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1 Non-intrusive real-time breathing pattern detection and classification for automatic abdominal functional electrical
2 stimulation

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5 **Abstract**

6 Abdominal Functional Electrical Stimulation (AFES) has been shown to improve the respiratory function of people
7 with tetraplegia. The effectiveness of AFES can be enhanced by using different stimulation parameters for quiet
8 breathing and coughing. The signal from a spirometer, coupled with a facemask, has previously been used to
9 differentiate between these breath types. In this study the suitability of less intrusive sensors was investigated with
10 able-bodied volunteers. Signals from two respiratory effort belts, positioned around the chest and the abdomen,
11 were used with a Support Vector Machine (SVM) algorithm, trained on a participant by participant basis, to classify,
12 in real-time, respiratory activity as either quiet breathing or coughing, and compared with the classification
13 accuracy achieved using a spirometer signal and a SVM. The signal from the belt positioned around the chest
14 provided a similar classification performance as the signal from a spirometer (mean cough (^c) and quiet breath (^q)
15 sensitivity (Se) of Se^c=92.9% and Se^q=96.1% vs. Se^c=94.0% and Se^q=95.5%). The abdominal belt and a combination
16 of both belt signals resulted in lower classification accuracy. We suggest that this novel SVM classification
17 algorithm, combined with a respiratory effort belt, could be incorporated into an automatic AFES device, designed
18 to improve the respiratory function of the tetraplegic population.

19 *Keywords:* Electrical stimulation, Respiratory function, Tetraplegia, Control system, Classifier, Spinal Cord Injury

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22 **1 Introduction**

23 An injury to the cervical (neck) region of the spinal cord can cause paralysis affecting all four limbs, known as
24 tetraplegia. People with tetraplegia also have paralysis or severe impairment of the respiratory muscles, resulting
25 in reduced respiratory function. Associated respiratory infections are a leading cause of rehospitalisation for this
26 patient group [1]. Functional Electrical Stimulation (FES), the application of a train of electrical pulses to a motor

27 nerve causing the associated muscle to contract, can be used to make paralysed muscle contract [2]. The
28 application of FES to the abdominal muscles, known as abdominal FES (AFES), has been shown to improve the
29 respiratory function of people with tetraplegia [3-5].

30 Gollee et al. [3] suggest that to maximise effectiveness, AFES for a quiet breath and a cough should be applied
31 at different points in the breathing cycle, using different stimulation intensities. They suggest that quiet breaths
32 should be stimulated at the start of exhalation, to support exhalation and avoid interfering with an inhalation,
33 while coughs should be stimulated during glottal closure (between the end of inhalation and the start of a cough
34 exhalation) in order to build up intrathoracic pressure, with a higher level of stimulation than a quiet breath. This
35 earlier and greater degree of stimulation for a cough is aimed to increase intrathoracic pressure and aid cough
36 generation. To enable the correct level of stimulation to be applied at the correct point in the breathing cycle, an
37 automatic AFES algorithm must be capable of using data from an inhalation to differentiate between a quiet breath
38 and cough in real-time. Gollee et al. [3] used the signal from a spirometer to identify a cough based on the
39 inhalation flow rate and a quiet breath based on a cross-correlation algorithm. This system required manual setting
40 of threshold values on a session by session basis. We have previously shown that the signal from a spirometer can
41 be used with a maximum likelihood classifier for accurate real-time breathing classification [6]. This program
42 required manual feature selection for each subject. For clinical use, it would be desirable to minimise manual
43 intervention (e.g. threshold or feature selection) during setup.

44 Support Vector Machines (SVMs) are a statistical learning technique for binary classification problems with a
45 good classification performance compared to other classifiers [7]. They require minimal operator intervention,
46 making them a suitable alternative to the solutions outlined above.

47 A spirometer is typically combined with a full face mask which is uncomfortable and intrusive, leaving the user
48 unable to eat, drink or verbally communicate while in use. Replacing a spirometer with a less-intrusive sensor
49 would make an AFES system considerably more practical. Non-intrusive respiratory effort belts are commonly used
50 to detect sleep apnea following offline breathing pattern analysis [8]. In a single subject feasibility study Gollee et
51 al. [9] report that respiratory effort belts may be suitable for real-time breathing pattern detection. This suggests
52 that they may provide a suitable non-intrusive signal for breathing pattern classification.

53 The aim of this study is to develop a SVM classification algorithm capable of classifying respiratory activity in
54 real-time, with minimal operator intervention, using the signal from a non-intrusive sensor.

55 **2 Methods**

56 Ten able-bodied participants (6 males, age 27.6 ± 5.2 years (mean \pm std)) were recruited and asked to attend two
57 sessions. The study was approved by the local ethics committee and conformed to the declaration of Helsinki. All
58 participants gave written informed consent.

59 **2.1 Data Collection Protocol**

60 The data collection protocol is summarised in Figure 1. Experimental sessions included runs consisting of six coughs
61 and one minute of quiet breathing, with and without the support of AFES. The order of these four breath types
62 within each run was randomised, with each breath type following directly one after the other. Each run was
63 repeated three times per session, separated by a rest period of approximately two minutes. The session was
64 repeated after a period of approximately seven days.

65 Figure 1: Data collection protocol showing two sessions, split into three runs, with each run containing a period of AFES assisted
66 and unassisted quiet breathing and coughing.

67 The data recorded during the two sessions were combined for each participant. Data sets containing all of the
68 cough data or all of the quiet breathing data were then created for each sensor.

69 **2.2 Equipment and signal pre-processing**

70 The participant's respiratory activity was recorded using a spirometer (Microloop, Micromedical, UK), connected to
71 a full face mask (Hans Rudolph Inc., KS, USA), and with two non-intrusive respiratory effort belts (Piezoelectric
72 belts, ProTech, USA), one positioned around the abdomen, at the umbilicus, and the other positioned around the
73 front of the chest, at the sternum. The signal from the spirometer provided magnitude and direction of respiratory
74 flow. The respiratory effort belts measured the stretch velocity at the chest and abdomen respectively, which is
75 directly related to the flow obtained using the spirometer.

76 The respiratory effort belts were connected to a custom amplifier and interfaced with a laptop computer via a
77 16-bit data acquisition card (NI DAQCard 6036E, National Instruments, USA), while the spirometer was connected

78 via a RS232 interface. Data was recorded in the Simulink modeling environment (The Mathworks, USA) using
79 custom-made blocks to enable real-time data acquisition at a sample rate of 50 Hz. The belt signals were high pass
80 filtered to remove signal bias (1st order butterworth, cut off frequency 0.04 Hz). The spirometer signal was low
81 pass filtered to remove high frequency noise (8th order simple moving average filter, cut off frequency 2.7 Hz).

82 **2.2.1 Stimulation System**

83 A neuromuscular stimulator (RehaStim v1, Hasomed, Germany) was used to stimulate the abdominal muscles
84 bilaterally using four channels. Stimulation was applied via surface electrodes (33 mm x 53 mm rectangular, PALS,
85 Axelgaard, USA) placed over the rectus abdominis and external oblique muscles on both sides of the body.
86 Stimulation was automatically triggered at the start of each exhalation, defined as the moment when the
87 spirometer signal crossed zero from a negative (inhalation) to positive (exhalation) value, and applied for a duration
88 of 1.5 seconds for a quiet breath and 1 second for a cough. Bi-phasic current controlled stimulation pulses were
89 applied at a frequency of 30 Hz. Stimulation current was adjusted on a channel by channel basis for each
90 participant (with a pulsewidth of 100 μ s) until a visible contraction was observed (range 10-60 mA for all
91 participants), with this current remaining fixed for the remainder of both sessions. Stimulation pulsewidth was
92 varied between 100 and 150 μ s within each session to account for muscle fatigue. A custom LabVIEW (National
93 Instruments, USA) interface, integrated with Simulink, was used to adjust the stimulation parameters.

94 **2.3 Support Vector Machine**

95 Features, extracted from each inhalation of the pre-processed data from each sensor were used to train a SVM. For
96 the spirometer the start of inhalation was defined as the moment when the signal crossed zero from a positive to a
97 negative value. For both respiratory effort belts the start of inhalation was defined as two consecutive negative
98 samples, preceded by three non negative samples, where the previous zero crossing was the end of inhalation. The
99 opposite logic was applied to detect the end of inhalation. Due to the a high signal to noise ratio (achieved using
100 the filtering techniques described in Section 2.2) these methods were found to be robust enough to minimise false
101 positive detection. The features from a subset of approximately 50 cough and 100 quiet breath inhalations,
102 together with information indicating whether the data represented a quiet breath or a cough, were used to train
103 the SVM on a participant by participant basis. After training, the SVM was used to classify all of the breaths

104 recorded from the participant which were not used to train the SVM as either a quiet breath or a cough. This was
105 achieved using features extracted from each inhalation. The classification structure is explained in further detail in
106 this section.

107 **2.3.1 Feature Extraction**

108 Initially a total of 28 features, extracted from both the time and frequency domain, were considered as classifier
109 inputs. To select features which were different in cough and quiet breathing, the following method was applied:
110 the features values were extracted from the spirometer signal for all participants, and a Wilcoxon signed-rank test
111 was performed. Those features which were found to be statistically significantly different ($p < 0.05$) for a quiet
112 breath and a cough were then selected, resulting in 21 features (listed in the supplementary material). Examples of
113 some of the quiet breath and cough features extracted from the time domain of the chest belt signal are shown in
114 Figure 2. A difference in both of the feature values can be seen for both breath types.

115 Figure 2: Chest belt signal showing example features for quiet breathing and coughing.

116 To evaluate the classification performance when using the signals from both respiratory effort belts, the
117 features from the belts positioned around the chest and the abdomen were combined, providing 42 features.

118 **2.3.2 Breathing Pattern Classification**

119 **Peak Expiratory Flow**

120 Peak expiratory flow (PEF), the maximum flow rate during exhalation (recorded with the spirometer), was used
121 offline to label each inhalation as a quiet breath or a cough, since PEF is greater for a cough than for a quiet breath.
122 The threshold for a breath to be deemed a cough was 0.1 L/s greater than the maximum expiratory flow recorded
123 during any of the quiet breaths recorded from that participant, and was set on a participant by participant basis.
124 This method provided a sensitivity of 100%. This labelled data was used to train the SVM and to allow the
125 performance of the SVM to be assessed. Note that a real-time classification must be made at the end of each
126 inhalation. For this reason PEF data, which is based on exhalation, would not be available for online classification in
127 real-time.

128 **Support Vector Machine**

129 The signals from the respiratory effort belts positioned around the abdomen and the chest, as well as a
130 combination of these signals, were used to construct separate Support Vector Machines (SVMs) for each subject.
131 The signal from the spirometer was used to create a separate SVM providing baseline performance and allowing a
132 comparison of the classification accuracies using the different sensor signals. To test the robustness of the SVMs a
133 simple cross validation method was used. The SVMs were trained on a participant by participant basis using the
134 data collected from session one (*Train 1*), session two (*Train 2*) and the first 50% of the data recorded from session
135 one and session two (*Mix*). This training data contained approximately 50 coughs and 100 quiet breaths. The
136 feature values and a label denoting whether each breath was a quiet breath or a cough were used to train the SVM
137 model, using the MATLAB Bioinformatics Toolbox (Version 3.5), with a linear kernel and a box constraint of 0.1.

138 **2.3.3 Classification Performance**

139 To evaluate the performance of the SVMs the data collected during the sessions which was not used to train the
140 SVMs was classified as either a quiet breath or a cough, using the previously trained SVMs. For each breath type
141 the classification sensitivity [10], Se , was calculated. Se is defined as the ratio of the number of breaths which were
142 correctly classified as that breath type, N_y^i , and the total number of breaths which should have been classified as
143 that breath type, N_t^i , where i denotes the breath type (c =cough, q =quiet breath).

$$144 \quad Se^i = \frac{N_y^i}{N_t^i} 100 [\%] \quad (1)$$

145 Sensitivity of one breath type alone is generally not a suitable parameter to evaluate a classifier: if every breath
146 was classified as a cough this would lead to 100% cough classification sensitivity, even though all quiet breaths had
147 been incorrectly classified as coughs, due to false positives not being accounted for. In the general case, *specificity*
148 can be used to include the effect of false positive detection. In our case where only two classes are to be
149 distinguished, the cough classification sensitivity is equal to the quiet breath classification specificity and vice versa.

150 2.4 Statistical Analysis

151 A Wilcoxon signed-rank test was used to test for a statistically significant difference ($p < 0.05$) in the classification
152 performance between each of the respiratory effort belt signal combinations and the spirometer, and between the
153 classification performance with only stimulated and unstimulated breaths.

154 3 Results

155 Boxplots showing the quiet breath and cough classification sensitivities when using the different sensors and
156 training methods, outlined in Section 2.3.2, are shown in Figure 3. The SVMs were trained on a participant by
157 participant basis and evaluated using the participant's data collected at the two sessions which was not used to
158 train the SVMs (approximately 100 coughs and 200 quiet breaths).

159 Figure 3: Boxplots showing the classification sensitivities for different sensors and training data sets. Each box shows the median
160 together with the inter-quartile range. (a) shows the quiet breath sensitivity for the spirometer and respiratory effort belts when
161 trained for each participant using: 1) all the data collected from that participant during the first session, 2) all the data collected from
162 that participant during the second session, *Mix* the first 50% of the data recorded from the first and second session. Classification
163 was performed on the data collected at the two sessions which was not used to train the classifier. (b) shows the cough sensitivity for
164 the same sensors using the same training data. * indicates statistically significantly different from spirometer when using the same
165 training data.

166 The classification sensitivities achieved using the signal from the chest belt and training the SVM with data
167 collected at both session 1 and 2 (*Train Mix*) provided the best combination of high cough and quiet breath
168 classification sensitivities, with mean cough and quiet breath sensitivities of 92.9% and 96.1% respectively. This
169 cough classification sensitivity was not statistically significantly different to that achieved using the spirometer and
170 the same training method, which was 94.0%. The cough classification sensitivity achieved using the signal from the
171 abdominal belt and any of the three training methods, or the combined belt signals and training with the data
172 collected at session 2 (*Train 2*), was statistically significantly inferior to that achieved using the signal from the
173 spirometer. The quiet breath classification sensitivity of 96.1% achieved using the chest belt and training with *Train*
174 *Mix* provided the highest quiet breath classification sensitivity. This sensitivity was not statistically significantly
175 different to that achieved using the spirometer or combined belt signals and the same training method, with

176 sensitivities of 95.5% and 91.5% respectively. However, the quiet breath classification sensitivity achieved using the
 177 signal from the abdominal belt and this training method of 89.4% was statistically significantly lower to that
 178 achieved using the spirometer. The inter-quartile range of the quiet breathing sensitivity achieved using the signal
 179 from the spirometer was consistently small, whereas the inter-quartile range was greater when using the signal
 180 from the belts, except for when using the chest belt and *Train 2* or *Train Mix*. It was also observed that for cough
 181 classification, the inter-quartile range was generally larger than for quiet breath classification. The variation in
 182 cough sensitivity with the abdominal and combined belt signals was particularly large, with minimal sensitivity as
 183 low as 50%. It should also be noted that when performing quiet breath classification using the chest belt and *Train*
 184 *1* there was one outlier, which had a classification sensitivity of 57%. This is believed to be due to non optimal
 185 training methods, detailed further in the discussion.

186 To assess the impact which AFES had on classification performance, the classification performance achieved
 187 when training with *Train Mix* and classifying only stimulated or unstimulated breaths was investigated, with the
 188 results shown in Table **Error! Reference source not found.** It was found that the classification performance was
 189 not statistically significantly different when classifying only breaths which were stimulated compared to those
 190 which were not.

191 Table 1: Mean percentage cough (^c) and quiet breath (^q) sensitivity (*Se*) (\pm standard deviation) of stimulated and unstimulated
 192 breaths achieved using the signals from respiratory effort belts placed around the abdomen and the chest, a combination of these
 193 signals, and the signal from a spirometer. The SVM was trained for each participant using a mix of the first 50% of the data recorded
 194 from session 1 and session 2, with classification performed on the data not used to train the SVM.

Sensor	Se^c Stimulated	Se^c Unstimulated	Se^q Stimulated	Se^q Unstimulated
	(%)	(%)	(%)	(%)
Spirometer	91.7	89.7	98.9	98.7
	± 7.6	± 8.3	± 2.0	± 1.9
Chest Belt	93.0	93.3	95.9	96.0
	± 6.3	± 6.0	± 4.9	± 4.0
Both Belts	90.1	90.7	89.9	91.4

	± 7.8	± 9.3	± 8.5	± 8.6
Abdominal	81.7	84.8	88.2	91.2
Belt	± 17.1	± 14.1	± 7.2	± 6.6

195 **4 Discussion**

196 The aim of this study was to develop a SVM classification algorithm capable of classifying respiratory activity in
197 real-time, with minimal operator intervention, using the signal from a non-intrusive sensor. This study found that a
198 non-intrusive respiratory effort belt positioned around the chest could be used as the input to a SVM to provide a
199 cough classification sensitivity similar to that achieved using the signal from an intrusive spirometer. It was found
200 that for all sensors the highest combination of quiet and cough classification sensitivities was achieved when
201 training the SVM with a mixture of data collected at session 1 and 2 (*Train Mix*). The mean quiet breath sensitivity
202 achieved using the chest belt and training with *Train Mix* of 96.1% was deemed acceptable for AFES, as it would
203 result in only one quiet breath every 2 minutes (assuming a breathing rate of 12 breaths per minute [11]) being
204 classified incorrectly. Using the signal from the belt positioned around the abdomen, or a combination of the
205 signals from the respiratory effort belts, provided an inferior classification performance compared to that achieved
206 using the spirometer. As the stimulation intensity applied during a quiet breath is lower than that applied during a
207 cough, it is more desirable to incorrectly stimulate coughs as quiet breaths, where a breath will be
208 understimulated, than quiet breaths as coughs, where a breath will be overstimulated. Therefore, while the cough
209 sensitivity achieved with the chest belt and *Train Mix* (92.9%) was lower than the quiet breath sensitivity (96.1%), it
210 is believed that this sensitivity, which would result in approximately 1 in every 12 coughs being incorrectly
211 understimulated, is acceptable for AFES. This suggests that a respiratory effort belt positioned around the chest,
212 together with the SVM classification algorithm, can be used to classify breathing patterns in the context of an
213 automatic AFES system.

214 To test the robustness of the classifier, the impact of training the classifier with data recorded on different days,
215 and of classifying only stimulated and unstimulated breaths, was investigated. It was found that the choice of
216 training data only caused small overall differences in classification performance. While training with a mix of data

217 (*Train Mix*) recorded at two different sessions provided the best combination of high quiet breath and high cough
218 classification sensitivities (see Figure 3), for the spirometer and chest belt these classification sensitivities were not
219 statistically significantly different to those achieved when training the SVM with the data collected at session 1.
220 This suggests that, with further refinement of the training protocol, only one training session per user may be
221 required to train the SVM which could then be used on subsequent sessions. Stimulation did not impact
222 classification performance (see Table 1), indicating that the classifier would be suitable for use with AFES. It was
223 also found that the optimisation of the box constraint value achieved small (<1%) improvements in classification
224 performance, but this was time consuming and would not be suitable in a clinical setting. The use of an RBF kernel
225 instead of the linear kernel did not improve classification performance.

226 While the current classification performance was deemed acceptable, the range of classification sensitivities
227 observed across the participants may be improved by optimising the selection of training data. This should enable a
228 better representation of a quiet breath and cough on which to base the classification. This may allow generation of
229 a 'universal' training data set which gives a high classification performance for all users. Development of the
230 classifier to utilise a hierarchy of SVMs, where one level decides whether a breath is valid for classification, and
231 another classifies a valid breath as a quiet breath or a cough, would enable the introduction of a 'zero class'. This
232 would allow all unusual situations to be classified as 'zero', where no stimulation is applied, further improving the
233 usefulness of the system.

234 Some people with tetraplegia exhibit paradoxically breathing, with the chest and abdomen moving in opposing
235 motions to that expected [12]. While the SVM will need to be trained individually for each subject, it is not
236 anticipated that paradoxical breathing will impact classification performance, as breath features should remain
237 present (with a phase shift of 180 degrees). However, further tests with tetraplegic patients who exhibit
238 paradoxical breathing are required to establish the suitability of the system for this patient group.

239 **5 Conclusion**

240 The signal from a non-intrusive respiratory effort belt positioned around the chest can be used to achieve real-time
241 breathing pattern classification, with a similar classification performance compared to that achieved using the
242 signal from an intrusive spirometer.

243 **Competing interests**

244 None declared.

245 **Funding**

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247 Universities of Scotland, respectively.

248 **Ethical Approval**

249 University of Glasgow Ethical Committee approval was obtained in February 2011. Local Code: FBLS 1034.
250 Participants gave informed consent to use their data.

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Figure 1

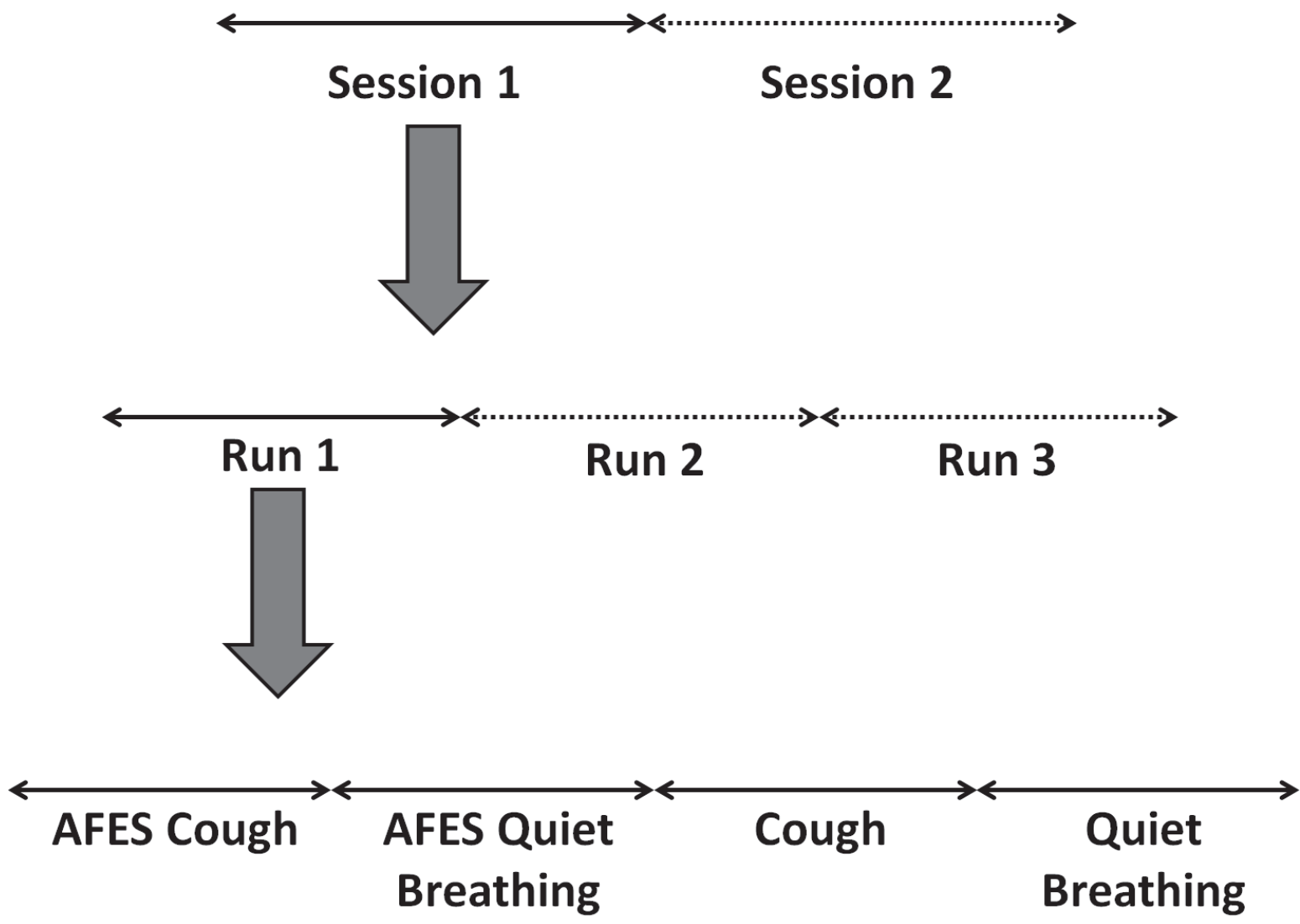


Figure 2

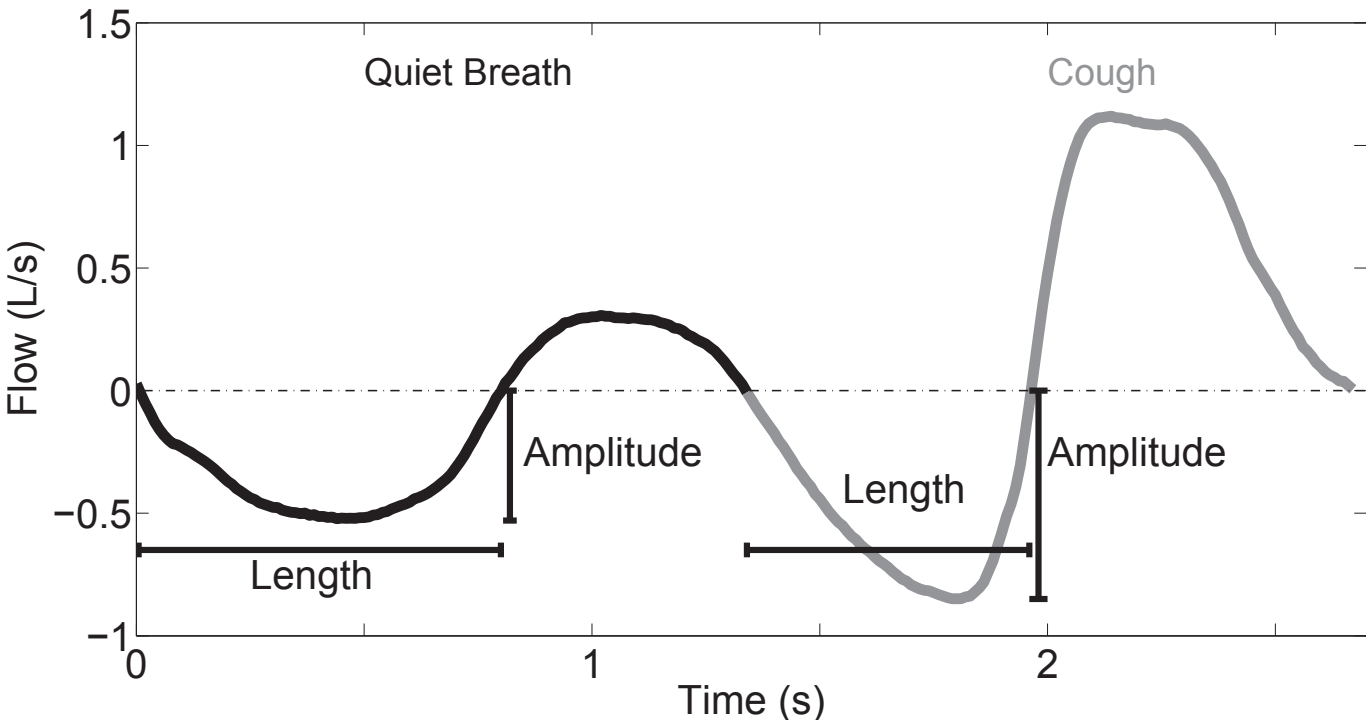


Figure 3a

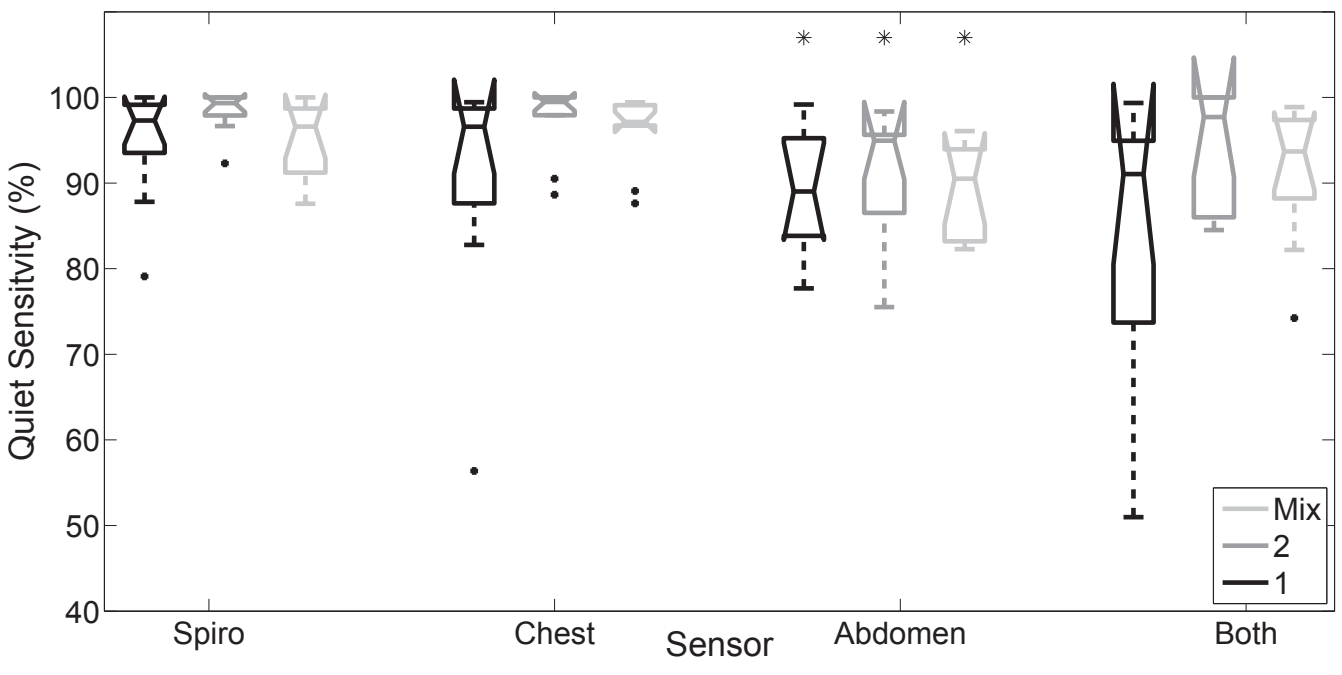
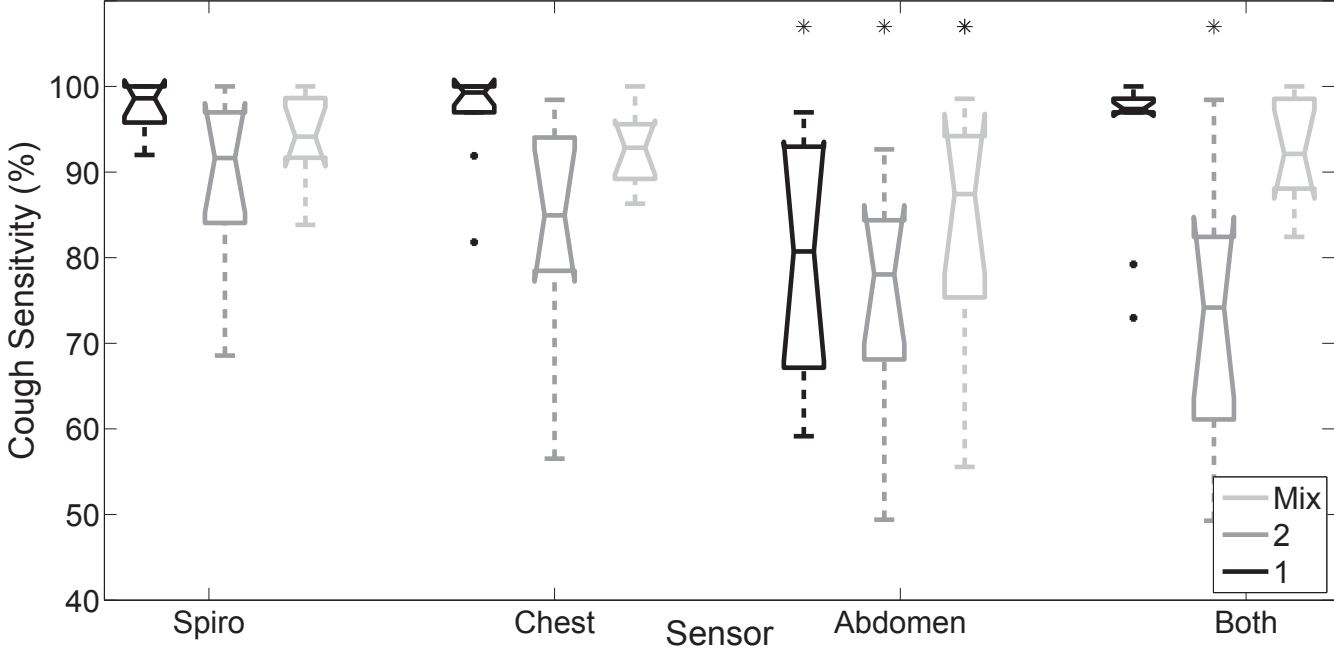


Figure 3b



Supplementary data

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