Non-invasive identification of inspiratory flow limitation in patients sleeping with an oral appliance in place

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Hypothesis

That analysis of respiratory airflow, snoring sound, and dental vibration can accurately identify inspiratory flow limitation (IFL) in patients sleeping with an oral appliance (OA) in place.

Methods

Ten subjects with suspected sleep disordered breathing (mean AHI = 14.8 ± 15.4) underwent standard polysomnogram (PSG) plus recording of supra-glottic pressure (P_{sg}), snoring sound, dental vibration, and nasal airflow. The participants slept with temporary dental trays in the mouth attached to a motorized mandibular positioner (MATRx, Zephyr Sleep Technologies).

P_{sg} was measured by a pressure transducer connected to a saline-filled naso-pharyngeal catheter. Airflow was derived from the air pressure recorded in each naris separately.

Snoring sound and dental vibration were recorded by a microphone (Panasonic, WM-61A) and accelerometer (B&K, 4508B) in the mandibular positioner.

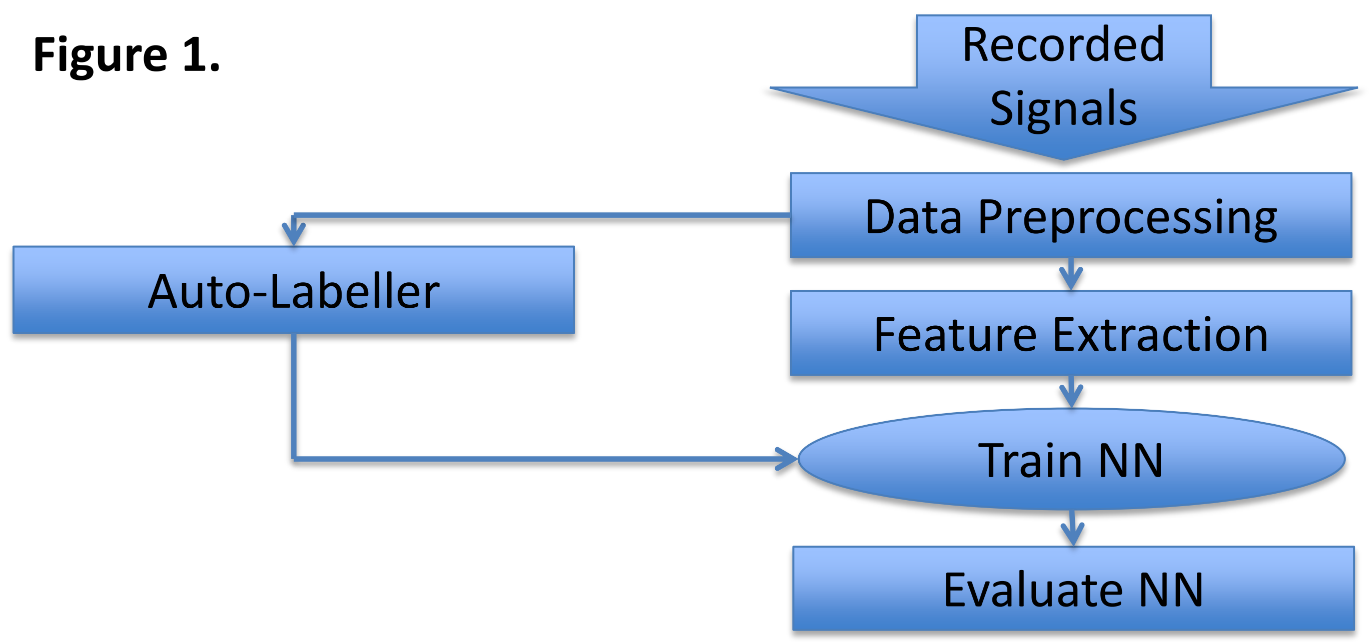
All signals were synchronized and preprocessed. The inspiration portion of each breath was detected by zero crossing of airflow signal. Breaths associated with swallows and sighs were excluded.

An auto-labeller (AL) used P_{sg} and airflow signals to designate each breath as IFL or non-IFL based upon the airflow response to an observed decrease in P_{sg}.

A multi-layer perceptron neural network (NN) (1 hidden layer, 10 nodes) was trained (back propagation) by AL identification of IFL breaths together with airflow, sound, and vibration recorded throughout inspiration as inputs. Shape, frequency, and time features of these signals were used (Figure 1). The NN was trained on a random selection of 80% of breaths and evaluated on the remaining 20%.

Methods cont.

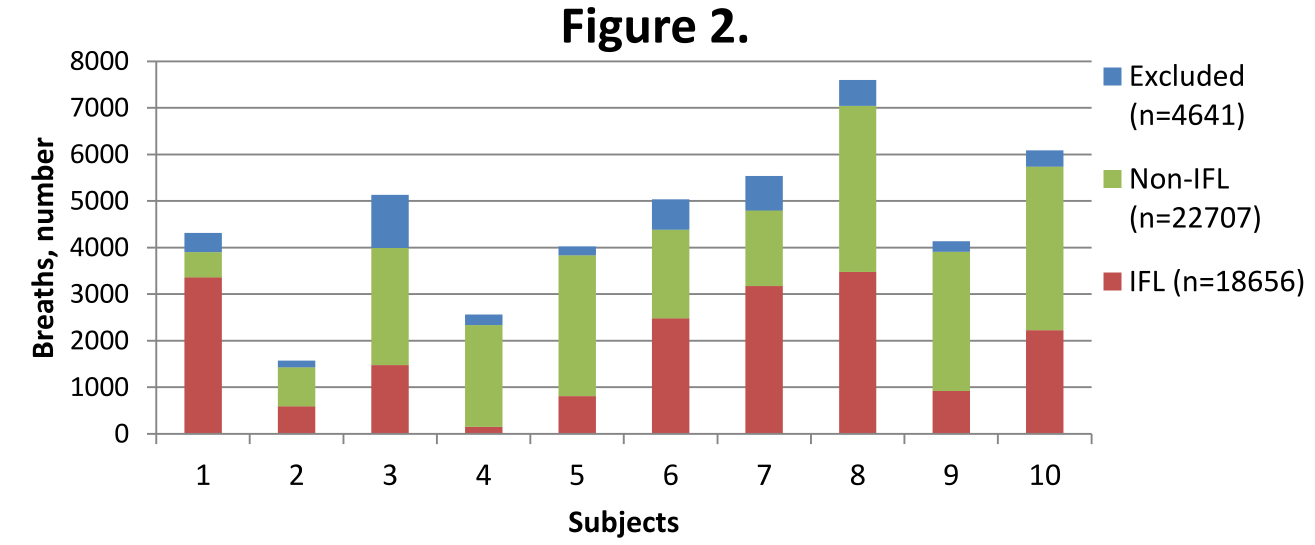
Figure 1.



Results

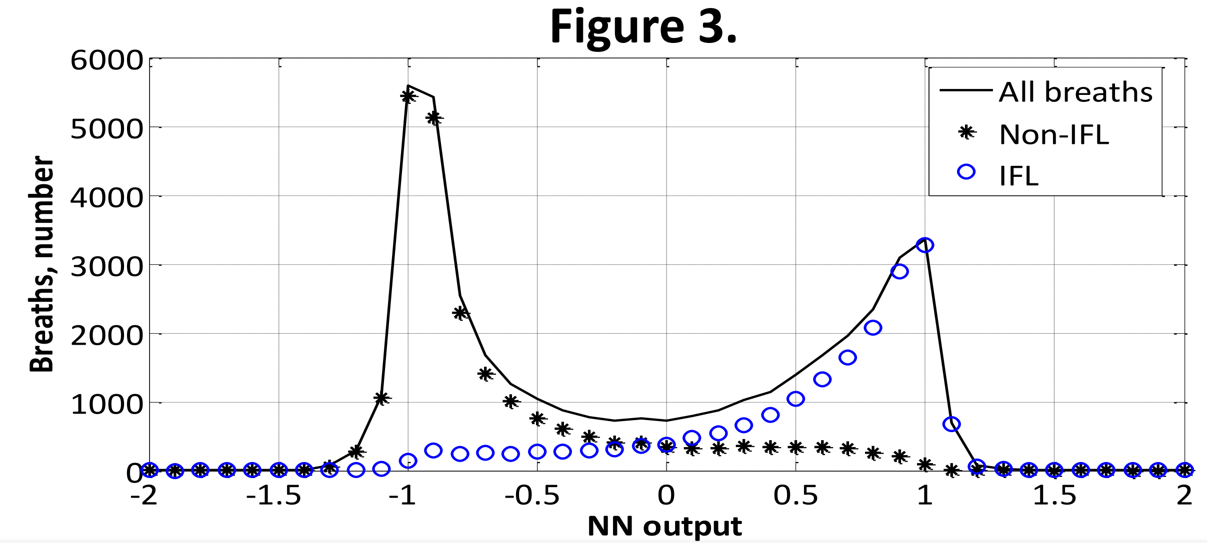
41,363 inspirations were labelled as IFL (45%) and non-IFL (55%), and the distribution amongst the 10 subjects is shown in Figure 2.

Figure 2.



Inspirations were distributed bi-modally in relation to NN output, and values > 0.75 and < -0.75 were strongly associated with IFL and non-IFL, respectively (Figure 3).

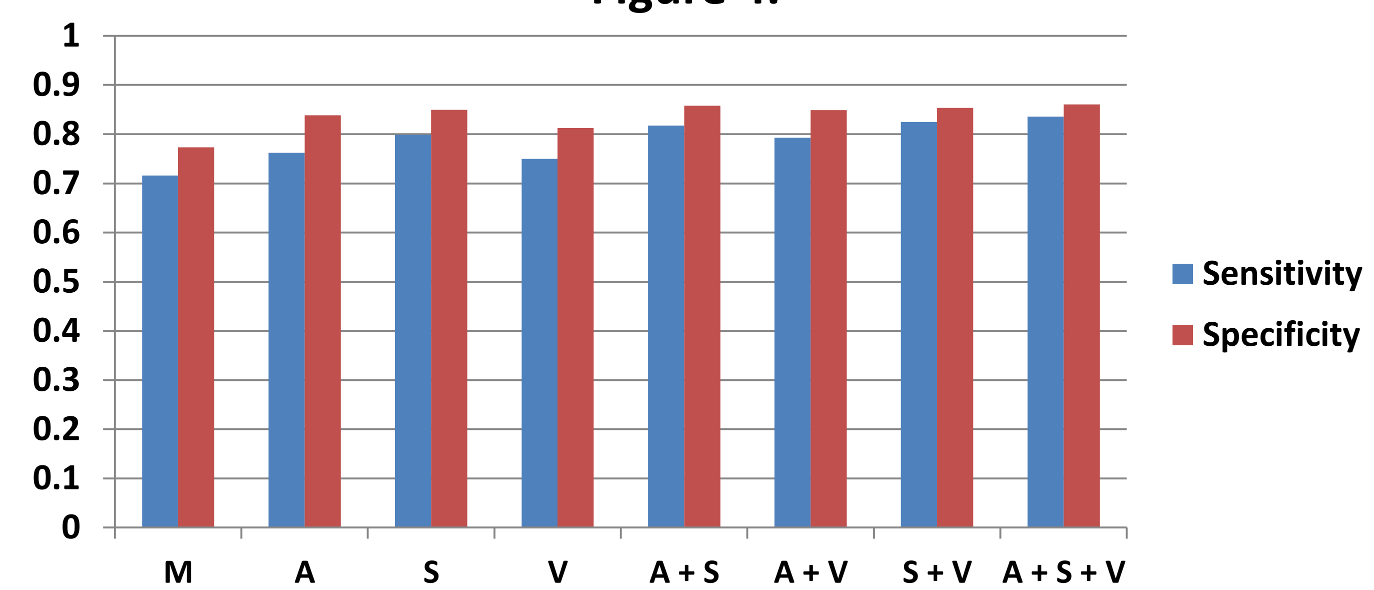
Figure 3.



Results cont.

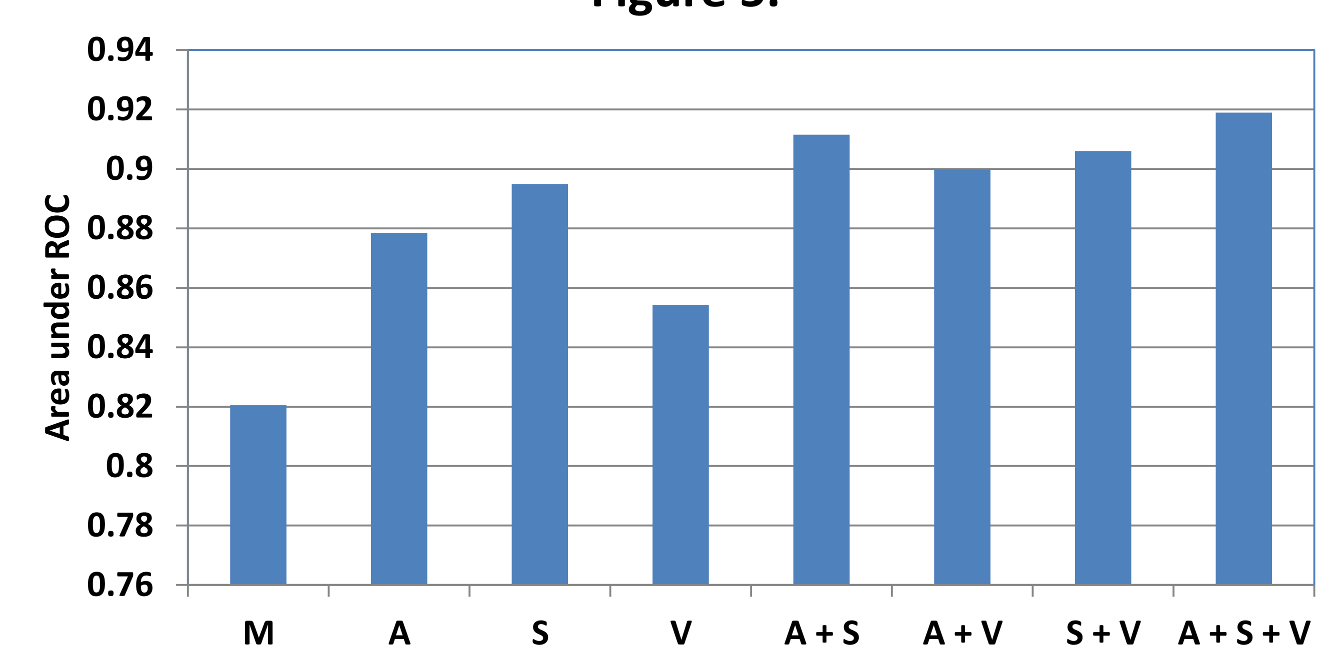
Using a NN output value of zero as a prediction threshold, sensitivity and specificity values varied from 0.72 to 0.86 depending on the input signals used, with the highest being 0.84 and 0.86 for all three inputs (Figure 4). Different combinations of input features from Morgenstern[1] (M), airflow (A), sound (S), and vibration (V) were tested.

Figure 4.



ROC curve areas for different NN inputs are shown in Figure 5. Sound was the richest single signal. Using a set of 11 features derived from airflow, Morgenstern reported ROC area of 0.91, whereas, in our study, these M features resulted in ROC area of 0.82. Yet, our features of airflow showed higher accuracy than M features (ROC area:0.88). Employing features from all three non-invasive signals resulted in the highest predictive accuracy (ROC area:0.92).

Figure 5.



Discussions

- A large sample of inspirations (41K) provided thorough training and testing of the NN.
- P_{sg} measurement allowed unequivocal identification of IFL by gold standard method.
- Identification accuracy varied depending on the NN input signal used, and the highest accuracy was obtained when airflow, sound and vibration were used.
- Our results differed from those of Morgenstern, which may reflect the changes caused by wearing oral appliances by our subjects.

Conclusions

- ✓ Airflow, sound and vibration were used as inputs in a neural network analysis to identify IFL.
- ✓ 41K breaths, labeled as IFL or non-IFL, were used to train and test the network.
- ✓ Our results observed with OA in the mouth differed from published results without OA.
- ✓ The use of all three inputs combined resulted in the most accurate prediction (ROC area:0.92).

Acknowledgements

Funding from NRC-IRAP, MITACs, Alberta Innovates – Technology Futures, and Zephyr Sleep Technologies supported this research.

References

1. C. Morgenstern, M. Schwaibold, W. J. Randerath, A. Bolz, R. Jané, *IEEE Trans. Biomed. Engineering 56*(8), pp. 2006-2015, 2009.