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].

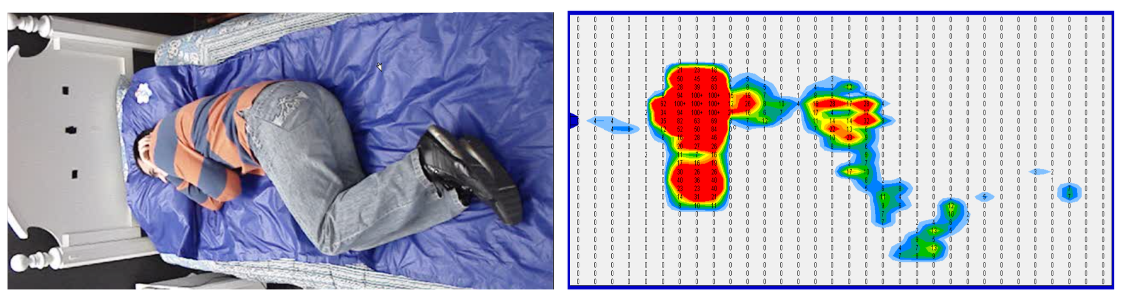
References

[1] V. Metsis, G. Galatas, A. Papangelis, D. Kosmopoulos, and F. Makedon, "Recognition of sleep patterns using a bed pressure mat," in *Proceedings of the 4th International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 2011, p. 9.

[2] V. Metsis, D. Kosmopoulos, V. Athitsos, and F. Makedon, "Non-invasive analysis of sleep patterns via multimodal sensor input," *Springer Personal and Ubiquitous Computing*, 2012.

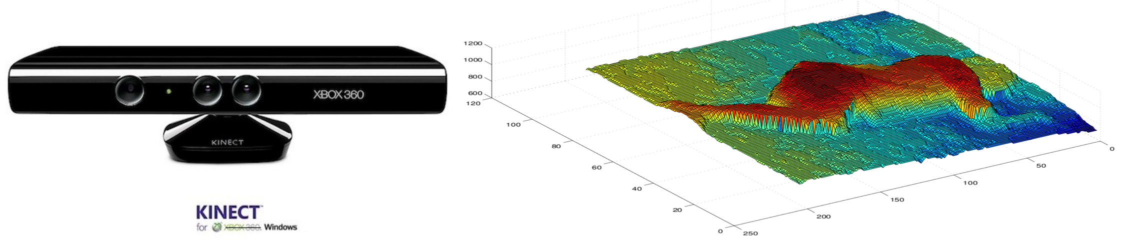
Sensing Devices

FSA bed pressure mat:



The FSA bed mat system produced by *Vista Medical Ltd* provides a $1920mm \times 762mm$ sensing area which contains an array of 32×32 pressure sensors.

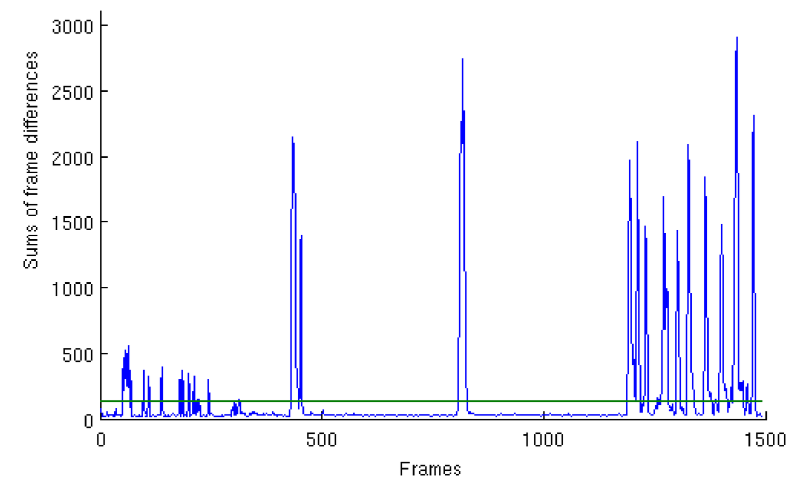
Microsoft Kinect sensor:



Kinect is a motion sensing input device designed by Microsoft for the Xbox 360 video game console. Kinect outputs 3 different data streams, RGB video, **depth sensing video** and audio. In our experiments we used only the depth sensing video stream. The depth sensor consists of an infrared laser projector combined with a monochrome CMOS sensor, which captures video data in 3D under any ambient light conditions.

Classification

Motion detection: Sum of differences of pressure/pixel values between consecutive frames. When Sum exceeds threshold T, motion is detected.



Classification of body postures: PCA used for dimensionality reduction and Template Matching (TM), K-Nearest Neighbors (KNN), Support Vector Machines (SVM) for classification.

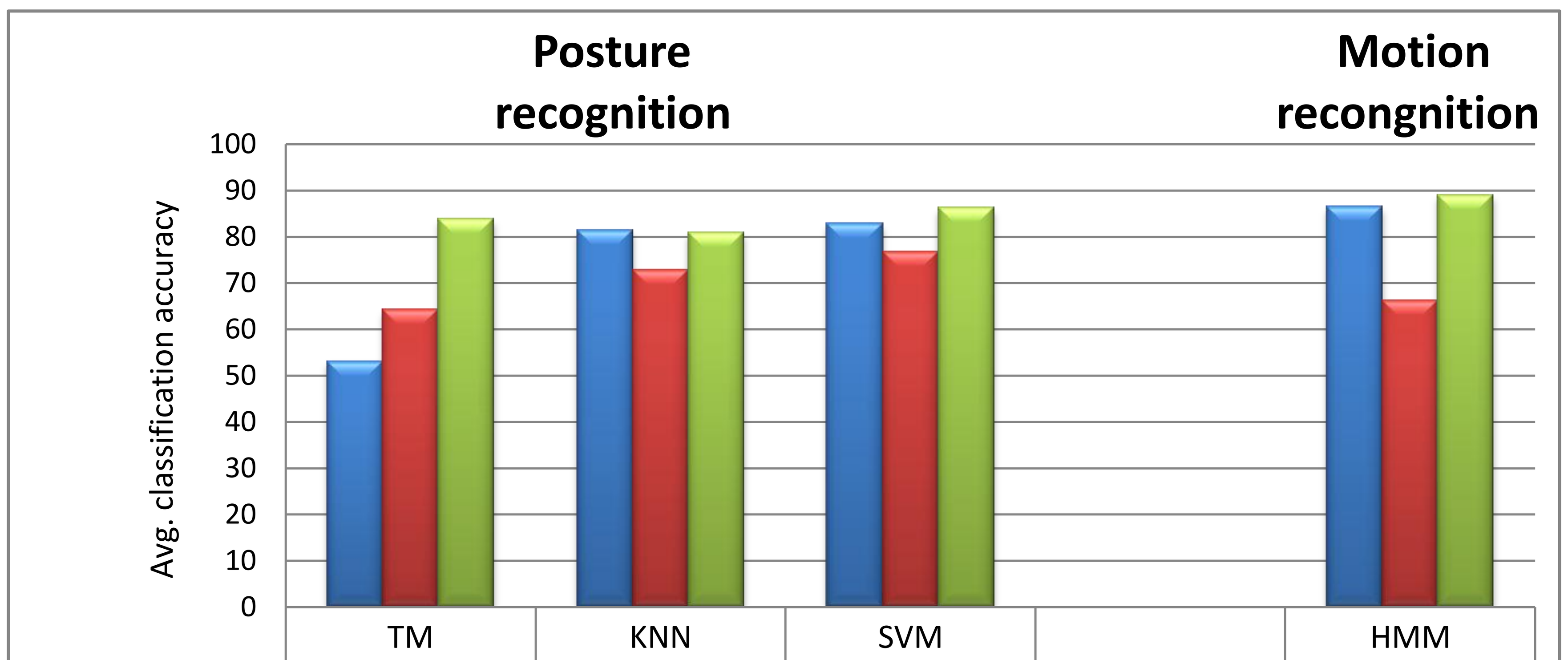
1. Back 2. Left 3. Right 4. Stomach 5. Sitting

Classification of motion types: 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.

Results

To evaluate our system's accuracy, all captured data were manually annotated by humans.

- Detecting when a *person gets in or out of the bed*: **100%** accuracy.
- Detecting when *motion occurs*: **97.57%** accuracy.
- Recognizing *body posture* (5 classes) and *type of motion* (4 classes):



	TM	KNN	SVM		HMM
Pressure data	53.1	81.38	82.76		86.5
Depth data	64.2	72.76	76.66		66.24
Combined	83.79	80.86	86.21		89.07

Future Directions

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.

Acknowledgement

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