Image and noise reduction for assessing driver incompetence in cases of sudden unintended acceleration

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Article Info	ABSTRACT
	This paper explores using cameras aimed at the accelerator and brake pedals during sudden unintended acceleration in cars, removing noise from captured images to determine driver incompetence. A car model was constructed using Raspberry Pi to simulate brake malfunction using random functions, increasing the revolutions per minute (RPM) to simulate sudden acceleration. By employing a DC encoder motor to measure the motor's rotational speed through waveform counts, the RPM was calculated. The study recognized sudden acceleration when the brake malfunctioned through the DC encoder motor, causing an abnormal RPM increase, allowing camera capture toward the accelerator and brake during sudden acceleration events. Precautions were taken for problems arising from noise in captured images. The Unix operating system was utilized to apply Gaussian filter image processing techniques for noise removal. While using an average value filter led to abrupt changes by replacing with the average of surrounding signals, resulting in an unsmooth image, a Gaussian filter was used in this study to decrease weights as distance from the center increased, mitigating these issues.

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1. INTRODUCTION

As cars become more widespread and their components increasingly electronic, incidents of sudden unintended acceleration in vehicles have been consistently occurring each year. In response, vehicles have been equipped with event data recorders (EDRs) to record accidents [1]-[3]. However, no cases have been acknowledged as due to mechanical faults. Most accidents involving sudden acceleration in cars occur when the revolutions per minute (RPM) increases without the accelerator being pressed and the brakes failing to function. Automotive companies often attribute these accidents to driver error or drowsy driving. Even in legal rulings, the conclusion often favors the automotive companies, citing driver incompetence. Sudden unintended acceleration in cars is a significant accident that can harm not only the driver but also numerous others. Therefore, determining whether it's due to driver incompetence or mechanical faults is crucial. Courts tend to accept the automotive companies' opinion that it's challenging to scientifically prove mechanical faults. Consequently, drivers find themselves in a situation where they must prove it's not due to their incompetence but rather a mechanical fault.

Proving a mechanical fault as a driver can be quite challenging. Consequently, when mechanical faults aren't acknowledged, it often leads to the situation being attributed to driver incompetence, creating an unjust scenario for the driver. Since drivers have to request and acquire evidence from automotive companies

to obtain proof, it puts them at a disadvantage. Therefore, it's crucial for drivers to possess intuitive data regarding their driving competence to avoid unjust situations. Capturing footage with cameras aimed at the accelerator and brake pedals during sudden acceleration incidents provides visual evidence [4]. This footage can then be used to assess the driver's competence. The aim of this research is to empower drivers by providing them with evidence to assess their own driving competence, ultimately preventing unjust situations.

In this paper, we simulate sudden acceleration incidents using Raspberry Pi. Upon detecting such an event, we identify it as a case of sudden acceleration. During this scenario, cameras are directed towards the accelerator and brake pedals to capture footage for assessing the driver's competence. Subsequently, we conducted research on a program that utilizes Gaussian filter image processing techniques to remove noise from the captured images.

2. SIMULATING SUDDEN ACCELATION ACCIDENTS
2.1. RAND function
RAND function is a programming function used to generate random numbers. Essentially, it's used for creating random numbers or randomization within a program. Typically, the RAND function generates random numbers starting from 0. When used as "rand() % 10", it generates numbers from 0 to 9. This method allows for controlling the range of random number generation [5], [6]. In C programming, to use the RAND function, we need to include the "stdlib.h" header file.

2.2. Algorithm for sudden acceleration accidents
Sudden acceleration in cars occurs when the RPM suddenly increases, and the brakes fail to function. In Figure 1, using the rand function, we simulated a situation where a brake malfunction was induced to create a sudden acceleration scenario. When a brake malfunction was introduced, the RPM was increased to simulate the sudden acceleration. When the brakes functioned normally, they were ensured to operate correctly. This study proceeded with a 20% probability of brake malfunction occurrence.
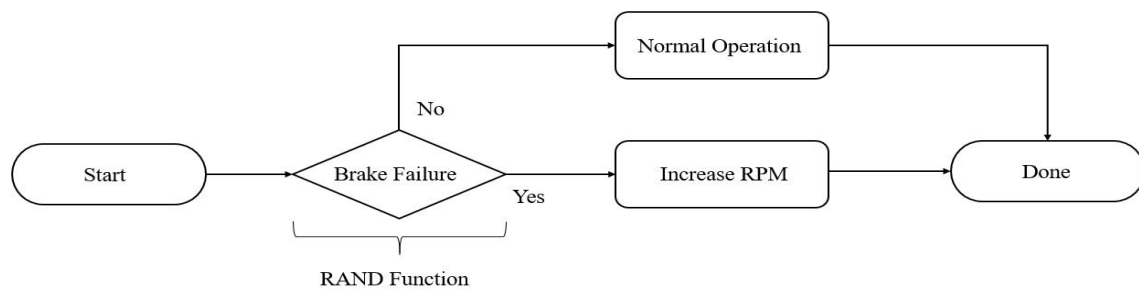

Figure 1. Flow chart for sudden acceleration accidents

3. RECOGNITION OF SUDDEN ACCELERATION INCIDENTS
3.1. DC encoder motor
The Incremental method of a DC encoder motor involves light emitted from light emitting diodes (LEDs) in Figure 2, shining onto phases A, B, and Z. As the encoder rotates, the light passing through the slits is alternately obstructed and allowed to pass through each phase [7], [8]. This method measures the rotational speed of the shaft by how the emitted light interacts with and is obscured by the rotation slits. A crucial aspect of encoders is their resolution. Higher resolution allows for finer measurement of the rotational speed. The signals generated by the encoder per one full rotation are determined by the resolution. For instance, with a resolution of 60, 60 pulses are produced per one complete rotation. This translates to 60/360 = 1/6°, resulting in one pulse per 1/6° of movement. The encoder's rotational angular velocity is measured in a given period, forming the basis for RPM measurement. In this study, RPM is measured as depicted in Figure 2, and this data is used to calculate velocity [9].

3.2. Algorithm for recognizing sudden acceleration
Sudden acceleration in a car occurs when the RPM and speed increase abruptly while the brakes fail to engage. Hence, as depicted in Figure 3, if the brakes are applied but fail to function while the RPM

increases, it's identified as a case of sudden acceleration in the vehicle. This study utilizes a DC encoder motor to measure RPM and thereby recognizes the increase in RPM.
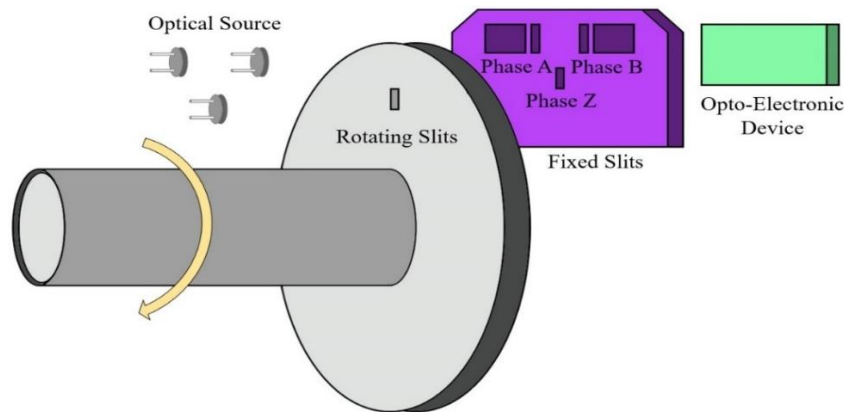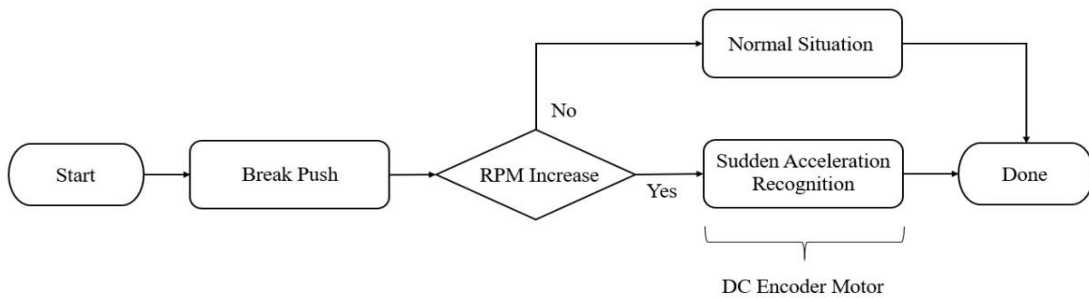

Figure 2. Incremental method of DC encoder motor

Figure 3. Flow chart for recognizing sudden acceleration

4. USING CAMERAS DURING SUDDEN ACCELERATION

Figure 4 implements and recognizes sudden acceleration scenarios based on brake engagement. Upon recognizing a sudden acceleration event in the vehicle, cameras are directed towards the accelerator and brake pedals. To accommodate nighttime driving, camera lighting is utilized. The camera lighting is activated before capturing footage and turned off once the recording ends. The filenames for the captured footage are based on the time of the sudden acceleration event. This study employs the localtime function to set filenames based on time, preventing file duplication and recording the time of the sudden acceleration event.
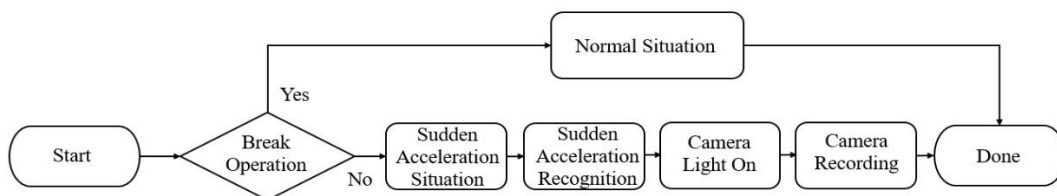

Figure 4. Flow chart for camera recording

5. NOISE REDUCTION
5.1. Noise

Noise refers to unwanted signals or unintended data, arising from interference or undesired distortions within the dataset [10]-[12]. In the case of image sensors, it occurs due to technical factors and external

influences, leading to irregularities in the images [13]. Noise can originate from various factors, primarily from prolonged exposure and high sensitivity. Types of noise include Gaussian noise [14]-[16], Salt and Pepper noise [17]-[19], uniform noise [20]-[22], photon noise [23]-[25], readout noise [26]-[28], reset noise [29]-[31], quantization noise [32]-[34], and more [35]-[37]. To mitigate such noise, noise filters are employed.

5.2. Gaussian filter

The Gaussian filter processes pixel values by computing a weighted average of neighboring pixel values, effectively removing noise. This is obtained through the Gaussian function. Due to its detailed removal, it results in a smoother image, also known as smoothing. In (1), when σ is small, the height increases, and the width decreases, allowing fewer low-frequency components to pass through [38]-[40]. Conversely, when σ is large, the height decreases, and the width increases, enabling more low-frequency components to pass through. Adjusting σ allows control over the amount of low and high-frequency content. As σ increases, the blurring effect intensifies [41]-[43]. Blurring involves passing through a low-pass filter, eliminating high-frequency components such as the image's contours, resulting in a smoother image. Gaussian filters render weight values nearly insignificant when the σ size is 3 or less or greater than -3.

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

5.3. Mean filter

The mean filter determines pixel values by computing the arithmetic mean of neighboring pixel values. It's a form of arithmetic mean filter, replacing the central pixel value with the calculated average of the image pixel values [44], [45]. This filter computes the mean of selected neighboring pixel values by summing up the values and dividing by the number of nearby pixels. The computed average value substitutes the central pixel value. Consequently, it reduces variations between pixels, blurring edges, and reducing noise in the image [46]. However, excessive use can cause blurring at object boundaries, making object recognition challenging. The mean filter typically utilizes a 3×3 mask or a 5×5 mask. Larger masks result in smoother images.

5.4. Image convolution

Image convolution is a technique used in digital image processing and computer vision. It involves transforming or enhancing images using filters or kernels [47], [48]. Image convolution performs operations between each pixel of an image and its neighboring pixels. It is also referred to as image filtering or convolution operation. Convolution involves multiplying each pixel of an image with its neighboring pixels and summing up the resulting values. Image rotation utilizes not only filters but also extracts high-frequency and low-frequency components, used in tasks like image pyramids creation, deep learning, and convolutional neural networks. The Gaussian filter can also be applied using image convolution. Typically, Gaussian filters, shown in Figure 5, use masks of sizes like 3×3, 5×5, or 7×7. As the mask size increases, the image becomes smoother but requires more computations, thus taking longer processing time [49], [50]. In other words, a larger mask size increases the blurring effect while slowing down processing speed. In the code, the reason for $y < YY - 4$, $x < XX - 4$ is as follows: a 7×7 image undergoes image convolution three times using a 5×5 mask, hence subtracting 4 from both the horizontal and vertical sizes. Figure 5 demonstrates an image after applying the Gaussian filter through image convolution.
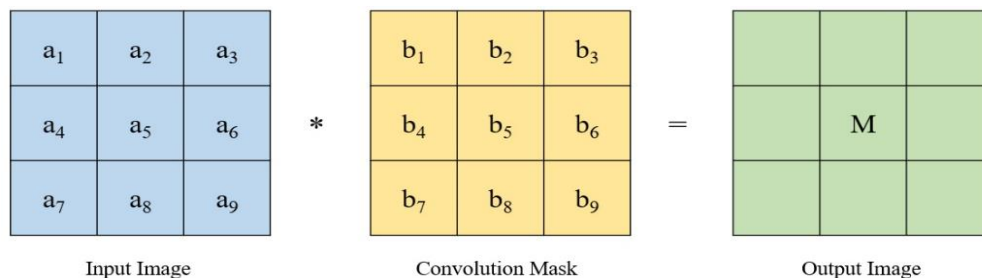
a_1	a_2	a_3		b_1	b_2	b_3				
a_4	a_5	a_6	*	b_4	b_5	b_6	=		M	
a_7	a_8	a_9		b_7	b_8	b_9				

Input Image   Convolution Mask   Output Image

Figure 5. Image convolution

5.5. FFmpeg

In this paper, noise reduction was performed on videos rather than photos. The videos are structured similarly to Figure 5, with no information on width, height, or maximum luminance. For this reason, FFmpeg

was utilized in this research. FFmpeg is a library or tool capable of handling various multimedia file operations such as decoding, encoding, conversion, and streaming for audio, video, and more. Therefore, video processing or conversion tasks were executed using FFmpeg. Various options of FFmpeg were set using commands. Table 1 highlights some key options. The structure of FFmpeg commands follows the pattern 'ffmpeg [options] -i input output'. There is a range of options available within FFmpeg, which are used together to perform video processing and conversion tasks. In this study, the Gaussian filter was applied using FFmpeg commands.

Table 1. Main options of FFmpeg

Option	Function
-i	Specifies the input file
-f	Specifies the output file format
-r	Sets the video frame rate
-s	Specifies the video resolution
-b	Sets the bitrate
-codec:a, -codec:v	Specifies audio and video codecs
-ss, -t	Specifies the time range to be used from the input file
-filter_complex	Applies filter graph
map	Selects streams from the input file to be used in the output

6. RESULTS

Using the rand function, a brake malfunction is implemented with a 20% probability. When a brake malfunction occurs, the RPM is increased, simulating a sudden acceleration situation. Continuously measuring RPM using the DC encoder motor, if the RPM measured after pressing the brake does not decrease but rather increases, it's identified as a sudden acceleration event in the car. Upon recognizing the sudden acceleration event, the camera initiates recording towards the accelerator and brake. Preventing duplicate file names using the localtime function, timestamps in file names record the time of the sudden acceleration incident. The recorded video's noise is removed using a Gaussian filter. As mentioned before, distinguishing whether the driver pressed the accelerator or the brake during a sudden acceleration event enables assessment of the driver's proficiency behind the wheel.

7. CONCLUSION

This research utilized C language functions such as rand and localtime, alongside a DC encoder motor and Gaussian filter for image processing. The rand function was employed to simulate sudden acceleration, while the DC encoder motor recognized and recorded instances of sudden acceleration. When a sudden acceleration event occurred, the program captured the driver's reaction. The use of localtime for file naming prevented duplicates and recorded the accident time. Additionally, noise reduction using a Gaussian filter notably improved the outcomes.

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