuStream Express HD, Foresight Imaging, Chelmsford, MA) was used. Frame rate for the frame grabber module was set at 60 frames per second,

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because HRCA signals require a higher sampling rate. This process of using a higher sampling rate is validated by Shannon's sampling theorem [47~~39~~]. After data collection, video segments were down sampled to 30 frames per second to eliminate duplicate frames before trained judges conducted temporal kinematic analyses.

To obtain HRCA signals, a tri-axial accelerometer (ADXL 327, Analog Devices, Norwood, Massachusetts) and contact microphone were placed on the anterior neck region of participants over the laryngeal framework at the level of the cricoid cartilage by using tape. The accelerometer and contact microphone were placed within custom casings to ensure flat contact surfaces with the skin to achieve best acoustic and vibratory signals during swallowing. The exact placement of the accelerometer and contact microphone can be seen in Figure 1. The accelerometer was placed at midline over the cricoid arch and the microphone was placed to the right of midline and inferior to the accelerometer to ensure that the sensor placement did not interfere with VF images [26,48]. In addition to this, the axes of the accelerometer (anterior-posterior, superior-inferior, medial-lateral) were aligned with the anatomical axes of each participant's neck. To power the accelerometer, a power supply with a 3V output was used (model 1504, BK Precision, Yorba Linda, California). After data collection, the raw HRCA signals were bandpass filtered (model P55, Grass Technologies, Warwick, Rhode Island) from 0.1 to 3000 Hz, amplified ten times, fed into a data acquisition device (National Instruments 6210 DAQ), and recorded at a sampling rate of 20 kHz by the LabView program Signal Express (National Instruments, Austin, Texas).

Kinematic analyses:

Before trained judges conducted temporal kinematic analyses, swallows were segmented into individual swallows for ease of analyses. The first frame in which the bolus head passes the shadow of the ramus of the mandible was defined as the swallow event onset, and the first frame in which the hyoid returned to its lowest position after clearance of the bolus tail through the UES was defined as the swallow event offset. It's important to note that while our definition of swallow event onset and offset is not identical to pharyngeal response duration or pharyngeal transit duration [49~~0~~], the goal of this study was not to equate HRCA results to these durational parameters. To measure temporal kinematic measures of DUESO, we used a custom image processing application that was developed within our lab with a similar interface to ImageJ software. UES opening was defined as the first frame in which separation of the posterior and anterior walls of the UES has begun and UES closure was defined as the first frame in which no column of air or barium contrast is seen separating the posterior and anterior walls of the UES.

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Prior to performing measurements on data, judges were trained and tested in temporal swallow kinematic analyses. Judges completed inter and intra-rater reliability tests for swallow segmentation, UES opening, and UES closure by analyzing a set of videos that were not included in the investigated dataset. Intra-class correlation coefficients (ICCs) were used to assess inter and intra-rater reliability [50~~41~~]. All trained judges had ICCs of 0.99 or above for initial inter and intra-rater reliability tests for all temporal kinematic measurements. For data analyses, trained judges were blinded to participant demographics, diagnoses, and bolus condition. To mitigate drift across measurements within a large dataset, trained judges maintained intra-rater reliability by randomly selecting one out of every ten swallows to re-analyze and compute ICCs. Inter-rater reliability was maintained across temporal kinematic measurements by randomly selecting 10% of swallows to re-analyze every 100 swallows across the dataset. All trained judges had ICCs of 0.99 or above for ongoing inter-rater reliability for swallow segmentation, UES opening, and UES closure.

To avoid measurement bias, different judges blinded to each other's measurements completed temporal kinematic analyses of DUESO and MBSImP ratings of DUESO. An MBSImP certified clinician completed all MBSImP DUESO ratings. Inter-rater reliability was established prior to performing ratings for this study by completing the MBSImP reliability test with a score of 80% exact agreement and by a reliability test between all MBSImP certified clinicians in our lab with greater than 85% exact agreement. Intra-rater reliability for MBSImP ratings was completed for 10% of swallows with 80% exact agreement.

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Feature extraction and machine learning algorithms:

To annotate temporal kinematic measurements of UES opening and UES closure, accelerometer signals alone were used as input to a 1D convolutional neural network with two convolutional layers and two max pooling layers. Convolutional neural networks are a machine learning method that mimic how human neurons fire to convey information. For this study, the accelerometer signals served as the input to the convolutional neural network. The convolutional layers were used to automatically extract~~detect~~ specific local features from small segments of the accelerometer signals. ~~and t~~The max pooling layers were used for dimensionality reduction in order to summarize the local features produced by the convolutional layers and increase the robustness of the upcoming model stages.~~combine the information extracted from each layer.~~ Then, t~~T~~he features from the convolutional neural network were used as input to a 3-layer recurrent neural network with gated recurrent units followed by 4 dense layers to generate the DUESO prediction profile. A 3-layer recurrent neural network is another machine learning method that can be used to model the temporal features and dynamics of time series data. As its name suggests, recurrent neural networks is composed of parallel units that receive ~~operate by receiving~~ the local features of successive signals segments produced by the convolutional neural network. The parallel units, the gated recurrent units, of the network function to model the temporal dependencies between the features from segments so that a dynamic map of the events occurring within the signals is learned. The units also learn how to tune information exchange among themselves to match patterns of different lengths. Such parallel architecture is repeated as mentioned for three layers leading to a more sophisticated learning process that is capable of modeling the dynamics of a complex process like swallowing. To summarize, the entire CRNN aims to first extract features from the signals and then model the changes in time to automatically identify the events occurring within a swallow. The dense layers are used to combine the temporal features coming from the last recurrent neural layer and form meaningful labels that identify the segments of the signals where the UES is open [32, 41].~~. input and producing output for the first layer. Then, this information from the first output is "remembered" and influences the input and output of the next layer. This process is repeated for all layers of the recurrent neural network. The gated recurrent units act as "gate-keepers" for the information that should be sent to the output and the dense layers detect and combine feature information that can be used to learn global patt~~

Once the convolutional recurrent neural network (CRNN) was built, the dataset was randomly divided into 10 equal groups for training and testing (10-fold cross-validation). This means that nine groups (~648 swallows) were used for training and one group (~71 swallows) was used for testing the accuracy of the CRNN to annotate UES opening and UES closure. This training and testing process was repeated ten times, so that each of the ten groups were used for testing one time. To determine the accuracy of the CRNN, a confusion matrix was constructed to calculate the accuracy, sensitivity, and specificity of the predicted UES opening and closure compared to the actual UES opening and closure as measured by a human judge. The difference between the predicted and actual measurements of UES opening and closure were also calculated to compare the CRNNs' performance to human judges' tolerance levels.

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To determine statistically significant ($p<0.05$) HRCA signal features for predicting "normal" or "impaired" DUESO (component # 14), generalized estimating equations (GEE) models were used. While the MBSImP has four ratings for pharyngoesophageal segment opening (0-complete distention and duration; no obstruction of flow, 1-partial distention and duration; partial obstruction of flow, 2- minimal distention and duration; marked obstruction of

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flow, and 3-no distention with total obstruction of flow), no swallows included in the analyses received a score of 2~~3~~ or 3~~4~~. For this reason, we dichotomized MBSImP ratings of DUESO into “normal” (score of 0) or “impaired” (score of 1) (See Table 3). After determining the statistically significant HRCA signal features, a support vector machine (SVM) classifier, which is a supervised machine learning technique, was trained to differentiate between swallows with “normal” DUESO and swallows with “impaired” DUESO. To assess the performance of the SVM classifier, a leave-one-out procedure was used, which involves training the classifier on all but one of the entire group of swallows, which is randomly selected to test the accuracy of the classifier. This process is repeated for the entire set of swallows until each swallow is tested at least once.

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Results

When examining the accuracy of the CRNN for detecting DUESO across the entire patient testing data set (719 swallows), the average accuracy was 0.9039, the sensitivity was 0.9145, and the specificity was 0.9119. For the patient data set, the CRNN detected UES opening within a 3-frame tolerance for 82.6% of swallows and UES closure within a 3-frame tolerance for 72.3% of swallows (See Figures 2 and 3). Likewise, the CRNN had similar performance on the healthy community dweller data set (50 swallows). For the healthy community dweller data set, the average per swallow accuracy of the CRNN was 0.8880, the average per swallow sensitivity was 0.8559, and the average per swallow specificity was 0.9356. In addition to this, the CRNN detected UES opening within a 3-frame tolerance for 84% of swallows and UES closure within a 3-frame tolerance for 66% of swallows for the healthy community dweller data set (See Figures 4 and 5). This demonstrates that a CRNN (using HRCA signal features as input) was able to detect DUESO within an acceptable human error-tolerance for the majority of swallows and that this CRNN was able to generalize to an outside data set that was not used during the training period. An example of the predicted DUESO by the CRNN compared to the actual DUESO as measured by trained human judges for one swallow can be viewed in Figure 6 demonstrating a 16msec (0.5 frame for DUESO offset) to 33msec (1 frame for DUESO onset) difference between human and CRNN measurements.

When examining the association between HRCA signal features and DUESO MBSImP ratings, accelerometer kurtosis, spectral centroid, and bandwidth in the anterior-posterior axis, wavelet entropy in the superior-inferior axis, and wavelet entropy in the medial-lateral axis were the only statistically significant signal features ($p<0.05$) out of the 36 signal features that were extracted. The definitions of the different signal features that were extracted can be viewed in Table 4. Table 5 shows the statistically significant results from examining the association between HRCA signal features and DUESO MBSImP ratings. Using the HRCA signal features as input, the SVM classifier was able to predict whether DUESO MBSImP scores were "normal" or "impaired" with 85.7% accuracy.

Discussion

This study provides preliminary evidence that HRCA signal features combined with machine learning techniques can annotate temporal swallow kinematic measurements of DUESO (UES opening and UES closure) and DUESO MBSImP ratings with a similar error-tolerance level that is acceptable for human judges (3-frames, 0.1 second) for the majority of swallows [49, 51-52]. This study found that the CRNN detected UES opening within a 3-frame tolerance for 82.6% of swallows and UES closure within a 3-frame tolerance for 72.3% of swallows for the patient data set, and UES opening within a 3-frame tolerance for 86% of swallows and UES closure within a 3-frame tolerance for 64% of swallows for the healthy community dweller data set. Additionally, HRCA signal features combined with an SVM classifier predicted DUESO MBSImP scores with 85.7% accuracy. While the CRNN performed with a high level of accuracy for both UES opening and closure, both data sets demonstrated greater overall accuracy with UES opening. This discrepancy in accuracy is likely related to greater disagreement between human judges for measurements of UES closure than for measurements of UES opening and has been found in other studies [51].

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Since machine learning is the process of teaching a computer to do something that a human normally does, machine learning algorithms perform best when clear patterns emerge from data analyses. As a result, machine learning algorithms have more variable performance when human judges (which are considered the gold standard) demonstrate greater measurement variability. Likewise, the CRNN performed with a higher level of accuracy for UES closure on the patient data set compared to the healthy data set. While this may seem surprising, the accuracy of machine learning algorithms improves with larger data sets. The patient data set included 719 swallows, while the healthy community dweller data set included only 50 swallows. In addition to this, the healthy community dweller data set was not included during the training period, which can impact the accuracy of the machine learning algorithm. Despite using a small subset of data for the MBSImP ratings, HRCA combined with a machine learning algorithm predicted MBSImP scores with a high level of accuracy. While these results are promising, it's important to note that the data was skewed to minimal-no impairment (scores of 0 and 1 only) on the MBSImP. In the future, it will be important to replicate the results of this study with larger sets of healthy community dweller data and patient data with more impaired MBSImP scores to improve the accuracy of the machine learning algorithms, to establish HRCA cutoffs for normal versus impaired DUESO, and to include swallows with more severely impaired DUESO.

This research finding contributes to a growing body of literature that demonstrates that HRCA may be an advantageous, non-invasive dysphagia screening method that provides insight into swallowing physiology [25-46]. In underserved settings in which imaging studies are not readily available, and in fast-paced medical settings currently constrained by pandemic-related changes in resource allocation, there is a strong need to improve upon the current dysphagia screening methods that lack specificity and provide little insight into swallowing physiology. An inexpensive, non-invasive dysphagia screening method that can assist with accurate and swift diagnosis and treatment of patients would be a novel and useful tool, especially in settings with reduced access to instrumental swallow evaluations. While HRCA is not ready to be deployed as a stand-alone dysphagia diagnostic method, it may be a useful adjunct to VFSSs by providing additional insight into impaired swallow physiology that may contribute to penetration/aspiration risk (e.g. DUESO). This may be beneficial for clinicians who are not trained or do not have time to perform kinematic analyses or when VFSSs are not immediately available or feasible. Likewise, with further research, HRCA has the potential to be a useful biofeedback method for dysphagia treatment for patients with reduced DUESO. In the future (and with further testing and validation), the machine learning algorithms developed in this research study to annotate and predict DUESO will be combined with other machine learning algorithms that have been developed to track hyoid bone movement, anterior-posterior distention of the UES, laryngeal vestibular closure, and penetration-aspiration scale scores [25~~1~~-44~~27, 32-35~~]. Combining the machine learning algorithms will allow clinicians to gain not only discrete individual parameter measurements, but also holistic information about a patient's swallow function using HRCA that could be used as an adjunct to VFSSs for dysphagia diagnostics, ~~and~~ treatment planning, and biofeedback during therapy when VFSSs are unavailable or not feasible.

Limitations

Although the preliminary results from this study demonstrate the potential of HRCA in dysphagia management, it is important to note several limitations of the present work. While it was not a primary aim of this study ~~to characterize DUESO in context of any other variable~~, we did not control for participant characteristics (e.g. participant age, diagnosis, posture in the sagittal plane during swallowing (i.e. flexion, extension)) or bolus characteristics (e.g. volume, viscosity, utensil) when analyzing DUESO. However, the variable patient and bolus characteristics used in this study further demonstrate the robustness of the

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Formatted: Font: (Default) Times New Roman, Font color: Auto machine learning algorithms deployed, because more variables result in more chaos for training and testing the algorithms. In the future, we plan to explore the associations between patient and bolus characteristics and HRCA signal features (a process that we have already begun by examining differences in HRCA signal features across different patient populations) [45-46]. ~~Because~~ In addition to this, the patient data set was collected in a manner that is consistent with standard clinical care, ~~this~~ which may limit the internal validity of our study results. ~~Yet, despite the non-standardized data collection methods for the patient data set~~Yet, few patients undergo completely standardized VFSS administration procedures, because ~~due to~~ abnormal findings requir~~eing~~ intervention-related protocol deviations. Hence, ~~these~~ our study methods may result in increased external validity/generalizability ~~of our study findings~~ by mimicking ~~ordinary~~ VFSS procedures in clinical settings. ~~In addition to this, the variable patient and bolus characteristics used in this study further demonstrate the robustness of the machine learning algorithms deployed, because more variables result in more chaos for the algorithms to be trained and tested. In the future, it will be important to explore the associations between patient and bolus characteristics and HRCA signal features, a process that we have already begun by examining differences in HRCA signal features across different patient populations [35, 38].~~ Another limitation of this study is that we did not determine cutoffs of normal versus impaired temporal swallow kinematic measurements of DUESO. While we demonstrated preliminary efficacy of producing cutoffs by predicting “normal” versus “impaired” DUESO MBSImP scores, future studies should examine the ability to establish cutoffs for temporal swallow kinematic measurements of DUESO ~~by using HRCA signal features and machine learning algorithms~~by~~. To assist with establishing cutoffs for DUESO, it will be important to~~ analyz~~inge~~ ~~additional~~ more swallows from healthy community dwelling adults to determine normative data for DUESO and other temporal swallow kinematic measurements (a process we have already initiated within our lab). Future studies should also include a larger sample of swallows with greater variability of DUESO MBSImP ratings. ~~While this study included a relatively large sample of patient data, future studies should replicate this work with larger data sets of swallows from patients and healthy community dwelling adults, because the accuracy of machine learning algorithms improves with larger sets of data.~~

Another limitation of the present study is that we used HRCA signal features and machine learning algorithms to annotate one specific temporal kinematic event (i.e. DUESO~~)and predict DUESO MBSImP scores alone~~. While DUESO is an important temporal kinematic event that is associated with pharyngeal residue and risk of

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penetration/aspiration [8~~4~~-11~~8~~], DUESO alone cannot be used to diagnose dysphagia. Clinicians must holistically evaluate a patient's swallow by analyzing all temporal and spatial swallow kinematic events to appropriately diagnose and treat dysphagia. Despite this limitation, this study brings us ~~one step~~ closer to developing a non-invasive dysphagia screening method that provides insight into swallowing physiology that may be deployed within clinical settings in the future. The results of ~~the present~~this study combined with other work which has shown ~~the~~ HRCA's ~~ability of HRCA signal features and machine learning algorithms to~~potential in accurately trac~~k~~king hyoid bone movement and laryngeal vestibular closure with HRCA feature analyses and machine learning algorithms demonstrates the future potential of ~~implementing~~ using HRCA within clinical settings [39~~2~~-41~~34~~].

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Conclusion

This study found that a CRNN (using HRCA raw signals as input) could detect UES opening for 86% of patient swallows and UES closure for 72.3% of swallows within an acceptable human error-tolerance for temporal kinematic analyses of swallowing (3-frame tolerance) and that this CRNN could generalize to an outside data set not used during the training period (e.g. healthy community dweller data set). In addition to this, this study found that HRCA signal features combined with an SVM classifier could predict DUESO MBSImP ratings with 85.7% accuracy. This research study provides preliminary evidence regarding the ability of HRCA to detect DUESO (temporal kinematic analyses, MBSImP scores) without the use of VF images or human supervision. The results of this study combined with other recent studies investigating HRCA provide growing evidence that HRCA may be an effective, non-invasive, and inexpensive dysphagia screening and diagnostic adjunct method.

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Compliance with Ethical Standards:

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Conflict of interest: We have no conflicts of interest to declare.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

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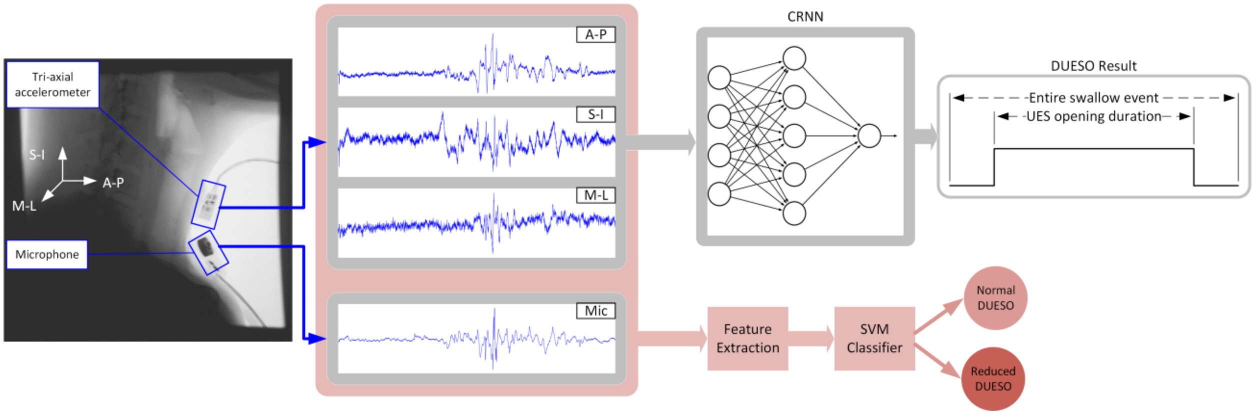
Figure

Figure 1: This shows the placement of the accelerometer and contact microphone during data collection and the extraction of the acoustic and vibratory signals for the machine learning algorithm to annotate temporal kinematic measurements and MBSImP scores of DUESO.



Figure

Figure 2: This figure shows the accuracy of the CRNN for detecting UES opening within a 3-frame (0.1 second tolerance) compared to human measurements of UES opening for the patient data set.

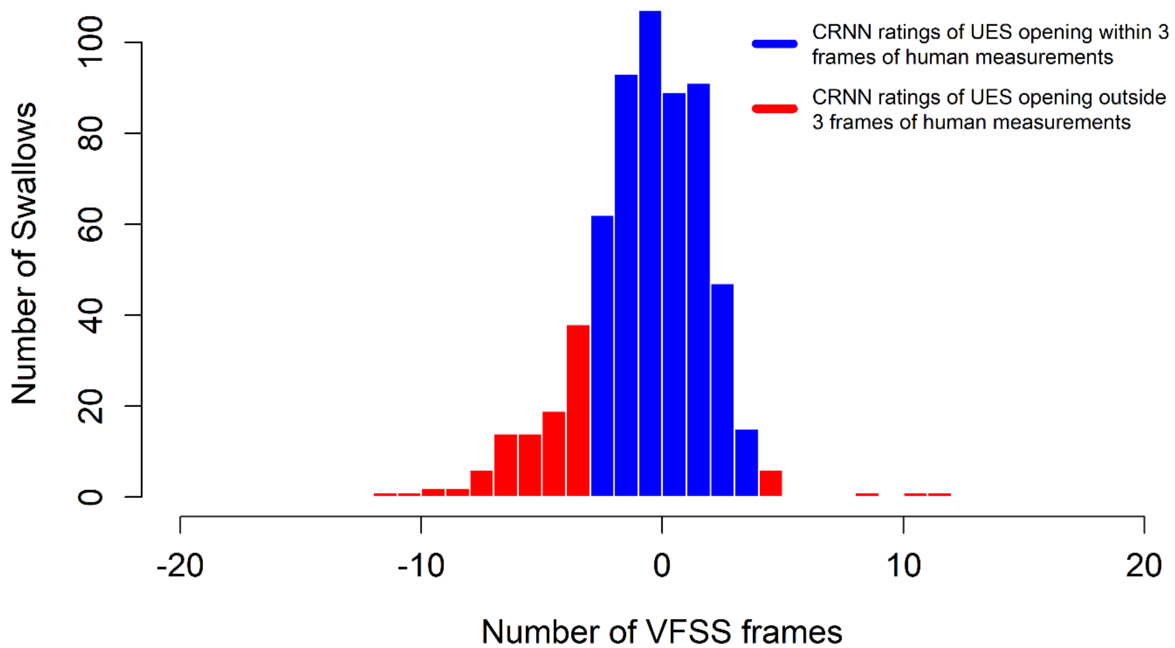
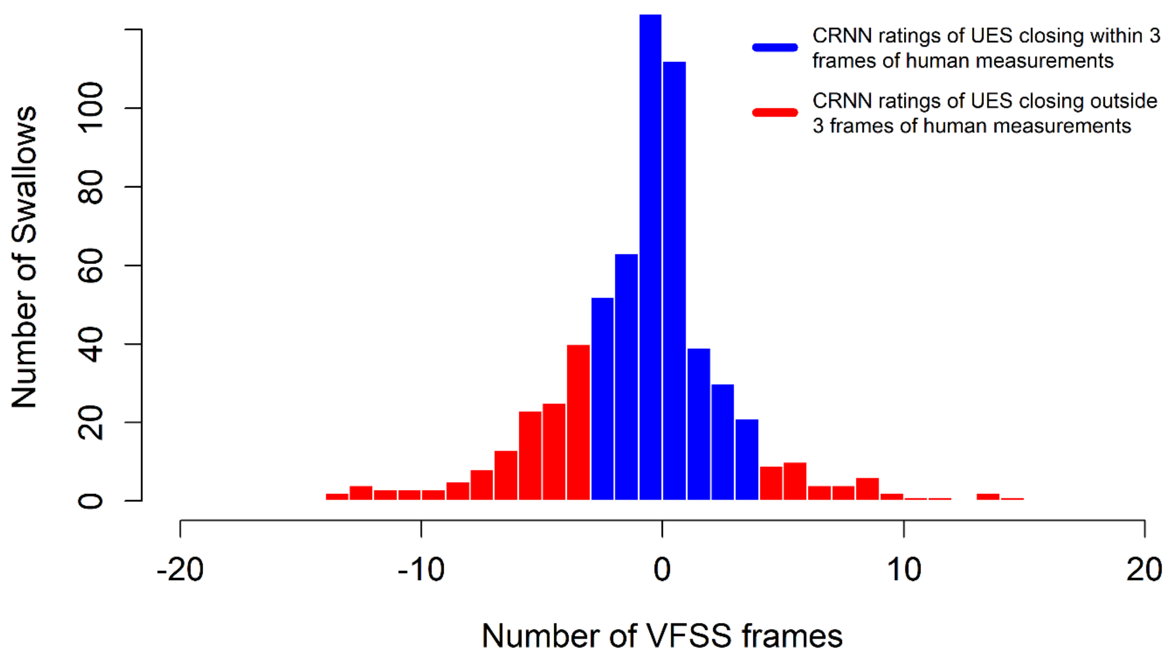
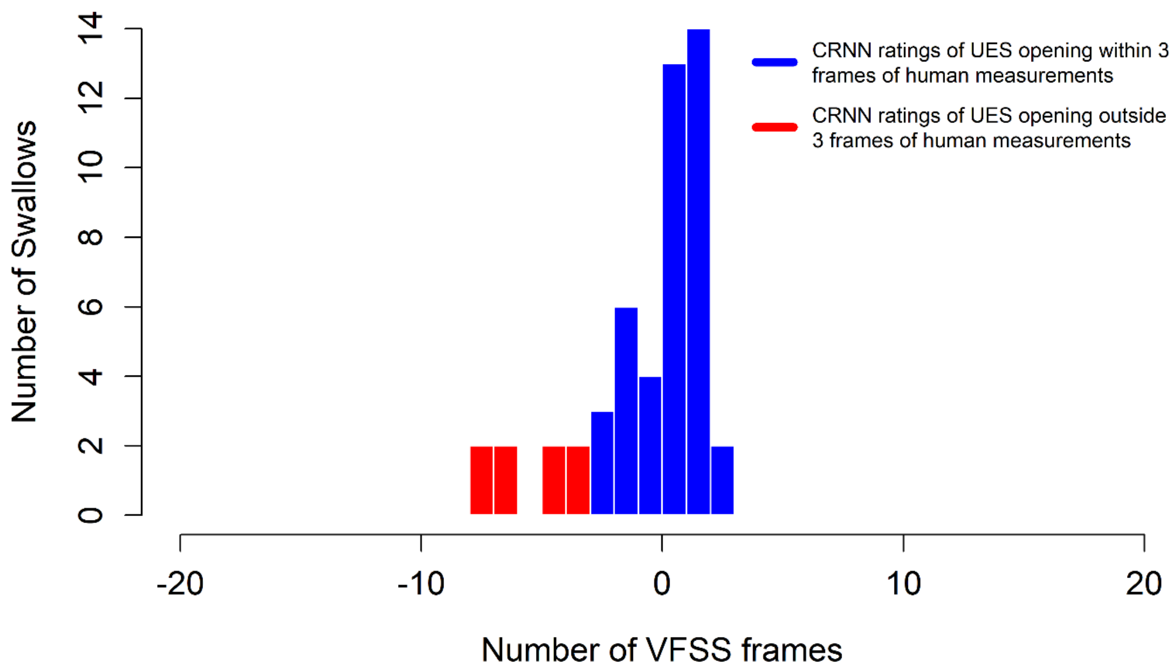


Figure 3: This figure shows the accuracy of the CRNN for detecting UES closure within a 3-frame (0.1 second tolerance) compared to human measurements of UES closure for the patient data set.



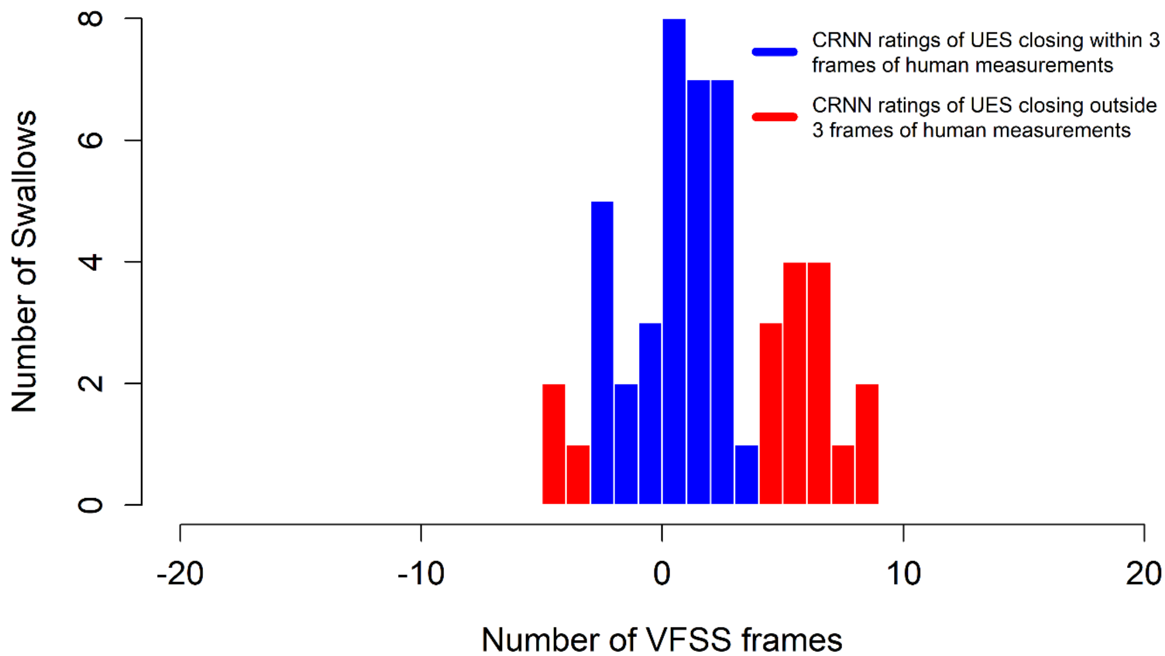
Figure

Figure 4: This figure shows the accuracy of the CRNN for detecting UES opening within a 3-frame (0.1 second tolerance) compared to human measurements of UES opening for the healthy community dweller data set.



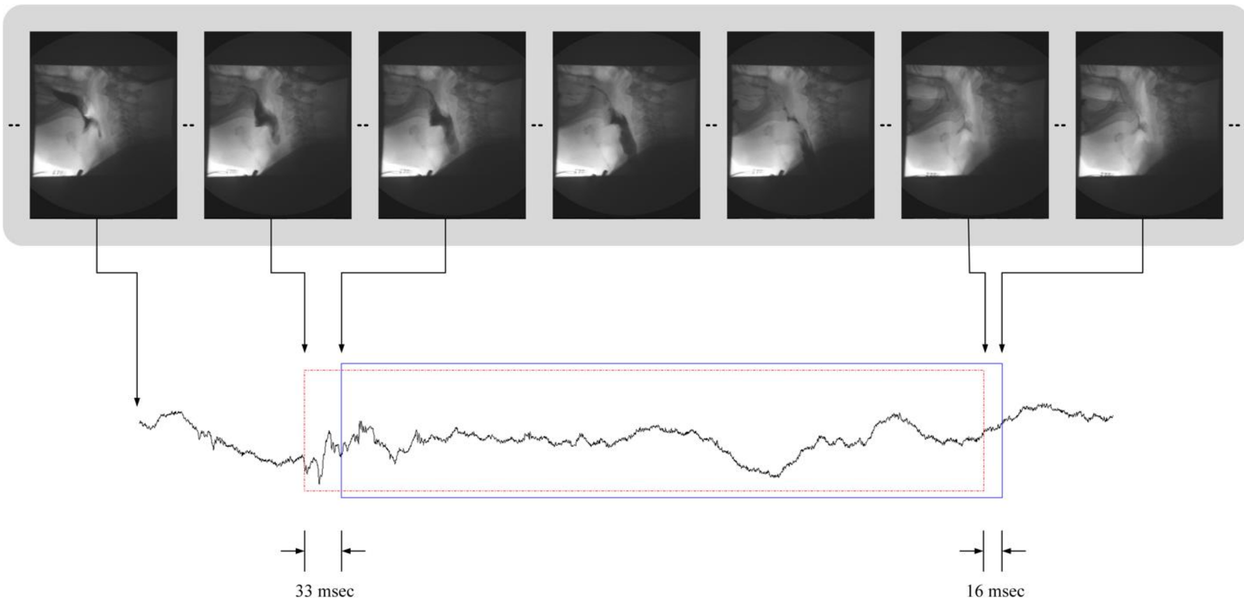
Figure

Figure 5: This figure shows the accuracy of the CRNN for detecting UES closure within a 3-frame (0.1 second tolerance) compared to human measurements of UES closure for the healthy community dweller data set.



Figure

Figure 6: This figure shows a sample full swallow with concurrent VF and HRCA signals. The predicted DUESO measurements by the RNN are shown in blue and the actual DUESO measurements by trained human judges are shown in red.



Table

Table 1: *Bolus characteristics for all swallows included in the original patient data set.*

Bolus viscosity and utensil	Number of swallows	Percentage of swallows
Thin by spoon	148	20.6%
Thin by cup	226	31.4%
Thin by straw	83	11.5%
Saliva swallows/other	10	1.4%
Nectar thick liquid by spoon	103	14.3%
Nectar thick liquid by cup	69	9.6%
Nectar thick liquid by straw	24	3.3%
Pudding by spoon	43	6.0%
Cookie	13	1.8%

Table

Table 2: *Bolus characteristics for all swallows included in the healthy community dweller patient data set.*

Bolus viscosity and utensil	Number of swallows	Percentage of swallows
Thin by spoon	25	50%
Thin by cup	25	50%

Note: Thin by spoon swallows were 3 mL and thin by cup swallows ranged from 3-60 mL.

Table

Table 3: *MBSImP pharyngoesophageal segment opening ratings for a subset of swallows (100).*

MBSImP score	Number of Swallows	Percentage of Swallows
Complete distention and complete duration; no obstruction of flow (0)	74	74%
Partial distention/partial duration; partial obstruction of flow (1)	26	26%

Table

Table 4: *Summary of the features extracted from the HRCA signals.*

Domain	Feature	Significance
Time Domain		
	Standard deviation	Reflects the signal variance around its mean value.
	Skewness	Describes the asymmetry of amplitude distribution around mean.
	Kurtosis	Describes the peakness of the distribution relative to normal distribution.
Information-Theoretic domain		
	Lempel-Ziv Complexity	Describes the randomness of the signal.
	Entropy rate	Evaluates the degree of regularity of the signal distribution.
Frequency domain		
	Peak Frequency (Hz)	Describes the frequency of maximum power.
	Spectral Centroid (Hz)	Evaluates the median of the spectrum of the signal.
	Bandwidth (Hz)	Describes the range of frequencies of the signal.
Time-Frequency Domain	Wavelet Entropy	Evaluates the disorderly behavior for non-stationary signal.

Table

Table 5: *Summary of the statistically significant HRCA signal features associated with MBSImP ratings of pharyngoesophageal segment opening*

	Standard Deviation	Skewness	Kurtosis	Lempel-Ziv complexity	Entropy Rate	Peak Frequency	Spectral Centroid	Bandwidth	Wavelet entropy
Microphone	0.162	0.435	0.594	0.402	0.065	0.564	0.359	0.089	0.634
Anterior-posterior	0.313	0.951	**0.014***	0.327	0.277	0.977	**0.014***	**0.009***	0.803
Superior-inferior	0.809	0.062	0.058	0.156	0.187	0.189	0.239	0.104	**0.018***
Medial-lateral	0.497	0.919	0.990	0.947	0.753	0.964	0.126	0.187	**0.009***

Note: *= $p<0.05$