A BAYESIAN NETWORK BASED APPROACH TOWARD AN ANTICIPATORY SAFETY REASONING SYSTEM AUTONOMOUS VEHICLE COPILOT

by

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TO MY FAMILY

"A bend in the road is not the end of the road… unless you fail to make the turn."

-Hellen Keller

I would first like to thank my wife Stephanie and my daughters Evalyn and Izabella for bearing through this journey with me and encouraging and pushing me to continue forward when I may have otherwise wavered. Your support, love, and sacrifice during this extended process was amazing. I would also like to thank my mother and father, MaryAnn and David Frederick, who set me on a path to believe that I can accomplish what I set my mind to, no matter where the starting or end point ends up being. To my extended parents, Stephanie and Stanley Bienkowski, thank you for your support and time over the years in assisting my family through this period. To my sister and sisters-in-law's and their families, I appreciate your support over the years in my pursuit of this life endeavor. Finally, to my son Alexander, I hope you can understand how much we all love you and that the dedication it took to complete this dissertation was inspired by your presence in our lives.

ACKNOWLEDGMENTS

"Success is no accident. It is hard work, perseverance, learning, studying, sacrifice and most of all, love of what you are doing or learning to do."

– Pele

I have many people beyond my family to acknowledge starting with the school, my advisor, my committee, and my work supervisors. I have had an unorthodox time as a Ph.D. student related to critical family health issues that have pulled me away from the program multiple times. I appreciate and thank the school, and all of the departments within the school, that have assisted me through these struggles. My appreciation holds especially true for my committee members and chair. As my chair, Dr. Ka C Cheok's guidance and assistance has guided me throughout my journey. His determination to base my assertoric concepts on strong mathematical underpinnings was critical to my success. Dr. Mohnar Das helped me understand the mathematical underpinnings of systems driven by signal analysis. Dr. Sankar Sengupta for helping me understand systems engineering from an industrial and supply perspective. Dr. László Lipták for introducing and guiding me in understanding discrete mathematical methods. My industrial board members Dr. Michael Del Rose as my mentor in the domain of reasoning systems and Dr. Robert Kania as my guide in robotic systems. Finally, many people at my employer US Army Ground Vehicle Systems Center, have assisted me through the years in making this possible, especially my recent direct supervisor Rakesh Patel and my former second-line supervisor Kevin Mills. Without all of this support, I would never have been able to complete this effort.

Philip A. Frederick

PREFACE

"It always seems impossible until it is done."

– Nelson Mandela

From some of my youngest memories, I have always been fascinated by trying to understand the "why" of decision outcomes in given situations and scenarios. Decision-making has always appeared to me to follow patterns and themes. Conclusions and consequences of any given decision have always seemed to be formed by the information and events surrounding the decision process. I firmly believe that favorable decision outcomes are directly related to the decision maker's ability to perceive and utilize the varying forms of information available to them in a timely and effective manner. For example, as a young child, I can remember wondering one day why my dog, Timmy, was barking so aggressively at the front door of my parent's home. Was my dog unaware that my grandparents were coming over that day and were likely the ones outside? From my perspective, this information was widely available and inherently embedded into this situation/scene as my parents announced my grandparents would be over very soon. Also, their arrival was expected as it was my sister's birthday. I remember thinking, why would Timmy be barking at grandma and grandpa? Who were the ones outside the door? For an adult, it is clear that none of that information was conditioned and made available to Timmy in a format he could utilize to inform his future actions. This curiosity about decision-making processes has driven many of my inquiries into uncertainty research, including this dissertation.

ABSTRACT

A BAYESIAN NETWORK BASED APPROACH TOWARD AN ANTICIPATORY SAFETY REASONING SYSTEM AUTONOMOUS VEHICLE COPILOT

by

PHILIP ALLEN FREDERICK

Adviser: Ka C. Cheok, Ph.D.

Future ground vehicle transportation is expected to rely heavily on autonomous mobility. However, the technical progress required to ensure a completely safe autonomous vehicle for unlimited roadway use, and reliable ways to measure its safety, is behind expectations. It is believed that a research breakthrough is required to address this gap.

This dissertation defines a novel method for addressing on-road autonomous vehicle safety, explicitly focusing on unsignalized intersections. A method is described to generate an anticipatory safety copilot to assist the autonomous system with motion decisions by combining data collected from global online sources and the local autonomous vehicle sensors. This anticipatory copilot reasons about the environment around the autonomous vehicle and projects the vehicle's real-time motion intent forward into a projected future version of the environment created via features from the combined local and global source information. Based on this processed information, the copilot anticipates the probabilistic success of the autonomous vehicle safely executing its intended action.

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LIST OF ABBREVIATIONS

AV	Autonomous Vehicle
FHWA	Federal Highway Administration
ASRS	Anticipatory Safety Reasoning System
DCC	Data Collection & Conditioning
SRS	Safety Reasoning System
BN	Bayesian Network
ADAS	Advanced Driver Assistance Systems
GP	Gaussian Process
SoD	Separation of Duties
AMC	Autonomous Mobility Controller
DAG	Directed Acyclic Graph
CPT	Conditional Probability Table
JPD	Joint Probability Distribution
V2X	Vehicle to Everything
ITS	Intelligent Transportation Systems
PL	Physical Layer
SL	Semantic Layer
W_S	World Semantic
W_P	World Physical
CS_D	Congestion Sufficiency $_{\text{Direction}}$
MDC	Map Data Congestion

LSC	Local Sensor Congestion
SA	Safet Action
EA	Execute Action
CRL	Congestion Reference Limit
VTE	Virtual Testing Environment
TTC	Time To Collision
MPH	Miles Per Hour
FPS	Feet Per Second
FHSA	Federal Highway Safety Administration
ROI	Region Of Interest
FOV	Field Of View
DBN	Dynamic Bayesian Network

CHAPTER ONE

FOUNDATIONAL OVERVIEW

This research aims to help address the gap between the world of human decision-making processes and machine-based decision-making processes, specifically in the domain of autonomous driving. The specific application domain is autonomous vehicle safety systems. This first chapter is an introduction and overview of the collective works and thoughts that have informed the basis of this effort.

1.1 Motivation

Human mobility is built around patterns and routines [1]. So much so that society is modeled around rules and laws established to leverage and encourage these concepts. Sidewalks exist where pedestrian foot traffic is expected, freeways are constructed where traffic flow is estimated to be congested, and rules exist to dictate how individuals operate vehicles on shared roadways. These mobility-oriented considerations influence human actions and, by design, encourage coherent decision-making that can result in predictable behavior patterns. Research has shown that human movement patterns can be up to 93% predictable [2]. This predictability is utilized by both commercial and government agencies in a multitude of private and public applications [3]. It is a natural sequence of thought to explore how these known probabilistic patterns can assist autonomous vehicles in navigating public roadways populated with human-driven vehicles.

1.2 Introduction

Future ground vehicle transportation is expected to rely heavily on autonomous mobility [4]. Market estimations indicate that between 2030 and 2060, autonomous vehicle sales will grow by 80%, and by 2060 half the vehicle fleet on roadways will be autonomously enabled [5]. However, technical progress required to ensure a completely safe autonomous vehicle for unlimited roadway use, and reliable ways to measure its safety, is behind expectations. It is believed that a research breakthrough is needed to ensure autonomous mobility software is mature to a point where it can handle complex driving scenarios the way humans do [6]. This research aims to provide an approach toward developing an autonomous vehicle safety reasoning system capable of emulating humanistic decision-making, specifically in Autonomous Vehicle (AV) safety.

The primary scenario for this application will be AV decisions at unsignalized intersections. One of the most challenging scenarios for AV decision-making is safely executing left-hand turns at these intersections into oncoming traffic [7]. Figure 1.1 displays a scenario where an AV Jeep attempts a left-hand turn into oncoming traffic. This scenario is a complex and unsolved problem for commercial and military applications.

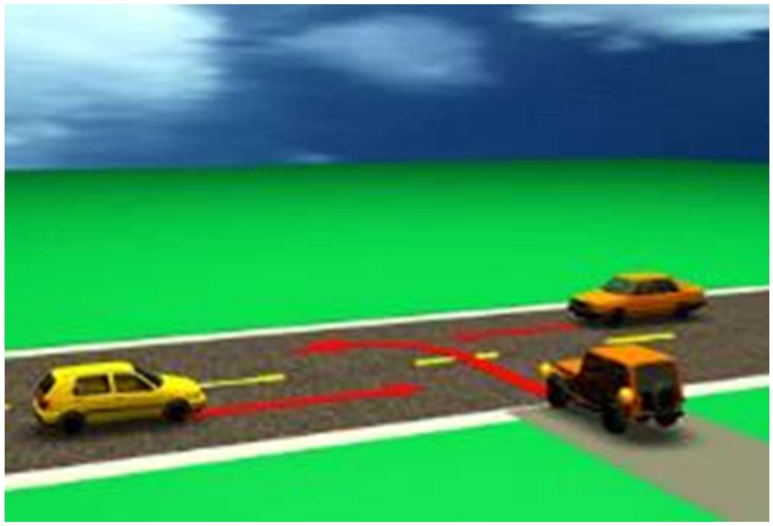


Figure 1.1 AV Jeep planning left-hand turn into oncoming traffic

1.3 Application Domain

The application domain this research is focused on is advancing autonomous mobility safety at unsignalized intersections. Per the Federal Highway Administration (FHWA), unsignalized intersections are the most common type of intersection in the United States [8]. These intersections account for 70% of the fatal crashes that occur yearly at US intersections. Unsignalized intersections are classified as either Stop Sign-Controlled, Yield Sign-Controlled, or Uncontrolled. Of these types of intersections, specifically t-intersections and roundabout entryways are the application focus for this dissertation. These two types of intersections represent some of the most dangerous [9] and more computationally challenging to negotiate for humans and AVs [10] as they involve both high-speed traffic interactions and unprotected turns into oncoming traffic.

1.4 Problem Statement/Hypothesis

AV motion safety at unsignalized intersections is an unsolved problem [6]. Unsignalized intersections are the most abundant type of intersection in the United States. These intersections provide for some of the more dangerous interactions between vehicles on roadways, given they involve both high-speed traffic interactions and unprotected turns into oncoming traffic [9,10]. Current techniques enabling existing AV testing on roads do not sufficiently address this situation, and a research breakthrough is believed to be required [6]. This dissertation presents novel research toward enhancing AV safety at these intersections.

Dissertation Hypothesis: An anticipatory safety reasoning system can improve AV motion decision safety at unsignalized intersections.

1.5 Technical Approach

This dissertation develops a statistical model-driven process to address AV decision uncertainty via a novel anticipatory inferencing technique implemented utilizing a Bayesian Network (BN). This development involves two primary processes: A custom environmental data conditioning component and a Bayesian Network (BN) approach to inferencing. These two processes combined constitute an anticipatory decision process titled an Anticipatory Safety Reasoning System (ASRS). This ASRS concept is the primary contribution of this dissertation.

1.5.1 Data Collection and Conditioning (DCC)

The first primary process of this dissertation involves environmental data conditioning. This is the process in which the systems model of the world is established. This facet of the research focuses on creating a probabilistic and projected segmented model of how traffic conditions likely will be chaining over a short duration window (due to local and global factors). This model filters down to a select series of traffic congestion variables. Each variable has a ‘current time’ value estimated forward and then recorded for a configurable number of time steps. These variables, and their future projections, are used to form evidence observations of an AV safety reasoning system, as shown in Figure 1.1.

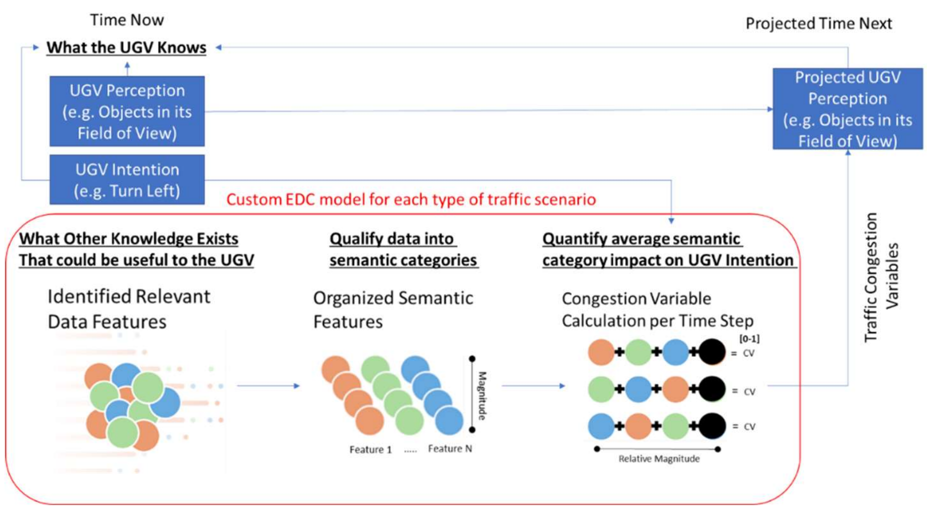


Figure 1.2 Example ASRS data manicure process

1.5.2 Safety Reasoning System (SRS)

The second primary process of this dissertation is concerned with developing, maintaining, and projecting a belief on the safety prospects of the AV’s intended motion. The traffic congestion artifacts produced by the DCC process inform observation data feeding a Bayesian Network (BN) to accomplish this task. The hidden state of the BN represents a belief in the safety proposition of the AV's intended action (e.g., the likelihood that a given AV motion decision will not result in colliding with other vehicles).

1.6 Outline

The rest of this dissertation will is organized in the following way. Chapter 2 will focus on the detailed background and review of existing work in the field compared to the dissertation topic. Chapter 3 will discuss the overlaying assumptions and factors that influence this research and describe in detail the application domain and how this dissertation topic addresses problems in that space. Chapter 4 will describe the DCC process in detail. Chapter 5 will discuss the sub-tasks of the SRS. Chapter 6 will talk about the simulation environment. Chapter 7 will discuss the test results and analysis. Chapter 8 will list alternative approaches to this research. Finally, chapter 9 will list contributions and conclusions.

CHAPTER TWO

BACKGROUND OVERVIEW

As introduced in chapter one, the primary purpose of this dissertation is to describe a method to help bridge the gap between human and machine-based AV decision-making during on-road scenarios. Specifically, the introduction of a process to emulate human anticipation for AV decision-making via an ASRS. This ASRS adds another layer of safety to AV decision-making, similar to how a back-seat driver or copilot would assist a human driver in making safety-based navigation decisions. This chapter will describe the relevant background related to the formation of the ASRS concept.

2.1 Problem Domain Background

Autonomous Vehicles are believed to be an enabler for increased safety for future transportation applications [12]. However, accumulated data on public roadways through 2021 has shown that there are, on average, 9.1 driverless car crashes per million miles driven compared to 4.1 human-driven car crashes per million miles driven [13]. This is especially concerning for the AV industry as research has shown that public support for these systems is based mainly on their safety rather than on economic benefits or privacy concerns [14]. In addition, only 14% of Americans have responded that they would feel safe riding in an AV [15]. According to US policy, each AV industry provider is expected to provide information and data to certify the safety of their systems [16]. Other parts of the world have followed suit in guiding their expectations of commercial AV providers [17]. In addition to this US recently revised its policies to enable future AVs to no longer require human-designed inputs to the vehicles, such as steering wheels and braking inputs [18]. There is an opportunity in this space to explore additional techniques to provide increased safety assurance to these systems.

2.1.1 Expected AV Improved Safety

According to a national survey of police-reported crashes, driver error is the final failure in the chain of events leading to more than 9 out of 10 crashes. However, crash incident research and analysis [19] suggest that only about a third of those crashes resulted from mistakes that automated vehicles would be expected to avoid because they have precise perception sensors and are not vulnerable to incapacitation. AVs must be specifically programmed to prioritize safety over speed and convenience to prevent the other two-thirds of accidents. Planning and decision errors contributed to about 40 percent of crashes in the study. For self-driving vehicles to live up to their promise of significantly reducing crashes, they will have to focus on safety rather than rider preferences when those two objectives conflict. Self-driving vehicles must obey traffic laws and adapt to road conditions while implementing driving strategies that account for uncertainty about what other road users will decide.

2.1.2 ASRS approach to Improve AV Safety

Studies such as the one in 2.1.1 highlight the importance of enhanced safety considerations for AVs. Especially for AVs operating on roadways with human-driven vehicles. The ASRS concept addresses some of these concerns within unsignalized intersections. The ASRS intends to work in conjunction with an AV's existing Autonomous Mobility Controller (AMC) to coordinate the safety prospects of a given mobility decision. The concept is similar in structure to how many newer vehicles operate today with respect to Advanced Driver Assistance Systems (ADAS) [20], as described in Figure 2.1.

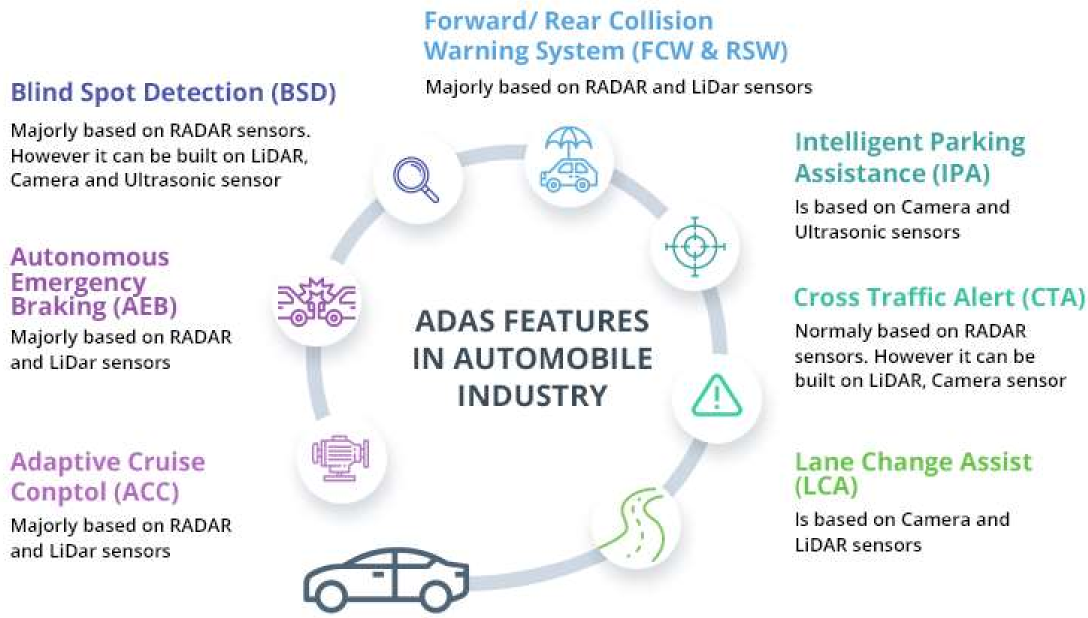


Figure 2.1 Example ADAS safety enablers on many commercial vehicles

There is a separation of duty between the Human Driver and the ADAS system on subfunctions of the driving task (vendor/vehicle specific) [21]. Humans are responsible for the overall driving task, while the automated ADAS subcomponents are responsible for assisting the human with the successful, safe execution of that task (whether it be via lane departure warnings, collision detection/mitigation when backing up, or speed control on highways). This concept of separating the safe driving functions between humans and automated sub-components has been a core component of US cars since the late 1970s with the introduction of electronic anti-lock braking [22]. The ASRS concept acts as an ADAS system for an AMC rather than a human driver (e.g., ADAS for AVs).

2.1.3 General AV Safety Research

Much of the automotive autonomous navigation literature research concerning safe motion-decision making within complex scenarios utilizes probabilistic techniques. In [23], the authors describe a control technique for determining control actions for robotic vehicles at intersections using probabilistic approaches that consider intended autonomous vehicle actions and the estimated intent of other vehicles within the scene. In [24], the authors present a method for an autonomous ground vehicle to present an optimization-based path planner capable of planning multiple contingency paths to predict future trajectories of dynamic obstacles. However, both of these approaches are limited to accounting for obstacles that can be seen at the local vehicle level, thus limiting their applicability to predict the actions of obscured vehicles. In [25, 26], the authors present a method to cluster vehicle actions into a set of policies to model and determine the behavior of the autonomous vehicle of interest and react to the actions of other vehicles. This policy clustering system allows the autonomous vehicle to predict the actions of other vehicles in the scene based on observed history states. However, it presents a very complex policy determination methodology that can only work in real-time scenarios if a small set of predetermined policies are considered. In [27, 28, 29], the authors assume that there is no uncertainty associated with future states of obstacle vehicles in their approach toward developing deliberate reactive control techniques. The assumption is that some communication exists where other scene actors broadcast their intentions over communication channels. In [24, 30, 31], the anticipation techniques consist of computing the possible goals of an obstacle vehicle by planning from its standpoint, accounting for its current state. This strategy is similar to the factorization of potential driving behaviors into a set of policies described in [26] but lacks a closed-loop simulation of vehicle interactions. In [32, 33, 34, 35, 36], Gaussian Process (GP) regression was utilized to learn typical motion patterns for classification and predict obstacle agent trajectories. In [37, 38], the authors propose hierarchical dynamic Bayesian Networks where some of the models on the network are learned from observations using an expectation maximization approach to execute behavioral goal selections.

2.1.4 Unsignalized Intersection AV Safety Research

Specifically, in the case of unsignalized intersections and AV motion, recent years have seen an uptick in research activity in this space. In [39], the authors use a multi-memory storage approach to predict the motion of humans at unsignalized intersections to address potential human AV collisions. In [40], the authors designed a controller that can effectively solve the collision avoidance of multiple vehicles at intersections under the framework of a scheduling problem. In [41], the authors proposed a system design for automated/connected and conventional vehicles approaching an isolated intersection, which can maintain shorter and more stable headways to the leading vehicles. In [42], the authors considered the interaction between automated and human-driven vehicles and proposed a decision algorithm by learning the typical behaviors of other vehicles. Finally, in [43], the authors used classic game theory to analyze the driver coordination mechanism, while there were few details about the payoff design in decision matrices.

These research approaches toward enhancing automotive safety in AV decision-making focus on implementing their designs directly into a vehicle's core AMC. They propose a means to address safety navigation challenges in complex and dynamic environments by applying specific new path planning, object motion estimators, or dynamic decision engines. None of these efforts look at the problem from the perspective of an independent process that monitors and observes the holistic output decision of the AMC. None consider the decomposition of the safety mission into a separate decision process, as in this research.

2.2 ASRS Description and Components

In contrast to the approaches described so far, the ASRS is designed to be a separate and independent processing system. Rather than an embedded sub-component of a specific AMC sub-process, the ASRS safety approach is designed as an independent co-component of the AV system. It is designed to interpret the world around it and separately reason upon the intended action of the AMC. It interprets the AMC decision based on its evaluation of the world where the AV is to be performed, as shown in Figure 2.2.

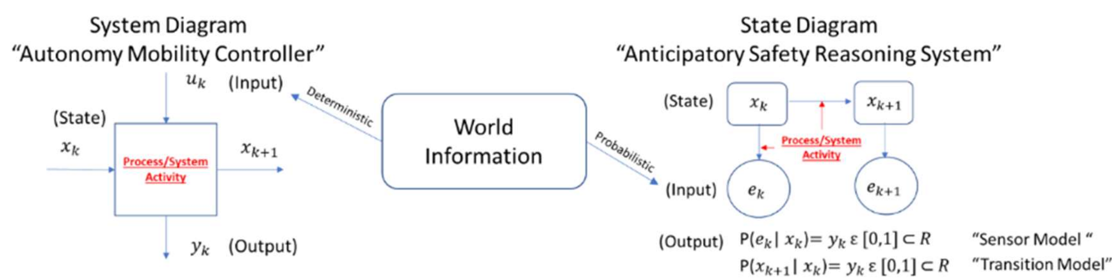


Figure 2.2. AMC vs. ASRS Processes interpreting the world around the AV

Breaking the AV navigation decision task into separate components is an intentional technique called separation of duty.

2.2.1 Separation of Duties (SoD)

A proven approach to accomplishing a complex task is to separate the job into simpler discrete components. This approach is taken in many domains/formats/fields (e.g., mathematics/decision-making/finance) to decrease the cost of a task/activity and increase the expectation of success and delivery. A common phrase used to define this method of problem-solving is referred to as decomposition. Once a task is decomposed, it is binned, prioritized, and assigned resources per the timelines/importance associated with it. One method to allocate resources is a separation of duties [44]. This concept is typically considered in business applications to have more than one person required to accomplish a complex task. This is done as an internal control to prevent fraud and errors in any given activity. There is an analogy in a complex driving task where there is a place for internal control on the safety consideration of any intended motion execution of the AV. This is especially true in heterogenous driving environments (e.g., human-driven and autonomous vehicles on a roadway simultaneously) where simple errors could result in loss of life.

It is also noteworthy to mention how the concept of separating driving tasks into components is closely related to what we do as humans when addressing complexity. For example, in rally car racing (Figure 3), the task of navigating the vehicle from the start line to the end is separated into two components. First, the driver deals with the real-time dynamics of moving the vehicle through the course. Second, the co-pilot is focused on providing the driver with information related to upcoming topology features on the path such that the driver can position the vehicle in an optimal orientation to negotiate these features (e.g., turns) as quickly and safely as possible.

Figure 2.3 Example case of SoD applied to Rally Car Racing

The utilization of SoD is of particular importance in the space of future AV navigation. The technical approach to AV control software design is moving to the domain of multi-layered deep-learning neural networks. The issue with the deep-learning-based AMC software is that the perception and control loop decisions become more tightly coupled. This coupling affects the interpretability of the AMC decision-making by human designers. Thus understanding why an AV AMC would make a given decision becomes more hidden and unexplainable. This move from the domain of deliberate human lead algorithmic design to layered trained neuron responses complicates the safety case for these systems. As a result, the human process and interpretation of safe actions become less apparent in the resulting action and any follow-on interpretation (say in accident analysis). Therefore, the ASRS system is designed to include human expert decisions in the AV motion decision space. This is accomplished by intentionally setting the values of the BN conditional probability tables with human expert knowledge (described in chapter 5). The output of the ASRS is the probability that the AMC desired AV action will be able to be safely executed via the anticipated changing scene.

2.2.2 Anticipation

As seen in Figure 2.2, both the AMC and ASRS systems work to reason about the world around the autonomous vehicle. Still, each utilizes a differently conditioned set of source information. For example, the AMC processes deterministic real-time information related to the current environmental state around the AV to make mobility decisions. On the other hand, the ASRS probabilistically rationalizes the mobility decisions of the AMC, given its understanding of the current and projected world. This utilization of the projected future world state into the AV's current-time safe motion decision processes produces a direct anticipatory feed into the vehicle's AMC, as shown in Figure 2.4.

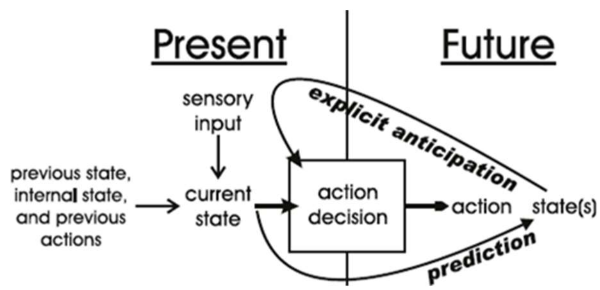


Figure 2.4 Explicit state-based anticipation influencing present-time decisions [45]

As Robert Rosen [45] described, an anticipatory system can anticipate the environment around it. Rosen explains how a natural system is internally guided and controlled via encoded information acting as an interactive set of models of self, environment, and relations between the two through time. These natural systems (physical things in the world) are modeled by formal systems, which are mathematical models. These formal models are used to simulate natural systems. But to provide anticipatory knowledge, they must produce predictions ahead of the predicted phenomena, as shown in Figure 2.4. The ASRS is an Anticipatory System designed to operate with an AV's AMC to separate the driving function into separate components. The AMC deals with the dynamics of the real world and provides the AV with immediate goals regarding the vehicle's motion decisions. The ASRS is meant to serve as a co-pilot to the AMC, focusing on monitoring and projecting the safety prospects of the AMC's intended actions via a limited duration projected future model of the scene (like the co-pilot in rally car racing in Figure 2.3). The ASRS is generally similar to an ADAS system, assisting with human driving tasks. However, the AMC is the driver, and the ASRS serves in the ADAS in this situation (but in a projective fashion as opposed to in real-time). The concept of an anticipatory robotic system is also a research topic in the industrial and service robotic space and within robotic soccer competitions and other domains [46]. The DCC and SRS subcomponents of the ASRS are described in the following two sections.

2.2.3 DCC Component and Math Principles

The DCC is the data conditioning process in which the systems model of the world is established. This facet of the research is focused on creating a probabilistic and projected segmented model of how traffic conditions likely will be chaining over a short duration window (due to local and global factors). This model is filtered down to a select series of traffic congestion variables. Each variable has a 'current time' value which is estimated forward and then recorded for a configurable number of time steps. These variables, and their future projections, are used to form evidence observations of the safety reasoning system.

The primary mathematical methods employed in this section are feature mapping, thresholding, and value aggregation.

- The feature mapping is performed with regard to the collection and assigning of impact scores to semantic features related to the AV's intended actions. For each feature set, an individual scale of impact on the AV's intended action is created that maps the value of the feature to the effect it will have on the AV's intended action, as shown in Figure 2.5.

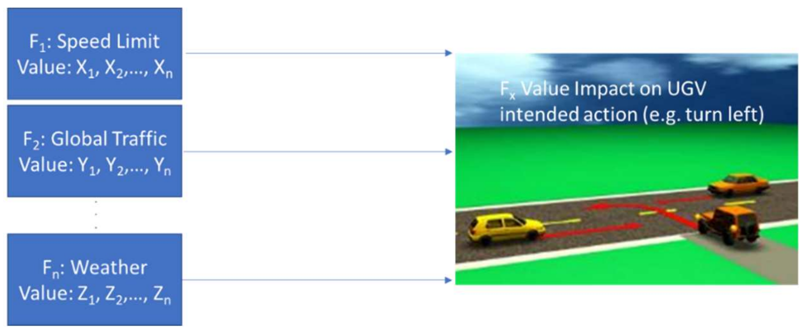


Figure 2.5 Illustration of Mapping Semantic Features to AV Impact Space

- For example, one feature is the distance of the AV unsignalized intersection to the next adjoining signalized intersection in each direction. A scale is created with distance values of the unsignalized (T-intersection) to the adjacent signalized intersection in each direction of travel. For all feature elements, the following scale range is used for mapping values [1 (low impact) – 10 (high impact)]. Next, a mapping to this scale is established for each feature element. In this case, the mapping is for distances with scores for each distance in parenthesis (<1/4 mile (10); 1/4 to 1/2 miles (8); 1/2 to 3/4 (6); 3/4 to 1 (4) mile; >1 mile (1)). The intersection distance in each direction is mapped to a value proposition related to the intended action of the AVs AMC. For example, if the AV turns left, both travel directions matter, and intersections to the left and right are considered. However, if the AV AMC turns right, only the distance to the junction of traffic going left to right is recorded. Chapter 4 goes into more detail about this mapping process.

- Thresholding is used in multiple places to determine whether a value is above, below, or between given parameters. Hard thresholding is utilized when a value is within a determined range or above or below. For example, in the signalized distancing example, all three cases of being above, in between, or below are used as threshold measures to determine the impact score of the situation.
- Value averaging is utilized to determine the combined impact of the semantic features. The total unweighted value of the feature scores are added together and then divided by the total score possible for all features (e.g., a multiple of 10 since each element can have a top impact score of 10).

The specific implementation of these mathematical functions related to their utilization is described in greater detail in chapter 4. Finally, alternative approaches that could have been utilized and the rationale why they were not are discussed in chapter 8.

The next component of this research is concerned with developing, maintaining, and projecting a belief on the safety prospects of the AV's intended motion (especially while negotiating congested complex traffic scenarios such as intersections).

2.2.4 SRS Component and Math Principles

This section is focused on generating traffic congestion variables. These variables are discussed in detail in Chapter 5. They are used as observation data feeding a BN with the hidden state represented as the belief on the safety proposition of the AMCs intended action (e.g., the likelihood that a given AMC motion decision will not result in colliding with other vehicles). A BN is a compact representation of a probability distribution over discrete variables [48]. Variables represent the uncertain knowledge of the given domain and are depicted as the network nodes. The structure of a BN is a Directed Acyclic Graph (DAG), where the arcs have an interpretation in terms of probabilistic conditional independence. The quantitative part of a BN is the Conditional Probability Tables (CPT), each attached to a node, expressing the probability of the variable at the node conditioned on its parents in the network as seen in Figure 2.6 (Uppercase letters (X) denote random variables; lowercase letters (x) denote values; vn denotes different decimal values between 0 and 1). The state of the parent node variables determines the values of the conditional node value. With binary networks, such as the one utilized in this dissertation, the state of parent nodes is typically represented by True of False representations of the activity the variable represents. For example, if variables X1 and X2 represent the state of traffic congestion from a local and global perspective. The values of these variables change based on evidence updates to the network. The change comparison to a set of threshold values, as discussed in Chapter 5.

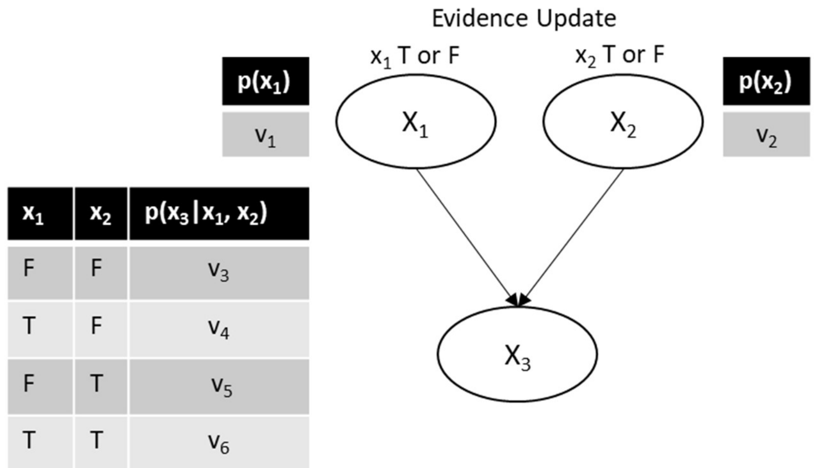


Figure 2.6 Example BN with CPT and parent variables

The Joint Probability Distribution (JPD) over all variables is computed as the product of all these conditional probabilities dictated by the arcs. The JPD entails enough information to attribute a probability to any event expressed with the network variables. BNs provide a compact representation of a JPD. Given a set of variables in Equation 1

$$X\left(X_1, X_2, \ldots, X_n\right) \qquad [1]$$

the JPD for those variables (Equation 2)

$$P\left(X_1, X_2, \ldots, X_n\right) \qquad [2]$$

Can be expressed using the chain rule as Equation 3

$$P\left(X_1, \ldots, X_n\right) = p\left(x_1\right)p\left(x_2 \mid x_1\right)p\left(x_3 \mid x_1, x_2\right)\ldots p\left(x_n \mid x_n \mid x_1, \ldots, x_{n-1}\right) \qquad [3]$$

Where P() is used to denote the joint distribution over all variables (usually expressed as a table), and p() denotes a local conditional distribution. Also, a generic entry in the joint distribution is the probability of a conjunction of particular assignments to each variable, such as $P(X_1 = x_1 \wedge \ldots \wedge X_n = x_n)$.

It is noteworthy that the JPD requires a number of variables that grow exponentially with the number of n variables (if all values are binary, you would need 2^{n-1} probabilities to solve the full UPD). By exploiting the conditional independence between variables, intractability can be avoided by using fewer parameters and a compact expression. Two random variables, X and Y, are conditionally independent given another random variable Z if (Equation 4)

$$p(x \mid y, z) = p(x \mid z) \quad \forall x, y, z \text{ values of } X, Y, Z \qquad [4]$$

that is, whenever Z = z, the information Y = y does not influence the probability of x. The equation can also be written as (Equation 5)

$$p(x, y \mid z) = p(x \mid z)\, p(y \mid z) \quad \forall x, y, z \text{ values of } X, Y, Z \qquad [5]$$

Conditional Independence is central to BNs. Suppose that for each X_i a subset $Pa(X_i) \subseteq \{X_1, \ldots, X_{i-1}\}$ such that given $Pa(X_i)$, X_i is conditionally independent of all variables in $\{X_1, \ldots, X_{i-1}\} \setminus Pa(X_i)$, where $Pa(X_i)$ represents parent nodes as in Equation 6.

$$P\left(X_i \mid X_1, \ldots, X_{i-1}\right) = p\left(X_i \mid Pa\left(X_i\right)\right) \qquad [6]$$

Then using Equation 6, the JPD in Equation 3 turns into Equation 7

$$P\left(X_1 = x_1, \ldots, X_N = x_n\right) = \prod_{i=1}^{n} p\left(x_i \mid Pa\left(x_i\right)\right) \qquad [7]$$

Which is the equation to calculate the joint distribution of a BN. Which states that for any set of random variables, the probability of any member of the joint distribution can be calculated from conditional probabilities using the chain rule with a DAG (establishes conditional independence assumptions)) and a set of numerical probabilities (for each variable given its parents). Inferencing in such a network entails executing Equation 7 whenever new information enters the network at specified parent nodes.

With the methodology background established, it is important to identify and elaborate on the conditions and assumptions being made within the dissertation. Chapter 3 will outline those assumptions and influences before explaining the methodology for the DCC and SRS in Chapters 4 & 5.

CHAPTER THREE

ASSUMPTIONS, INFLUENCERS, APPROACH

Every research effort or designed system is based on a list of assumptions, influences, and approach-specific considerations. This chapter will detail these aspects as it relates to this dissertation.

3.1 Top Level Assumptions

Some assumptions must be detailed before understanding this dissertation's design-specific details. The list of top-level assumptions and their rationale are listed below in the bulleted format:

- The application domain of this research is only focused on a subset of unsignalized intersections and is only focused on vehicle detection and motion estimation.
    - As detailed in the introduction, unsignalized intersections represent the largest portion of intersections in the United States. They are the deadliest roadway intersection and usually do not have heavy pedestrian footprints (one of the reasons only vehicle objects are considered in this effort).
- Human-driven vehicles on roadways exhibit predictable characteristics that can be collected and leveraged by autonomous vehicles to enable anticipatory reasoning.
    - Vehicle motion on roadways is driven by rules and enforced by laws associated with those rules. These facts and the habitual nature of

human movement are used as the justification for the focus of this dissertation on anticipatory AV reasoning.

- Traffic-related semantic meta-data (features) acquired and utilized in this research to determine traffic congestion exist in various digitized formats and are available to the AV via vehicle-to-everything (V2X) communication systems.
    - Such data has been used in analyzing traffic at intersections and found to be effective [47].
    - For this dissertation's purposes, the semantic meth-data data collection is not in focus, and it is assumed that the semantic data included in this dissertation is made available to the AV through the V2X systems.
- Simulation can and must be used to prove the ASRS system's successful effects.
    - Simulation has been shown as an effective tool for validating AV traffic scenarios [49].
    - With the utilization of semantic meta-data as a core component of the ASRS, a simulation environment is a requirement to stimulate and evaluate the system to repeatable real-world-informed scenario data (this assumption and concept will be elaborated on in Chapter 6).

3.2 Influencers

Below is a brief discussion of the influences that informed this research effort.

3.2.1 Personal Experience

The work performed in this dissertation is influenced by deep personal experience via a family member's medical condition [50]. The first dissertation first concept concerned digitally modeling an anticipatory process and was focused on the methods used by audiologists working with children with hearing devices in sound booths. Very you children do not understand the process that an audiologist is trying to execute to tune their hearing device. As a result, they tend to lose patience, and eventually, when they reach a breaking point, the session is over, whether the tests were complete or not. As mentioned, this effort's first concept was a method to anticipate when a child, with little to no communication skills, is close to reaching their breaking point. The approach was to utilize data inferred from the child through technical means such as facial feature tracking, heat signatures, etc. Such a system would be of great assistance to those performing the tests. Audiologists need to acquire as much clean evidence from the child as possible to assess an assistive device's effectiveness in enabling sound. Given brain plasticity, there is a small window for assistive devices to be most effective in allowing sound comprehension and language development in biologically deaf children [51]. The experience of learning and living through this reality was a motivating factor that excited thoughts about an anticipatory approach to attempt to help extend these auditory sessions with young children.

3.2.2 Professional Experience

Given the personal experience that influenced this interest in anticipatory design, it was determined that the requisite medical domain knowledge would not be easily obtained to develop a practical solution in that domain. With 25 years of professional experience in AV systems, this became the natural focal point for applying the anticipatory design concept.

In the audiology case, the anticipatory concept was to devise a method to anticipate when a child would be entering a condition where they would be throwing a fit. This was to be done by knowing what inputs were being sent to the child's hearing device and then tracking features expressed by the child given current inputs via technical means. Then, based on understanding the current state of the child from the tracked features and knowing what inputs were being planned, the concept was to predict a few time cycles forward to determine when the child might enter a fit stage (as demonstrated in Figure 3.1).

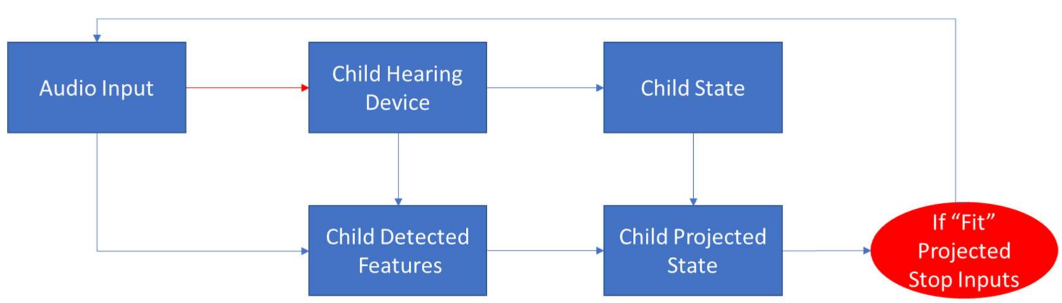


Figure 3.1 Example anticipatory concept for pediatric audiology

In Figure 3.1, a projection is made, each cycle, on the child's "Fit" state. If the system anticipates that the inputs sent to the child will cause a Fit in a future cycle, then the system stops the inputs to the hearing device (depicted by the red line if the fit condition is projected as true). Similarly, Figure 3.2 is a simple diagram of how an ASRS system would operate in conjunction with an AMC to avoid a “Fit” by keeping the AV from moving if projected conditions indicate a potentially unsafe action in future cycles.

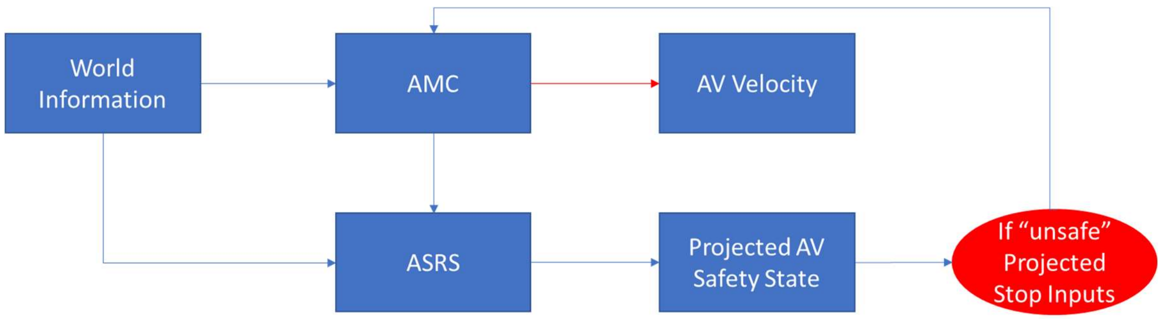


Figure 3.2 Example AV safe motion decision with AMC and ASRS

In Figure 3.2, the ASRS takes inputs from the world and takes in the intended action of the AMC. Then, it calculates the safety of the intended AMC action, based on its interpretation of the world as in Figure 2.2, into future time cycles (described in detail in Chapter 4). For example, suppose the AMC action is projected to be unsafe in the future. In that case, the system stops the AMC from providing the velocity input to the AV (similar to how the system described in Figure 3.1 works, and it is denoted by the red arrow between the AMC and the AV velocity input).

3.3 Approach

This effort focuses on unsignalized intersections for reasons discussed in Chapters 1 and 2. Scenarios are depicted throughout this dissertation to explain the actions the ASRS system would take in those situations. The primary scenario utilized is that of an AV at a T-intersection attempting to make a left-hand turn (as shown in Figure 3.3). The other primary scenarios are a right-hand turn into traffic and merging into traffic at a roundabout.

3.3.1 Template Scenario

The example scenario depicted in Figure 3.3 portrays a primary use case application of this dissertation focus domain. A jeep AV plans to turn left at a T-intersection into oncoming traffic. The green box in the image represents the vehicle's sensor field of view. According to the content of the green box (e.g., nothing in the sensor field of view), the AVs AMC would likely instruct the system to begin its intended left turn in the below scenario. However, if additional available scene information was captured, conditioned against the AV's intent. Then that information was projected forward and inferenced upon by an ASRS system that advises the AV's AMC. The AV may decide not to turn based on the anticipated safety of that action when considering it X-time steps forward. The remainder of this dissertation describes a reasoning process for such a scene-inferencing technique.

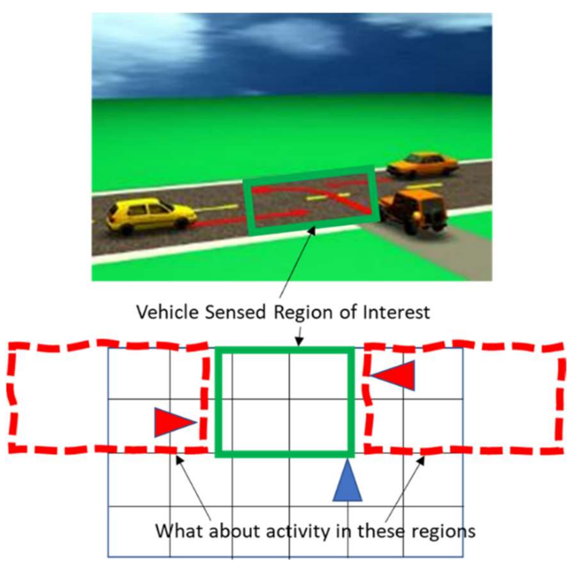


Figure 3.3 AV example use case application for dissertation

3.3.2 ASRS Impact Scenario

Figure 3.4 describes the potential impact of an ASRS system working with an AMC to execute the left-hand turn and the impact of an AV executing that turn with only a limited field of view AMC. The first row of Figure 3.4 is an example of the AV in Figure 3.3 making a left turn using only the local sensor informed AMC. In the second row of Figure 3.4, the AV uses the local sensor-informed AMC and V2X-informed, and time-step-projected, ASRS to determine if it should execute the turn.

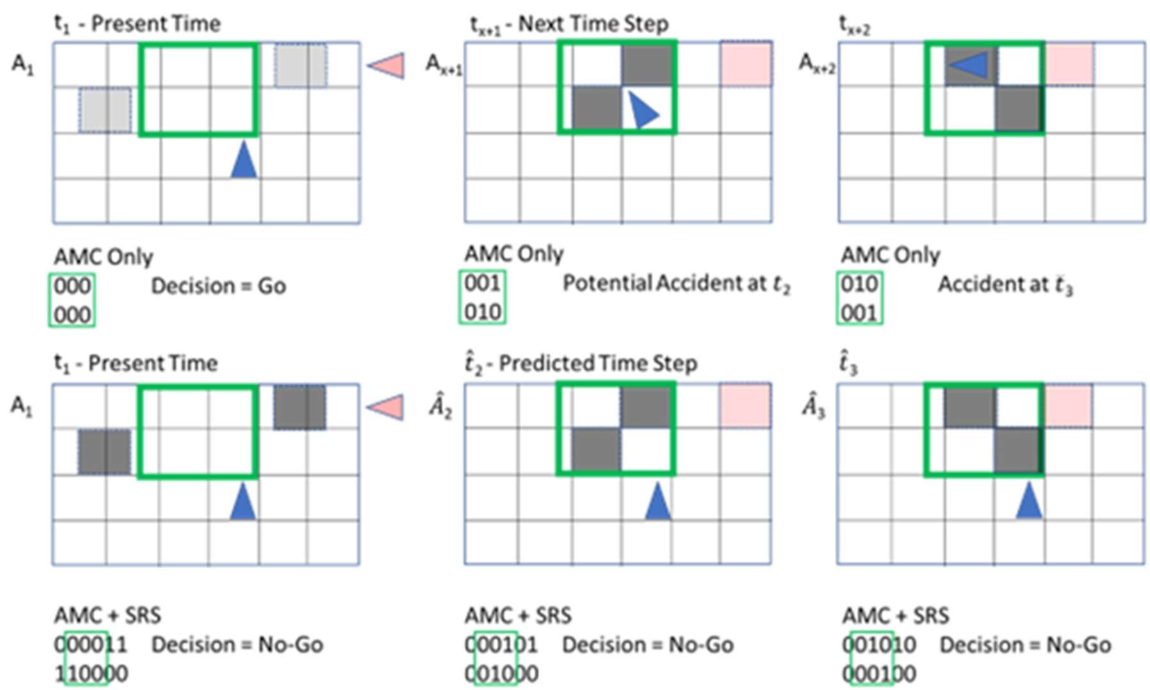


Figure 3.4 AV making a left-hand turn using AMC and AMC+ASRS

As seen in the first row, if the AV uses only an AMC, with the field of view depicted by the green box, it would start its turn at t_1. This would result in a crash of the AV in either t_{x+1} or t_{x+2} time steps. If the AV was enabled with both the AMC and ASRS as in Row two, the AV does not execute the turn at t_1 given its projections of how traffic congestion would change the scene in projected time steps $\hat{t}_2$ and $\hat{t}_3$.

Chapter 4 describes the first of the two primary components of this research effort, the DCC. The DCC collects scene information and organizes this information into categories that can be transformed into simple artifacts and used to interpret the congestion projections of the AVs environment. These artifacts are then passed to the second major component, the SRS (Chapter 5), to calculate the percent chance the AV will be able to protectively execute the AMCs directions safely given how the scene is expected to change.

CHAPTER FOUR

DATA COLLECTION & CONDITIONING

As introduced in Chapter 2, this dissertation proposes an SoD approach toward the safety assurance of AV motion decisions. There is an AMC and ASRS component to the AV decision process. Both systems interpret the world from different perspectives. The AMC interprets the world in real-time and with determinism to make motion decisions. The ASRS is interpreting the world probabilistically and theoretically faster than in real-time to make future projections of the safety prospects of the AMCs intended action. The ASRS system is acting passively and not producing outputs unless the AMC passes it an intended action. In other words, the ASRS always observes the environment but does not always produce a probabilistic safety belief.

4.1 Data Capture, Structure, Storage and Variable Formation

To understand the data conditioning steps of the DCC (which turns the world into a set of traffic congestion attributes), it is first necessary to introduce the data utilized in capturing the objective properties of the traffic scenario (such as the one in Figure 3.3).

4.1.1 Data Capture

The information utilized by the DCC system is captured from the world from two primary sources.

- The first type of data captured is from vehicle sensors with respect to the world in which the AV operates. This type of data is collected from various AV sensors on the vehicle, as represented in Figure 4.1. For this dissertation, there is only a concentration on data captured from forward-looking sensors. The sensor processing and collection are assumed to come from the AV and be provided to the DCC system as roadway vehicle object data relative to the position of the AV. This type of data is stored in a matrix and referred to as the DCC's Physical Layer (PL) data.

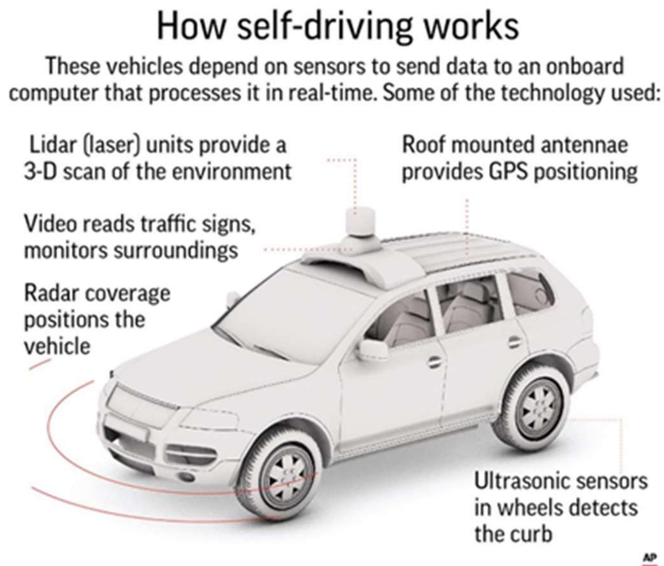


Figure 4.1 Example AV Autonomy Sensor System

- The second type of data captured originates from off-board the AV and comes from Intelligent Transportation Systems (ITS) Data [52, 53]. ITS Data comes from V2X communications (Figure 4.2) and incorporates traffic, weather, topology, and historical roadway information. In addition, this wireless technology connects vehicles to other vehicles, the internet, local infrastructure, and remote infrastructure. This dissertation assumes the availability of this type of information. It focuses on conditioning this information into a context related to the action the AV AMC intends to perform. This type of data is stored in a one-dimensional array [54, 55] and is referred to as the DCC's Semantic Layer (SL) data.

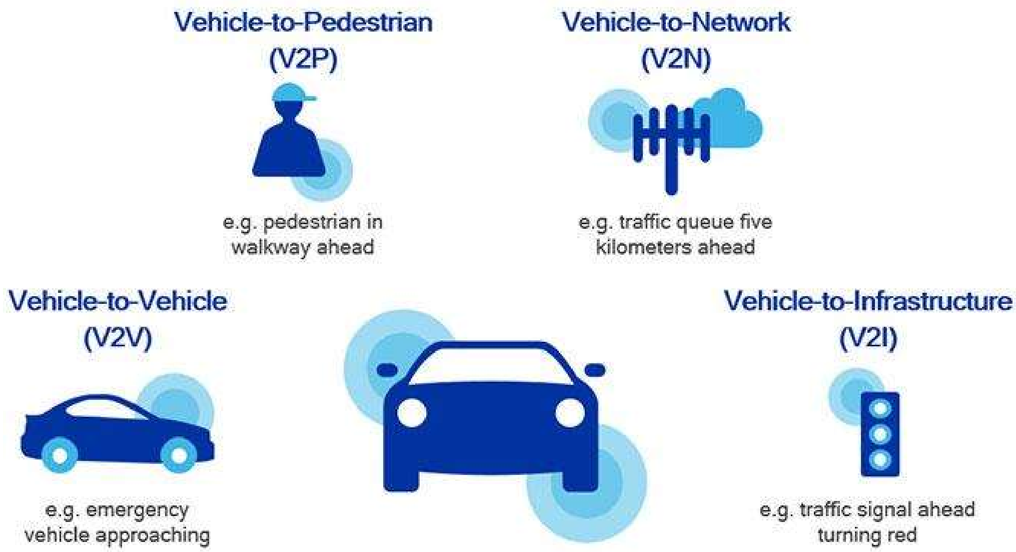


Figure 4.2 Types of V2X communications

4.1.2 Data Structure and Layers

Within the DCC, data structures are established to label and categorize the two types of captured data, introduced in section 4.1.1., as physical or semantic. The physical layer is the section of the AV's world knowledge that deals with information captured from the AV sensors (see Figure 4.1). This information is stored in a matrix format and is processed to project future instantiations of itself. The semantic layer is the AV's world knowledge section that comes from V2X information (see Figure 4.2). Again, this information is stored in a one-dimensional array and processed to help determine future iterations of the physical layer. Figure 4.3 depicts a visualization of the DCC system's two separate data structures.

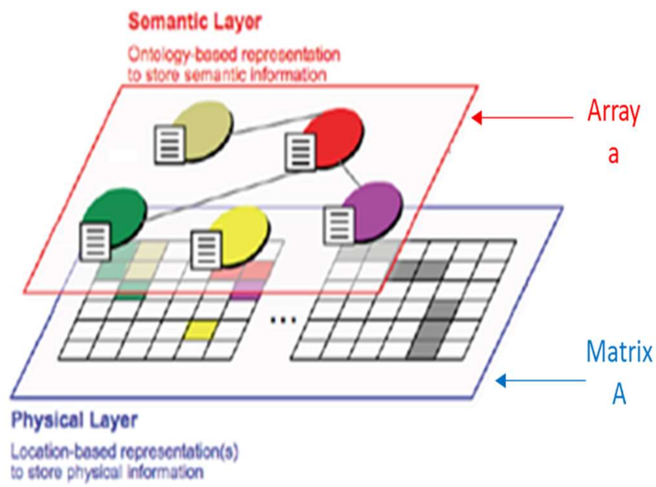


Figure 4.3 Example DCC world knowledge data structure

4.1.3 Data Storage

The captured world data, described in section 4.1.1, is labeled into two data categories (physical and semantic). First, the sensor data from the AV represents the current and projected obstacle map in front of the AV. This physical layer data is described in a matrix labeled 'A.'

- Matrix 'A' is utilized to store roadway occupancy values, as depicted in Figure 4.4. Each cell of 'A' represents a subsection of roadway (as depicted in Figures 3.3 and 3.4) with cell occupancy values (a_{mn}) being either occupied (1) or unoccupied (0) by a vehicle. Matrix 'A' represents the data storage component of the DCC physical layer.

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}$$

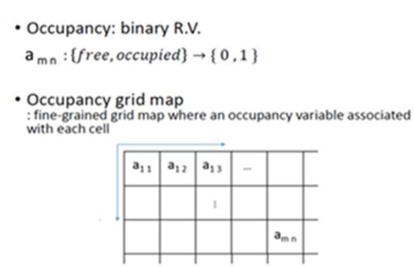


Figure 4.4 Example DCC 'A' matrix data structure

- Array ‘a’ is utilized to store the ITS data that is available and relevant to the AV's intended action, as seen in Figure 4.5. Each array element stores a value between 1-10, representing the inferred impact of that ITS data object on the AV's intended action. For example, if an ITS item of interest was identified to be the traffic congestion at adjoining signalized intersections to the unsignalized T-intersection of the AV, then a high traffic value at the adjacent intersection would have a value of 10 (a low traffic at that signaled intersection would have value 1). The process for how the data is managed and utilized within ‘a’ is discussed in section 4.2.

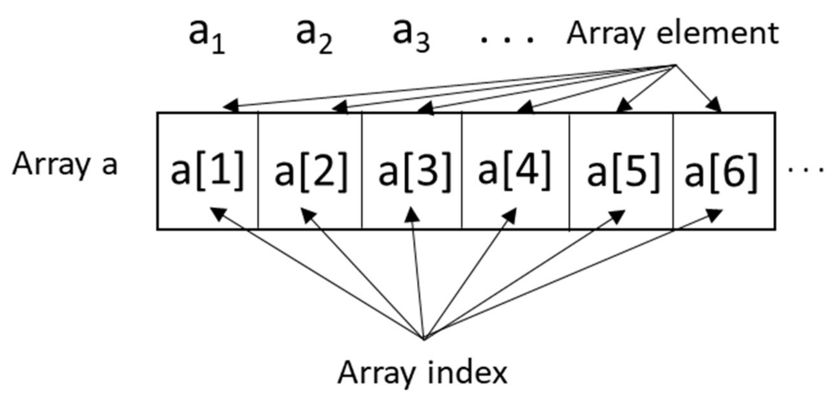
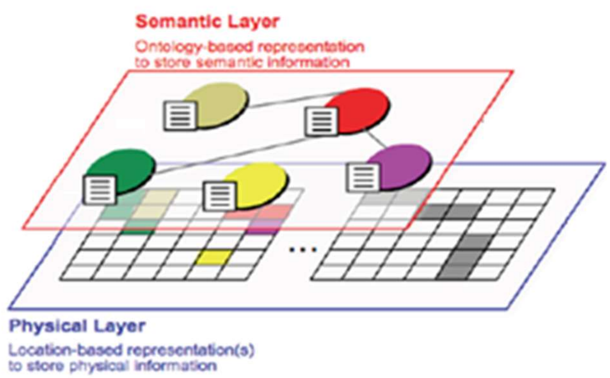


Figure 4.5 Example DCC ‘a’ array data structure

4.1.4 DCC Data Structure and Utilization

The purpose of the physical and semantic DCC data structures and related storage formats is to create a layered representation of the world around the AV that is utilized when determining the projected safety of its motion decision (e.g., more than just what the sensors on the vehicle can perceive, it also provides an ability to consider other available scene information via ITS data as well). This is done by specific data conditioning on the information within each indexed cell of the semantic and physical data storage structures, as shown in Figure 4.6.



Semantic Layer Data Structure Details

- A one-dimensional array of the form:

$$\mathbf{a} = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix}, \quad \mathbf{a} = \begin{pmatrix} a_1 & a_2 & \cdots & a_n \end{pmatrix}$$

- Array 'a' data elements (a_n) update every ASRS system cycle
- Data elements within the semantic layer are integers
    - Semantic Layer → $a_n \in [1, 10] \subset \mathbb{Z}$

Physical Layer Data Structure Details

- A matrix of the form:

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}$$

- Matrix 'A' data elements (a_{mn}) update every ASRS system cycle
- For every 'A' a fixed number of '$\widehat{A}$' projected matrices are generated representing estimated ASRS A cycle states
    - e.g. A → $\widehat{A}_1, \widehat{A}_2, \ldots \widehat{A}_j$
- Data elements within the physical layer are integers
    - Physical Layer → $a_{mn} \in [0,1] \subset \mathbb{Z}$

Figure 4.6 DCC Semantic and Physical Layer Data Structure descriptions

The data within the semantic and physical layers of the DCC is reduced to represent decimal belief values between 0 and 1 (the process for how this occurs is detailed in section 4.2). These resulting variables are referred to as congestion variables within this dissertation. Congestion variables are defined as variables that have instances of themselves projected forward for a given number of time steps. For example, if X were described as a congestion variable over Y time steps, X would have instances of itself between X1, X2,…XY that all stored decimal values between 0 and 1. There is a congestion variable to represent the reduced form of the semantic layer data referred to as the semantic congestion variable World Semantic (W_S). In addition, a congestion variable represents the reduced form of the physical layer data referred to as the physical congestion variable World Physical (W_P). Figure 4.7 further illustrates and describes the congestion variables within this dissertation.

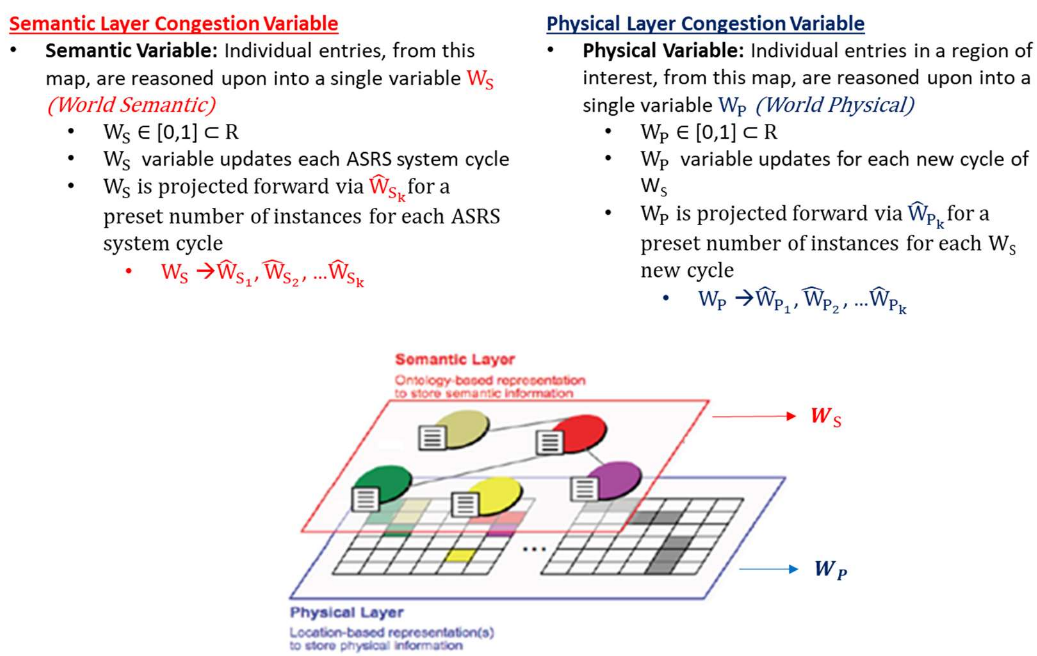


Figure 4.7 DCC Congestion variable illustration and definition

4.2 DCC ASRS Data Conditioning Process

The data structures described in section 4.1 are the data components of the DCC ASRS system. The data conditioning process utilizes these data storage techniques to produce the projected evidence information that feeds the ASRS SRS safety reasoning process (discussed in chapter 5). This section details the process by which the projected evidence is manufactured utilizing the information available to the AV from the physical and semantic data layers.

4.2.1 Semantic Data Pre-Processing Description

The first item to address is how information captured and stored in the semantic layer is transformed into the congestion W_S variable. The types of semantic information captured consist of a configurable ITS data model specific to the intersection type. As first addressed in chapter 1, this dissertation addresses two types of intersections. Those intersection types are the FHSA standard two-lane T-intersection and standard roundabout, as shown in Figure 4.8 [56]

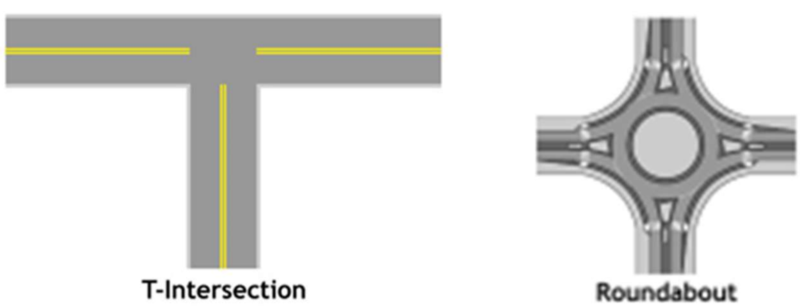


Figure 4.8 FHSA Depictions of T-intersection and Roundabout

- For T-intersections, the features selected are influenced by features used in traffic prediction survey models [47, 57]. The specific features for this model are assigned positions within the semantic layer array 'a' :
  - a_1 at a[1] – Projected Traffic Intersection Flow
    - Global source information about roadway traffic flow at the location of the T-intersection (e.g., Google Maps traffic information)
    - Values are standstill traffic (10), slow traffic(5), no traffic (1)
  - a_2 at a[2] – Distance to next signalized intersection
    - The distance of the AV T-intersection geolocation to the nearest signalized intersection
    - Values are <1/4th miles away (10), ¼-½th (8), ½-3/4th (6), ¾-1 (4), >1 miles (1)
  - a_3 at a[3] – Number of roadway inlets between signalized intersections
    - The number of roadway inlets between the AV T-intersection and adjoining signalized intersections
    - Values are >3 (10), 3 (6), 2(4), 1(2), inlets
  - a_4 at a[4] – Weather and Environmental Conditions
    - The weather and road conditions the AV is experiencing at the intersection
    - Values are for Road Conditions (select one from each category and sum the three values)Road Surface: Icey(3)|wet(2)|dry(1); Vision: night (3)|day (1); Weather: snow(4)|rain(3)|fog(2)|clear(1)

- a_5 at a[5] – Roadway Speed Limit Adjustments
    - The speed limit of the roadway the AV is attempting to turn into
    - Values are ¼ normal (10), ½ normal (5), and normal posted speed (1)..normal is 45 Miles Per Hour (MPH) (speed on a normal roadway).
- a_6 at a[6] – Projected adjoining signalized intersection traffic
    - The traffic congestion at the nearest adjoining signalized intersection to the AVs intersection.
    - Values are green light stopped traffic (10), red light stopped traffic (5), red light no traffic (1)
- a_7 at a[7] – Road Construction
    - Influence of what known road construction has on traffic build-up
    - Values are construction-caused traffic stops (10), construction-caused traffic slow-downs (5), no construction (1)

- All or none of these cells could be chosen to be active during ASRS execution. They could also be replaced, decreased, or increased based on the needs of the implementation. The values of the cells are integer values between 1-10.. A value of 10 implies a high impact on the AV's intended action, and a value of 1 has a low impact on the AV's intended action. For example, a value of 1 for the a[1] cell index would indicate that the state of global traffic (from google maps or another networked ITS global traffic application) is such that it would have a low impact on the AV's intended action. On the other hand, a value of 10 in the a[1] cell index would indicate that the traffic traveling in one, or both, of the directions on the high-speed intersection, is globally congested to the point that it would have the highest impact on the AV's intended action of turning right into traffic as illustrated in Figure 4.9.

10	a_2	a_3	a_4	a_5	a_6	···

Figure 4.9 Illustration of ITS high impact Intersection Traffic Flow

The data in array 'a' of Figure 4.9 contains an impact score for the first element of the array. During actual ASRS operation, each element of array 'a' would assume an impact score. Figure 4.10 details an example of applying the criteria to determine feature scores in this dissertation.

<u>Inputs (1-10 values; 1 (low impact)- 10 (high impact))</u>

- Projected Intersection Traffic Flow (a[1]) = 1
    - Influence of global ITS congestion on UGV intended action
    - Values are standstill traffic (10), slow traffic(5), no traffic (1)
    - Value 1 indicates low traffic from map application and thus low impact
- Distance to next intersection (a[2]) = 6
    - Influence of relative distance to signalized intersections on UGV intended action
    - Values are <1/4th (10), ¼-½th (8), ½-3/4th (6), ¾-1 (4), >1 miles (1)
    - Value 6 indicates the T-Intersection is 3/4th – 1 mile to a signalized intersection thus slight impact
- Number of roadway inlets between intersections (a[3]) = 2
    - Influence of # of primary roadway inlets between T and Signalized Intersection on UGV intended action
    - Values are >3 (10), 3 (6), 2(4), 1(2), inlets
    - Value 2 indicates that there is 1 inlets between T & signalized intersections and thus slight impact
- Weather and environmental conditions (a[4]) = 8
    - Influence of current weather conditions on UGV intended action
    - Values are Road: Icey(3)|wet(2)|dry(1); Vision: night (3)|day (1); Weather: snow(4)|rain(3)|fog(2)|clear(1)
    - Value 8 indicates Icey road surface (3) + daytime (1) + snow (4) and thus high impact
- Roadway Speed Limit (a[5]) = 5
    - Influence of speed limits above average speed for given roadway type on UGV intended action
    - Values are ¼ normal (10), ½ normal (5), normal posted speed (1) due to temporary roadway postings
    - Value 5 indicates reduced speed from 45 mph on rural two lane and thus medium impact
- Projected adjoining signalized intersection traffic (a[6]) = 10
    - Influence of the traffic congestion at the nearest adjoining signalized intersection on UGV intended action
    - Values are green light stopped traffic (10), red light stopped traffic (5), red light no traffic (1)
    - Value 10 indicates green light stopped traffic at the adjoining signalized intersection and thus high impact
- Road Construction (a[7]) = 10
    - Influence of what known road construction has on traffic build-up
    - Values are working with dir. traffic stops (10), working with reduced speed (5), no construction (1)
    - Value 10 indicates roadway work with occasional traffic stops

Figure 4.10 Example ASRS semantic data influence model

Regarding the impact score determination processes of Figures 4.10 and 4.11:

- Each data array element is assigned values specific to the impact of that source information's state (e.g., speed limits, weather, location) on the AV's intended action. The collection of the source information is not the focus of this dissertation. Instead, it is assumed to be collected through ITS information sources described in this chapter and Chapter 3. However, the allocation of the degrees of impact (values from 1-10) is a component of this dissertation, and the factors utilized are detailed in Figure 4.10.
- In the roundabout scenario, a simpler feature model is utilized for the semantic data within array 'a'. The roundabout is a secondary scenario in this dissertation, and not as much emphasis is placed on a detailed feature model. In addition, the features are more dependent on vehicle communications than a mix of vehicle-to-network and vehicle-to-vehicle communications (thus less available) due to the dynamics of the interactions within the scenario. Figure 4.11 describes the features captured for this intersection type.

a[1] – If vehicles are utilizing a network map use their map plan to know their outlet
- If plan indicates cars are exiting after your entrance (10), at your entrance (3), before your entrance (1)

a[2] – If vehicles not sharing mapping application but have vehicle-to-vehicle communication & GPS
- Use information about when vehicles entered roundabout to predict their exit intent: one outlet passed (10),two outlet(5) new vehicle (3), exiting vehicle (1)

a[3] – Use own network mapping application (gaps) for congestion at each inlet
- Congestion at nearest inlet to UGV (10), congestion at 2nd nearest inlet (8), congestion at 3 inlet (5), no congestion (1)

a[4] - Weather and environmental conditions
- Values are Road: Icey(3)|wet(2)|dry(1); Vision: night (3)|day (1); Weather: snow(4)|rain(3)|fog(2)|clear(1)

a[5] - Roadway Speed Limit
- Values are ¼ normal (10), ½ normal (5), normal posted speed (1) due to temporary roadway postings

Figure 4.11 AV roundabout array ‘a’ features

4.2.2 ASRS DCC Semantic Data Conditioning

The semantic data collected in array ‘a’ provides the means to predict the future states of traffic congestion in the physical layer matrix ‘A.’ This occurs through averaging the array element impact scores within an instance of ‘a’ to create an instance of the congestion variable W_S as seen in the following equations.

$$a = (a[1], a[2], a[3], a[4], a[5], a[6], a[7]) \tag{8}$$

$$p = \text{size}[a] \text{ where } p \in \mathbb{Z} \tag{9}$$

$$W_S = \frac{\sum_{i=0}^{p} a[i]}{\sum_{i=0}^{p} \max a[i]} \text{ where } i \in \mathbb{Z} \tag{10}$$

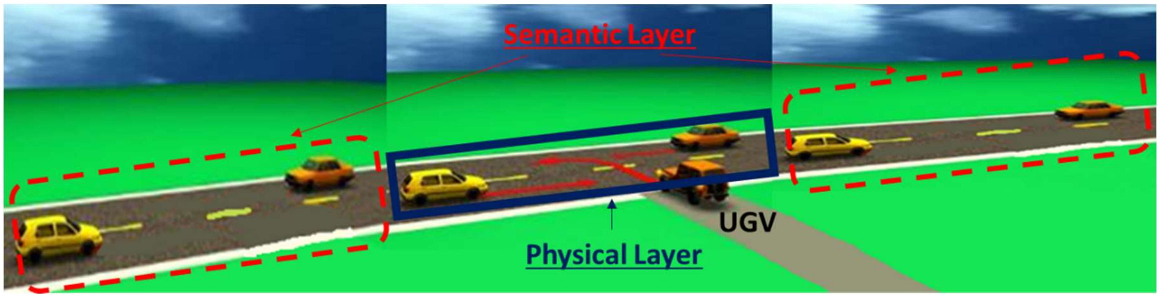
$$CS_D = \text{Congestion Sufficiency}_{\text{Direction}} \text{ where } [0,1] \in \mathbb{R},\ D = \{Left \,||\, Right\} \tag{11}$$

$$\widehat{W}_{S_j} = W_S - CS_D \text{ where } j = 1,\ j \in \mathbb{Z} \tag{12}$$

$$\widehat{W}_{S_{j+1}} = \widehat{W}_{S_j} - CS_D \text{ where } \widehat{W}_{S_0} = W_s,\ j = 0, 1, 2, \ldots \tag{13}$$

These equations produce a result at a configurable update rate associated with the prescribed passage of time for each cycle of the ASRS, as first introduced in Figures 4.6 and 4.7. Equation 8 defines the array ‘a’ for the features used in this dissertation (detailed in Figure 10). Equation 9 captures the size of ‘a’. Equation 10 defines the process to calculate W_S based on the impact score data values of ‘a’. Equation 11 defines the Directional Congestion Sufficiency (CS_D) value. Equation 12 calculates the first projected instance of $\widehat{W}_S$. Equation 13 calculates projected instances of $\widehat{W}_S$ beyond the first instance. An example of how these equations are used is detailed below.

Assume the AV jeep in Figure 3.3 receives an update every i^{th} cycle of the ASRS with updated ITS state information. First, that state information is processed according to the rules denoted in Figure 4.10 for the t-intersection or Figure 4.11 for a roundabout to determine impact scores for the elements of array ‘a’. Next, for each cycle, the W_S congestion variable is calculated to represent the ITS belief on potential congestion in the region of interest of the AV. Next, a W_S score is calculated for each direction of travel on the subject t-intersection being negotiated. Finally, those W_S scores are compared to a configurable preset Congestion Sufficiency $_{Direction}$ (CS_D) variable to determine if the combined average score of the semantic features is viable enough to project a change in the physical layer of the ASRS for the given direction of traffic, as shown in the below conditions and Figure 4.12.



if Left $W_S \geq CS_{Left}$ then Physical Layer impacted

if Left $W_S \leq CS_{Left}$ then Physical Layer not impacted

if Right $W_S \geq CS_{Right}$ then Physical Layer impacted

if Right $W_S \leq CS_{Right}$ then Physical Layer not impacted

Figure 4.12 Illustrative semantic and physical layer regions of interest depiction

In Figure 4.12, traffic congestion outside the region of interest of the AV intersection comes from both the left and right direction of the AV on the two-lane roadway. As described above, in the conditions listed in Figure 4.12, a W_S score is calculated for each direction of oncoming roadway traffic and compared to a CS_D sufficiency score for the given direction. The CS_D is a preset value between 0 and 1 that determines whether the combined value of the information in the semantic layer reaches a level significant enough to make predictions on vehicles that could be entering into the physical layer in the next system cycle. A value of 0 represents no impact on the physical layer, while a value of 1 would be an absolute predicted vehicle to the physical layer. For this dissertation, the value of CS_D is set at design time. In future work, this variable could be learned by the ASRS DCC over a period per intersection type and experienced physical layer conditions.

4.2.3 ASRS DCC Physical Data Conditioning

The physical layer of the ASRS is comprised of vehicle objects from the AV's processed sensor data and inputs related to potential vehicles that arise from the semantic layer processing discussed in section 4.2.2. As discussed in chapter 3, this dissertation focuses on only vehicle objects within the physical layer and assumes processed sensor data that provides that information. Precise sensor processing and sensor development related to AV applications is an active area of research. Many approaches utilizing different sensor modalities and configurations could provide this information [58,59,60,61]. These systems generally work to collect identifying object data from scene information gathered from one or many sensors on an AV to identify a litany of objects surrounding the AV, as seen in Figure 4.13.

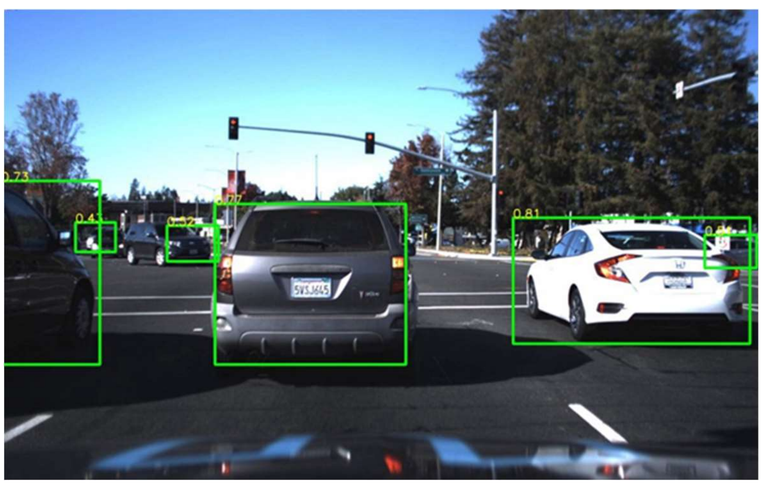


Figure 4.13 Example of vehicle detection from an AV

In Figure 4.13, vehicle objects are identified by a software algorithm running on a computing device from the perspective of a trailing vehicle. This data could be from a single sensor or multiple sensors that produce the classified data objects (in this case, vehicle objects highlighted with green boxes). All the other objects in the scene are filtered, and only vehicle object data is the algorithm's output. This is an example of the type of input that the physical layer requires and is expected to be received from other algorithmic processes running on the AV. Also apparent in Figure 4.13. is the fact that the vehicle capturing the object data is behind other vehicles stopped at a signalized intersection. In this dissertation, the AV could be similarly behind other vehicles but at an unsignalized intersection (t-intersection or roundabout). Suppose vehicle object data was detected directly in front of the AV and oriented such that the object was not on the intersecting roadway. In that case, that data could be used as a queue for the ASRS not to run (though this is assumed for an operational system and not a process implemented in this dissertation). The ASRS is meant to operate only when the AV enters the intersection unobstructed. Thus, it is established that the ASRS DCC physical layer only operates on vehicle object data and must have an unobstructed view of the intersection.

With an unobstructed view of the intersection, the physical layer operates based on a two-dimensional grid representation of the scene in front of it. The matrix ‘A’ is a grid cell representation of the world where each grid is sized, pre-determined, such that it approximately represents the dimensions of an average-sized US vehicle, given that the AV has an unobstructed view of the unsignalized intersection. Figure 4.14 demonstrates placing a grid cell representation over the cartoon scenario in Figure 3.3.

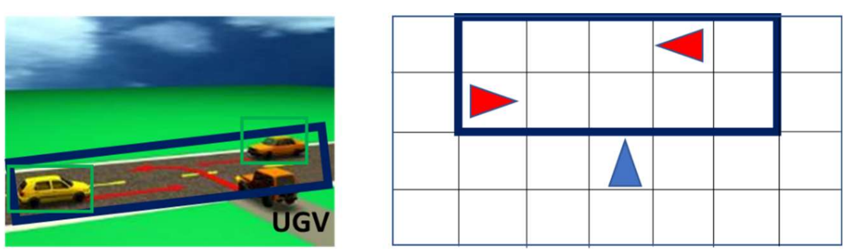


Figure 4.14 Illustration of physical layer ‘A’ grid cell to scenario data

Figure 4.13 demonstrates what an AV unobstructed view of an intersection would look like regarding the sensor field of view (blue rectangle) and vehicle object detection (green rectangles). The vehicle object data from the scene is captured in matrix 'A' where each cell is sized to represent an average vehicle (as previously discussed). The cell size embodies the vehicle's expected motion through space in a one-second interval. This interval is the simulation time for this dissertation, not the real-world ASRS operational time. Real-world ASRS cycle time would be expected to be on the order of milliseconds, or possibly nanoseconds, depending on the update rate of the AMC the ASRS is assisting (given the ASRS is expected to operate in between AMC decision cycles). The initial capture of the scene forms the base 'A' matrix for each update of the semantic cycle. The physical layer has a different cycle than the semantic layer. For every update of the semantic layer, there are a preset configurable number of updates to the physical layer. Upon a semantic layer update, the physical layer creates a Matrix 'A' filled with the information from the AV sensors as illustrated in Figure 4.13. Per the physical later update rate j number of Matrix 'A' projected instances are created. Each instance is a projection from the previous instance of the unsignalized intersections' spatial topology. The predicted instances of 'A' are denoted by '$\widehat{A}_j$,' and there is j of them per each semantic update. The update rate of the physical layer is designed to be correlated with the expected motion of the vehicle objects based on the speed limit of the unsignalized intersection and in accordance with the following assumed properties.

- For each semantic update cycle, a base ‘A’ is either created or updated if the ASRS is operating and filled with the initial physical vehicle object data
    - For each semantic cycle *i*, *j* predicted version of ‘A’ is created and denoted as ‘$\widehat{A}_j$’
    - Each *i* and *j* update by 1, and each cycle, ‘$\widehat{A}_j$’ is an updated version of the prior ‘A’ or ‘$\widehat{A}_j$’
- Each vehicle object within an instance of ‘A’ or ‘$\widehat{A}_j$‘ is a still capture of a vehicle in motion
- Each vehicle object within an instance of ‘A’ or ‘$\widehat{A}_j$’ moves only in the assigned roadway direction between array elements per physical layer update
- Each vehicle object within an instance of ‘A’ or ‘$\widehat{A}_j$’ moves one element in its assigned direction

The above semantic rules are derived from an abstraction of rules of the road standards that encourage maximum speed limits as the intended traversal speed of vehicles on unobstructed roadways [62, 63]. In this dissertation, per United States general rules of the road, object vehicles are expected to move at the posted speed limits on roadways. With these assumptions defined and illustrated in Figure 4.15, an algorithmic approach can be described to update and process the physical layer data.

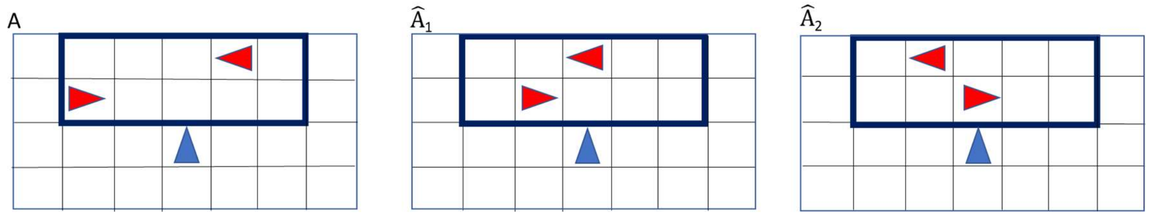


Figure 4.15 Example matrix ‘A’ update for a two-cycle physical layer system

Each semantic layer update produces *j* updates to the physical layer, as shown in Figure 4.15 (which represents a j=1 & j=2 physical layer update). Per each semantic update *i*, the base matrix ‘A’ would be updated with new vehicle object data collected from the AV AMC sensors. From this base matrix ‘A’ predictions for future ‘$\widehat{A}_j$’ matrices are made (‘$\widehat{A}_1$’ and ‘$\widehat{A}_2$’ in this case) within the physical layer. These physical layer predictions predict the motion of the AMC-generated physical vehicle objects present in ‘A’ (as introduced in 3.3.1) and predict potential generation and movement of semantically generated vehicle objects. If either of the conditions introduced in Figure 4.12 are met regarding Right $W_S \geq CS_{Right}$ or Left $W_S \geq CS_{Left}$. Then in the next cycle j of the physical layer, a new vehicle object is projected to be entering ‘$\widehat{A}_j$’ from the associated direction ‘D: Figure 4.16 demonstrates an example semantic update to ‘a’ for both the right and left directions of oncoming intersection traffic.

Inputs (1-10 values; 1 (high impact)- 10 (low impact)) – Left W_S

- Projected Intersection Traffic Flow (a[0]) = 1
  - Influence of global ITS congestion on UGV intended action
- Distance to next intersection (a[1]) = 6
  - Influence of relative distance to signalized intersections on UGV intended action
- Number of roadway inlets between intersections (a[2]) = 8
  - Influence of # of primary roadway inlets between T and Signalized Intersection on UGV intended action
- Weather and environmental conditions(a[3]) = 8
  - Influence of current weather conditions on UGV intended action
- Speed Roadway Speed Limit (a[4]) = 5
  - Influence of speed limits above average speed for given roadway type on UGV intended action
- Projected adjoining signalized intersection traffic (a[5]) = 10
  - Influence of the traffic congestion at the nearest adjoining signalized intersection on UGV intended action
- Road Construction (a[6]) = 10
  - Influence of what known road construction has on traffic build-up

Inputs (1-10 values; 1 (high impact)- 10 (low impact)) – Right W_S

- Projected Intersection Traffic Flow (a[0]) = 5
  - Influence of global ITS congestion on UGV intended action
- Distance to next intersection (a[1]) = 2
  - Influence of relative distance to signalized intersections on UGV intended action
- Number of roadway inlets between intersections (a[2]) = 2
  - Influence of # of primary roadway inlets between T and Signalized Intersection on UGV intended action
- Weather and environmental conditions(a[3]) = 8
  - Influence of current weather conditions on UGV intended action
- Speed Roadway Speed Limit (a[4]) = 5
  - Influence of speed limits above average speed for given roadway type on UGV intended action
- Projected adjoining signalized intersection traffic (a[5]) = 5
  - Influence of the traffic congestion at the nearest adjoining signalized intersection on UGV intended action
- Road Construction (a[6]) = 10
  - Influence of what known road construction has on traffic build-up

Figure 4.16 Illustration of a semantic update into the ASRS for Left/Right W_S

Figure 4.17 demonstrates the left and right traffic-direction W_S calculations associated with the physical layer update based on Equation 10 for the two directions of traffic.

$$\text{Left } W_S = \frac{\sum_0^2 a[p]}{\sum_0^2 \max a[p]} = 0.69 \qquad \text{Right } W_S = \frac{\sum_0^2 a[p]}{\sum_0^2 \max a[p]} = 0.53$$

Figure 4.17 Calculated W_S values for semantic update detailed in Figure 4.16

Figure 4.18 compares the calculated W_S variables for each direction to the preset CS_D variable to determine if a new vehicle object is predicted to be entering '$\widehat{A}$' at the next physical layer update. For this scenario, the value of CS_D is set to 0.6 for each direction of oncoming traffic.

$$\text{Left } W_S \geq CS_{Left}\text{ ; } 0.69 \geq 0.6\text{ ; Predict New Vehicle}$$

$$\text{Right } W_S \leq CS_{Right}\text{ ; } 0.53 \leq 0.6\text{; Do Not Predict New Vehicle}$$

Figure 4.18 Conditions that determine whether W_S predicts new vehicles in '$\widehat{A}_1$'

As determined in Figure 4.18, a new vehicle enters '$\widehat{A}_1$'given that the value of Left W_S is higher than $CS_{Left,}$ but Right W_S is not higher than $CS_{Right,}$ so there is not a predicted vehicle entering the physical layer from that direction, as shown in Figure 4.19

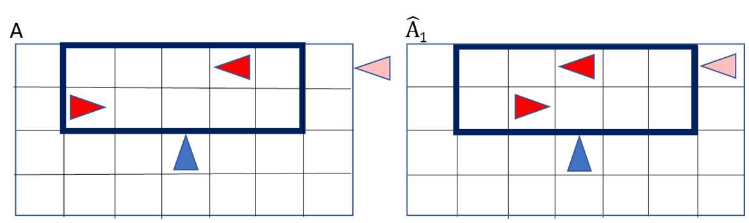


Figure 4.19 Example of W_S congestion variable generating a vehicle entering '$\widehat{A}_1$'

Future $\widehat{W}_S$ calculations are determined by calculating the value per Equations 11 and 12 and then comparing that resulting value to half the CS_D variable, as shown in Figure 4.20 and Figure 4.21.

$$\text{If Left } \widehat{W}_{S_1} \geq \frac{CS_{Left}}{2};\ 0.09 \leq 0.3;\ \text{Do Not Predict New Vehicle in } \widehat{A}_2$$

$$\text{Left } \widehat{W}_{S_2};\ \text{No New Vehicle Prediction via no vehicle prediction for prior } W_S$$

$$\text{Right } \widehat{W}_{S_1};\ \text{No New Vehicle Prediction via no vehicle prediction for prior physical cycle}$$

$$\text{Right } \widehat{W}_{S_2};\ \text{No New Vehicle Prediction via no vehicle prediction for prior physical cycle}$$

Figure 4.20 Conditions that determine if W_S predicts new vehicle object in '$\widehat{A}_2$'

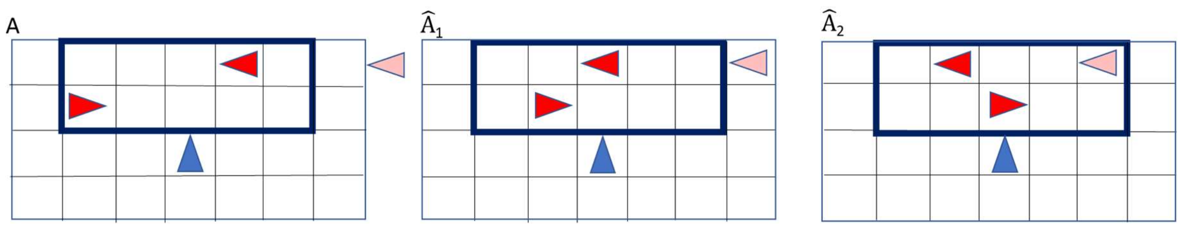


Figure 4.21 Resulting physical layer 'A' and '$\widehat{A}_1$'|'$\widehat{A}_2$' given inputs to 'a'

It is important to reinforce that the number of cycles of the semantic layer is determined by the counter *i* and that there are a configurable number of j physical layer updates for each semantic update. In this extended example description, there are j=2 predetermined physical layer updates per semantic layer update.

In the case of the roundabout scenarios, the same process is executed to predict the future versions of A. However, fewer complete sets of features are available to make predictions, with the predictions only for one direction of traffic. Also, the scenarios as essentially the same, with concern for only one traffic direction shown in Figure 4.22

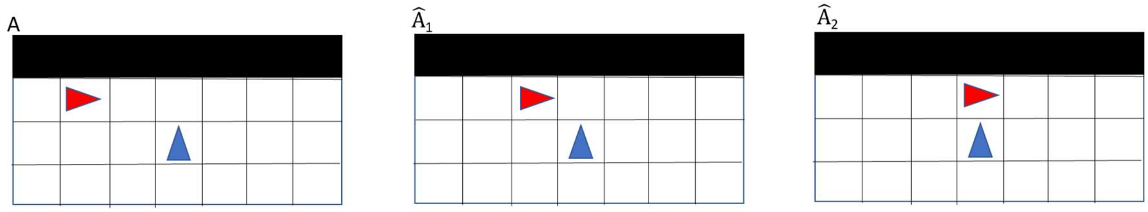


Figure 4.22 AV intending to merge into traffic at a roundabout

In Chapter 5, the physical layer matrices generated in chapter 4 will lead to the generation of the physical layer congestion variable W_P, which will be used to create the congestion evidence for the anticipatory BN reasoning process.

CHAPTER FIVE

SAFETY DATA REASONING

Chapter 4 outlined the data conditioning processes that feed the safety data reasoning system. The conditioned A and $\widehat{A}$ matrices from chapter 4 are the primary inputs that feed the safety reasoning processes detailed in this chapter. These matrices start the process of reasoning upon the safety prospects of the AVs AMC generated intended intersection actions.

5.1 ASRS Physical Data Reasoning

The ASRS semantic data conditioning, described in chapter 4, focused on interpreting and quantizing semantic scenario information so that a single variable representation of that information (W_S) can be generated. It used that value to project vehicle-based physical world changes in future time steps of the current intersection scene (e.g., if a new car is likely to appear in one or two time steps of that current physical world representation). The results of this process is that matrix A and *j* number of $\widehat{A}$ projected matrices are reasoned upon to generate the evidence utilized in the SRS that determines the safety proposition of a given AV intended AMC action.

5.1.1 Simplifying Physical World Data To Congestion States

Starting with the input's 'A' and *j* numbers of '$\widehat{A}$' the following steps are performed to create the physical world congestion variable W_P. W_P is used to determine the congestion sate of each matrix 'A' or related.'$\widehat{A}$'. This congestion state information is used in determining the predictions for the evidence variables in the safety reasoning BN of the SRS.

- Separate ‘A’ into Regions of Interest (ROI) dependent on the AVs intent (turning left, right, merging into the round-about) as shown in Figure 5.1.

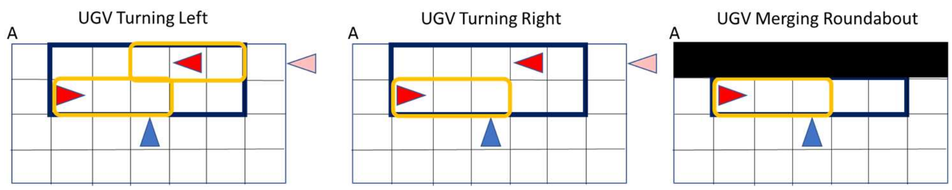


Figure 5.1 Different ROIs based on intended AV action

- Calculate the number of unoccupied vs. total cells in the orange ROIs of Figure 5.1. For the AV turning left scenario, there are two ROIs for traffic flowing in each direction on the primary road (top and second row). The combined unoccupied vs. total cells score is collected in this setting for turning left. For both the AV right turn and AV roundabout merging scenario, only the traffic coming from one direction of travel is relevant, as seen by the orange highlighted ROIs. As seen in the figure, the right-turn scenario has traffic in the opposing direction, but it is irrelevant to the right-turn action. The same modeling style is used for the roundabout merging scenario, but there are not two lanes of traffic in opposite directions to detect (thus the black bar in the top row). For all three scenarios, the calculation for occupied vs. unoccupied values is as detailed in Equation 14.

$$W_P = \left(\frac{\text{Unoccupied Cells}}{\text{Unoccupied Cells} + \text{Occupied Cells}} \right) \qquad [14]$$

- Compare the calculated ROI W_P values, for the last cycle of the physical layer, to a Congestion Reference Limit (CRL) to determine if the predicted values should classify the scene as congested or non-congested. This CRL can be specified via learning, expert, or statistical processes. For this dissertation, the number is an expert set value. In the case of the example, T-intersection left-hand turn scenario used throughout this dissertation (as seen in Figure 3.3), the value is set to CRL = 0.8. The following conditions of Equation 15 describe the CRL determination.

$$\mathrm{CRL} \in [0, 1] \sqsubseteq \mathbb{R} \tag{15}$$

$$\text{IF } W_P \geq \text{CRL THEN A} \parallel \widehat{A}_J \text{ is classified uncongested}$$

$$\text{IF } W_P \leq \text{CRL THEN A} \parallel \widehat{A}_J \text{ is classified congested}$$

The output of this section is the classification of each A value label into the category of either congested or not congested, as well as the W_P scores. This information is utilized in determining the evidence variable states and resulting variable values, as discussed in this chapter's subsequent sections.

5.2 Forming SRS BN

The prior sections within Chapters 4 and 5 have focused on conditioning data around the AV into formats specific to the preparation of accessing the safety of an AV's intended AMC motion decision at unsignalized intersections. This focus was on global semantic data from ITS sources and physical data collected from the AV sensors that are processed into roadway vehicle objects. This complex data was reduced to W_S scores that are compared to preset congestion sufficiency values (CS_D) to predict if there will be a vehicle occurrence in future iterations of the AV's physical world. Per semantic update *i*, the AV physical world is projected forward for *j* iterations, and that data is reduced to a classification of overall scene congestion for each projected physical world representation of ‘A’ or ‘$\widehat{A}_J$‘. The remainder of this chapter will focus on setting up the SRS model, a BN, to reason upon the safety belief of the AV's action based on the CDD artifacts, which produce the evidence and conditional variable inputs.

5.2.1 SRS Variables, DAG, and CPT Introduction

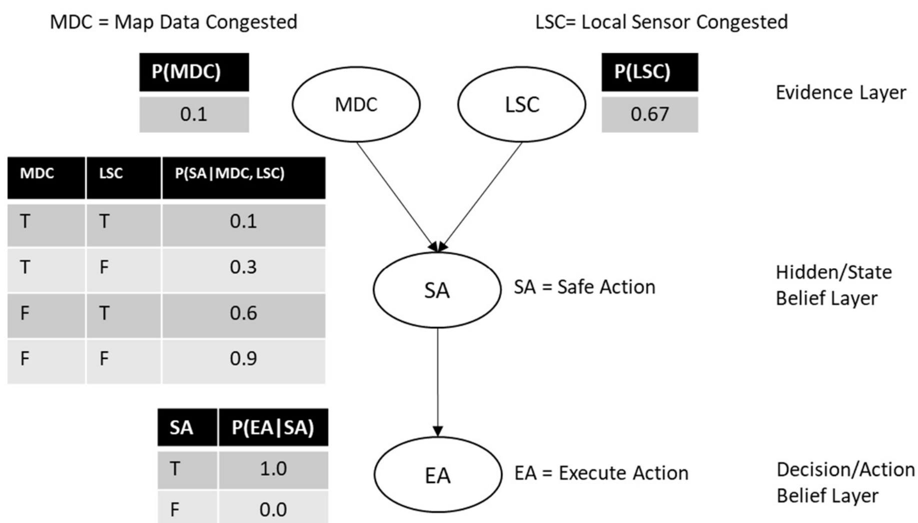


Figure 5.2 Example DAG representing SRS BN

Figure 5.2 details the design of the basic BN that is utilized for the SRS the portion of the ASRS system. This simple DAG is comprised of an evidence layer that contains two variables Map Data Congestion (MDC) and Local Sensor Congestion (LSC), a hidden belief state with one variable Safe Action (SA)) and a decision belief state with one variable, Execute Action (EA). Each variable has a CPT, as shown with reference sample values related to the scene in Figure 3.3. The values for the evidence variables are modified and updated utilizing information generated in Chapters 4 and 5 for each system cycle. The hidden state and belief variable values are set at design time via expert knowledge. Both of these variables could have their values set via parameter learning techniques, but that is outside the scope of this effort and addressed in chapter 9 as future potential work [64]. The SRS DAG is an intentionally basic representation of what a safety reasoning copilot system could represent. The simplistic design allows for a simple process description and reduced computational complexity for this dissertation.

5.2.2 SRS DAG Structure Description

The structure of the SRS BN is based on the directed influence between the listed variables detailed in Figure 5.2. The edges between values denote the direction of the influence. As in all BNs, the nodes represent the variables, and the edges are the relationships between them. The evidence variables feed the hidden state variable and form a conditional relationship on the safety belief of the AV AMCs prospective action (e.g., left turn, right turn, merge into). The safety belief formed in the hidden/belief layer feeds the execute action variable of the decision/action layer. The decision belief layer enables the query to the network to be determined based on a resulting percentage belief of whether the projected AMC action should be executed based on system-level ASRS reasoning on the projected safety of the given action. The directions of the DAG arrows and node placement are a function of answering the single repeated query to the network.

5.2.3 SRS Evidence and CPT Descriptions

The evidence layer inputs to the SRS BN shown in Figure 5.2 are the inputs to the reasoning system. These probability values are formed from the predictions that occur in the physical layer data conditioning processes described in section 5.1. The specific activities related to the formation of probabilities listed in the evidence variables and the truth values of the belief layer's conditional variables are discussed below.

- Map Data Congestion Evidence: The probabilities of the MDC input variable come from V2X ITS information discussed in chapter 4 and displayed in Figure 4.2. A V2X communication to a mapping traffic service is assumed for the AV. A mapping service, such as google maps, contains information regarding traffic flow on roadways given the use of aggregated user location data [67, 68]. If the AV action decision provided to the SRS by the AMC is to turn left, the traffic flow for both directions on the reference road is considered. If the decision is to turn right or the AV is entering a roundabout, then only the traffic congestion in the direction of the intended action is considered. Traffic flow is usually divided into three main speed categories designated by green, yellow, and red map overlays Each mapping service provides a slightly different variation of mapping overlays and classifications. For this dissertation, the google maps format is assumed as it is the most popular of the mapping services [65, 66]. Given the data classifications utilized in Google Maps, Table 5.1 indicates how that information is used for determining the probability of traffic congestion from map data.

	Not Congested	Congested	
	Green	Yellow	Red
Current Time Traffic (MDC)	0.9	0.6	0.1

Table 5.1 Table Detailing Potential MDC Evidence Inputs

Depending on the traffic speed per the mapping application, a value is assigned to represent the percentage of traffic congestion at the given intersection. For example, higher-speed traffic (Green) indicates low congestion, and lower-speed traffic (Red) indicates higher congestion. Given the state of the mapping software overlays at the AV intersection, one of these values is selected as the value for MDC for each cycle. For example, if Google Maps indicated high-speed traffic flow at the AV's current intersection, the probability value for MDC would be 0.1. The MDC probability value updates every cycle of the semantic layer update.

- Local Sensor Congestion Evidence: The probabilities of the local sensor congestion data input variable are set utilizing the predictions of the W_P variables detailed in equation 13. The W_P value of the j^{th} step of the physical layer update for $\widehat{A}$ is used as the value for the LSC variable. The value for W_P at $\widehat{A}_J$ becomes the probability input value for LSC. In Figure 5.2, the example LCM evidence input of 0.67 is because the $\widehat{A}_J$ predicted that the matrix had 4/6 unoccupied cells in the ROI because the AMC desired a left turn at an unsignalized T-intersection. However, if the AMC were intending on a right-hand turn or were entering a roundabout, then the 0.33 value would indicate that 1/3 of traffic cells were occupied.
- Safe Action CPT: The probabilities of the Safe Action CPT are set by expert knowledge at the design time of the BN. The possibilities are applied per the conditional relationship with the evidence variables (whether each variable is true or false). The values currently listed in Figure 5.2 are a surrogate

representation of what an expert would estimate is a safe posture for the vehicle if they were presented with the truth state of the parent evidence variables (e.g., a higher value represents a firmer belief in the action safety based on the conditional relationship to the evidence variable inputs). For the LSC variable, the criteria of being True is decided by whether the W_P value of the last matrix $\widehat{A}_J$, per each update to the semantic layer, is greater than the CRL, as described in section 5.1.1. If that relationship holds, then the value of LSC is False (uncongested). Otherwise, it is classified as congested or True. For the MDC variable, the criteria of being True is decided if the feed from the mapping service indicates that traffic at the given intersection is not green. If the mapping service (google) is green, then the value is False (not congested). Otherwise, it is True (congested).

- Execute Action CPT: The probabilities of the Execute Action CPT are set as 1 and 0 for True and False. As with the SA variable, the value of EA is conditioned on the prior state information. If the value of SA is greater than a given threshold, then Execute Action is True. Otherwise, it is False. The probabilities, however, could be adjusted based on the location of the AV at a given unsignalized intersection (addressed in Chapter 8 as future work) if there is a relatively high rate of yearly accidents at a given road section compared to other adjoining road sections. Then, based on that averaged yearly crash data, the value of trust in the True probability could adjust according to Table 5.2. This table could also be modified to increase the value of the False probability from zero so that the decision to execute the action is not just a binary decision of go or no go.

	Greater Than 25% and less than 50% accident difference compared to adjoining road intersections	Greater Than 50% accident difference compared to adjoining road intersections
Road Section	1.0*0.9	1.0*0.7
Intersection	1.0*0.8	1.0*0.6
Both Intersection and Road Section	1.0*0.7	1.0*0.5

Table 5.2 Table to modify EA True value based on historical accident data

5.3 SRS BN Mathematics and Inference Examples

The concepts utilized for the BN of this effort are simplistic in mathematical concept and follow the BN description detailed in chapter 2 in terms of utilization. The DAG is simple in structure and has a limited number of random variables that contain binary inputs for value probabilities calculated by processes in DCC or provided by expert knowledge. The SRS network is designed to answer the query of whether the AVs AMC intended action should be executed based on the evidence inputs and the CPT probabilities of the conditional variables. Finally, the method to infer if the AVs AMC action should be executed, based on predicted data from the ASRS system, is based on the joint probability distribution of Equation 7.

5.3.1 SRS BN Mathematics

As stated above, the mathematics for the Bayesian Network utilization is straightforward. The Joint Probability of the ASRS BN is known and utilized in performing the inference/query to the network, as detailed in Equation 16.

$$P(EA, SA, MDC, LSC) \qquad [16]$$

This query utilized is the Joint probability equation detailed in Equation 7 that produces Equation 17 when the SRS variables are factored.

$$P(EA, SA, MDC, LSC) = P(EA \mid SA) \cdot P(SA \mid MDC, LSC) \cdot P(MDC) \cdot P(LSC) \qquad [17]$$

EA|SA can be determined by a simple threshold comparison with a user-set SA Threshold real value between zero (no belief in safety) and one (full belief in safety). This threshold is used to determine if the value of SA is of a high enough magnitude level for the AV to execute the intended turn/merging actions (such as SA Threshold being set to 0.5 and SA needing to be higher than that to turn). However, in the testing described in Chapter 7, each SRS EA|SA cycle is set to True (e.g., ea = T), and the comparison is not executed. This is done to provide a non-zero value for EA in cases where SA would be False compared to the SA Threshold. This has no impact on the result of the testing and is done to understand the magnitude of SA during test runs within the simulation. Given what was stated in this section for chapter 7, equation 18 sets the EA|SA value. However, this is not the case for the example test cases in section 5.3.2.

$$P(EA = ea \mid SA) = p(ea \mid SA) \qquad [18]$$

The remainder of the values of the SRS BN are also known, but they are set based on DCC and SRS prior calculations and resulting congestion thresholding results (as described in section 5.2.3). Thus, an example calculation performed using the SRS BN with Equation 16 is be described in Equation 19.

$$P(EA = ea,\ SA = sa,\ MDC = mdc,\ LSC = lsc) = P(EA \mid SA) \cdot P(SA \mid MDC,\ LSC) \cdot P(MDC) \cdot P(LSC) \qquad [19]$$

Equation 19 represents an example query to the SRS BN, given that all of the evidence and conditional variables are set based on the prior processing of the DCC and SRS components. The values utilized represent the example scenario described in scenario 1 represented by Figure 5.4 and Table 5.3 in section 5.3.2. Figure 5.3 demonstrates the inference, in this case, using the SRS BN.

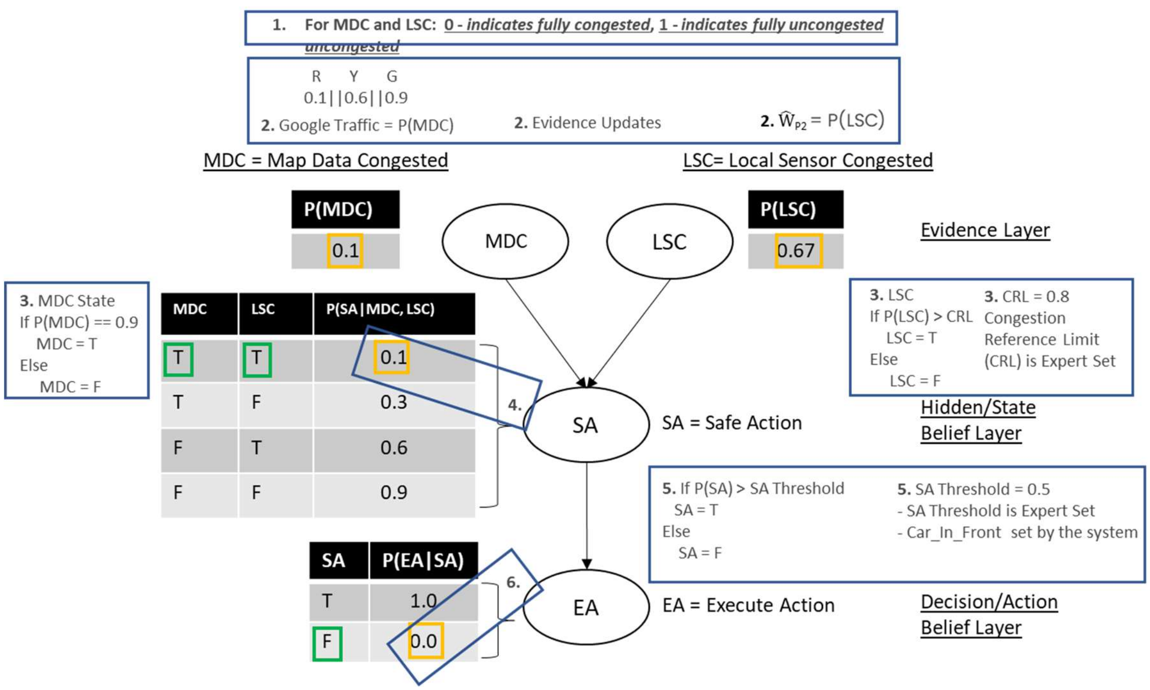


Figure 5.3 Inference example for SRS BN given Figure 5.2 Network

The process flow of the BN in Figure 5.3 is described below:

1. Establish for MDC/LSC values – 0 is fully congested, 1 is fully uncongested
2. Evidence updates come into the network at the Evidence Layer Nodes
3. Determine the truth state of MDC/LSC for conditional SA value selection
4. The value of SA is set once the states of evidence parent's nodes are known
5. Determine the truth state of SA based for conditional EA value selection
6. Value of EA is set once the state of parent node SA is known

More details of the BN inferencing procedure described above, for Figure 5.3, are detailed in section 5.2.3 for each variable in the BN. Additionally, in Figure 5.3, the blue boxes represent the step of the inferencing process, the green boxes represent the determined state of the parent nodes, and the yellow boxes represent the determined value for each variable.

Given the BN process described in Figure 5.3, the calculations for SRS reasoning are reduced to simple variable multiplication via look-up tables. The BN could be significantly expanded to add additional layers of detail that may be desired for dealing with more than just the unsignalized intersections discussed in this dissertation. Adding additional variables would increase computational discerning ability of the network for either unsignalized or other roadway scenarios. For example, more input variables could be added to the evidence layer to increase the accuracy of the ASRS. However, adding these additional variables comes with a cost, as BNs have a complexity of 2^{n-1}. Therefore, it becomes intractable quickly when the network is expanded to include many variables. Other inferencing methods could be implemented to combat this effect rather than the direct inferencing of the full JPD as implemented in this effort.

5.3.2 Inference Examples

As shown in equation 16, the intended query to the BN is the same as calculating the joint probability of the network with a series of given CPT input values. The evidence values are determined through the data conditioning processes of Chapter 4 or utilization of available V2X-delivered global information, as introduced in section 4.1.1. The hidden and decision layer values are determined by the expert set CPT value inputs given the states of the variable parent nodes.

So far, many figures in this dissertation have had a sequenced nature where the information in one feeds the information in the next figure. However, multiple independent complete SRS example scenarios are described in this section that do not sequence information from one figure to the next. In addition, in these examples, both the conditional criteria for determining truth for the EA|SA variable (as discussed in step 5 of Figure 5.3) and the modifier for the CPT values of that variable detailed in table 5.2 are implemented.

Despite the discussion above, the first scenario in this section is one that has been carried through many of the preceding figures, including Figure 5.3. This scenario contains the two vehicles, in the AV sensor field of view and the ROI, approaching from each direction of the T-intersection where the AV AMC intends to make a left-hand turn. In addition, the global semantic information has indicated that a vehicle will be entering the sensor field of view of the AV in a future cycle of the physical layer 'A' matrix. Figure 5.4 below demonstrates this complete scenario.

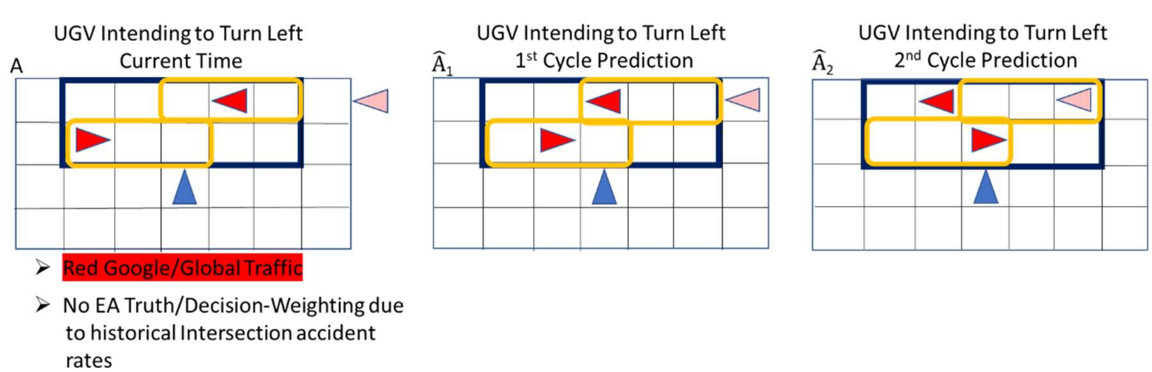


Figure 5.4 Full example Scenario 1 of the SRS BN process

The input variables and the CPT tables for this example scenario are shown in Figure 5.3. The description of the conditions used to form the input variables and CPTs is discussed in section 5.2.2. The SA Threshold for these examples is 0.5. Finally, the inputs to the BN of this scenario are shown in Table 5.3.

	MDC	LSC	SA	EA
Evidence Input	0.1	0.67		
CPT Inputs	MDC=T	LSC=T	LSC=T MDC=T Given V2X & Data Conditioning	SA=T Given Google Maps = Red Traffic Speed
Resulting CPT Value			0.1	
V2X Inputs			Google Maps =Red Overlay for Traffic Speed	No Historical Traffic Inputs to decrease the weight of EA True Value
Resulting CPT Value				0.0 (0.1 !> 0.5)

Table 5.3 Example 1 SRS BN input conditions

Applying Equation 16 (resulting in Equation 19) to the information in Figure 5.4 and Table 5.3 enables the ASRS to predict the safety prospect of the AMC's desired decision to turn left results in the following calculation.

$$P\left(\mathrm{EA}=\overline{\mathrm{ea}},\ \mathrm{SA}=\mathrm{sa},\ \mathrm{MDC}=\mathrm{mdc},\ \mathrm{LSC}=\mathrm{lsc}\right) = 0\cdot 0.1\cdot 0.1\cdot 0.67 = 0$$

So, there is a 0% probability that the ASRS believes that the AMC should execute the intended left-hand turn based on the ASRS calculations that include the semantic and physical world inputs and ASRS projections. This process repeats for every update of the semantic layer, configurable based on the receipt of any semantic layer feature updates from the V2X system or a preset design determination.

In the second scenario, the only change is that the traffic condition is fast-moving and green from Google Maps.

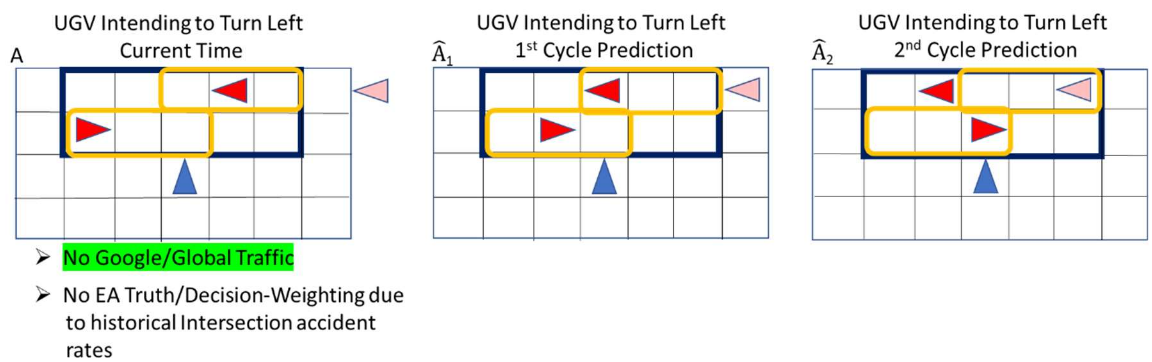


Figure 5.5 Full example Scenario 2 of the SRS BN process

The inputs to the Bayesian Network for this scenario are as described in Table 5.4.

	MDC	LSC	SA	EA
Evidence Input	0.9	0.67		
CPT Inputs			MDC=F LSC = T Given V2X & Data Conditioning	SA=T Given Google Maps = Green Traffic Speed
Resulting CPT Value			0.3	
V2X Inputs			Google Maps =Green Overlay for Traffic Speed	No Historical Traffic Inputs to decrease the weight of EA True Value
Resulting CPT Value				0.0 (0.3 !> 0.5)

Table 5.4 Example 2 SRS BN input conditions

The difference in this table is that the map data indicates no traffic congestion concern regarding the AV's intended left-tun action. However, the local sensor data still indicates a congestion concern at the third predictive step of the ASRS. Therefore, applying Equation 17 to the values within Table 5.4 results in a 0% suggestion from the ASRS to the AMC to execute its intended left-hand turning action.

$$P\left(EA=\overline{ea},\ SA=sa,\ MDC=\overline{mdc},\ LSC=lsc\right) = 1.0\cdot 0.3\cdot 0.9\cdot 0.67 = 0$$

In Scenario 3, the AV is attempting to turn left into the intersection with no predicted vehicles approaching from the semantic layer process, with vehicles clearing the ROI by the 2nd prediction of the physical world, with medium(yellow) traffic flow from Google Maps and finally with a limited feature set update from the semantic process as shown in Figure 5.6.

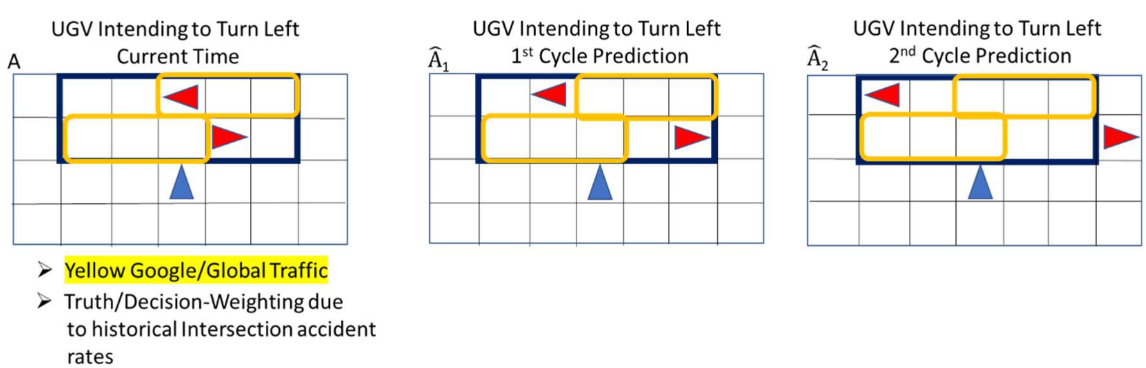


Figure 5.6 Full Example Scenario 3 of the ASRS BN Network Process

Only five of the seven features in the semantic update produced an update this cycle, so the weighting to the belief in EA is decreased by the semantic layer, producing a reduced belief in the truth value of the EA variable, as shown in Table 5.5.

	MDC	LSC	SA	EA
Evidence Input	0.6	1		
CPT Inputs	MDC=T	LSC=F	MDC = T LSC=F Given V2X & Data Conditioning	SA=T Given Google Maps = Yellow Traffic Speed
Resulting CPT Value			0.6	
V2X Inputs			Google Maps =Yellow Overlay for Traffic Speed	Historical Traffic Inputs to decrease the weight EA True Value by 0.1
Resulting CPT Value				0.9 (0.6 > 0.5)

Table 5.5 Example 3 BN Input Condition Summary

In this scenario, SA|MDC, LSC is over the SA Threshold of 0.5. Using the JPD equation 0.32, which normalizes to a 40% belief that the ASRS should execute the AMC intent (given that the top value that can be achieved with the CPT values is 0.81). The values set for SA CPT and MDC input (both expert set) impact max value possible/

$$P\left(EA=ea,\ SA=sa,\ MDC=mdc,\ LSC=\overline{lsc}\right) = 0.9 \cdot 0.6 \cdot 0.6 \cdot 1.0 = 0.32$$

In the 4^{th} the fourth scenario, there is no congestion per LSC or MSC. For this example, the AMC desired AV action is to turn right. In addition, there is no historical traffic data to alter the AC truth action percentage. So only the ROI for traffic in the direction of the right-hand turn is considered, as shown in Figure 5.7

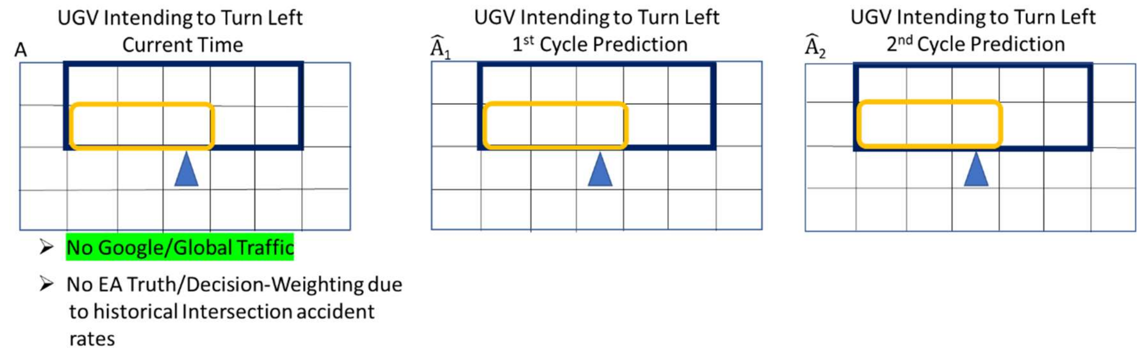


Figure 5.7 Full Example Scenario 4 of the ASRS BN Network Process

The inputs for the resulting BN are seen in Table 5.6.

	MDC	LSC	SA	EA
Evidence Input	1	0.9		
CPT Inputs	MDC=F	LSC=F	MDC = F LSC=F Given V2X & Data Conditioning	SA=T Given Google Maps = Yellow Traffic Speed
Resulting CPT Value			0.9	
V2X Inputs			Google Maps =Yellow Overlay for Traffic Speed	No Historical Traffic Inputs to decrease the weight of EA True Value by 0.1
Resulting CPT Value				1.0 (0.9 > 0.5)

Table 5.6 Example 4 BN Input Condition Summary

As a result, there is a 100% belief that the AMC action should be executed by the ASRS with the given input and set CPT values for this example set of trials (these preset values could be altered for other operations and experiments with this system of system).

$$P\left(EA=ea,\ SA=sa,\ MDC=\overline{mdc},\ LSC=\overline{lsc}\right) = 1.0\cdot 0.9\cdot 0.9\cdot 1.0 = 0.81$$

In the 5th scenario, the AV performs a merge action into oncoming roundabout traffic, as seen in Figure 5.8. No conditions apply in terms of previous traffic accidents.

However, the semantic features used collected are a more limited set, as shown for roundabouts in Figure 4.11. Out of these potential data inputs, only the Google Maps traffic flow information is available for each roundabout and its immediate entryways. Given that for the semantic features collected, less than 50% of them are available for consideration in forming the feature array ‘a’. Thus, the ASRS does not run in this scenario as insufficient information is available to produce a viable result, and the AMC is left to make the motion decisions independently. This is similar to how a human co-pilot would only assist the vehicle driver if there were relevant information to provide.

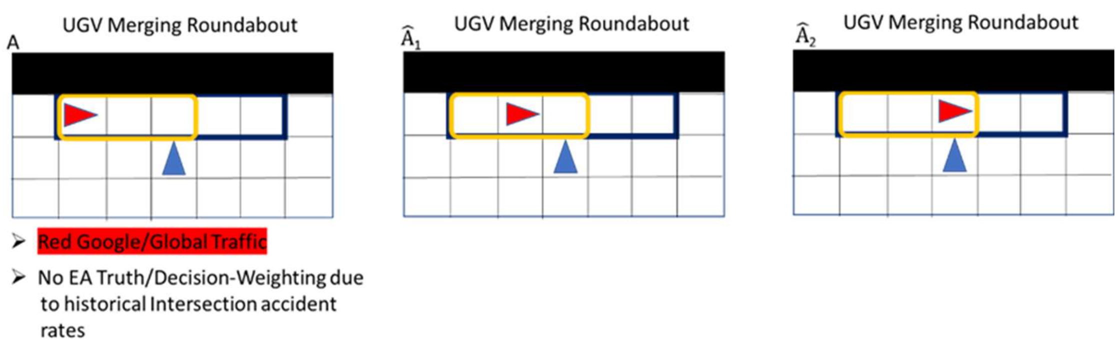


Figure 5.8 Full Example Scenario 5 & 6 of the ASRS BN Network Process

Scenario 6 is the same situation as displayed in Figure 5.8. However, more than 50% of the features are available in array ‘a’. In this scenario, the ASRS system produces the values in Table 5.7.

	MDC	LSC	SA	EA
Evidence Input	0.1	0.33		
CPT Inputs	MDC=T	LSC=T	MDC = T LSC=T Given V2X & Data Conditioning	SA=T Given Google Maps = Yellow Traffic Speed
Resulting CPT Value			0.1	
V2X Inputs			Google Maps =Yellow Overlay for Traffic Speed	No Historical Traffic Inputs to decrease the weight of EA True Value by 0.1
Resulting CPT Value				0.0 (0.1 !> 0.5)

Table 5.7 Example Scenario 6 BN Input Condition Summary

As a result, there is a 0% percent belief that the AMC action should be executed by the ASRS with the given input and set CPT values for this example set of trials (these preset values could be altered for other operations and experiments with this system of the system).

$$P(\text{EA}=\text{ea},\ \text{SA}=\text{sa},\ \text{MDC}=\text{mdc},\ \text{LSC}=\text{lsc}) = 0 \cdot 0.1 \cdot 0.1 \cdot .33 = 0$$

These example scenarios are intended to explain the functional process in the ASRS every cycle of the semantic update. This BN process is tested against real-world scenario data and against how an AV would perform with an ASRS input vs. an AV just utilizing an AMC for decision-making. Chapter 7 is where this data analysis will occur, but before that, the simulation environment and the evaluation of this system must be discussed, which is the focus of Chapter 6.

CHAPTER SIX

VIRTUAL TESTING ENVIRONMENT (VTE)

To achieve the testing and validation of the proposed ASRS system, it was necessary to develop a testing environment capable of considering the semantic and physical data features required to excite and evaluate the system. It was also necessary to simulate an AMC system working within the simulation environment to compare the result of an AV with an AMC and ASRS system to one with just an AMC. Finally, the environment had to be configurable to support the real-time operation of the AMC and ASRS together and be able to be designed to reflect real-world traffic conditions based on surveyed data collections (discussed in Chapter 7).

6.1 Developed Simulation Environment

A simulation environment is utilized to test the ASRS in various dynamic environments to create simulated traffic situations and model real-world traffic conditions. This environment must simplify and capture the various inputs the ASRS system needs to operate, such as semantic and physical world features. It was determined that no existing known simulation environment was viable for executing the procedures of this research effort. Therefore, one was created in MATLAB using the app designer [69] environment, as seen in Figure 6.1.

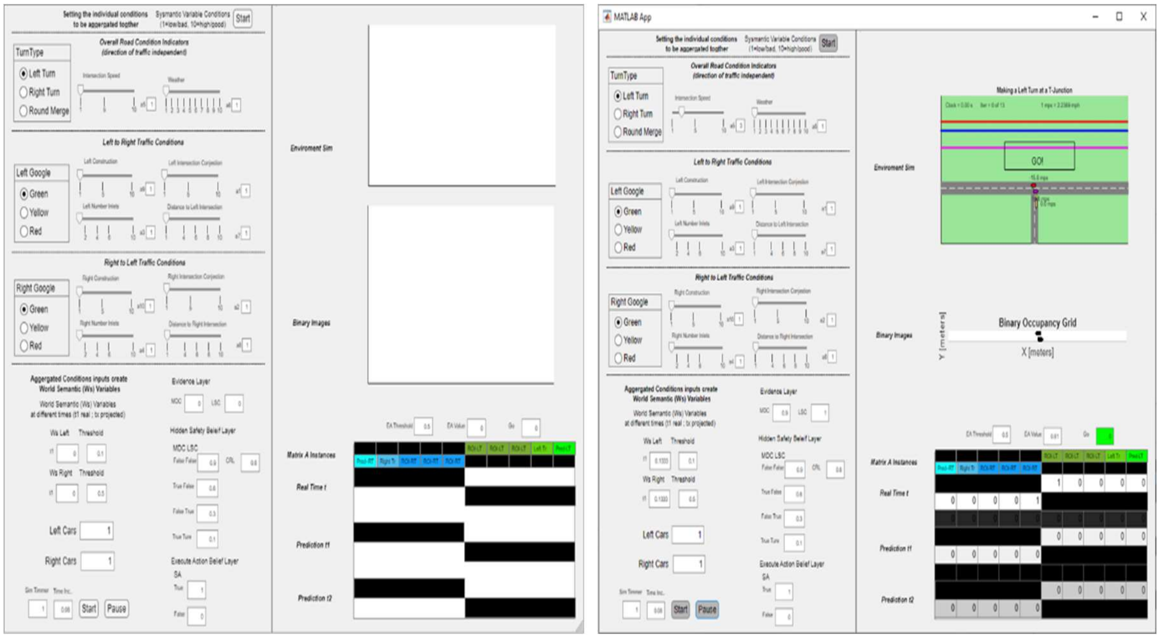


Figure 6.1 Example ASRS simulation environment (both initial and populated).

The ASRS simulation environment displayed in Figure 6.1 allows for introducing various reference semantic data features that can influence the physical world knowledge utilized in the safety reasoning process. This virtual environment allows real-world T-intersection data to be captured and modeled (as discussed in chapter 7). In addition, it will enable real-world data to be iterated against changing environmental conditions per the needs of the test plan. If one thing is clear from the commercial automotive AV providers' actions, virtual testing and simulation is a top priority related to their overall product release plans [70].

6.2 Simulation Environment ASRS Process

The simulation environment allows for the linking of the DCC and SRS systems of the ASRS. The simulation environment provides all the manual and automated inputs to the ASRS subcomponents. Figure 6.2 Describes the relationship between the DCC and SRS processes. As mentioned in this chapter and Chapter 5, the DCC process drives the SRS process. The DCC semantic updates are the outer loop (red outline) of the nested system, and the SRS process runs (blue outline) for each DCC semantic update.

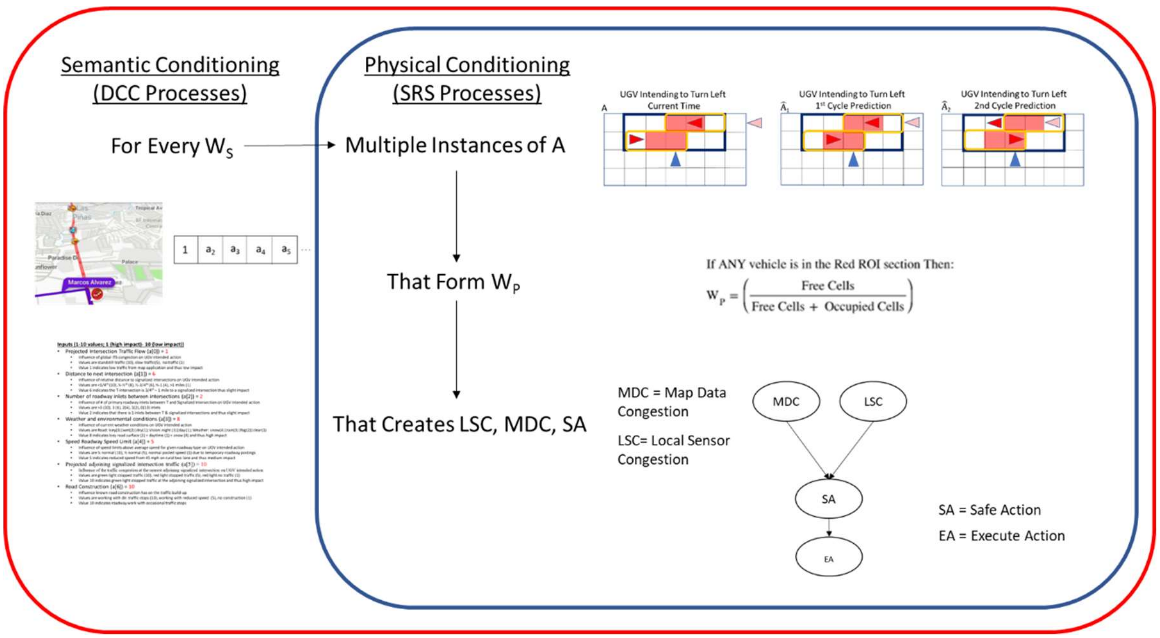


Figure 6.2 SRS system loop that describes DCC and SRS interactions

6.2.1 DCC Simulation Component

The DCC component is the feeder for the SRS component. The overall approach of the dissertation has the DCC as the feeder component necessary to occur first for the SRS to operate. The DCC takes the complex inputs of the world information and translates that information into simple artifacts that feed the SRS reasoning process. Below is a description of the different inputs that drive this system.

Entering the W_S "Element" Data

- Background: W_S is the World Semantic Variable. This variable is meant to capture the impact of all the features in an unsignalized intersection scenario that do not have direct physically perceivable representations but still affect the outcome of an AVs action.

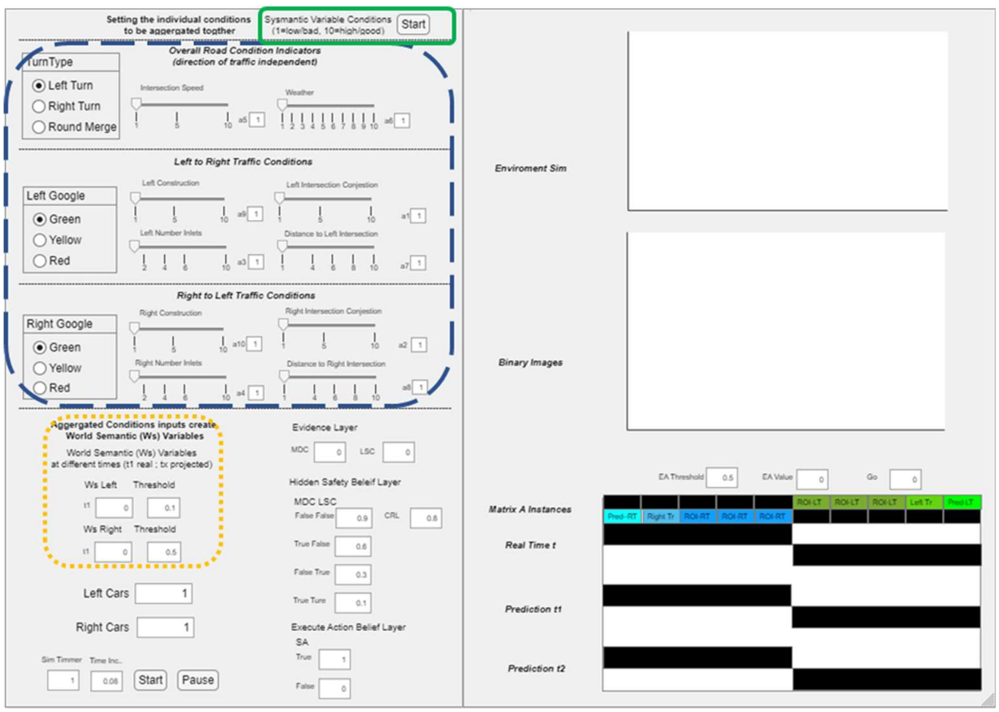


Figure 6.3 Simulation user enters DCC W_S data

  - W_S Feature Input Mechanism - These features are those detailed in Figure 4.10 for T-intersections and Figure 4.11 for roundabouts. These features are highlighted in the large blue hash box in Figure 6.3.

        - It is assumed that in the real world, this information comes from V2X ITS information and is translated to the feature space of its impact on the AV's intended action. Therefore, these impact scores are entered into the system via these input mechanisms.
    - Congestion Sufficiency $_{Directional}$ (CS_D) Values - User inputs/sets these W_S Threshold comparative values (real values between 0-1). The medium-sized orange plus-outline box in Figure 7.3 shows the input fields for the CS_D values next to the calculated W_S value display fields.
        - The CS_D values are used to determine if the calculated W_S values are significant enough to generate predicted instances of expected vehicles entering the physical domain.
    - Calculate the W_S Values for Right/Left Traffic - The user hits the start button, outlined in the green solid line bounding box of Figure 7.3, to calculate the W_S for each direction of travel of traffic.
        - The system calculates the W_S variables (Left and Right) and compares them to CS_D comparative values discussed in section 4.2.3.
            - If the W_S magnitude is greater than CS_D Threshold, create a new vehicle in the given direction (Left/Right) at t=2; If WS is two times greater than the Threshold, create a new vehicle at t=3.

Set the Number of Cars Generated in Each Direction

- Background: Set the number of vehicles generated from the simulation in each direction. This enables this simulation to represent many different scenarios, as seen in Figure 6.4

Figure 6.4 Setting the traffic conditions for the Simulation

  - User inputs the number of vehicles to be generated – This occurs in each direction of traffic in the unsignalized intersection via the green solid line bounding box in Figure 6.4
    - This is the simulated traffic conditions unaffected by the W_S inputs. This allows the simulation to model recorded traffic

conditions at real T-intersections or for random T-intersection traffic conditions to be generated

- User inputs the simulation duration and update rate – This allows to user to orient each run of the simulation to occur for a given time duration and speed. The orange plus-outline box in Figure 6.4 highlights these input fields.
  - This feature is critical for matching real-world unsignalized intersection traffic conditions in the simulated environment. Each simulated scenario is meant to match specific real-world conditions.
- Start and Pause button – Once the W_S simulation parameters are set, the start button generates the traffic conditions, and the pause button allows for paused scenario analysis when needed. The blue hash box highlights these buttons in Figure 6.4.

6.2.2 SRS Simulation Component

The SRS component takes the inputs from the DCC component to create the simulations and resulting BN-based total system ASRS calculations.

Working Traffic Simulations and Models

- **Basic Background:** The dynamic configurable traffic simulations provide the evidence data for the SRS system to process. This is demonstrated in Figure 6.5.

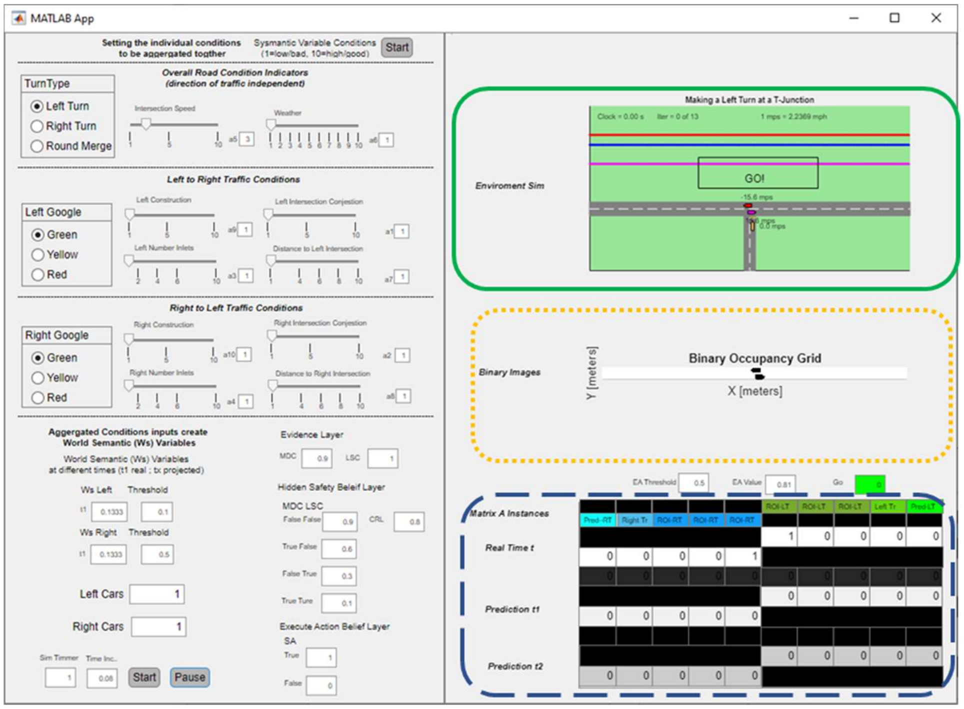


Figure 6.5 Dynamic Simulations that are created

- Created Intersection Simulation – This simulation is based on inputs from the Set Number of Cars step of section 6.2.1.
  - This simulation is the means to model real-world collected data within the system. The simulation subsystem enables all ASRS calculations as it serves as the stated natural environment for the ASRS. The AMC of the AV also works off this substem. This simulation compares how the ASRS improves the safety performance of an AMC-only AV. This is shown in the green solid line bounding box of Figure 6.5

- The box in the middle of the figure that says go is the AMC decision for the AV at the T-intersection in terms of its intended turning action. This value changes from Go to No-Go based on cars being within the bounds of the AMC field of view, which is the black box in the scene. The Go/No-Go AMC determination is compared to the ASRS Go/No-Go determination (as demonstrated initially and discussed in section 3.3.2 and specifically Figure 3.4)

- Filtered image of the scene – This filtered binary image representation of the cars on the road is used to calculate each car in a grid cell overlayed on this image. This process is similar to what an AMC would do to provide vehicle objects to the ASRS (but in an overhead perspective where an AMC would provide forward-looking detected car objects similar to what is shown in Figure 4.13). This is shown in the orange plus-outline box section of Figure 6.5.
- Representations of Matrix A, $\widehat{A}_1$, $\widehat{A}_2$ – From top to bottom of the image, the first two rows with 0 and 1 values represent the current time Matrix A (where 1 represents a car in the given cell). The second set of rows with 0 and 1 values is Matrix $\widehat{A}_1$, The final rows of 0 and 1 values represent Matrix $\widehat{A}_2$. This is shown in the blue hash box of Figure 6.5.
  - These Matrix A representations include vehicles currently in Matrix in the original scene and any projected values the ASRS

systems predict based on the semantic layer inputs (none of these predicted vehicles are shown in the current figure).

<u>SRS Bayesian Network Inputs and Results</u>

- **<u>Basic Background:</u>** Mechanisms to prepare the BN with expert-initiated conditional dependence data and view the calculated inputs of BN and the outputs.

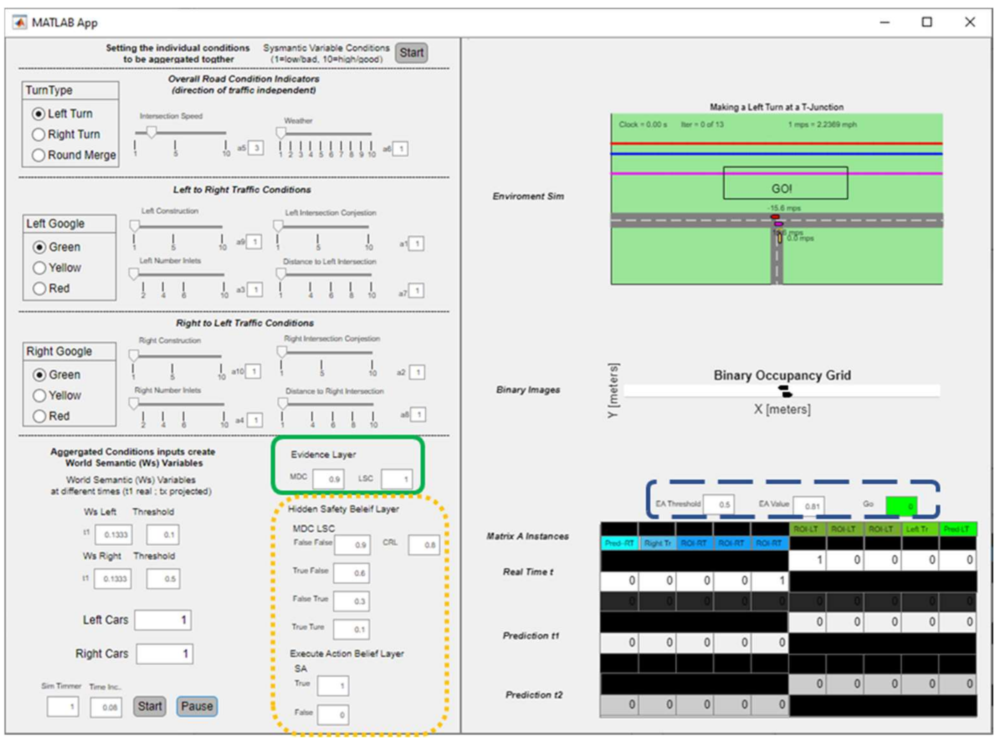


Figure 6.6 SRS BN Inputs and Outputs

   - MDC and LSC input values are displayed – The values for these evidence layer inputs are calculated from the earlier DCC and SRS processing discussed in Chapter 5. This is shown in the green solid line bounding box of Figure 6.6.

- Setting the BN SA and EA conditional probability table and CRL values – The expert sets the values for the Safe Action (SA) Conditional Probability Table (CPT) and the initial EA CPT values. In addition, the expert also sets the value for the Congestion Reference Level (CRL), which is used to determine if LSC is classified as congested or uncongested, as discussed in Chapter 5. This is shown in the orange plus-outline box section of Figure 6.6.
- ASRS Output – There is an input for the EA Threshold value, which is an expert set input to whether or not allow the ASRS output to modify the AMC decision to execute the turn (essentially enable the AMC to send the velocity command to the vehicle as displayed in Figure 3.2). The next two fields present the calculated ASRS value and show whether the AV would execute the action (the third field is green if yes and red if no) based on comparing the EA Threshold value to the calculated ASRS value (allowing the expert to compare the output of the AMC compared to the ASRS each step of the simulation). The blue hash outline box outlines these fields in Figure 6.6.

The VTE is the means to evaluate the effectiveness of the ASRS approach. The simulation allows for recreating real unsignalized intersection scenes and comparing what an AMC would do in those scenarios. The simulation demonstrates what an AMC would do to execute an action using AV-collected vehicle object data vs. what the ASRS system would do. Chapter 7 will discuss the testing of this approach using real-world data processed through the virtual simulation environment.

CHAPTER SEVEN

TESTING PROCESS AND RESULTS

The simulation environment detailed in chapter 6 is the means to evaluate the effectiveness of the ASRS. The simulation environment and the test plan described within this chapter are the means to produce results that substantiate the conceptual and technical approach of the ASRS. This chapter details the data collection and testing plan, the experimental design of the testing process, the result analysis approach and findings, and finally states the significance of the results to the problem domain.

7.1 Data Collection and Utilization Plan

The data collection and utilization plans are the first components of the testing procedures. Real-world data is collected and used to represent simulated scenarios as part of the utilization plan. Each of these processes are discussed in detail below.

7.1.1 Data Collection

The world intersection physical and semantic data was collected and categorized in a Microsoft OneDrive online storage environment [71]. This environment includes data artifacts for recreating VTE scenarios from semantic and physical perspectives. The list of data items collected in this environment is given below in Table 7.1

Data Item	Data Format	Data Description	Data Purpose
Surveyed T-Intersections	Video	Core intersection data of interest. 5 Minutes of video Per Data Capture Instance	Data collected for scenario recreation in VTE for ASRS analysis
Surveyed Adjoining Signalized Intersections	Video	Data for W_E Semantic Calculations. 5 Minutes of video Per Data Capture Instance	Data that supports W_E value creation Per T-Intersection Instance
Surveyed Round About	Video	Round About Traffic	Data collected for scenario recreation in VTE for ASRS analysis
Intersection Speeds	Infrastructure	Posted speed limit of surveyed intersections	Data that supports W_E value creation
Intersection Global Traffic – Current Time	Picture	Google Maps Traffic with current traffic overlays	Data that supports W_E value creation
Intersection Global Traffic – Historical Data	Picture	Google Maps Traffic with historical traffic overlays	Data that supports W_E value creation
Road Segment Overhead Data	Infrastructure	Overhead road segment data allowing for calculation of the distance to intersections and the number of inlets	Data that supports W_E value creation
Time of Day	Picture	The capture of time of data for data collect	For W_E calculations via heavy/light traffic time expectations

Table 7.1: Data Types Captured and Categorized in ASRS Data Center

The data listed in Table 7.1 is collected and organized into folders on the ASRS OneDrive share space based on the date, geo-location, and data-type categories. Most of the data can be collected post-process from online sources. However, one data item required special acquisition considerations.

- The surveyed intersections required in-the-field data collection procedures.
  - These procedures included time-synchronized T-intersection and adjoining intersection video collections to estimate data flows at the T-intersection
  - Incremental time recordings of traffic entering and leaving roundabouts in all directions
  - Time of day collections to represent heavy and light traffic conditions
  - In-field data collection procedure for capturing global traffic conditions for these intersections (roundabouts and T-intersections) via google maps

7.1.2 Data Utilization

The data detailed in Table 7.1 is utilized to form the simulations within the VTE that are used to evaluate the value and effectiveness of the ASRS concept and technical approach. The real-world data captures are utilized to replicate traffic scenarios where a surrogate AMC and the ASRS system responses can be evaluated within the VTE. These real-world data-enabled VTE simulations excite the AMC and ASRS code to produce both an AMC decision for the AV to turn (given the AV sensor world conditions only) and a ASRS decision (given the sensor and semantic world conditions and projecting them forward). A picture of what these results look like in the VTE can be seen in Figure 6.6. The 'Go' text surrounded by the black box in the upper right is the AMC determination if the AV at the T-intersection should execute its intended action (Turn Left/Right) at each cycle of the system. The Green box above the A matrix table is the

ASRS determining if the AV should execute its intended action. If the AMC determines the vehicle should not turn, then a 'Stop' text is detailed inside the box in the upper right of the figure. If the ASRS determined the AV in the scene should not turn, the color of the box on the lower right of the figure would change to red (for each instance). The AMC makes decisions on whether the vehicle should turn or not based on if vehicles are approaching the middle of the intersection from either direction or inside the box. Once the vehicles cross the intersection, they are no longer considered risks to the vehicle executing its intended action.

7.2 Test Plan/Design of Experiment

As discussed in section 7.1, the test plan and experimental procedures involve using real-world survey data to set the simulation conditions of the environment. Each simulation run is set up as an approximation of a scenario that occurred in the world. Figure 7.1 is a zoomed-in view of the generalized T-intersection simulation that can have the conditions set for it in terms of the number of vehicles crossing the intersection, the speed of the vehicles, the direction of the vehicles, and initial locations. Figure 7.2 shows that the semantic conditions of reference are also captured for these intersections, as detailed in Chapters 4 and 6. These features are turned into W_S impact scores used to determine the new vehicles are likely to enter the physical layer of the scene (represented by the box around the Go text in Figure 7.1).

Figure 7.1 Example VTE simulated environment at rest

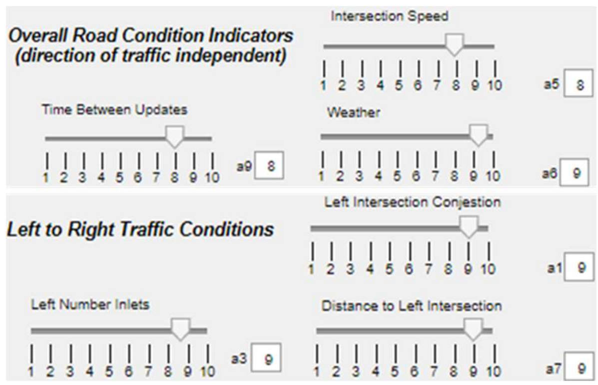


Figure 7.2 Example slider inputs for W_S calculations to VTE

The test plan involves utilizing the VTE to recreate multiple traffic scenarios (high traffic, low traffic, left turns, right turns, etc.…) and to test the results of the ASRS decisions vs. the decisions that just the AMC-enabled AV would make. In addition, the test plan also is set up to evaluate the number of times a W_S predicted vehicle enters the T-intersection AVs sensor field of view. Finally, the number of times the ASRS correctly predicts whether the AV should initiate the turn is captured.

7.2.1 <u>Methodology to Assess Semantic Predictions</u>

The ASRS predictions of traffic originated from the aggregation of semantic features discussed in Chapter 4, which results in those aggregated features potentially generating a prediction of a vehicle to appear in the AVs new physical layer (which includes vehicle sensor and semantic data…as discussed in Chapter 5) requires a method of assessment. The approach for this assessment is to utilize the real-world inspired VTE traffic simulations as a comparison method. The VTE traffic simulations can have the traffic conditions modified according to simulation time, the number of vehicles entering the intersection, and the level of separation of those vehicles' initial placement in the scene (as discussed in section 6.2.1). The method of assessment is based on a process. The process has the following steps:

- Setting up VTE traffic conditions to represent a designed traffic scenario occurring at the intersection (e.g., heavy fast-moving traffic, stop-and-go traffic, little to no traffic, etc..).
- Record the number of times a VTE-generated vehicle enters the AMC sensor FOV to the times an ASRS vehicle enters the AVs physical world
- Record the number of times a VTE-generated vehicle enters the physical world that the ASRS did not project
- Record the number of times an ASRS vehicle entered the physical world when the VTE-generated vehicle did not enter the physical world

Based on the above criteria, Table 7.2 presents an example of how data would be recorded to assess the accuracy of the semantic prediction process with the given individual features. Figure 7.3 presents an example of how ASRS vehicles were compared to-be entering the physical world simultaneously with VTE-generated actual vehicles.

VTE Intersection Test Setup	W_s Prediction Window	VTE Generated Cars Entering Physical Layer (e.g., Not originating in Physical Layer)	W_s Generated Cars Entering Physical Layer	WS & VTE Notes	Correct Detection (CD): WS cars matching VTE car within 4 SI or 2s No Detection (ND): VTE cars without matching WS cars is 4 SI or 2s False Cars: Cars generated by WS that are not generated by VTE
3 seconds (s)	Left Traveling Cars: 0 Right Traveling Cars: 2	Left Traveling Cars: 0 Right Traveling Cars: 2	Left turn with 3s prediction.	Correct Detection (CD): 2 No Detection (ID): 0	3

Table 7.2 Example case of determining the effectiveness of W_S

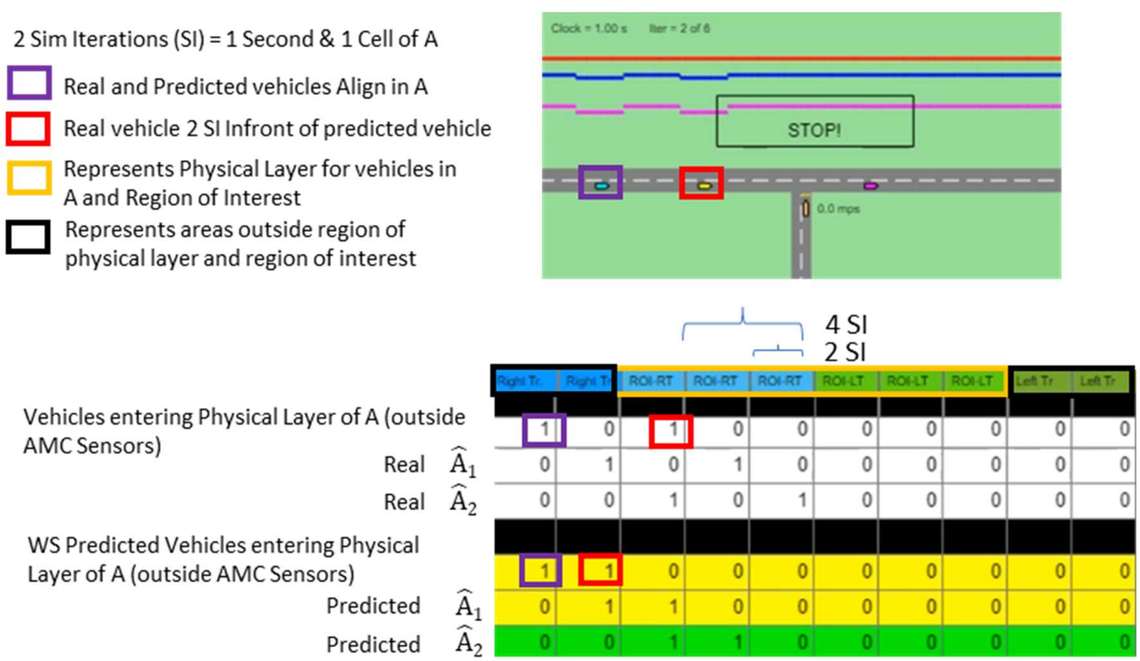


Figure 7.3 Example case of comparing VTE and W_S vehicles entering PL

7.2.2 Methodology to Assess ASRS Outputs

The ASRS and AMC traffic simulations analyzed are based on small segments of time traffic conditions centered on the intersection between the roadways (whether T-intersection or roundabouts). A determination on whether the ASRS or AMC decision to turn or not was correct is based on a Time To Collision (TTC) calculation. TTCs are based on vehicle velocity and distance to the intersection, as seen in Equation 20 and Figure 7.4. However, depending on the application, TTCs can be calculated using numerous values, methods, and terms. Specifically for this dissertation, the TTC is computed using Equation 21 and Figure 7.5.

$$\text{TTC} = \frac{\text{Distance To Collision Point}}{\text{Vehicle Velocity}} \qquad [20]$$

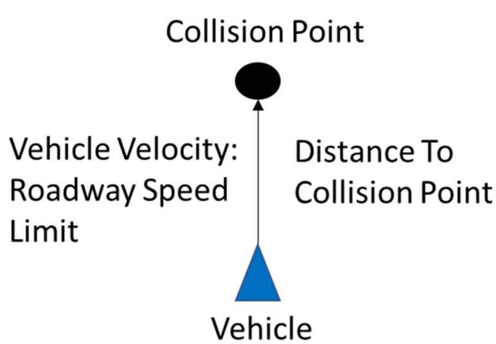


Figure 7.4 TTC General Case Descriptive Diagram

$$\text{TTC} = \frac{\text{Cells to Collion Point}}{\text{Cells traversed per time step}} \qquad [21]$$

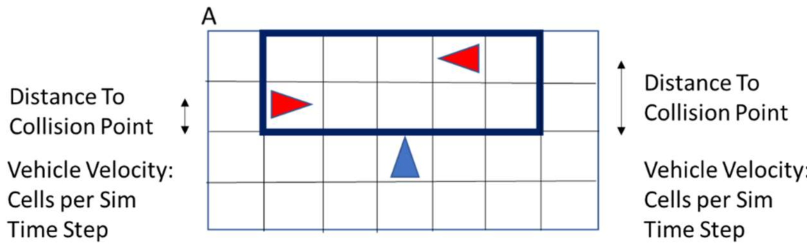


Figure 7.5 TTC Dissertation descriptive diagram

TTC-based safety determinations are a standard method in assessing the effectiveness of motion safety systems and decisions for many traffic collision mitigation techniques [72, 73, 74, 75]. In this dissertation, the TTC is utilized to determine if the potential motion action of the AV would put the AV into a collision scenario with the predicted location of a vehicle on the roadway. This is accomplished using Equation 21 with the details presented in Figure 7.5 to calculate the TTCs for the AV at the intersection. The process described assumes that the AV would be making a left-hand turn as the process is the same with right-hand turns and roundabouts but only needing the left-to-right traffic portion in those scenarios.

The time it would take the blue AV in Figure 7.5 (as an example) to collide with one of the oncoming red vehicles (assuming they were predicted to be in one of the cells in front of the AV) from left-to-right traffic or right-to-left traffic is what the TTC is calculating. For the calculation, it is assumed the AV only moves forward toward a stationary collision point, as illustrated in Figure 7.4. It is also assumed that the AV velocity is measured in cell traversal time, as denoted in Equation 21. Thus, the TTCs being calculated are for collisions that could occur if the AV moved into either of the two cells directly in front of it. For the first cell in front of the AV (assuming left-to-right predicted traffic results in a vehicle in this cell), the calculation would produce a TTC value of 2 sim cycles. This assumes a given sim cycle time of 0.5 seconds (the sim time for cycles is configurable in the VTE), the travel distance of half a cell, and the max potential speed of the AV being half the posted speed limit (which means the AV would have half its potential velocity). Using Equation 21, the following result is produced

$$\text{First Cell TTC} = \frac{\text{Cells to Collion Point}}{\text{Cells traversed per time step}} = \frac{0.5 \text{ cells}}{0.25 \text{ cells/ cycle}} = 2 \text{ cycles} = 2(0.5) = 1 \text{ seconds}$$

This means that within two sim cycles (1 second in this case), the AV would collide with a vehicle if it were in the first cell in front of it.

To reach the second cell, assuming no collision occurred in the first cell, the TTC value of the AV in this scenario would be three sim cycles (1.5 seconds). In this situation, the distance traveled is 1.5 cells before reaching the collision point, and the velocity is no longer half the posted speed limit (as the AV has now had time to establish a velocity closer to the relative posted limit and thus a normal cell traversal rate is utilized)

$$\text{Second Cell TTC} = \frac{\text{Cells to Collion Point}}{\text{Cells traversed per time step}} = \frac{1.5 \text{ cells}}{0.5 \text{ cells/ cycle}} = 3 \text{ cycles} = 3(0.5) = 1.5 \text{ seconds}$$

Next, the calculated TTCs for the AV are combined with the roadway vehicles' calculated stopping time to assess the ASRS outputs' effectiveness in anticipating and thus avoiding potential accidents. The stopping time of the vehicles on the roadway is determined by dividing the vehicle roadway speed limit (assumed speed of the roadway vehicles) by the assumed human controllable stopping rate of an average-sized vehicle [76], as seen in Equation 22.

$$\text{Vehicle Stopping Time} = \frac{\text{Vehicle Speed Limit (feet/ second)}}{\text{Controlable Stopping Rate (feet/ second/ second)}} \quad [22]$$

Using Equation 22, a vehicle stopping time of 3 seconds is calculated as shown below

$$\text{Vehicle Stopping Time} = \frac{\text{Vehicle Speed Limit (feet/ second)}}{\text{Controlable Stopping Rate (feet/ second/ second)}} = \frac{66 \text{ f/s}}{15 \text{ (f/s) /s}} \approx 4 \text{ seconds}$$

Accounting for a one-second delay in human reaction, a 5 second time window for safety stopping is established as a minimum expectation for the vehicles on the roadway to potentially avoid crashing into the AV if it were to enter the intersection. Combing the vehicle stopping time and the TTCs an inevitable crash zone is established for vehicles traveling in either direction in front of the intersection, as illustrated in Figure 7.6.

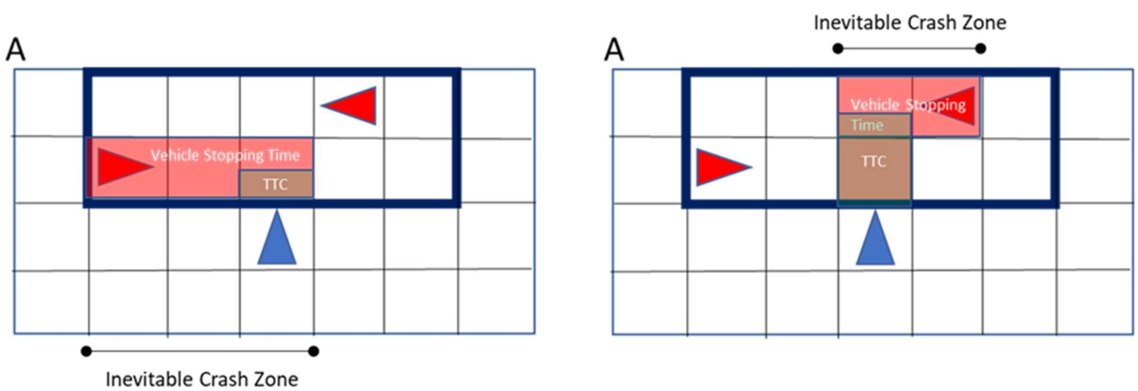


Figure 7.6 AV imminent crash zones for each direction of traffic at T-intersection

The inevitable crash zones illustrated in Figure 7.6 are established based on the TTC and vehicle stopping values. These zones are based on the fact that the intersection road section in the VTE represents approximately 1/16 of a mile of roadway in each direction from the intersection center (in the case of the T-intersection). This means 330 feet of roadway in each direction from the middle of the intersection, shown in Figure 7.1. The Matrix A within the VTE breaks each 330-foot road section into five 66 foot cells. All vehicles on the roadway move at 45 mph or 66 Feet Per Second (FPS) (given that all T-intersections surveyed for the dissertation were average country roads with 45 mph speed limits). Given that the sim update of half a second is used in all runs, it takes, on average, two sim cycles for a vehicle in A to move from one cell to the next cell. Thus, with a 5-second window for safe stopping for the vehicles moving on the roadway at 66 FPS, there would need to be three cells of motion before one of those roadway vehicles would stop. Thus, the inevitable crash zone for left-to-right traffic is three cells from the center, as shown in red in Figure 7.5. The inevitable crash zone for right-to-left traffic is two cells from the center as the TTC is over a second long, thus taking up one of the three motion cells.

The inevitable crash zones are used in determining if the ASRS anticipated decision not to execute a turn is effective by tracking the number of times the AMC system tells the AV to go. At the same time, the ASRS advises waiting and cross-referencing how often those two situations occur. The ASRS predicts the AV would experience an inevitable crash as one of the roadway vehicles was in the inevitable crash zone, as described in Table 7.3.

Test Condition	Prediction Window	ASRS Predicted Crash	ASRS Errors
Left Cars: 3 Right Cars: 1	3 seconds	1	False Crash Prediction: 1 Missed Crash Prediction: 0

Table 7.3 Example of determining the effectiveness of ASRS crash prediction

Table 7.3 describes an example case of determining how the potential effectiveness of the ASRS system is established. The ASRS Predicted Crash indicates that the ASRS system identified a potential crash for the AV, if it were to execute its intended AMC action, based on the predicted crash zone position of a W_S-generated vehicle that matches a VTE-generated vehicle outside the AV AMC field of view. The ASRS False Crash Prediction indicates that the ASRS system indicated for the system not to go when in reality, there were no VTE vehicles in the scene for a Sim Iteration (e.g., false positive).

7.3 Test Results and Analysis

The simulation environment discussed in Chapter 6 is aligned with multiple sets of real-world survey data conditions and set up to represent those conditions in high and low-traffic intersections. The simulation was set up to run representing the conditions of the roadway over a window of time and the semantic features during those periods were assigned impact values based on the conditions of the scene. Each intersection scenario was run and the results of the accuracy of the traffic predictions based on W_S data were captured and analyzed as well as the decisions of the ASRS for AV motion. Real-world data was used to feed the creation of the VTE scenarios, including a series of intersection data collections, as demonstrated in Figure 7.7.

Figure 7.7 Example images from a T-intersection data collect

7.3.1 Test Setup

Several initial runs were executed to represent a variety of scenarios for each of the cases of the ASRS (for Left, Right, and Roundabouts). The system was tested for accuracy of how well it

- Operates given the semantic condition values in terms of not running when they are not met and always running when the thresholds are met. The system operated correctly through 7 different test scenarios in terms of engaging in cases when it should and not engaging when it should not
- Semantically predicts vehicles entering the physical scene (via W_S calculations) vs. actual appearance rates
- Effectively serves as a predictive safety reasoning system

These three test result data sets represent the object results used in assessing the viability of this concept vs. real-world scenarios via simulation.

Two primary simulation conditions were established to standardize results into categories to capture these initial data sets.

- VTE test simulations with a 3-second prediction window before new scene updates (e.g., new W_S and W_p values)
- VTE test simulations with a 6-second prediction window before new scene updates (e.g., new W_S and W_p values)

These two primary test cases are driven by the calculated vehicle stopping time of 3 seconds for a normal-sized vehicle moving at 45 mph on a roadway. Due to this calculated timeline, the tests were run at that timeline (3-seconds) and at double that timeline (6-seconds) windows. The combined test results for the ASRS system are displayed in tables 7. 4, and 7.5.

7.3.2 Test Result

The combined initial test results for the ASRS system are displayed in tables 7. 4, and 7.5. Table 7.4 contains the results of the semantic prediction testing. The primary takeaway from this testing set is that the approach to predicting vehicles entering the AMC of the AV, per semantic predictions of the ASRS, indicates valid results. For example, in 18 of 23 opportunities, the WS predictions of a vehicle entering the AMC were correct detections, defined as W_S-generated vehicles predicted to enter the AMC of AV within 2 seconds. This indicates that a semantically predicted vehicle was detected, per the ASRS W_S process, 87% of the time before it entered the AVs AMC field of view in the 30 trials performed that are detailed in Table 7.4. Out of the 13% of vehicles that were not detected, 5% of those cases were due to the system failing to predict oncoming VTE-generated vehicles. 8% of the time, the system detects vehicles but in a window greater than 2 seconds. Finally, the ASRS system predicted vehicles that did not relate to the VTE-generated vehicles 25% of the time.

These results are partially influenced by the conditions of the VTE testing environment and partially due to the realities of prediction approaches in highly uncertain environments, such as what is happening outside an AVs AMC field of view. With regard to the VTE, the speed of the calculations are slower than would be the case within a fielded system. The 2-second window for vehicles entering the field of view of the

AMC would be closer to 2 milli-seconds in a real-time system. This delay is due to the high-level MATLAB development environment in which the system is developed. These development environment delays need to be considered and accounted for in the ASRS model regarding the VTE to produce viable predictions based on objective world evidence. The sizing of the cells accomplishes this within the A matrix and correctly sets the interval time between simulation iterations (0.5) for all tests performed and recorded in this dissertation. Even with this mitigation, there are still issues with aligning the cell transition timing of the VTE-generated vehicles with the time of the semantically W_S-produced vehicles. This error is greater the longer the duration of the prediction window for W_S. Six seconds is close to the window limit in which you would expect to get valid results in the VTE.

Even with the stated issues with the timing of vehicle transitions due to the VTE environmental constraints, the mitigations mentioned above regarding limited prediction windows, setting of the correct matrix A cell size, and finally setting the correct simulation iteration time, the environment is able produces valid conditions where W_S generated, and VTE generated vehicles can match transition timing correctly. Due to these mitigations, the results produced from these tests can be compared to those made by other vehicle detection algorithmic approaches. When comparing these results to a series of techniques for AV detection of other vehicle objects in an environment, the state-of-the-art deep learning algorithms are detecting vehicles (within the AMC sensor field of view) at rates near 65-70% of the time in open traversal through varying roadway conditions [77].

VTE Intersection Test Setup	W_S Prediction Window	VTE Generated Cars Entering AMC (e.g., Not originating in AMC)	W_S Generated Cars Entering AV AMC	Correct Detection (CD): W_S cars matching VTE car within 2 seconds No Detection (ND): VTE cars without matching W_S cars within 2 seconds False Cars: Cars generated by W_S that are not generated by VTE	Success Score: 4 - Great (All cars detected in 1 SI window, No ND or False Cars 3 - Very Accurate (All cars detected in 2 SI windows) 2 - Accurate (at least one car detected in 4 SI windows) 1- Inaccurate VTE cars not detected by WS in 4 SI window
Totals:	3 second 10 Tests	Left: 1 Right: 10	Left: 3 Right: 14	Correct Detection: 14 No Detection: 0 False Car: 5 CD Rate: 14/17 ND Rate: 0/17 False Car Rate = 5/20	Avg: 29/40 *4= 2.9
	6 second 10 Tests	Left: 1 Right: 8	Left: 2 Right: 11	Correct Detection: 20 No Detection: 2 False Car: 7 CD Rate: 20/22 ND Rate: 2/22 False Car Rate = 7/28	Avg: 25/40*4 = 2.5
Combined Totals:	3 seconds: 10 6 seconds: 10	Left: 3 Right: 19	Left: 5 Right: 25	Correct Detection: 34 No Detection: 2 False Car: 12 CD Rate: 34/39 ND Rate: 2/39 False Car Rate = 12/48	Avg: 45/80 = 2.7

Table 7.4 WS Prediction Cumulated Results

Table 7.5 shows the results of the ASRS safety testing. The primary takeaway from this testing is that on 14 of the 20 test opportunities, the ASRS system correctly predicted potential crashes that the surrogate AMC might have caused in the given scenarios. That is a potential 70% accident-avoidance rate when using the ASRS with the surrogate AMC. Furthermore, if you look at the 6-second window in which these situations occurred, the system predicted an accident 78% of the time outside the standard AMC perception window (e.g., the accident would have likely occurred). This rate mirrors rates of current warning systems for human vehicles making left turns that reactively detect potential collisions based on the scene's layout to assist the human with collision avoidance at effectiveness rates of 32 – 60% [78].

Test Condition	**Prediction Window**	**SRS Predicted Crash**	**SRS Errors**
Totals:	3 seconds	7 out of 11	False Crash Prediction: 4 Missed Crash Prediction: 0
	6 seconds	7 out of 9	False Crash Prediction: 7 Missed Crash Prediction: 4
Combined Totals:		14 out of 20	False Crash Prediction: 11 Missed Crash Prediction: 4

Table 7.5 ASRS Safety Prediction Results

The results of this chapter came from executing the ASRS concept utilizing the mathematical methods discussed in Chapter 2. Chapter 8 will discuss other potential techniques that could have been employed for both the DCC and SRS systems and discuss potential future work that could be performed to improve the utility of this approach.

CHAPTER EIGHT

ALTERNATIVE APPROACHES AND POTENTIAL FUTURE WORK

A specific approach toward the ASRS concept of this dissertation has been primarily described to this point. However, other approaches could have been taken to demonstrate this concept. This Chapter talks about some of those alternative approaches and discusses potential future work that could be done to improve the system's performance.

8.1 Alternative Technical Approaches to ASRS

As detailed in Chapter 2, specific design decisions were made on implementing the various techniques utilized in this dissertation. However, other alternative approaches were considered or, in some cases, partially implemented early on. This Chapter is meant to discuss those alternative approaches and the merits and reasons why they were not implemented vs. the chosen path. As in chapter two, the discussion will be broken down to represent the two major technical components of the ASRS, the DCC and SRS subsystems.

8.1.1 DCC Alternative Approaches

As described in Chapter 2 the work performed in the DCC section was mainly accomplished by utilizing feature mapping and threshold comparison techniques to enable the scoring of the elements in array ‘a’. In addition, simple aggregate mathematical calculations were used to produce the W_S value via subtraction, division, and greater-than-thresholding.

Alternatively, assigning values to the WS variable could have been accomplished using a fuzzy logic approach [79]. Fuzzy logic allows the determination of variable truth values to be real number values between zero and one. It enables the concept of partial truth determinations for these variables as opposed to Boolean logic-based approaches, which only allow for complete truth or complete false determinations via integer values.

Utilizing a fuzzy logic approach to determine the values of W_S would be an alternative approach that would eliminate the need for Equations 8-10. Membership functions would be modeled for each element of array ‘a’, and a defuzzification technique would be chosen to determine the resulting W_S value when comparing all inputs. This technique was not selected due to desires to simplify the mathematical concepts utilized initially and to design a simple method to modify the elements within array ‘a’ when adding or changing features. Fuzzy logic would have provided a more eloquent approach to determining W_S values. However, it is a technique that requires additional modeling and modification to condition inputs to a valid state for calculation (e.g., forming a membership function and modifying comparative logic rules for each change to the system inputs). While there may be other techniques to perform the WS calculations for the same reasons for not choosing the fuzzy logic approach, the most straightforward and most generalized approach (for input modeling) was chosen.

8.1.2 SRS Alternative Approaches

A Bayesian network is the core component of the SRS system and the core reasoning technique of the ASRS concept. Alternative reasoning approaches were also initially explored that included the use of Neural Networks [80], Hidden Markov Models [81], Partially Observable Hidden Markov Models [82], Dynamic Bayesian Networks (DNB) [83], and other approaches discussed in Chapter 2 that others have used. The primary alternate technique that was explored was the DBN. A DBN is a type of BN that relates variables to each other over adjacent time steps. Each time slice of a DBN can have any number of state and evidence variables, as seen in Figure 8.1.

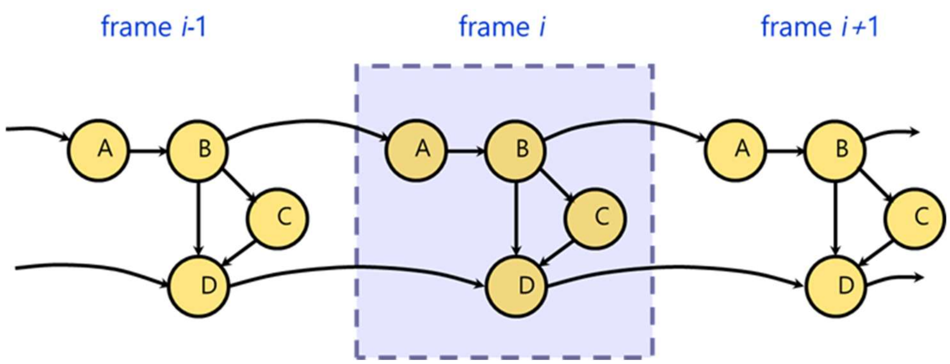


Figure 8.1 Example DBN representing three-time slices of a BN

The initial interest in the DBN approach was due to the ability to embed the temporal nature of this research into the reasoning system. However, this would entail more record-keeping and calculations to register and update the state of each frame (as seen in Figure 8.1) of the BN. Therefore, it was determined that a more straightforward approach was to manage the temporal nature of the ASRS system in the DCC component by predicting future versions of matrix ‘A’.

Statistically based modeling approaches, such as Bayesian Networks, were favored over data-intensive learning approaches for the reasoning component. While learning-based procedures have been widely popular in the academic community over the past ten years, there are strong indications that the brute force approach to addressing uncertainty through mass data accumulation and processing is reaching an efficiency and effectiveness limit [84]. The overall objective of this research effort was to take the most simple, computationally efficient, and flexible approach to model the environment. A learning approach to reasoning on data runs contrary to this objective.

Of the available statistical modeling approaches represented by Bayesian techniques were favored for the following reasons

- BN are graphical models and are thus very explainable/understandable to include expert design/modification/interpretation
- BN natively handle missing due to their probabilistic foundations
    - Suitable for when a variable does not report information due to the unavailability of the evidence update
- BN allows for simple methods for mixing probabilistically inferred data with expert knowledge
    - Such as with expert knowledge for the safe action variable
- BN are directed graphs and inherently are utilized for causal analysis given their directed graphical nature with no cycles (unlike a Markov network)
    - Roadway movement is intrinsically a causal process

- BN has no minimum sample sizes to perform analysis, as you may find in many learning-based approaches

The next section will discuss the future work that could be performed to enhance either this approach or to modify this approach to address other areas of interest.

8.2 Future ASRS Work

As in any research effort, opportunities exist to improve and build upon the results of this dissertation approach. These opportunities can be grouped into two categories near-term and long-term. The near-term opportunities are based on adaptations that could be made to modify the currently implemented and tested approach to improve the current performance. The longer-term options could be implemented with a higher level of modification to the current approach.

For near-term opportunities, the following list of changes could be implemented:

- Fix some of the Object Detection Problems related to VTE
    - The modification to adjust the Conditional Probability Table values of the Execute Action variable discussed in Chapter 5, specifically Section 5.2 and Table 5.2, was not implemented in the formal testing of the ASRS addressed in Chapter 7. This system would change the output of the ASRS from being essentially a Go/No-Go decision. In its ideal configuration, the ASRS provides the AMC with a level of confidence in cases where the conditioned state of the parent variable is false (the system already provides a level of confidence when the conditioned state of the parent variable is true).

    - Using the MATLAB getFrame function to capture the image of the animated simulation causes significant delays in the processing time of the approach. A more streamlined process to capture the frame data for each simulation iteration would provide much greater speed in the core simulation.
- Add motion of the AV vehicle at the intersection when the AMC and ASRS indicate go depending on the intent to show accidents occurring between dynamic objects or to show that when ASRS is used, the system could avoid accidents (as demonstrated in Chapter 3 in Figure 3.4).
    - For visualization and explain-ability effectiveness
- Automate some of the data collection and testing procedures as they are currently manual labor intensive.

For long-term opportunities, the following list of changes could be implemented:

- Work on a concept for an off-road version of an ASRS based on the safety of AV teams moving in a coordinated fashion
    - Investigations have begun to turn this concept into a potential Defense Advanced Research Projects Agency (DARPA) as this would have potential as a defense project.
- Implement a version of the system into ROS code for potential integration into the Army's Robotic Technology Kernel (RTK) autonomy code library of capability
    - The transition would be simplified because that library partially falls under the dissertation author's responsibility.

- Modify the system to work with more complex intersections such as four-way intersections and potentially include the anticipation of pedestrian motion in these intersections as well

The final chapter of this dissertation will briefly summarize the contributions that have been accomplished during the execution of this dissertation. Also, it will provide a statement on the success of this effort in addressing its primary objective.

CHAPTER NINE

CONTRIBUTIONS AND CONCLUSIONS

This chapter will detail the final contributions and conclusions of this research dissertation. It is an honor to have the opportunity to have performed this research and present these findings.

9.1.2 Contributions

In the process of performing this dissertation research, the following list of contributions where accomplished:

- Detailed a technique to combine local vehicle sensor and vehicle-to-everything global sensor information into a single representation of the world to be reasoned upon
- Modified a Rosen Anticipatory model (Figure 2.4) representing anticipation into a form that can be implemented in for this ASRS application (Figure 3.2)
- Modified a Joint Probability Distribution graphical modeling approach to allow for user inputs into the calculation via BN DAG
- Generated a method to reduce complex scene information into simple congestion variable levels W_S and W_P
- Quantified Semantic/probabilistic information (W_S) to vehicle intent
- Quantified Physical information (W_P) to vehicle safety predictions
- Formulated steps to predict future scenes of vehicles through W_S levels
- Developed MATLAB App to simulate ASRS system using both Semantic and Physical world source information

- Developed a method to collect and use real-world intersection data and related semantic information verification of process
- Extend the ability for AV object awareness outside of its sensor field of view via anticipatory reasoning
- Authored four papers in this subject area [46, 85, 86, 87] and co-authored multiple papers in related fields that influenced this dissertation topic [88, 89, 90, 91, 92, 93, 94, 95]

9.2 Conclusion

The Dissertation Hypothesis: An anticipatory safety reasoning system can improve AV motion decision safety at unsignalized intersections

Dissertation Summary:

This dissertation demonstrated the viability of an ASRS approach to assist an AMC with anticipating potential crashes related to projected vehicles outside the AVs sensor field of view.   Test evidence was provided and analyzed based on real-world data models. The results of these tests were compared to the results of other autonomous vehicle safety systems (Chapter 7) and different autonomous vehicle perception and reasoning approaches (Chapters 2 and 8). The overall conclusion of this research is detailed below.

The Final Conclusion:

This dissertation demonstrated the viability of an independent and separate Anticipatory Safety Reasoning System (ASRS), improving the safety prospects of an Autonomous Vehicles Autonomous Mobility Controller (AMC) at achieving safe outcomes in unsignlized intersections (specifically T-intersections and Roundabouts). The sub-approach to predicting traffic entering the Autonomous Vehicles (AVs) sensor field of view showed an 87% success rate. The sub-approach to anticipating potential crashes due to those predicted vehicles showed a success rate of 70%. Both results exceed current documented measures to achieve these goals. The combined results of these two ASRS core sub-system efforts compare favorably to the state-of-art and currently implemented success rates of similar approaches. This fact substantiates the dissertation hypothesis that an anticipatory safety reasoning system can improve AV motion decision safety at unsignalized intersections

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