Automated Tripod Leveling and Parameter Estimation for a Granular-fill Insulation Distributing Robot ⋆

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Abstract:
In this paper, an approach to modeling, controller design, and parameter estimation for a self-leveling tripod base is presented. The foldable tripod requires manual set-up and its exact leg positions are therefore unknown, although knowledge of the leg configuration is needed for motion planning and also allows better control of the leveling task. An analysis of the geometry is presented, enabling parameter estimation based on finding the tilt axes of the tripod by moving both actuators separately in sequence. This is then generalized for the estimation from an arbitrary movement of the actuators. Further, a linear state-space model is derived with the estimated parameters, which serves as the basis for LQG controller design. The tripod configuration estimation is experimentally verified and provides sufficient accuracy for both the motion planning and leveling tasks. By using a linear Kalman filter, the leveling control achieves good results despite significant measurement errors caused by structural vibrations.

Keywords: Robotic manipulators, Linearization, Kalman filters, Parameter estimation, LQG control method

1. INTRODUCTION

The distribution of floor insulation material on construction sites is currently a demanding manual task. Automation of this task will improve work and health conditions for the construction workers and enable higher throughput. A stable and level base is needed to fulfill the requirements on millimeter precision of surface evenness. This base should be light-weight and portable for ease of use.
The task of leveling robotic platforms is required in various fields of engineering, such as high precision machining, welding, automotive engineering and agricultural engineering (Yang and Lee (1984); Chen et al. (2018); Yang and Li (2006)).
Qiliang et al. (2015) propose a leveling control strategy for a three-point fixed supported automated platform. This approach is completed under the mutual cooperation of signal collection system, tilt sensors, servo encoders, and a control system.
A similar approach is conducted in Zhang et al. (2007), although the auto-leveling platform has four legs. With help of model dynamics, derived via the method of linear graphs, a circular leveling strategy is developed and applied to the leveling system. Also, Wang and Xia (2018) are considering a four-legged platform, though the height actuation of the leg is performed by a hydraulic system. Furthermore, the control algorithm is realized with a cascade control: The outer loop consists of a Backstepping control for the full platform suspension, while the inner loop is integrated as a Sliding Mode Control (SMC) of the desired tracking force.
The control of a parallel robot platform with 6-DoF presented in Jouini et al. (2013) is realized with two model-based control laws, PID and SMC.
For the design and control of Hexapod platforms, Zak and Rozman (2015) use legs equipped with force-sensitive resistor to detect ground. Additionally, each servomotor has an encoder to determine joint's current position. In the case of inclination control for hexapods, a body leveling algorithm (Copot et al. (2017)) uses the hexapod's forward and inverse kinematic model, basic geometry, and the Cartesian plane equation to calculate the leg tip displacements necessary for counteracting the fused orientation data obtained from an inertial measurement unit (IMU).
The aforementioned approaches on the leveling of robot platforms are relying on either fixed leg positions or the incorporation of positioning sensor units in the joints. Since this is not the case for the considered system, a new approach enclosing modeling, controller design and

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parameter estimation of a self-leveling tripod base for a robotic arm is presented. The developed methods allow automatic leveling of a variable-configuration tripod with only a two-axis inclination sensor and the encoders of the servomotors controlling the height of two leg stands.

Section 2 contains a description of the system and two methods for estimating its configuration. In Section 3, a linear state-space model is used to obtain an LQG controller, enabling the leveling of the platform. Experimental results and discussion are presented in Section 4, followed by conclusion in Section 5.

2. SYSTEM DESCRIPTION AND MODELING

The considered system, shown in Fig. 1, is a SCARA-like robotic arm with an end-effector tool that is used to distribute granular insulation material in sweeping motions. The arm is mounted on a portable tripod that is manually set-up with each placement of the robotic arm. Leg 3 is fixed in orientation and the height of its stand can only be adjusted by manually turning its height-setting screw. Legs 1 and 2 are foldable for ease of transport and to provide flexibility for various spatial conditions. The unknown angles of the foldable legs introduce uncertainties into the system. In order to ensure that the robotic arm requires no additional compensation of any torque resulting from a tilted base, it is needed to level the base after each set-up of the robot arm on the construction site. This will also reduce the effect of end-effector tilt on the quality of the finished surface.

The commercially available and manually operated platform Granubot [1] is used as the basis for the automation task. Two of the tripod legs have been equipped with synchronous servomotors to enable platform self-leveling. Driving the height-setting screws on the leg stands allows movement of these two legs in the vertical z-axis and thus provides control of the two degrees of freedom necessary to tilt the tripod plane.

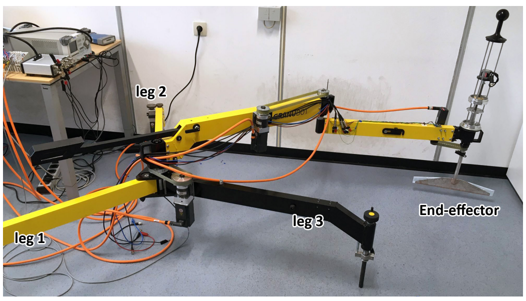

Fig. 1. Robotic arm mounted on a foldable tripod. The end-effector is a blade that moves material across the floor and must be kept level to ensure good quality of the worked surface.

In order to level the tripod, it is necessary to measure its tilt. A TMM55E-PMH010 two-axis inclination sensor from SICK is mounted on the triangular base of the tripod, providing measurements with a resolution of 0.01° in a ±10° range and a sampling frequency of 1.95 kHz. One axis follows the stationary leg and the other is perpendicular to it and horizontal, giving measurements of pitch and roll angles. The control system consists of PLC-controlled I/O terminals connected to two AM8113 geared synchronous servomotors with absolute position encoders serving as the actuators, provided by Beckhoff. The motors are mounted on the side of the leg stands and drive the height-setting screws via a spur gear connection. A schematic drawing of the tripod is shown in Fig. 2.

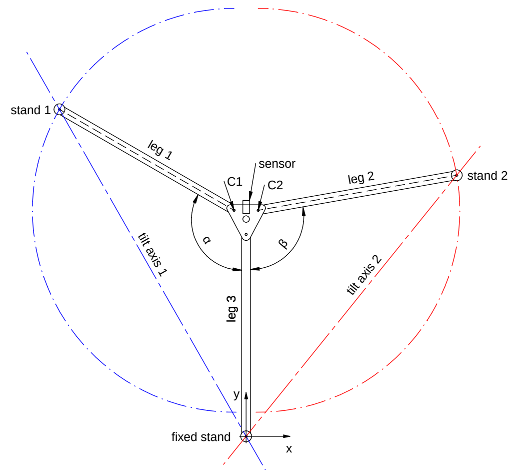

Fig. 2. Schematic drawing of the tripod, showing the relevant dimensions and angles, as well as the chosen system of coordinates and the two tilt axes.

2.1 Tilt axis model

The first method for estimating the leg stand positions and thus the leg angles is derived from the geometric relationships shown in Fig. 3 and described by equations (1) and (2). After moving one of the motors, tilting the tripod plane along one of its tilt axes, the ratio of the sines of the inclination angle changes is the same as the ratio of the x and y positions of the unmoved leg stand. This relationship is only valid under the assumption that the changes in pitch and roll angles are very small, allowing the use of the small-angle approximation. This assumption holds in practice, as the tilt angles are within the range of $< -1.5°; 1.5° >$.

$$h = \Delta x \sin \phi_x = \Delta y \sin \phi_y \tag{1}$$

$$y = \frac{\Delta y}{\Delta x} x \approx \frac{\phi_x}{\phi_y} x \tag{2}$$

Combined with the fact that the leg stand must be located on a semicircle centered on the leg's axis in the triangular base, finding the correct position is reduced to finding the intersection of a line defined by its slope and the semicircle. As seen in Fig. 2, there can be two points where the tilt axis intersects the semicircle. However, as the tripod has to provide a stable base for the robot arm, the legs will never be set at angles smaller than 90°, allowing the

[1] Product webpage [accessed 2019-01-31]: https://www.granubot.de

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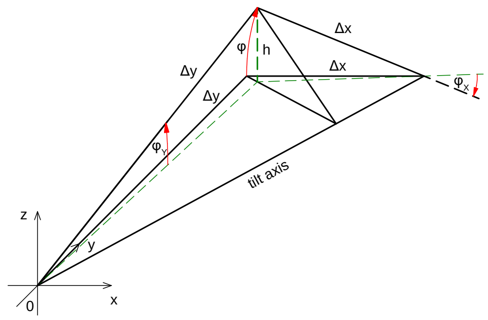

Fig. 3. Schematic drawing of the angles and dimensions for deriving the position of one leg stand from the ratio of tilt angle differences after changing the height of the other leg stand.

elimination of one of the solutions and determining the leg stand position uniquely. This method provides a closed-form solution, but requires two separate movements to find the positions of both legs.

2.2 *General geometric model*

The approach for computing the tilt axis can be extended to the more general case of both actuators moving. Using the geometric analysis of the tripod, a relationship can be found between the changes of the pitch and roll angles and the height differences traveled by the two actuators, shown in (3). This again uses the small-angle approximation for the inclination angles ϕ_x and ϕ_y, giving a set of linear equations.

$$\begin{aligned} \Delta\phi_x &= b_1 h_1 + b_2 h_2 \\ \Delta\phi_y &= b_3 h_1 + b_4 h_2 \end{aligned} \tag{3}$$

The tilt angle changes are a linear combination of the two height differences, where the coefficients b_i are dependent on the positions of the two foldable leg stands as expressed by (4).

$$\begin{aligned} b_1 &= \frac{y_2}{x_1 y_2 - x_2 y_1}, b_2 = -\frac{y_1}{x_1 y_2 - x_2 y_1} \\ b_3 &= -\frac{x_2}{x_1 y_2 - x_2 y_1}, b_4 = \frac{x_1}{x_1 y_2 - x_2 y_1} \end{aligned} \tag{4}$$

The leg positions x_i and y_i are four parameters, so the system of equations from (3) needs to be completed by adding the conditions (5) that the leg positions can only lie on circles centered in the leg mounting points in the triangular base,

$$\begin{aligned} (x_1 - x_{C1})^2 + (y_1 - y_{C1})^2 &= r^2 \\ (x_2 - x_{C2})^2 + (y_2 - y_{C2})^2 &= r^2 \end{aligned} \tag{5}$$

where r is the leg length and circle radius and the C subscript signifies the position of the circle center. The set of equations formed by (3) and (5) is complete, however, an explicit analytical solution is unavailable, making a numerical approach necessary. The limited computational resources and programmatic capabilities of typical low-end PLC control hardware mean that it may be advantageous to try a different approach based on linearization.

2.3 *Linearization*

The leg positions can be expressed with the use of the two leg angles α and β from Fig. 2 with the equations

$$\begin{aligned} x_1 &= x_{C1} - r\sin\alpha \\ y_1 &= y_{C1} - r\cos\alpha \\ x_2 &= x_{C2} + r\sin\beta \\ y_2 &= y_{C2} - r\cos\beta \end{aligned}, \tag{6}$$

leading to the coefficients b_i in (4) being only dependent on these two angles.
As can be seen on the example of b_1 in (7), the parameters b_i are still nonlinearly dependent on α and β. Furthermore, the evaluation of trigonometric functions only adds to the computational complexity. However, if the coefficients b_i are approximated by linear functions of these two variables, the angles α and β can be explicitly computed. In order to linearize the b_i coefficients, their value at a linearization point and their partial derivatives are needed.

$$b_1(\alpha,\beta) = \frac{1}{x_{C1} - r\sin\alpha - \frac{y_{C1} - r\cos\alpha}{y_{C2} - r\cos\beta}(x_{C2} + r\sin\beta)} \tag{7}$$

The linearization point is chosen as $[120°; 120°]$ due to the fact that this is the most balanced configuration with ends of the three legs forming an equilateral triangle and is the typical way of setting up the tripod in practice. Fig. 4 shows the value of the coefficient b_1 depending on the two leg angles in the range of $< 100°; 140° >$ for each of the angles. Coefficients c_i for the linear equations are computed according to (8).

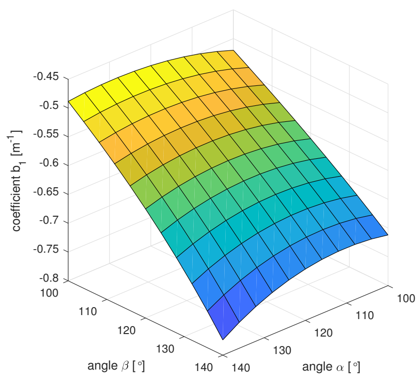

Fig. 4. Visualization of the coefficient b_1 depending on the leg angles α and β in the range $< 100°; 140° >$. Linearization of the equation for b_1 will approximate this surface by a plane tangent at the point $[120°; 120°]$.

$$\begin{aligned} b_1(\alpha,\beta) &\approx c_1\alpha + c_2\beta + c_3 = \\ &= \frac{\partial b_1(\alpha,\beta)}{\partial\alpha}(\alpha - \alpha_0) + \frac{\partial b_1(\alpha,\beta)}{\partial\beta}(\beta - \beta_0) + b_1(\alpha_0,\beta_0) \end{aligned} \tag{8}$$

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With this approximation, the leg angles can be found by solving the matrix Equation (9). As the matrix inverse is only of a 2×2 matrix, its calculation can be performed very efficiently and is easily implementable on any control hardware.

$$\begin{bmatrix}\alpha\\ \beta\end{bmatrix} = \begin{bmatrix} c_1h_1 + c_4h_2 & c_2h_1 + c_5h_2\\ c_7h_1 + c_{10}h_2 & c_8h_1 + c_{11}h_2\end{bmatrix}^{-1} \begin{bmatrix}\Delta\phi_x - (c_3h_1 + c_6h_2)\\ \Delta\phi_y - (c_9h_1 + c_{12}h_2)\end{bmatrix} \quad (9)$$

By linearizing the coefficients b_i, an error is introduced into the estimate of the leg angles. The error for each of the two angles is found to be asymmetric with respect to the other angle. For example, if the actual angle α is close to the linearization point of 120°, it will be estimated correctly (under 1° deviation) regardless of the angle β. A further measure is thus introduced to give a more useful picture of the method's accuracy, as both angles should be estimated correctly for optimal control and the later motion planning stages for the robot arm. This is the mean squared error, described by Equation (10). This error $\Delta\gamma$ is visualized in Fig. 5. As expected, linearization provides good results in the vicinity of the optimal configuration of [120°; 120°]. Interestingly, the estimate will also stay reasonably accurate along the diagonal $\alpha + \beta = 240°$. Considering the leg length is 91.8 cm, an error of 1° in leg angle estimation translates to a leg position error of 1.6 cm. Errors of a few centimeters will not seriously affect modeling accuracy and controller performance. Obstacle avoidance of the tripod legs will also be unaffected, having larger safety margins.

$$\Delta\gamma = \frac{1}{2}\sqrt{\Delta\alpha^2 + \Delta\beta^2} \quad (10)$$

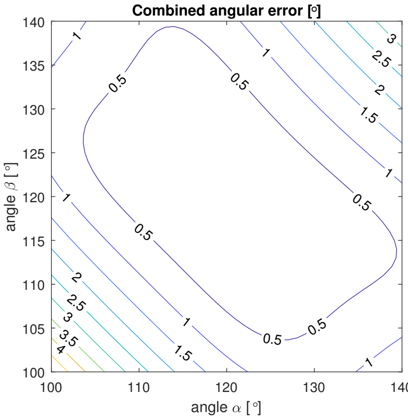

Fig. 5. Contour plot of the combined angular error due to linearization, computed from the individual errors according to (10).

3. LEVELING CONTROL

Using the previously derived mathematical model (3) of the tripod, a state-space representation of the system can be obtained. The states to be controlled are the two inclination angles. The two actuators provide the means to change these states and serve as the system inputs. It is first necessary to relate the inclination angular velocities to the actuator velocities by

$$\begin{aligned}\dot{\phi_x} &= b_1v_1 + b_2v_2\\ \dot{\phi_y} &= b_3v_1 + b_4v_2\end{aligned} \quad . \quad (11)$$

Note that the angular velocities do not depend on the angular values themselves, signifying a purely integrating behavior. The states are also the directly measured outputs of the system. Combining these considerations leads to the state-space form

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{Ax} + \mathbf{Bu}\\ \mathbf{y} &= \mathbf{Cx} + \mathbf{Du}\end{aligned} \quad (12a)$$

$$\mathbf{x} = \begin{bmatrix}\Phi_x\\ \Phi_y\end{bmatrix}, \mathbf{y} = \begin{bmatrix}\Phi_x\\ \Phi_y\end{bmatrix}, \mathbf{u} = \begin{bmatrix}v_1\\ v_2\end{bmatrix} \quad (12b)$$

$$A = \begin{bmatrix}0 & 0\\ 0 & 0\end{bmatrix}, B = \begin{bmatrix}b_1 & b_2\\ b_3 & b_4\end{bmatrix}, C = \begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}, D = \begin{bmatrix}0 & 0\\ 0 & 0\end{bmatrix} \quad . \quad (12c)$$

The measurement of the inclination sensor is highly sensitive to mechanical vibrations of the tripod, which are mainly caused by the eccentricity of the leg stand screws. As can be seen in Fig. 6, the error caused by vibrations is significant, rendering the measurement unsuitable for feedback control without appropriate processing. Using the linear state-space model of the system, a linear Kalman filter can be derived to serve as an estimator of the inclination angles. The measurement of velocity provided by absolute encoders in the servomotors is very precise, partly due to a high gear ratio, making input uncertainties negligible.

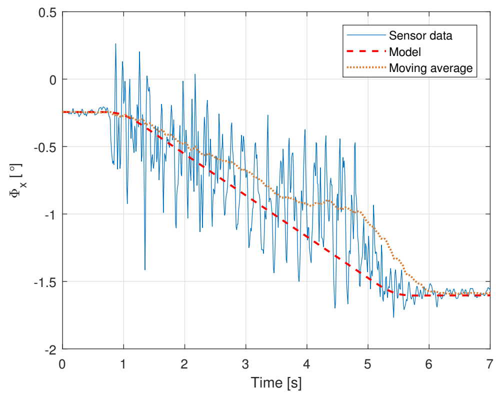

Fig. 6. Measurements of the roll angle ϕ_x taken during a point-to-point actuator movement with a tripod configuration of $\alpha = 130°$, $\beta = 110°$ show considerable noise due to mechanical vibrations. Also shown is the predicted behavior based on the state-space model (12) and a moving average for comparison.

The state-space model described in (12) shows a good match with experimental data taken from a point-to-point actuator movement. When the system is simulated

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with the same initial conditions and measured input data, the resulting estimation error is 0.96%, probably due to the system linearization. The estimates remain valid over larger timescales and multiple movements. A linear Kalman filter based on this model should therefore provide a better state estimate than low-pass noise filtering, such as with a moving average filter.

The model is fully controllable and observable, but does not consider the dynamics of the actuators. However, approximating the actuator behavior by a first-order system does not provide a good fit and brings no marked improvement for the leveling task. Higher order systems that would more accurately describe actuator behavior include unmeasurable states that must be estimated and bring higher computational complexity. Actuator dynamics are therefore neglected.

Assuming good state estimates from the Kalman filter, a proportional feedback controller can be designed. A common method is the LQR algorithm, which designs an optimal controller minimizing the cost function

$$J = \int_0^\infty \left(x^T(t)Qx(t) + u^T(t)Ru(t)\right)\, dt \quad . \tag{13}$$

By choice of the weighting matrices Q and R, either the states or the inputs are assigned more weight. The combination of a Kalman filter and an LQR controller is commonly known as the LQG controller. For the presented system, the weight matrices

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, R = \begin{bmatrix} 0.3 & 0 \\ 0 & 0.3 \end{bmatrix} \tag{14}$$

provide the best results in terms of settling time. Depending on the tripod configuration, the proportional feedback gain K changes along with the system model, e.g. for a configuration of $[130°; 110°]$, the resulting gain matrix is

$$K = \begin{bmatrix} -1.165 & 1.406 \\ 1.406 & 1.165 \end{bmatrix} \quad . \tag{15}$$

4. EXPERIMENTAL RESULTS

4.1 Tripod configuration estimation

Measurements have been taken with defined tripod configurations to verify the tripod leg position estimation methods. Sensor data have been averaged over several seconds, lessening the impact of sensor noise. The results are shown in Table 1. The tilt axis method described in Section 2.1 provides consistently accurate results across the measured configurations, with the two sources of error being the distance measurement errors in the defined measured configurations and inclination sensor noise. The general method described in Section 2.2 that requires solving a system of nonlinear equations should provide comparable results, however, the measured error is an order of magnitude higher in some cases. Aside from the poorer performance of the general method, the effect of linearization is roughly consistent with the predictions.

The discrepancy between expectation and experiment for the general method can be caused by multiple factors. Thorough calibration of the mounted inclination sensor has yet to be performed to correct some known uncertainties in the sensor readout. Any additive or multiplicative

Table 1. Mean squared error of the leg position estimation methods in various configurations.

$(\alpha;\beta)[°]$	Tilt axis method $\Delta\gamma[°]$	General method $\Delta\gamma[°]$	Linearized general method $\Delta\gamma[°]$	Predicted linearization error $\Delta\gamma[°]$
100; 100	0.23	3.36	5.67	5.00
100; 110	0.29	2.36	4.74	2.70
100; 120	0.22	0.55	1.83	1.22
100; 130	0.62	1.44	2.98	0.80
100; 140	0.30	1.08	2.06	1.30
110; 110	0.74	1.82	1.83	1.14
110; 120	0.31	1.20	1.68	0.29
110; 130	0.20	0.75	0.88	0.30
110; 140	0.25	0.28	1.82	0.62
120; 120	0.08	0.55	0.55	0.00
120; 130	0.28	0.41	0.25	0.24
120; 140	0.30	0.33	2.80	0.86
130; 130	0.34	0.54	1.81	0.94
130; 140	0.34	0.33	4.51	2.00
140; 140	0.20	0.35	9.27	3.46

error on both angles would affect the general method more, since the tilt axis method only evaluates the ratio of the angle changes and not their absolute value. The choice of the test motion also plays a large role in the estimation accuracy, as smaller angle changes are more affected by sensor inaccuracies. Further experiments are needed to evaluate this.

Both the general method and the tilt axis method provide sufficient precision to be usable in practice. The linearized method is the fastest to compute and easiest to implement. However, its large errors further away from the linearization point mean that its use is only justified if initial manual leg positioning is ensured with a ±15° accuracy around the optimal 120°. This could be accomplished by the use of visual guides on the tripod.

4.2 Leveling control

The LQG controller designed in Section 3 is tested with various tripod configurations and initial conditions, with one example shown in Fig. 7.

During movement, the noise is very prominent and the measurement cannot be used for feedback control without processing. The results of the model verification, partly shown in Fig. 6, indicate accurate modeling of the system, providing good results even over longer periods of time. Therefore, the discrepancy between the predicted state and a moving average suggests that low-pass filtering does not give a good estimate of the state during movement. Furthermore, while computationally efficient, low-pass filtering introduces a trade-off between noise suppression and phase lag that a model-based Kalman filter avoids.

More precise evaluation of the Kalman filter would be provided by accurate angular measurements by other means. As it is, the developed Kalman filter can only be evaluated based on its effects on the leveling control and its settling time, overshoot and steady-state error. These are improved when the Kalman filter is set to place more importance on the model and input data, while paying less attention to the sensor measurements.

In practice, the model will not describe the system perfectly, partly due to the linearizations performed. The

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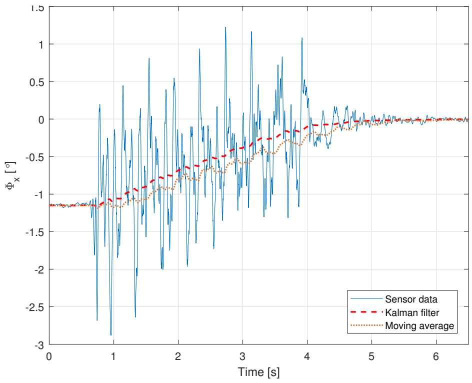

Fig. 7. Inclination sensor measurement of the roll angle ϕ_x during a leveling operation with the initial conditions $\phi_x = -1.15°$, $\phi_y = 0.29°$ and tripod configuration $\alpha = 130°$, $\beta = 110°$. The influence of sensor noise is greatly reduced by using a Kalman filter. A moving average is shown for comparison.

accuracy of the parameter estimation done in the previous step also has a large effect on the validity of the model. Sensor data is therefore still necessary for the estimate to converge to the current state. The Kalman filter can be adjusted to reflect these considerations by changing the covariance matrices of the sensor noise and process noise. Experiments have shown that the optimal ratio of sensor to process noise covariances is on the order of 10^6.

The LQG controller achieves smooth leveling without overshoots for all tested configurations, which correspond to the intended use on construction sites. Leveling precision is within sensor noise, which in steady state is approximately Gaussian with a standard deviation of 0.018°. Besides leveling, control of the platform to arbitrary pitch and roll angles is also achieved, limited only by actuator stroke.

5. CONCLUSION

In this paper, the task of automatically leveling a tripod platform with variable leg positions is analyzed. Two methods for estimating the unknown configuration are presented. The method based on finding the tilt axes of the system provides the most accurate results with a leg angle estimation error of generally less than 0.5°. However, more time is required for its two separate test movements. A more general method only needs one test movement and also provides useful estimates, however its accuracy is below expectations. This is presumably due to uncertainties in the measurement and sub-optimal choice of test movement. The method also requires numerically solving a system of nonlinear equations. A linearization of the parameters allows straightforward implementation and fast execution on any PLC hardware and provides satisfactory results in a narrower range of configurations expected to be used in practice.

Knowledge of the leg positions will provide obstacle information to a motion planning algorithm in future work. The estimate is further used to obtain the parameters of a state-space model of the system. The model is found to describe system behavior accurately and serves as the basis for a Kalman filter. This reduces the influence of sensor noise caused by mechanical vibrations and allows smooth control without overshoots with a proportional feedback controller designed by the LQR algorithm. The system can be controlled to arbitrary achievable pitch and roll angles with a precision only limited by steady-state sensor noise. Ongoing work focuses on proper calibration of the inclination measurement and further development of the parameter estimation methods. One possible option would be the use of joint or dual unscented Kalman filtering, as seen in other work, e.g. Wielitzka et al. (2018), allowing estimation of the states and parameters at the same time.

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