Research Statement

Ruimin Ke (ker27@uw.edu)

Research vision and background: Urbanization has been posting significant challenges in different areas due to people's increasing demand for daily-life convenience and insufficient supply of urban resources. To improve the situation with existing infrastructures, it is necessary to develop innovative techniques in not only the **understanding of existing urban data** but also the **generation of new types of data** for specific problems. To fulfill the needs, **my Ph.D. research** primarily focuses on *advanced urban sensing systems* on both the road user side and the infrastructure side, and *data-driven urban modeling* based on both the state of the arts in data science and the domain knowledge in civil engineering. Under the context of Smart City, **my long-term goal** is to bring highly automated urban transportation and infrastructure systems with efficiency, safety, and reliability to the society.

Thus far, my research in the area of *advanced urban sensing systems* has pushed the boundary of sensing algorithms and systems that target providing cost-effective and scalable solutions for key components in Smart City. On the other hand, my research has advanced the state of the arts in the area of *data-driven urban modeling* by designing data-driven methods and urban computing systems to answer the critical needs in modern transportation and infrastructures. In summary, the **key contributions** of my Ph.D. research are as follows.

1. Advanced the state of the arts in *Unmanned Aerial Vehicle (UAV)-based traffic data collection*. This group of work [2,3,4,9,10] solved the issue of *UAV video background motion* and proposed *real-time frameworks* that can extract vehicle information, road information, macroscopic traffic parameters, and microscopic traffic parameters in *different scenarios* such as daytime, nighttime, free flow, congestion, unidirectional road, and bidirectional road (Section 1.1).
2. Developed *edge computing systems* for *realtime sensing of traffic and infrastructures*. Based on the latest Internet-of-Things (IoT) technologies, this group of work [5,6,12,13,14] aims to *extend the abilities* of existing urban infrastructures and in-vehicle devices to *handle the exploding quantities of urban data* and *generate useful information to support advanced applications* such as autonomous driving evaluation, transit event logging, and smart parking facility (Section 1.2).
3. Filled research and application gaps in *critical topics in understanding urban data*, including traffic pattern learning and prediction, traffic bottleneck identification, traffic safety modeling, traffic big data management, and smart intersection, etc. [1,7,8,10,11,15,16]. The *key idea* is to provide professionals and policymakers with more straightforward understandings of a city's infrastructures and transportation. It also *lays the foundation* for future work in advanced urban computing with the new data sources that are generated from the sensing systems (Section 1.3).

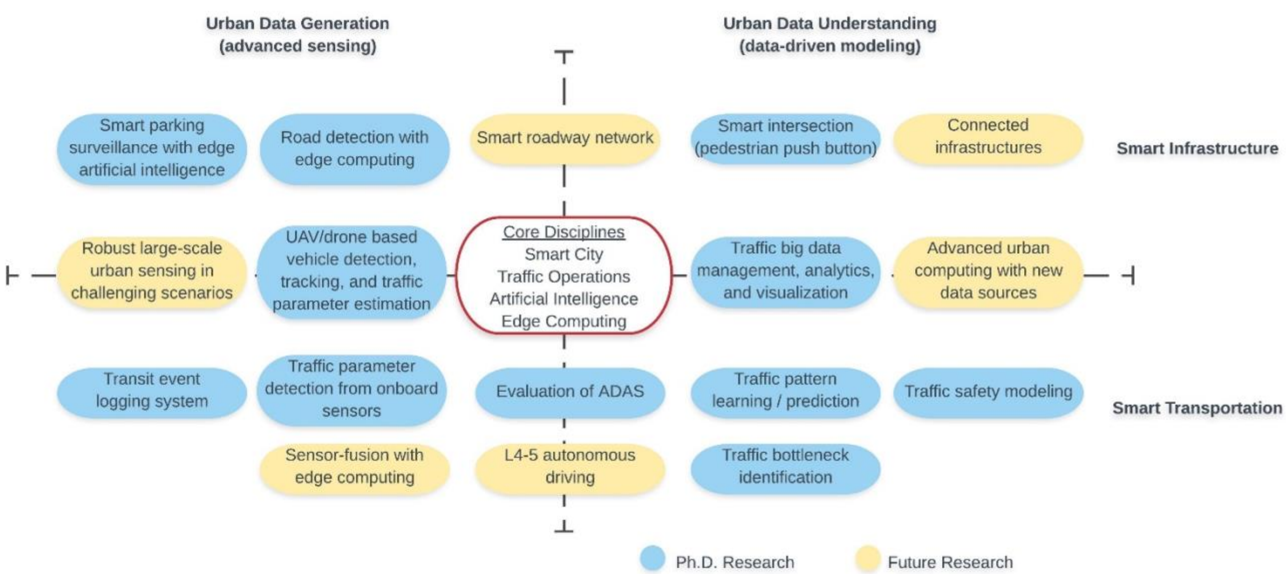

Figure 1 Ph.D. research (blue) and future research plans (yellow)

I believe we are now on the right track to realize the highly automated urban transportation and infrastructure systems. As we think of a future with such urban systems in the world, many research problems emerge and remain to be solved. Based on my research contributions and experience, I propose three primary research directions for the near future: 1) robust large-scale urban sensing in challenging scenarios with sensor fusion and edge computing, 2) autonomous driving with the support of smart and connected infrastructures, and 3) advanced urban computing with new data sources. These directions and how I come up with them are introduced in the Section 2: Future Research Directions. It is just the beginning of a new era of Smart City, and I am excited to be part of it.

1. Ph.D. Research on Advanced Sensing Systems and Data-Driven Urban Modeling

1.1 Realtime UAV-Based Sensing and Traffic Data Collection

UAVs are gaining popularity in Smart City as an emerging sensing platform due to their low cost, high flexibility, and wide view range. Under this context, extracting useful data from UAV video is considered one critical Smart City application. However, different from stationary surveillance cameras, the UAV camera moves irregularly with the aircraft, which creates extra challenges for the design of video sensing algorithms. I have proposed a few new frameworks to address this background motion challenge and realize traffic data collection with state-of-the-art efficiency, accuracy, and robustness.

Clustering-based bidirectional macroscopic traffic data collection: Most pioneering studies proved the possibility of extracting traffic parameters from UAV video, but they either *adopted inefficient methods or simplified the problem by assuming the UAV was stationary*. I started the topic by just extracting one type of data (i.e., traffic flow speed) from moving UAV videos. I first proposed a k-means-based motion-vector clustering method to separate the foreground and background and then use the clustered motion-vectors to calculate traffic flow speeds [2]. Based on this work, I developed *a more sophisticated unsupervised learning framework* that can *distinguish the directions of traffic streams* and extract the *three key macroscopic traffic flow parameters* (i.e., speed, volume, and density) in a *real-time manner* [4]. This is also among the first efforts to extract the three key macroscopic traffic parameters from *moving UAVs* in both *daytime and nighttime*.

Deep-learning-based vehicle detection and macroscopic traffic data collection: I noticed that the unsupervised-learning-based method worked not very well in congestion situations due to the use of *motion cues for traffic detection*. Hence, I then designed *supervised-learning-based frameworks* for macroscopic traffic flow parameters estimation [3,9]. In the study [9], I proposed *a* new *ensemble vehicle detector* with Haar cascade + convolutional neural network (CNN), and *published the 20,000 training image samples* we manually labeled to the research community. A *general process* for supervised-learning-based macroscopic traffic data collection and a method to *compensate UAV height changes* are proposed as well. This is the first framework that works for both *free flow* and *dense traffic* regarding traffic flow parameter estimation in UAV video with background motions. It also achieves *real-time* performance and high accuracy.

Microscopic and lane-level macroscopic traffic data collection: Recently, considerable progress has been achieved on the estimation of aggregated macroscopic traffic parameters. At the same time, there has been extensive attention on *higher-resolution traffic data* such as microscopic traffic parameters and lane-level macroscopic traffic parameters since they can help deeply understand *traffic patterns* and *individual vehicle behaviors*. However, little existing research can automatically estimate microscopic traffic parameters and lane-level macroscopic traffic parameters using UAV videos with a moving background. To fill this gap, an advanced framework was carefully designed with the consideration of *UAV video features* and *traffic flow characteristics*. It not only extracts *seven more types of traffic parameters* compared to the state of the arts but also *significantly improves the extraction accuracy* [10].

1.2 Edge Computing Algorithms and Systems for Urban Sensing

Smart City applications have a *high demand for computing services* to process and store big data. Cloud computing was widely recognized as the best computing service for big data processing and artificial intelligence tasks. Nevertheless, with the urban data enlarged at explosive speed, cloud computing is no more the optimal solution in some cases because it not only consumes *large bandwidth* but also brings *latency* in information transmission. The Smart City community has been aware of the needs to *transfer computing workload to the edges* of systems. Edge computing, as an answer to this, allows data generated from Internet-of-things (IoT) devices to be handled closer to where it is produced rather than transmitting it to the cloud or data server. In recent years, I have been *exploring the edge computing solutions* for smarter and more efficient urban transportation and infrastructure systems.

Edge computing for in-vehicle sensors and advanced driver assistance systems: In-vehicle sensors are valuable sources for research and applications in Smart City. However, their potentials are far from being fully developed due to a *large amount of raw data* and the *lack of cost-effective computing algorithms*. In my Ph.D. research, I have been making great efforts in edge computing for traffic safety data generation, transit event logging system (TELS) development, and evaluation of commercial advanced driver assistance systems (ADAS). I developed the first framework that extracts *vehicle-pedestrian near-miss* event data from *monocular onboard vision*, which provided *a new data source* for traffic safety modeling and supported the evaluation of the *latest MobilEye Shield+ technology* [5, 14]. In an ongoing Federal Transit Administration (FTA) project with Pierce Transit, I have developed a system for *real-time transit event logging* with *edge artificial intelligence (AI)* based on the Nvidia Jetson TX2 platform [13]. The TELS takes input from cameras, telematics units, and signals from an onboard LiDAR-based collision avoidance system.

Smart parking surveillance with edge artificial intelligence: Realtime surveillance video analytics is called the *"Killer App"* for edge computing [17]. But with the rich information in city-wide surveillance cameras, it is a must for us to face the challenge. Existing surveillance cameras are mostly at roadside and parking facilities. In a recent study with Sound Transit, we developed *a multi-sensor solution* for large-scale parking surveillance. I led the efforts in the development of a *video-based* parking surveillance system with *edge computing and online surveillance*. It enabled AI at the edge by implementing an enhanced single shot multibox detector (SSD). A few more algorithms were deployed on the edge and the server targeting optimal system efficiency and accuracy. Thorough field tests were conducted at the Angle Lake parking garage for *three months*. The video system reached 95% accuracy and advanced the state of the arts in parking surveillance [12].

Smart roadway surveillance for road detection and traffic monitoring: Roadside surveillance cameras have been widely used for urban surveillance [6]. With edge computing, it can produce much richer data. In an ongoing project with the Norwegian Public Roads Administration, I have developed a video-based surveillance system with edge computing for road condition detection and traffic monitoring. The edge computing is implemented on the popular IoT device, Raspberry Pi. Traditional road detection methods either do not work well in *extreme conditions* (low lighting, snow, etc.) which are typical in Norway or have *high computational complexity* that would overwhelm IoT devices. To address this issue, I designed a new road detection algorithm for edge computing that achieved excellent efficiency and reliability in extreme conditions using *optical flow and DBSCAN clustering*. At the same time, the road detection results are also used as *an input* to the traffic monitoring function to improve traffic detection accuracy.

1.3 Data-Driven Urban Modeling Methods and Applications

With the rapid growth in urban data, there are increasing needs and challenges in *data management* and *pattern analysis* for the purpose of leveraging the power of big data to help build smarter, more efficient, and more reliable urban systems.

Urban data management and analytics for traffic operations: Digital Roadway Interaction Visualization and Evaluation Network (DRIVE Net) is a region-wide and web-based urban data management and decision support system that adopts digital roadway maps as the base and provides data layers for integrating and analyzing a variety of data sources [16]. The *primary user* of the system is Washington State Department of Transportation (WSDOT) and transportation professionals. I was a *chief developer* of DRIVE Net for two years. In the DRIVE Net Phase II project, the system capability was significantly enhanced by incorporating more heterogeneous datasets and functions. This platform has not only helped WSDOT produce the quarterly reports, but also provided valuable resources for researchers. For example, one of my recent publications was based on the data on DRIVE Net. This study proposed a *new freeway bottleneck identification and quantification method* that bridged gaps in the areas of *traffic operations* as well as *wavelet analysis research* [7]. New data generated by the aforementioned edge computing systems can also help traffic operations. In 2017, we proved the availability of using *edge devices to automatically control pedestrian push-buttons* with pedestrian detection data.

Urban mobility pattern learning and prediction: The recent progress on artificial intelligence inspires me to explore new angles to understand urban mobility. To address the challenges in *network-scale traffic pattern learning and prediction*, we extended the traditional long short-term memory (LSTM) neural network to the bidirectional LSTM (BDLSTM) [1]. To our best knowledge, this was the first time that BDLSTM was applied as *building blocks* for a deep architecture model to measure the *backward dependency* of traffic data for prediction. In addition to moving from individual location to the roadway network scale, there is need for moving from aggregated data to high-resolution data [8]. To this end, I designed a two-stream multi-channel convolutional neural network (TM-CNN) targeting multi-lane traffic speed learning and prediction [11]. This model *combined the knowledge in artificial intelligence* and *transportation engineering* so that the *traffic spatial-temporal dependencies* and *speed-volume correlations* were greatly utilized. Besides macroscopic patterns, I also collaborated on microscopic pattern learning research such as *lane-changes prediction* [15] and *car-following analysis* [10].

2. Future Research Directions

In order to achieve the long-term goal, I will continue my research along the aforementioned directions and also branch out to explore problems related to *robust large-scale urban sensing*, *autonomous driving*, and *advanced urban computing*.

Robust large-scale urban sensing in challenging scenarios with sensor fusion and edge computing: Urban sensing tasks that seem simple could become extremely complicated with low reliability and accuracy in challenging scenarios or large scale. A typical example is video sensing. In the recent parking surveillance project, the video-based detector performs much more reliable indoor than outdoor due to extreme lighting conditions and adverse weather. Even the cutting-edge commercial product – the MobilEye Shield+ ADAS system, is not recommended for nighttime operation [9]. Another problem with large-scale sensing is failure tolerance. **The failure probability could turn from negligible for individual sensors into a norm for large-scale sensor networks according to probability theory.** One key reason that L5 autonomous driving is still not even close to reality is the unreliable sensing performance in corner cases and large scale. In my future research, **I will continue to explore cost-effective algorithms for urban sensing in challenging scenarios and study how to optimize the failure probability of large-scale urban sensing systems to the minimum.** Sensor fusion and edge computing will be the basis for my future design of urban sensing systems.

Autonomous driving with the support of smart and connected infrastructures: Autonomous vehicles will be a critical component in the future automated urban systems. Over the past years, investments in autonomous driving technologies have been booming all over the world. However, the timetable for L4-5 autonomous driving keeps being postponed. **Despite the enormous efforts on the vehicle side, the investment on the infrastructure side is quite limited.** Imagine smart cars running on smart roads: The smart and connected roads, bridges, tunnels, etc. would actively share traffic and environment information with vehicles nearby rather than the vehicles detecting all information by their own sensors. Building smart and connected infrastructure would speed up the development of fully autonomous vehicles. In my future research, **I plan to spend my time and energy on the development of smart and connected infrastructures as the support for L4-5 autonomous driving**.

Advanced urban computing with new data sources: In my research scope, the future urban sensing systems will generate new types of data to enable the understanding of urban patterns from different angles. In some cases, the new angle could improve the solution to an existing problem by using more straightforward methods. However, **the primary objective of generating new data sources is to enable advanced solutions to the issues that remain to be solved on our way to realizing highly automated urban systems.** To this end, I believe it is necessary to propose advanced urban computing models to handle the combined data sources of existing data and new data. I expect this scope to bring the general AI to the smart cities in place of the weak AI we have at present.

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