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Autonomous Vehicle Safety Reasoning Utilizing Anticipatory Theory

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ABSTRACT

Today we have autonomous vehicles already on select road-ways and regions of this country operating in and around humans and human operated vehicles. The companies developing and testing these systems have experienced varied degrees of success and failure with regard to safe operations within this public space. There have been safety incidents that have made national headlines (when human fatalities have occurred) and their also exist a litany of other physical incidents, usually with human operated systems, that have not grabbed the headlines. Some of the select communities where these autonomous systems have been operationally tested have revoked access to their roadways (kicked out) some of these companies. As a result of these incidents recent data suggests that the public trust in autonomous vehicles is eroding [1]. This situation is couponed by the fact that there are no established safety standards, measures or technological methods to help local, state or national entities to ensure that these systems are operating under any level of safety scrutiny. This situation has accelerated the need for innovative research within the domain of autonomous vehicle safety approaches.

This paper describes a new methodology for automated driving to address these safety issues that entails the creation of a new computational process we call the Safety Reasoning System (SRS). This system will monitor and adjust the actions of an autonomous vehicle operating in highly cluttered scenarios with a focus on traffic intersections (specifically T-intersections). The SRS works in probabilistic space and models the world into propositions informed by both current and projected data sets. By inferencing on the relationships between data sets we are able to form anticipated safety propositions on the likely effects of the autonomous vehicles projected actions. Thus, potentially reducing the occurrence of catastrophic outcomes.

1. INTRODUCTION

This past decade we have experienced the introduction of autonomous vehicle technologies into our societal norms. In certain part of the United States it is more common, on a daily basis, to witness an autonomous vehicle driving (manually or autonomously) on public roads ways than it is to not see one. Many corporations have made public projections that this technology will become even more prevalent across the country in the coming years (many projecting a large increase before 2025). This situation exists while public trust in these systems has eroded [1] due to the widely publicized examples of catastrophic events that have occurred in this domain [2, 3]. It is clear that there is opportunity for innovative research into the safety case for these systems.

We introduce a new technique to assess the safety case of motion decisions made by autonomous planning agents/systems in complex but structurally causal scenarios. One such structurally causal scenario is autonomous agents making navigation decision at roadway T-intersections as seen in figure 1.

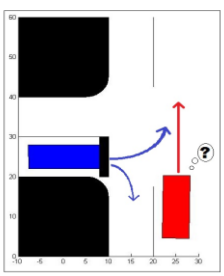

Figure 1: Autonomous vehicle (blue) at a T-Intersection with traffic

This scenario is structurally causal in the fact that the logical action decision space for the agent is limited (turn left, turn right, hedge forward, do nothing) and both the factors influencing these potential actions and consequences of executing them can be derived from pervious scenario states.

A significant portion of research in the automotive autonomous navigation literature on safe motion-decision making within complex scenarios utilize probabilistic techniques. In [4] the authors describe a control technique for determining control actions for robotic vehicles at intersections using probabilistic approaches that consider intended autonomous vehicle actions along with the estimated intent of other vehicles within the scene. In [5] the authors present a method for an autonomous ground vehicle to present an optimization-based path planner that is 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 [6, 7] the authors present a method to cluster vehicle actions into a set of policies in order 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 of nearby vehicles. However, it presents a very complex methodology of policy determination that is only able to work in real time scenarios if a small set of predetermined policies are considered. In [8, 9, 10] the authors assume that there is no uncertainty associated with future states of obstacle vehicles in their approach toward the development of deliberate reactive control techniques. The assumption utilized is that there is some type of communication that exists where other scene actors broadcast their intentions over communication channels. In [5, 11, 12] 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 as described in [7], but lacks closed-loop simulation of vehicle interactions. In [13, 14, 15, 16, 17] Gaussian

Process (GP) regression was utilized to learn typical motion patterns for classification and prediction of obstacle agent trajectories. In [18, 19] the authors propose hierarchical dynamic Bayesian Networks where some of the models on the network are learned from observations using an expectation maximization (EM) approach to execute behavioral goal selections.

All of these approaches toward automotive safety in autonomous decision-making focus on implementing these processes directly into the vehicles core Autonomous Navigation System (ANS). They propose a means to address safety navigation challenges, in complex and dynamic environments, through application of 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 ANS. None consider the concept of Separation of Duties (SoD) [20] which entails the decomposition of the safety mission into a separate decision process. This approach to SoD adds another layer of safety to the autonomous vehicles driving controller (currently consisting of only ANS inputs) and operates similar to how Advanced Driver-Assistance Systems (ADAS) operate to enhance the performance of human drivers. In addition, the SoD concept could enable for advancement in the testing of autonomous vehicles as it introduces a method to independently asses the safe actions of a vendor’s particular ANS approach.

In this paper we propose an approach toward the generation of an autonomous vehicle Safety Reasoning System (SRS) based on the SoD concept and the utilization of anticipation theory. This approach takes advantage of the temporal causality that exists in scenarios that have rules and topologies that can dictate and reasonably bound the dynamics that cause navigational decision uncertainty. We consider this approach akin to creation of an ADAS component designed specifically for automotive autonomous navigation. These ADAS systems have been proven to improve human driving performance through the separation of specific driving functionality into separate computational functional tasks.

2. Safety Reasoning System - Concept

The proposed SRS concept is based on two primary foundational components. The first foundational component being the computational SoD between the driving and safety functionality of an autonomous vehicle. We propose there should be one process optimized and focused on performing the omnipresent task of negotiating the dynamics of the world and one process designed to ensure the safety of the decisions made to negotiate through that complex world. This concept is something we note is utilized today in many complex driving tasks involving humans. For example, in rally car racing the task of negotiating the vehicle to the finish line, in the most optimal and safe fashion, is a two-person job. First there is a driver who has the responsibility of negotiating the dynamics of the vehicle through the terrain and then there is the co-pilot whose responsibility is ensuring the driver makes the safest and optimal driving decisions by continuously evaluating the vehicles current orientation to upcoming terrain conditions as in figure 2.

Figure 2: Separation of Duties concept in Rally Car racing between driver (negotiating dynamics) and copilot (focused on optimization)

In addition, the SoD concept similarly is implemented in the military domain for complex driving tasks. A main battle tank has four crew members assigned to operate the vehicle (driver, gunner, loader and commander). The commander is responsible for guiding the activities of the other members to ensure the effective utilization and safe operation of the system. The driver is again solely responsible for the focusing on the dynamics of the driving task.

In our SoD concept we propose the separation of the autonomous driving task into two separate computational processes: Autonomous Mobility Controller (AMC) and Safety Reasoning System (SRS) as described in figure 3.

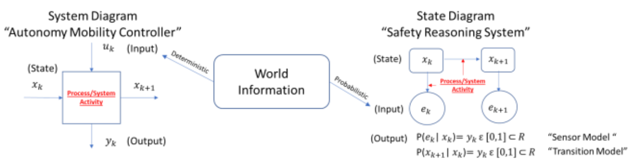

Figure 3: The relationship between a control space system diagram (representing an autonomous vehicles control system) and a State Based Probabilistic Diagram (representing the Safety Reasoning System).

Both of these computational systems work together to reason about the world around the autonomous vehicle but utilizing differently conditioned sets of the source information. The AMC processes deterministic real time information related to the current state of world around the vehicle to make mobility decisions. The SRS rationalizes about the mobility decisions of the AMC probabilistically as it relates to the current and projected world states around the vehicle to provide current-time safety decisions. This utilization of projected future world state information into the vehicles current-time safe-motion decision processes produces an explicit anticipatory feed into the vehicles ANS as shown in figure 4 [21]. This anticipatory decision process is the second fundamental conceptual component of the SRS.

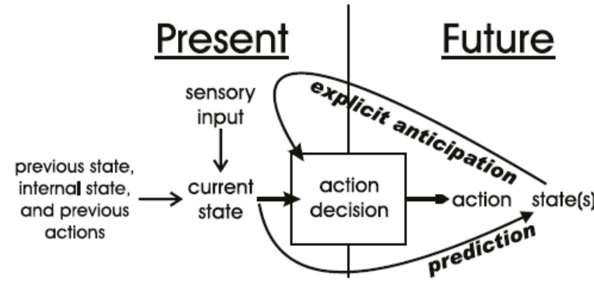

Figure 4: Explicit State Based Anticipation. Influence actual action decision making due to future predictions, expectations, or intentions.

As described by Robert Rosen [22] an anticipatory system is one that can anticipate the environment around it. Rosen describes the means by which a natural system is internally guided and controlled via encoded information acting as an interactive set of models – of self, of environment, and of 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 in order to provide anticipatory knowledge, they must produce predictions ahead of the predicted phenomena (as shown in figure 4).

In our approach we implement anticipation through the utilization of propositional logic and probabilistic graphical models. We use these techniques to correlate select information sources available within an autonomous vehicles operating environment (both physical and semantic) into probabilistic safety variables. These probability variables are projected forward in the scene via small-time windows by leveraging the casual nature of information changes within rule-defined environments (such as roadways). This inferenced information is compared against the intended current-time actions of the autonomous vehicle of interest (called Ego vehicle) attempting to autonomously maneuver within this complex rule defined environment (such as a T-intersection).

3. Safety Reasoning System - Specifics

The anticipatory SRS predicts changes in the Ego vehicles environment from a global (infrastructure-based sensing) and local (vehicle-based sensing) perspective as shown in figure 5.

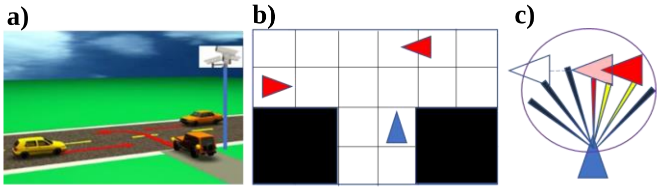

Figure 5: a) T-intersection with Ego vehicle (making turn) and traffic with overhead camera b) Overhead intersection information from infrastructure-sensing c) Vehicle-based sensing of traffic moving right to left from ego vehicle (dark red – vehicle sensed at t_i; pink – vehicle sensed at t_{i+1}; while – projected vehicle location at t_{i+k}

This sensory information is reasoned upon to produce the probabilistic safety variables via conditional and logical propositions in each sensor domain. These variables are updated as the scene conditions are simulated forward at a rate of time faster than the Ego vehicles ANS decision cycle. The SRS will then determine a percent safe probability for the vehicles intend action (provided by the ANS) based on this forward safety-oriented predicted scene information. Based on the percentage of safety provided by the SRS the autonomous vehicle will either perform, modify or cease to perform its intended action.

3.1. Infrastructure-sensing

The sub process for producing safety variables is calculated utilizing a sensory decomposition process involving grid occupancy calculations as described in figure 6.

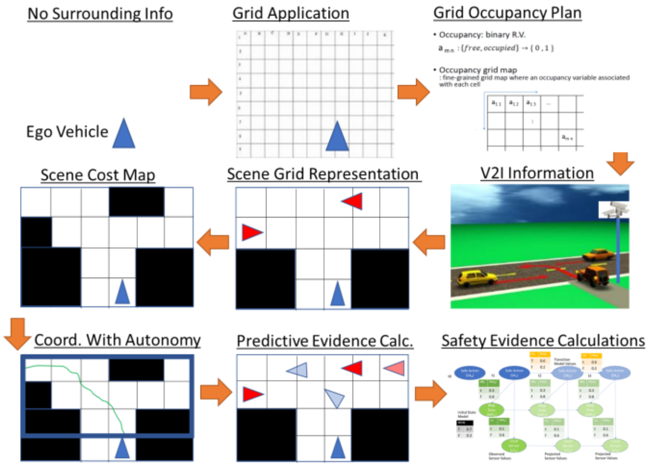

Figure 6: Pictorial representation for process of decomposing overhead infrastructure-based sensing into probabilistic safety variables

A key component in figure 6 is the predictive evidence calculation. This is accomplished utilizing a series of semantic propositional thresholding techniques as shown in in figure 7:

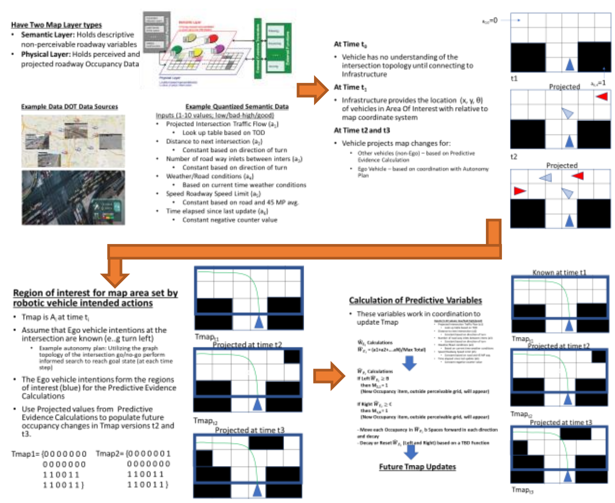

Figure 7: Pictorial representation for the Predictive Evidence Calculations in figure 6. Where t_i represents time; W_E is a semantic variable representing the world environment; W_P is a physical variable representing grid occupancy; T_{map} is a database of grid cells

From the process described in figure 7 a probabilistic variable MD (Map Data) is produced that represents the safety proposition of the Ego vehicles intended action in the T-intersection scene, based on infrastructure-sensed/projected scene changes across multiple time slices. This MD variable is an evidence input to the Dynamic Bayesian Network (DBN) that produces the holistic robotic vehicle safety evidence calculations shown in the final step of figure 6.

3.2. Vehicle-based sensing

The sub-process for calculating the vehicle safety information from vehicle-based sensor information begins with collecting and projecting obstacle data as described in figure 8.

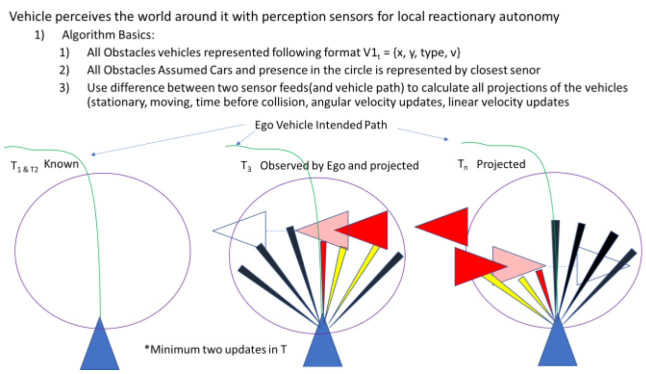

Figure 8: Vehicle senses the world around it with perception sensors. Closest obstacle within the disk sensor region provides information related to objects seen from the vehicle perspective. Blue vehicle is the robotic vehicle, Red vehicle is location of obstacle vehicle for first sensor cycle reading, pink vehicle is location of obstacle vehicle for second cycle sensor reading, white vehicle is the projected location of the vehicle based on analysis from first two sensor readings. Yellow sensor feeds utilized sensor feeds determining vehicle location. Red sensor feeds are not used. Black sensor feeds are unaffected sensors in the scenario

These sensor feeds in figure 8 are used to perceive and sample the environment at given time steps. We are using a simplistic sensing model described below.

1) Using two-time steps, the vehicle can infer the nature and velocity of obstacles in its direct environment.
2) Using knowledge of the sensor characteristics, if the first cluster region of points classified as a vehicle object does not appear in the next time step in the same position (e.g. time of flight calculation is longer) then it is assumed the vehicle is moving (only focusing on closet points).
3) If the vehicle is moving a closest cluster of points will be captured in two sensor time steps, thus future locations are projected forward based on this inferred velocity information.

The simple projective process described above is viable for the purposes of this research proposal. A more elaborate scheme would be utilized in a realized automotive system where the dynamics of the world, that can cause sensor anomalies, cannot be so easily abstracted away. The sensor information collected/projected in these time intervals is translated into a probabilistic variable Local Sensor (LS). This variable represents a safety proposition of the autonomous vehicles intended action in the T-intersection scene, based on vehicle-sensed/projected scene changes across multiple time slices. This LS variable is also utilized in the DBN similar to MD.

3.3. Anticipatory process

For safety evidence calculations, the final step of figure 6, we utilize a Dynamic Bayesian Network (DBN) [23]. A DBN is a generalization of linear state-space models such as Kalman filters [24] and simple dependency models such as Hidden Markov Models (HMMs) [25] into a probabilistic representation and inference mechanism for time-dependent domains. DBNs are a methodology becoming more common in probabilistic robotic applications as they are computationally more effective than HMMs, when dealing with more than a single random variable in the inference process, and they allow for consideration of both linear and non-linear distributions within their transition and sensor models (unlike Kalman Filters).

All three of these methods are a means to probabilistically reason about the belief state of a variable over time. From a prior probability distribution (initial probability of safely executing the turn in our T-intersection case) and a transition model (influence time has on relevancy of projected data in the intersection scenario) one can predict how the world might evolve over the next time step. From the observations (Ego vehicle intended actions at each time step) and a sensor model (reliability of the sensor data in that scenario (MD – accident rates at intersection; LS – reliability of on vehicle sensor readings) an agent can update its belief state (belief in safety of intended action given inferenced data). A changing world can be modeled by using a variable X_t for the set of state variables (x_t for a single value at a given time t), E_t for the set of observable evidence variables (e_t for a single value at a given time t) for each aspect of the world state at each point in time.

A DBN, like any other temporal state-space predictive inferencing technique, is composed of an acyclic graph of conditionally dependent variables represented by nodes and arcs, a prior probability distribution variable (equation (1)), a transition model (equation (2))) and sensor model (equation (3)).

$$P(X_0) \tag{1}$$

$$P(X_t|X_{0:t-1}) = P(X_t|X_{t-1}) \tag{2}$$

$$P(E_t|X_{0:t}, E_{0:t-1}) = P(E_t|X_t) \tag{3}$$

From these models you can form the networks joint probability distribution function as represented by equation (4).

$$P(X_{0:t}, E_{1:t}) = P(X_0) \prod_{i=1}^{t} P(X_i \mid X_{i-1}) P(E_i \mid X_i) \tag{4}$$

With the joint probability distribution function established we need to choose the inferencing method that will be utilized for updating the belief state queries to the DBN network over time. We will be utilizing the DBN for predictive analysis but we will be using the filtering method of inferencing (equation 5) for this activity as opposed to the predictive technique (equation (6)).

$$P(X_{t+1} \mid e_{1:t+1}) = \alpha P(e_{t+1}|X_{t+1}) \sum_{x_t} P(X_{t+1}|x_t) P(x_t|e_{1:t}) \tag{5}$$

$$P(X_{t+k+1} \mid e_{1:t}) = \sum_{x_{t+k}} P(X_{t+k+1}|x_{t+k}) P(x_{t+k}|e_{1:t}) \tag{6}$$

We are able to utilize the filtering method for inferencing, which computes the belief state given all evidence to date, as opposed to the predictive method, which calculates the posterior distribution over the future state, as we are inferencing forward in the network with predictive evidence in place of observable evidence (as seen in figure 9).

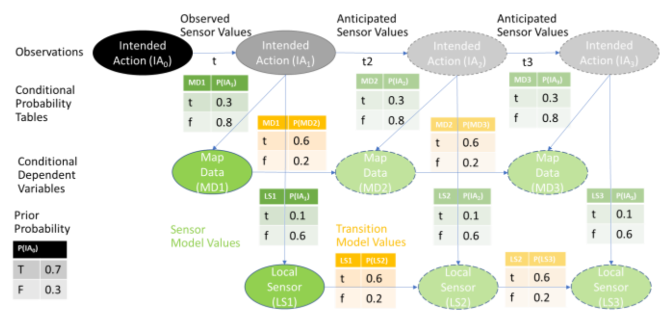

Figure 9: Example Acyclic DBN Graphical Model of an Anticipatory Safety Calculation system for the T-intersection problem utilizing real and anticipated binary evidence updates to conditionally dependent variables MD and LS.

In figure 9 we utilize real and projected binary evidence updates to the conditionally dependent variables Map Data (MD) and Local Sensor (LS) through the intended action observational sensor inputs of the network. These sensor inputs are condition, as briefly described in sections 3.1 and 3.2, and projected forward in the network to allow for queries concerning the safety of the vehicle such as P (Safe Turn at t=1 | MD3, LS3). As seen in this query the network can be utilized to make current time safety decisions based on both current time and anticipated observations. This allows a decision to make a left turn in a T-intersection more than a function of what the vehicle sees in from of it or can extrapolate from current overhead data. It adds to that function the consideration of how those scenes may change in a short window of time given other information projected into the world from correlated semantic projections that form particular potential physical world inputs (like a vehicle appearing into an overhead scene based on reasoning on a series of semantic indicators…as briefly shown in the first part of figure 7).

4. Initial Results

We test the results of the SRS concept utilizing the simple left turn T-intersection scenario detailed in the predictive evidence calculations in figure 7. We compare the results of a traditional temporal inferencing technique utilizing the predictive inferencing method described in equation (6) against the SRS concept utilizing a filtering temporal (equation (5)) method with predicted evidence updates coming in the form of intended-action safety-state variable binary updates to Map Data (MD) and Local Sensor (LS) data. The intended action of the vehicle is a Safe Turn (ST) at the T-intersection. The queries to the network to predict the safety of the intended action, in this example, would be as described below:

A) Traditional Inferencing Method with query $P(ST_3|md_1, ls_1)$, (see figure 10)
   a. Where you are using the network to predict the probability of the intended action, safe turn (ST), being true three time steps into the future given the last evidence update being provided at the current time step t=1. In this scenario you are querying the network utilizing only the established conditional probability table for transition model.

B) SRS Inferencing Method with query P (ST_1| MD3, LS3) = $P(ST_3|md_2, ls_2, md_3,\ ls_3)$ (see figure 11)
   a. Where you are using the network to predict the probability of the intended action, safe turn (ST), being true, at t=1, assuming two predicted sets of data for MD and LS that are reduced into truth variables of safety at each future time step.

An additional assumption in this example is that we have the variables of the conditional probability tables for both the sensor and transition models of the network through expert acquired previous knowledge.

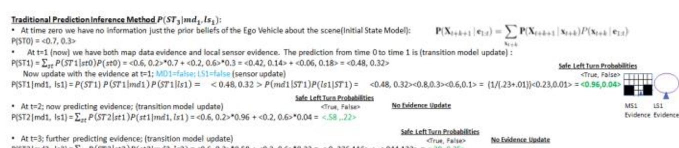

Figure 10: Calculations for prediction inferencing technique utilizing only network transition model Conditional Probability Tables (CPTs) with a last evidence update to the DBN at time step =1 for the state safety cases of P(ST_3|md_1 = F (meaning no evidence of concern), ls_1 = F)

In figure 10 the inference calculations for the DBN network and Conditional Probability Table (CPT) tables asserts that the network inferenced belief of a safe turn decays from 96% at time step 1, to 58%

at time step 2 to 38% at time step 3. This means given evidence at time step 1 of no safety concern from either MD or LS data the transition model of the network would reduce the probability of making a safe turn at time step 3 from 96 to 38% given the uncertainty embedded into the transition model CPTs.

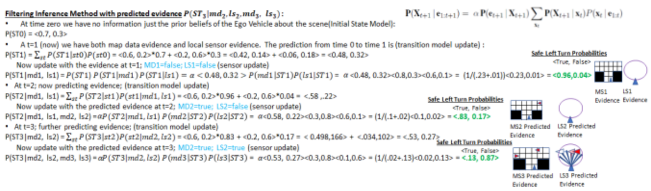

Figure 11: Calculations for prediction inferencing technique utilizing transition and sensor models with Conditional Probability Tables (CPTs) with evidence updates to the DBN at time step 1 $P(ST_1|md_1 = F, ls_1 = F)$; at time step 2 $P(ST_1|md_2 = T, ls_2 = F)$; at time step 3 $P(ST_1|md_3 = T, ls_3 = T)$;

As shown in figure 11 the filtering inference method with predicted evidence produces a safe turn probability belief decay from 96% at time step 1, to 83% at time step 2 (even with predicted MD evidence changing) and finally to 13% at time step 3 with both MD and LS data representing a safety concern of T.

The analysis from this example demonstrates how the concept works as would be expected regarding forward projected variable/query belief states given properly configured evidential and conditional data sets. If variable temporal informational can be believed to be sequential and linear in nature, regarding its evolution, the results of using projected evidence and the filtering inferencing technique, to determine the belief state of a query/variable, is more accurate than inferencing with the prediction method and previous evidence. This also assumes that the temporal predicted information is simple as well (e.g. binary). If the predictions in evidence are wrong then the results of the inferencing will also be incorrect. However in the cases where you have a high degree of sequential causality related to changes in evidence, such as T-intersections, those concerns are of lessened concern regarding holistic impact.

5. Conclusion

We are proposing a new method of utilizing Dynamic Bayesian Networks (DBN) in anticipatory configuration via the utilization of the temporal filtering inference technique with predicted sequential binary evidence. This utilization assumes that the binary observable evidence, that are the inputs into the DBN, is based on preprocessed and filtered information. This filtering process is utilized to ensure that this base reference information is relevant, salient and sufficiently sequential and linear in nature such that binary truth estimations can be reasonably believed to be the "best estimation" possible.

This modified approach to temporal projective inferencing tracks with the concept that Robert Rosen introduced in his book "Anticipatory Systems". The methods described in this paper are derived and explained in reference to the modeling techniques he introduced.

The intended application domain for this research is within the domain of autonomous vehicles. Specifically associated with the proposed concept of a Separation of Duties (SoD) consideration between and autonomous vehicles motion planning (managed by one of any given Autonomous Navigation Systems (ANS)) and motion execution (enabled after evaluation via the anticipatory Safety Reasoning System (SRS)).

In this paper we gave a simple example demonstrating the potential utility of this approach could be applied. More work needs to be done in ensuring this technique works across a multitude of intersection scenario's as well as with a series of data sets and data reduction techniques.

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