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MACHINE VISION BASED PARALLEL NAVIGATION FOR TRACTOR-HARROW

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ABSTRACT: A machine vision based row tracking system was developed for a tractor-harrow as an auto-pilot supplement. Analysis of the working environment variation was conducted and critical factors were mapped out. The system used a special marking device attached to the harrow to create a distinct regular pattern on the field surface. A log-Gabor filtering scheme was used to extract features and the regularity of the pattern was utilized for fitness evaluation and outlier rejection. Several test runs were conducted in varying outdoor conditions with real time processing. The principles of the system were proven to work, although severe reliability issues were encountered.
KEYWORDS: machine vision, parallel tracking, navigation, agricultural machines

INTRODUCTION: GPS and automation technology has enabled auto-pilot or automatic guidance systems for agricultural machines. GPS itself is not precise enough for navigation as the noise is clearly over one meter in position and more precise positioning is required. Differential GPS or real-time kinematic GPS provides more accuracy, but the problems are high initial cost and possible cost of usage. Even with those improved GPS systems there exist problems near forests or some other obstacles that block the visibility of GPS. Also there is no certainty that GPS satellites are available forever.

It is also possible to make parallel tracking in fields with agricultural machines using other sensor techniques than global positioning. Several machine vision based systems have been proposed for different navigation or analyzing tasks on the field, like weed mapping (DOWNEY et. al., 2004), cut edge detection (BENSON et. al., 2003) and crop row detection (SØGAARD et. al., 2003). However, using a marker for making patterns to the field surface to aid machine vision seems to be a novel approach. Using this method, a machine vision system can be used for tracking the previous row made by the harrow so that the next one is driven optimally compared to it.

For this prototype, low cost Logitech Quickcam 5000 webcams were attached to the front corners of the towed harrow, one to each side. The metallic camera mounts were damped with rubber padding to filter out some of the vibrations the cameras were experiencing. The cameras were connected to a small form factor PC in the tractor cabin via extended USB-cables. MATLAB was used for programming the image processing algorithms and a C++ program (with openCV library) was used to interface the cameras and the MATLAB algorithms.

Varying outdoor conditions and the chaotic nature of the process of marking soil surface are the greatest challenges in this method. Weather conditions, lighting and soil composition vary each time a test is being made. Figure 1 depicts the interconnections different crucial elements have in this study. It is quite clear just by looking at the graph, that the features made to the field will see considerable change as the conditions vary. While some attempts of robust outdoor feature segmentation have been made (TIAN & SLAUGHTER, 1998), they usually rely on color information, which is not available in this case.

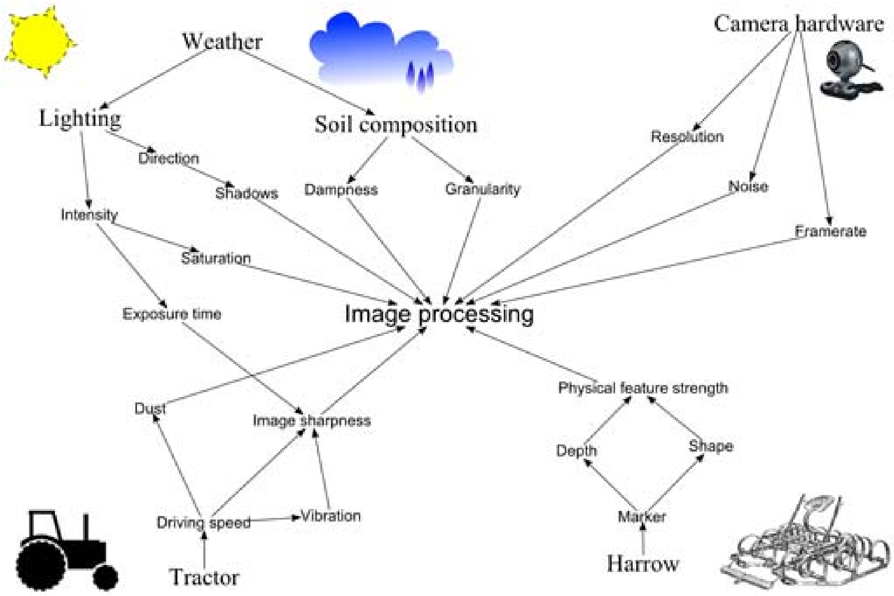

FIGURE 1. Factors affecting the system.

METHODOLOGY: The natural markings left by the harrow are not ideal for detection. Therefore an additional marking device was developed and attached to the harrow. The marker used was basically a turning wheel with eight dual spike blades attached for marking the soil (Figure 2). The rotation frequency was linked to the land speed of the tractor so that the marker would always produce straight lines tilted 45 degrees relative to heading (Figure 3). The wheel is rotated with hydraulic motor and the speed is closed-loop controlled by prototype-ECU using tractors proportional valve over ISO 11783 network.

FIGURE 2. The marking device.

FIGURE 3. Line features made by the marking device (taken with a normal digital camera).

The basic idea behind the detection algorithm was that having three to five lines of the artificial regular pattern in each image would be enough to pick them up from the otherwise chaotic soil. The method used for extracting the line features was log-Gabor filters tuned to specific angle and size responses. The unavoidably noisy output of the filter was further processed with a fitness evaluation logic that utilized the known information about the markings to find out if there is a fitting regular trend in the data.

The log-Gabor filters used in this project are constructed with some suitably edited pieces of Peter Kovesi's MATLAB code (KOVESI). The filter parameters were adjusted to detect the known sized shapes in a known orientation.

After log-Gabor filtering the output image is segmented. First the filter output is binarized with the mid value of the realised dynamic range as a threshold. Then morphological opening with a 9x9 kernel is used to clean the image. Up to ten peaks sufficiently far away from each other are then extracted from the filter response using the binary image as a region of interest. The fitness of the vectors connecting the peaks is evaluated based on the distance and angle between them and the strength of the filter response at that spot. Gaussian membership functions are constructed for each of the fitness parameters. The length function has its centre at the known feature spacing and a sigma of 30. The angle function has its centre at zero (zero angle relative to heading) and a sigma of 15. The strength function has its centre at the maximum filter response value with a sigma set to one quarter of the dynamic range. The final fitness of a connection is the weighted average of the three evaluated membership functions, with distance weighted by 1.3, angle by 0.8 and strength by 0.9.

The connection with the best fitness was chosen as a starting point and additional peaks were connected to the graph as long as good enough connections were available (Figure 4). The values used in this scheme were chosen by offline experimentation to give good distinction between real features and noise. Three and two peaked Gaussian mixtures were also tried for the length membership function to take into account situations where one or more of the pattern markings were missed and the peaks would have to be connected over multiple line spacings. That however led to a situation where the system was too easily fooled by outliers.

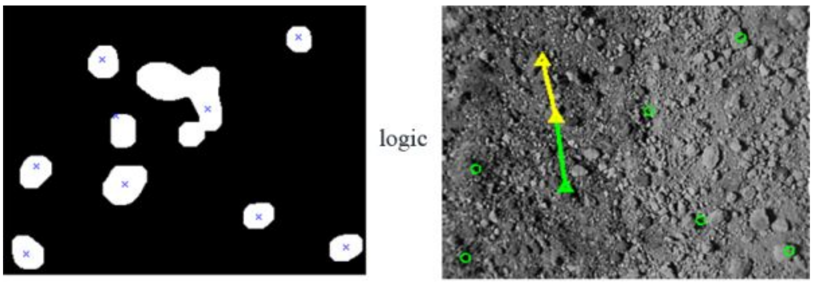

FIGURE 4. Segmentation and the fitness evaluation logic. The green arrow is the connection with the best fitness, and the yellow one is the only suitable connection.

RESULTS AND DISCUSSION: Six test runs were made with the final version of the prototype on two different fields in Southern Finland during the summer of 2007. The algorithm analyzed the images in real time and saved them for later manual verification. For each of the runs, the number of frames with the marker features visible were counted as well as those cases where the algorithm succeeded in detecting the markings correctly. The results, shown in Table 1, show the dependency of the system to good environmental conditions. When the conditions are suitable, the method could reach promising figures. However, it is often the case that the conditions turn out to be totally adverse for the system. It should be noted, that the correct detections are not evenly distributed in any test run. The detection capability rather changes in larger steps. Detection can be near perfect for some time (Figure 5) and then disappear completely for a considerable duration. This is quite bad when considering possible continuous tracking scenarios.

TABLE 1. Test results.

Run	Detection %	Remarks
1	0	disruptive shadows, heavy saturation, weak features
2	12	disruptive shadows, heavy dusting
3	20	drastically changing feature strength
4	20	feature strength fluctuation
5	44	some feature strength fluctuation
6	60	strong features, some disruptive shadows

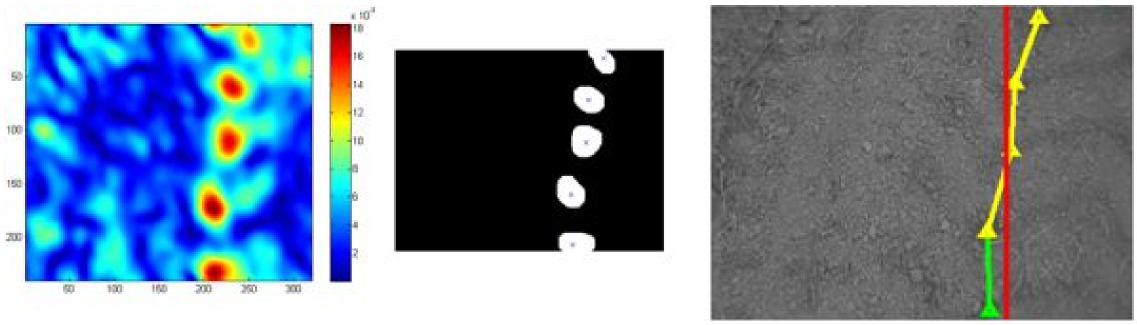

FIGURE 5. Filter output, segmentation and evaluation in an ideal case.

CONCLUSION: The principle of using artificial markings on a field as features for 2D machine vision working as parallel navigation support for a tractor-harrow combination was proven to work in good conditions. Also, the regularity of the artificial pattern was successfully utilized in filtering out the non-pattern features with very few false positives generated. Unfortunately, the overall variability of the outdoor conditions proved too much for the system in practice. The visibility of the markings is too much dependent on the angle and intensity of the sun and the dampness of the soil as well as several other factors. Cross shaped or round markings could have stronger invariance to lighting direction, but they are more difficult to produce. Other serious problems would also remain, like the dust issue and the strong shadows cast by the machinery itself as well as the inherently limited localization accuracy dictated by the dimensions of the markings used.

For further work, either stereo cameras or laser scanners should be used for the added benefit of 3D profiling, which could bring the robustness of the system one step forward. Some sort of probabilistic tracking system should also be implemented when the basic detection capabilities reach suitable levels. Other future improvements could include vibration stabilized sensors and integration with other localization methods.

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