Assessing snore sounds recorded in the home via smartphone

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Aims

• Sleep-disordered breathing ranges from simple snoring to obstructive sleep apnoea (OSA), where there is a cessation or significant decrease in airflow.
• OSA, accompanied by daytime sleepiness, affects >100 million people worldwide [7] and is dangerous when left untreated.
• A home-based OSA screening tool is needed to overcome inconvenience, cost and waiting times for sleep clinics [6].
• Our project proposes to assess snore sounds recorded in the home via smartphone. The data collection phase of this work is described below.

Data collection

• Snore sounds are recorded in the home via smartphone.
• Static data collected at registration: age, gender, ethnicity, height, weight, collar size, smoker, snoring self-assessment.
• Variable data updated daily by snorer and bed-partner.

Event detection

• Published segmentation methods rely on high-quality audio.
• e.g. In [5]: tracheal microphone attached to neck with elastic band; sound events classified snore/non-snore using 2-layer feed-forward NN.
• e.g. In [4]: non-contact but close, directional microphone; adaptive noise suppression based on spectral subtraction; duration-based non-snore definition; AdaBoost classifier.
• Auditory approaches proposed to improve segmentation in low-quality, high-noise signals obtained via smartphone.

Health tracking

• Alternative approach is to enhance audio with other channels.
• e.g. Fitbit Charge HR –Web API, OAuth 2.0 authentication, returns JSON – continuous heart rate, sleep state via movement.

Data challenges

1. Exterior noise, e.g. passing aircraft
2. Interior noise, e.g. snoring bed-partner
3. Mild snoring (vs. heavy breathing)

Supplementary data from Fitbit.
Audio (mp3, WAV) energy signal supplemented by heart rate (beats per minute, BPM, middle) and body movement (e.g., bottom) highlighting restless periods (peaks).

Summary

• A smartphone app would be extremely convenient for home-based OSA screening and snoring assessment.
• Smartphone app records challenging data (cf. high quality audio and quiet environments in sleep clinic studies).
• Our project will assess whether such signals are sufficient to predict snoring severity, social nuisance, and apnea risk.

References


Acknowledgements

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Innovate UK

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Aims

Snoring and apnoea

• OSA is typically diagnosed via an overnight multi-channel sleep study (polysomnography, PSG).
• PSG involves numerous contact sensors (shown below).
• Snoring is the most prevalent nocturnal symptom of OSA, and PSG involves numerous contact sensors (shown below).
• Recently studies suggest it may be possible to diagnose OSA in sleep labs using audio signals alone [1, 2].
• However, these methods assume high-quality recordings, a quiet environment, and that the sleeper is alone.

Variable data updated daily by snore and bed-partner.

Table 1: Sleep-disordered breathing ranges from simple snoring to obstructive sleep apnoea (OSA), where there is a cessation or significant decrease in airflow.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple snoring</td>
<td>Breath</td>
</tr>
<tr>
<td>Cessation</td>
<td>Heart rate</td>
</tr>
<tr>
<td>High oxygen</td>
<td>Blood oxygen levels</td>
</tr>
<tr>
<td>Movement</td>
<td>Movement</td>
</tr>
<tr>
<td>Sleep patterns</td>
<td>(snore, non-snore)</td>
</tr>
<tr>
<td>Apnea</td>
<td>Apnea</td>
</tr>
</tbody>
</table>

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