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RESEARCH ARTICLE

Safer Stack: Safe Dump of Off-Highways Trucks in Slope Crest Windrows

Safer Stack: Basculamento Seguro de Caminhões em Leiras de Crista de Talude

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Abstract: During operation, the dump truck sometimes needs to operate close to a slope crest windrow. This article aims to present the experimentation of a system, called Safer Stack, to assist the dump truck operator when reversing in front of a slope crest windrow, with the purpose of informing him the safe distance to perform the dump and generating alerts when there is a risk. The system includes computer vision, through image recognition, and distance measurement, through a LiDAR. The information will be used in a graphical interface, with visual alerts and audible alarms for the dump truck operator. Based on the tests carried out, it was confirmed that the combination of technologies in a final solution, since it presented 98% accuracy in the trained scenarios, has the potential to generate highly efficient results and make the operation safer.
Keywords: Computer Vision — Image Recognition — Dumping Trucks — Safety

Resumo: Durante a operação, o caminhão basculante por vezes necessita atuar próximo a uma leira de crista de talude. Este artigo visa apresentar a experimentação de um sistema, o Safer Stack, para auxiliar o operador do caminhão basculante durante manobra de ré perante a uma leira de crista de talude, com o propósito de informá-lo qual a distância segura para executar o basculamento e gerar alertas quanto estiver em risco. O sistema contemplará visão computacional, por reconhecimento de imagens, e a medição da distância, por um LiDAR. As informações serão apresentadas numa interface gráfica, com alertas visuais e alarmes sonoros para o operador do caminhão basculante. Com base nos testes realizados, foi confirmado que a combinação de tecnologias em uma solução final, apresentou 98% de acurácia nos cenários treinados, tem potencial para gerar resultados altamente eficientes e tornar a operação mais segura.
Palavras-Chave: Visão Computacional — Reconhecimento de Imagens — Caminhões Basculantes — Segurança

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1. Introduction

The transportation of materials by off-highway dump trucks is a major concern for mining, since it continues to be responsible for approximately 50% of fatal accidents. Of the fatal mining accidents that occurred in the US in 2017 and 2018, 12 were related to off-highway dump trucks [1].

These accidents can be attributed to the lack of visibility from the equipment cab. There are systems to monitor blind spots near vehicles, but few are designed specifically for mining equipment. Of the mining equipments, the most popular are video camera systems. The benefit of cameras is that they provide a view of blind spots. However, there are concerns that an operator may miss a potential collision if he does not check the video monitor before moving the truck. Cameras do not provide an alarm function when the truck is too close to an obstacle, such as a windrow [2].

This study aims to pilot a system that assists the operator of a dump truck in a reverse maneuver when near a slope crest windrow. The system, called Safer Stack, consists of a camera, a LiDAR, a graphical interface, and an on-board computer.

From the video capture, the image frames obtained will be processed by the on-board computer to recognize whether a slope crest windrow is behind. The LiDAR will generate a cloud of points that will be processed by the on-board computer to verify the distance between the dump truck and the slope crest windrow. The on-board computer will unify the information presented in the graphical interface, so that the operator will see whether he is at a safe distance from the slope crest windrow. If not, an alert will be displayed on the graphical interface.

This article is distributed as follows: section II will address Related Works, such as the current research on the subject explored. Section III will present Dump Trucks Accidents in Mining. Section IV presents Image Recognition. Then, section V presents Safer Stack and the aspects of this project. Finally, section VI provides the Discussion and Analysis of Results. Final observations and suggestions for future work will be presented in the Final Considerations section.

2. Related Works

During the research that led to the development of this experiment, different approaches to solving the problem were found.

A 3D assisted steering system was developed based on trucks GPS and wireless mesh networks, integrated with the Google Earth engine as a graphical interface and mine mapping server [3]. This information is presented to the truck operator in a remote system in real time. The results show that personalizing the mine map for the operator helps predict risk scenarios and escape routes. However, the constant need for map updates can influence the response time of the system in the truck.

Radar proximity warning system was evaluated in [2], to determine whether the system would be effective in detecting objects in the blind spots for the off-highway truck. The researchers worked on dump trucks in a mine for two years. The data showed that the system reliably detected small vehicles, windrows, people, other equipment. However, alarms from objects that did not pose an immediate danger were common, supporting the contention that sensor-based proximity warning systems should be used in combination with other devices, such as cameras, that would allow the operator to verify the source of any alarm.

When attention is needed in a large scenario, image stitching is typically used, i.e., several cameras are positioned and the images are stitched together to obtain a panorama of the entire scenario. Yu uses this technique in trucks for safety during reversing [4]. The proposed system contains three main steps: stitching the view of the binocular camera, pedestrian detection and tracking a reverse speed control method. The binocular camera is used to perceive the reversing environment. The YOLOv3 framework and the discriminative correlation filter-based tracking method are used to detect and track pedestrians in real time. Finally, a method is inserted to control the reversing speed to avoid collisions automatically.

Research for related works was carried out using different tools and several articles and pages were evaluated. Based on these references, it was confirmed that there are still opportunities to develop technologies to support the truck operator during the dumping process. The difference in this experiment is the combination of image recognition and LiDAR technologies to solve the scenario under discussion.

3. Dump Trucks Accidents in Mining

The main objective of any project is to maintain the safety in mining operations. Dump trucks are one of the most vital operational components in the mining industry. This type of equipment is complex to operate and demonstrates the need for its safe operation [5].

The accident analysis carried out by the Mine Safety and Health Administration in the United States reported 216 fatal accidents from January 2008 to January 2024. Of these, 73 were accidents involving off-highway dump trucks [6]. The leading causes of these accidents are: low visibility during the reverse maneuver, dumping due to overload, dumping on uneven roads, driving with the bucket raised and inexperienced drivers [7].

Given the study scenario in the article, accidents that occur during dumping near a slope crest windrow may be due to these causes. Considering the reverse maneuver, the low visibility factor has a higher recurrence among the reported accidents. Figure 1 shows the blind spots (areas with gray color) near an off-highway dump truck. Although the example is smaller than the trucks used in mines, the configuration of this truck is very similar. The blind spots around the larger trucks are even more extensive, the right front can extend for 18 meters or more [2].

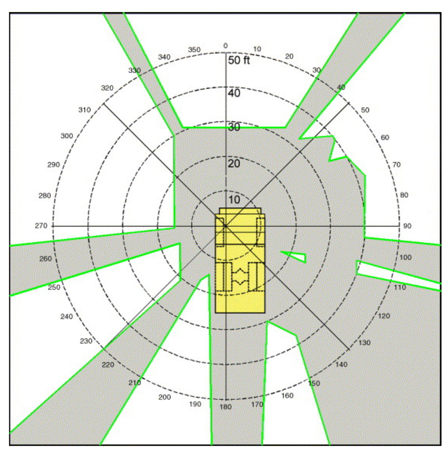

Figure 1. Blind spots near the dump truck [2].

Early and accurate windrow detection is crucial to ensure that a dump truck can operate safely in areas close to slope crest windrows. There are two challenges in this regard: first, the location of slope crest constantly changes as the pile is formed, and consequently new windrows are formed and others are no longer present; second, windrows are often irregular in shape, i.e. they are neither straight lines nor smooth curves. This experiment proposes a system that primarily addresses these two challenges.

4. Image Recognition

Currently, image recognition systems developed for dump trucks and vehicles in general are installed in the vehicle itself. These systems include, for example, collision avoidance, lane detection, lane departure systems, parking assistants, etc. They are typically composed of sensors and cameras located in strategic areas of the vehicle. The data collected by these systems are processed using Computer Vision and Machine Learning (ML) algorithms. When a potential risk is detected, the response time must be short. Therefore, the effectiveness of these systems depends directly on the time required to identify the anomaly. For object detection using Convolutional Neural Networks (CNN), several pre-trained models are available, which can be classified according to the time required [8].

A standard neural network consists of many connected processors, called neurons, each producing a real-valued activation sequence. Some input neurons are activated by sensors that perceive the environment; others are activated by weighted connections of previously active neurons. Learning or feature assignment consists of finding features that make the neural network exhibit the desired behavior, such as detecting a specific scenario in an image. Depending on the problem and how the neurons are connected, such behavior may require long causal chains of computational stages, where each stage transforms (often non-linearly) the aggregate activation of the network. Using Deep Learning (DL) it is possible to assign features accurately in many of these stages [9].

DL, as an important branch of ML, has developed rapidly during the last decade, especially representative CNN architectures, demonstrating excellent performance in image processing tasks. Much work has been done to apply CNNs to image classification tasks. DL-based image classification mainly consists of: image acquisition, segmentation, preprocessing, modeling, training and deployment. These models can automatically extract image features, avoiding the problem of manual feature extraction and selection of classical methods [10].

5. Safer Stack

Safer Stack is an experiment with a system that aims to assist a dump truck operator when reversing towards a slope crest windrow. The system will identify if there is a slope crest windrow, inform how far the truck is from the windrow and issue alerts if it is at a risk distance. The requirements established for its operation are:

1. Installation of the system in a dump truck or other vehicle that can simulate its operation;
2. Data processing is fast enough to generate safety alerts as soon as an unsafe condition is detected;
3. The system must operate 24 hours a day and in any season or weather condition;
4. Image recognition must identify whether or not there is a slope crest windrow;
5. Display the camera video, the distance and an icon representing the slope crest windrow detection in a graphical interface;
6. Display visual alerts and emit an audible alarm when in front of a slope crest windrow, with a distance of less than 7 meters.

Based on these requirements, it was defined that the tested system would use computer vision technologies to recognize the slope crest windrow and LiDAR to measure the distance between the dump truck and the windrow. The camera and LiDAR will be installed in the rear of the vehicle. The images collected will be used in a hybrid DL and ML algorithm that, through training and classification of target recognition in images, will be able to identify the slope crest windrow.

There will be an on-board computer that will support the computer vision operation, which will process and send the information, whether the slope crest windrows are identified along with the distance, to the graphical interface that will be presented to the operator, both installed in the dump truck cabin. When the distance is less than 7 meters between the slope crest windrow and the dump truck, a visual alert will appear on the graphical interface and an audible alarm will be emitted. Figure 2 is a representation of the system.

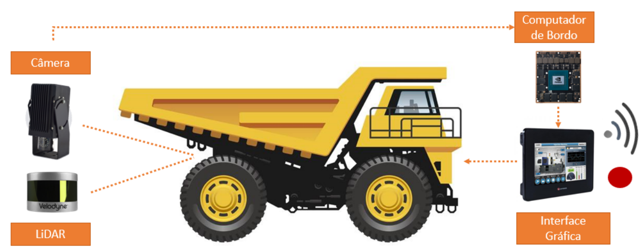

Figure 2. Representation of the system on the dump truck.

5.1 Hardware Project

The Safer Stack experiment will therefore consist of a camera, a LiDAR, a graphical interface and an on-board computer. The camera and LiDAR, as mentioned, will be installed at the rear of the dump truck and positioned in the direction of the road, Figure 3, while the on-board computer and the graphical interface will be installed in the trucks operating cabin, Figure 4.

The camera selected for the tests was a self-cleaning model from ExcelSense Company; it automatically cleans the camera's field of view without any regular maintenance. This reduces the cleaning cycle of the camera in the truck and allows a clear view of the scene for the operator. The LiDAR, Velodyne VLP-16, has a range of 100 mm with 3 cm accuracy, supports 16 channels, approximately 300,000 points/second, a 360º horizontal field of view and a 30º vertical field of view,

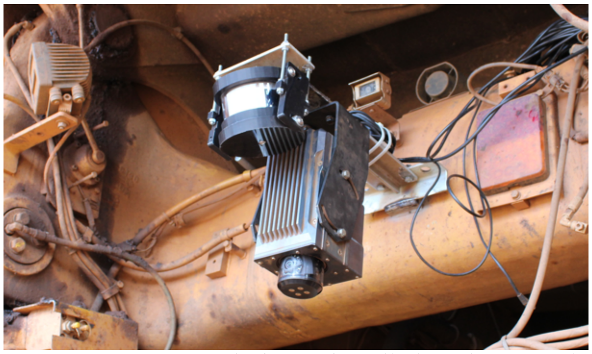

Figure 3. Camera and LiDAR installed on dump truck.

Figure 4. Encapsulation with the on-board computer and the graphical interface.

with 15º up and down, important characteristics in this experimentation considering the variable shape of the slope crest windrow.

As for the on-board computer, the Nvidia Jetson Xavier was selected, it has the performance and resources necessary to execute the workloads of the model to be used. The information will be presented on the graphical interface through an Android application; thus, it will be possible to unify the data on a single screen. Therefore, a tablet with the Android operating system capable of meeting the requirements was selected for use.

Finally, the encapsulation of the on-board computer and LiDAR and the support for installing the camera on the dump truck were designed using Fusion 360 software. For the experiment, the manufacturing method used for the encapsulations was 3D printing, using PLA filament (polylactic acid), a thermoplastic polymer made with lactic acid. As for the camera support, it was made of SAE 1020 STEEL so that it could support the weight of the camera.

5.2 Computer Vision Model

The image recognition and classification performance of this experiment were divided into two main phases: the collection of videos and images and algorithm training. These phases will be described below.

5.2.1 Data Set Collect

At this stage, the goal is to create the data set needed to train the algorithm. Only the camera and the onboard computer of the Safer Stack system were installed in the dump truck. The computer was programmed to collect videos from which the images would be separated to train the algorithm.

First, some tests with the camera were performed to determine with which camera configuration the images would be captured and which process the on-board computer would execute to collect the videos. A resolution of 480p with 30 FPS and H.264 streaming was defined and each time the system was turned on, 15 minutes videos would be recorded with 5 minutes intervals, storing them on a memory card.

Next, a collection routine was programmed to be performed in six time slots to capture images with different daytime and nighttime lighting to ensure good generalization of the model. This operation was carried out for approximately 2 months, with the memory card being replaced with an empty one every 3 days and the videos being uploaded to a cloud repository for processing, to obtain a minimum image bank to achieve a stable result with the algorithm.

5.2.2 Algorithm Training

From the video bank, the images were captured in the divisions of frames per second, then, they were classified into two groups - images that represented locations with the slope crest and those that did not - to finally start the algorithm.

Since this was an experiment, to achieve favorable results it was decided to use a strategy that would allow it, quickly and sufficiently to validate the expected results. Initially, it was understood that a ML model would be sufficient, it can achieve acceptable results with a relatively small number of images.

However, computer vision models that use ML need to be fed with features, image characteristics that are detectable parts or have some meaning, and these features need to be extracted from the images. Therefore, it was decided to use the convolutional layers of pre-trained models to extract the features. It is known that the convolutional layers of DL models are excellent tools for extracting features from images, which is why the convolutional layers of two DL models were used.

After extracting the features, the dimensionality was reduced, since ML classifiers have limited performance with an excess of features. To do this, dimensionality reduction algorithm Linear Discriminant Analysis (LDA) was used. The objective of LDA is to perform a linear discriminant analysis to reduce the number of features, placing greater weight on the most determinant features so that the classifier can generalize better.

The remaining features, after LDA, are fed to a ML classifier, XGBoost, to identify whether there is a slope crest windrow. Specifically for this experiment, the XGBoost classifier was trained with the default hyperparameters, without the need to perform a tuning process. Figure 5 represents the structure of the algorithm performed.

The metrics selected to evaluate the model were: Accuracy, Precision, Recall and F1-Score. Accuracy is a simple and widely used metric that measures the proportion of correct predictions made by the model. Precision is a metric

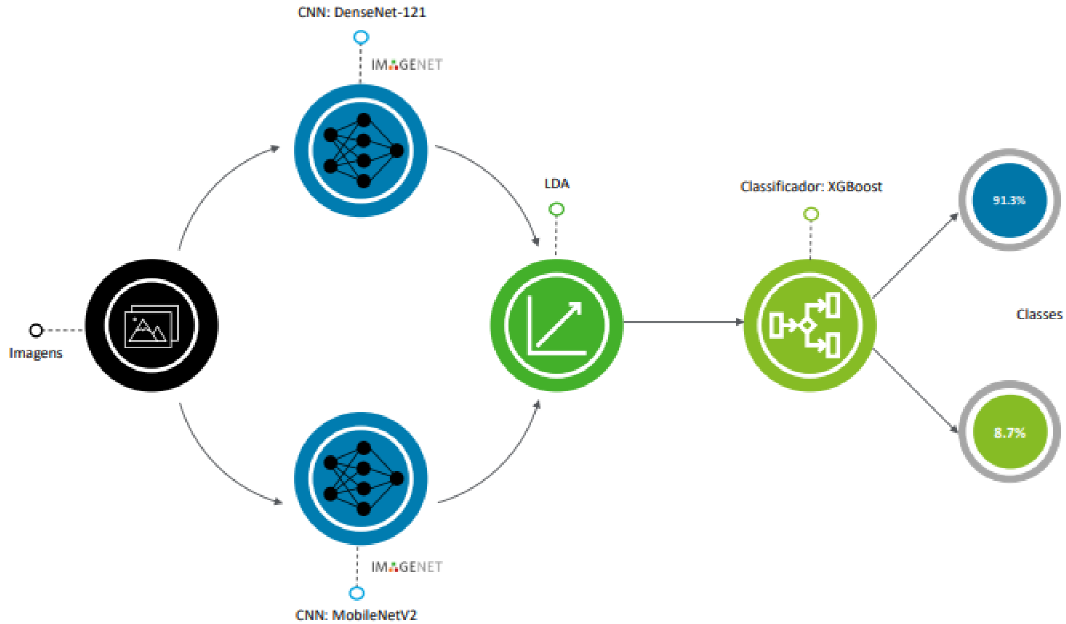

Figure 5. Structure of the algorithm.

that measures the proportion of positive predictions made by the model that are correct. Recall, also known as Sensitivity, measures the proportion of positive examples that were correctly identified by the model. The F1-Score is the harmonic mean between Precision and Recall and provides a balance between these two metrics [11]. After the final tests, it was observed that these metrics were above 98%, both for daytime and nighttime images.

5.3 Application

The proposed application was developed in Flutter, intended for testing on Android. The WebView library was used to display the video, which, for the chosen language, presented the best result in response time between image capture and display. Communications between the application and the on-board computer were carried out from a server with HTTP protocol. It was necessary to synchronize the time between the application and the server, along with the distance request sent to the LiDAR server, thus determining the sending of the current date and time as a parameter of the request. The return of the request will be a JSON containing the measured distance and whether it refers to a slope crest windrow or not. The application was developed to start by itself when turning on the system (after the tablet initialization process), without the need to manually turn on the aplication and log in, thus going directly to the main menu, Figure 6.

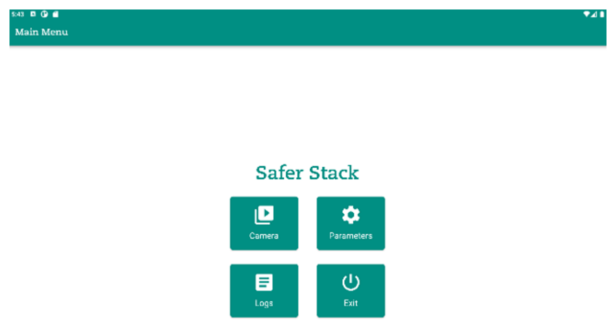

Figure 6. Application main menu.

5.4 Operation Mode

Safer Stack operation begins when the system is powered up. Two models were developes during modeling, one for each phase of the day. The system has an internal clock to first check the time. If it is daytime, between 6 am and 6 pm, the daytime model starts. Otherwise, the nighttime model is started.

The firmware was divided into two independent programs that run in parallel. One is responsible for image processing, while the other processes the LiDAR data and combines the distance information with the image processing result and sends the information to the Tablet.

In the image processing part, from the moment the model is executed, the images generated by the camera are analyzed and the return of "identified" or "not identified" windrow is stored in a log. The information contained in this log will be important for the application that will interface with the Tablet.

The identification of the slope crest windrow is done based on the average of the processing result of a predetermined number of frames. If it is configured for 20 frames, the program analyzes these frames and if there is a greater number of positive results, it writes a message in the log, recording that a slope crest windrow was identified. The time is checked after processing each frame, if it gets dark and the model being executed is daytime, the program is automatically restarted to start the correct model. This also happens when it is dawn and the model being executed is at night.

The second program will initialize a server, which can receive requests via HTTP protocol. Once started, the server waits for a request from the Tablet to perform its functions. In the first, and only the first, request received, the program updates its date and time to match the date and time of the Tablet. After that, the program executes the LiDAR packet processing and distance calculation functions, and reads the log produced by the program responsible for image processing to check whether a slope crest windrow is being identified at that moment. A JSON is then sent with the distance and windrow identification information, being true if it is identified and false if not.

6. Results and Discussion

The fundamental requirements for the experiment were distance measurement with adequate precision, detection of the slope crest windrow from the camera image, visualization of the camera image, distance, a slope crest windrow detection icon in a graphical interface and an audible alarm for when the dump truck is in a risky situation, that is, when a windrow is detected and the distance is less than 7 meters. All of these requirements worked both during the day and at night.

To facilitate verification of the algorithm's training, the tests were carried out with the system installed in a pickup truck where a metal structure with a height that simulated the operation of the dump truck was used. With the pickup truck, there was time available to validate at different times and scenarios, without impacting the operation. After the tests were completed, the system was installed in the dump truck.

The development team followed the route in the pickup truck, where some points of the model mine were selected for the tests.

Reverse maneuvers were performed to observe the behavior of the system in order to detect the slope crest windrow. During the maneuvers, a delay of a few seconds in detection was noticed. Therefore, instead of the pickup truck simulating the way a dump truck makes the route, the test was adapted so that it was positioned at specific points, to give the system time to process the information from the images. The system was able to successfully detect the windrows that presented similarities to the image bank used for training, that is, windrows of slope crests. When the camera was positioned towards the slope, as expected, the system did not detect any risk, confirming the assertiveness of the model for the situations in which it was trained.

The results obtained from the perspective of Machine Learning metrics are: Accuracy - 98%, Precision - 98%, Recall - 98% and F1-score - 98%. These are positive results that show that, even with a small number of images, structuring an excellent model is essential to obtain good results.

The distance assessment was performed by positioning the pickup truck at a distance of at least 10 meters from a crest and slowly reversing to check the change in the value displayed on the Tablet. This process was repeated several times to confirm that the distance measurement was working. The accuracy of the distance shown on the screen was checked with a tape measure and, in general, the error was below 10 centimeters.

As can be seen in Figure 7, the observed scenario is a slope crest windrow, with a distance greater than 7 meters and with green icons representing safety. In Figure 8, the observed scenario is the same, but with a distance of less than 7 meters and red icons, representing a risk scenario. At this time, the Tablet emitted a sound, as expected. Figure 9 presents a scenario in which the slope crest windrow was not identified. Although the distance was less than 7 meters and contained a windrow, it did not emit an audible alarm and did not display a visual alert.

Figure 7. Safe scenario.

Figure 8. Risk scenario.

Regarding the test on the dump truck, it was not possible to obtain a conclusive result. The lack of robustness of the experiment and the vibration of the equipment is believed to have caused some damage to the system that led to the interruption of operation.

With these validations, it is considered that the objectives were achieved in all aspects. The distance measurement presented an error in the range of centimeters and it was possible to develop an algorithm capable of detecting the slope crest windrow. As for the graphical interface, it was possible to view both the image and the distance measurement on the

Figure 9. Scenario not identified as slope crest windrow.

Tablet, in addition to the icon that appears when the system detects a slope crest windrow. The audible alarm was emitted only in the correct condition, distance less than 7 meters and slope crest windrow detected. In situations where a slope crest windrow was not detected, even if the distance was below the stipulated value, the system did not emit an alarm and did not display the slope crest windrow icon. Regarding the processing time for presenting the information on the Tablet, a variation between 30 seconds and 1 minute was noted for display.

Regarding the purpose of the experiment to assist the operator of a dump truck during the reverse maneuver towards a slope crest windrow, the developed system proved to be a potential solution to the problem. The test presented a satisfactory result and it was concluded that the selected technologies can be used and are efficient in generating positive results with improvements and optimizations.

7. Final Considerations

It is known that mining activities currently involve a series of risks for those involved in the process. There are points in mines where the dumping of material by trucks becomes a high-risk activity for the operator, such as when approaching a slope crest windrow. Due to the weight of the equipment, the proximity of the slope crest windrow can cause the floor to slide, creating the possibility of the dump truck falling.

This experiment aimed to provide an initial assessment of the possibility of using computer vision in conjunction with LiDAR for a future solution to the problem presented, the need for a tool to support dump truck operators when reversing when facing a slope crest windrow.

The technology used proved to be consistent with expectations. The positive evaluation was based on the confirmation that the use of these technologies is viable, that is, computer vision for detecting slope crest windrows and the use of LiDAR for distance measurement, in a final solution, have a real chance of producing highly efficient results and making the operation safer.

As next steps, the development of a comprehensive and generalized solution will require time, training and improvement of what was tested in this experiment. It is recommended that the proposed improvements be evaluated for future projects, especially the direct intervention of the system in the asset, in the brakes, which is a valid topic for implementation, as it would eliminate the risk of operator distraction or similar situations, stopping the dump truck and preserving its safety. In addition, the solution should undergo industrialization to obtain robustness for the industrial environment, given the problems found during the tests on the dump truck.

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Author contributions

Lorrainy Rembiski Delfino, Allan Lorenzoni Canal, Gabriel Flausino de Souza and Yargo Ales Sampaio, with their technical knowledge, they designed the structure of the tested prototype, physically built it and carried out field tests together with the off-road truck operators.

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