Soil Tillage Quality Measurement: A Methodical Approach

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Abstract

This paper presents a methodical approach for measuring the process quality of the agricultural task soil tillage. This is a crucial step towards the development of automation in the context of autonomous agricultural field work. Therefore, the relevant parameters that define the process quality for autonomous tillage must be identified. These parameters depend on the agricultural task, such as primary tillage, stubble cultivation, or seedbed preparation, and are based on the farmer's expertise and focus. The quality parameters are the identified set of parameters for each task that indicate the quality of the process. For each individual parameter, the proposed measurement method can be applied. The method involves three basic steps. (1) Different algorithms are implemented to characterize the quality parameter based on, e.g., 3D point cloud data or image data. The algorithms are verified in a deterministic environment, such as a simulation environment or a test bench. (2) Afterwards, the Spearman correlation coefficient of the various parameter metrics is analyzed to cluster the metrics into groups with similar physical properties. Based on the clustering, parameters can be chosen considering defined criteria (low resource-intensive, sensor-setup specific, etc.). (3) Finally, the selection of the parameter metric is validated by testing the implementation infield, considering challenging cases, anomalies, and influencing factors such as working speed or soil dependencies. The measurement method for the quality parameter could be used to derive a model that describes the variation of the parameters concerning the degrees of freedom of the agricultural task, e.g. the working speed or working depth for the tillage process.

Keywords: Tillage, Agricultural Process Quality, Measurement Method, Process Sensor Technology

1. Introduction

Soil tillage in agriculture aims to create an optimal soil structure for the crop, including the processes of germination and growth. Tillage tasks vary throughout the year, depending on the crop rotation. Farmers perform primary tillage before seedbed preparation and sowing to mix and loosen the soil. This is typically accomplished using implements such as plows or heavy cultivators. During seedbed preparation, the uppermost layer of soil is loosened, finely crumbled, and reconsolidated, typically with implements like a seedbed combination or rotary harrow. Stubble cultivation after harvest in summer and the incorporation of cover crops in spring are carried out only as deep as necessary to break the soil's capillarity and protect the water content in the soil. A fine cultivator or disk harrow can be used here.

Despite the diversity of the tasks, objectives, and implements, tillage is often a research focus regarding automation in agriculture. A potential explanation is its greater tolerance to error than other tasks, such as sowing. The interest in tillage automation is also underlined by the scarcity of skilled labor in agriculture, especially for tasks with low area performance (ha/h). In addition to these benefits, there are also sustainability aspects in the automation of tillage. Automation of the tillage process can improve energy efficiency or help protect the soil through minimized soil intervention, enhancing biological activity and forming a more resilient soil structure with higher resistance to erosion.

Features such as guidance systems and telemetry solutions are already established in the market. Streitberger et al. (2018) state that these features are classified within automation levels 1 and 2. Moving on to automation level 3, the automated vehicles must monitor the process and environment. Verband Deutscher Maschinen- und Anlagenbau (VDMA) Landtechnik & Bayerischer Bauernverband (2020) specifies autonomy level 2 concerning soil tillage as manual adjustment and guidance of the implement with an assistance system. In contrast, level 3 describes the automatic control and documentation of subtasks according to the farmer's specifications. A measurement system is required to assist during the process and assess and document the process's output, which is here defined as process quality.

Surface roughness, crop residue cover, and aggregate size distribution are potential process quality parameters that could be considered for measurement in the context of tillage. Most metrics and algorithms for the description of surface roughness are based on height profiles. These height profiles can be derived from contact-measurement devices like relief meters (Kuipers, 1957) or non-contact-measurement devices like laser scanners or stereo vision systems (Boysen et al., 2023; Martinez-Agirre et al., 2016; Riegler-Nurscher et al., 2017; Taconet & Ciarletti, 2007; Thomsen et al., 2015). The evaluated metrics range exemplary from the prediction of the surface storage capacity (Hansen et al., 1999) over to the standard deviation of individual elevation points, respectively, the index of Currence and Lovely (1970) to the Peak Frequency (Römkens & Wang, 1986).

Sieve analysis is widely applied to determine the aggregate size distribution. However, it can be influenced by changes in aggregate structure resulting from frictional effects caused by transport, filling the sieve, and oscillation motion of the sieve (Anisch et al., 2016). Sensor-based evaluations may be based on 3D data, as exemplified by the method presented by Steinhaus and Frerichs (2020), or on the evaluation of image data. The various image-based algorithms can be classified into computer vision (e.g. Bosilj et al., 2020; Itoh et al., 2008) or machine learning approaches (e.g. Ajdadi et al., 2016; Alirezazadeh et al., 2021; Azizi et al., 2020). The aggregate size distribution can be described over the working width or summarized as the mean weighted diameter. Furthermore, it is possible to describe aggregates' spatial distribution.

There are several methods for determining crop residue cover. The so-called meter stick or line method determines the degree of cover based on the overlap of organic material with a placed stick. Another method is to compare images indicating a specified crop residue cover level. Measurement methods can also be based on image data (e.g. Pforte, 2010; Riegler-Nurscher et al., 2018; Schmidt, 2022). Potential metrics for describing the parameter include crop residue cover based on individual detected pixels/grid points, the area with a defined percentage of crop residue cover, or the distribution of the crop residue cover. In addition, it could be possible to determine the orientation of the crop in 3D data and verify if the organic matter has been effectively pulled out/separated from the soil.

Measurement methods based on non-contact measurement devices like laser scanners or camera systems provide higher accuracy for these exemplary process quality parameters. However, they need manually labeled data as a reference. Regarding crop residue cover, Riegler-Nurscher et al. (2018) demonstrated that these human-labeled data also underlay uncertainty. They examined the standard deviation of ten evaluators and showed that the deviations for soil, living biomass, and remains in the classes to be labeled were 5.5 %, 4.2 %, and 3.5 %, respectively. Analyses of aggregates are similarly subject to uncertainty. The intricate fracture patterns observed in soil mechanics can impede the clear identification of aggregate boundaries.

Despite the large variety of potential metrics and algorithms for the various process quality parameters, there is still no commonly applied framework for comparing measured and evaluated parameters in the field. Therefore, this paper presents a methodical approach to identify the most relevant metric to describe the individual process quality parameter to monitor and measure the quality of the tillage process. The method ensures that the measured parameters are verified in controlled, reproducible conditions to derive reference values. The validation is then conducted by field trials.

2. Methodical Approach for Tillage Process Quality Measurement

Before the measurement, it is necessary to identify the process quality parameters to be measured. The process quality parameters are selected after literature research and interviews with experts (farmers, agronomists, etc.). This parameter identification step, exemplary for the tillage process with a cultivator, is visualized in the bottom line in **Figure 1**. For the tillage process with a plow, process quality parameters candidates are crop residue cover (target value 0...5 % (Bernacki et al., 1972)), furrow width, depth, and evenness or shape of cut soil bar.

After identifying the process quality parameters, the measurement method for each parameter itself can be applied. The first step involves the implementation of various metrics to characterize process quality parameters related to the tillage process. Different metrics can evaluate varying data fundamentals, such as 3D point clouds for spatial metrics and 2D images for texture analysis. Testing the algorithms for the different parameter metrics under various conditions in a deterministic environment is necessary to verify the algorithms. In this verification step, it is possible to ascertain whether the metric accurately reflects the intended process quality parameter and its behavior, as well as to derive reference values from simulations. Simulation techniques or controlled experiments conducted in laboratory settings (e.g., soil bin) can be utilized for this purpose. The validation of the simulation or the test bench setup is not part of the proposed measurement method.

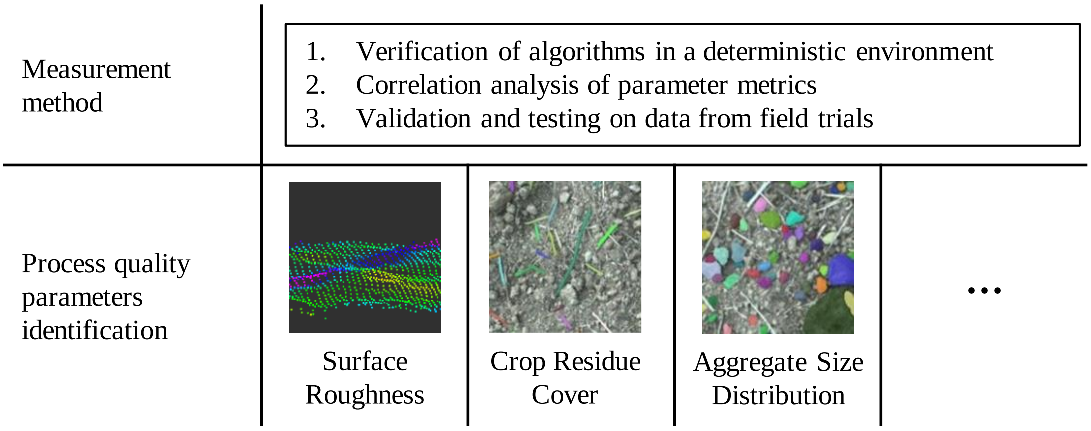

Figure 1. Proposed Methodical Approach to measure process quality in tillage processes.

In the second step, the evaluated metrics undergo statistical evaluation using Spearman's rank correlation coefficient. Spearman rank correlation coefficient is relatively robust against outliers and therefore preferred to the Pearson correlation coefficient (Bortz & Schuster, 2010). The reason for this is the use of the ranks of the analyzed values instead of their actual value. The Spearman’s rank correlation coefficient r_S is calculated

$$r_S = \rho_{R(X),R(Y)} = \frac{\operatorname{cov}(R(X),R(Y))}{\sigma_{R(X)}\sigma_{R(Y)}} \tag{1}$$

where $\rho_{R(X),R(Y)}$ is the Pearson correlation coefficient of the ranked variables $R(X), R(Y)$, $\operatorname{cov}(R(X),R(Y))$ is the covariance matrix, and $\sigma_{R(X)}, \sigma_{R(Y)}$ are the standard deviations of the ranked variables $R(X), R(Y)$ (Bortz & Schuster, 2010). This analysis enables the identification of parameter metrics that share similar physical properties. The correlation of metrics with r_S values close to 1 or -1 suggest similar physical properties. By identifying clusters among the parameters, we can efficiently select those from the cluster that describe a process quality parameter, for example, with minimal computation time or the best fit with the existing sensor setup. Parameters that do not fit into any cluster require special consideration as they could indicate a distinct property or be suited only for specific circumstances.

In the third step, the chosen process quality parameter metrics must be validated using data from field trials. The investigations under determinate environmental conditions ensured the metrics' correctness. So, for infield data, the process quality parameter values classified on an ordinal scale must correspond to the subjective classifications of a sample of farmers and agronomists. Anomaly cases should be considered. In addition, Spearman correlation coefficients can again be calculated. In addition to the parameters’ sensitivity to e.g. anomaly cases, the agreement of the results with those of the deterministic environment should also be analyzed. Any unexpected differences must then be investigated in more detail.

The following chapter outlines the methodological approach for the tillage task with a cultivator as an example. The cultivator, characterized by its limited adjustment options and wide range of applications, facilitates data generation across various scenarios with differing quality requirements and long operating times throughout the year. This design supports a focus on data collection rather than attachment settings, thereby focusing on the methodological approach.

3. Methodical Process Quality Measurement of the Cultivator

In textbooks by authors such as Köller (1981), Köller and Hensel (2019), Soucek & Pippig (1990), or Estler & Knittel (1996), the primary objectives of tillage are to maintain or enhance the soil's characteristics to create favorable germination and growth conditions for crops and to minimize the growth of undesirable vegetation. Surface roughness, residue crop cover, and aggregate size distribution are possible parameters to determine the quality of tillage using a cultivator. The optimal parameter values and their relative importance vary from case to case and are, therefore, at the process planner's discretion, namely the farmer.

To extract suitable metrics to describe the process quality parameters, the method presented in Chapter 2 is used. A simulation environment represents the deterministic environment. Since the widely used sieve analysis, for instance, only measures static diameters, modeling the soil aggregates with hemispheres is proposed in the initial step. Based on this, deformed spheres (modified in size and shape) can also be used. These spheres are distributed on a ground plate based on the Rosin-Rammler-Sperling-Bennett distribution (Hillig, 1986; Soucek, 1986). The ground plate can imitate the landscape with heights and depths and thus, for example, represent an uneven terrain. In addition to the soil aggregates, organic material can be simulated in various distribution densities on the ground. It is recognized that the simulation approach offers the potential to investigate a range of sensors and their suitability efficiently. Nevertheless, it is crucial to acknowledge that this simplified simulation approach does not fully reflect the complexities of reality. As an alternative to the simulation, a test bench scenario, such as a soil bin, also provides a deterministic environment.

The Spearman correlation coefficient is then calculated for the various metrics described in Chapter 2 and analyzed in correlation matrices. Correlating parameters form a cluster. Metrics are selected based on the clusters and the decision criteria, e.g., low resource-intensive, sensor-setup specific.

The selection of the parameter metrics must then be validated. An experimental setup is suitable for this purpose. **Figure 2** shows three field sections (peat soil). Section 1 is not processed, while sections 2 and 3 are processed at different working speeds with the same cultivator and cage roller. If, for example, the selected roughness metric is to be validated, the metric for section 2 should give the smallest values. Larger values should result for section 3 and 1. An alternative value system that is entirely at odds with the aforementioned one would also be acceptable.

Figure 2. Soil surface after the tillage process with a cultivator with cage roller.

4. Discussion

This paper's measurement method could help identify suitable metrics for measuring the tillage process quality. Such a measurement system would be necessary for the next tillage autonomy level 2 and 3, as outlined by VDMA Landtechnik & Bayerischer Bauernverband (2020). The assistance system (level 2) and the automatic control and documentation of subtasks according to the farmer's specifications (level 3) require a control loop, as exemplified in **Figure 3**. The farmer is still responsible for the process planning and specifying the agronomical boundary conditions and process parameters (working depth, implement, objectives, …). Furthermore, the farmer defines the process quality parameters as reference variables for the automated system. The proposed measurement method supports the selection of the measured input values for the controller. Influences on the soil fracture behavior, like non-homogeneous soil type, moisture, or density, must be considered in the modeling (Bögel, 2022; Elijah, D. L. & Weber, 1971). The control idea can be expanded by the efficiency aspect, as suggested by Kazenwadel et al. (2023), so that it results in a multicriterial optimization problem. It should be considered that it is not easy to model all the influences cleanly, as the implement itself (roller, type of tines/blades) also strongly impacts the process quality. Therefore, modeling will probably first run out for separate implement configurations. By adopting this modeling approach, the necessity for continuous measurement in the control loop could eventually be significantly reduced.

The methodology primarily focused on process quality parameters, assuming optimal implementation functionality. However, process parameter monitoring is imperative for the automated system. This includes, for example, the material flow in the implement (detection of blockages) or the condition of the tines or blades.

Additionally, the proposed method omits the validation of the simulation itself, noting that the simulation environment serves as a means to an end. Nonetheless, given the method's requirement for validation on real data for each parameter, the authors find this approach acceptable.

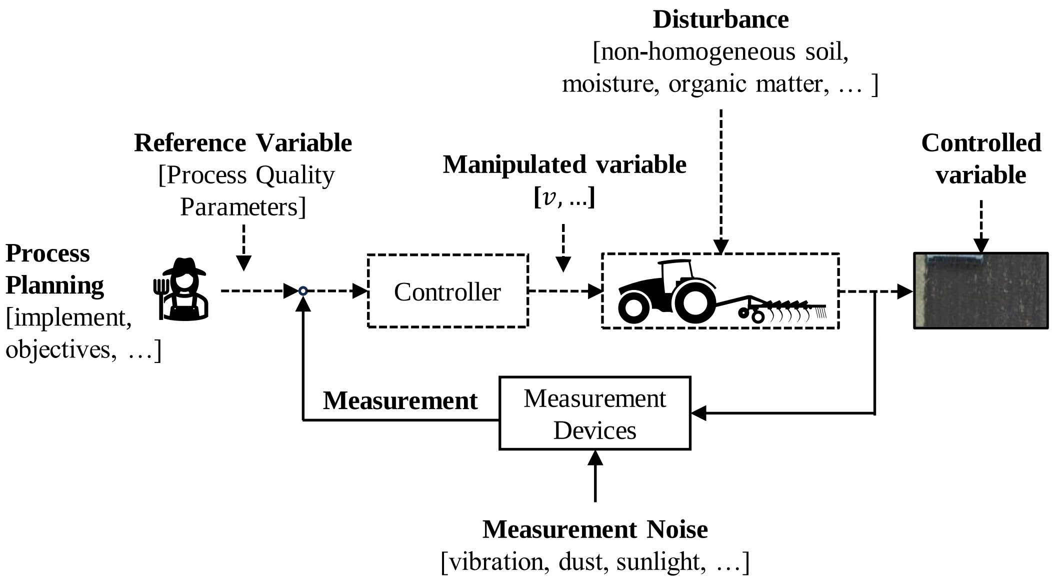

Figure 3. Exemplary Closed Control Loop of an automated tillage process.

5. Conclusion

The literature introduces various parameters with many metrics to describe the quality of the tillage process. This paper presented a methodological approach to evaluate the different metrics to find the most relevant ones. Therefore, the method consists of three steps: In the first step verifying the parameter's metric in a deterministic environment (simulation, test bench) is done. In the second step, the available metrics are clustered based on similar physical properties identified using the Spearman correlation coefficient. In the last step, the most significant metrics are validated on infield data. The idea of modeling the parameters over the possible degrees of freedom (manipulated variable and disturbances) needs further investigation but could be one possible use case for the method.

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