Online Estimation and Control of Soil Forces in Autonomous Cultivation

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***Abstract*—This paper proposes an online method for estimating and controlling soil forces in autonomous cultivation. A linear quadratic (LQ) controller controls tool depth and soil reaction forces, adapting to unknown and spatially varying conditions through an iteratively updated nonlinear gray-box model. Simulation of the soil force estimation demonstrate superior performance over traditional Kalman filtering, highlighting rapid model convergence. This showns potential for predictive control methods like Model Predictive Control (MPC) in the future.**

***Index Terms*—Automatic Control, Nonlinear System Identification, Autonomous Agriculture**

I. Introduction

The growing global population, climate change, and an aging labor force present significant challenges in agriculture. To address these issues, farming practices need to become more efficient, with increased automation being a promising solution.

Soil cultivation, the process of preparing the field for sowing, currently depends on experienced operators to tune the tool settings to adapt to varying field conditions. To automate cultivation, the machine needs to replace the operator's sensory perception and its expert knowledge. Consequently, the problem can be divided into two key components: sensing and control. In this work, the focus is on formulating and proposing solutions to the control problem.

Control of soil cultivation is here formulated as controlling the reaction forces between cultivation tools and the soil, while simultaneously maintaining a consistent working depth. These reaction forces depend on the machine configuration (e.g., tool geometry, operating speed, and intended working depth) and the soil condition (e.g., moisture content, soil type). The machine configuration and dynamics are assumed to be known a priori, whereas soil conditions are treated as unknown disturbances. The goal is thus to achieve stable and consistent cultivation performance by effectively managing both soil forces and working depth, despite varying and unpredictable soil properties.

Soil properties vary spatially across fields and change over time due to weather and previous farming activities. Consequently, effective predictive control strategies, such as Model Predictive Control (MPC) or feedforward control, require continuously updated soil condition models estimated online during operation.

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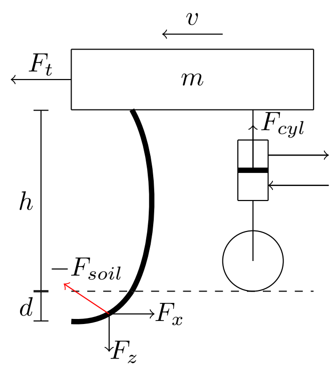

Fig. 1. A simple system of a machine with one tool. Controlled by a hydraulic force and a pulling force.

II. Problem Formulation

To describe the problem of controlling a soil cultivation process, a simple system has been derived, see Fig. 1. Here the depth of a tine d is controlled by a hydraulic cylinder with force F_{cyl}. The speed of the machine v is controlled by the tractor pulling force F_t. The goal is then to control the depth, and the reaction force F_{soil}. This soil force can be described as

$$F_{soil} = K(p,t) f_s(v,d) \tag{1}$$

where $K(p,t)$ is the spatial soil conditions, p is the position in the field, t is the time for which the field conditions changes and $f_s(v,d)$ is the flow forces in the soil. Despite seasonal and weather-dependent changes, the soil conditions are for simplicity in this work assumed to be a continuous quadratic function and time independent, see Fig. 2.

The dynamical model of the system is derived by Newton's second law, resulting in a nonlinear model $\dot{x} = f(x,u)$. The motion is described in x and z direction, respectively, and is coupled by the soil-force F_{soil}.

Available measurements from the system are the tine depth, the speed and the control force inputs. The soil reaction force is not measurable and needs to be estimated, either by filtering or by calculations with (1).

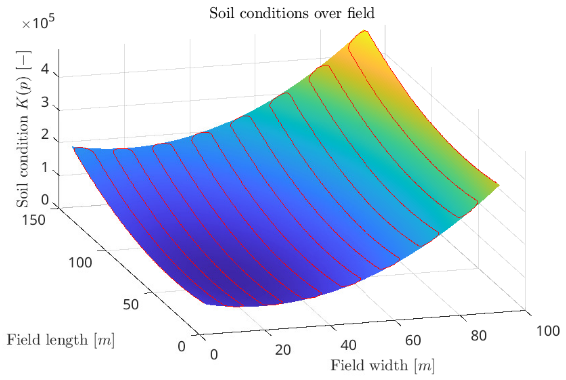

Fig. 2. Visualization of the changing field conditions $K(p)$. The planned tractor path is shown in red.

III. Control Evaluation

To control this MIMO system, a linearized model was used to compute a Linear Quadratic (LQ) controller with integral action [2]. To calculate the prediction of F_{soil}, (1) has been used with $f_s(v, d) = v^2 d$ and different gray box models of $K(p)$. The model of the soil condition was estimated iteratively throughout simulation, getting more and more data for each iteration. The algorithm used linear regression with nonlinear regressors derived from the dynamical model of the system. The parameters were found with the method Least Squares (LS) [1]. Since the system is both nonlinear and simulated with feedback the LS estimate will not find unbiased estimates, but was chosen due to its simplicity. To get unbiased estimates, other techniques will be evaluated, like Instrumental Variables (IV) approaches [1].

The method of estimating the force through sequential model estimations of 1 was compared to a filtering approach with a linear Kalman filter designed from the same linearized model used in the LQ design, see Fig (3).

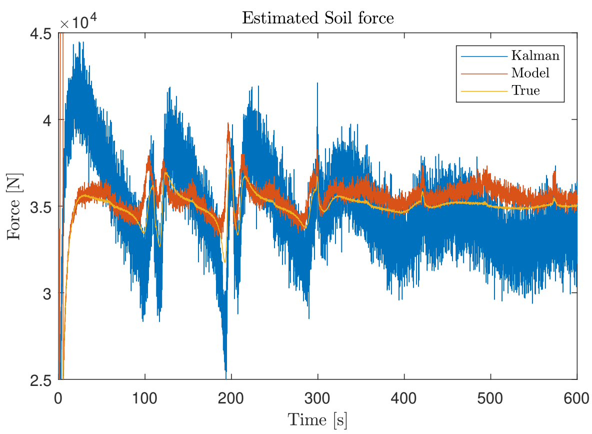

Fig. 3. Force estimation from Kalman filtering and model estimation, compared to the true soil force.

TABLE I
Comparison of control performances for different model orders using normalized Mean Square Error (MSE)

	Constant	Linear	Quadratic
MSE d	0.0364	0.0354	0.0126
MSE F_{soil}	0.4234	0.2416	0.0086

The simulation shows that the model estimation, with sufficient model order, outperforms the Kalman filter while having the benefit of quite quickly (after $\sim 300s$) converging to estimates close to the true model. This model could be used to predict the future forces and opens up the possibility to use predictive control methods, like Model Predictive Control (MPC).

Using the model estimation approach, the control performance was evaluated using different model orders, see Table I. It is quite clear that as long as the true system is contained within the proposed model set, then a linear controller is quite sufficient. However, there are several transients in both the depth and force control that would be desirable to counteract with MPC.

IV. Further Work

Since this is a new research project, there are still many open questions to research. The identification of the soil properties $K(p)$ is most interesting in the near future. Considering the nature of cultivation, quickly identifying an optimal control law is essential. It is not always possible to go back and correct poorly cultivated soil. Therefore, suboptimal cultivation in some parts of the field leads to direct loss of yield. Together with the fact that the soil condition is unknown prior to cultivation, the efficiency of online estimation is crucial.

In this early work, $K(p)$ is simulated as a quadratic function. It is also of high interest to research what other kind of model structures can be used to simulate the conditions as close to a real field as possible. Related to that, what model structures should be used to effiently estimate the conditions.

The soil condition is in this work modeled as a real value $K(p) : \mathbb{R}^2 \to \mathbb{R}$. But in practice it is very likely to be a result of several different field conditions, e.g., moisture content, soil type, prior operations, and prior crops. In other words, with each condition in a vector $\phi(p, t) \in \mathbb{R}^n$, then it would be a fair assumption that $K_\phi(\phi(p, t)) : \mathbb{R}^n \to \mathbb{R}$. Then, would it be possible to benefit from the prior knowledge of some of these conditions? Or is it possible to find a latent space $\tilde{\phi}(p, t) \in \mathbb{R}^m$, $m < n$ with the most contributing conditions, and what does that transformation $\tilde{\phi}(p, t) = B\phi(p, t)$ say about the system?

References

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