Automated Sleep Pattern Monitoring for Sleep Disorder Assessment

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Problem
Monitoring of sleep patterns is of major importance for various reasons, such as the:

- Detection and treatment of sleep disorders.
- Assessment of the effect of different medical conditions or medications on the sleep quality.
- Assessment of mortality risks associated with sleeping patterns in adults and children.

Sleep monitoring by nature is a difficult problem due to both privacy and technical considerations.

Current methods for sleep pattern assessment require the patient to spend one or more nights at a clinic which induces high costs and inconvenience for the patient.

Contributions
1. Development of a system for sleep pattern monitoring which is non-invasive, it is cost effective and can be easily used at home.
2. Use of Machine Learning methods for automatic data analysis and sleep pattern recognition.
3. Fusion of different data modalities to produce more robust and accurate results.

Methods
Our system uses Machine Learning techniques to analyze the collected data and recognize sleep patterns. Steps followed:

1. Data from pressure mat and Kinect sensor were collected and temporally synchronized.
2. Dimensionality reduction was performed to each data stream.
3. Cross validation was performed to evaluate posture and motion recognition accuracy using well-known classification algorithms.

To evaluate our system we used real data collected in Heracleia Lab’s assistive living apartment. 7 volunteers used our system for a predefined time duration, simulating normal and abnormal sleep patterns. For more details see [1, 2].

Classification of body postures: PCA used for dimensionality reduction and Hidden Markov Models (HMM) for classification. 1. Changing body posture. 2. Moving arms or Legs. 3. Getting in bed or out of bed. 4. Making bed.

Future plans include the extension of sensing capabilities of the system by including other inexpensive, non-invasive sensors, such as audio and temperature and apply it to large-scale clinical tests. We believe it will be possible to associate our findings with pathological cases such as SDB, RLS/PLMS as well as depression.

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References