Identification of learner's distraction using mobile device's sensors

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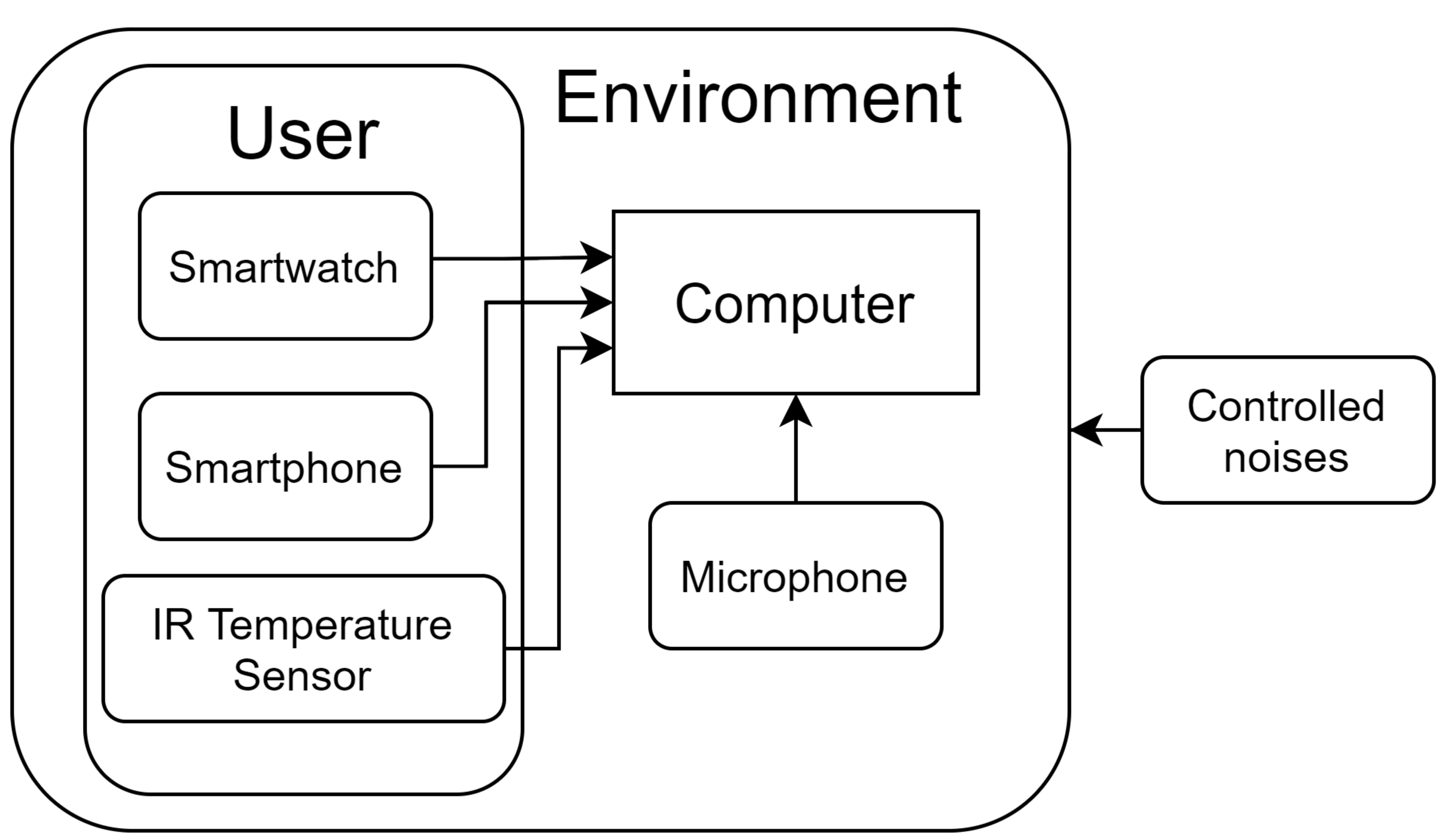
1. Background

- Distraction is a major influence in sustained attention and learning process
- Existing research on identifying learning activities using smartwatch data[1]
- Body movement is related to distraction[2]
- Mobile devices are able to identify absolute orientation and movement data

2. Questions

- **How mobile devices sensors can indicate learner's distractions in the remote learning context?**
- What is the most effective way to use and position a mobile device to gather data related to a learner's distraction?
- How can the mobile device data be individually analysed for a learner's distraction?
- How can mobile device sensor data improve multimodal learning analytics of sustained attention?

3. Method

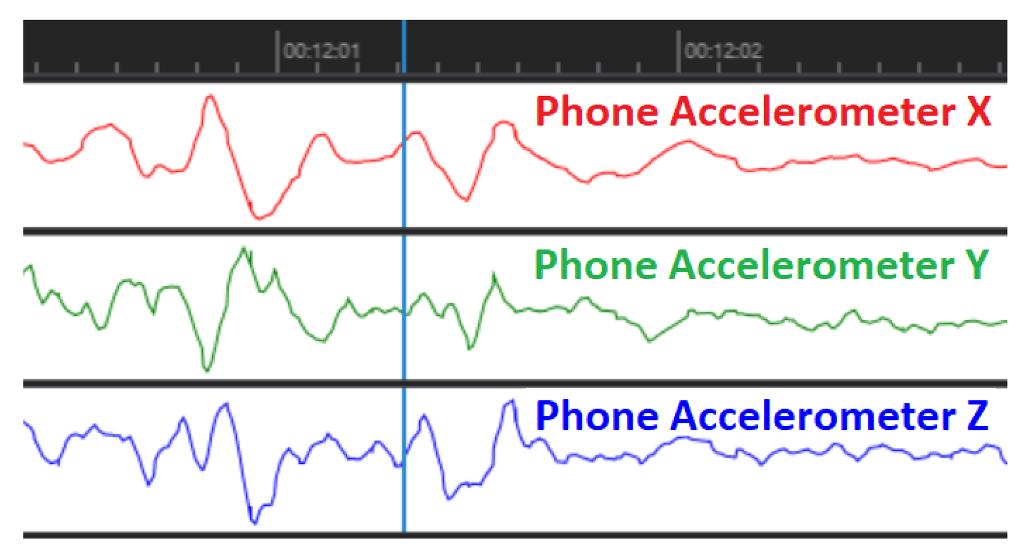


Sensors used:

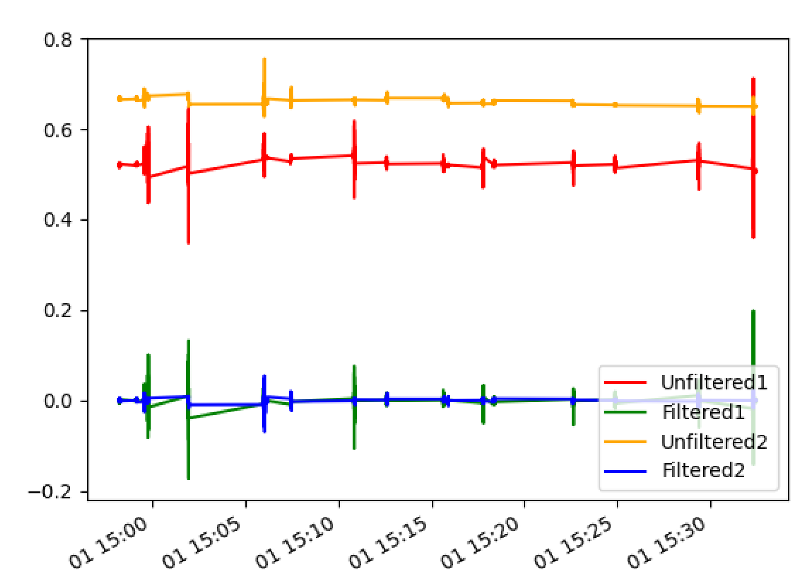
- Acceleration
- Orientation
- Rotation Rate
- User Acceleration
- Quaternion
- Gravity

- Experiment 1: Reading small texts (under 1 minute of reading time) and reacting to a bluring screen
- Experiment 2: Reading small texts while being fully attentive
- Experiment 3: Reading long texts (around 45 minutes of reading time), reacting to bluring and self-reporting loss of attention

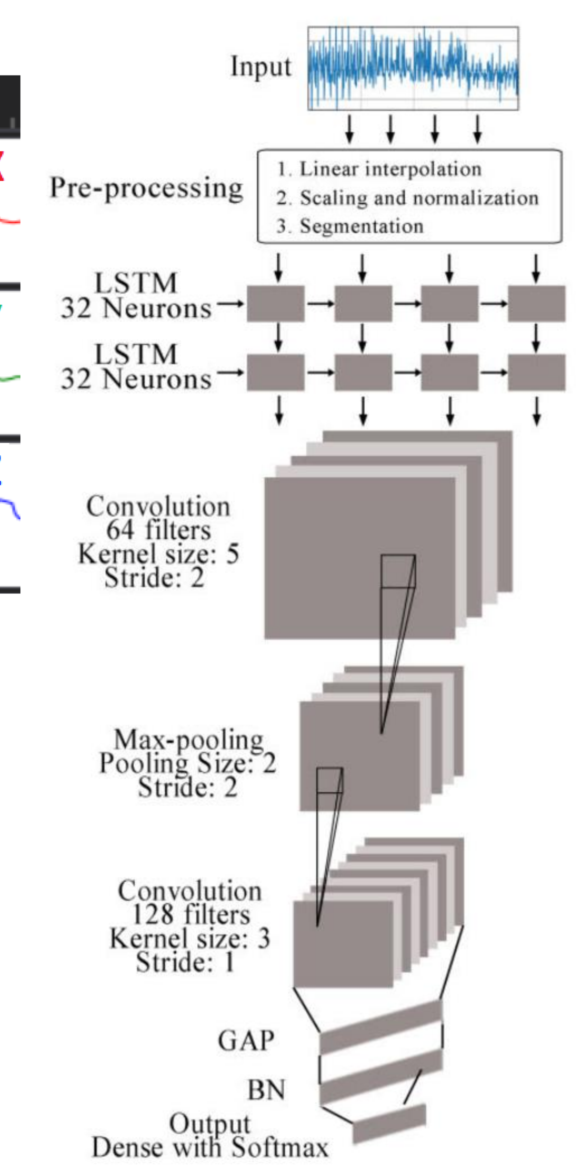
- In experiments 2 and 3 the subjects had data being collected for multiple researches. The mobile devices used were a smartwatch and a smartphone
- The data recorded was labeled as attentive and inattentive and used to train a Convolutional LSTM model to detect distraction in a 5 second window



Raw data visualization at Psi Studio



Data filtering

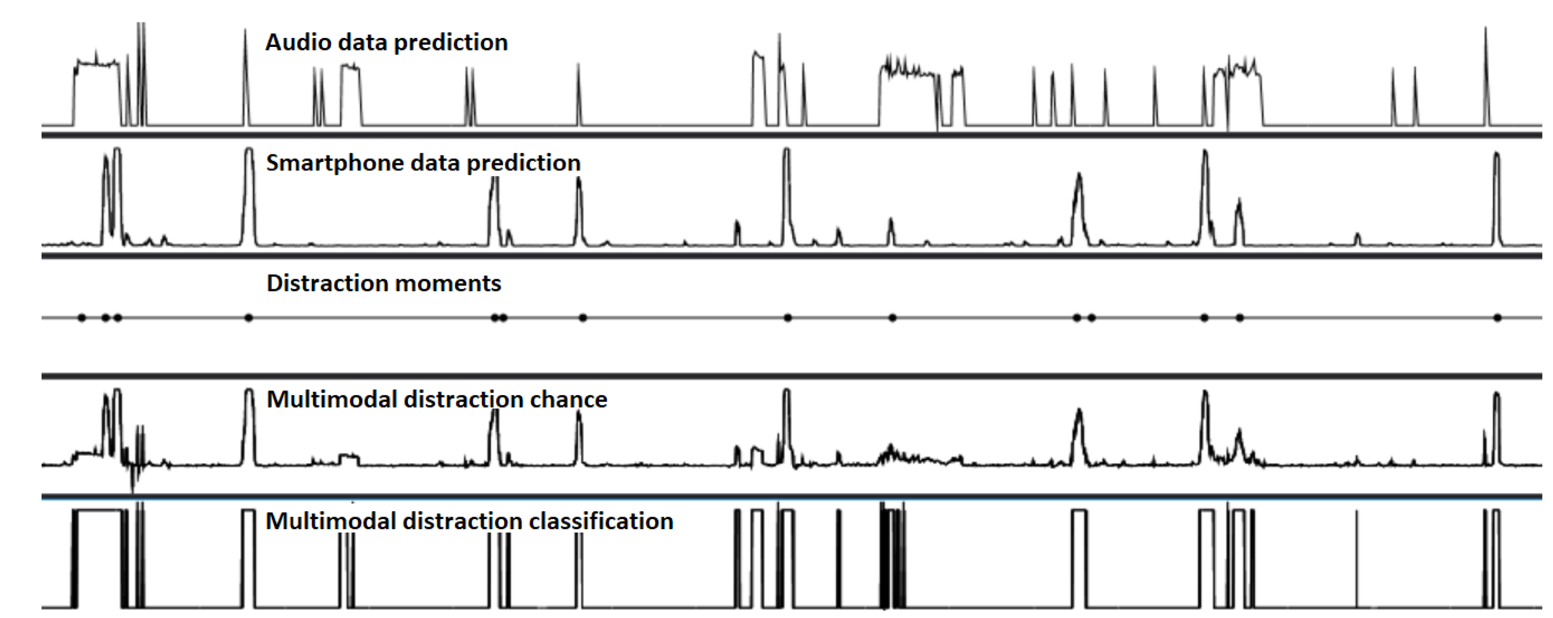


Example of Convolutional LSTM

4. Results

	Phone		Watch	
	Accuracy	F1	Accuracy	F1
Acceleration, Rotation Rate, User Acceleration	92.50%	91.89%	81.88%	80.64%
Acceleration, Rotation Rate	91.25%	90.29%	81.88%	80.54%
Acceleration, User Acceleration	87.50%	85.25%	78.75%	76.25%
Rotation Rate, User Acceleration	89.38%	88.00%	81.25%	79.68%

	Phone		Watch	
	Accuracy	F1	Accuracy	F1
Acceleration	86.25%	84.46%	78.12%	75.50%
Orientation	68.12%	67.69%	71.88%	69.40%
Rotation Rate	91.25%	90.29%	83.12%	82.04%
User Acceleration	84.38%	80.82%	77.50%	74.75%
Quaternion	65.00%	66.67%	74.38%	70.44%
Gravity	67.50%	66.67%	76.25%	72.52%



5. Conclusion

- Very good performance when combining sensors that measure speed or acceleration
- Can't always detected distraction originating from external sources
- Combining the resulting model with the ambient sound model showed better performance than both individually
- Collecting more data from a more diverse group of subjects is advised to confirm the generalization of the model

6. Acknowledgements

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7. References

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