SPEED BUMP DETECTION FOR AUTONOMOUS VEHICLES USING SIGNAL-PROCESSING TECHNIQUES

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Abstract

Autonomous vehicle (AV) is one of the emerging technologies that have far-reaching applications and implications in smart cities. Among the current challenges of the Smart City, Traffic management is of utmost importance. AV technologies can decrease transportation cost and can be used for efficient management and control of traffic flows. Traffic management strongly depends on the road surface condition. Abnormalities in the road, such as manholes and potholes, can cause accidents when not identified by the drivers. Furthermore, human-induced abnormalities, such as speed bumps, could also cause accidents. Detecting road abnormalities provide safety to human and vehicles. Current researches on speed bump detection are based on using sensors, accelerometer and GPS. This makes them vulnerable to GPS error, network overload, delay and battery draining. To overcome these problems, we propose a novel method for speed bump detection that combines both image and signal processing techniques. The advantage of the proposed approach consists in detecting speed bumps accurately without using any special sensors, hardware, Smartphone and GPS.

Keywords

1. INTRODUCTION

Humans dreamt of autonomous transportation since the middle ages and until today are still working on achieving the perfect autonomous vehicle. Wired Brandlab states that the autonomous feature was first introduced to the automobile industry in 1945 in the form of the Teetor cruise control [Wired, 2016]. It enabled the driver to set the car to a certain speed and lift his foot off the throttle which made the car automatically cope with changing road levels to keep the moving speed constant as set by the driver [Lehman, 2014]. Then the automobile underwent a series of autonomous upgrades in the last decade like introducing the anti-lock braking system, electronic stability control systems, self-parking features, lane assist, speed-limit adherence, and collision avoidance systems. In 2015, the car manufacturer Tesla introduced the autopilot feature that makes its cars navigate with no human input at all on highways and open roads only. Tesla's car falls in the semi-automated vehicles category as its automation feature assists the driver in certain and limited situations.

From this point, it was important to differentiate between five levels of car automation. In 2013, the US National Highway Traffic Safety Administration (NHTSA) developed classification levels for autonomous vehicles [Basset, 2015]. Level 0 represents the early vehicles that relied on pure human input with no sort of driving aids. Level 1 automated vehicle include cars that contain basic automated driving assist systems that don't eliminate a certain human input but improves the driving experience like anti-lock brakes and electronic stability control systems. A level 2 autonomous vehicle contains systems that reduce human input such as lane departure systems and cruise control. Level 3 comprises vehicles that enable the driver to completely release all vehicle controls in certain situations for instance while highway cruising and parking. Level 4 cars are those that do not even have manual controls and operate autonomously at all times.

One of the systems that need to be implemented in level 3 and level 4 autonomous cars is speed bump detectors. Sometimes, a "slow traffic" sign or low posted speed limit does not do so much to slow down traffic. It is easy for drivers to ignore or miss these types of signs altogether. Therefore, speed bumps are used to reduce the speed of the vehicle near schools, colleges, hospitals, pedestrian crossing, etc. However, if the driver misses reducing his speed while crossing a speed bump due to distraction for example, this could harm the vehicle and passengers' comfort.

Several approaches have been proposed to detect speed bumps [Celaya-Padilla, 2018]. They are based on using dedicated sensors, a three-axis accelerometer and smartphones. The drawback of using such approaches is that the system is relying on sensors that may have vibration patterns of sensor data, GPS error, network overload, delay and battery draining. In this paper, we propose a novel approach for speed bump detection that notifies the driver when a bump exists on the road. The proposed approach combines image processing and signal processing techniques in a very efficient way, which allows the detection of speed bumps without the need for sensors, network connection and GPS.

The remainder of this paper is organized as follows: Section 2 presents the related work. Section 3 introduces the profile line technique and how it can be used to detect periodic patterns in an image. Section 4 presents our proposed method based on the analysis of the profile lines using signal-processing techniques. Section 5 shows the experimental results. Conclusions appear in Section 6.

2. RELATED WORK

Maximum Several works have been proposed for speed bump detection. Most of them try to detect bumps using sensors, accelerometer and smartphone apps.

Zein et al. [Zein, 2018] detected bumps at short distances, up to one meter, using ultrasonic sensor. This technique is useful at very low speeds (less than 1 m/s). Therefore, at high speed, the driver will not have time to react and slow down. Eriksson et al. [Eriksson, 2008] developed the patrol system, which uses vibration and GPS sensors installed in vehicles to gather road surface conditions data. The gathered data are then processed using a simple machine-learning approach to assess road surface conditions. Chen et al. [Chen, 2011] developed a low-cost vehicle-based solution for road condition monitoring with three-axis accelerometers and GPS Sensors embedded in a vehicle to monitor the road condition. They analyzed the Power Spectral Density (PSD) of pavement roughness to classify the pavement roughness level. Mohan et al. [Mohan, 2008] proposed a system called Nericell that uses the accelerometer, microphone, GSM radio, and/or GPS sensors in smartphones to detect potholes, bumps, braking, and honking in roads. Recently, Arroyo et al. [Arroyo, 2016] proposed an Adaptive Fuzzy Classifier to identify sudden driving events such as acceleration,

steering, braking and road bumps from the inertial and GPS sensors. Aljaafreh et al. [Aljaafreh, 2017] proposed a speed bump detection method based on a fuzzy inference system. The proposed system detects and recognizes the speed bumps from the variance of the vertical acceleration and the speed of the vehicle by utilizing the embedded sensor (accelerometer) in the Smartphone. Astarita et al. [Astarita, 2012] developed a multi smartphone system to detect speed bumps; the proposed algorithm analyzes the acceleration signal in terms of high-energy events to detect road bumps and potholes. González et al. [González, 2017] developed a methodology to analyze the road surface condition using a smart-phone and the embedded sensors, the approach used the accelerometer data and a Bag of Words representation in order to characterize the road surface condition. Salari and Yu [Salari, 2011] explored the use of genetic algorithms using images as a source of information to detect potholes and pavement distress, the proposed methodology was able to detect the pavement distress with an accuracy of 97%. Finally, Celaya-Padilla et al. [Celaya-Padilla, 2018] proposed a method for the detection of road abnormalities (i.e., speed bumps). They make use of a gyro, an accelerometer, and a GPS sensor mounted in a car. After collecting data from the sensors by cruising through several streets, they use a genetic algorithm to find a logistic model that accurately detects road abnormalities.

As listed above, most to the existing approaches are based on smartphones and sensors to detect speed bumps. The drawback of using such approaches is that, in addition to vibration patterns, GPS errors and network overload, they do not suit real-time scenarios as the information collected about speed bumps are stored in databases and thus it become offline data.

Only one identified work has been performed on detecting speed bumps using image processing techniques. Devapriya et al. [Devapriya, 2016] proposed a real-time speed bump detection system by analyzing the images from the road and applying computer vision enhancement based on a Gaussian filter then performing image segmentation to separate the bump object from its background. The system was able to detect the speed bumps with a true positive rate between 30% and 92%. Nevertheless, in this approach, they assume that the segmentation will be perfectly performed and the bump is always well segmented. However, in real life, this is not the case since the road is not always free of objects and the speed bumps are not always correctly painted and labeled which prevents getting a well-segmented image that separates the bump from its background.

3. PROFILE LINE

A profile line is a histogram that shows the intensity of pixels for an image row. The x-axis corresponds to the pixels' position in the image row and the y-axis corresponds to the intensity of the pixel at the given position. Figure 1 shows an example of a profile line that corresponds to the image row highlighted in red that crosses the upper side of the image. We can see that this profile line starts with a homogenous zone of high-intensity pixels that correspond to the sky (white region).

The profile line then drops to a zone of low-intensity pixels, which correspond to the trees (dark region) in the image. Based on a combination of many profile lines useful information could be extracted from the image. For instance, image homogeneity or image texture could be analyzed based on the shapes and the variations of the profile lines. In fact, if the profile line has a continuous small variation in line shape this means that we are inside a homogenous region. This is illustrated by the left region of the profile line in Figure 2 (x=0 to x =1600). On the other hand, if the profile line has strong variations, this means that we are in edge regions. In figure 2, this illustrated by the drastic drop of the profile line from high to low at x = 3000 which corresponds to the edge between the sky and the trees.
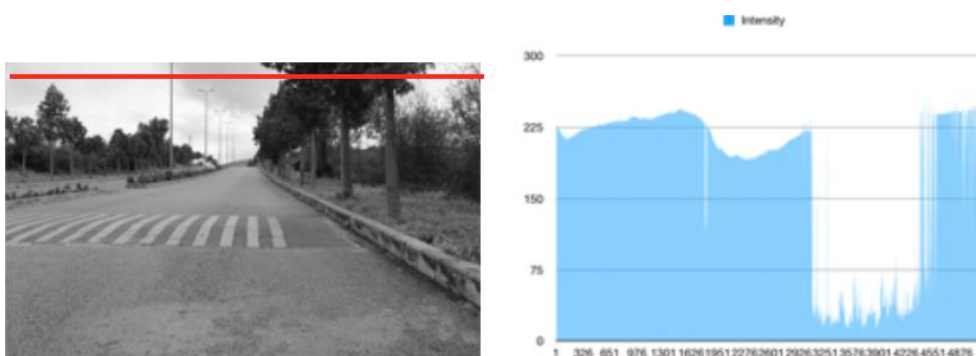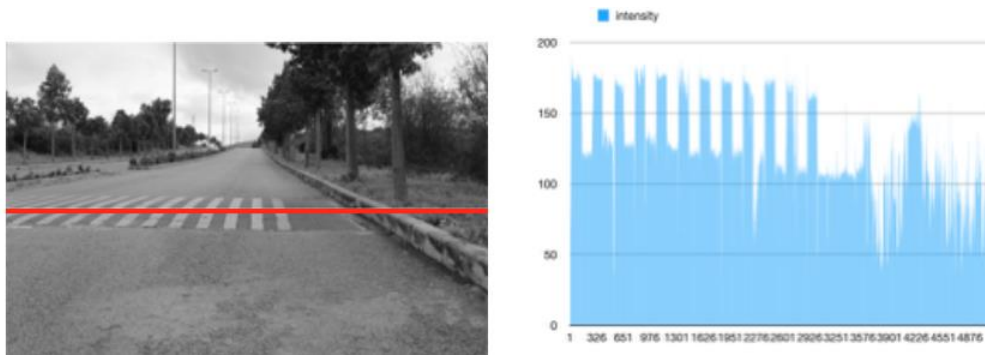

Fig.1: Example of a profile line

Fig.2: Example of a profile line containing a periodic variation

Depending on the zone that the profile line is crossing, the variation in its shape could be periodic or non-periodic. For example, if the profile line crosses an object in the image that has a periodic pattern, this will be reflected as a periodic variation in the profile line. Figure 2 shows an illustration of such case. We can see clearly the periodic alternation of a region of high-intensity pixels with low-intensity ones. This periodic pattern reflects the shape of the speed bump which based on the profile line, it starts from x = 0 to x =3000 approximatively. The remaining of the profile line is an aperiodic signal that does not reflect any valuable information. If we manage to differentiate between these two types of variations (periodic and aperiodic) in the profile line, we can detect the objects that have periodic patterns.

The profile line that represents an image row can be considered as a signal. Therefore, signal processing techniques can be used to study and analyze different aspects of the profile line and specifically the periodicity of the signal as we are interested in detecting bumps that have periodic patterns.

4. PROPOSED METHOD

To detect speed bumps, we propose to use the profile lines combined with signal processing techniques. Figure 3 shows the flowchart of the proposed method. A video camera is installed in front of the car. The captured video is then converted to images. These images are then processed to detect the potential bumps. The detection process starts by converting the captured image into grayscale. It is then parsed row by row from the top to the bottom. For each row, a profile line is created. Each profile line is then checked to detect if it contains a periodic pattern. In this paper, we consider only the detection of speed bumps that has a zebra crossing pattern. They could have various lengths, width and thickness but they all alternate dark and light stripes on the road surface.

The idea of parsing the image row by row consists in detecting the exact location and dimension of the bump in the image. We start by creating of profile line from the first top row of the image all the way to the last row in the image. A periodicity check is then performed on each profile line to check if it contains a periodic pattern. When a first profile line containing a periodic pattern matches the shape of the bump, it is labeled as the start of the speed bump. If periodic patterns continue to appear in the consecutive profile lines and in the same pixels' location, they are interpreted as a part of the bump. When periodic patterns stop to be detected in the consecutive profile lines, we can, therefore, locate the end of the bump.
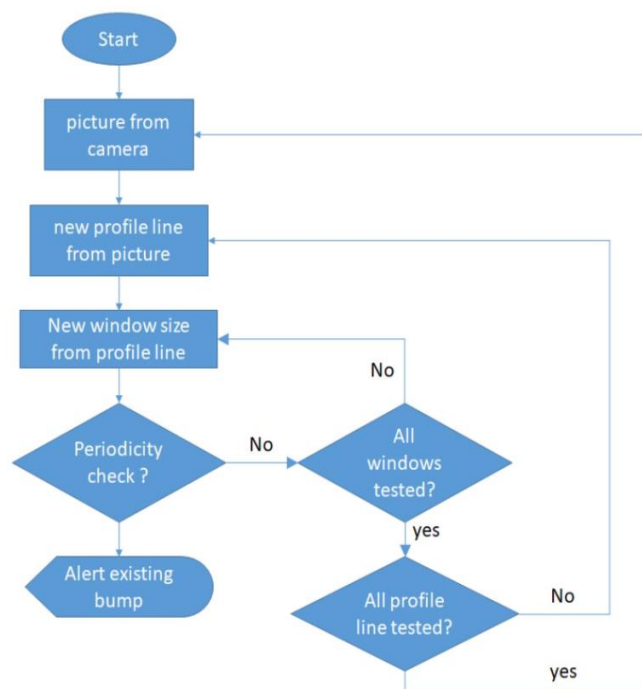

Fig.3: Flowchart of the proposed method

The power of our method is that we are able to detect the exact boundaries of the bump in the image. In fact, based on signal processing techniques, we are able to locate where the periodic signal starts and ends and therefore detect the width of the bump. Furthermore, as all the consecutive profile lines that contain periodic patterns are known, this means the high or thickness of bump could also be located on the image. By locating the boundaries of the speed bump in the image, many options could be conceived to notify the driver. In this paper, we just highlight the bump in the image as shown in Figure 4.
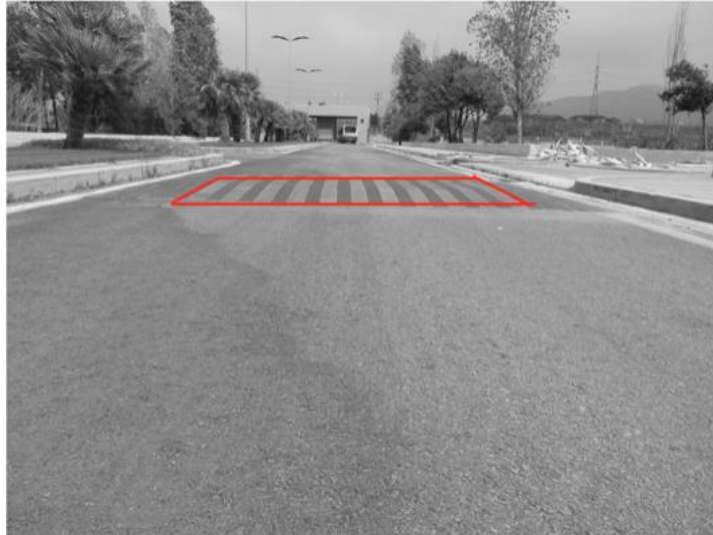
Fig.4: Detected speed bump highlighted

4.1 Sliding Window

To detect the periodic pattern we consider the profile line as a signal where the time axis is the row pixels of the profile line and the amplitude is the intensity of the pixels. Figure 5 shows an example of a profile line signal. As it can be seen, the signal contains noise, which may influence negatively the periodic pattern detection process. Therefore, we start by smoothing the signal to eliminate noise. The smoothing technique used is called median filtering. An example of the resulted filtered signal is shown in figure 6.

After filtering the signal, we can see clearly that the signal contains a periodic pattern located in a segment between points 1000 to 2800. This periodic pattern constitutes a small part of the signal. The question that arises now is how to detect periodicity in a given signal if it contains small parts of periodic patterns. The easiest way to detect these periodic parts in a signal is to decompose the signal into segments and perform a periodicity check in each segment.
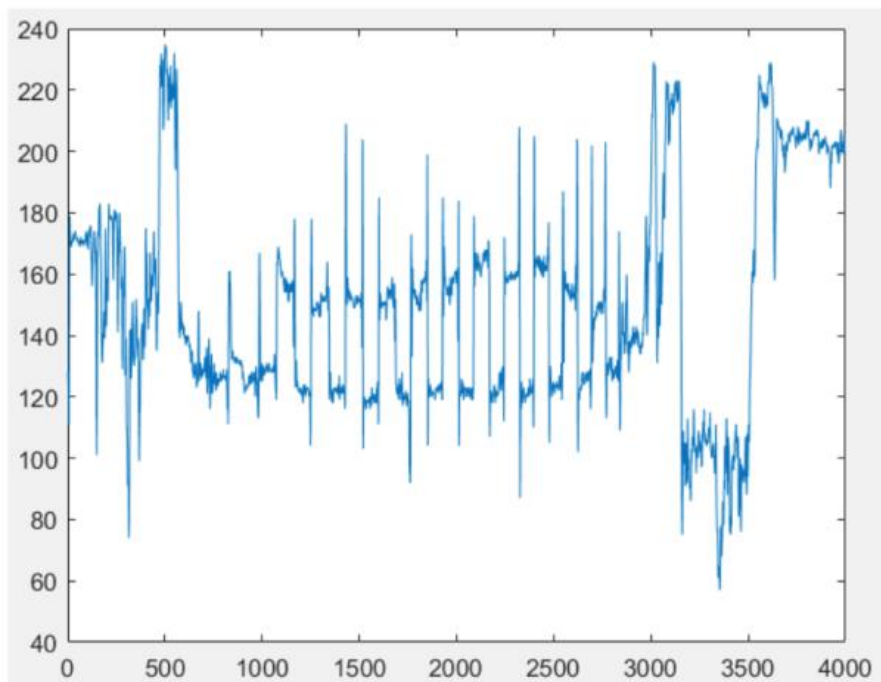
Fig.5: Profile line signal

For instance, in Figure 6, instead of checking the periodicity on the entire signal with no reliable results guaranteed, we could perform this check only on the signal segment which contains the periodic pattern between points 1000 to 2800. This technique used is called the sliding window technique where each window contains part of the signal [Sachin, 2015].
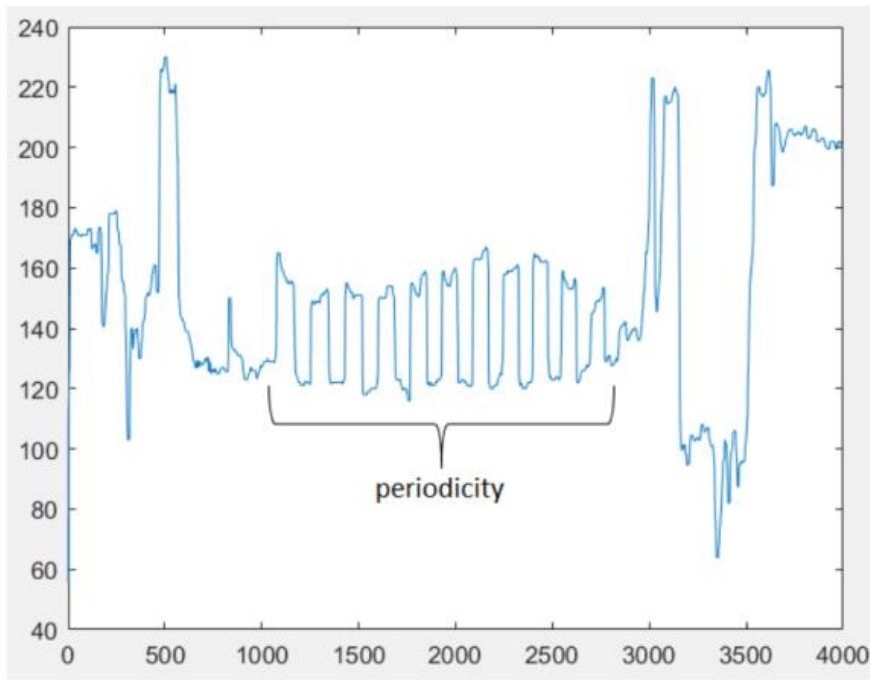

Fig.6: Profile line signal after filtration

The detection process starts by specifying the window size which will define the part of the signal to be analyzed. The window is then shifted one step to the right of the profile line to include new parts of the signal. The shifting process continues until reaching the end of the profile line. This technique is illustrated in figure 7.
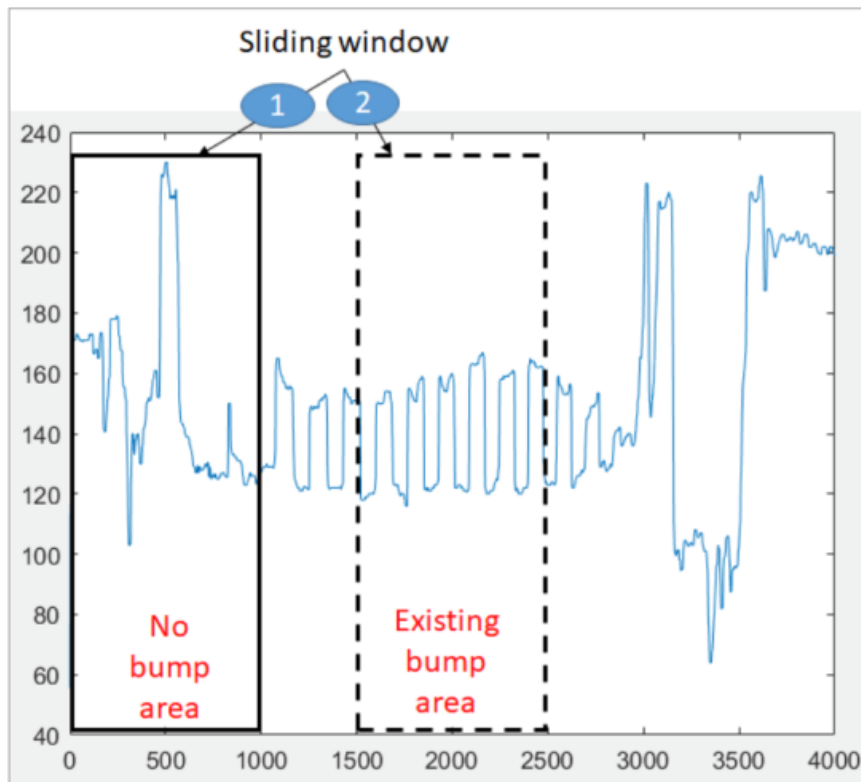

Fig.7: Sliding window

Another problem that needs to be tackled is how to determine the size of the window that allows the detection of the periodic pattern in the signal. For instance, Figure 8 shows an example of the profile lines created for a speed bump from four different distances. We can see clearly that the periodic pattern dimension in the profile line decreases as the distance from the bump increases. Therefore, to detect the periodicity in the profile lines we need to define a specific window size suitable for each distance, large window size for near speed bumps and narrow window size for far speed bumps. However, during real-time detection process, the images will be captured for the road with no information about the presence of a speed bump in the captured image or how far it is from the car. To overcome this problem, we propose to scan each profile line using four windows of sizes 80%, 60%, 40% and 20% of the width of the image. This technique will guarantee the detection of speed bumps at different distances without prior knowledge of their location.
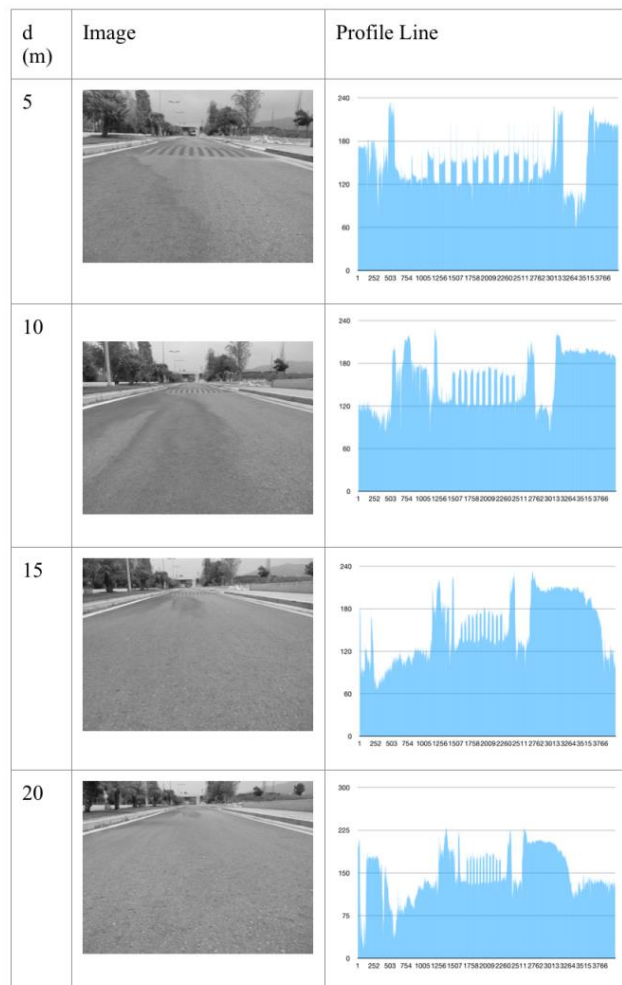

Fig.8: Profile lines from various distances

4.2 Periodicity Check

The detection of periodicity in a sliding window starts by setting a threshold value in each window. This threshold is calculated by getting the mean value of the intensity pixels contained in the window. The segment of the signal in the window is then converted to digital such that the intensity values that are greater or equal to the threshold are set to 1 and the others are set to 0. This process is illustrated in Figure 9. The profile line in Figure 9 (a) corresponds to the sliding window in Figure 7 that does not contain a bump area whereas Figure 9 (b) shows the profile line corresponding to the bump area sliding window between points 1501 to 2500 in Figure 7. In both Figures 9 (a) and Figure 9 (b) the threshold value used to convert the signal to digital is highlighted by red line. Figure 9 (c) and Figure 9 (d) show the two profile lines converted into squared signals with two values 0 and 1.

Based on this technique, the rising edge of the squared signal can be detected allowing to calculate the ΔT (delta time) between two consecutive rising edges. If the ΔT between all points is

nearly equal, then we conclude that the signal is periodic and therefore a bump exists. Figure 9 (e) and (f) depict respectively the rising edges corresponding to the signal segments in Figure 9 (a) and (b). When analyzing ΔT between all rising edges in figure 9 (e), we can conclude clearly that no bump is present as ΔT is not uniform between all the rising edges. On the other hand, in Figure 9 (f), ΔT is approximatively the same between all rising edges which correspond to a perfectly periodic signal, and therefore the existing of a bump.

a. No bump area window signal

b. Bump area window signal

c. No bump area window in digital format

d. bump area window in digital format

e. No bump area window edges
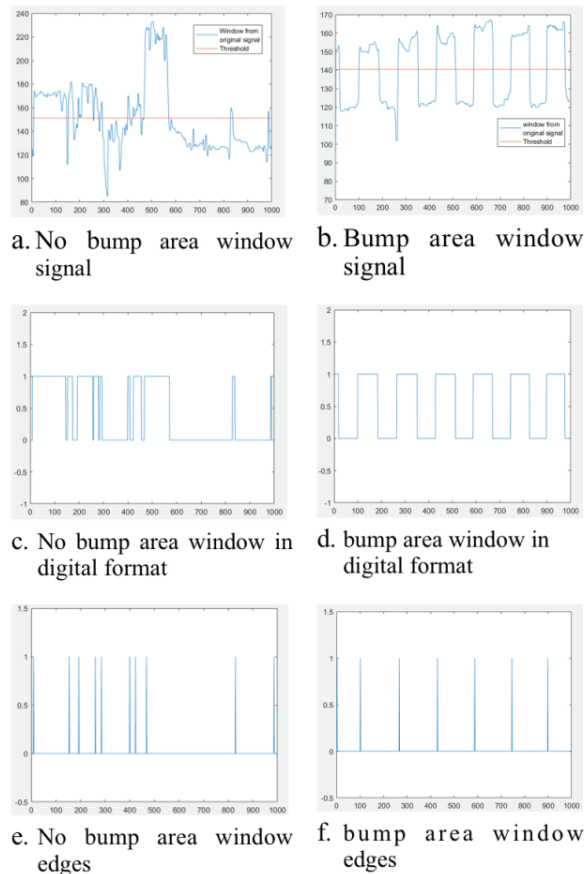
f. bump area window edges

Fig.9: Windows as digital signal and edges

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

To analyze the performance of our methodology, we tested it on a speed bump dataset created by us and includes 56 speed bump images captured from the Lebanese roads. Four images were captured for each bump at a distance varying from 5, 10, 15 and 20 meters. The images in this dataset correspond to different types of speed bumps with various dimensions in terms of length, width and thickness designed with zebra crossing pattern. The goal of this experimental test is to validate that our proposed methodology is suitable for all speed bumps designed with zebra crossing pattern and located at different distances.

The results performed on this dataset show that all the bumps were detected. This result was expected since all the images in this dataset were captured in high resolution and the bumps were perfectly horizontally aligned in the images. This allows having excellent profile lines for analysis. Figure 8 shows four images from this dataset with their corresponding profile lines. We can see how the periodic patterns are clearly depicted in these profile lines. The speed bumps at distance 5 meters were captured using an 80% window size, those at 10 meters were captured using a 60% window size, at 15 meters using 40% window size and finally the speed bumps at 20 meters were captured using a 20% window size.

It is worth to mention here that if an image contains a bump which is not well aligned horizontally and has a small thickness as shown in Figure 10 taken from dataset [Varma, 2018] then the profile line will pass through a small part of the bump and therefore we will not have enough periodicity in the signal that can be detected. We can see how the profile line crosses the bump without covering enough stripes. However, if the bump is not perfectly aligned horizontally but is has some

thickness this may increase the detection probability since the profile line may cross enough stripes in the bump to be detected.

Fig.10: Example of undetected speed bump

This problem of speed bumps not well aligned horizontally can be solved using the proposed approach for periodicity check. In fact, the speed bump detection accuracy could be parametrized by varying the number of rising edge needed to decide if a bump exists. If the number of rising edge specified is small this could solve the problem of speed bumps not well horizontally aligned. For instance, in Figure 10, the profile line passes through three bump stripes. This will result in having three rising edges. If the number of required rising edge is three then the bump will be detected. The drawback of such a process is overfitting where false bumps will be detected. On the other hand, if the number of rising edge required is set too high this may lead to under-fitting where true speed bumps will be missed.

6. CONCLUSIONS

In this paper, we have proposed a novel methodology for speed bump detection using what we called profile lines. The idea was to locate in the profile lines the periodic regions that correspond to the bump pattern using the sliding window technique. This robust and effortless methodology can easily detect speed bumps with zebra-pattern. It can be also embedded in higher-end vehicle and especially in self-driving cars. The proposed methodology does not need any external hardware, sensors or smartphones and therefore it liberates the user from congesting the GPS network and disturbing the mobile battery.

Future work will concentrate on enhancing our method to solve the problem of overfitting and under-fitting. Furthermore, we will try to support the detection of speed bumps in more complicated scenarios, for instance, the detection of bumps in night vision and bad illumination conditions like raining and mist. Other future work will concentrate also on the calculation of the distance that separates the car from the bump and try to determine the maximum distance a bump could be detected.

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