Improving Dependability of Vision-Based Advanced Driver Assistance Systems Using Navigation Data and Checkpoint Recognition

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Abstract. Advanced Driver Assistance Systems (ADAS), like adaptive cruise control, collision avoidance systems, and, ultimately, piloted and autonomous driving are increasingly evolving into safety-critical systems. These ADAS to a large degree rely on proper function of in-vehicle Computer-Vision Systems (CVS), which is hard to assess in a timely manner, due to their high sensitivity to the variety of illumination conditions (e.g. different sun positions, weather conditions, light reflections and glares, artificial light). On the other hand a diverse set of self-awareness information is commonly available in the vehicle, such as maps and localization data (e.g. GPS).
This paper, therefore, studies how the combination of diverse environmental information can contribute to improving the overall vision-based ADAS reliability. To this extent we present a novel concept of a Computer-Vision Monitor (CVM) that regularly identifies checkpoints (predefined landmarks) in the vehicles surrounding, based on digital maps and localization data, and that checks whether the CVS correctly identifies said landmarks. We formalize and assess the reliability improvement of our solution by means of a Fault-Tree Analysis (FTA).

Keywords: Computer-vision system, computer-vision monitor, latent failures, external environmental disturbances, fault tree analysis.

1 Introduction

With approximately 1.24 million deaths and another 20 to 50 million of non-fatal injuries on the world's road in 2010, road traffic injuries are estimated to be the eighth leading cause of death nowadays [1]. Additionally to the human tragedies, the cost of dealing with the consequences of these road traffic crashes runs to billions of dollars.

Among the strategies which are proven to reduce road traffic injuries like reducing the urban speed limits, reducing drunken driving and increasing seat-belt use is the strategy of providing new passive and active vehicle safety systems.

Today, there is a strong development focus on active safety systems ranging from Anti-lock Breaking Systems (ABS), Electronic Stability Control (ESC), Emergency Brake Assistant (EBA) to complex Advanced Driver Assistance Systems (ADAS) with accident prediction and avoidance capabilities [2]. Such systems are increasing the traffic safety either by informing the driver about the current situation (e.g. night vision, traffic sign detection, pedestrian recognition), by warning the driver with regard to hazards (e.g. obstacle and collision warning, lane departure warning, blind spot detection), or by selective control of actuators (e.g. Adaptive Cruise Control (ACC), adaptive headlights, pedestrian protection, collision avoidance) [3].

To perform functions, such as those listed above, ADAS rely heavily on environment perception. Examples for the most widely used sensors are ultrasonic sensors, Long and Short Range Radars (LRR, SRR), Light Detection and Ranging sensors (LiDAR) and video cameras (vision systems). Video cameras have an important role in ADAS, because of their ability to give more detailed representation of the environment than the other sensors. Therefore, special attention should be paid to vision systems which are used in safety-related and safety-critical systems. Furthermore, an automotive vision system also integrates Electronic Controller Units (ECUs) and a communication subsystem connecting the cameras to the ECUs and the ECUs to each other. Thus, automotive systems in general and Computer-Vision Systems (CVSs) in particular become quite complex. The safety standard ISO 26262 has been introduced for automotive Electrical/Electronic (E/E) systems to address the potential risk of malfunction for automotive systems [4], and ensuring correct functionality of ADAS becomes mandatory from a qualification perspective.

One way to satisfy the safety standards is by designing systems to be dependable. According to Laprie [5], dependability is the ability of the system to deliver service that can justifiably be trusted. It encompasses the concept of reliability, availability, safety, maintainability, integrity and confidentiality which are measures used to quantify the dependability [5][6]. Fault tolerance and fault prevention are among the means capable of achieving dependable systems. While fault prevention techniques prevent the occurrence of Hardware Failures (HF) and Software Errors (SE) by selecting high-quality components, design rules, etc., fault-tolerance techniques handle HF and SE, when they occur by fault masking and reconfiguration techniques (fault detection, location, containment and recovery). Fault masking simply “hides” the faults by using available redundancy. In case a given redundant component fails, the failure is mitigated by using majority voting. Therefore faults are contained or in other words the effect of faults does not propagate throughout a system, and stays local [6]. A drawback of this approach is that if faults are only “hidden” and fault detection is not used, the faulty components will not be detected, the available redundancy is going to decrease and the system will not be aware of that - a process called redundancy attrition [7]. Thus in real fault-tolerant system, it is common to use a combination of fault masking and fault detection. Fault detection can be accom-

plished through dedicated hardware circuitry, software code and test methods. Some of these various failure detection methods are referred as monitors [8].

One assumption is that the monitor provides 100% diagnostic coverage of the item performing a given function and a monitor verification operation ("scrub") verifies (with 100% diagnostic coverage) that the monitor is fully operational. Unfortunately, real life monitors, firstly (i) may fail before the component fails, allowing the failure to spread and secondly (ii) may not provide 100% diagnostic coverage. Both cases are known as latent failures - faults whose presence is neither detected by a monitor, nor perceived by the driver within a time interval, after which it will contribute to a failure ([9] - part 1). The remainder of this paper will use the terms monitor and internal monitor interchangeably, where in both cases referring to monitors implemented locally in the CVS.

In this paper we are introducing a novel concept of Computer-Vision Monitor (CVM), whose aim will be to detect latent failures (i) by verifying that the internal monitors of the CVS are fully operational ("scrub") and (ii) by detecting failures which are not in the diagnostic coverage of the internal monitors. Furthermore, the paper demonstrates in a step-by-step manner, how to perform reliability analysis of ADAS with and without CVM and proposes a solution, how to include the issue of detecting a special case of latent failures (leading directly to a hazard in a very short time) to the fault tree analyses.

The paper is organized as follows. In section 2, the problem statement and the chosen ADAS scenario are presented. The CVM concept is introduced in section 3, followed by section 4, where reliability analysis of the proposed solution will be done. Conclusions and future work will be presented in section 5.

2 Problem Statement

In the field of vision-based ADAS, latent failures, resulting from not full diagnostic coverage, very often are consequences of External Environmental Disturbances (EED). A typical example in the automotive environment is the illumination, which can be barely controlled, due to weather conditions, different sun position and brightness, and artificial light (headlights, street lamps). The situation, such as direct sun light for instance, highly affects the image acquisition and processing, thereby, decreasing the abilities of computer vision algorithms to interpret the environment correctly, which in turn might lead to wrong decisions and actions of the system. A solution for that issue could be the fast Automatic Exposure Control (AEC), which ensures, that the right amount of light is perceived from the camera.

As regards to the effects of the bad weather conditions, various image enhancement methods are used to improve the dependability of CVS. Image deweathering is used in [10] to remove the weather effects from images. Image based fog detection and visibility estimation is presented in [11]. Raindrop detection and removal techniques can be seen in [12].

Furthermore, often used in ADAS is the competitive (redundant) sensor fusion, where different types of sensors deliver measurements of the same property.

An example for ACC where safe distance to the front vehicle is measured by four different sensors (LRR, SRR, CVS, LiDAR) is given in [13]. The main idea of using different types of sensors to measure the same property is that the sensors will fail in different environmental conditions, but less likely in the same.

Even though, there are particular solutions, such as AEC for direct sunlight and image enhancement methods against the effect of bad environmental conditions, the diversity of EED scenarios are difficult to be covered exhaustively.

As far as to the competitive sensor fusion, it must be emphasized, however, that this example is not the only way of realization of ACC or any other ADAS functions. In case of pedestrian detection for instance LiDARs and vision sensors are used collaboratively, where the first one is ensuring the detection and tracking and the second one is responsible for the classification of the object in the ROI (Region of Interest) [14]. In another example of ACC, active sensors (radar and LiDARs) and vision sensors do not exchange information between each other, but the data from each one is used for different functions of the ADAS. In that case the active sensor is used to detect obstacles and to provide directly the distance to the obstacle, while the camera is used to support the other ACC related functions, such as lane detection and traffic sign recognition [15].

In this paper we are interested in improving the dependability (in particularly the reliability attribute) of vision-based systems. Thus, the reminder of this paper is focused on a scenario, where ADAS relies only on vision for given functions, such as pedestrian detection and tracking, obstacle detection, lane and traffic sign recognition, night vision - each of which can be used in autonomous vehicles (Fig. 1).

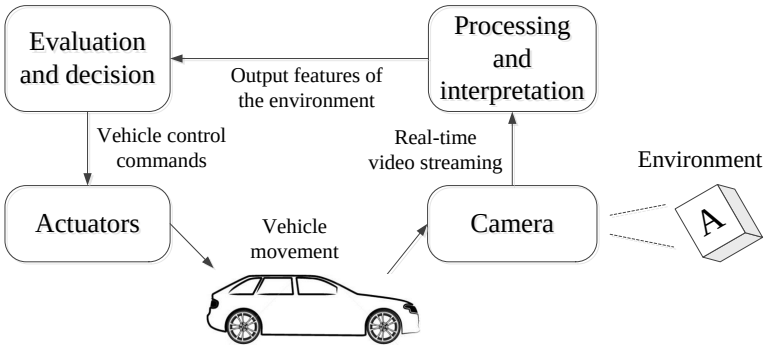

Fig. 1. High-level overview of vision-based ADAS.

Figure 1 depicts an exemplary control system of an autonomous vehicle. The environment is captured by the camera and the information is transmitted to the processing and interpretation subsystem. After processing the image and extracting the useful data, the information is given to the evaluation and decision subsystem. According to the features of the environment, as well as on the implemented logic, the evaluation and decision subsystem generates the vehicle control commands, which in turn are executed by the actuators.

3 The Computer-Vision Monitor (CVM) Concept

Current research in the field of digital maps, GPS and intelligent vehicles is focused on mainly two areas. On the one hand GPS-based systems combined with data from laser scanners, cameras, on board sensors are used to localize the precise position and orientation (especially in the urban areas, where the accuracy of the GPS alone is limited and unreliable) of the vehicle, using knowledge regarding mapped landmarks (traffic signs, lanes, traffic lights, etc.) on a digital map [16][17]. On the other hand data from digital maps and vehicle position, direction and speed are fused in order to improve the success rate of vehicle camera traffic sign recognition [18][19].

While the research shown above focus on a precise localization of vehicles and improving success rate of traffic sign recognition using pre-mapped landmarks and various sensory systems, we propose a complementary approach using the same resources. Labeling the precise position of the traffic infrastructure objects, such as traffic signs, road markings, traffic lights, etc. as checkpoints on a detailed digital map can be used to identify the correct functionality of CVS (Fig. 2).

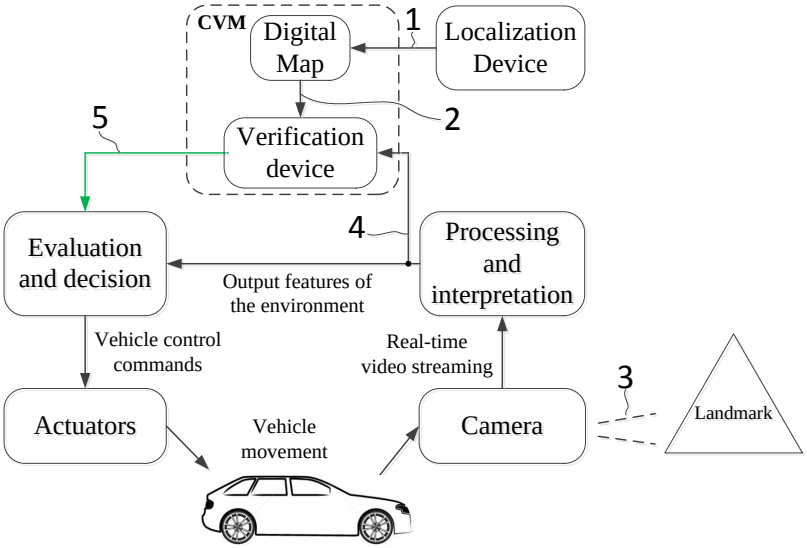

Fig. 2. Conceptional view of vision-based ADAS with CVM.

Our approach is to place new landmarks to the road or use the already implemented road infrastructure on the road, as landmarks in digital maps. Knowing their exact position in the digital map, the ability of the vision system to find a given traffic sign will be verified. According to the results from the CVS, whether the traffic sign is found or not, the correct operation of the computer vision system will be assessed.

The steps depicted in Fig. 2 are the following:

1. Receiving the vehicle coordinates via localization device (e.g. GPS),

2. Gathering the landmarks from the digital map corresponding to the current coordinates,
3. CVS checks for landmarks,
4. CVM receives the information for the landmarks, which CVS has detected,
5. CVM verifies and validates the correct operation of the CVS and sends that information (reliability estimate) to the evaluation and decision unit.

According to the reliability estimate, the evaluation and decision block will decide whether it can rely on CVS or to put the vehicle to a safe state.

4 Reliability Analysis

In this section, we use a simplified Functional Hazard Analysis (FHA) and Fault Tree Analysis (FTA) in order to analyze the reliability of the vision-based ADAS with and without the proposed CVM. Furthermore in the future, both, FHA and FTA could be used in a safety assessment process.

4.1 Functional Hazard Analysis

FHA is an approach which identifies and classifies the failure conditions related to a given function, according to their severity. An example of a system level FHA, according to [8], for the vision-based ADAS is depicted in Table 1. The columns in the table include the reference of the failure, function name and the phase in which it is used, as well as its probable failure condition and effects, followed by classification of the failure by its severity.

Table 1. Example System Level FHA.

Function failure ref.	Function	Phase	Failure Condition	Failure effect	Classification
F_1	Lane departure warning	Highway	Inability to detect the road lanes	Driver is not informed upon leaving the lane	S2
F_2	Traffic sign recognition	Highway/ Urban	Inability to detect the traffic sign	Vehicle does not stop on a “STOP” sign	S3
F_3	Blind spot detection	Highway/ Urban	Inability to detect the car in the blind spot area	Driver is not informed of a car in the blind spot area	S2
F_4	Pedestrian protection	Urban	Inability to detect the pedestrian	Vehicle does not decrease the speed to protect the pedestrian	S3
F_5	Collision avoidance	Highway/ Urban	Inability to detect the obstacle	Vehicle does not decrease the speed in order to avoid or mitigate the collision	S3

The classification of the failures was made according to ISO26262 standard ([9] - part 3), where the severity classes range from S0 to S3 (Table 2).

Table 2. ISO-26262 Severity classes [9].

Class	S0	S1	S2	S3
Description	No injuries	Light and moderate injuries	Severe and life-threatening injuries (survival probable)	Life-threatening injuries (survival uncertain), fatal injuries

In this example, we assume, that a failure of the CVS may lead to a life-threatening or fatal injury. Therefore the reminder of the paper will assume that each CVS failure not detected by the monitor might lead to high-level severity class.

4.2 FTA for Vision-Based ADAS

FTA is a deductive (top down) approach, which is used to (i) determine what single failures or combination of failures can exist at the lower levels, that might cause each failure condition in the FHA and (ii) to evaluate qualitatively or quantitatively the probability of the top-level event. The level of details of the Fault Tree (FT) is dependent upon the overall knowledge and experience, and requires consultation of numerous specialists. Figure 3 presents a high-level FT of a vision-based ADAS, where the internal monitor has only 90% coverage of the function F_i failures and the monitor might fail before the failure in F_i occurs.

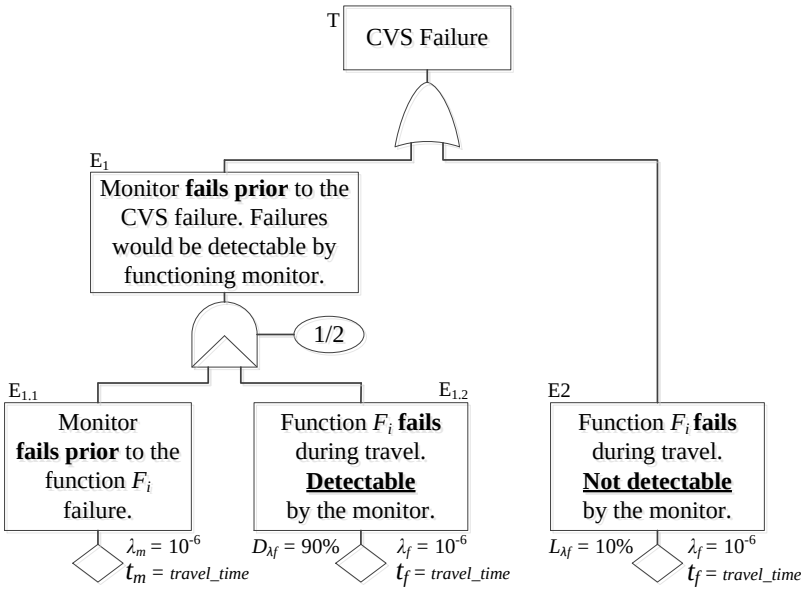

Fig. 3. High-level FT for vision-based ADAS.

The variables depicted in the Fig. 3 are as follows:

- λ_f - Function F_i failure rate per hour,
- λ_m - Monitor failure rate per hour,
- $travel\_time$ - time of travel of the vehicle,
- t_f - Function F_i exposure time,
- t_m - Monitor exposure time,
- D_{λ_f} - percentage of function F_i failures detectable by the monitor,
- L_{λ_f} - percentage of function F_i failures not detectable by the monitor.

The FT shown in Fig. 3 has the following main events:

- Event E_1:
  - The internal monitor has only 90% (D_{λ_f}) coverage of the function F_i failures.
  - The internal monitor might fail prior to the function F_i failure of the CVS and there is no monitor verification. Thus, t_m is equal to $travel\_time$, addressing the need for "scrubbing".
- Event E_2:
  - Presents the rest of the failures which are not detectable from the monitor ($L_{\lambda_f} = 10\%$). Thereby, addressing the latent failures, resulting from not full diagnostic coverage (section 2).

Having the approximate failure rates and exposure times, the probability of each primary event in the FT can be calculated according to equation 1:

$$P_f = 1 - e^{\lambda_f t} \tag{1}$$

In case when $\lambda_f t < 0.1$, the equation can be simplified to:

$$P_f = \lambda_f t \tag{2}$$

Thus, the top level event failure probability can be calculated as:

$$\begin{aligned} P_f^{Top} &= E_1 + E_2 \\ where: & \\ E_1 &= \frac{1}{2} E_{1.1} E_{1.2} = \frac{1}{2} \lambda_m t_m D_{\lambda_f} \lambda_f t_f \\ E_2 &= L_{\lambda_f} \lambda_f t_f \end{aligned} \tag{3}$$

The probability of elements failing in a certain sequence (monitor fails prior to the function F_i failure) is included via multiplication by $\frac{1}{2}$. For illustration purposes, we assume a failure rate of 10^{-6} per hour for both λ_f and λ_m, which is about the best a component can be constructed and analyzed by means of testing. Monitor exposure time t_m and function exposure time t_f are equal to the $travel\_time$. Within this paper we assume maximum travel time of two hours. Given the values, the top level event probability is $P_f^{Top} = 2 \times 10^{-7}$.

4.3 FTA for Vision-Based ADAS with CVM

Figure 4, presents a high-level FT of vision-based ADAS with CVM, where CVM is able to detect 5% out of 10% of the non-detectable by the internal monitor function F_i failures and 95% of the monitor failures. The new variables depicted in FT are as follows:

- T_{CVM} - CVM diagnostic test interval,
- P_{cvm} - The probability, that CVM will fail to detect the function F_i latent failures within the sufficient time, required to put the vehicle in a safe state,
- D_{λ_f} - percentage of function F_i failures detectable by the monitor,
- $L_{\lambda f1}$ - percentage of function F_i failures not detectable by the monitor, but detectable by the CVM,
- $L_{\lambda f2}$ - percentage of function F_i failures neither detectable by the monitor, nor by CVM,
- D_{λ_m} - percentage of monitor failures detectable by CVM,
- L_{λ_m} - percentage of monitor failures not detectable by CVM.

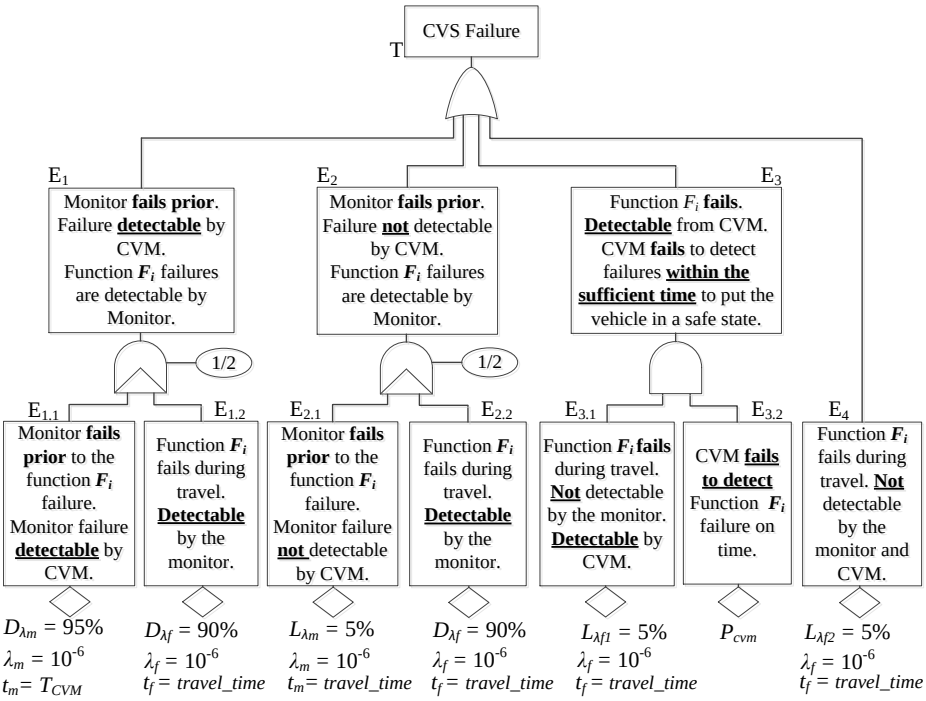

Fig. 4. High-level FT for vision-based ADAS with CVM.

The main events of the fault tree depicted in Fig. 4 are as follows:

- Event E_1:
  - The internal monitor has 90% (D_{λ_f}) coverage of the function F_i failures, but monitor fails prior to the function F_i failure.

  - CVM has 95% (D_{λ_m}) diagnostic coverage of the monitor failures. Therefore, monitor exposure time (t_m) for failures detectable by CVM is equal to the time interval in which CVM diagnoses the monitor (T_{CVM}).
- Event E_2:
  - The internal monitor has 90% (D_{λ_f}) coverage of the function F_i failures, but monitor fails prior to the function F_i failure.
  - CVM does not have coverage on 5% (L_{λ_m}) of the monitor failures. Therefore, monitor exposure time (t_m) for failures not detectable by CVM is equal to the $travel\_time$.
- Event E_3:
  - CVM is able to detect 5% ($L_{\lambda f1}$) out of 10% of the function F_i failures, which are not detectable from the internal monitor. This percentages are taken as an example. Sensitivity analysis with different diagnostic coverage will be performed later in the paper.
  - Probability (P_{cvm}) that CVM will fail to detect function F_i latent failure within the sufficient time, required to put the vehicle to a safe state, also effects the event E_3 probability. P_{cvm} will be estimated in Sect. 4.3.1.
- Event E_4:
  - Presents the rest 5% ($L_{\lambda f2}$) of the failures which are neither detectable by the internal monitor, nor by CVM.

4.3.1 CVM Failure Probability

Latent failures can persist for a time interval which is either greater or shorter than the time of travel. Latent failure in CVS, used to keep the vehicle on the road for instance, will lead directly to a hazard in short time. In that case, the time interval in which a failure remains latent (not perceived) is comparable to the time interval before the hazardous event can take place. In ISO26262, this interval is referred as Fault Tolerant Time Interval (T_{FTTI}), (Fig. 5).

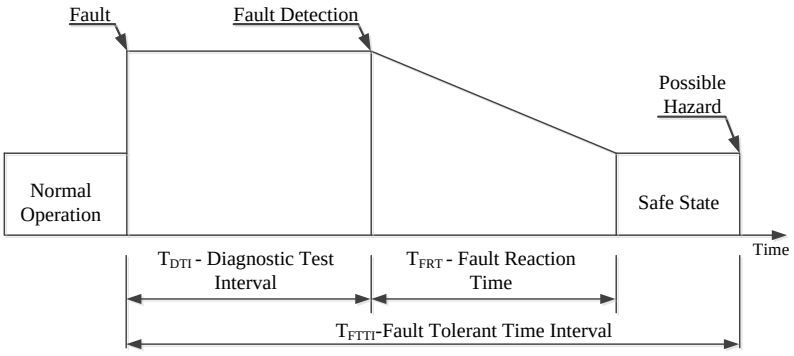

Fig. 5. Fault reaction time and fault tolerant time interval (source: [9] - part 1).

The rest of the variables depicted in Fig. 5 are the diagnostic test interval (T_{DTI}), which is the amount of time between executions of diagnostic test by

a safety mechanism (monitor) and the fault reaction time (T_{FRT}) which is the time-span from the detection of fault to reaching to the safe state.

We assume that the diagnostic test interval (T_{DTI}), for failures, not in the diagnostic coverage of the internal monitor, but in the diagnostic coverage of CVM, is equal to the time interval in which CVM diagnoses the system (T_{CVM}):

$$T_{DTI} = T_{CVM} \tag{4}$$

If T_{CVM} is greater than T_{FTTI}, CVM might fail to detect the failure within the sufficient time, required to put the vehicle to a safe state (T_{FRT}) or even to miss the latent failure. Therefore to guarantee that the latent failure will be detected and the vehicle will enter to a safe state, the difference between T_{FTTI} and T_{CVM} should be less than T_{FRT}:

$$T_{FTTI} - T_{CVM} < T_{FRT} \tag{5}$$

This is an essential issue for systems in which latent failures lead to hazards in very short time. Because our system is such, the probability (P_{cvm}), that the CVM will fail to detect function F_i latent failures within the sufficient time required to put the vehicle to a safe state has to be estimated and included properly in the FTA. This estimation is made according to ISO 26262 - part 3:

$$P_{cvm} = \lambda_f \delta T \tag{6}$$

Where:

- δ - rate of occurrence of the hazardous event.
  For non-autonomous vehicles this rate could vary from occurs less often than once a year to occurs during almost every travel. For the scenario we have chosen, the rate occurrence for fully autonomous vehicle is considered as each time when the system does not get correct information from CVS about the environment for $10ms$. Thus, $\delta = 10ms$.
- T - the duration of time that the failure is not perceived.
  Failure might be perceived in two ways - (i) by leading to a hazard and (ii) by being detected from a safety mechanism. Therefore T could be taken from one of the two cases:
  1. T is equal to the time between latent failure occurs and leads to possible hazard. This interval of time is also referred as Fault Tolerant Time Interval (T_{FTTI}).
  2. T is equal to the time between latent failure occurs and its presence is detected by a safety mechanism. Also referred as Diagnostic Test Interval (T_{DTI}), (Fig. 5).

According to equations 4 and 6, the probability that CVM will fail to detect function F_i failure within sufficient time is:

$$P_{cvm} = \lambda_f \delta T_{CVM} \tag{7}$$

Having $\lambda_f = 10^{-6}$ and $\delta = 10ms$ as constant values, the only variable is T_{CVM}. Within this paper we assume a maximum travel time of two hours. Thus, we consider T_{CVM} to vary from $1ms$ to $7200sec$.

4.3.2 CVS Failure Probability

Top level event probability for the vision-based ADAS with CVM is equal to:

$$
\begin{aligned}
P_f^{Top} &= E_1 + E_2 + E_3 + E_4 \\
where: & \\
E_1 &= \frac{1}{2} E_{1.1} E_{1.2} = \frac{1}{2} D_{\lambda_m} \lambda_m t_m D_{\lambda_f} \lambda_f t_f \\
E_2 &= \frac{1}{2} E_{2.1} E_{2.2} = \frac{1}{2} L_{\lambda_m} \lambda_m t_m D_{\lambda_f} \lambda_f t_f \\
E_3 &= E_{3.1} E3.2 = L_{\lambda f1} \lambda_f t_f P_{cvm} \\
E_4 &= L_{\lambda f2} \lambda_f t_f
\end{aligned}
\tag{8}
$$

Top level event probability for the current FT depends (i) on the diagnostic test interval (T_{CVM}) and (ii) on the percentage of the latent failures CVM may detect. Therefore sensitivity analysis on different diagnostic coverages $L_{\lambda f1}$ will be performed. Sensitivity analysis on D_{λ_m} is not done, due to the fact that its weight on the top level event probability is very low.

Figure 6 depicts the top level event probability (P_f^{Top}) results for different diagnostic coverage percentages of CVM ($L_{\lambda f1}$) and diagnostic test interval (T_{CVM}) ranging from $1ms$ to $7200sec$.

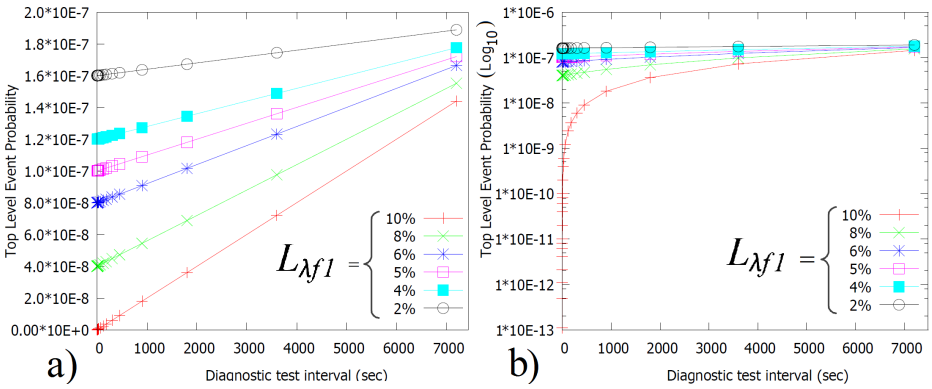

Fig. 6. Figure 6a): P_f^{Top} results for different $L_{\lambda f1}$ and T_{CVM} ranging from $1ms$ to $7200sec$. Figure 6b): Logarithmic scale (log_{10}) of P_f^{Top}.

Results from Fig.6 show that depending on the diagnostic coverage of CVM and on the diagnostic test interval, the failure probability of top level event (P_f^{Top}) can be decreased up to 10^{-13} when the CVM has full coverage of the latent failures ($L_{\lambda f1} = 10\%$) and diagnostic test interval of $1ms$.

However, diagnostic test interval of $1ms$ is difficult to be achieved. Therefore Fig.7 presents top level event probability (P_f^{Top}) results for different diagnostic coverage percentages of CVM ($L_{\lambda f1}$) and T_{CVM} ranging from $1sec$ to $300sec$.

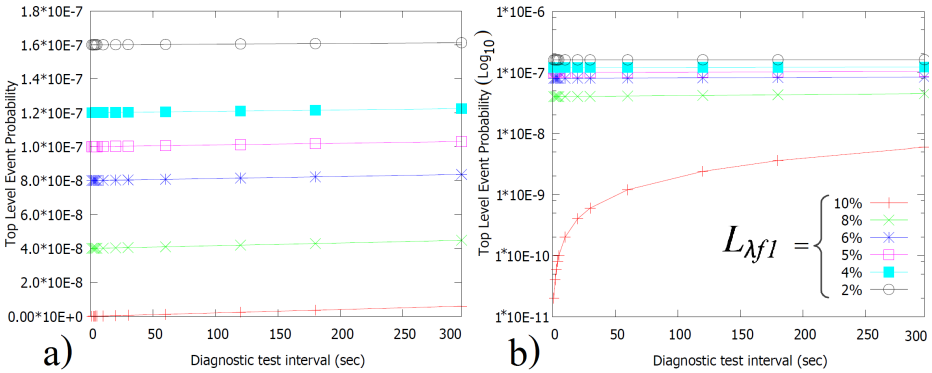

Fig. 7. Figure 7a): P_f^{Top} results for different $L_{\lambda f1}$ and T_{CVM} ranging from $1sec$ to $300sec$. Figure 7b): Logarithmic scale (log_{10}) of P_f^{Top}.

The results from Fig. 7 show that, when T_{CVM} is under $50sec$ and $L_{\lambda f1} = 10\%$, P_f^{Top} decreases to less than 10^{-9}. In the case when the T_{CVM} is $1sec$ and CVM has full diagnostic coverage ($L_{\lambda f1} = 10\%$), the top level event failure probability is 2.01×10^{-11}, which is sufficient for safety-critical functions.

5 Conclusions and Future Work

Autonomous vehicles are no longer a distant future goal. Top vehicle producers invest serious amount of resources in research, development and testing in the said area. When it comes to the need of collecting detailed information for the environment, vision systems are inevitable part of the autonomous vehicles. Therefore, the vision-based systems have to be dependable enough in order to be used for vehicle safety-critical functions.

In this paper we have proposed a concept of CVM which combines environmental information to enhance the reliability of CVS in ADAS. Using FT and sensitivity analysis, we have shown, that the proposed CVM can contribute to improving the overall reliability of the in-vehicle computer-vision system, by achieving top level event probability of failure of 2.01×10^{-11}, given that the diagnostic test interval is $1sec$ and full coverage of possible latent failures is achieved. This is certainly optimistic and a consequence of idealized failure rates and conditions, but gives us sufficient motivation to consider CVM as a realistic candidate approach to making automobiles more safe. Last but not least we have proposed a solution how to include the issue of detecting latent failures within the required sufficient time, to the fault tree analysis.

Ongoing and future work is focused on modeling and simulations in the Möbius software tool in order to validate the presented estimations.

Acknowledgments

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