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Detecting Anomalous Behaviors of Air Traffic Controllers in Time Series of Facial Expressions and Head Poses

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Outline

1. Introduction
2. Methodology
3. Experiment
4. Preliminary results

Introduction

Air Traffic Controllers

+

Situation awareness

Fatigue

Cognitive Workload

Density

Separation

Weather

Operational Errors

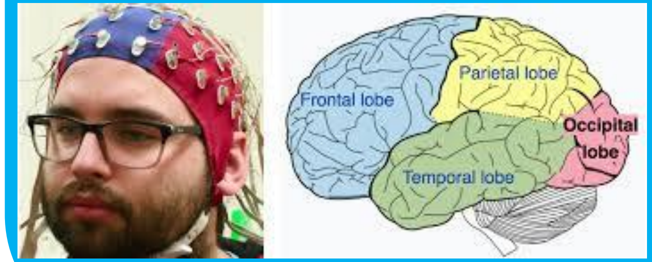
Safe &
Effective NAS

Need access to real-time data that provides information on problematic human states that may lead to operational error

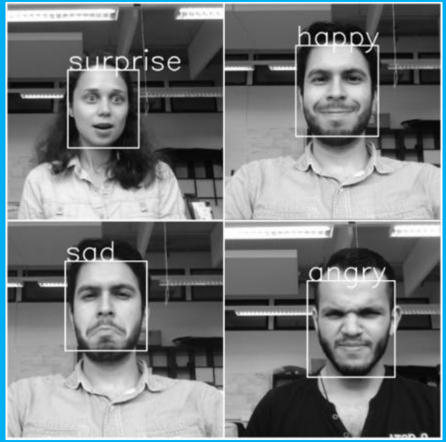
Motivation

Changes in the Air traffic controller state may correspond to changes in communication patterns which can signal potential operational errors/risk.

Electroencephalography (EEG)
- Intrusive
- Not real-time
- Not practical

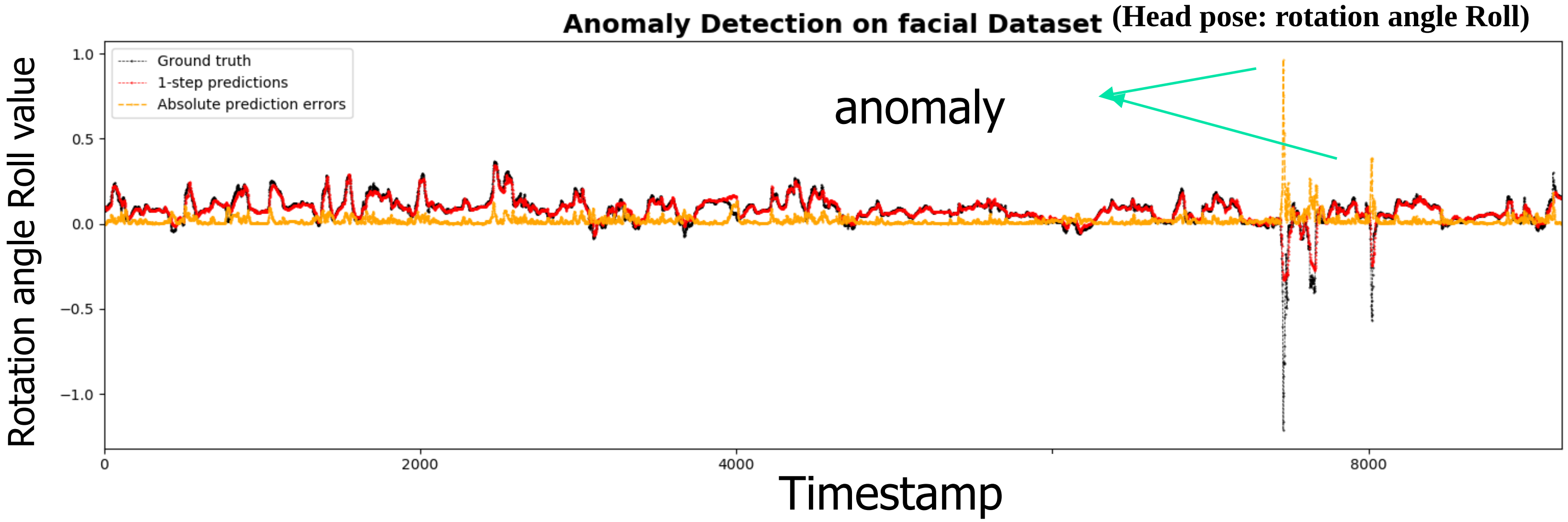


Computer vision
- Easy to implement
- Real-time



O. Arriaga, P. G. Plöger, and M. Valdenegro, "Real-time Convolutional Neural Networks for Emotion and Gender Classification."

Motivation



- For every air traffic controller, we trained neural network to learn their individual behavior pattern.
- Based on the behavior pattern in the past few seconds, we predict their behaviors in the coming seconds. If the prediction is different from the ground truth captured by algorithm, then we consider the behavior as an anomaly.

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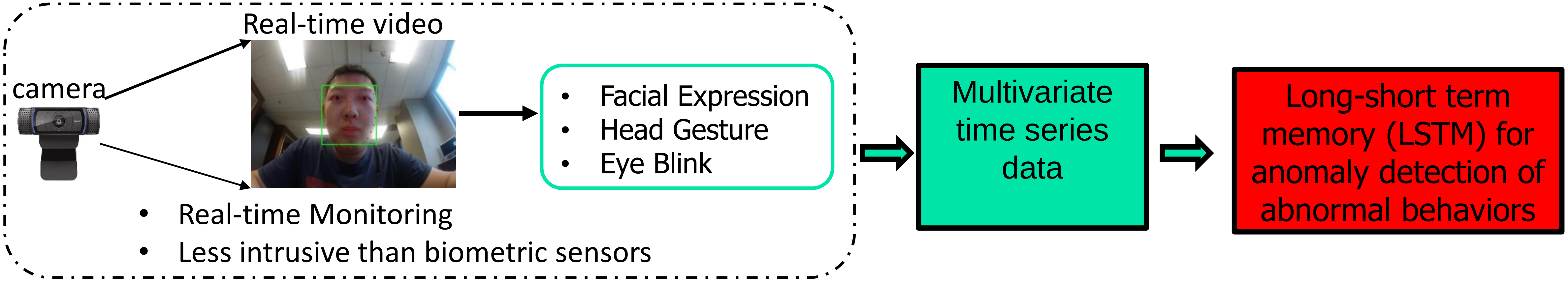
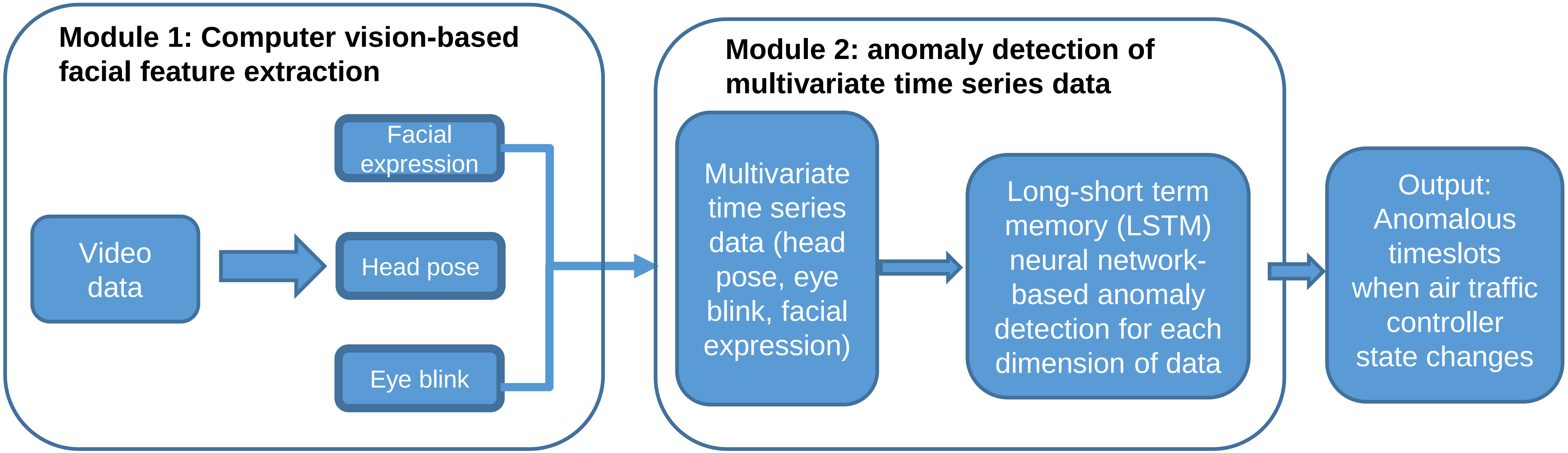
Methodology



- LSTM is one type of recurrent neural network models and can be used for time series analysis.
- Use video data collected during the simulator experiments for capturing face changes of air traffic controllers
- Two subjects participating the experiments were retired air traffic controllers
- Biometric and communication data were collected to validate the anomaly detection results.

Data processing pipeline



Facial expression recognition

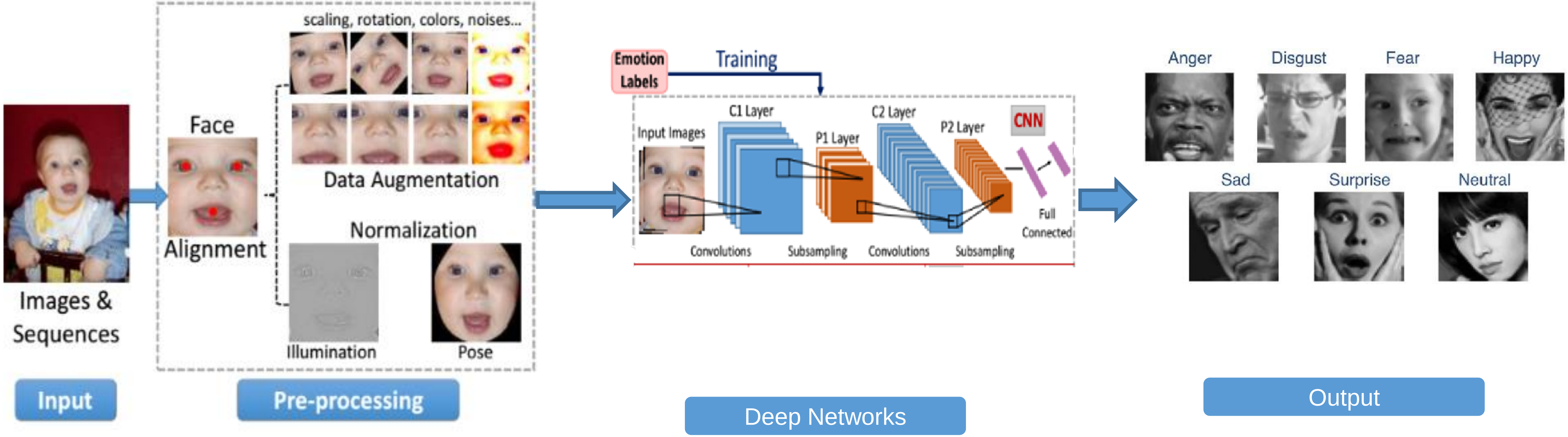
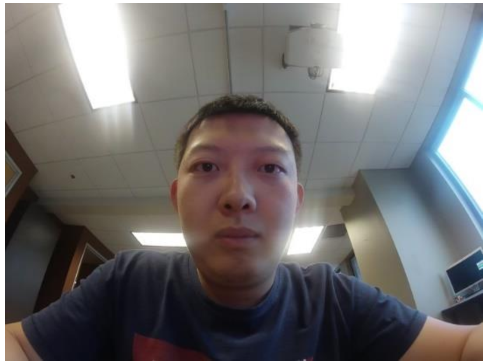
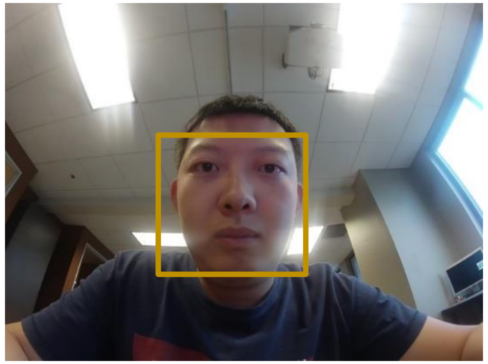


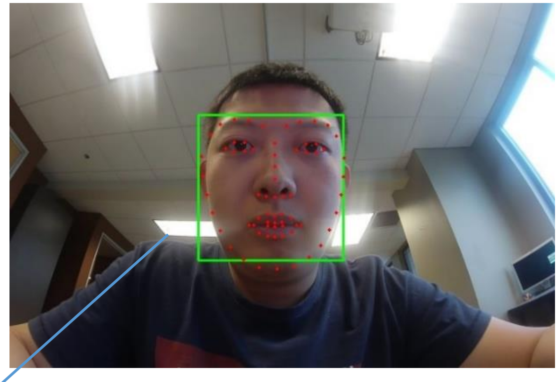
Image from https://www.google.com/url?sa=i&source=images&cd=&ved=2ahUKEwirqOiC_eniAhXUvJ4KHQMKBFoQjRx6BAgBEAU&url=https%3A%2F%2Fwww.semanticscholar.org%2Fpaper%2FFacial-Expression-Recognition-Using-a-Large-Dataset-Tran Mayhew%2F3e3227c8e9f44593d2499f4d1302575c77977b2e%2Ffigure%2F0&psig=AOvVaw1OmuS7rKJizt4SAP5eVl7r&ust=1560636070566161

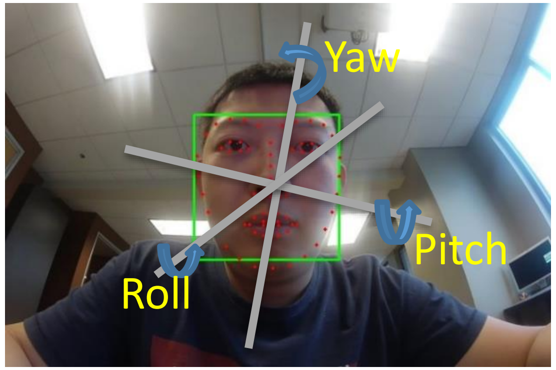
Head pose estimation

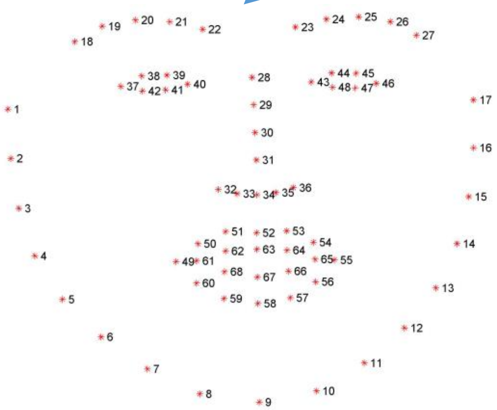
Input Image → Face Detection → Facial Landmark Detection → Pose Estimation





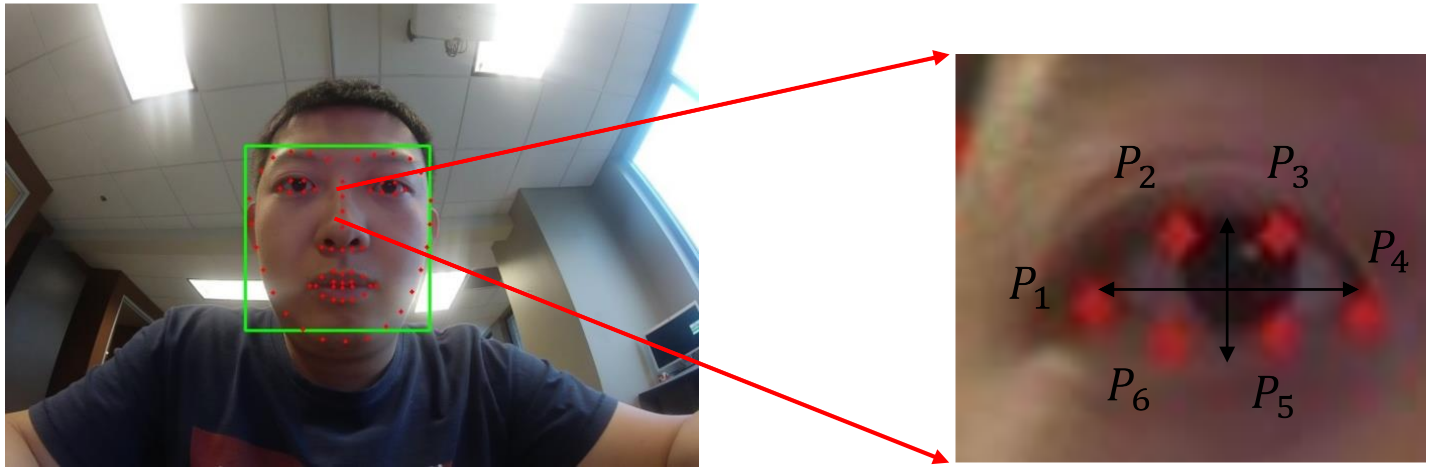


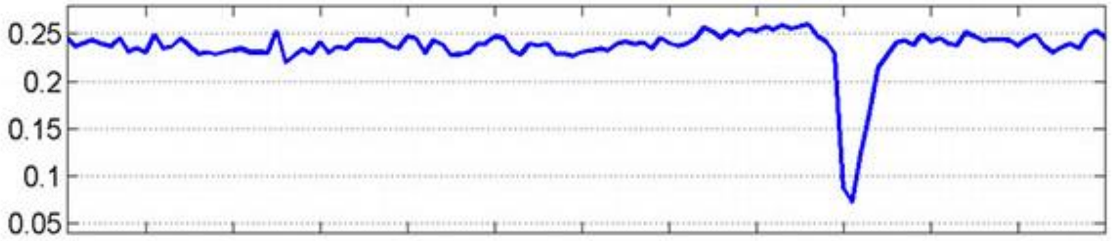




The 68 facial landmarks

Eye Blink Extraction





EAR: eye aspect ratio

$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

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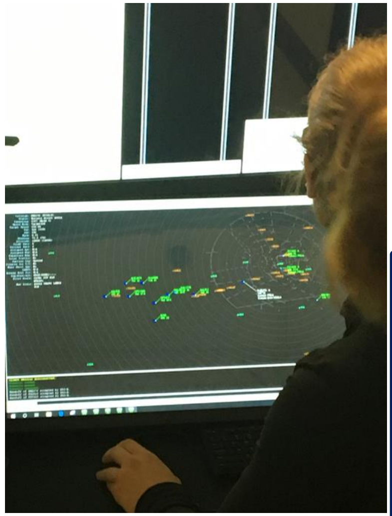
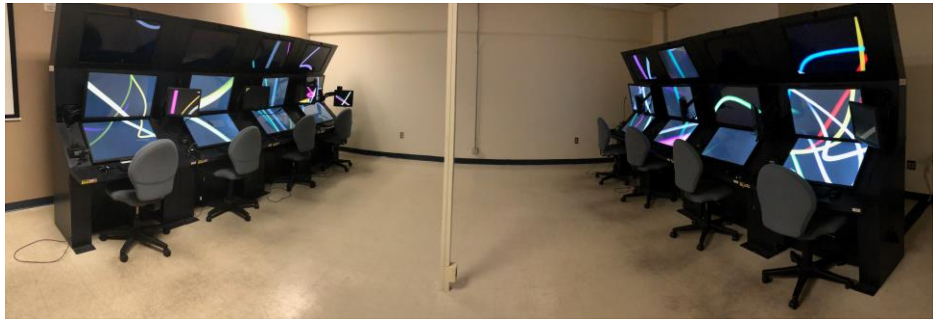
Experiment

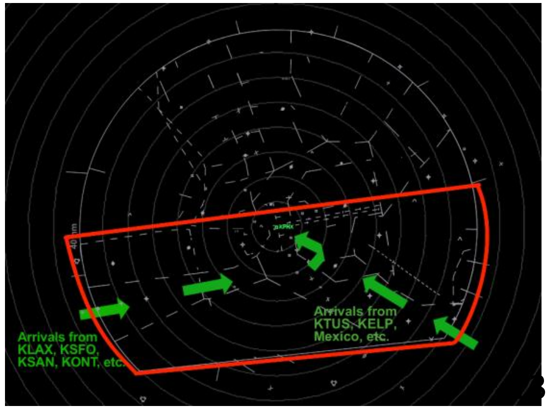


3 Pseudo Pilots (Remote Pilot Operators)



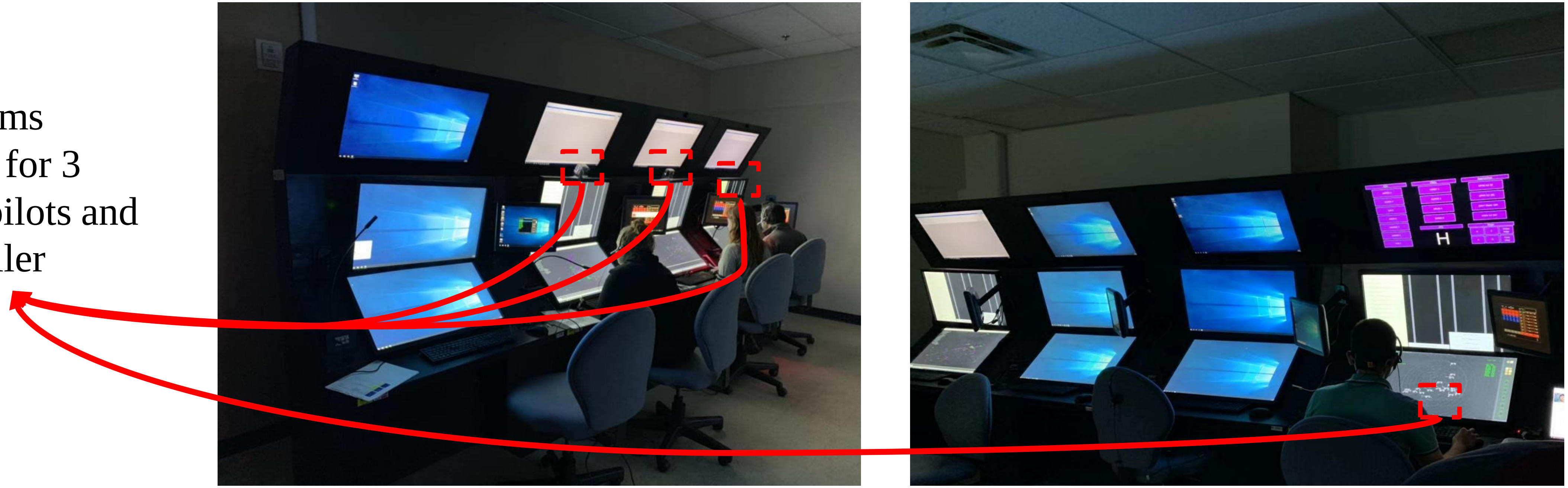
- 2 of 12 Experienced (retired) ATCs
- Three pseudo pilots (students) each controlling 4-8 planes
- 20-25 min simulated approach scenarios
  - 4-5 aircraft at once, moderate workload (15 aircraft)

Single Air Traffic Controller



Video data collection

4 Webcams installed for 3 pseudo pilots and 1 controller



Data collection at the TRACON Simulator at Poly campus, ASU

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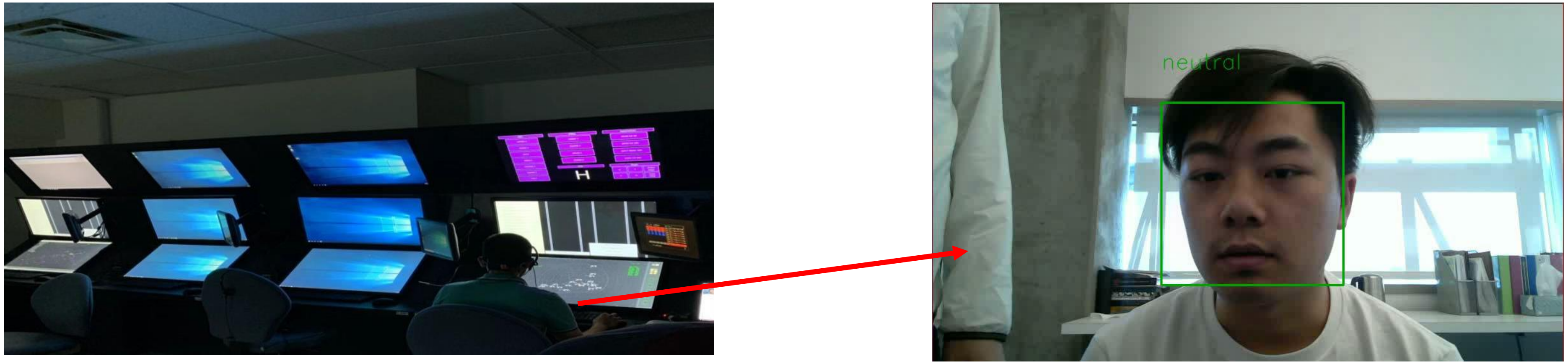
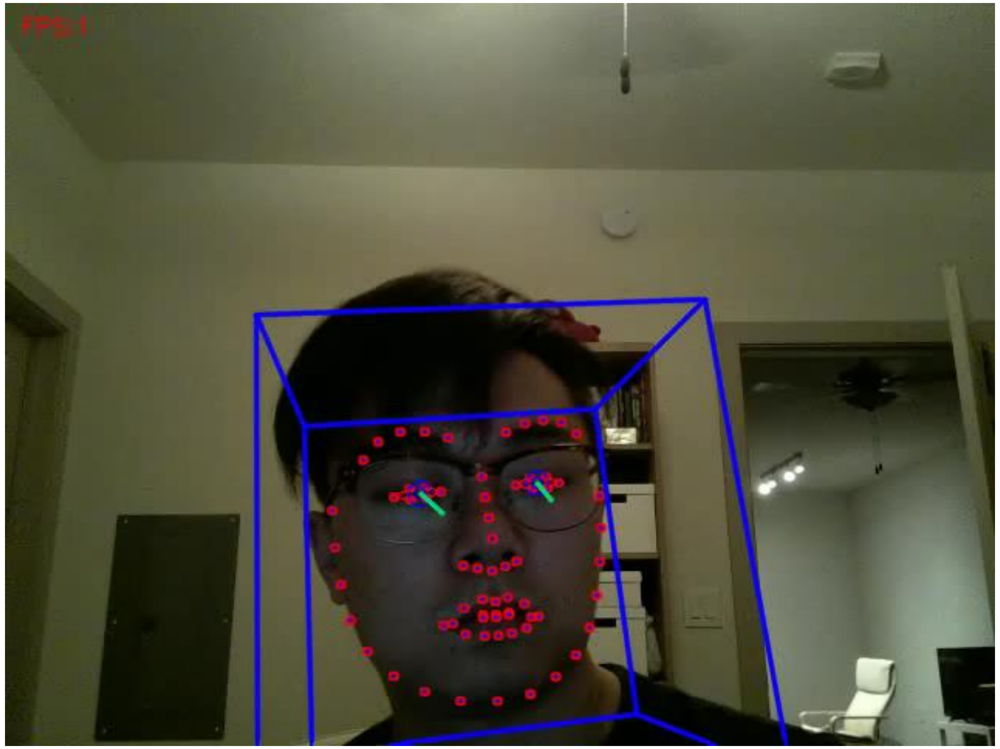
Preliminary results: facial expression recognition



Preliminary results: head pose estimation



Baltrusaitis, T., Zadeh, A., Lim, Y. C., & Morency, L. P. (2018). OpenFace 2.0: Facial behavior analysis toolkit. Proceedings - 13th IEEE International Conference on Automatic Face and Gesture Recognition, FG 2018, 59–66. https://doi.org/10.1109/FG.2018.00019

Preliminary results: extracted time series data

frame	pose_Rx	pose_Ry	pose_Rz	AU45_c	AU45_r	expression
1	-0.359	0.48	0.105	1	0	
2	-0.391	0.379	0.114	1	0	
3	-0.462	0.317	0.126	1	0	
4	-0.511	0.281	0.135	1	0	
5	-0.544	0.255	0.139	1	0	
6	-0.554	0.237	0.142	1	0	
7	-0.563	0.232	0.145	1	0	
8	-0.566	0.229	0.145	1	0	
9	-0.563	0.23	0.147	1	0	
10	-0.562	0.229	0.149	1	0	
11	-0.561	0.226	0.151	1	0	
12	-0.554	0.222	0.152	1	0	
13	-0.543	0.213	0.152	1	0	
14	-0.51	0.197	0.14	1	0.08	neutral
15	-0.473	0.197	0.12	1	0.41	
16	-0.407	0.207	0.095	1	0.85	
17	-0.363	0.21	0.075	1	1.28	
18	-0.323	0.222	0.065	1	1.38	sad
19	-0.274	0.227	0.062	1	1.24	fear
20	-0.234	0.225	0.062	1	0.93	
21	-0.203	0.222	0.063	1	0.56	fear
22	-0.181	0.215	0.064	1	0.42	fear
23	-0.157	0.207	0.064	1	0.3	happy
24	-0.143	0.192	0.067	1	0.48	happy
25	-0.143	0.187	0.074	1	0.57	neutral
26	-0.145	0.186	0.08	1	0.62	neutral
27	-0.134	0.186	0.085	1	0.55	neutral

frame	pose_Rx	pose_Ry	pose_Rz	AU45_c	AU45_r	expression
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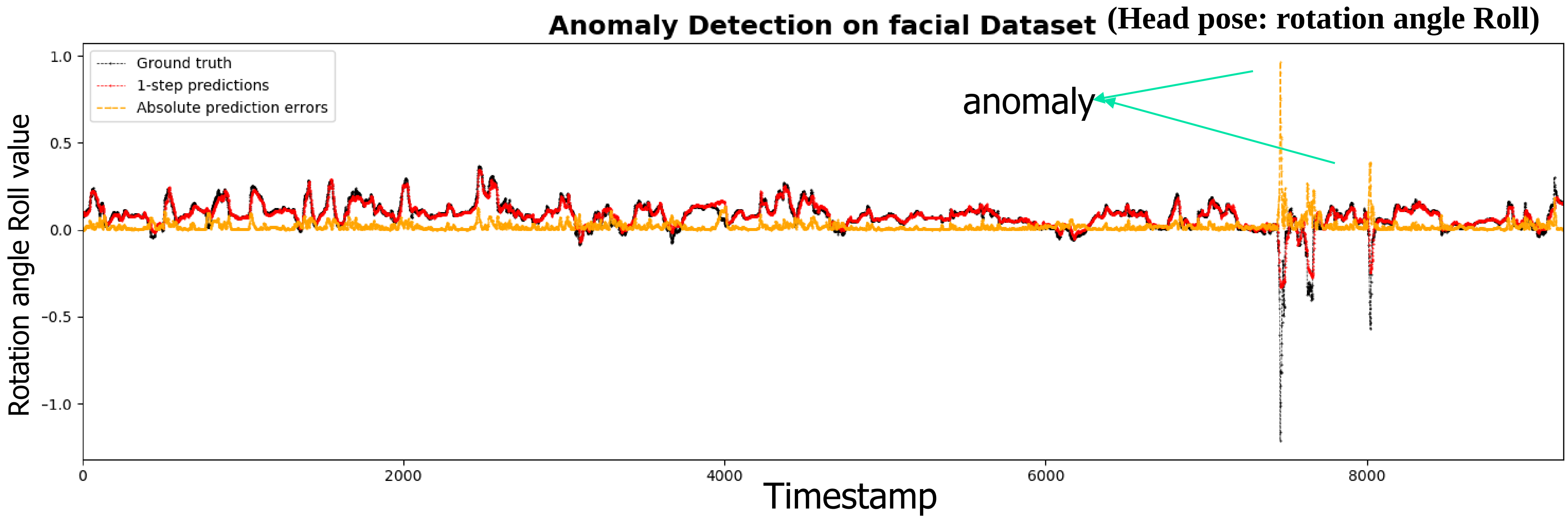
Pose_Rx: rotation angle along x axis
Pose_Ry: rotation angle along y axis
Pose_Rz: rotation angle along z axis
AU45_r: Eye blink intensity
Expression: Facial expression of the controller

Preliminary results of time series analysis



- Use rotation angle Roll of head pose as an example
- The black line means the ground truths which are captured by the computer vision module.
- The red line means the predicted value by LSTM.
- The yellow line presents absolute prediction errors.
- The arrow indicated the anomaly found by the algorithm.

Conclusions and future work

Conclusions:

- This paper presents a real-time methodology to identify the anomalous behaviors of ATCs using computer vision.
- This methodology utilized different facial features including head pose, eye blink, and facial expression. The researcher demonstrated the viability of using LSTM for identification of anomaly in time-series data

Future work

- The researchers will synthesize the anomaly scores from all the channels to make the time series analysis more reliable.
- The researchers will conduct further characterization and quantitative assessment of this methodology.

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