Identifying Worker Motion Through a Manufacturing Plant: A Finite Automaton Model

SHAOZE YANG, **SHREYAS BHAT**, YUTONG REN, TERRA STROUP, AL SALOUR, PAUL PRIDHAM, X. JESSIE YANG

IOE INDUSTRIAL & OPERATIONS ENGINEERING UNIVERSITY OF MICHIGAN

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Introduction

- Transitioning from Industry 4.0 to Industry 5.0
- Smooth and trustworthy human-AGV interaction
- Increasing the efficiency of manufacturing plants

Motivation

Pedestrian-AV Interaction

- Three broad approaches: Physics-based, pattern-based, and planning-based [1]
- Majority of literature studies intersections with crosswalks [2]
- Such structures are absent in manufacturing plants

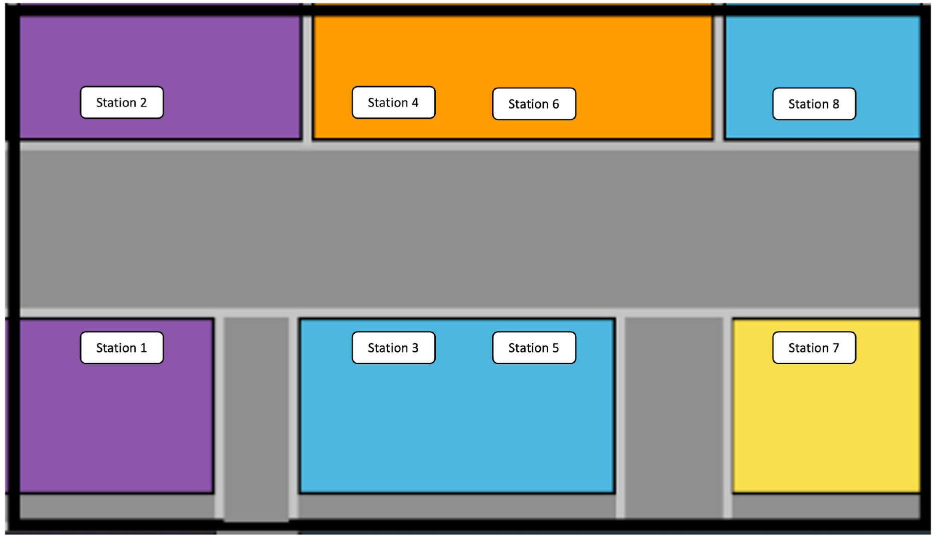
Worker-AGV Interaction

- Modeling and designing safe interaction [3]
- Underlying structure to worker motion through manufacturing plants
- Prior literature has not leveraged this structure

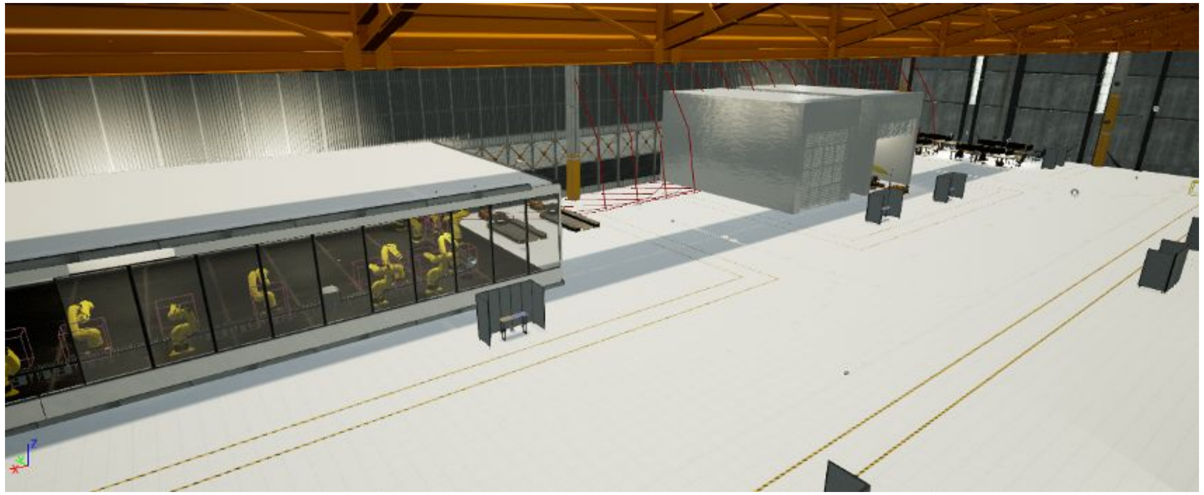
1. RUDENKO ET AL (2020)   2. JAYARAMAN ET AL (2021)   3. TUBIS ET AL (2024)

VR Environment Design

- We built a Virtual Reality (VR) environment to represent a typical manufacturing plant in which humans and AGVs share space
- The AGVs carry parts around the plant
- The humans move between the workstations

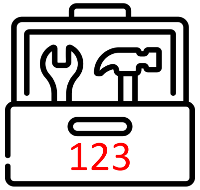


Bird's-eye view plan of the manufacturing plant

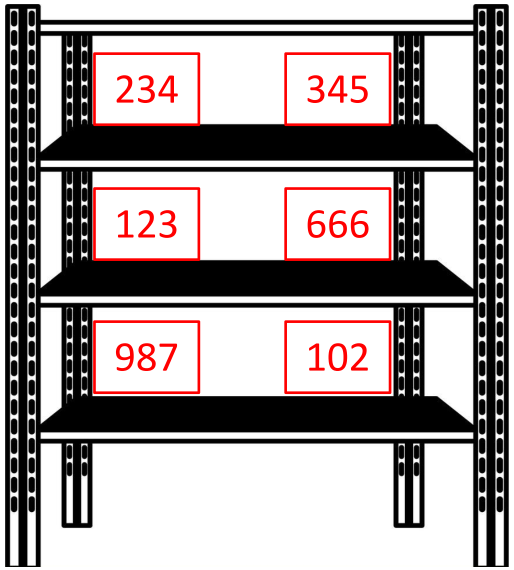


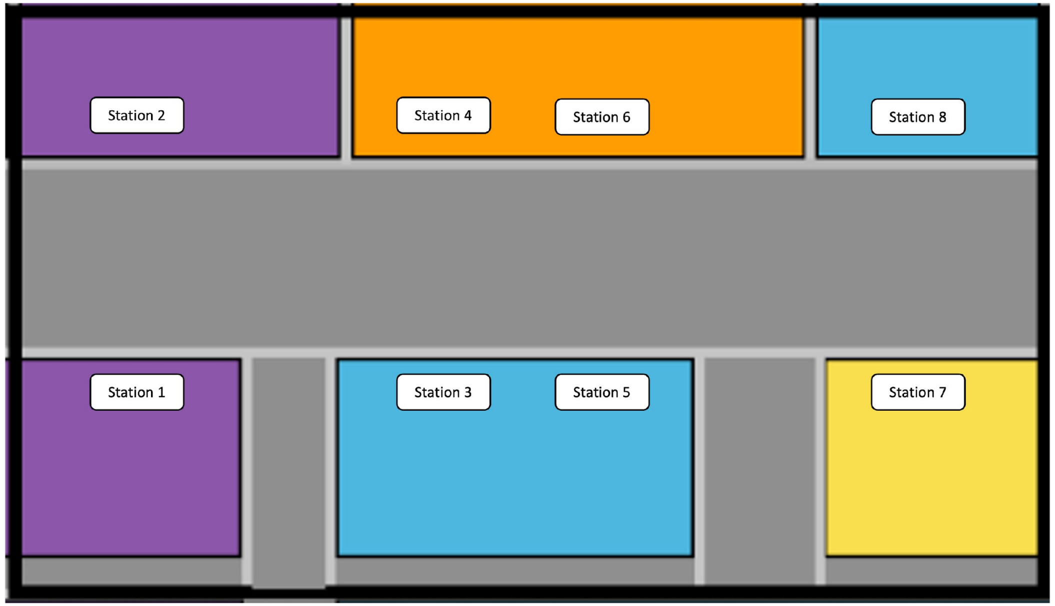
Screenshot of the VR environment built in Unreal Engine 5

Task Design



The number disappears
in three seconds





Human Subjects Study

- We designed 16 AGV trajectories to showcase all possible types of interactions between the workers and the AGVs [4]

- Participants interacted with the VR environment using the Meta Quest Pro headset and the Kat Walk C2 omnidirectional treadmill

- We recruited 19 participants (10 male, 9 female, Age = 23.3 ± 3.6 years)

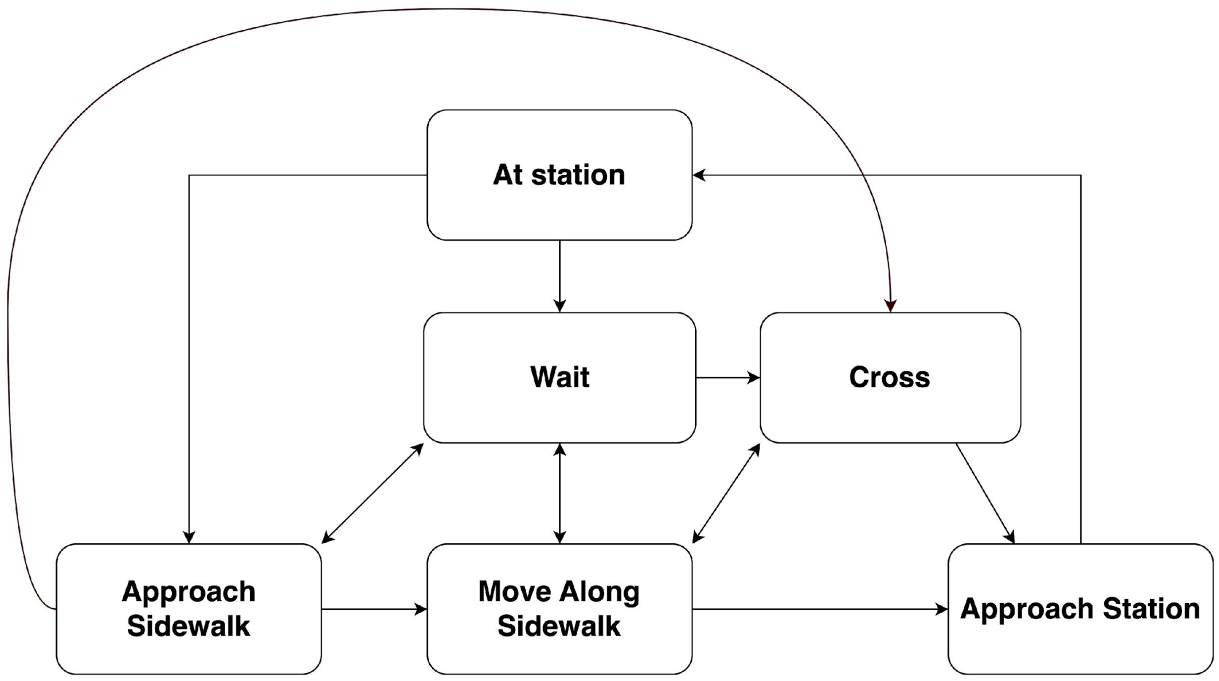
Actual AGV Photo

Our Custom-built AGV

A participant wearing the VR headset and standing on the omnidirectional treadmill

Finite Automaton Model (FAM)

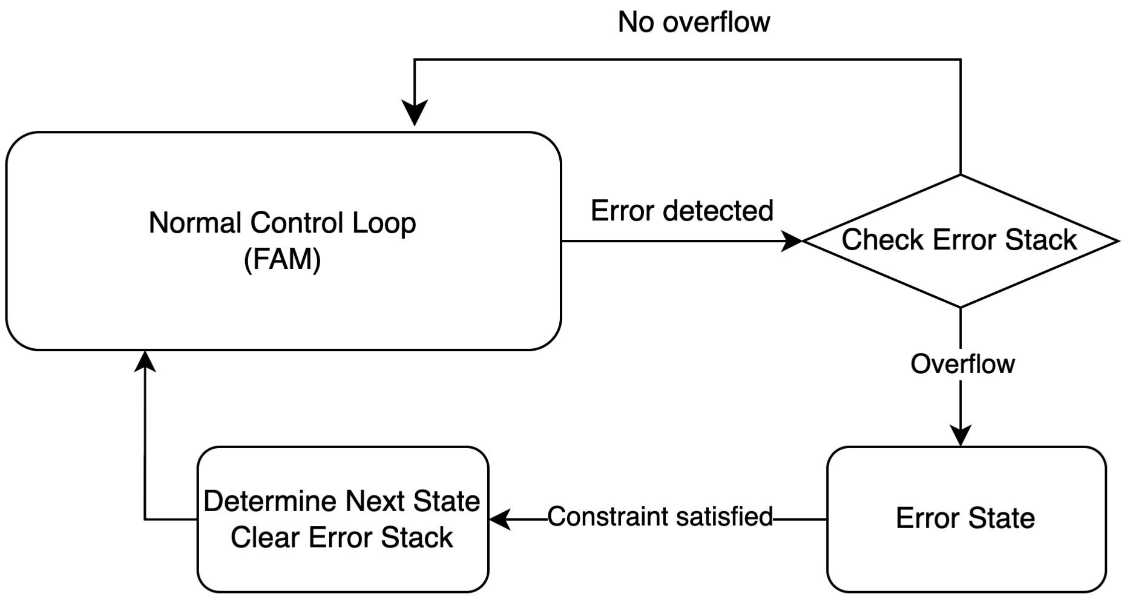
- We designed 6 intuitive states for a worker to be in at any given moment
  - At station
  - Approach sidewalk
  - Wait
  - Cross
  - Move Along Sidewalk
  - Approach Station

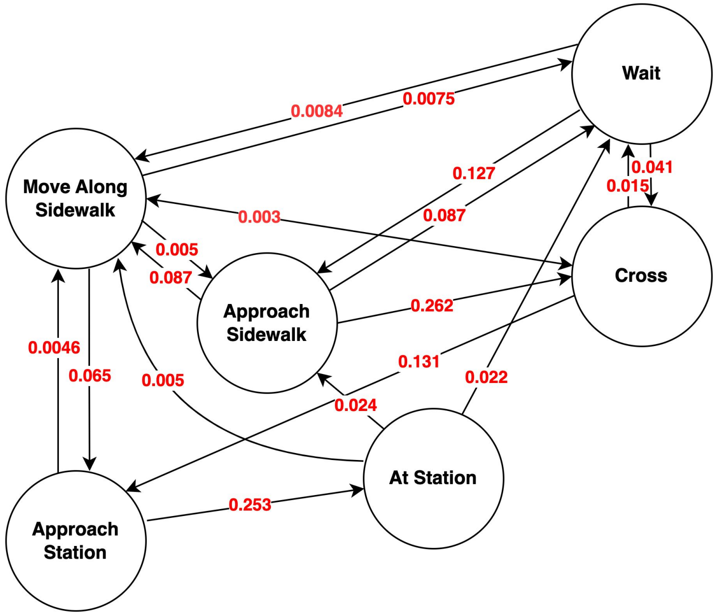


- We also defined transitions between these states depending on the features of the worker’s trajectory

Error Feedback Loop

- There is a tendency for any FAM to get stuck in incorrect states
- To alleviate this problem, we implemented an error feedback loop
- We monitor constraint satisfaction in each state. If enough errors are detected, the FAM goes into a special “error” state
  - The error state can then transition back to any other state based on constraint satisfaction





Methodology: Ground Truth

- 3 coders manually labeled states for 18 worker trajectories to test agreement
  - A total of 834 seconds of data was manually labeled by 3 coders
- The agreement between the coders was computed using Light's Kappa
  - A score of above 0.8 is considered to signify good agreement
- We then evaluated our model's performance on 87 trajectories
  - A total of 3362 seconds of data was manually labeled for this

TABLE III: Inter-Rater Reliability For Rater A, B and C

Rater 1	Rater 2	Kappa Score
A	B	0.919
A	C	0.917
B	C	0.907

Results

TABLE VI: Model Comparison

Model	Accuracy	Precision	Recall	F1 Score
Neural Network	0.2362	0.2653	0.2105	0.1915
SVM	0.3303	0.1486	0.2348	0.1780
KNN	0.3440	0.3368	0.3497	0.3396
Logistic Regression	0.4656	0.3917	0.4105	0.3825
Decision Tree	0.5872	0.5518	0.5982	0.5600
LGBM	0.6583	0.6062	0.5783	0.5634
Ours	0.8068	0.7029	0.6994	0.6950

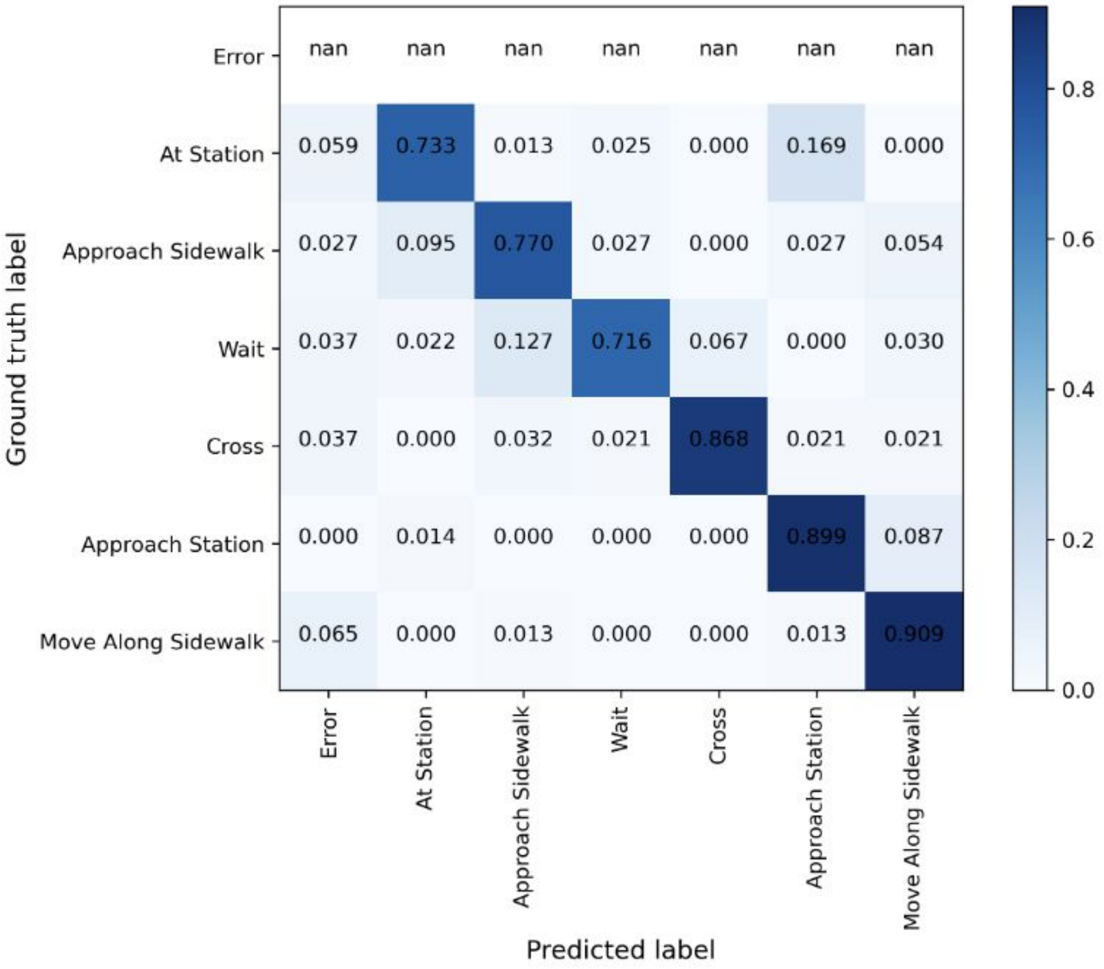
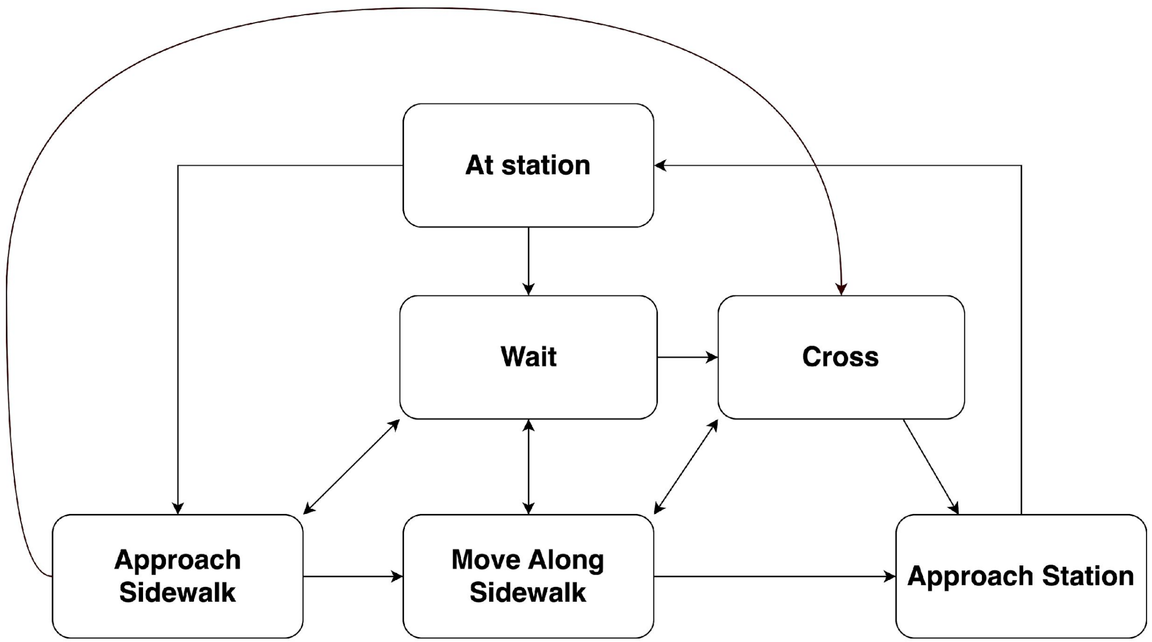


Fig. 6: Normalized confusion matrix of model's prediction.

Summary

- We proposed a Finite Automaton Model (FAM) to identify the state of a worker moving through a manufacturing plant
- Our model leverages the underlying structure of worker motion to define intuitive states and state transitions
- Our model achieves **80.7%** accuracy on labeling worker states, which is considerably more than learning-based methods with limited data



Limitations and Future Work

- Limited predictive power
- Necessity of hand-crafted states and state transitions
- Human-subjects study dealt with only one worker at a time
- Modifying AGV behavior based on the model outputs

Thank you

SHREYAS BHAT (SHREYASB@UMICH.EDU)

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