Research Statement

1 Research Overview

Vision: My research interests are broadly in the areas of **big data** and **cyber-physical systems** (CPS). My research is driven by rich data collected from urban CPS and focus on the integration of **human behavior learning** and **urban CPS**. In particular, my research vision is:

With the big data collected from urban CPS infrastructures, understanding human behavior can successfully bridge humans and CPS in the Human-in-the-Loop Urban CPS to maximize the benefits of CPS for humans.

Motivation: Since the "only" Coke machine was connected on the Internet, an idea began to spread: a vision of an interconnected world where information on most everyday objects was accessible. Following this vision, scientists and engineers have developed this idea into a concept *Cyber-Physical Systems (CPS)* or broadly *Internet of Things (IoT)*, which interconnects a large number of heterogeneous devices, from traditional desktop PCs to smartphones, from household appliances to wearable devices [1]. However, a key element, e.g., human being, is neglected, which is of great importance considering the intrinsic purpose of CPS is to serve humans. Nowadays, with the various data collected from urban infrastructures, we have an unprecedented opportunity to understand and incorporate human behavior into CPS, which motivates my research.

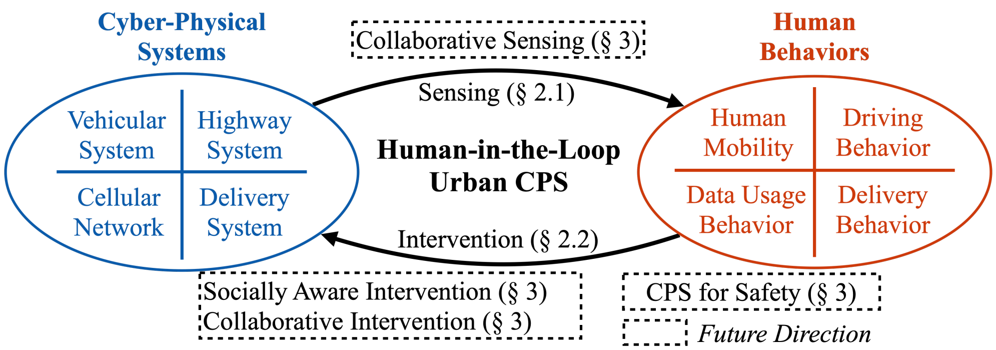

Figure 1: Thesis Research Framework

Thesis Work Summary: The framework of my thesis work is shown in Figure 1. My dissertation explores a wide range of large-scale cyber-physical systems such as a citywide cellular network system, a citywide on-demand delivery system, a statewide highway toll collection system, and a nationwide vehicular system. Based on the data collected from these systems, a set of human behavior is studied to improve the benefits of CPS such as human mobility, driving behavior, data usage behavior, and delivery behavior. In particular, my work focuses on two fundamental challenges that are unique in the human-in-the-loop urban CPS:

(1) **Sensing:** sensing and learning human behavior based on the data collected from urban CPS;

(2) **Intervention:** intervening based on the knowledge from human behavior sensing.

I address these challenges in practice by integrating the fundamental characteristics of human behavior and several domain-specific insights in the urban CPS, and maximize the benefits of urban CPS with state-of-the-art machine learning solutions. The unifying theme underlying these human behavior characteristics is the uniqueness and conformity that different humans have their unique behavior while also conform to the crowds. With these characteristics, human behavior models are incorporated into the design and operation of CPS considering the domain-specific insights. Following this framework, my work is evaluated based on the real-world data from the aforementioned urban CPS and demonstrated to advance the state-of-the-art human-in-the-loop urban CPS.

Thesis Work Impact: The impact of my thesis work is substantiated in both academia and industry.

- **Academia**: My research results have led to more than 10 publications in the premier conferences and journals such as MobiCom, NSDI, UbiComp, and TMC. Among them, several papers have been adopted as graduate-level course materials such as CS 672: Data Science for Smart Cities in Rutgers University; several results are also selected to be discussed in the seminar of several universities such as the University of Virginia, Tsinghua University, and Shanghai Jiao Tong University. Given my research experience, I also actively serve the community. I was invited to serve on program committees for The Tenth International Conference on Mobile Services, Resources, and Users. I was also invited as (external) reviewers for several top journals and conferences such as IEEE Journals/Transactions and IMWUT.
- **Industry**: My work is also adopted in the real world industry scenarios. *Eleme*, an on-demand delivery company of Alibaba Group, has used my result [2] in a pilot platform to infer the status of delivery couriers; the preliminary result has shown the effectiveness of reducing the overdue rate. Also based on my result [3], *Eleme* has deployed and operated one of the largest Bluetooth beacon systems *aBeacon* with more than **12 thousand beacons** to support the delivery workflow of **100 thousand** couriers and **64 million** orders. Shenzhen Institutes of Advanced Technology has been working with Shenzhen Government to use my result [4] for a pilot program to monitor the status of the highway system.

Future Directions: Following the framework of my current work, my future directions will extend the depth.

(1) **Socially Aware Intervention:** The objective of the current CPS generally only focuses on the effectiveness while neglects social properties such as diversity, fairness, and equity. I envision a socially aware management theory that benefits both the effectiveness and social properties.

(2) **CPS for Safety:** Safety is also an important application scenario for CPS. I am especially interested in the safety on the road and aim to reduce the fatalities and injuries with advanced CPS and machine learning techniques.

(3) **Collaborative Sensing and Intervention:** Most of the current work is based on a single CPS, which does not reveal the collaboration between CPS. I envision a collaborative sensing and intervention approach that fills the gap between CPS.

2 Thesis Work

My thesis work shows that human behavior can be well learned based on the data collected from urban CPS and the knowledge can be looped back for CPS intervention. This section presents two themes, each representing a significant component of my research framework.

2.1 Human Behavior Sensing in CPS

In this part, I show two directions including human behavior sensing in a single CPS and across multiple CPS.

2.1.1 Sensing in Single CPS

When sensing human behavior, an ideal scenario would be there is a system that is specifically designed to collect human behavior data. However, in real-world scenarios, these systems are generally designed for other purposes such as billing and monitoring purposes. They do not provide sufficient or fine-grained human behavior data, which introduces an unique challenge for human behavior sensing in the CPS. By addressing this challenge, we can potentially extend the sensing ability of the existing deployed CPS.

A concrete work in my research is to utilize a highway toll collection system to learn vehicular mobility [4]. Originally, the highway toll collection system is for billing purposes that only collects the entering/exiting time and locations (i.e., toll booths) of vehicles. With the very sparse information, it is challenging to learn the fine-grained vehicular mobility such as the route, speed, and locations between entering and exiting. To address this challenge, based on the human driving behavior analysis, I identified two insights: (i) humans have the personal driving pattern in the route and driving speed (e.g., used to drive on the same route with a similar speed); (ii) the personal driving pattern is also constrained by the crowd driving pattern (e.g., the more people on the same route, the lower speed they are). Based on these two insights, I designed a system *VeMo* and formulated vehicular mobility learning as a collaborative optimization problem with the personal driving pattern and the crowd driving pattern. Based on the real-world data evaluation, my work achieved an accuracy of 82% when inferring the vehicular locations on the highways.

The insights of the driving pattern turn out to be more general. I have also applied the same insights to the other work: the estimation of the fine-grained travel time on the highways [5], which leads to an average of 1.2 minutes on highways.

2.1.2 Sensing Across Multiple CPS

A single CPS generally only reflects a single view of human behavior. To overcome this limitation, cross-CPS human behavior sensing provides a potential way to learn human behavior from multiple views. A unique technical challenge in cross-CPS sensing is that different CPS general collect data with different spatial-temporal characteristics, which is difficult to be unified for human behavior sensing.

A work in my research exactly provides a practice to address this challenge [6]. In particular, I studied human mobility across two CPS: a stationary sensing system (i.e., a highway toll collection system) and a mobile sensing system (i.e., a vehicular GPS system). However, the stationary sensing system only provides human mobility information in limited coverage (e.g., camera equipped roads) and the mobile sensing system only captures a limited number of humans (e.g., humans using a particular smartphone app). To overcome the limitation, we fuse them and extend the sensing ability of a single system. The insight is that humans move in their own patterns and are generally independent of the types of sensing systems they are exposed. It indicates that human mobility at the individual level, as a behavior, is inherently consistent in two systems. Based on this intuition, I designed a model *Mohen* and evaluate it based on 114 thousand vehicles. Our model outperforms two state-of-the-art methods by 35% and achieves a competitive result to an Oracle method.

Besides the highway environment, my other work also demonstrated the benefits of sensing across multiple CPS such as vehicular localization [7] and behavior-aided cellular data usage prediction [8].

2.2 Human Behavior Intervention in CPS

In this part, I illustrate how human behavior is altered including explicit intervention and implicit intervention.

2.2.1 Explicit Intervention

Explicit intervention means the human behavior is directly changed by orders, commands, or schedules. A representative work in my research is to change the couriers' delivery behavior in one of the largest on-demand delivery companies *Eleme* based on indoor location inference by couriers' reporting behavior learning [2].

In general, achieving accurate indoor localization requires densely deployed indoor infrastructures such as beacon devices [9] or densely collected indoor fingerprinting such as Wi-Fi signals [10]. Both solutions lead to a high expense and low scaleability to be deployed at a large scale such as a nationwide operational company. To address the limitation, my intuition is that indoor localization can be achieved if the couriers' indoor movement (e.g., walking time to different locations) can be modeled. However, the challenge in such an indoor environment is that there is no sufficient human behavior data (i.e., walking route and speed) for behavior modeling. To solve this challenge, I found two insights: (i) couriers report coarse-grained arriving time at specific locations; (ii) these coarse-grained arriving time can be further improved based on couriers' reporting behavior. Based on these two insights, I modeled the couriers' indoor movement (especially the walking time and route), based on which I designed a system *TransLoc* to infer the couriers' indoor locations without any pre-deployed infrastructures. With the inferred indoor locations, I improved the order dispatching system by explicitly changing couriers' delivery behavior that minimizes their indoor walking time. The results show that the indoor walking time was reduced by 24% and the overdue rate was reduced by 2.5%.

2.2.2 Implicit Intervention

Implicit intervention means we provide notifications, suggestions, and advice that influence human behavior instead of directly altering human behavior. My work provides a good practice following this idea.

One of the real-world problems in the delivery platform is that couriers tend to not report when actually arriving at the pickup merchants to avoid the late-delivery fee. For example, if couriers report arrival earlier, they can argue the reason for the late delivery is because of the merchants' late preparation that makes them wait at merchants. To address this problem, we deployed an arrival detection system [11]. Specifically, we converted more than 2.5 million merchants' smartphones into virtual beacons that broadcast Bluetooth signals. If couriers report arrival while their smartphones do not detect the signal, instead of explicit intervention, a notification system in couriers' smartphone app would post a suggestion to notify couriers they may not have arrived. Based on this implicit intervention, we reduced the wrong arrival reporting rate by 14.2%.

3 Future Directions

Following the research framework, my future directions will extend the depth of the framework.

Socially Aware CPS Intervention: In the existing CPS, the general objective is focused on the effectiveness and efficiency of the systems. Even with humans in the loop, the main goal is still to incorporate human behavior or knowledge to improve the systems. So far, very few researches, if any, work on the social properties of Human-in-the-Loop Urban CPS such as diversity, inclusion, and equity. Without considering these social properties, the practical effectiveness and efficiency of CPS would be constrained when deploying such a system to serve humans. As one future direction, my research will explore the integration of Social Science (e.g., Intervention, Deliberation, Focus Group Study) and Human-in-the-Loop Urban CPS. To best serve humans, I envision a *socially aware human-in-the-loop urban CPS*, which jointly optimizes the system effectiveness/efficiency and the social properties.

CPS for Safety: An important application of CPS is for safety. Recently, urban transportation is experiencing rapid changes with the spreading of new micro-mobility options including shared e-scooters, e-bikes, and a range of other options. However, these options have a potential risk due to a variety of factors such as human behavior, road design, and environmental conditions. In this direction, I envision *an integration of vision sensors and computer vision techniques* to improve the safety of pedestrians.

Collaborative Sensing and Intervention: As demonstrated in our preliminary results [6] [7] [8], cross-CPS sensing has great potential to improve the sensing ability of CPS. In my future research, I will explore collaborative sensing and intervention that different CPS work together. However, in practice, different CPS generally belong to different parties or departments that work independently from each other. The key gap is there is no trustful protocol for cross-CPS collaboration. Recently developed *Federated Learning* framework brings us a new opportunity that it is promising to achieve collaboration between parties without exchanging sensitive information. I envision a *federated learning based protocol for collaborative sensing and intervention* could synergistically improve the efficiency across multiple CPS.

The past years have witnessed the coming age of various CPS infrastructures empowered by advances in system and networking research. Now, I believe the focus can move to humans; I am excited to explore the direction to reconsider the role of humans in CPS and maximize the benefit of CPS for humans.

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