ALGORITHM FOR SEPARATING WORKED SURFACES IN AGRICULTURE

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Abstract

Since the popularisation of IoT devices and GPS tracking systems, it has become easier and faster to develop automatic solutions to both manage agriculture machinery and collect and process the unlimited amount of data that can be extracted. This article studies a way to separate regions that were worked by the machinery from road sections or turns in order to further process the results in areas such as field areas or fuel consumption computations.

Keywords: GPS, agriculture machinery tracking, turns detection

The subject of how agricultural machinery moves while working a field has become increasingly popular since the development of motion planning and control systems (Reid J.F., 1998, Bayar G., 2022). As a result of these motion planning systems, the movement of agricultural vehicles has become more regular and predictable. This research seeks to utilise this predictability by automatically detecting the lines worked by the agricultural vehicle, using only geographic coordinates and speed information. However, the challenge lies in distinguishing between the worked lines and the points where the vehicle simply transits between fields. Additionally, the vehicle executes multiple turns that may take it outside the work area, and there may be obstacles within the fields that need to be excluded from area computation. All these requirements have generated a need to develop a new algorithm that filters the work points and can identify and remove turns and obstacles from area computation.

The detection of turns is a well-known area of research that has various practical applications. The complexity of finding solutions to this problem can depend on the particular field in which it is being applied. One study (Wan Z. *et al*, 2022) utilised an LSTM (Roy D. *et al*, 2019) model to identify vehicle trajectories at different types of intersections, which was effective for intersection detection and classification. However, this approach proved too cumbersome for our specific purposes, as we do not require the classification of turns, and the movement patterns are less diverse. As a result, we focused our investigation on analysing vehicle speed and movement during turns. In a previous study (Xiang *et al*, 2016), researchers examined turns, skips, and overlapping in agricultural machinery to gain insights into their operation and set appropriate thresholds for line detection algorithms. Additionally, a study on optimal travel speeds for agricultural vehicles (Grisso R., *et al*, 2019) was used to identify work points based on speed and set corresponding thresholds.

MATERIAL AND METHOD

The data is collected with the help of IoT devices installed on agriculture machinery. These observations are completed by manual observations such as real parcel surface and fuel consumption to develop the algorithms.

The first step is organising the work points as lines based on latitude and longitude. After two different points are added, the line equation is. The next step is separating the lines that represent actual machinery work from the lines that represent moving between parcels or turns. Here, the algorithm takes into account that a machine working on a field tends to move on multiple parallel lines. Therefore, for each line, we identify the existing parallel lines and the minimum distance between the current line and a parallel one. If the distance is small enough, around 50 meters, taking into account the vehicle width and possible errors. A vehicle tends to move faster when moving between parcels and has a constant small speed while working the field. This is why the moving speed is also relevant at this step, as it can further help the filtering process. After this step, we would have a line separation that can be seen in Figures 1, 2 and 3 below.

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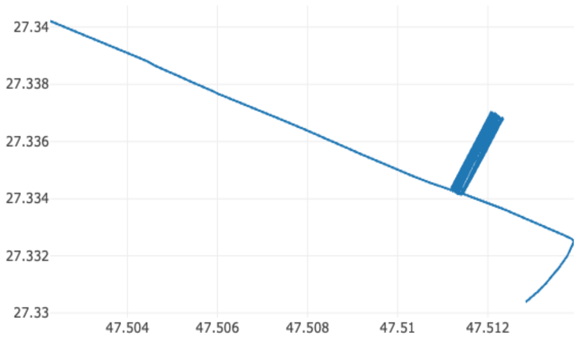

Figure 1 **Data points for the entire route**

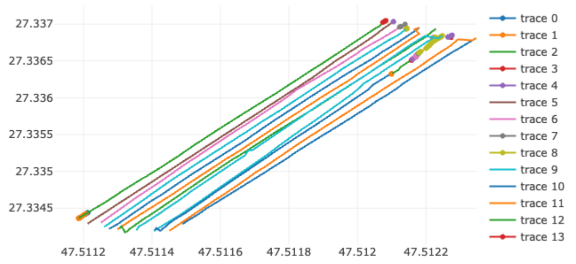

Figure 2 **Separation of work lines**

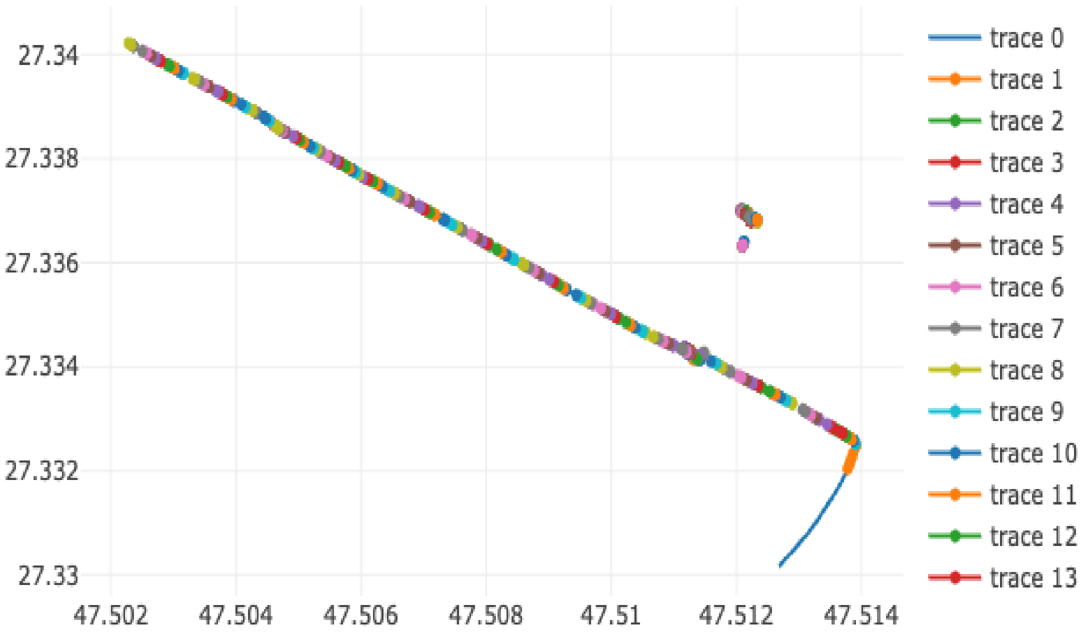

Figure 3 **Separation of road points**

A challenge at this step was identifying the road portions that were parallel with the working lines, and the vehicle would have a reduced speed. Moreover, because the vehicle exited the work area in the same place as it entered, the road portion of the data would also contain parallel lines. With this type of data, the previous steps are not efficient; the result can be seen in Figures 4 and 5 below.

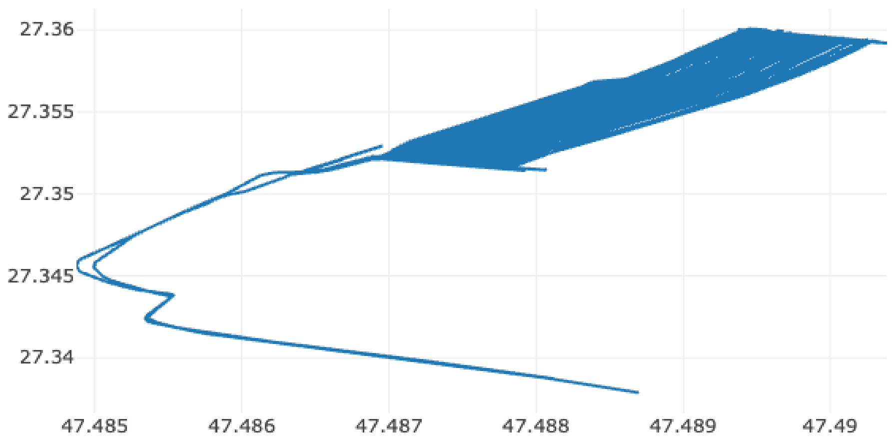

Figure 4 **Data points for the entire route**

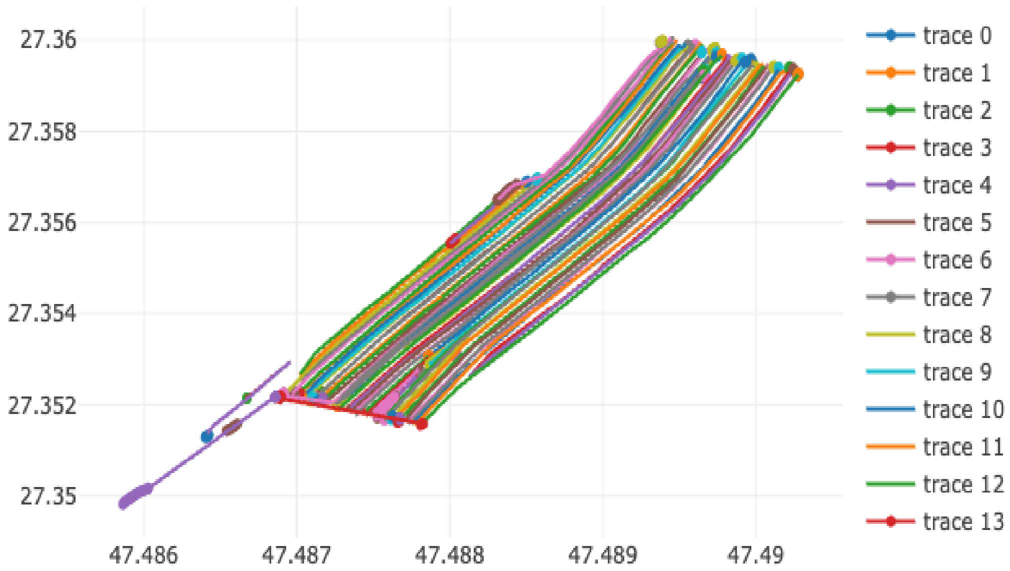

Figure 5 **Initial separation of work lines for data containing road lines parallel with working lines**

For this, we implemented an algorithm that computes points density along the work lines and removes points in regions of low density. The first point in each line is in the centre of a circle with a radius of 50 meters; the next centre will be a point on the same line at a radius distance. A KD-tree is used to efficiently compute the points inside the circle radius. After computing the densities, sections that have less than 50% of the average density will be removed from the lines. Using this approach, the work area will be correctly identified, as in Figure 6 below.

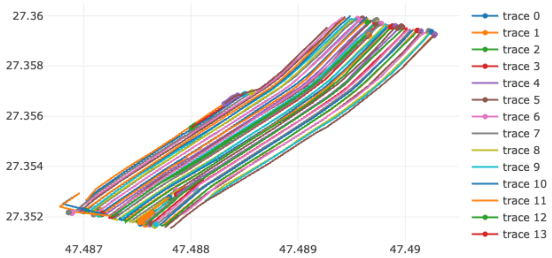

Figure 6 **Lines separation after using the points density metric**

RESULTS AND DISCUSSIONS

A mapping of the actual work lines was not available. What we used to determine the accuracy of point separation is computing the area of the point surface and comparing it to the actual area. For this evaluation purpose, a simple method of area calculation was used, multiplying the distance worked by the vehicle and multiplying it with the vehicle width.

Using this kind of evaluation, the algorithm has an average error of 35%. The error ranges from 1 to 3% when the work lines are correctly identified, but it’s highly influenced by results where the algorithm failed to correctly identify and separate the lines. These kinds of errors usually occur when the actual work area is too small or its shape is extremely irregular.

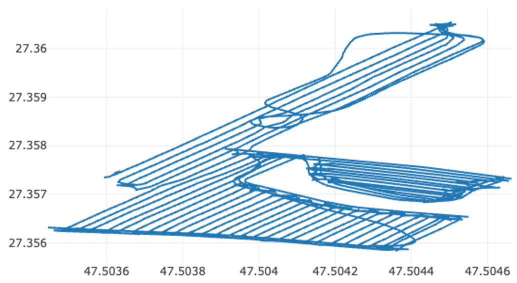

Figure 7 **Data points an irregularly shaped field**

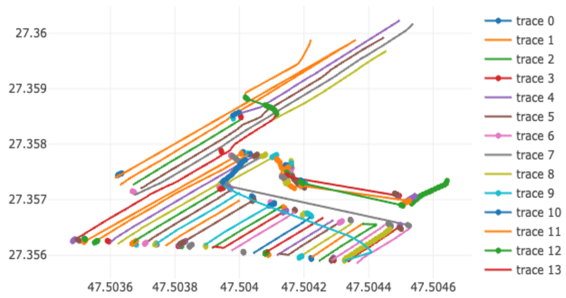

Figure 8 **Detected work lines**

CONCLUSIONS

The algorithm proved to be a good data processing technique for computing the area of a work surface. If the points are correctly identified, the accuracy remains high. However, irregular shapes and curved work lines are still a challenge.

As a part of future work, the line equation used could be extended in order to adapt to slightly curved work lines better, while still identifying and eliminating the turns. Moreover, a clustering algorithm could be used to identify big clusters of points that represent a work surface in order to not miss any sections of irregularities in the field.

ACKNOWLEDGMENTS

This research is co-financed by the European Fund for Regional Development through the Competitiveness Operational Program 2014 – 2020, project “Establishment and implementation of partnerships for the transfer of knowledge between the Iasi Research Institute for Agriculture and Environment and the agricultural business environment”, acronym “AGRIECOTEC”, SMIS code 119611.

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