Autonomous driving on skid tracks for forestry machines.

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Abstract

Since labor costs make up a significant portion of the total cost of ownership and due to the severe labor shortage, research and development have increasingly focused on automating mobile machines. Due to its technical and sociological aspects, the Forestry offers high potential for using (semi-) autonomous machines. A significant proportion of forestry work consists of recurring processes. This paper introduces a framework for autonomous driving on skid tracks with forestry machines. Forwarders navigate skid tracks to the felled trees, collect them, and return to the forest roads, where the sorted piles are stored. During this process, the driver primarily focuses on the loading process, with driving being a secondary task. Automating the driving process reduces the driver's workload and allows them to concentrate on the more critical tasks. The proposed system comprises four submodules: localization, object detection, path planning, and driving. In forestry environments, GNSS signal reception is limited due to the treetops, and the system utilizes an adapted feature SLAM method to determine the vehicle's relative position. The object detection module covers the surrounding environment, detecting obstacles, such as stems and stumps, crossing persons, and the path of the skid track. Path planning uses the output of object detection to find a suitable path for the vehicle, while the driving module controls the actual steering and velocity. The presented system is implemented on an HSM Forwarder 208f, and its functionality is shown in a proof of concept on a skid track. The results prove that the autonomous system can relieve the driver of the driving task. The performance of the autonomous driving system is similar to that of a human driver, and the modules can be executed on currently available embedded hardware in real time.

Keywords: Autonomous Forwarder, Driving Assistance, Forestry, Feature SLAM

1 Introduction

Forestry offers great potential for using (semi-)autonomous machines as a significant proportion of forestry work consists of recurring processes. Due to the high danger posed by felling, work sites are already cordoned off, and no persons are allowed in the work area. Possible wrong decisions by the AI do not lead directly to personal injury. Regulatory requirements, e.g., in road traffic, are easier to manage in forestry operations. In addition, operating the machines is physically and cognitively demanding. The increasing shortage of qualified specialists from Germany presents forestry companies with significant challenges.
Today, driver assistance systems in agriculture, such as automatic tracking guidance, use RTK-GPS to localize the vehicle precisely, [1], and use this information to control the vehicle. In addition to

agriculture, efforts are being made to implement assistance systems and autonomous vehicles in material extraction. Examples of this are a project by Volvo Construction Equipment with the HX02 vehicle, [2], or the autonomously operated vehicles of the Rio Tinto Group [3]. As in agriculture, GNSS is used here for vehicle guidance and cannot be transferred to GNSS-denied areas.
At the Swedish University of Agricultural Sciences, research was carried out into the automation of forwarders for timber harvesting on clear-cut areas, [4]. For this purpose, a forwarder was equipped with RTK-GPS to follow a predefined path autonomously. Global localization via GNSS is only possible to a limited extent in the forest due to the shielding canopy, [5]. Therefore, GPS-based systems are unsuitable for sustainable forest management in Germany, where clearcutting is rare.
In the indoor sector, the missing GPS signal is compensated for by simulated GNSS networks and visual object recognition, [6]. Due to the large expanse of managed areas, the construction of simulated GNSS networks using own base stations is not economically feasible for the forestry industry. For this reason, these solutions cannot be transferred, and new technologies need to be developed for use in forestry.

2 System Architecture

The proposed system comprises four sub-modules: object recognition, localization, path planning, and a lane controller. In forestry environments, the reception of GNSS signals is limited due to the tree canopy. For optimum GNSS positioning, the angle between the received satellites should be between 60° and 120°. This is impossible perpendicular to the skid track due to the treetops, so GNSS does not achieve the sub-centimeter accuracy required for lane control. The system uses an adapted SLAM method using lidar to determine the local position of the vehicle relative to the skid track. The object recognition module detects the surroundings and recognizes obstacles such as trunks and tree stumps, people, and the trajectory of the skid track. The basis for training the object recognition is an extensive data set labeled with the object classes: tree, trunk section, stump, skid track, person, pile, and unknown object. Path planning uses object recognition and position determination results to determine a suitable path for the vehicle, while lane control calculates the actual steering and speed specifications. Currently, the system is implemented on a forwarder, while the system calculates the speed and steering control input, the driver supervises the system and limits the speed with the throttle pedal.

2.1 Object Recognition

The object recognition module uses a neuronal network for instance segmentation. It is uses the Mask-RCNN architecture with a ResNet101 feature backbone. All backbones were initialized with pre-trained weights from the COCO dataset. The weights were obtained from the MMDetection library. Training detection backbones is time-consuming; pre-trained backbones allow fast transfer learning on new datasets and minimize the computational time for training adapted detectors. Additionally, the first stages of the backbone layers have been frozen, as studies indicate that retraining the complete backbone has no significant benefit [7]. The network was trained on three datasets: *Mobimalogs* from [8], *MobimaWoodlands* (doi:10.35097/1749) consisting of two subsets, *MobimaWoodlands/Winter* and *MobimaWoodlands/Summer,* with 126 images each, and *MobimaSkidroads (*doi:10.35097/1750)*,* consists of 293 images captured while driving on a skid track or forest road with an industrial camera mounted on a vehicle. Example images with annotations are displayed in **Error! Reference source not found.**.1. The object recognition architecture has been published in detail in [9].

(a) (b)

Figure 2.1: Example images with annotations showing stems (blue), trees (purple), and stumps (green)

2.2 Localization

The localization module uses a feature SLAM algorithm in combination with a Kalman Filter to track the vehicle localization. The state vector of the Kalman Filter consists of the vehicle position in UTM coordinates (x, y, z), the vehicle orientation in quaternions $(\varphi_x, \varphi_y, \varphi_z, \varphi_w)$ and its velocity (v).

$$\vec{x} = (x \quad y \quad z \quad \varphi_x \quad \varphi_y \quad \varphi_z \quad \varphi_w \quad v)^T \tag{2.1}$$

The Kalman Filter combines the orientation measurements from a gyroscope (IMU), the GNSS velocity, the theoretical drivetrain velocity, and the position determined by feature matching. Sensor fusion increases position accuracy considerably compared to a GNSS-only system.

Forest environments differ highly from typical artificial surroundings like cities or buildings as few distinct edges or flat surfaces are present. Therefore, a feature extraction algorithm extracts the tree positions from a laser scan, which are used as features in the SLAM algorithm. As for the SLAM, the accuracy of the feature's position is more important than being certain that the object is a tree. Therefore, the extracted features are not additionally cross-checked with the result of the object recognition module.

Evaluating the accuracy of the localization is challenging, as no reference is available in a forest environment. However, for lateral control on a skid track, repeatability on a skid track is more important than absolute accuracy, and, therefore, the localization was evaluated regarding its drift during a typical forwarder cycle, entering the skid track backward and reversing afterward. The evaluated skid-track cycle with two parallel tracks is shown in Figure Figure 2.2.

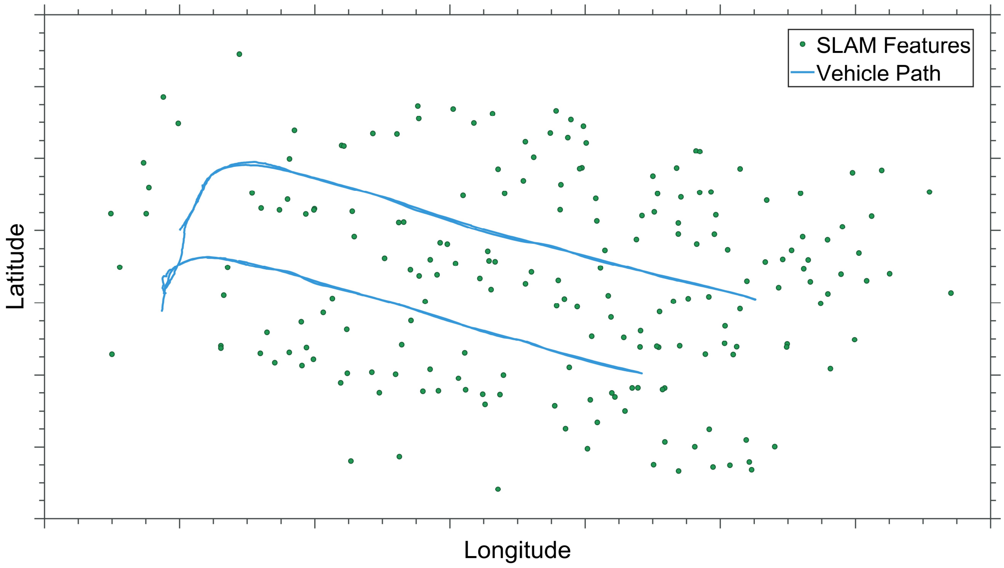

Figure 2.2: Driven Forwarder Cycle with two parallel skid-tracks.

2.3 Path Planning

The path planning module aims to recognize the skid track and determine a possible path for the forwarder. In contrast to most path planning approaches, it does not aim to find a suitable path between points but to follow the predefined skid track. It uses the trajectories driven by a human driver in previous runs as primary input. Not every skid track has been recorded previously, so it combines prior knowledge with a potential field approach.

The superposition of multiple base functions defines the potential field. Each tree or obstacle has a radial base function Φ that decreases rapidly with increasing distance (radius r).

$$\Phi(\mathrm{x},\mathrm{y}) = e^{-(ar(x,y))^2} \tag{2.2}$$

In consequence, the path with a semi-optimal distance to every obstacle has the lowest summarized potential along its path. However, to achieve a forward trajectory, an overall base potential decreasing to a target position within a specific look-ahead distance must be superposed. Figure 2.3 displays an exemplary potential field for a skid track with the corresponding path. The target position is the point with the lowest absolute potential.

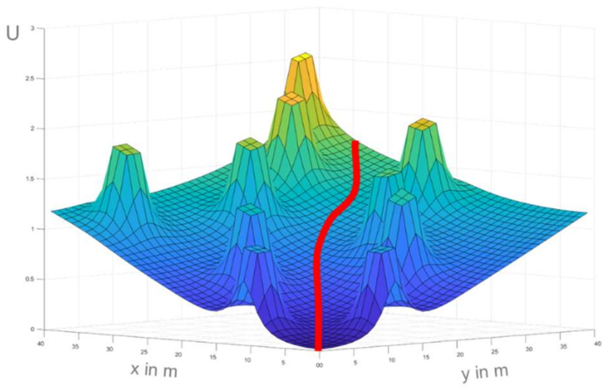

Figure 2.3: Exemplary potential field of a skid track with path planning (red) to the target position (0,0), [10]

In combination with the previous knowledge, the forward path is determined, as shown in Figure 2.4, which is then used as a reference by the lane controller.

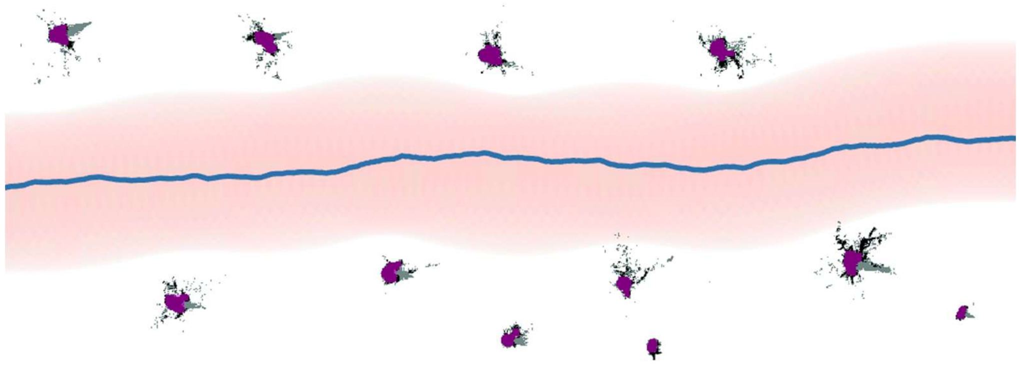

Figure 2.4: Planed Forwarder Trajectorie for a skid track with homogenously spaced trees [11].

2.4 Lane Controller

The lane controller consists of two separate controllers. A simple feed-forwarder controller uses the path orientation as control input and calculates the theoretical steering angle at this path point. However, this simple feed-forward controller does not achieve steady-state accuracy. Therefore, it is supplemented with a Stanley controller, which minimizes the remaining control deviation, [12].
The steering angle δ results from the addition of the feed-forward steering angle δ_{ff}, and the Stanley error controller as:

$$\delta(t) = \delta_{ff}(x,y) + \left(\theta_p - \theta_v\right) + \arctan\left(\frac{k \cdot d_q}{|v_v| + 0.25\frac{m}{s}}\right) \tag{2.3}$$

The output of the Stanley controller depends on the alignment error $\left(\theta_p - \theta_v\right)$, and the lateral path deviation d_q, the Stanley gain k and the absolute value of the current vehicle speed v_v. The vehicle speed is increased by a factor of 0.25 m/s to avoid extreme steering angle deviations at low speeds. Figure 2.5 shows the controller results for a simulated sinusoidal trajectory.

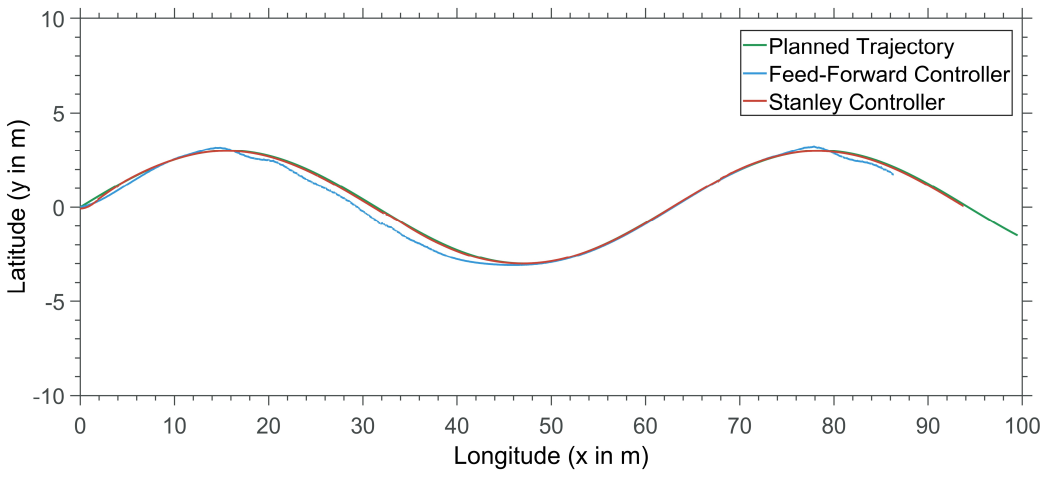

Figure 2.5: Simulated controller response for a sinusoidal trajectory. The aspect ratio of the x- and y-axis is 1:2.

3 Conclusion

In this paper, we present a system architecture for semi-autonomous driving on skid tracks. The four modules—object recognition, localization, path planning, and lane control—isolate the different functional parts. The system was implemented on a prototype forwarder, and its functionality was demonstrated on selected skid tracks. While the presented system still requires supervision by a driver, it presents a first step towards fully autonomous forest machinery.

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