Safety Diagnostics and Degraded Operational Modes for Off-road Unmanned Ground Combat Vehicles

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Abstract

Unmanned ground combat vehicles are obligated to traverse safely to their destination in an extensive variety of hazardous situations along with challenging terrains and the objective of the paper is to aid this intent. In circumstances of restricted operations of the autonomous vehicle, the composite systems of the vehicle should ensure its safety. However, the current fleets of autonomous vehicles are lacking the ability to predict and operate as effectively as possible in a restricted operational domain. This paper proposes an approach to create safety diagnostics for unmanned ground combat vehicles by mainly depending on probabilistic predictions of critical situations. The predictions are achieved by a recursive Bayesian model along with constantly examining the changing environments which effect the perception sensor readings and the current behavior of the unmanned ground combat vehicles. To verify and validate the approach that this paper describes, the Mississippi State University autonomous vehicle simulator was used to run simulations of an autonomous vehicle affected by a fixed set of environmental parameters which were also used for computing the risk of failure using a Recursive Bayesian and Markov models. Finally, simulations are conducted for two scenarios to illustrate the effectiveness of the proposed approach.

1. Introduction

The last decade has witnessed eruptive growth in the field deployment of unmanned systems, which include unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs). The UGVs have been routinely used for surveillance, providing a relatively safe impasse in the scrimmage against improvised defence technologies, and in aiding the process of search and rescue efforts. For unmanned ground combat vehicles (UGCVs) to perform autonomously in all kinds of terrains, research has shown that UGCVs must be capable of adapting and learning from the environment rather than having the behaviour of the system to be hard coded. As an outcome, these adaptive systems utilize various approaches that empower them to respond to different operational environments and to carry out desired maneuvers based on the limit of their capabilities. One such role for the adaptive system is to engage the UGCV into a minimal risk condition in situations of the vehicles operational design

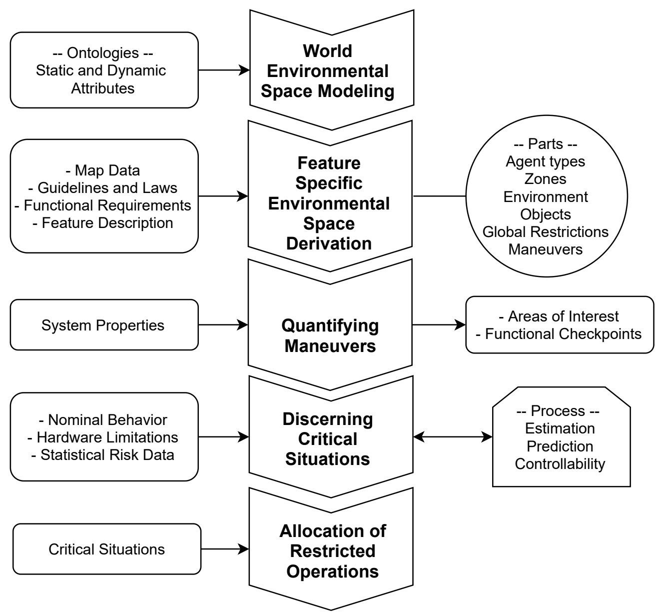

Figure 1. Sequential ODD Architecture.

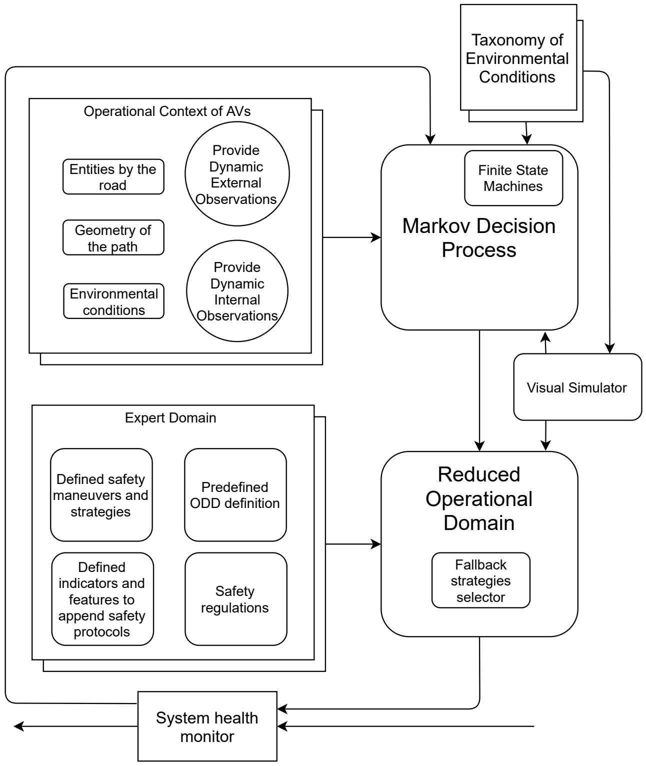

Figure 2. Process of Discerning Critical Situations.

domain (ODD) suffering from a deteriorated functionality (Koopman & Fratrik, 2019) (Colwell, Phan, Saleem, Salay, & Czarnecki, 2018). The ODD for autonomous vehicles (AVs) can help specify the safe operational domain of the vehicle (Hillen & Reich, 2020). The development process of the AV domain directly aligns with functional safety aspect of the vehicle and the processes involved in defining an ODD are shown in Figure 1. For most modern AVs, the system boundaries were exclusively considered to identify failures of the automated driving systems (ADS) and these failures were recognized through different analysis methods like fault tree analysis or hazard and risk analysis. The complexity of this research lies in how a UGCV in a military applications can overcome the challenges of traversing through ever changing natural obstacles when compared to the reinforcing obstacles which are encountered by autonomous vehicle in a conventional structured scenario.

The limitation in sensing capabilities under certain conditions would lead to the reduced operation of the UGCV. A failure operational analysis involves a sequence of steps which initially start out as recognizing possible failure modes and their root causes, this is followed by prioritizing those modes based on the level of risk that they hold and finally associating the appropriate risk diminution or correct strategy.

In AVs, the limited availability of perception sensors is overcome by using a different sensor configuration. The finite state essence of the discrete controller may possibly lead to incorrect behaviour of the complete system if an unforeseen situation occurs and for which there is a lack of any predefined contingency. For this reason, it becomes important to have a sense of a complete set of admissible scenarios and also to develop a structured decision-making process for each of the previously mentioned scenarios. The failure probabilities can be determined with the help of state machines and failure propagation trees and they can be updated with any changes on circumstances as this would help define if a maneuver should continue. With the decision-making process realized, the state sequences could be compared and this in turn would help in realizing better manoeuvrability of the vehicle.

Current generation of autonomous vehicles do not rely on predicting critical situation and hence are restricted in defining an effective reduced operational domain (ROD) which is adequately functional even in a hazardous situation. The ROD is essentially a limited ODD which an AV system shifts to in scenarios of reduced functional capacity. This paper emphasizes on a prediction model in situations where an AV has to traverse in extreme weather conditions. In order to model the real-life performance of safety critical systems and make accurate predictions, the Markov chain and Recursive Bayesian methods are used.

Predicting future state transition sequences is the main contribution of this paper to eventually form RODs. The modelling of a complete ROD is outside the scope of this paper. Existing models do not utilize probabilistic methods to predict occurrences of a failure which consequently may affect the state transitions of vehicle maneuvers (Colwell et al., 2018). Figure 2 gives a good representation of the role played by the process of discerning critical situations probabilistically to eventually determine the ROD of the vehicle and this paper gives more emphasis on the Markov process. The operational context of AVs and the expert domain as depicted in Figure 2 are reminiscent to the world environmental space modeling and feature specific environmental space derivation from the ODD architecture.

The paper is organized such that section 2 focuses on the process of addressing the risk probabilities followed by section 3, which describes the off-road vehicle simulations along with the reasoning for how well the risk probability predictions align with the simulation results. Section 4 reports the resulting state sequences based on the simulation results and finally, section 5 presents the conclusion for this paper.

2. RISK PROBABILITIES

This paper manly emphasises on determining the risk probabilities of a vehicle travelling in an unstructured scenario (off-road). The finite state machine (FSM) shown in Figure 3 is derived specifically to address states that would represent ve-

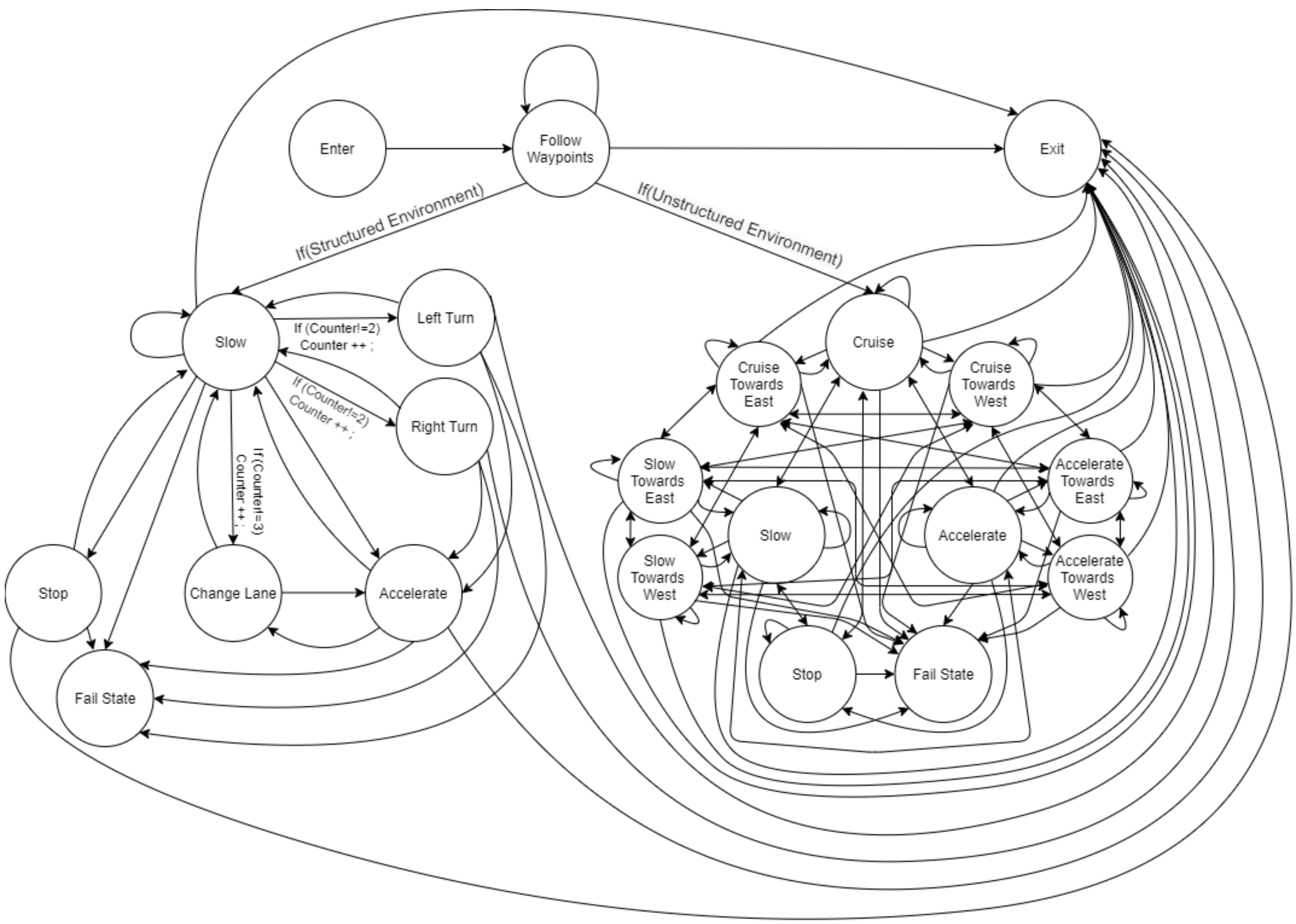

Figure 3. Ideology-Specific Finite State Machine.

hicle maneuvers both for structured and unstructured environments faced by UGCVs. In this paper, we propose to use the Bayes Filter to predict the probability of transitioning to a particular state based on the previous state and the sensor noise affecting the stochastics of transitioning. Scenario conditions that will be utilized as an example in the analysis of the presented approach include bad weather conditions like rain and snow. The probability of transitioning to a particular set of conditions is achieved using the Recursive Bayesian method, then the Markov process is used to predict future state transition probabilities assuming that the transition probabilities are constant over time and not affected by changing environmental parameters.

2.1. Finite State Machine

Usually, a number of aspects have to be taken into consideration when developing an ODD for an autonomous vehicle. In case of no fallback contingency, the finite state nature of a controller could lead to inappropriate behaviour when encountered with an unforeseen situation (Balogh & Obdržálek, 2019). The finite state machine in this paper has emphasis on unstructured environments which is pristine to this field of research. It is important to have an organized decision-making process for maximum possible situations and this can be done by hierarchically designating standard decision-making processes along with finite state machines (FSM) (Sales, Fernandes, Osorio, & Wolf, 2012).

Since this paper focuses on traversing through unstructured or off-road environments along with structured counterparts, there is an adjoining challenge of facing a lack of a prior knowledge of an AV traversing through various terrains. Similarly, there are other challenges like restricted sensing ranges, motion planning and motion control across inconsistent vegetation categories, elevation changes, localization limitation in remotely operating scenarios (Park, Ramezani, & Grizzle, 2013).

The finite state machine proposed in Figure 3 provides fundamental maneuvers of an autonomous vehicle which can also drive off road. However, the FSM's states will be fundamentally used to study the stochastics of the autonomous vehicle's maneuvers. The state selection aspect of FSM's mainly relies

Table 1. Predefined Probability References for Environmental Parameters.

States	Obstacle Coverage 0%	Obstacle Coverage 33.3%	Obstacle Coverage 66.6%	Obstacle Coverage 100%	No Snow (Visibility < 3km)	Light Snow (Visibility < 2km)	Moderate Snow (Visibility < 1km)	High Snow (Visibility < 0.5km)	Extreme Snow (Visibility < 0.2km)
Enter	1	1	1	1	1	1	1	1	1
Follow Waypoints	1	1	1	1	1	1	1	1	1
Exit	1	0.8	0.6	0	1	0.8	0.6	0.4	0
Cruise	1	0.8	0.6	0	1	0.8	0.6	0.4	0
Cruise Towards East	0.1	0.4	0.6	0	0.1	0.2	0.4	0.4	0
Cruise Towards West	0.1	0.4	0.6	0	0.1	0.2	0.4	0.4	0
Slow	0.2	0.4	0.6	0.8	0.2	0.3	0.4	0.6	0.7
Slow Towards East	0.2	0.6	0.8	0	0.2	0.3	0.4	0.6	0
Slow Towards West	0.2	0.6	0.8	0	0.2	0.3	0.4	0.6	0
Accelerate	1	0.6	0.4	0	1	0.8	0.6	0.2	0
Accelerate Towards East	0.1	0.4	0.6	0	0.1	0.3	0.4	0.4	0
Accelerate Towards West	0.1	0.4	0.6	0	0.1	0.3	0.4	0.4	0
Stop	0	0.2	0.6	0.8	0	0.2	0.4	0.6	0.8
Fail State	0	0.2	0.6	1	0	0.2	0.4	0.8	1

on corroboration and observability of the vehicle's stochastics (Hejase, Kurt, Aldemir, & Ozguner, 2018). So, to capture the resultant probabilistic models, state transition probabilities are required, and these transition probabilities can be best represented by a trellis diagram in terms of simplifying probabilistic calculations (Kurt, 2011).

The stochastics of a Trellis-based representation can be obtained by appointing probabilities to the edges of the trellis representation which tally to the FSM's state transitions. Once the probabilities are assigned, graph search methods can be implemented to compute the probability of the vehicle to reach either a desired state which is *n* transitions away or a potentially desired final state from an initial state representing the current system conditions. By implementing the graph search method, it is possible to establish a probability estimate of a coveted outcome. It is important to notice that there are certain states in the FSM that require a restriction in terms of the number of transition and so the concept of an extended finite state machine is adopted to apply counters to the number of transitions (Huang & Shi-yu, 2001). With a counter as a trigger condition for the finite state machine as shown in Figure 3, when the trigger condition is fulfilled, the transition is set off and thereby bringing the state machine to the following state from the current state. For example, the Figure 3 shows a counter set to a limit of 3 when the state transition occurs from *slow* to *change lane*, this counter prevents the transition to *change lane* if the transition occurs more than twice consecutively.

It is also crucial to mention that this paper focuses on off road or unstructured environments in which case counters are not applied due to the repetitive nature of most actions in such scenarios. The FSM is mainly used for the understanding of AV predictions rather than the control of a vehicle.

2.2. Recursive Bayesian Method

Based on the level of risk encountered which can be represented as the probability of failure caused by environmental conditions, the recursive Bayesian method will be used to calculate decision probabilities. Given an explicit situation along with its consequent decisions for traversal, with all the motion planning and vehicle control defined, the actual traversal tends to vary with the dynamic environment effecting vehicle's sensor readings, which in turn force the decision-making process of the vehicle to choose a safer traversal domain with a better probability of reaching the destination (Brito & Griffiths, 2016). Incorrect control input to the UGCV could essentially lead to catastrophic failures in multiple security levels and the risk for the vehicle can be identified as a degree of probable consequences or a threat symbolizing both the chance and sternness of something undesirable happening or a critical situation transpiring. Bayesian methods rely on new information to revise probabilities. Since we have the inflow of different observation data (s which is the snow parameter and o is the obstacle coverage parameter) from the sensors, we could determine the state (x) transition probability as given by

$$P(x_t|s,o,x_{t-1}) = \frac{P(o|x_t)P(x_t|s,x_{t-1})}{P(o|x_t)P(x_t|s,x_{t-1}) + P(o|\neg x_t)P(\neg x_t|s,x_{t-1})} \quad (1)$$

In Eq. (1) which is a Recursive Bayesian method representation, $P(x_t|s,o,x_{t-1})$ represents the probability of transitioning to a future vehicle state from the current state given the perceived vehicle sensor data for various scenarios. The sensor data used in Eq. (1) is from Table 1.

Table 1 can be referred for predefined probability values which are derived from the PAS 1883:2020 standard. The PAS 1883:2020 standard is generally for ODD scenarios definition, where the specifics of environmental factors affecting the vehicle at different intensities are explained. The environmental factors at different intensities are broken down into probability values for different states and these values are shown in Table 1. Stochastic analytics and model prognosis help in enabling decision capabilities for reduced operational domain of autonomous vehicles.

From Eq. (1) the state transition probability values for different state transitions can be obtained based on the defined scenario (Fox, Hightower, Liao, Schulz, & Borriello, 2003).To be more specific, for our example, Eq. (1) would use values from the Table 1 assuming that the combined transition probability has to be calculated for multiple factors like obstacle coverage and different snow levels affecting the probability of transitioning to a particular state. Once calculated for a single iteration, all the transition probabilities for the finite state machine would form the transition probability matrix (TPM). The TPM is represented in Eq. (2). More details about the TPM calculations are described in the next section.

2.3. Markov Process

With the transition probabilities achieved from Bayesian methods in different scenarios, these probabilities can be used to interface with the Markov process which integrates ambiguousness of the adeptly developed initial probabilities and the quantified errors obtained from network's inspection. In the Markov process, the probabilities can be defined by the waning of the vehicle's behaviour over a certain set of duty cycles. A transition probability matrix (TPM) with *n* number of states is shown in Eq. (2), where p_{ab} is the probability of transitioning from state *a* to state *b* in a single phase or duty cycle.

$$TPM = \begin{pmatrix} p_{11} & .. & .. & p_{1n} \\ : & : & : & : \\ p_{n1} & .. & .. & p_{nn} \end{pmatrix} \tag{2}$$

By Markov theory, the future criterion of a state behaviour is independent of past behaviours in every manner and so, the probability of p_{ab} only depends on its present state's (a) behaviour. To generate a homogeneous Markov chain, the transition probability matrix used for every phase would be one and the same along with independence of time. We use homogeneous Markov chains because the transition probabilities between two different states depend on the time step difference. So, as shown in the Eq. (3), the prospective state vector is achieved by multiplying the current phase state transition probabilities by the transition probability matrices from current phase to all the previous ones. In Eq. (3), the transition probability at duty cycle t would be $P(t)$. TPM_t would be the transition probabilities from t to $t+1$ transitions phases (Tabatabaee & Ziyadi, 2013).

$$\begin{aligned} P(t+1) &= P(t) \times TPM_t \\ &= P(0) \times TPM_1 \times TPM_2 \times ... \times TPM_t \end{aligned} \tag{3}$$

Back to our example, the homogeneous Markov chain can be used to predict the transition probabilities of *Follow Waypoints* and *Fail State* scenarios, as shown in Figure 4 and Figure 5, respectively.

$$\begin{array}{cccccccccccccc} \text{Enter} & \text{Follow Waypoints} & \text{Exit} & \text{Cruise} & \text{Cruise Towards East} & \text{Cruise Towards West} & \text{Slow} & \text{Slow Towards East} & \text{Slow Towards West} & \text{Accelerate} & \text{Accelerate Towards East} & \text{Accelerate Towards West} & \text{Stop} & \text{Fail State} \end{array}$$

$$\text{TPM}_1 = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.2 & 0 & 0.8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.3 & 0.2 & 0.2 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.3 & 0.2 & 0.2 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.3 & 0.2 & 0.2 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0 & 0 & 0.3 & 0.2 & 0.2 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0 & 0 & 0.3 & 0.2 & 0.2 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0 & 0 & 0.3 & 0.2 & 0.2 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0.3 & 0.2 & 0.2 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0.3 & 0.2 & 0.2 & 0 & 0 \\ 0 & 0 & 0.1 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0.3 & 0.2 & 0.2 & 0 & 0 \\ 0 & 0 & 0.1 & 0 & 0 & 0 & 0.4 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$\text{P(0)} = (0 \quad 0.2 \quad 0 \quad 0.8 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0)$$

Result of the evaluation $\text{P(1)} = \text{P(0)} \text{ x } \text{TPM}_1$

$$\text{P(1)} = (0 \quad 0.04 \quad 0.08 \quad 0.4 \quad 0.16 \quad 0.16 \quad 0.08 \quad 0 \quad 0 \quad 0.08 \quad 0 \quad 0 \quad 0 \quad 0)$$

Figure 4. TPM and Markov Model for Follow Waypoints State.

The states representing each transition probabilities are shown in Figure 4 and Figure 5 in a column manner above the TPMs for both the scenarios. The results from the Markov chain show that we are able to predict the system's risk probabilities with the help of sensor readings for weather and environmental obstacles faced by the UGCV, these results have been persistently observed by simulating a vehicle with the above discussed environmental parameters (Hejase, Kurt, Aldemir, & Özgüner, 2018). The simulation results are discussed in the next section.

In Figure 4, the TPM is calculated with the obstacle coverage at 0% and with no snow levels leading to visibility of less than 3 *km*. The TPM_1 matrix contains state transitions from a $from\ state$ represented by rows of the matrix to a $to\ state$ represented by columns of the matrix and the exact values of the TPM are calculated using Eq. (3) and the above mentioned environmental parameter values for obstacle coverage and snow levels. The Markov chain is used to predict the state transitions from the *Follow Waypoints* state (represented by row 2 of the TPM_1 matrix) at its next phase, which ends up being the *Cruise state* at 40%, assuming that the environmental parameters remain the same. Figure 5 shows a TPM which is calculated with obstacle coverage at 100% and with high snow levels leading to visibility of less than 0.5*km*. In this case, the Markov chain is used to predict the state transitions from the *Accelerate Towards West* state after 5 duty cycles, which ends up being *Fail state* at 98%, this probability is assuming that the environmental parameters remain the same.

$$\begin{array}{cc} & \begin{array}{cccccccccccccc} \text{Enter} & \text{Follow Waypoints} & \text{Exit} & \text{Cruise} & \text{Cruise Towards East} & \text{Cruise Towards West} & \text{Slow} & \text{Slow Towards East} & \text{Slow Towards West} & \text{Accelerate} & \text{Accelerate Towards East} & \text{Accelerate Towards West} & \text{Stop} & \text{Fail State} \end{array} \\ TPM_1 = & \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.19 & 0 & 0.81 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.31 & 0 & 0 & 0 & 0 & 0 & 0.32 & 0.37 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.16 & 0 & 0 & 0 & 0 & 0 & 0.26 & 0.58 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{array}$$

$$P(0) = (0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0.31 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0.32 \quad 0.37)$$

Result of the evaluation $P(5) = P(0) \text{ x } (TPM_1)^5$

$$P(5) = (0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0.01 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0.01 \quad 0.98)$$

Figure 5. TPM and Markov Model for Fail State.

3. OFF-ROAD VEHICLE SIMULATION

To simulate an off road or unstructured environment for an autonomous vehicle to traverse in different weather condition, the Mississippi State University Autonomous Vehicle Simulator (MAVS) (Hudson, Goodin, Doude, & Carruth, 2018) is used. The goal of simulating the vehicle's traversal is to illustrate the results with the previously discussed TPM and Markov chain approach.

The following sub sections discuss and show the simulation results for a good weather condition scenario and a bad weather condition scenario, respectively. The results obtained are categorized based on the FSM (shown in Figure 3) into state sequences that help in breaking down the vehicle's state at every sampling time of 2 *s*. Some parameters have been commonly utilized to have less discrepancies when comparing the simulation results between the good weather and the bad weather scenarios. The destination point is (32 *m*, 130 *m*) and source point is (0 *m*, 0 *m*) for both simulations with randomly placed obstacles. LIDAR and camera data is used for both the simulations to determine their states or maneuver criteria. However, MAVS provides the ability to use radar data as well. The sensor data for the LIDAR and the camera are replicas of the Velodyne's Puck lidar sensor and the Flea3 USB3 camera unit, respectively.

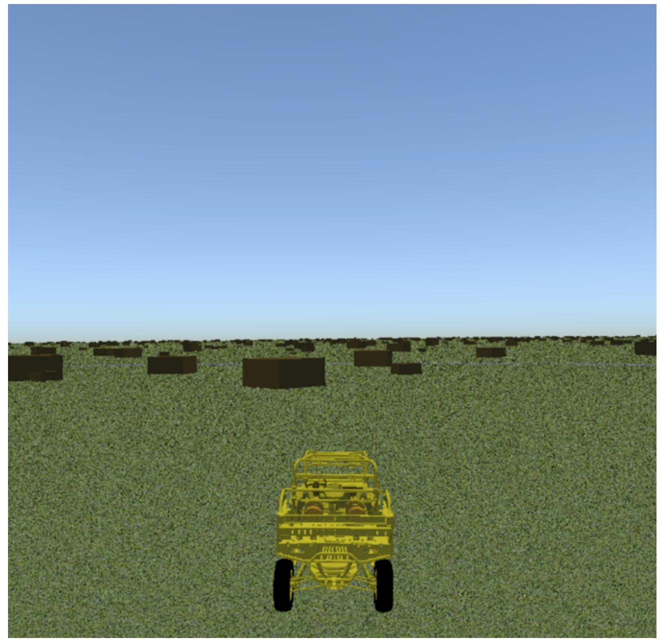

Figure 6. MAVS Simulation of a Clear Weather Scenario.

3.1. Good Weather Leading to Exit State

In the case of good weather scenario, the MAVS simulator containing the cube scene scenario (Hudson, Goodin, Miller, Wheeler, & Carruth, 2020) file which contains a flat terrain and randomly placed obstacles is used. Obstacles are randomly placed, and the vehicle uses A* algorithm to traverse across the terrain (Li, Liu, Zhang, & Zhao, 2014). However, when the path is not found the vehicle has a fallback to the Potential Field, RRT, and RRT* path planning algorithms sequentially (Qureshi & Ayaz, 2016). The good weather simulation does not contain any extreme weather parameters set to the simulation.

The complete simulation takes 22.92 *s*, and Figure 6 shows an image of the simulation in a good weather scenario. Figure 7 shows the path traversed by the vehicle by avoiding obstacles. The vehicle is set to traverse at a desired speed of 18 *m/s*. Figure 8 shows the speed data of the vehicle at intervals of 2 *s* and the throttle is set using a PID controller.

The vehicle's orientation data from source to destination at intervals of 2 *s* is shown in Figure 9 and the vehicle control module is set to use the pure pursuit algorithm. It can be observed that with a clear weather scenario, the vehicle is able to reach its destination by avoiding all the obstacles successfully.

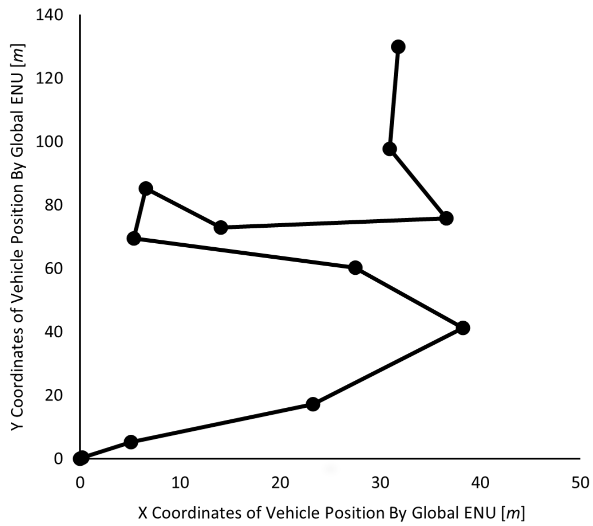

Figure 7. Vehicle Path Data for Good Weather Simulation.

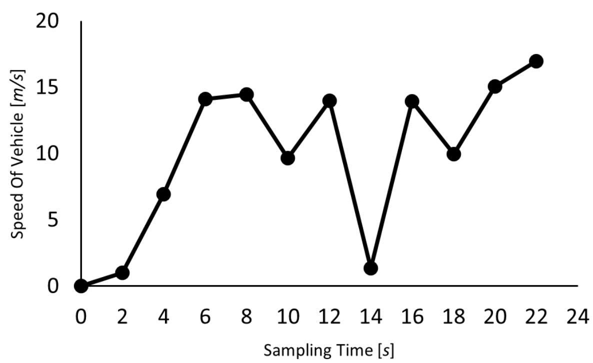

Figure 8. Vehicle Speed Data for Good Weather Simulation.

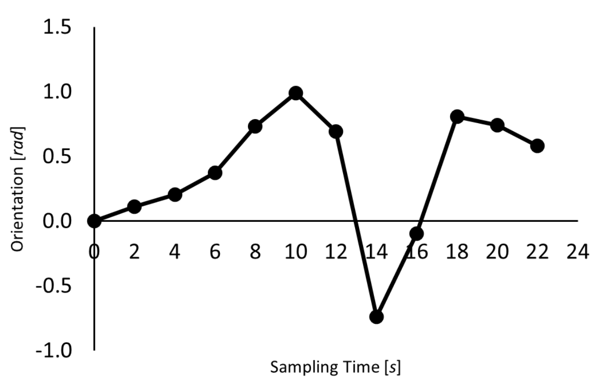

Figure 9. Vehicle Orientation Data for Good Weather Simulation.

3.2. Bad Weather Leading to Fail State

The scene used for bad weather scenario is the same as good weather scenario. The vehicle uses A* algorithm to tra-

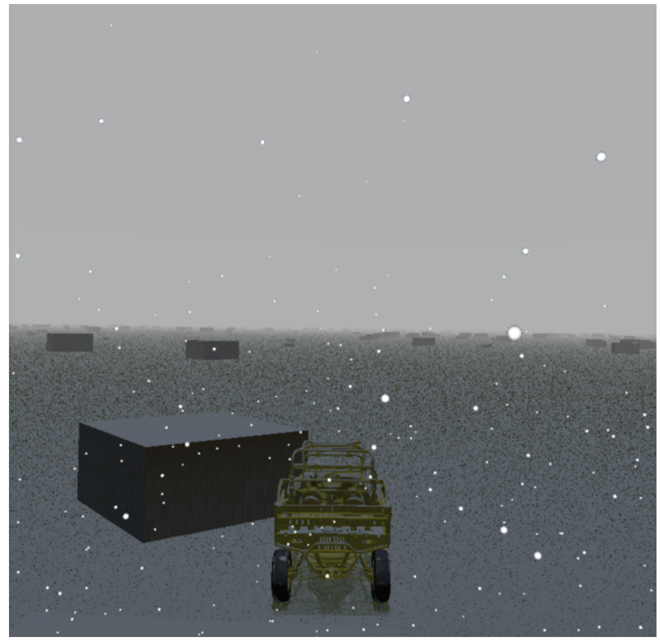

Figure 10. MAVS Simulation of a Snowy Weather Scenario.

verse across the terrain and similar to the good weather scenario, the vehicle has a fallback to the Potential Field, RRT, and RRT* path planning algorithms sequentially. The bad weather simulation is set to high snow which indicates that the visibility is less than 0.5 *km* (Czarnecki, 2018).

The complete simulation takes 25.5 *s*, and Figure 10 shows an image of the simulation in a bad weather scenario. Figure 11 shows the path traversed by the vehicle by avoiding obstacles. Figures 12 and 13 show the speed data and orientation data of the vehicle at intervals of 2 *s*, respectively. Similar to good weather scenario, PID controller and pure pursuit algorithm are used. Since the particulate matter of snow affects the LIDAR readings, we observe that the vehicle does not reach its destination and goes into Fail state. The vehicle is blocked by an obstacle at coordinates (26.1 *m*, 92.8 *m*). The next section describes how the states were assigned based on the observation data from the simulations

4. STATE SEQUENCE RESULTS

After analysing and combining the observation data from both the good and bad weather simulations, each maneuver made by the vehicle is divided into states from the FSM. The changing speed is divided into different states based on a change in speed of 3 *m/s* from the previous value. In a similar manner, the orientation data is used to determine the vehicle's state if there is an orientation change of 0.3 *rad* in either the towards west or towards east direction.

The state sequences are arranged for both the good weather scenario and the bad weather scenario as shown in Figure 14. It can be observed that the state sequence for the good

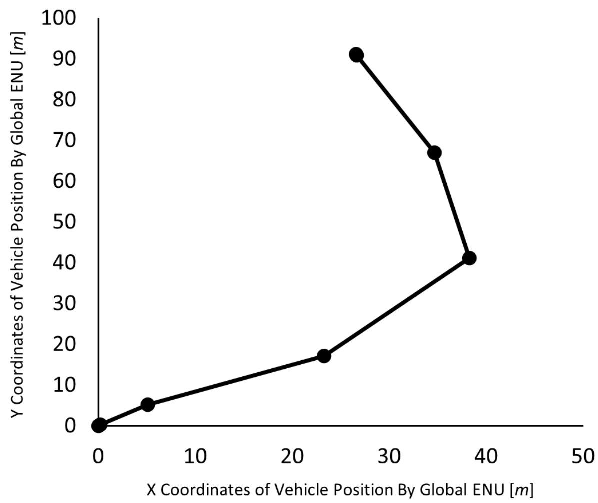

Figure 11. Vehicle Path Data for Bad Weather Simulation.

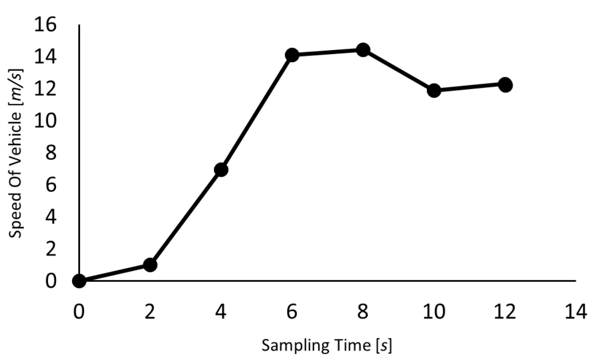

Figure 12. Vehicle Speed Data for Bad Weather Simulation.

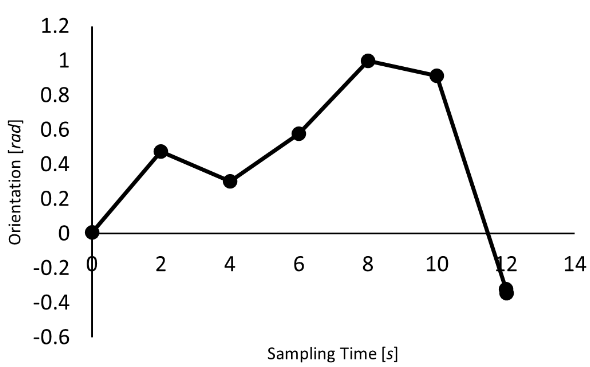

Figure 13. Vehicle Orientation Data for Bad Weather Simulation.

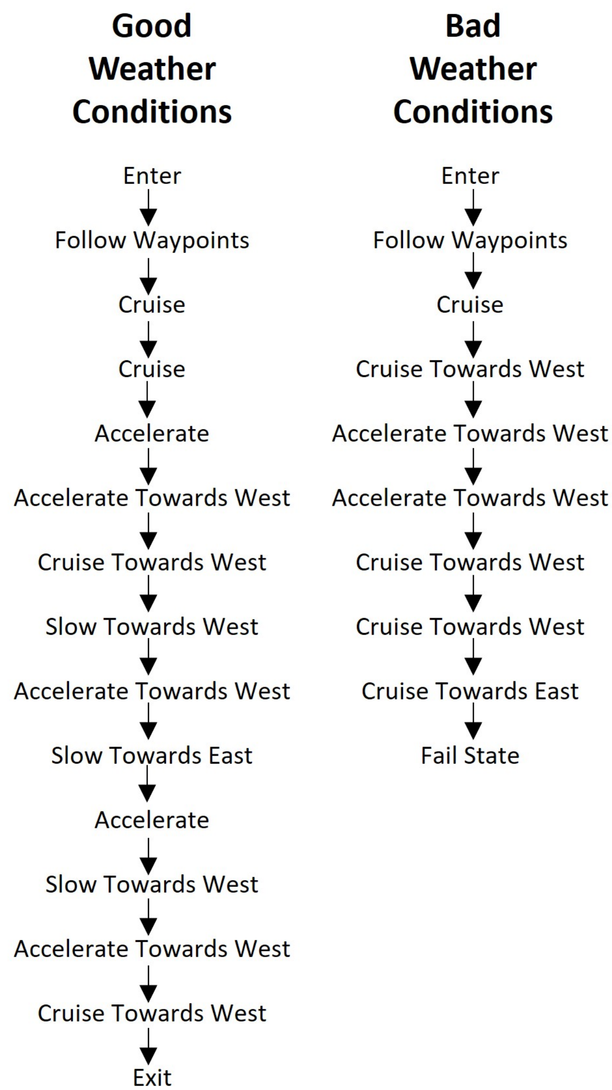

Figure 14. State Sequence Results.

weather enables the vehicle to safely maneuver around the obstacles and reach its destination. However, the bad weather leads the vehicle into a *Fail state* before reaching its destination, this was observed to be caused by the snow effecting the LIDAR's ability to detect obstacles. Since the vehicle gets blocked by an obstacle and is not able to find an alternative path, the vehicle goes into *Fail state* from *Cruise state*.

The probability distribution in Figure 15 and Figure 16 represent the sequence of state transitions from Figure 14 for good weather and bad weather conditions respectively. The probability distributions are computed from the methodology described in the risk probabilities section of this paper.

Using Recursive Bayesian method, we can realize that with progressive sampling time, the fail state for bad weather conditions tends to show a gradual increase in probability, and this can be considered as a prediction for critical situations. The sampling time considered is 2 s and prediction is 6 s into the future as shown in the Figure 17 for 3 state sequences of

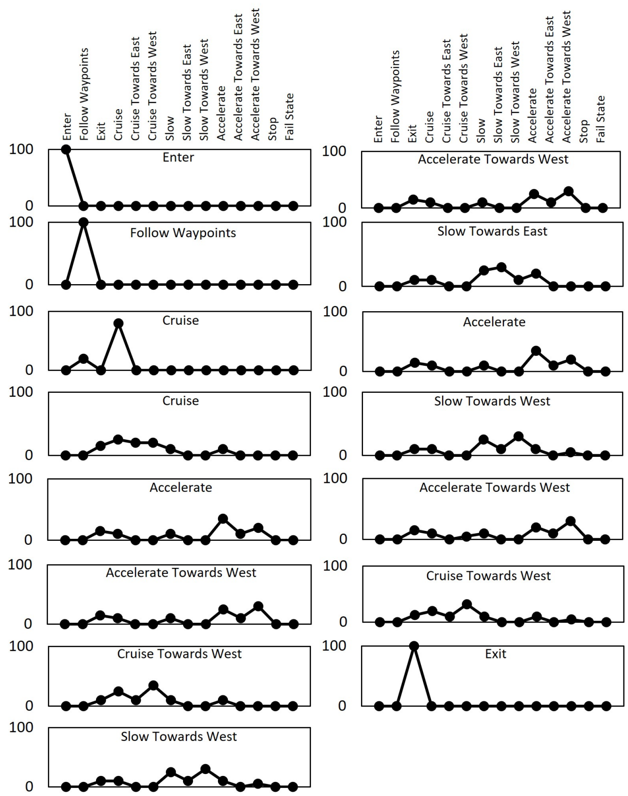

Figure 15. Probability Distribution Good Weather.

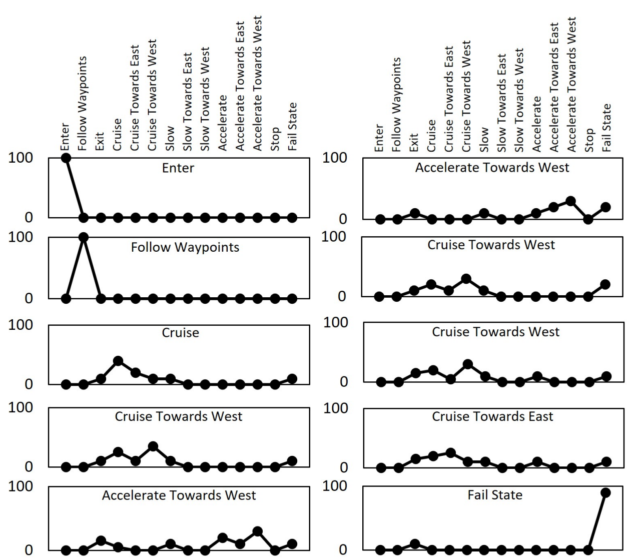

Figure 16. Probability Distribution Bad Weather.

good and bad weather conditions. In Figure 17 each state in each plot has 3 stages for the 3 successive sampling times. The upper end of the floating bar is representative of the 6th sampling time, the middle part of the bar is representative of the 4th sampling time, and the lower end of the floating bar is representative of the 2nd sampling time. The predicted probability is observed with the updated value substituting the prior value for the state transition probability in the Recursive Bayesian formula.

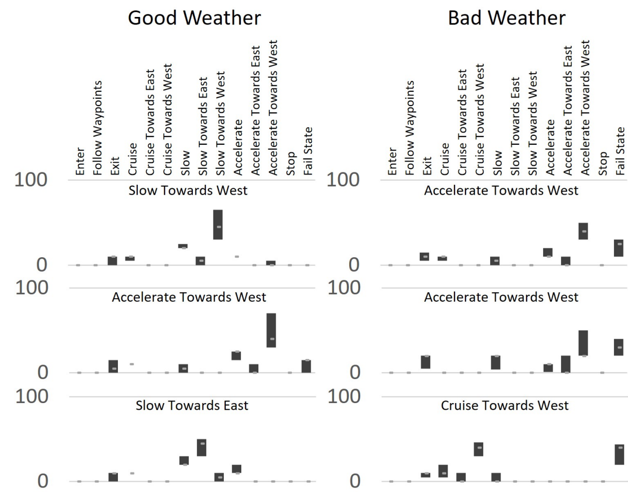

Figure 17. Predicted Probability Distributions.

5. CONCLUSION

The above-described simulations manifest the Markov decision probabilistic evaluation and shows that the risk estimation for a vehicle can be achieved by breaking down the vehicle's maneuvers into states and predicting how different environmental parameters can affect the vehicle's ability to reach its future states. By estimating the risk, it can form a major part of later defining the reduced operational domain (ROD) for an autonomous vehicle and this in turn would enable the safe traversal of the vehicle across any terrain.

The paper helps in understanding how a bad weather scenario leads to increased risk of failures along with estimating the prediction of a potential crash at different sampling times. With the results provided by the paper, adequate preventive measures can be taken depending on how soon a failure might occur.

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NOMENCLATURE

s	observation data for the snow parameter
o	observation data for the obstacle coverage
x	states from the Finite State Machine
km	kilometer
s	seconds
m	meter
rad	radians

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