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Safety Analysis of Autonomous Ground Vehicle Optical Systems: Bayesian Belief Networks Approach

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Abstract—**Autonomous Ground Vehicles (AGV) require diverse sensor systems to support the navigation and sense-and-avoid tasks. Two of these systems are discussed in the paper: dual camera-based computer vision (CV) and laser-based detection and ranging (LIDAR). Reliable operation of these optical systems is critical to safety since potential faults or failures could result in mishaps leading to loss of life and property. The paper identifies basic hazards and, using fault tree analysis, the causes and effects of these hazards as related to LIDAR and CV systems. A Bayesian Belief Network approach (BN) supported by automated tool is subsequently used to obtain quantitative probabilistic estimation of system safety.**

I. Introduction

Light Detection and Ranging (LIDAR) combined with dual-camera computer vision (CV) are used as a primary technology for navigation representing a typical optical sensor systems for autonomous ground vehicles (AGV). Researchers at the National Institute for Standards and Technology [1], [2], [3], the U.S. Army [4], and Carnegie-Mellon University [5] have been using such systems to detect obstacles and navigate at ever increasing speeds. Obviously, AGVs combing physical and computing components are typical cyber-physical systems.

AGVs may also be equipped with other navigation technologies such as Inertial Measurement Units (IMU) or Global Positioning System (GPS) receivers; however, the accuracy provided by optically-based navigation controls is absolutely necessary for a safe and precise vehicle operation. Since GPS position errors may be in the range of several meters, GPS alone is not sufficient to safely control a vehicle in urban environment without endangering street signs, pedestrians, and other vehicles. Additionally, GPS reception is obstructed by tall buildings, making GPS unsuitable as a primary navigation tool in an urban environment. IMUs may be used to supplement GPS in low signal areas. However, as kinematic devices, IMUs quickly build up internal error, making them essentially useless for prolonged autonomous navigation. Due to these issues, it is necessary to navigate with a combined system which relies heavily upon optically-based sensor devices.

The paper specific focus is on dependability of the LIDAR and CV sensor systems. It is critical to analyze how the systems work jointly during normal operations and how they work separately under exceptional conditions. To encourage simplicity and maintain focus on the technology, the LIDAR and CV systems are viewed in a generic manner with no effort to model a specific brand of sensor platform. The increasing importance of these issues is realized as fully autonomous vehicles begin to find their way onto roads. Environmental sensing i.e., the capability of the AGV to recognize its location with respect to the environmental obstacles, is the major reason why LIDAR and CV systems are required. Since any unsafe AGV operation may result in violation of safety (property loss or harm to people), there is an evident need for safety analysis. The AGV is safety-critical, software intensive system and potential faults or failures could result in mishaps leading to loss of life and property. By analyzing the hazards posed by the system, the chance of mishap may be reduced or, in some cases, entirely eliminated.

The paper classifies the risk related to AGV operations and describes hazard analyses focusing on impact of LIDAR and CV systems on these operations. Fault Tree Analysis (FT) is used to identify undesirable events and sequences of events leading to top level mishaps such as pedestrian injury, vehicle damage, and external property damage. The Bayesian Belief Network (BN) was modeled based on the FT diagrams along with estimations of likelihood of the events and decision nodes. The presented model can be a good estimator of AGV optical navigation systems as a whole.

II. System Description

A. The AGV Sensor Systems

LIDAR and CV systems are optical sensor systems typically installed on AGV. Together with other sensors they are capable of providing kinematic information about a vehicle (position, velocity, acceleration) and physical information about surroundings (obstacles, road signs, pedestrians, etc). The information from the sensors feeds into a sensor integrator subsystem which filters and integrates data from all vehicle sensors. Detectable anomalies and erroneous data are typically filtered at this stage.

Having been filtered, the input data are packaged and sent to a state estimator which performs additional filtering and estimates the current state of the vehicle. This state data are then sent to the navigation module which acts as a high-level controller for the individual control algorithms related to degrees of freedom of the vehicle (velocity, heading, etc).

The navigation module (i.e., waypoint manager) handles high level control of the AGV's navigation. In the event of an optical sensor failure, the data passed on to the state estimator will be either corrupt or missing, generating a biased position estimate for the navigation module. The navigation module relies on this data to know where in the world the AGV is with respect to the waypoints, so a simple LIDAR failure could result in the navigation module thinking that the AGV is only 10 meters away from the target when in reality it is 100 meters away.

B. LIDAR

Regardless of measurement technique, all LIDAR units include the following (often redundant) components: laser, lens filter, receiver, power regulator, rotating mirror, position encoder, and onboard processors. As an example, Fig. 1 shows a LIDAR unit (by SICK) with panoramic scanning using rotating a mirror, allowing the laser diode to remain stationary. Detection is accomplished through a complicated combination of synchronizing hardware (including precision motors, and position encoders), and onboard processing capabilities. LIDAR systems typically use a lens filter to block wavelengths of light not identical to that emitted by the laser diode, thus passively reducing interference in the receiver and avoiding the additional complexity, software, circuitry, and cost associated with active filtering. Received laser signals are processed based on this synchronization data to produce a two or three dimensional point cloud. Any error in the system can obviously lead to incorrect depth or position calculations.

Despite being designed for an outdoor use, the high-precision moving parts and optics in modern LIDAR systems are very sensitive to shock. It is important to always place the device at safe, strategic locations around the vehicle. LIDAR should be placed at high clearance locations from the ground, minimizing the amount of vehicle parts obstructing the field of view. Precautions should be taken to protect the device. Foreign-object impact, shock, and vibrations resulting from crashes or rough terrain navigation could cause device failure.

The LIDAR optical filter is one of the most important components of the device. Any damage to the filter will adversely affect measuring accuracy. The LIDAR filter should be protected with a shroud to prevent or reduce impacts and scratches due to vegetation.

C. Computer Vision

Similar to the LIDAR, the CV camera system can produce a two dimensional image using a single camera (or a three dimensional image using dual camera system with two cameras arranged stereoscopically). Using two cameras also allows the failure of a single camera to degrade but not completely void the CV system functionality.

Fig. 1 Example LIDAR

Computer vision software is fundamentally bounded by image quality which is often related to the number of pixels. As each pixel must be processed at least once, the quantities of data and necessary memory may be overwhelming for a system with limited resources. With sufficient processing hardware it is possible to extract quantitative information from scenes, detect obstacles, or track targets using nothing but CV software.

Computer vision algorithms depend upon the video signal received from the camera device. Almost every camera generates some form of distortion which may degrade or even prevent a CV algorithm from operating properly. For this reason, it is necessary to properly calibrate camera and correct image distortion prior to using the image as a source for CV. Improper lighting typically affects both cameras at the same time due to overcast or night condition etc. High-intensity headlights and ambient light sensors on the cameras would be the mitigation technique.

LIDAR failure alone should not significantly degrade system performance. Cameras misalignment would occur if they are displaced by an impact or vibrate free (which can be mitigated with appropriate hardware, e.g., lock washers) and periodic maintenance. Optical receiver misalignment should be extremely rare and can only be caused by manufacturing defect or by physical stress on the device over time (i.e., vibrations from road).

III. Safety Assessment

A. Risks and Hazards

Incorrect operation of AGV may result in mishaps of various severity levels (Table I). One may identify risk as a measure of potential consequence of a hazard representing both the likelihood and the severity of something bad or undesired happening. During the hazard identification stage, hazards are classified according to their risks. A Preliminary Hazard Analysis (PHA) is the starting point to classify these hazards. As with most safety critical systems, the AGV system hazards can be classified in a qualitative manner, using pre-defined arbitrary categories known as risk classes computed as a product of severity and the likelihood of occurrence. For the AGV system, these levels are: negligible

(RV < 1), marginal (1 < RV < 10), critical (10 < RV < 100) and catastrophic (RV > 100).

TABLE I
MISHAP SEVERITY LEVELS

Severity Level	Description
1	No loss of any kind
2	Minor property loss (low cost hardware parts)
3	Major property loss, damage to the environment
4	Loss of critical hardware, human injuries, major damage to the environment
5	Catastrophic loss of life, loss of the entire AGV system, serious environment damage

From a safety standpoint, hazards become the source for safety requirements. Typically, loss of any system functionality may lead to a hazard (e.g., if the laser head of the LIDAR system stops rotating due to mechanical failure). The loss of functionality usually allows identifying a hazard. In turn, the hazard identification allows determining a control measure to be established to prevent or control this hazard. Finally, this control measure can be then converted into a safety requirement for the system and thus be considered in the system development lifecycle.

For the LIDAR example, there is a known hazard of losing the mechanical functionality of the laser rotor head due to wear or manufacturing defects. Typically, engineering department would design and test systems well enough to provide recommendations of conditions for safe operation of their product. Furthermore, manufacturers will typically add recommended maintenance checkups to prevent hazards from transforming into accidents and mishaps. Hazards are always dormant, that is, they exist harmlessly unless certain conditions and/or set of events occur, transforming the hazard into an accident or mishap. Hazards by themselves are not doing any harm unless some transformation takes place. For instance, an energy build-up (e.g., stress due to shaft miss-alignment) would be required for the electric motor that rotates the laser head to eventually give up and stop working. This process takes time. As time passes, wear and stress builds up on the weakest motor parts (with more critical defects). Eventually there will be enough wear and stress accumulated that a point of no return will be reached and a triggering event occurs. That is, at this point there is nothing else that can be done to prevent this hazard from transforming into some accident or mishap. As all this is happening, the system safety levels are gradually degrading from an initial “safe and controlled state” to a final “unsafe and uncontrolled state” leading eventually to a mishap. In all cases a hazard is a prerequisite to the final accident or mishap.

Since an AGV system is dependent on both LIDAR and CV subsystems to assure proper navigation and avoidance of obstacles, any hazards of either subsystem constitutes also a hazard for the AGV system. From this perspective, both LIDAR and CV are safety-critical. Any failure of these subsystems could propagate and lead to a disaster with severe consequences for the AGV. Preliminary list of hazards for LIDAR and CV subsystem, including also hazards and their severity levels is shown in Table II.

TABLE II
HAZARDS IDENTIFICATION

Item	Sub-item	Fault Condition	Hazard	Severity Level
LIDAR	Position Encoder	Fails to read position data	Mirror Motor Malfunction	4
	Electrical	Short circuit	Electrical Failure	4
	Electrical	Overvoltage	Electrical Failure	4
	Optical Receiver	Misalignment	Optical Receiver Error	3
	Optical Filter	Damaged	Optical Receiver Error	3
	Mirror Motor	Malfunction	LIDAR Failure	4
			laser Radiation	4
CV	Camera	Misalignment	CV Failure	3
	IR Filter	Missing	CV Failure	3
	Lens	Damaged	CV Failure	3
	Camera	Improper Lighting	CV Failure	3
Navigation Module	N/A	LIDAR Failure	Navigational Failure	4
		CV Failure	Navigational Failure	4
		Navigational Failure	Property Damage	5
			Vehicle Damage	5
			Pedestrian Injury	5

The most critical sequence of events is one that eventually leads to top level mishaps in the AGV system. Top level mishaps typically relate to loss of life, property or severe damage to the environment. The main goal of Safety Engineering is to prevent these mishaps from happening.

Generally, mishaps are not caused by single events. The accidents are almost always caused by a sequence of events that eventually take the system to an unstable and unsafe state causing the mishap. In the case of the AGV system there are three major top level mishaps: Critical Vehicle Damage, Pedestrian Injury, and Other Property Damage. Critical Vehicle Damage refers to a sequence of events leading to an accident in which the AGV is lost. This type of mishaps results from uncontrolled travel that leads to a physical contact involving substantial volume of kinetic energy between the AGV system and the physical world (i.e., crash or collision) which results in property loss. Pedestrian injury or fatality is by far the most undesirable top level mishap that may be caused by an uncontrolled travel of the AGV system. Other property damage refers to loss of property caused to third parties that are not a part of the AGV system. For instance, during collision with another vehicle the AGV system may cause damage to the other vehicle. All three above mentioned mishaps can be categorized at the highest severity level.

B. Fault-Tree Analysis

Based on the preliminary hazard identification presented in Table II, we may use Fault Tree Analysis (FTA) to show the chain of events that may lead to mishaps. FTA allows us not only to identify the set of events leading to top level mishaps but also determine the intermediate events that constitute a cause-effect chain [6].

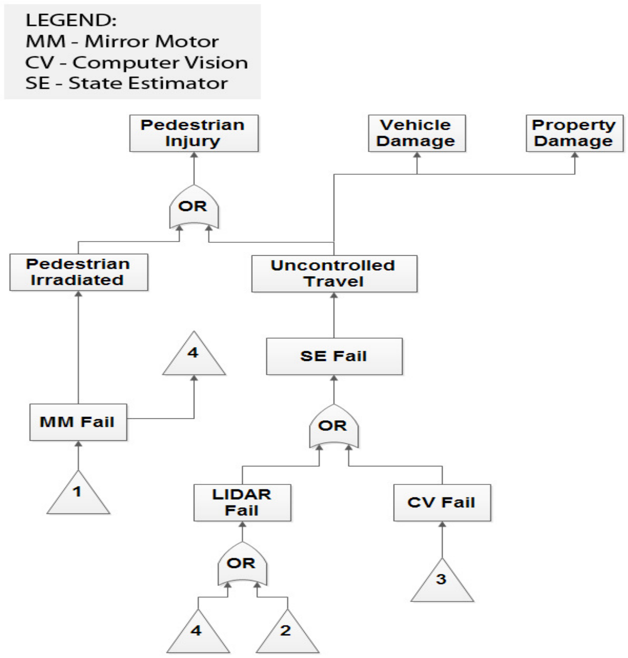

Figure 2 Top-level FTA for UGV

Fig. 2 presents top-level fault tree identifying three top-level mishaps and the LIDAR/CV contribution to these mishaps. LIDAR and CV subsystems fault trees are presented in Fig. 3 and 4. As Portinale [7] observed: "*Any FT can be transformed into a corresponding BN, by creating a binary BN node for each event in the FT, and by setting the probability of BN root nodes (corresponding to basic events in the FT).*" Thus, the cause-effect relations between the events are the basis of subsequent quantitative probabilistic analysis using a Bayesian Belief Network.

The FTA analyses show that any major mishap will involve the failure of one or more subsystem components. In the case of both subsystem components failing (CV and LIDAR) the resulting behavior of the AGV system will always reach a top level mishap scenario.

IV. Bayesian Belief Networks

A. Background

Bayesian Belief Networks have been widely used in Industrial Information Systems for solving variety of computational problems with insufficient information and excessive uncertainty [6, 8, 9]. Since the 18th century mathematician Rev. Thomas Bayes introduced the concept of updating probabilities based on new information, the method has been widely applied in probability and statistics. The basis for the

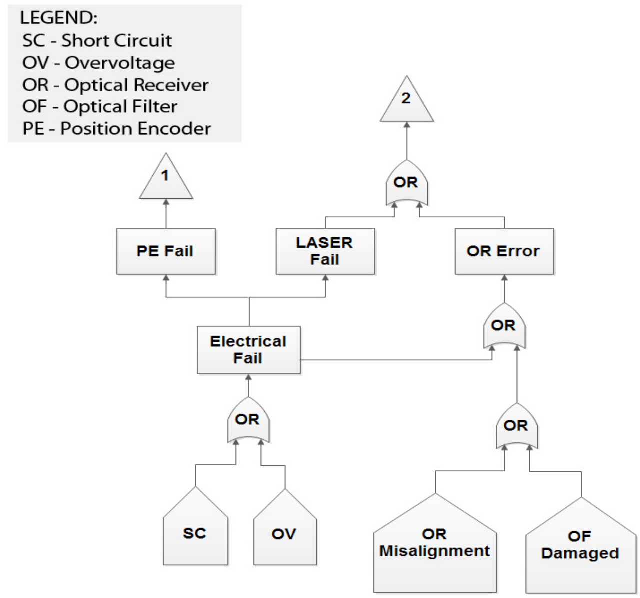

Figure 3 Low-level FTA for LIDAR

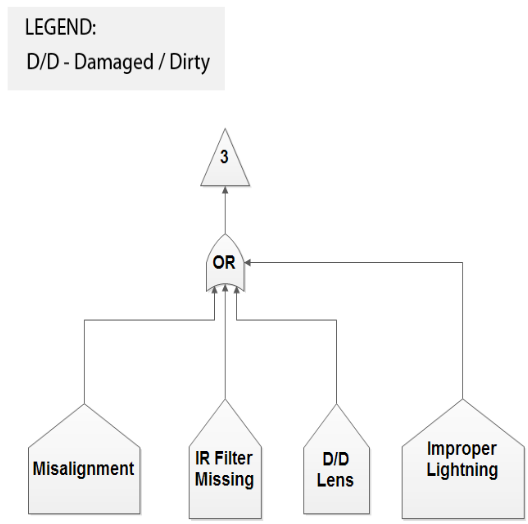

Figure 4 Low-level FTA for CV

method is the inversion formula for belief updating from evidence (E) about a hypothesis (H) using probability measurements of the prior truth of the statement enhanced by posterior evidence:

$$P(H|E) = (P(E|H)*P(H)) / P(E) \qquad (1)$$

A Bayesian belief network is a probabilistic graphical model. The belief network represents the joint probability distribution of a set of random variables with explicit interdependence assumptions. In this research a Bayesian network is defined by a directed acyclic graph of nodes representing variables and arcs representing probabilistic dependency relations among the variables [9].

An arc from node A to another node B indicates that variable B depends directly on variable A. If the variable represented by a node has a known value then the node is said to be observed as an evidence node. A node can represent any kind of variable, be it a measured parameter, a latent variable, or a hypothesis. Nodes are not restricted to representing random variables: this is what "Bayesian" is about a belief network.

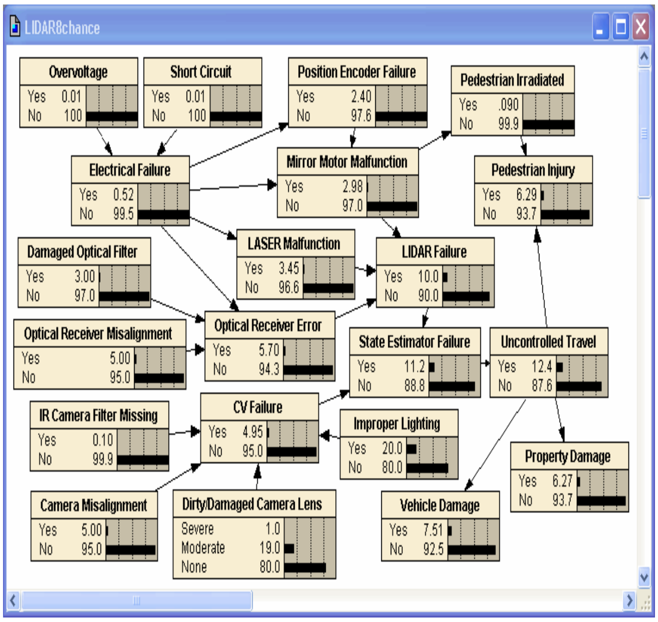

Figure 5 BN of the AGV System – a nominal scenario

The approach supports three types of reasoning. Predictive reasoning observes the causal evidence and updates the middle and upper layer nodes reasoning from a cause to the effects. Diagnostic reasoning observes the evidence of effects and updates the middle and the bottom layer causal variables, reasoning from an effect to the cause. The BN's also allow explanatory (inter-causal) reasoning, in which middle layer reasoning evidence is used to update both the causal and the effect variables.

B. Preliminary Modeling

There is a variety of tools supporting BN modeling: www.dsl-lab.org/ml_tutorial/software_bayesian_networks.html. The computations were done using Bayesian Networks generated by the tool Netica [10]. Based on the fault tree diagrams, along with assumption of base events likelihood (leaf nodes) and the conditional probabilities, it was possible to create a model which represents a good estimator of AGV optical navigation systems dependability. Using nominal likelihood values based on the system analyses and the available data, i.e., assuming no deterministic evidence about the status of the system components, we were able to assess the likelihood of top level mishaps and thus identify their criticality. Fig. 5 presents a screenshot of the tool in such nominal scenario.

From this nominal scenario the BN allows to introduce evidence of selected events and analyze the impact of this evidence on other events. The predictive reasoning property of BN allows us to introduce the evidence of base events (as an example: a camera misalignment) and observe the impact on intermediate events and ultimately on the top level mishaps (Fig. 6).

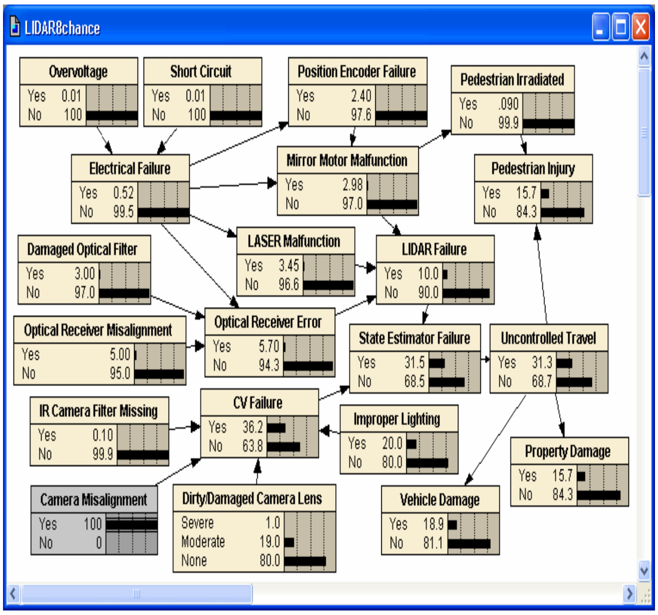

Figure 6 BN predictive reasoning – evidence of camera misalignment

Another scenario allows the presentation of the inter-causal reasoning property of the BN, i.e., analyzing impact of known evidence of intermediate events (e.g. malfunction of laser, mirror motor, optical receiver) up and down the causal chain. As an example, we show how introducing evidence of LIDAR failure results in over fivefold increase of pedestrian injury and property/vehicle damage probabilities (Fig. 7).

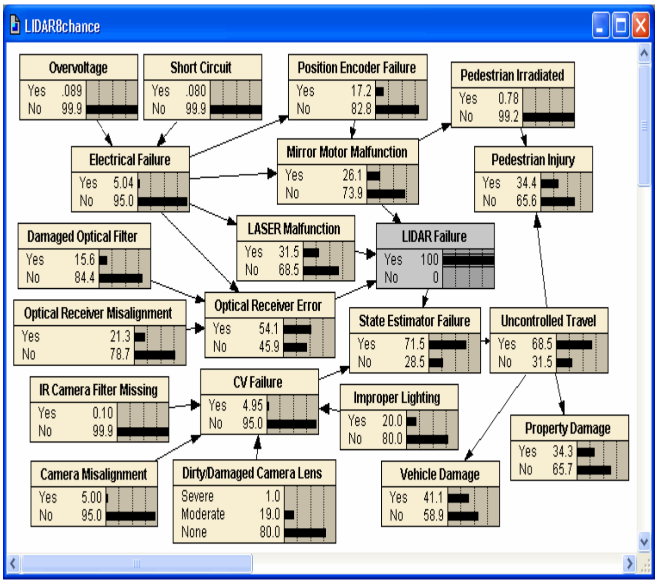

Figure 7 BN inter-causal reasoning – effect of the LIDAR failure

Similarly, the evidence of CV failure results in significant increase to the likelihood of top level mishaps (Fig. 8). Using the inter-causal reasoning one can also assess the potential causes of the malfunctions observing increased likelihood of causal events such as electrical failure, optical filter damage, or misalignment of the receiver.

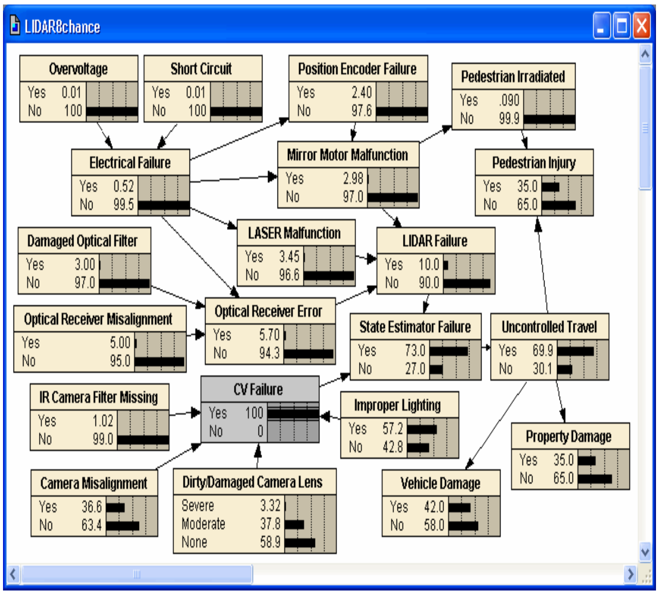

Figure 8 BN inter-causal reasoning – effects of CV failure

B. *Detailed Analysis*

Subsequently, a variety of scenarios were attempted to identify the impact of specific events and the criticality of top level mishaps. The model base probabilities are the best reasonable estimate numbers. Due to uncertainty built into the model, the top-level mishaps show relatively high likelihood of occurrence even with the evidence of correct operation and lack of any problems. The model thus implicitly accounts for unidentified hardware failures and other potential system defects that may cause uncontrolled travel. Table III presents partial results of the predictive and inter-causal reasoning modeling. In a nominal scenario (when all base nodes probabilities are "unknown" i.e. set to the assumed values based on the system analyses and available data), the probability of pedestrian injury is 6.29%. Given evidence of events such as overvoltage or damaged optical filter allows one to predict 200-400% increase in the likelihood of mishap. However, improper lighting or damaged camera lens increases the probability by less than twofold.

TABLE III
PREDICTIVE AND INTER-CAUSAL REASONING – IMPACT OF THE EVIDENCE ON PEDESTRIAN INJURY

Evidence	Pedestrian Injury Likelihood %	Impact (in relation to evidence unknown)
All base nodes "perfect"	***3.82***	***-39%***
All base nodes "unknown"	***6.29***	***0%***
All base nodes "bad"	***48.20***	***666%***
Improper lighting	9.07	44%
Severe damaged camera lens	9.76	55%
Camera misalignment	15.70	150%
Optical receiver misalignment	16.50	162%
Damaged optical filter	19.50	210%
Mirror motor malfunction	31.00	393%
Overvoltage	31.40	399%
LIDAR failure	34.40	447%
CV failure	35.00	456%
CV and LIDAR failures	47.70	658%

Using the predictive and inter-causal reasoning capabilities of Bayesian networks, it is possible to gain additional insight into improvements. For example, simply reducing the chance of inferior lighting is sufficient to remove catastrophic risks and substantially reduce the number of critical risks.

The BN also allows for a diagnostic reasoning (i.e., from effects to cause). For example, having evidence of pedestrian injury the BN estimates that the probability of mirror motor malfunction grows to over six times, CV failure five times, and state estimator failure nearly eight times its original value (Fig. 9).

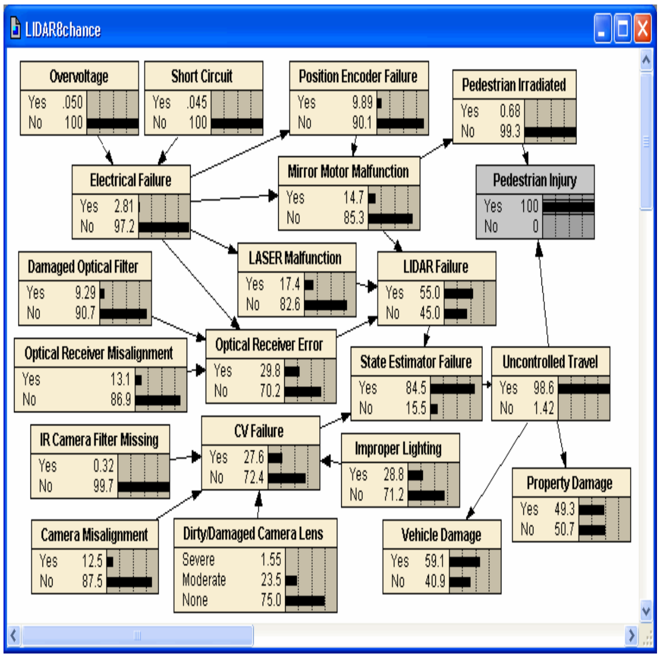

Figure 9 BN diagnostic reasoning – causes of pedestrian injury

Diagnostic reasoning is the most desirable in this research, since it allows making predictions on potential causes of mishaps, including quantitative assessment of risk. This, in turn, makes it possible to prepare for catastrophic events by minimizing their consequences or avoid them by paying closer attention to potential causes.

Using diagnostic reasoning it is possible to derive interesting statistics about the system, such as the rate of property and pedestrian damage in incidents of uncontrolled travel involving vehicle damage. Using available evidence it has been determined that vehicular damage will result in nearly

50% likelihood of property damage and pedestrian injury. It is also possible to estimate that, given the evidence of pedestrian injury, there is a 98.6% chance that it is caused by uncontrolled travel. Having evidence of vehicle damage, the reasoning allows us to estimate the likelihood of LIDAR failure to be 55% and CV failure 27.6%. However, with the evidence of no CV failure the likelihood of LIDAR failure increases to 70.8%. The proposed approach allows thus to analyze impact of given evidence on system in a variety of scenarios.

Table IV presents another partial result of the modeling. The columns present likelihood of the model events in two scenarios: when there is no evidence and when there is evidence of pedestrian injury. The LIDAR and CV failure show as the leading causes of potential pedestrian injury.

TABLE IV
DIAGNOSTIC REASONING – POTENTIAL CAUSES OF PEDESTRIAN INJURY

	No evidence of pedestrian injury	Evidence of pedestrian injury
Electrical failure	0.52	2.81
Damaged optical filter	3.00	9.29
Position encoder failure	2.40	9.89
Camera misalignment	5.00	12.50
Optical receiver misalignment	5.00	13.10
Mirror motor malfunction	2.98	14.70
Laser malfunction	3.45	17.40
CV failure	4.95	27.60
Improper lighting	20.00	28.80
LIDAR failure	10.00	55.00

Interestingly, and in accordance with the hazard table, the BN analysis shows that in the case of total state estimator and thus navigation failure, improper lighting bears a significant probability of being the reason, with CV and LIDAR being evidently on the top. The risk value corresponds equally well to LIDAR failures on the BN, with the laser malfunction as the primary cause. This correlation between the hazard table and the BN implies that the proposed approach provides reasonable base for quantitative assessment of system dependability.

V. CONCLUSIONS

This paper describes the analysis of autonomous ground vehicle system optical navigation components to identify hazards leading to potential safety violations and top level mishaps. We used safety analytical modeling techniques including Fault Tree analysis and Bayesian Belief Networks to better understand the sequence of events that could lead to a major accident or mishap. The quantitative analysis helps to determine the most important hazards that need to be mitigated or controlled. Analysis results confirmed the importance of the reliability and availability of the AGV sensor LIDAR and CV subsystems. Based on the analysis, specific mitigation measures can be recommended in order to reduce the risk of loss of life and/or property. These risk mitigations would lead to reducing the probability for subsystem and system malfunction.

By utilizing both Fault Tree Analysis and Bayesian Belief Networks it is possible to better determine what the sequences of events and their impact on the top level mishaps. From the FTA results it is clear that any major mishap will always involve the failure of one or more subsystem components. In the case of both subsystem components failing (CV and LIDAR) the resulting behavior of the AGV system will always reach a top level mishap scenario. Using predictive reasoning capabilities of Bayesian Networks, it was possible to gain additional insight into the system operation and identify the potential mitigation sources.

Future work would need to assure that the numerical values for the likelihood of events as well as the dependency relations between the nodes closely represent reality. A good source for these values would be published equipment failure rates (e.g. based on military handbook MIL-HDBK-217F 1995) or collected from industry studies related to safety incident rates [11].

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