Safe and Sound

AI In-Home Motion Monitoring for Elderly Care

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Problem

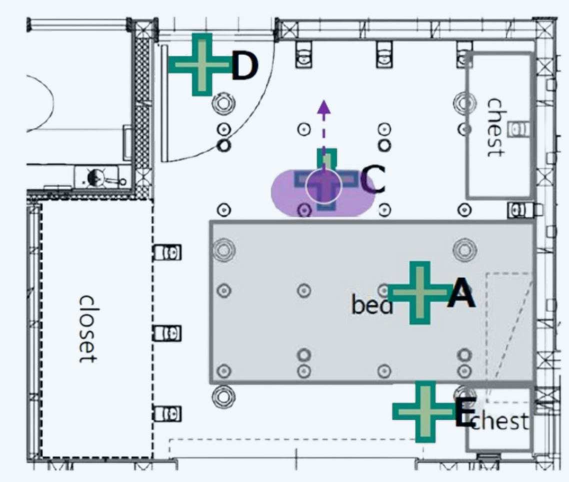
The shortage of caretakers and institutions increases the challenge of **elderly care**. More senior citizens want to age in their home and live independently

Sekisui House is one of the largest home builders in Japan and wants to create value beyond construction services by offering **smart home** products that tailor to elderly care in an unintrusive manner

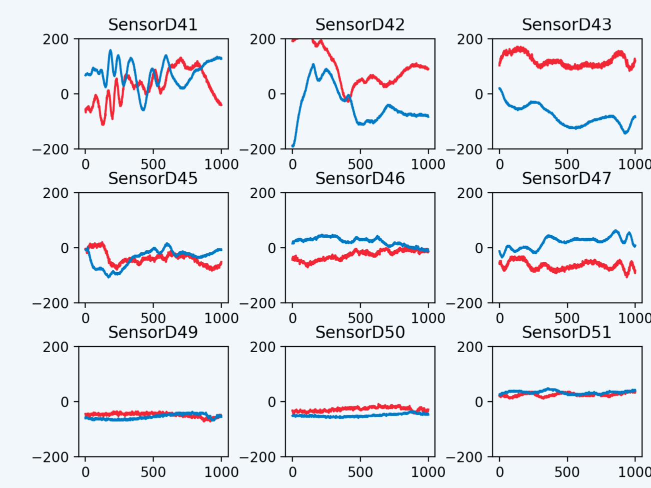
How do we know **what the person is doing at what time in what place**, and further detect **anomalous behaviors** with signal data?

Data

24-hour data stream collected from the test room, **13** motions from controlled experiments, **15** motions from self-reported activities



Testing House Sensor Arrangement



Signal Visualization

Methodology

What are you doing? Where?

Phase I Supervised Multi-Output Classification

- We extract **2** types of labels from meta information
- We treat signal input data as **image** (2D)

2 labels: Activity, Location

2D Signal Data: Sensors, Time

Input

Shared ResNet Layer:
Learn shared representation of signal patterns from multiple sensors

2 Output:
Independent output channels predict activity and location simultaneously

ResNet → Activity, Location

Training

You are **standing**

You are **in front of the bed**

What / Where

Output

Our model is able to predict both activity and location with accuracy of **97.2%** and F1 score of **98.4%**

Benefits:
- Mutual information sharing of multi-task learning can extract correlation between activity and location
- Optimize computational resources for training

Result

When did you start?

Phase II Unsupervised Contrastive Learning

Due to the inaccuracy of self-reported labels, we want to explore an unsupervised approach

3D Signal Data: Sensors, Time, Sensors

We treat a record of signals as **video** (3D) to maintain the spatial and temporal information

Encoder, Conv-LSTM, Decoder, Contrastive Loss

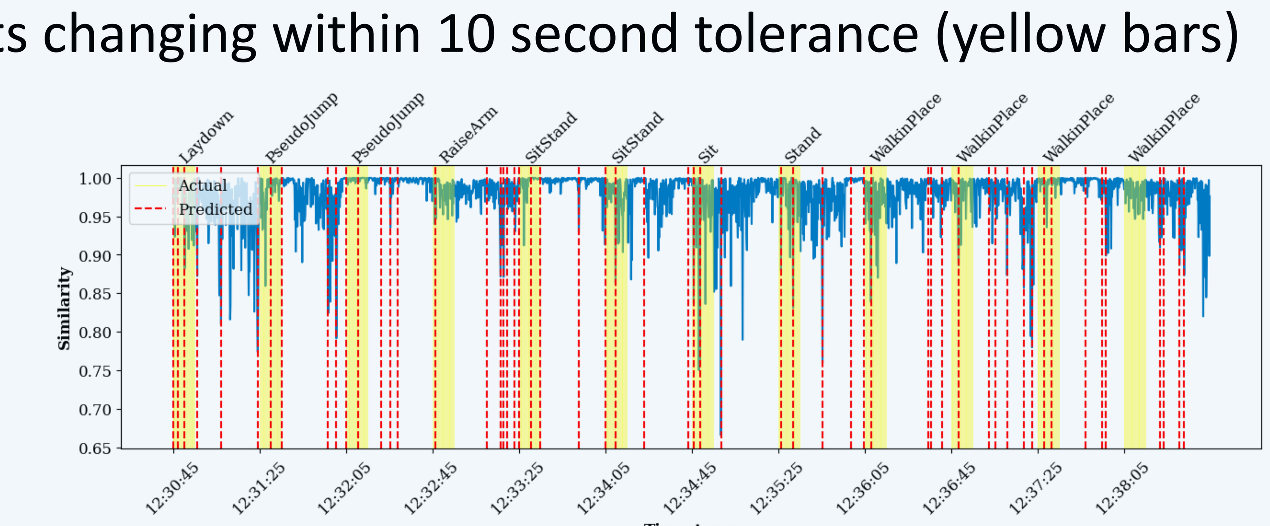
Conv LSTM:
Learn both spatial (CNN2D) and temporal information (LSTM)

Contrastive Loss:
Differentiate between similar and dissimilar pairs of data

The encoder converts complex data into lower-dimension embeddings

Change point detection based on similarity between frames

Our model is able to detect **91.7%** of the time when the activity starts changing within 10 second tolerance (yellow bars)



Benefits:
- Less reliance on inaccurate labels
- Helpful for evaluating which sensors are more important

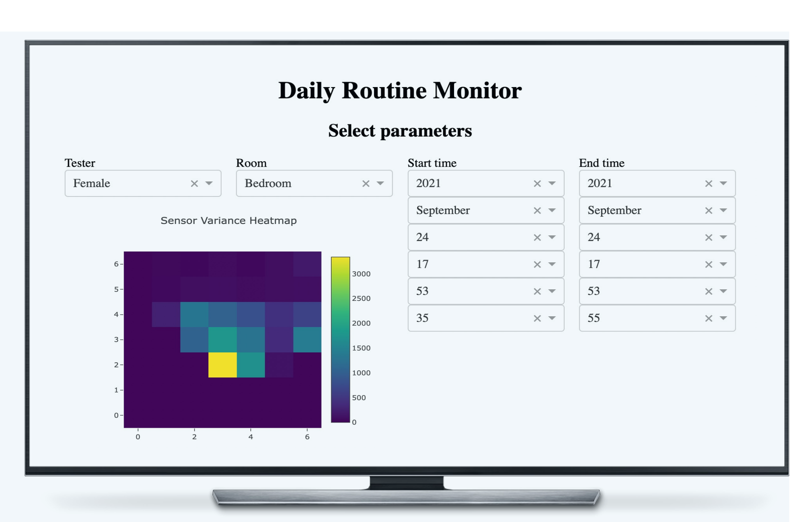
Future Works

Short term:
- Improvement on web interface
- **Combine Phase I and II:** Use the change point prediction as new labels for multi-output classification
- **Anomaly Detection:** Collect or simulate more anomalous behaviors and develop algorithm

Long term:
- **Implementation:** Real time monitoring with our model
- **Integration:** Use our model as foundational steps for Sekisui House's post-construction services, including medical assistance and accident alerts

Impact

Interactive Web Interface: a working demo for the internal team at Sekisui House



High adaptability: our model can be further applied to Sekisui House's new data

Downstream Algorithms: our model facilitates the downstream algorithm of anomaly detection and Early Detection System