Characterisation of Breathing and Physical Activity Patterns in the General Population Using the Wearable Respeck Monitor

D. K. Arvind[1(✉)], D. J. Fischer[1], C. A. Bates[1], and S. Kinra[2]

[1] Centre for Speckled Computing, School of Informatics, University of Edinburgh, 10 Crichton Street, Edinburgh EH8 9AB, Scotland, UK
dka@inf.ed.ac.uk

[2] London School of Hygiene and Tropical Medicine, Keppel Street, London WC1E 7HT, England, UK

Abstract. Clinical trials employing manual processes for data collection and administering of questionnaires are time-consuming, expensive to run and result in noisy data. Wireless body-worn sensors coupled with mobile applications can be harnessed to automate the data collection process during clinical trials. This paper describes the use of the Respeck monitor, worn as a plaster on the chest, for characterising breathing and physical activity patterns in the general population during their normal everyday lives. Respeck data collected from 93 subjects for periods ranging between 24 to 72 h, amounting to a total of 106 days of continuous Respeck data. Analysis of the data revealed new insights, such as the respiratory rate levels dropped by 4.39 breaths per minute (BrPM) on average during sleeping periods, compared to the preceding day-time periods. This change is higher than typically reported levels when normally measured directly before the subjects fall asleep. Previous research in activity patterns in the general population were based on high-level activities logged using questionnaires. A method is presented for clustering simple, yet high-dimensional, activity patterns based on the Respeck data, by first extracting relevant features for each day. The results reveal four distinct groups in the cohort corresponding to different identifiable lifestyles: “Sedentary”, “Moderately active”, “Active walkers” and “Active movers”.

Keywords: Wearable sensors · Respiratory rate · Physical activity

1 Introduction

Respiratory rate, pulse/heart rate, oxygen saturation, body temperature and blood pressure are vital signs to be monitored when assessing the state of health of a person. The measurement of respiratory rate is normally confined to clinical settings using nasal cannulae, masks, belts or similar devices. The Respeck [11] (Fig. 1) worn as a plaster on the chest monitors continuously the respiratory rate and respiratory effort/flow, by measuring the rotation of the chest wall using a triaxial accelerometer. Respeck data is communicated wirelessly to a mobile application on a phone for

L. Mucchi et al. (Eds.): BODYNETS 2019, LNICST 297, pp. 68–78, 2019.
https://doi.org/10.1007/978-3-030-34833-5_6

onward transmission to the server via WiFi or the cellular network [12]. The Respeck device is programmed to report "quiet breathing at rest", which is the metric used for comparing breathing rates in clinical pulmonary studies. The Respeck device detects physical activity [5] and filters those periods of rest to report respiratory rate and flow. The periods of physical activity are classified into different states, such as walking and other movement, and the periods of rest into sitting, standing and lying down. In summary, a single Respeck device provides respiratory data on breathing rate and flow, and information on the intensity of physical activity and its classification.

The paper reports on a study to investigate the respiratory rate profile and physical activity patterns in the general population during their everyday lives. The method uses the Respeck sensor which replaces the manual method of surveying the population using questionnaires, interviews and personal diary, which is expensive, time-consuming, and produces noisy data. The contributions of this paper are a novel method to monitor simultaneously the respiratory rate and flow and classification of physical activity using the wearable Respeck device, and the characterisation of 93 subjects aggregating to 106 days of continuous Respeck data. Breathing rate levels and variance are reported for day and night periods, together with results on clustering the activity data into four identifiable groups corresponding to different lifestyles.

Respiratory rate in the general population has traditionally been studied during the night-time, as wearing cumbersome recording equipment during day-time when people are going about their every-day lives was impractical. Respiratory rate levels are typically reported as being lower during sleep [10], although other studies [2] have reported higher levels during sleep compared to wake-time. One possible explanation for the disagreement in this regard is the ambiguous definition of the wake period. Respiratory rate will typically slow down during rest periods and if the wake levels of respiratory rate are only measured after the subject is already in lying position and preparing for sleep, the average levels will naturally be much lower than during the day-time.

There is a large body of research devoted to classifying activities such as walking, running, sitting, standing, lying down, cycling, and climbing stairs [1], using a single 3-axis accelerometer attached to different parts of the body, such as the wrist or the lower leg. In contrast, the Respeck is attached to the chest wall just below the last rib, in order to measure the breathing rate, and is unique in identifying these activities when attached to this part of the body. The recognition of these activities is helpful in providing contextual information to the subject [4], or in detecting abnormal behaviour [7], but it requires the combination of several activities into activity patterns to infer the lifestyle of the subject.

Clustering activity patterns to categorise subjects into groups is a well-known technique used in the field of social sciences. Questionnaires record high-level activities of the subjects, such as working, watching TV, or food shopping and one can infer levels of different types of activities and nutrition of sub-populations [6], or about typical work-habits and weekend activities [8]. In contrast to the questionnaire-based approaches, this paper presents the clustering of activities derived from the Respeck data recordings for the cohort of 93 subjects.

In the rest of this paper, Sect. 2 describes the methodology employed in this study and features selected for activity clustering, with Sects. 3 and 4 devoted to results and conclusions, respectively.

2 Methodology

The Respeck sensor (Fig. 1) developed at the Centre for Speckled Computing was validated in clinical trials at the Royal Infirmary Edinburgh against the nasal cannula as the reference monitor for measuring breathing rate/flow [3]. The Respeck also tracks continuously the activity of the wearer, such as sitting, standing and lying down based on the orientation of the device in relation to the direction of gravity, which is computationally inexpensive. Movement is detected based on the magnitude of the acceleration vector, and when it crosses a threshold level, fixed by analysing the training data, six times in succession regularly spaced with a tolerance of half-a-second, it is categorised as walking. The subjects in the cohort wore the device continuously for periods ranging between 24 to 72 h, only taking it off during their bath/shower. The dataset from the 93 subjects was analysed to offer cohort-level insights far more efficiently in terms of time and resources than the traditional manual approaches described in Sect. 1.

Fig. 1. The Respeck sensor worn as a plaster on the chest.

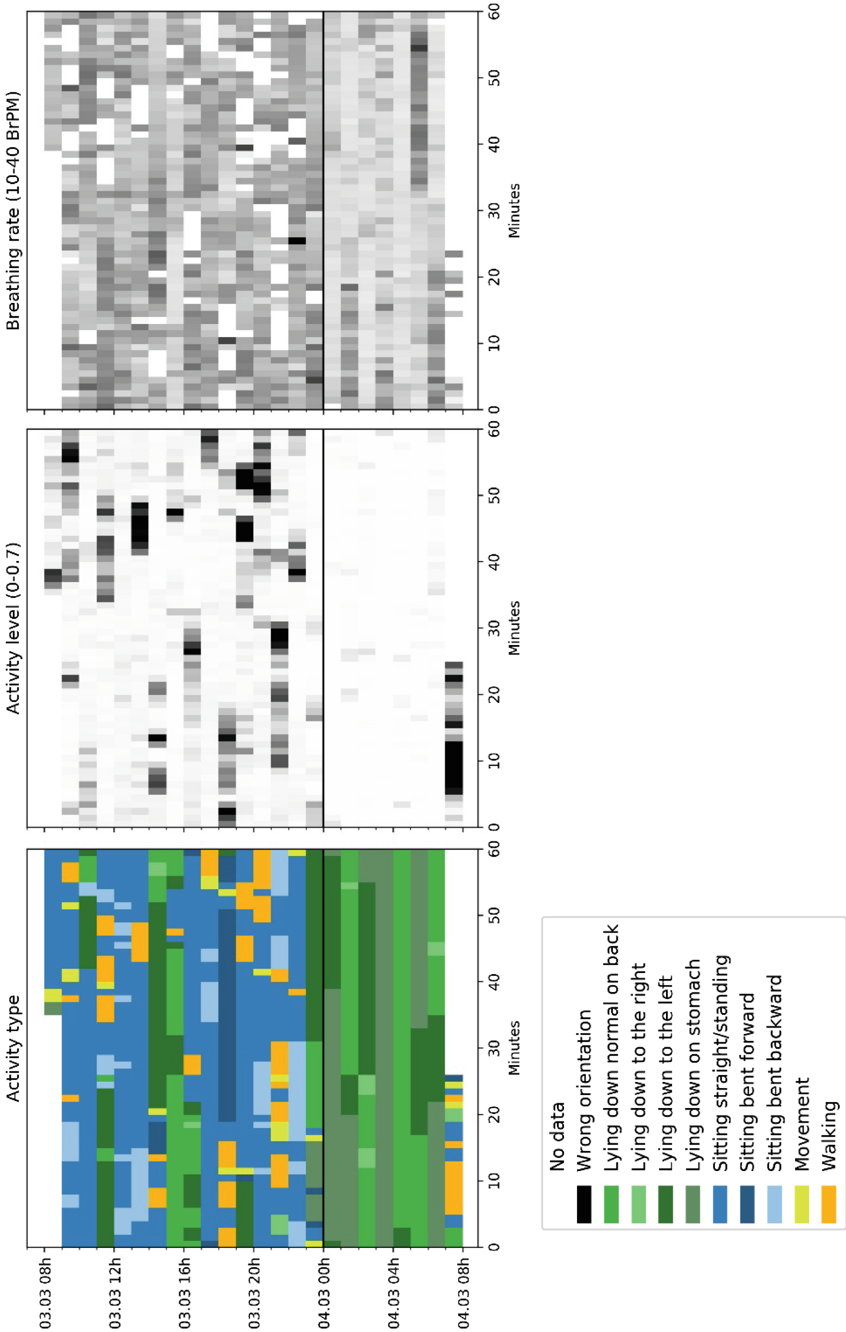

Fig. 2. "Pixelgram" for one valid day-night period. The darker shades represented higher values in Columns 2 and 3. (Color figure online)

2.1 Data Preparation

Of the-158 subjects recruited in a rural constituency, the data of 7 subjects were rejected as they were recorded incorrectly. The remaining 151 subjects were manually processed to remove records which were either too short (less than two hours during the day-night period), had too many interruptions, or the sensor was wrongly attached during the recording. The remaining 93 subjects (54 male and 39 female) had an average age of 42 ± 15 years. Figure 2 is an illustration of a Pixelgram representing three information channels, with each channel illustrating specific information for one subject over a day-night period. The sixty pixels along the x-axis in each information channel represents one minute-average recordings for one hour, and the 24 rows represent a day-long capture. In the first column on the left, activity types are colour-coded: blue - sitting/standing, orange/yellow - movement, and green - lying down. The other two columns display the activity levels, i.e., the intensity of movement [5], and the breathing rate, with darker shades representing higher values. The values in the brackets of the column titles show the minimum (white) and maximum (black) values of the grey scale. By scanning this plot, one can infer that this subject lay down approximately between 23:00 until 07:00 on the next day. The time of sleep onset can be inferred based on the following rules:

- The subject is lying down and stays that way for at least the next hour.
- The mean breathing rate level drops noticeably [10].
- The activity level is close to zero.

Conversely, waking up can be detected by a change in activity to sitting or movement, and a rise in activity level and breathing rate. Based on these rules, the subject in Fig. 2 slept from approximately 23:20 until 07:05 on the next day. The day period was then simply the start of the recording, or end of the previous sleeping period, until the start of the next day. Using this process for all 93 subjects, 84 subjects recorded one day and night period, five subjects recorded two valid periods and four subjects recorded three periods, resulting in a total of 106 day-night periods. As there are 2–3 recordings at most for any subject, and each day will be sufficiently different for the same subjects, it was decided to include all 106 periods for the following analysis, and treat them as 106 independent recordings.

2.2 Features for Activity Clustering

The activity patterns in the first column in Fig. 2 are prominently visible and the subjects can be clustered into groups, such as highly active groups and less active ones for those who take an afternoon nap. Jiang et al. [8] classify subjects into groups based on their work and leisure time-patterns, using nine activities logged with a questionnaire, such as at home, work, or school. The subjects are clustered based on this activity pattern, by first turning the 5-minute activity logs into a binary matrix (yes/no for each activity in the five-minute period), reducing the dimension using Principal Component Analysis, and applying K-means clustering on the resulting features. Their approach works well, but will not translate to the Respeck application for three principal reasons: the sample size is much smaller; the dimensionality is higher due to one-minute intervals as opposed to five-minute ones; and the activities are more abstract, and will therefore change more often.

Instead, a new set of features was chosen which best represented the patterns visible in the Pixelgrams during the day periods.

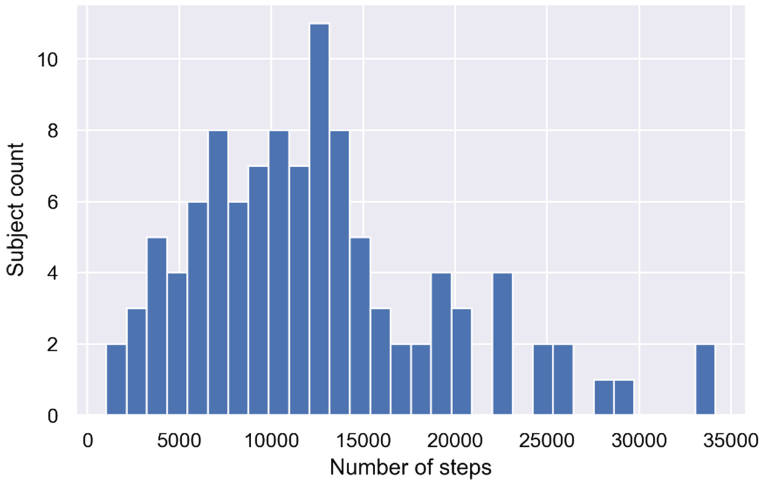

Fig. 3. Distribution of step counts for the cohort.

- **Step count:** The step count is recorded as part of the walking classification of the Respeck. A step is recorded when the mean length of the acceleration vector crosses a certain threshold several times in a row, regularly spaced. Figure 3 shows the distribution of step counts for all the 106-day periods.
- **Mean activity level:** The mean level of activity over the entire day [5].
- **Walking/Moving/Lying percentage:** The percentage of time spent walking, moving and lying down. Sitting/Standing is implicitly contained, as it is the absence of the other three.
- **Number of Walking/Movement/Lying/Sitting period:** The number of uninterrupted periods of that type.
- **Afternoon nap:** The number of instances of naps in the afternoon. A nap was registered when the subject lay down for at least 20 uninterrupted minutes and had a reduced breathing rate of at least two breaths per minute compared to the average.

The K-means module of the sklearn Python library [9] was employed to cluster the periods based on these features.

3 Results

3.1 Breathing Patterns

Taking the mean respiratory rate (RR) over day-night period for all 106 periods reveals the following pattern: The median (25th percentile, 75th percentile) RR during the day was 22.86 (21.67, 23.92), and during the night: 18.36 (17.02, 19.76). The median difference between day and night RR was 4.39 (3.29, 5.53). The median RR variance also dropped noticeably by 7.21 (3.39, 10.08), from 12.27 (10.13, 14.46) during the day to 4.84 (2.98, 7.33) during the night.

These findings support previous research [10], although the differences between day and night are bigger than so far reported. A likely explanation for this is that the RR during wake-time were only reported 20 min before the subject went to sleep, when they were already lying down. The RR would naturally be lower in that case and the difference between sleep and wake breathing would be smaller.

The significant differences in RR level also support the hypothesis that sleep onset may be detected with the RESpeck by a drop in RR level more accurately than by other accelerometer-based devices based on wrist movement, for instance.

This statement is valid even though one criteria for selecting the sleep periods in this study was the reduced RR itself, which would, by design, lead to a lower RR during that time. However, as this only affected the exact beginning of the night period, but not at other parts of the night, this intervention has a negligible effect on the statistics reported above.

3.2 Activity Patterns

Figure 4 shows the results using K-means clustering, by setting the number of clusters to four. Each plot corresponds to one cluster, with each line being the activity pattern for a subject over an entire day. The colour coding matches those in Fig. 2. The plots clearly show four different types of activity patterns:

- Sedentary (first graph): These are the least active subjects with few movement/walking periods during the day. Many subjects in this cluster take a nap in the afternoon. As this is a rural cohort, even the less active people show patterns more active than a typical urban office worker. This can also be seen in the step count histogram in Fig. 3, which shows a high level of step counts for the entire cohort.
- Moderately active (second graph): More active than the "Sedentary" cluster, with few subjects taking nap breaks.
- Active walkers (third graph): Subjects with an unusually high percentage of walking periods and a high step count.
- Active movers (fourth graph): Subjects with an unusually high percentage of non-walking movement, such as farmers and workers.

Six of the nine subjects with more than one day of recording were classified into more than one cluster. This is not surprising given the rural setting of the study, with less regular job activities than in an urban environment. In the future, recording data for

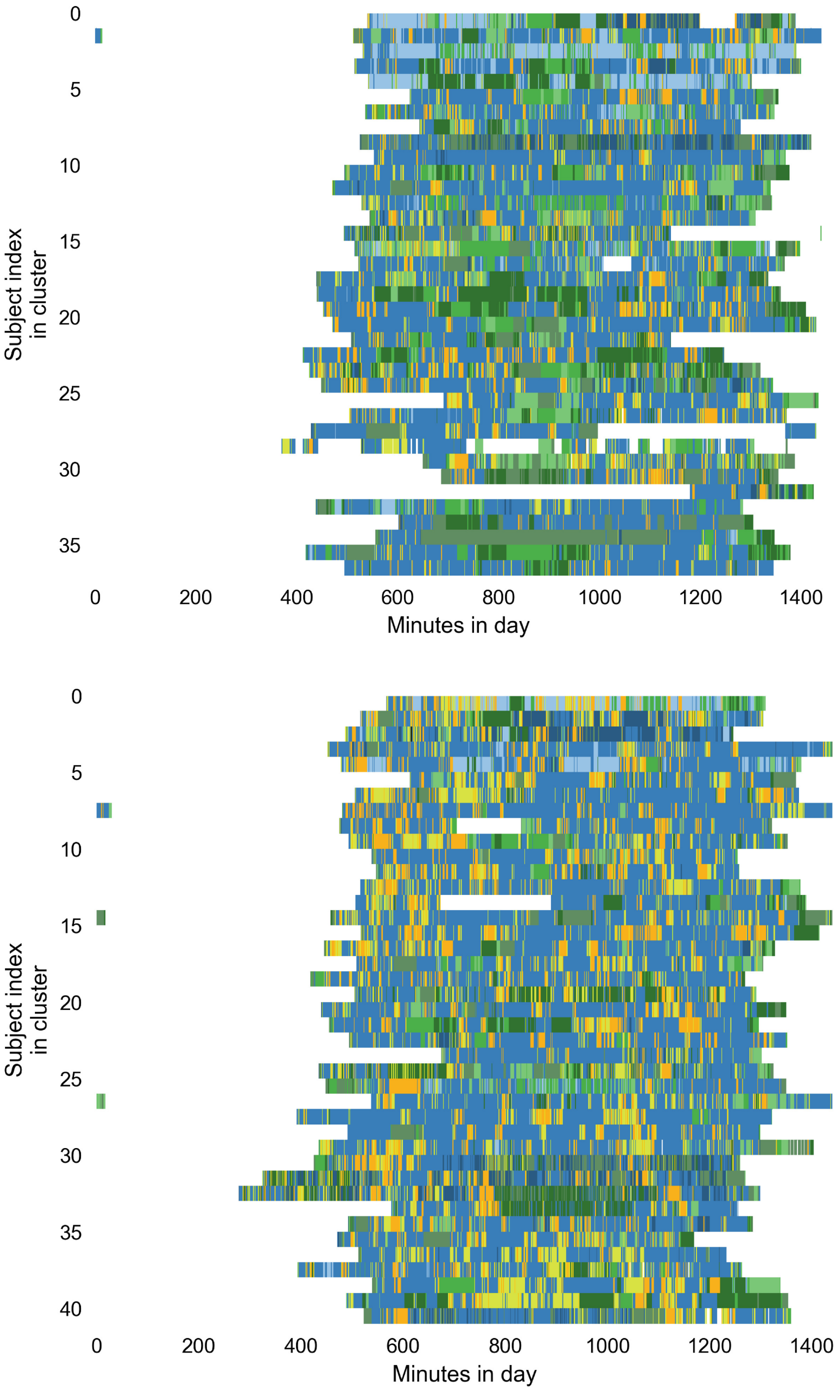

Fig. 4. Clustering activity patterns from 106 days of Respeck recordings. Colours encode the same activities as in Fig. 2. "Sedentary", first; "Moderately active", second; "Active walkers", third; "Active movers", fourth.

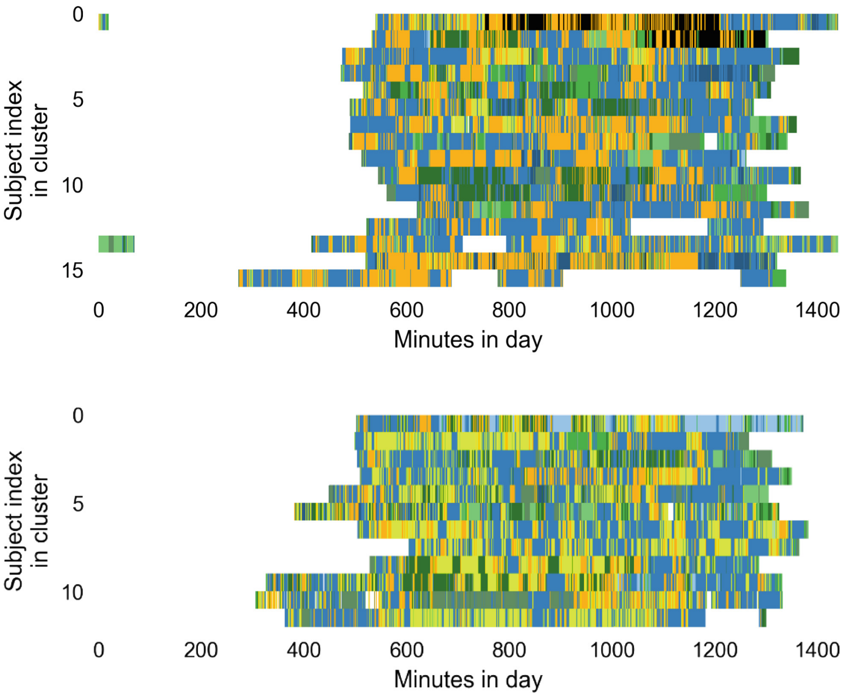

Fig. 4. (*continued*)

a full week, classifying each day into one of the clusters and taking the mode of all classifications as the predicted cluster will result in more accurate assignments.

This information about cluster affiliation can be used to estimate the lifestyle of a subject and is more stable and expressive than a single metric such as the activity level or number of walking periods alone. In future work, a sedentary lifestyle of subjects in the "Sedentary" cluster, coupled with a bad diet could be linked to health issues [6].

4 Conclusions

A novel methodology has been described for characterising respiratory and physical activity patterns in the general population during their normal every-day activities using the Respeck wearable sensor. Derived from 106 day-night recordings gathered from 93 subjects, the RR dropped by 4.39 breaths per minute (median) during sleep compared to the RR during day-time. The breathing rate variance also dropped by 7.21 (median), implying that the breathing is both considerably slower and more regular during sleep periods. Future work will validate the classification of other activities extracted from Respeck data: sitting straight/standing, sitting bent forward/backward, lying on back/stomach/left/right, walking and moving. Calculating the main activity performed in each minute of recording and plotting the values in a heatmap-like plot termed as *Pixelgram* revealed discernible activity patterns for each subject.

A selection of features extracted from this activity report enabled the clustering of all 106 day-night periods into four distinct groups, each containing visually similar records. The four groups corresponded to different lifestyles: “Sedentary”, “Moderately active”, “Active walkers” and “Active movers”. Calculation of the most common label across several days of recording will lead to a relatively stable measure of lifestyle and will be a useful metric in assessing health parameters of subjects wearing the Respeck. Future studies are planned with patients with respiratory diseases such as asthma, emphysema, chronic bronchitis and upper airways obstruction to characterise causal relationships between physical activity and respiratory patterns. Other breathing rate patterns during the night, although not analysed in this report, could reveal information about the sleep quality in addition to its duration, once validated against reference polysomnography data.

Acknowledgements. This research was funded partially by the Centre for Speckled Computing, University of Edinburgh; the UK Medical Research Council, and the Natural Environment Research Council (NE/P016340/, project DAPHNE - Delhi Air Pollution: Health and Effects); and, the UK Medical Research Council and the Arts and Humanities Research Council (MC_PC_MR/R024405/1, project PHILAP - Public Health Initiative on LMIC Air Pollution). We wish to thank Ms. Santhi Bhogadi, Project Co-ordinator of APCAPS for managing the data collection and the volunteers who participated in the study.

References

1. Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., Amirat, Y.: Physical human activity recognition using wearable sensors. Sensors **15**(12), 31314–31338 (2015). https://doi.org/10.3390/s151229858
2. Douglas, N.J., White, D.P., Pickett, C.K., Weil, J.V., Clifford, W.: Respiration during sleep in normal man. Thorax **37**(11), 840–844 (1982)
3. Drummond, G.B., Bates, A., Mann, J., Arvind, D.K.: Validation of a new non-invasive automatic monitor of respiratory rate for postoperative subjects. Br. J. Anaesth. **107**(3), 462–469 (2011). https://doi.org/10.1093/bja/aer153
4. Google: Activity Recognition API | Google Developers (2018). https://developers.google.com/location-context/activity-recognition/
5. Mann, J., Rabinovich, R., Bates, A., Giavedoni, S., MacNee, W., Arvind, D.K.: Simultaneous activity and respiratory monitoring using an accelerometer. In: 2011 International Conference on Body Sensor Networks, pp. 139–143 (2011). https://doi.org/10.1109/BSN.2011.26
6. Ottevaere, C., Huybrechts, I., Benser, J., et al.: Clustering patterns of physical activity, sedentary and dietary behavior among European adolescents: the HELENA study. BMC Public Health **11**(1), 328 (2011). https://doi.org/10.1186/1471-2458-11-328
7. Gayathri, K.S., Sukanya, P.: An unsupervised pattern clustering approach for identifying abnormal user behaviors in smart homes. IJCSN Int. J. Comput. Sci. Netw. **2**(3) (2013). ISSN 2277–5420
8. González, M.C., Jiang, S., Ferreira, J.: Clustering daily patterns of human activities in the city. Data Min. Knowl. Discov. **25**(3), 478–510 (2012)
9. Sklearn: sklearn.cluster.KMeans (2018). http://scikitlearn.org/stable/modules/generated/sklearn.cluster.KMeans.html

10. Snyder, F., Hobson, J., Morrison, D.F., Goldfrank, F.: Changes in respiration, heart rate, and systolic blood pressure in human sleep. J. Appl. Physiol. **19**, 417–422 (1964). https://doi.org/10.1097/00132586-196508000-0000. (Bethesda, Md.: 1985)
11. Bates, C.A., Ling, M., Mann, J., Arvind, D.K.: Respiratory rate and flow waveform estimation from tri-axial accelerometer data, In: Proceedings of 2010 International Conference on Body Sensor Networks, BSN 2010. IEEE, Singapore (2010)
12. Arvind, D.K., Bates, C.A., Fischer, D.J., Mann, J.: A sensor data collection environment for clinical trials investigating health effects of airborne pollution. In: Proceedings of 2018 IEEE International Conference on Biomedical and Health Informatics, 4–7 March 2018, USA (2018)