Analysing the Impact of Vibrations on Smart Wheelchair Systems and Users

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Abstract. Mechanical vibrations due to uneven terrains can significantly impact the accuracy of computer vision systems installed on any moving vehicle. In this study, we investigate the impact of mechanical vibrations induced using artificial bumps in a controlled environment on the performance of smart computer vision systems installed on an Electrical powered Wheelchair (EPW). Besides, the impact of the vibrations on the user's health and comfort is quantified using the vertical acceleration of an Inertial Measurement Unit (IMU) sensor according to the ISO standard 2631. The proposed smart computer vision system is a semantic segmentation based on deep learning for pixels classification that provides environmental cues for visually impaired users to facilitate safe and independent navigation. In addition, it provides the EPW user with the estimated distance to objects of interest. Results show that a high level of vibrations can negatively impact the performance of the computer vision system installed on powered wheelchairs. Also, high levels of whole-body vibrations negatively impact the user's health and comfort.

Keywords: Computer vision · Mechanical vibrations · Powered wheelchair · Semantic segmentation.

1 Introduction

Smart computer vision systems based on Deep Learning (DL) are widely used in semi-autonomous and fully autonomous systems for several purposes such as object detection [2, 5], scene understanding [11, 16], and object interaction [15, 9]. A hostile environment can negatively impact the performance of these systems, which may result in inaccurate human-system interaction. Mobile robots and smart vehicles are susceptible to mechanical vibrations due to traversing rough and uneven terrains. The ability to estimate the impact of vibration on the system performance is the first step to mitigating undesirable vibrations. This can enhance the system performance in challenging conditions; consequently, better human-system interaction can be attained.

Marichal et al. [10] investigated the impact of vibration produced by a helicopter on a vision system. It is concluded that the quality of the captured images is negatively impacted due to the undesirable movement of the camera . The proposed semi-active frequency isolation technique has proved efficiency in improving the captured images with low vibrations. Consequently, the subsequent utilise of the captured images is enhanced. However, the proposed technique needs prior knowledge of the vibration frequency in order for the system to be able to isolate it.

Periu et al. [14] studied the impact of the vibrations on the performance of obstacle detection using a LIght Detection And Ranging (LIDAR) sensor. The LIDAR sensor is installed on a tractor for obstacle detection and guidance purposes. Generally, agriculture vehicles do not have a suspension system, similar to the EPW used in our experiments. The measurements of the LIDAR sensor can be significantly impacted by mechanical vibrations induced during the operation of the vehicle on rough and bumpy terrains. The study proposes supporting bars and stabilising systems to counteract the vibrations impact. It is concluded that with the increase in the tractor speed, the accuracy of the LIDAR decreases due to high levels of mechanical vibrations; consequently, the position estimation error increase. Thus, the mean error distance and the standard deviation between the actual and the detected position increase.

Vibrations due to ramps, damaged terrains, and uneven tarmacs are not only impacting the accuracy of the smart systems installed on the powered wheelchairs but also can impact the health and comfort of disabled users. This paper investigates the impact of vibrations on a semantic segmentation system used by visually impaired EPW users to understand their surroundings by providing environmental cues. Environmental cues can help visually impaired users to locate objects in their surroundings [12]. The paper also investigates the vibration impact on users' health and comfort and how it can be related to the impact on the computer vision systems of the powered wheelchair.

The paper is organised as follows: experimental setup is presented in section 2. Section 3 discusses the results and the outcomes of the study. The study is concluded in section 4, where future work is highlighted.

2 Methodology

A powered wheelchair is driven for 11 meters on a carpet floor with and without artificial bumps in a controlled indoor environment. The chosen distance represents the maximum straight route of the corridor without turnings. The bumps, which are used to introduce the vibrations, are installed 1.5 meters apart (Fig. 1) to keep the seven bumps equally distanced throughout the route length and to provide enough space for the powered wheelchair to stabilise before the next bump. Two kinds of data are collected: the accelerations using an IMU sensor installed on the powered wheelchair seat and videos using a camera installed beneath the joystick (Fig. 2). The acceleration data has been processed for the two scenarios (with and without bumps) to quantify the impact of whole-body vibrations on user's health and comfort with respect to the ISO-2631 standard [8]. The two 21-seconds videos are annotated on the pixel level for the assessment of the semantic segmentation system, with around 26.8 million pixels are annotated for each video.

The extracted 65 ground truth images from each video are compared with the corresponding predictions using a semantic segmentation system trained on data from the same distribution (the same indoor environment) [12]. The proposed system is based on Deep Lab Version 3 plus (DLV3+) [3] with some modifications [12]. The system [12] uses ResNet-18 [7] as its feature extraction network. ResNet-18 is a perfect choice as it uses residual blocks that help the system to process high-resolution images ($960\times540\times3$ pixels) using a deep network (many layers) without losing information because of the vanishing gradients problem [1, 6]. Besides, using ResNet-18 as a base network for the DLV3+ has achieved better results and processing speed [12] compared to the usage of ResNet-50 or Xception [4] base networks that are used in the original implementation of DLV3+ [3].

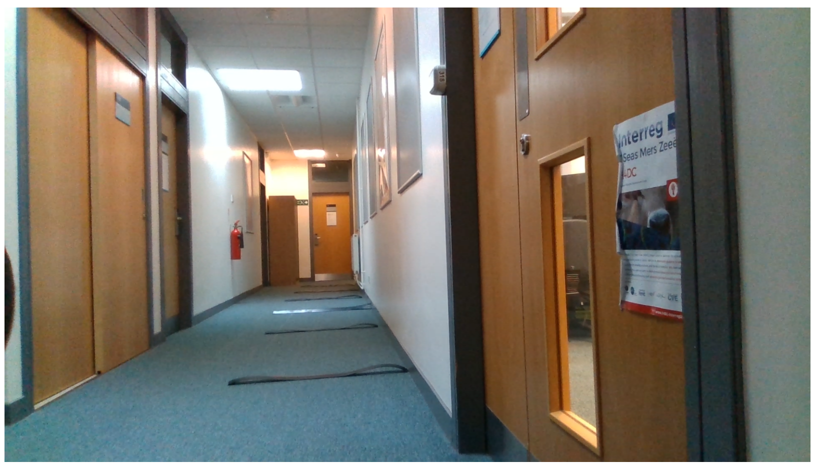

Fig. 1: Artificial bumps to introduce vibrations fixed 1.5 meters apart.

3 Results

Results show the impact of undesirable vibration on both the semantic segmentation systems and the user's health. Table 1 shows the impact of vibration on the user's health and comfort. The calculations are made according to the ISO-2631 standard [8]. Driving the powered wheelchair on the carpet floor presents neither a health risk nor discomfort to the user. The user of the powered wheelchair weighs 95 Kg and is 184 cm tall. As users' weight can impact the vibration levels [13], further studies with different weight users will be implemented in future work.

(a) Powered wheelchair weight: 59.5 Kg. (b) Intel® RealSense™ Depth Camera. (c) Mounting disk with IMU sensor.

Fig. 2: **System installation for data collection.**

On the other hand, the introduced bumps make the situation a potential health risk and uncomfortable to the user. Fig. 3 shows the vertical acceleration of both scenarios (with and without the introduced vibrations). The vertical accelerations of the seven bumps can be clearly seen from the sudden changes in the signal's amplitude (blue signal). In contrast, the red signal, which represents the 'no vibration' scenario, does not have any sudden changes in the amplitude.

The analysis of the whole body vibration of the two scenarios is comparable with user 3 in [13], for which the user drives the powered wheelchair on the carpet floor for the no vibration case and the tiled concrete for the vibration case.

Table 1: Vibration impact on user's health and comfort.

State	No vibration					With vibration				
Assessment	Health				Comfort	Health				Comfort
Metric	$a_w(m/s^2)$	$MTVV(m/s^2)$	$MTVV/a_w$	$eVDV(7.5h)$	VTV	$a_w(m/s^2)$	$MTVV(m/s^2)$	$MTVV/a_w$	$eVDV(7.5h)$	VTV
Values	0.07	0.07	1.04	1.37	0.12	1.11	1.32	1.19	19.91	1.30
Result	No health risk				Not uncomfortable	Potential health risk				Uncomfortable

Fig. 4 shows the detection performance of the system in the absence (first column) and the presence (second column) of the introduced vibrations. It can

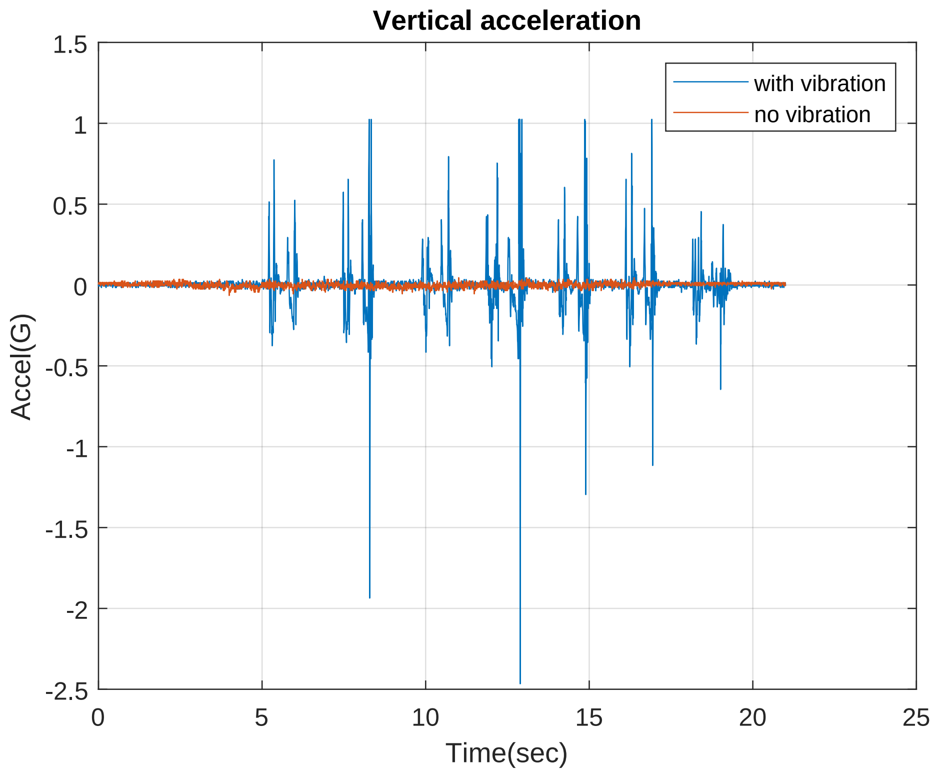

Fig. 3: Vertical accelerations with and without the introduced vibrations.

be seen that the vibrations have dramatically impacted the detection of objects such as the movable door handle, which the semantic segmentation system could not detect due to the sudden vibrations. Generally, the ability of the semantic segmentation system to classify the image pixels has degraded due to the introduced vibrations. Qualitatively, the degradation can be seen in the fourth row of Fig. 4, where the intense green and magenta colours indicate these differences between the ground truth data and the system predictions. These pixels are unannotated or misclassified. The green colour shows the unannotated pixels which do not belong to objects of interest. At the same time, the magenta one shows the misclassified objects.

Quantitatively, the first two rows of Table 2 shows the evaluation metrics of the two scenarios (with and without the introduced vibrations). It can be observed that the performance of the semantic segmentation system degrades as a result of the introduced vibrations. Thus, it can be concluded from the results that the performance of the semantic segmenting system can be negatively impacted by the vibrations encountered while driving the powered wheelchair. Also, the change in performance is directly proportional to the amount of vibration.

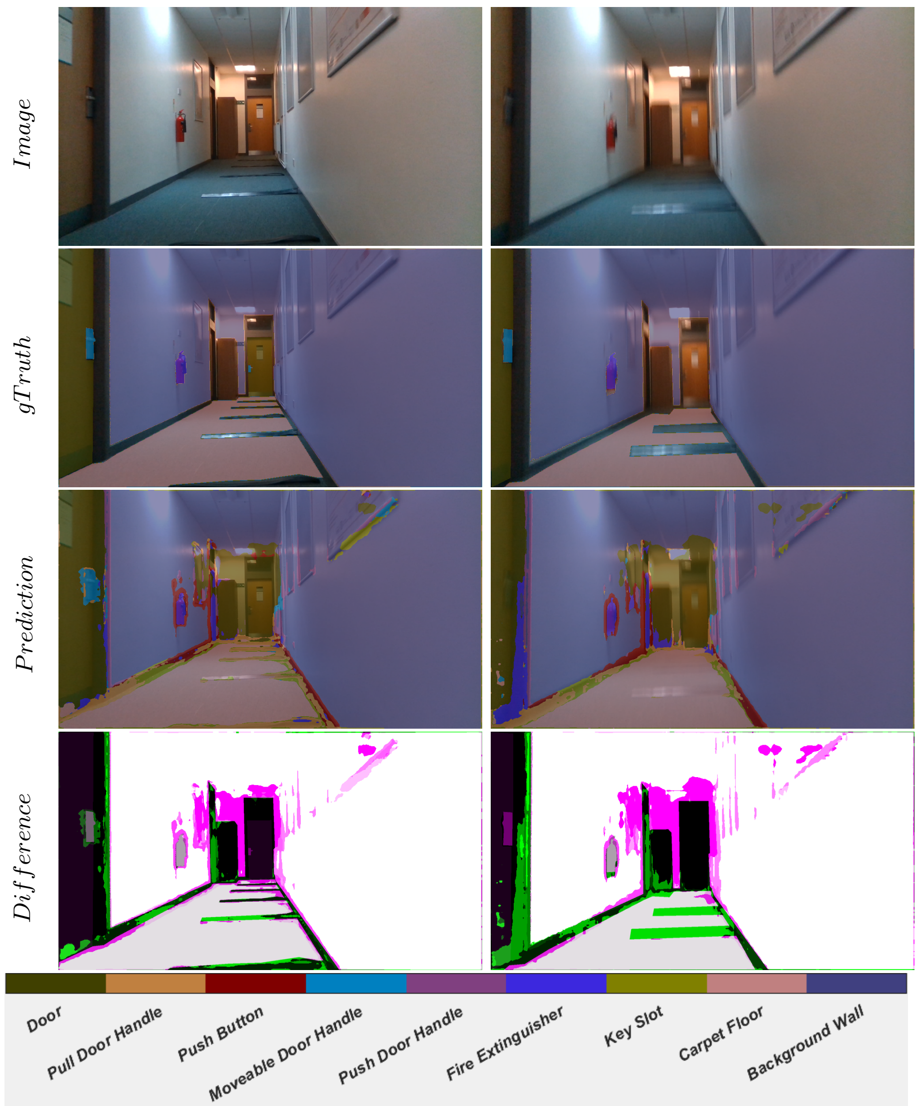

Fig. 4: **The impact of vibrations on the performance of the semantic segmentation system.** First column represents an image without vibrations and second one represents an image with vibration.

To further investigate the vibration impact on the semantic system accuracy, we segregate the images of the vibration dataset (when the artificial vibrations are introduced, the second row of Table 2) into two categories (last two rows of Table 2): images during the vibration incident and images before or after the vibration incident. The first group of images represents the times when the

Table 2: Evaluation metrics with and without the introduced vibration on the images level.

State	Metrics	Global Accuracy	Mean Accuracy	Mean IoU	Weighted IoU	Mean BF score
Without vibrations (65 images)	Mean	0.914	0.492	0.340	0.889	0.508
	Std	0.040	0.061	0.034	0.051	0.075
With vibrations (65 images)	Mean	0.877	0.475	0.309	0.842	0.472
	Std	0.062	0.054	0.041	0.081	0.075
Without vibration incident (50 images)	Mean	0.882	0.485	0.315	0.847	0.484
	Std	0.057	0.051	0.038	0.078	0.071
During vibration incident (15 images)	Mean	0.863	0.444	0.287	0.826	0.435
	Std	0.078	0.056	0.047	0.092	0.080

powered wheelchair encountered a bump, such as sub-figures b and d in Fig. 5. The second group of images represents the times when the powered wheelchair does not encounter a bump, such as sub-figures a and c in Fig. 5. Then, the mean and the standard deviation of accuracy, IoU, and Mean BF score on the level of the images are calculated. The number of captured images during a vibration incident due to a bump is 15. The remaining images (50) are considered as images without vibration incident, although the total 65 images are captured together. Table 2 shows the metrics of the two groups of images (last two rows).

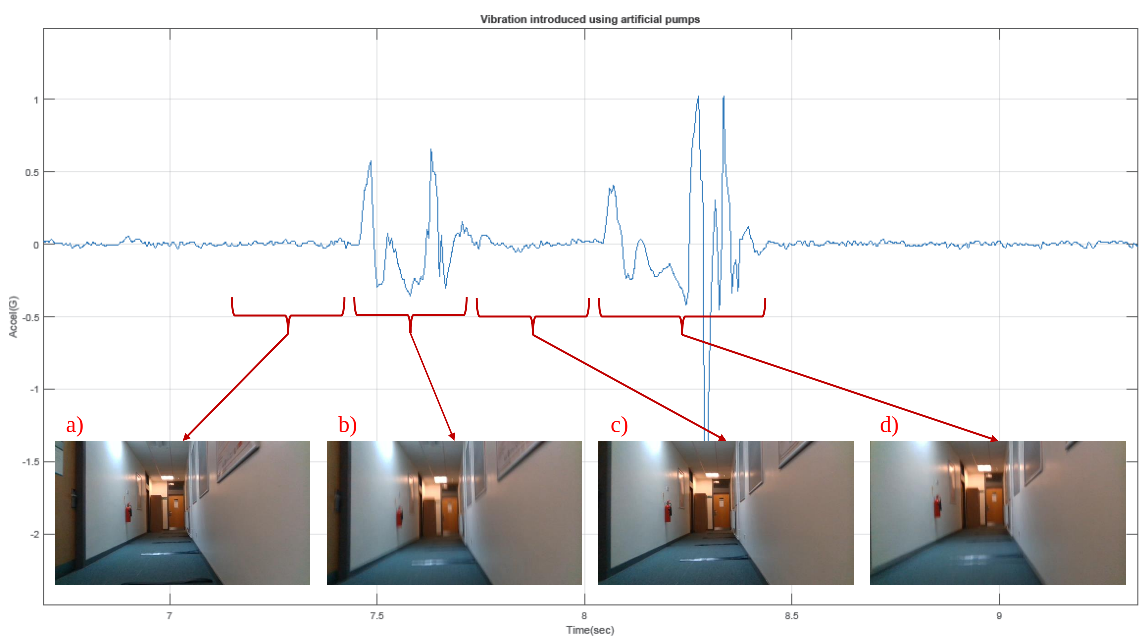

Fig. 5: Segregation method for the vibration dataset images.

It can be noticed that the portion of images from the vibration dataset that are collected without the incident of external vibration (before or after the bumps) has convergent metrics to the dataset which has been collected without any external vibrations. At the same time, the portion of images that are captured during the incident of vibration has been significantly impacted by the vibrations resulting in the lowest accuracy amongst all datasets. This emphasises the results and highlights the impact of vibrations on the semantic segmentation system.

The study has been conducted on a Roma powered wheelchair that does not have a suspension system, similar to the tractor used in [14]. A powered wheelchair suspension, mainly used to dampen vibrations, may negatively impact the system's performance by introducing more vibrations to counter the external ones. This will be investigated in the future work of this study.

4 Conclusion

In conclusion, we can anticipate a deterioration in the semantic segmentation system performance when driving a powered wheelchair on types of terrains that can cause health risks or discomfort for the user. Therefore, we recommend that the developers and researchers consider the impact of vibrations on the computer vision systems installed on powered wheelchairs. A shock absorption system or a camera stabiliser holder can reduce the negative effects of the vibrations on the system's accuracy, as shown in the literature. On the other hand, reducing the speed of the powered wheelchair can lower the potential risks to the users' health and comfort. Producing an accurate semantic segmentation system is beneficial for visually impaired disabled users to increase their independence. Besides, it can allow the approval of using electrical powered wheelchairs for those users who currently are not permitted to use powered wheelchairs due to their disabilities. The future step of this study is to investigate and compare the impact of vibrations on users' health and the performance of smart vision systems using powered wheelchairs with suspension systems.

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