Windrow Perception for Smart Farming Guidance Systems

Edmond DuPont, Prasanna Kolar

Applied Sensing Department

Southwest Research Institute

San Antonio, TX USA

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Abstract. The practice of bale production, in forage agriculture, involves various machines that include tractors, tedders, rakers, and balers. As part of the baling process, silage material is placed in windrows, linearly raked mounds, to drive over with a baler for easy collection into bales. Traditionally, a baler is an implement that is attached on the back of a tractor to generate bales of a specific shape. Forage agricultural equipment manufacturers have recently released an operator driven, self-propelled round hay baler. This automated platform allows the driver to seamlessly navigate windrows while quickly and easily creating round bales. The current automation control involves releasing the bale at the push of a button. It is conceivable that this will advance to a fully autonomous baler requiring intelligent steering control along windrows and reduce driver fatigue. To support this advancement, we present an innovative low-cost camera-based solution named Synchronized Windrow Intelligent Path Estimator (SWIPE). SWIPE provides a smooth, accurate path along a detected windrow to support seamless autonomous control of the platform under various lighting conditions. It applies advanced sensing, to handle high contrast and low light conditions, combined with artificial intelligence algorithms to predict the windrow center out to 12 meters. This paper details the results of applying artificial intelligence to stereo cameras to extract the windrow in the field. The extracted windrow is used to generate a smooth spline along the center in the presence of gaps, multimodal peaks, and along curves. The developed system is designed to interface with the navigation and control system of an autonomous baler.

Keywords. Windrow, Perception, Artificial Intelligence, Forage, Stereo Vision, Hay Bales.

Introduction

An important process in forage agriculture is the generation of bales for feed production. The practice of bale production involves various machines, most importantly balers. As part of the baling process, silage material is collected into windrows where a baler drives over along the path of the windrow for easy collection into bales. Windrows are the raked rows of silage material that are allowed to dry prior to bale collection (Figure 1). The baling process requires traversing large acre fields of windrows, collecting bales. This simplified process can become routine and tedious leading to driver fatigue. If this process can be automated or autonomous, that would lead to a large improvement to this operation. Balers can be an implement attached to the back of a tractor or, more recently, a fully integrated self-propelled vehicle. Recent research in the forage industry has led to the discovery of such a round hay baler with an integrated cab for an operator. This platform allows the driver to seamlessly navigate windrows while quickly and easily creating round bales. While this system provides added comfort and an automated bale release, driving the windrow is still a manual process. Having a system to detect the windrow on the ground and translating that into a drivable path would provide an added automated functionally to reduce the load on the driver.

Figure 1: A field of windrows

Current approaches to detecting a windrow use single plane lidars (Chateau, et al. 2000), (SICK Lidars 2022), to measure the cross-section of the windrow at a distance in front of the vehicle. The lidar approach observes the windrow at a defined forward distance and provides offsets from the center. This approach lacks the perception of the entire windrow which can hinder the vehicle's control system's ability to smoothly navigate between offset updates. In practice, this can result in overcorrecting by the control system and frequent stops in the case of gaps in the windrow. In addition, this approach presents challenges when multiple windrows are near each other creating a multimodal cross-section within the lidar scan. Infrared cameras are also used (Schellberg, et al. 2008) to detect windrows in grasslands for precision agriculture. Time of Flight cameras have been used by Castillo-Ruiz et. al., (Castillo-Ruiz, et al. 2021) to detect windrows in olive pruning tasks.

Agricultural guidance systems like the one developed by (Fleischmann 2013) use sensors to feed information to a model-based detection algorithm for typical agricultural structures. Their technique relies on distance information from a laser scanner which makes the detection robust despite varying illumination. This system used less computational power, but the data was restricted to individual scans that appear as a slice of the agricultural structure artifact and require additional computation to enable queuing up the scans into a complete point cloud which can be used later. Janine Ryan and team developed a lidar based windrow detection system (Ryan 2022) which they have used for square/cube hay baling. Guidance systems by SICK provides a windrow detection system using a 2D lidar system that detects windrows and provides centerline offset updates (SICK Lidars 2022).

The presented system, SWIPE, was developed and evaluated to address these challenges. SWIPE is an intelligent depth-based system that classifies and estimates a smooth path along the center of a windrow that can operate within day or low-light conditions.

Methodology

For this research, the authors developed a camera system to determine the center of a windrow as a path for automated navigation. The SWIPE system comprises the following three main elements:

- a low-cost integrated camera and embedded processing system.
- integrated artificial intelligence for robust classification of the windrow.
- projection of the navigation path to integrate with autonomous vehicle navigation.

Prototype System

A benefit of lidar based systems is their ability to operate under all lighting conditions. This can be a limitation for cameras that often use illumination to operate in low light conditions. To overcome this limitation, modern cameras using back-illuminated technology have provided the capability to perceive a scene with additional illumination and no software processing of the image data. As a result, a custom stereo pair of this camera technology was integrated into a prototype system (Figure 2).

Figure 2: SWIPE Prototype System

The camera provides improved dynamic range over comparable cameras and generates a brighter image output as shown in Figure 3. This is significant for observing the environment under different lighting contrasts and under low light conditions. During this cloudy dusk scene, the camera on the left has challenges adjusting between the brighter sky and the darker field terrain. The SWIPE camera system adjusts to capture the environment to clearly observe the underlying terrain and windrow.

Figure 3: Camera comparison (left: traditional camera, right: high dynamic range low light camera).

Artificial Intelligence System

The developed SWIPE system integrates intelligent processing algorithms with unique cameras to provide a robust output for autonomous navigation. Artificial Intelligence (AI), a subset class of Machine Learning, is commonly applied across various industries to solve challenging problems. Providing a large dataset of ground truth labeled samples to an AI model allows the system to optimize a mathematical relationship to predict the targeted output. This enabling technology is being applied within various aspects of agriculture to support automation capabilities. This system leverages AI in a unique way to directly classify the center of a windrow. Prior to classification, a rich database of training data needs to be captured, organized, and labeled. The field silage materials were previously raked into windows within the field. The data was captured using two surrogate systems mounted on manually driven vehicles across different fields. The resulting database contained over 64,000 captured left/right image and depth data under varying lighting conditions with windrows of different widths, densities, and curvatures.

The database was then manually labeled by and operated to highlight the center of the windrow. It is important to maintain consistent labels across frames to ensure a robust dataset. Figure 4 depicts an example view of the data labeling showing a green line along the center of the windrow. The unique approach for this AI system is that it directly classifies the center of the windrow compared to classifying which pixels correspond to the windrow. This simplifies the AI model in size and complexity with improved performance, enabling more seamless integration onto an embedded processor.

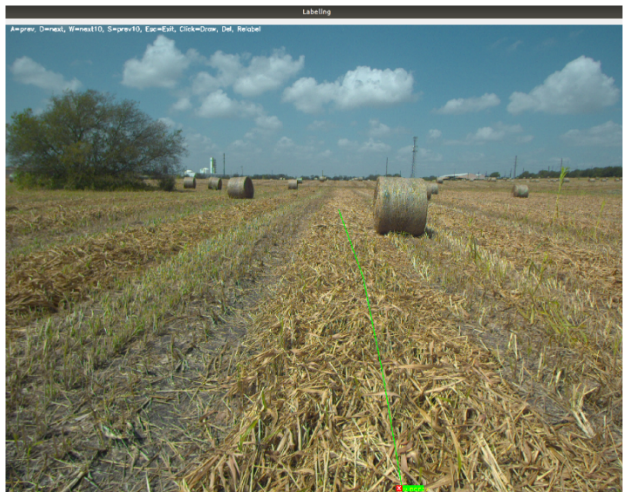

Figure 4: Ground truth labeling of windrow

The output of the AI (Figure 5) model is the direct identification of the windrow center within the image. The system can classify the center independent of the windrow width, curvature, and density.

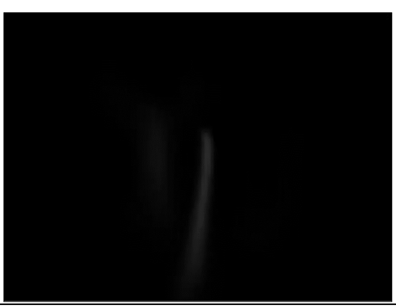	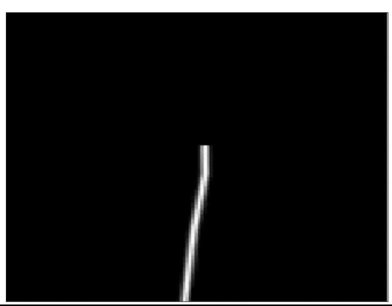	
a.)	b.)	c.)

Figure 5: AI windrow classification a.) AI raw output, b.) AI threshold output, c.) AI output overlay on input image

Path Estimation

While the AI system classifies the windrow center, this output is with respect to the input images pixels. For autonomous navigation, the image path needs to be transformed into a navigational coordinate system. The path estimation is performed by applying an image-to-world transformation and corrections to refine a smooth navigational path. This utilizes the intrinsic and extrinsic calibration of the camera system. The intrinsic calibration transforms the image pixels into 3D camera coordinates using a pinhole camera model. The extrinsic calibration transforms the camera coordinates to world coordinates determined by the system's mounting location. In addition, stereo camera depth information is used to extract the ground surface and correlate resulting path estimate along the windrow (Figure 6).

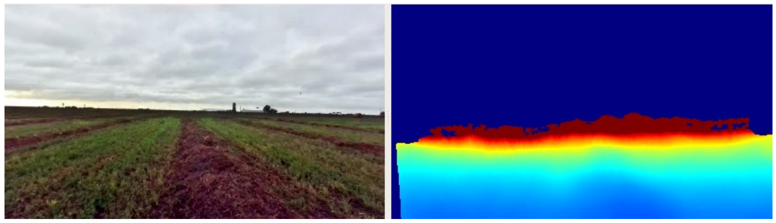

Figure 6: Input stereo depth (left: Left camera's image, right: stereo depth)

The stereo depth information is projected from the 2D image into the 3D navigation frame of the vehicle. This converts the path classified in image pixels to navigation points on the ground. A spline fit is applied to generate a smooth path along the ground in front of the vehicle (Figure 7). The path is estimated in front of the vehicle to the depth of the segmented ground.

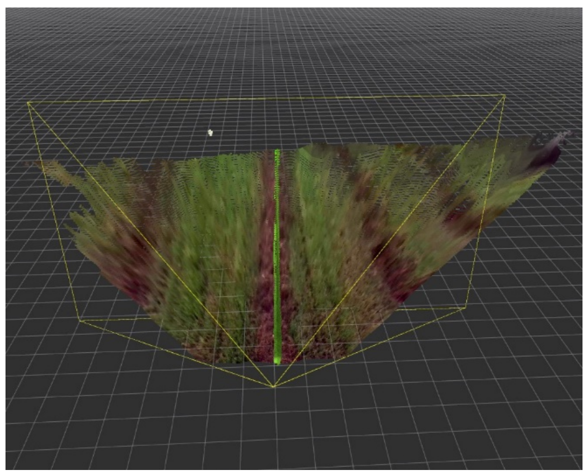

Figure 7: Projected path estimation on ground plane

Results and Discussion

This work developed a system to estimate a navigation path along the center of a windrow. The system was benchmarked against numerous images within an offline test database. Using the collection database, a subset of approximately 1000 images was annotated and divided into training (80%), validation (10%), and testing (10%). The training frames were used by the AI system to generate a classification model to predict the center along the length of the windrow. The database contained variations of windrow types including different sizes, turns, and gaps to build a robust model of these conditions. In the cases of turns and gaps, the ground truth labels define the expected navigation path to train the AI model. For benchmarking, the classification was evaluated by distance error between the ground truth and the predicted label. The resulting windrow path was estimated out to 12 meters with an offset less than 0.3 meters. Within the test database, this resulted in a 96% positive classification to accurately predict the center along the windrow.

The system was demonstrated to estimate the path width of the windrow under conditions that include straight, curved, and offset from the center. Figure 8 shows the results of the path estimates in the left stereo camera's image for these various conditions. The system is robust against these variants to account for operation on an automated or autonomous platform. In this aspect, the system must be able to initiate or regain the path during navigation.

Figure 8: Estimated windrow paths

Conclusions

This technology provided an enhanced way to estimate the path of windrows for robust autonomous navigation. In practice, windrows comprise various silage materials, are formed at different shapes, and may contain breaks for gaps. In addition, the baling operations will occur under various conditions including during low light. This system addresses these challenges using a unique low-light camera combined with AI processing to develop the SWIPE system. The system leverages a low-cost camera and embedded processing to deliver a solution that easily interfaces with navigational systems. The system achieved the direct classification of the windrow center with low error creating a robust approach to generate a smooth navigation path for baling a windrow. As the agriculture industry grows with autonomous technologies, this perception system provides a navigation output that can easily integrate with these systems. This technology will be further advanced through integration on an autonomous platform and field tested to validate the ability to navigate windrows.

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