

Online Calibration of a Compact Series Elastic Actuator

Steven Ford, David Rollinson, Andrew Willig and Howie Choset

Abstract—We present a method for the online calibration of a compact series elastic actuator installed in a modular snake robot. Calibration is achieved by using the measured motor current of the actuator's highly geared motor and a simple linear model for the spring's estimated torque. A heuristic is developed to identify operating conditions where motor current is an accurate estimator of output torque, even when the motor is heavily geared. This heuristic is incorporated into an unscented Kalman filter that estimates a spring constant in real-time. Using this method on a prototype module of a series elastic snake robot, we are able accurately estimate the module's output torque, even with a poor initial calibration.

I. INTRODUCTION

Most mobile robots rely on highly-geared electric motors for actuation. While this makes the robots capable of delivering large torques and forces, and precisely executing commanded motions, the stiffness of the actuators makes it difficult to sense and comply to contact with the environment. Force and torque sensors can provide the necessary information, but are often difficult to integrate into a compact mobile robot. Theoretically, one could estimate the output torque of this system by measuring the current drawn by its motor, but many confounding factors are present. Common nonlinear effects such as the friction, stiction, backlash, and reflected inertia in the gear train create significant discrepancies between the expected and actual torques at the output of the actuator.

Incorporating series elasticity into robots has the potential to mitigate the problems of stiff actuators [1], while also facilitating more accurate estimation of the actuator's output torque. Our group has recently developed a series elastic actuator based on shearing a rubber elastomer that is bonded to two rigid plates integrated in the robot's drive train [7]. This design provides mechanical compliance and energy storage an order of magnitude greater than traditional springs [2].

Unfortunately, these rubber springs display significant variance. Repeated cyclic loading, as seen in robotic applications, changes the stiffness of the rubber. Inconsistencies in the manufacturing process also introduce variance in spring constants. This work focuses on compensating for these issues through online estimation of the spring's parameters. We show that an unscented Kalman filter can estimate the spring constant in real-time.

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Fig. 1: Photo of a prototype SEA Snake Module. The module is 5 cm (2 in.) in diameter and provides a 1-DOF rotary motion of $\pm 90^\circ$. The module contains a rubber-based series elastic actuator that can output over 6 N-m of torque.

II. PRIOR WORK

Series elastic actuation was first proposed by Pratt as a way of achieving compliant actuation along with low-bandwidth force control [1]. Most work in series elastic actuation design has been focused around robotic legged locomotion applications using metal or composite springs [3]–[6]. Recently, our group developed a compact rubber-based series elastic actuator for use in modular snake robots [7].

Snake robots were first explored by Hirose in his pioneering work with the Active Cord Mechanism (ACM) [8]. Our lab has developed snake robots [9] similar to Hirose's ACM [10] and other snake robots that share some characteristics of reconfigurable modular robots [11].

Online parameter estimation has a long history in robotics and automation, which is often performed with various recursive least-squares estimation techniques [12]. One specific technique that is commonly applied to parameters is Kalman filtering. The extended Kalman filter (EKF) and, more recently, unscented Kalman filter (UKF) were developed to extend for non-linear state and parameter estimation [13]. The UKF and its variants avoid the linearization step of the EKF by using deterministically sampled sigma points to estimate the mean and covariance of a parameter, resulting in more robust estimation in the face of large non-linearities. The estimator implemented in this paper is a spherical simplex

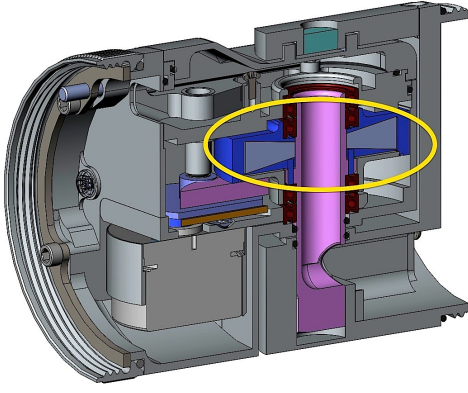


Fig. 2: Cross-section of the SEA Snake Module. Series elasticity is achieved by shearing a conical rubber section embedded in the final stage of the module's gear train (circled area).

unscented Kalman filter (SSUKF) [14], which employs fewer sigma points than the traditional UKF. We should point out that the choice of the SSUKF for parameter estimation was chosen mainly for convenience, and it is likely that many other recursive least-squares techniques could be used to achieve similar results. We already had an implementation of the SSUKF developed for other related research, and it will easily allow us to move to more sophisticated models in the future that have more parameters.

Sensorless force/torque sensing with highly geared motors is another area of active research. In particular, Stolt et al. used the error in the de-tuned control loops of a robotic arm to estimate force during the onset of contact with the environment [15]. In general, existing methods rely on detailed models of well calibrated system observers [16] and are difficult to apply to mobile and field robots that often operate with crude or simplified models.

III. PLATFORM

The platform used for experimentation was a prototype module for the Biorobotics Lab's latest snake robot, the Series Elastic Actuator Snake (SEA Snake), shown in Fig. 1. A single SEA Snake module has one degree of freedom actuated by a brushless DC motor connected to a custom spur gear train with gear ratio of 349:1.

The series elastic element consists of a conically shaped layer of rubber molded into the the final stage of the gear train, as shown in Fig. 2. The SEA Snake module contains two absolute magnetic encoders that measure the input and output angles of the spring. A detailed description of the design and properties of this spring and its retrofit into a previous snake robot can be found in [7].

IV. TORQUE ESTIMATION

Output torque of a series elastic actuator can be estimated using one of two different sensing modalities. The first is by using the sensed spring deflection in the series elastic element. The second is using the sensed electrical current

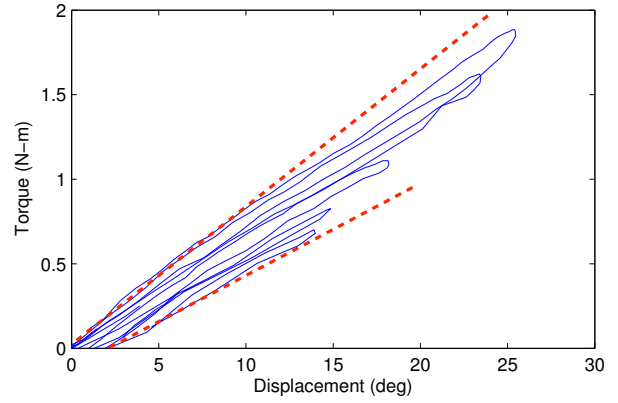


Fig. 3: Graphical example of the Mullins effect in our rubber springs. The Mullins effect is the viscoelastic softening of rubber that occurs after repeated loading. In this trial, the spring constant changed by about 25%.

drawn by the actuator's motor. This section details the simplified models for both of these measurements.

A. Spring Models

One method for estimating output torque is to assume the parameters of the spring are constant and construct a dynamic model around it. A simple linear model would follow Hooke's Law

$$T_{spring} = k\theta \quad (1)$$

where T_{spring} is the output torque, θ is the angular displacement of the spring, and k is the torsional stiffness. For steel coil springs this is often an accurate model and in some cases can be applied to rubber, particularly if it is stressed in shear rather than in tension or compression.

B. Motor Current Model

An alternative and more traditional method of estimating joint torque is to measure the current draw of a DC motor. Such models often employ a linear relationship between torque and current. Our model also considers gear train inertia

$$T_{current} = (\tau I + \ddot{\theta} \sum_{i=1}^4 J_i r_i) \eta \quad (2)$$

In (2), τ is the motor's torque constant, I is the motor current, J_i is the inertia at stage i of the gear train, r_i is the gear ratio from the motor at stage i in the gear train, $\ddot{\theta}$ is the acceleration of the motor output shaft, and η is the gear train efficiency.

C. Issues

The accuracy of the spring model suffers from the assumption of constant spring parameters. In fact, rubber stiffness depends on a number of variables, such as temperature, duration of use, and most recent peak amplitude. These relationships are often complex and codependent, rendering

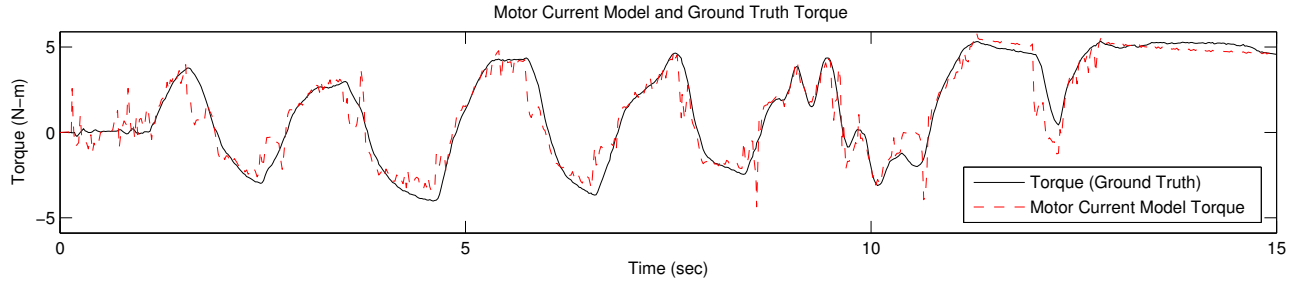


Fig. 4: Estimated torque from motor current compared to the measured output torque of the module..

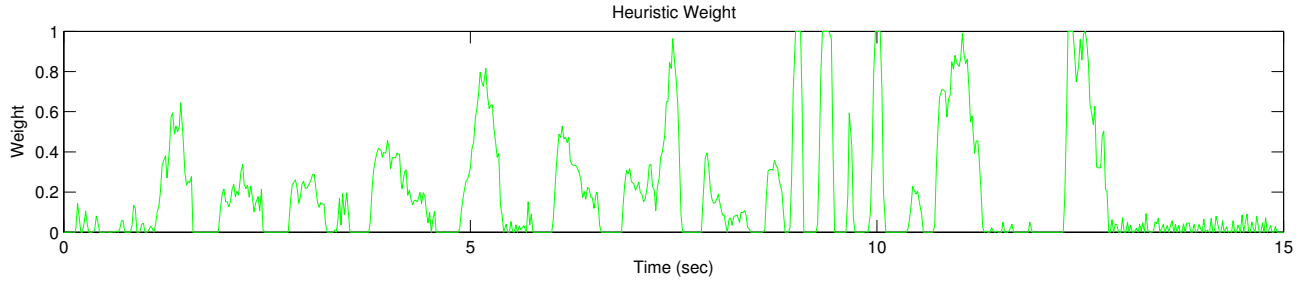


Fig. 5: The heuristic weighting factor for motor current measurements. A higher weight means the measurement is used to estimate the output torque.

them difficult to isolate and identify. For example, due to the Mullin's effect, spring stiffness decreases while the spring is sheared back and forth, but recovers upon resting [17]. Figure 3 shows the reduction of the spring constant upon repeated cycling.

Another consideration is that a one-size-fits-all approach to spring stiffness may not hold across different springs. Due to variation in the molding process, there is as much as a 10% variation in the stiffnesses of springs that are nominally the same. Rather than performing a detailed calibration procedure every time a spring is changed, we would much rather have a method where the modules self-calibrate.

While measured motor current would ideally map accurately to output torque, gear trains cause a number of issues in practice. For instance, static friction in the gear train causes a sticking effect, such that the required torque of the motor is reduced. Backlash causes problems when the actuator changes directions and reflected inertia causes problems when the actuator accelerates aggressively. These issues are highlighted by Fig. 4 and Fig. 7. However, we note that there are specific operating conditions where motor current is an accurate predictor of output torque. In the following section, we develop a heuristic that will enable a measurement model to be developed for the parameter estimator.

V. ONLINE PARAMETER ESTIMATION

To avoid the difficulties of modeling history-dependent spring constants, we instead approach the problem by estimating spring parameters online using sensor data and the associated error model.

A. Motor Current Heuristic

For our experiments, motor current feedback is selectively observed in order to actively update the spring stiffness. While motor current does not provide an accurate estimate of output torque over the full operating envelope, there exist certain states in which a motor current model accurately tracks output torque. By observing the feedback from our prototype modules, it was found that motor current is most accurate when the spring displacement and the rate of change of its displacement are in the same direction, and the output velocity is above a certain threshold. This heuristic differentiates useful data from data that might be corrupted by backlash or static friction. That is, backlash often occurs when there is a change in the sign of velocity, whereas static friction is prevalent when velocity is near zero.

A heuristic trust function is applied that describes the confidence in a motor current measurement based on these intuitive observations

$$w = \min(1, \max(0, \frac{\theta\dot{\theta}}{\gamma})) \quad (3)$$

In (3), θ is the spring displacement, $\dot{\theta}$ is the rate of spring displacement, and γ is a factor that adjusts the scaling of the resulting weight. For our tests, γ was set to 20. Essentially, negative weights are discarded and large weights ceiling at 1. The weights from this heuristic function on motor current data is visually illustrated in Fig. 5.

B. Kalman Filter

We chose to use a spherical simplex unscented Kalman filter (SSUKF) for parameter estimation. Rather than present

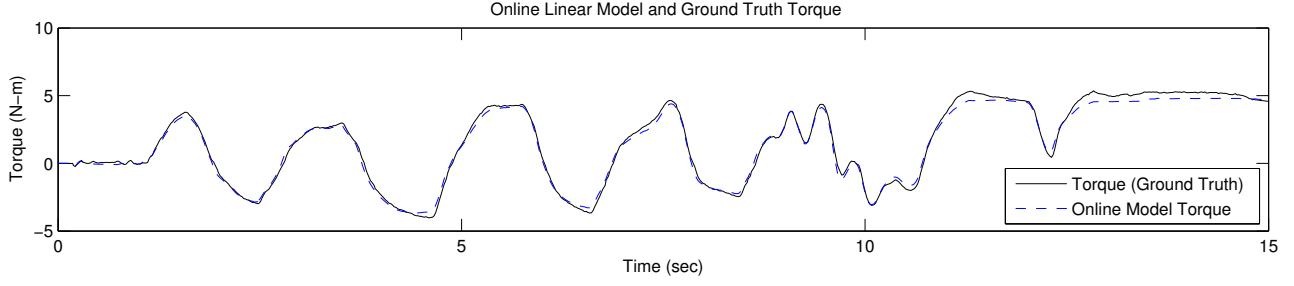


Fig. 6: The estimated torque based on spring deflection and the estimated spring constant compared to the measured output torque of the module.

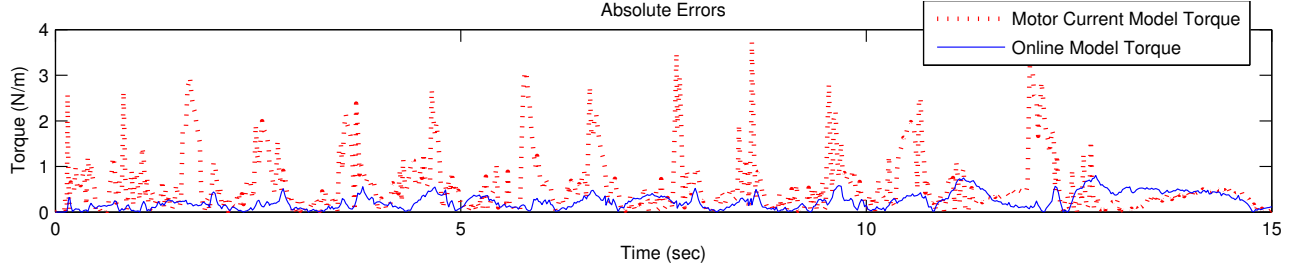


Fig. 7: A comparison of the errors in predicted torque from motor current and from spring deflection.

the SSUKF in detail, here we will focus on the aspects that are unique to our application, namely the formulation of the state and measurement models. Like other varieties of Kalman filter, the SSUKF operates recursively on a state vector $\mathbf{x}$ and a corresponding covariance matrix $\mathbf{P}$. In the case of estimating a single linear spring parameter, the state is simply

$$\mathbf{x} = k. \quad (4)$$

The filter also uses a process model for propagating the state estimate forward in time and a measurement model for generating measurements or observations based on the current state estimate,

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}) \quad (5)$$

$$\mathbf{y}_t = h(\mathbf{x}_t). \quad (6)$$

C. Process Model

Since the filter is being used for parameter estimation, the process model is a trivial stationary model,

$$\hat{k}_t = k_{t-1}. \quad (7)$$

D. Measurement Model

The measurement model of the filter is somewhat unusual in that it is actually an error function that compares the difference between a linear spring model (1) and the motor current (2)

$$\epsilon = w(T_{current} - T_{spring})^2. \quad (8)$$

The filter then ‘observes’ an error of 0 during the update step, so that parameter is always driven in a direction that

minimizes the error. In a sense, this uses the filter to perform a single step of gradient descent on the unknown parameter with every iteration. Formulating the measurement model this way has two advantages. The first is that more complex heuristics or cost functions can easily be developed and worked into the framework of the filter, since it only requires modifying the measurement function (6).

Additionally, if the filter is run at a lower frequency than the module’s measurements, each step can be run on all the history since the last update,

$$\epsilon = \sum_{i=t-n}^t w_i \frac{(T_{current} - T_{spring})^2}{n}. \quad (9)$$

This error function is essentially a weighted average of the error between the models over the last n samples.

E. Noise Parameters

The Gaussian process and measurement noise of a Kalman filter serve as the tuning parameters. The relative weights of the parameter uncertainty compared to the measurement uncertainty are what control the performance of the filter. The process noise is denoted by the matrix $\mathbf{Q}$ and is added to the state covariance during the prediction step of the filter. In our estimator, the magnitude of the process noise is scaled by the estimated spring stiffness, $\hat{k}$,

$$\mathbf{Q} = \alpha \hat{k}. \quad (10)$$

The measurement noise, $\mathbf{R}$ is set to a fixed value,

$$\mathbf{R} = \beta. \quad (11)$$

For our experiments we set $\alpha = 1 \times 10^{-4}$ and $\beta = 1$.

VI. EXPERIMENT

To measure the true torque exerted by the module, a test rig was built that allowed an external force to be applied manually during the module's operation (Fig. 8). This force was measured with a small load cell, logged at 50 Hz with an Arduino microcontroller, and synchronized with the measurements of spring displacement and motor current from the module itself.

VII. RESULTS

The online estimate model tracks torque accurately and converges quickly. Table I summarizes the accuracy of the various approaches. Using a good initial input of spring stiffness to minimize required convergence, the online estimate performs significantly better than the motor current model, as can be seen in Figs. 6 and 7. It also matches about as well as a linear model which uses a prescribed spring constant that best fits the data. While this is easy to implement with an offline calibration, the best fit spring stiffness requires full knowledge of our torque and thus can only be calculated after measurement. Averaging spring stiffnesses from other trials does not work as well due to the variation in rubber properties over time and between springs. Hence, this online result is promising as it requires no previous knowledge of the rubber, and yet it converges on a spring stiffness that is nearly as accurate as the best fit for any given data set.

Figures 9, 10, and 11 illustrate the convergence of the estimate given a poor initial input of spring stiffness. Even with a starting point that is an order of magnitude too high, the filter converges on an accurate spring stiffness in a matter of seconds.

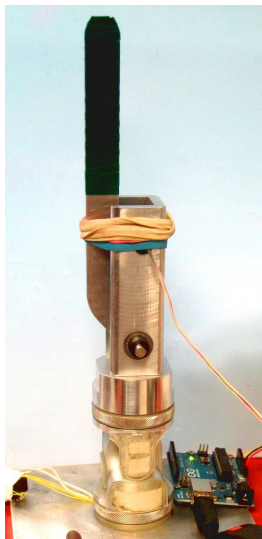


Fig. 8: The test rig used for the experiments in this paper. External forces were applied to the handle. The forces were recorded with a load cell under the rubber bands and logged with an Arduino to provide ground truth.

Torque Model	Error
Linear (Best Fit)	7%
Online	8%
Motor Current	21%

TABLE I: The average error for the 3 different models of torque.

VIII. CONCLUSIONS

We have presented a method of calibrating the spring constant of a series elastic actuator using carefully sampled measurements of the actuator's motor current. The key insight is to update the estimate based on the occasional points where motor current is an accurate indicator of torque. This allows us to begin operation with only an approximate estimate of the spring constant and gradually refine it over time. In addition to the heuristic to identify useful motor current measurements, we modified a spherical simplex unscented Kalman filter to provide efficient online estimation.

It should be noted that the specific methods chosen here are by no means the only or best means of online calibration. Instead of using the measured motor current, one could easily use control-loop error instead, with certain caveats as noted in [15]. Finally, the use of the SSUKF for parameter estimation was chosen by our group for convenience, but other non-linear optimizers and formulations of models can also be used and would likely perform similarly.

IX. FUTURE WORK

Depending on the spring design and rubber materials, hysteresis, velocity dependence, and other non-linearities limit the accuracy of a simple linear model spring. The SSUKF and other filter frameworks can easily accommodate more complex models by expanding the state vector and measurement models. Moving forward, we plan to explore the use of more complex models for predicting the output torque of the model. For instance, including a viscous damping term with damping coefficient c in our dynamic equation helps account for velocity dependent effects

$$T = k\theta + c\dot{\theta}. \quad (12)$$

Additionally, higher-order physical models [18], non-physical models [19], and models that take into account environmental effects like temperature could be applied.

We are also working to implement this estimator efficiently in the firmware of each module. This will have the advantages that the estimator will have access to motor current and spring deflections at up to 1 kHz, and that the module will always have an accurate a self-calibrated torque during operation.

X. ACKNOWLEDGEMENTS

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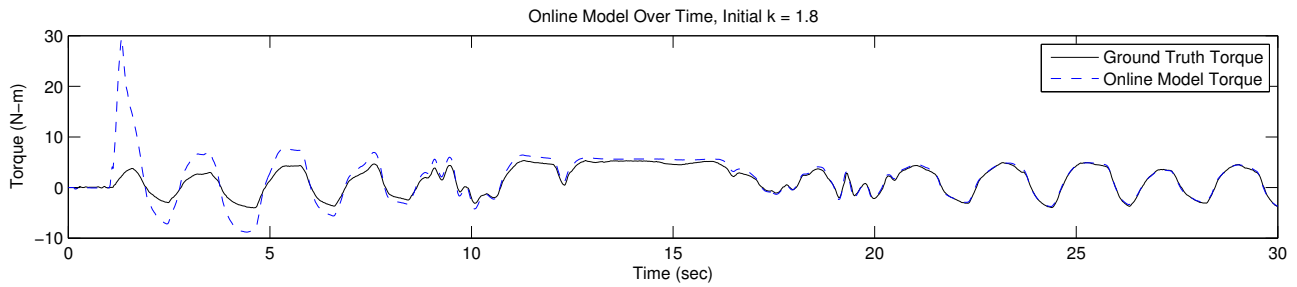


Fig. 9: The estimated torque based on the online linear model compared to the measured output torque of the module, given an initial spring constant that is off by a factor of 10.

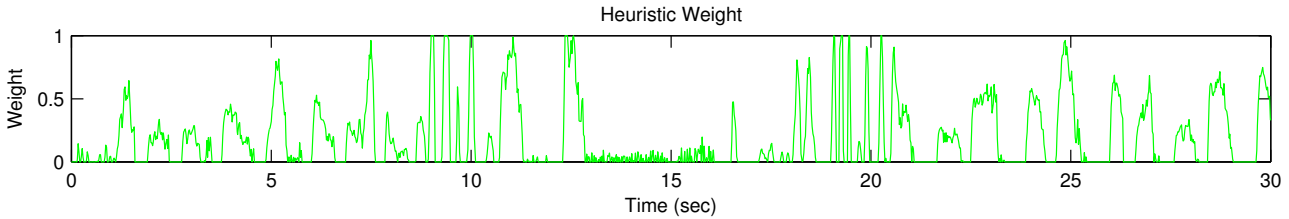


Fig. 10: The corresponding weighting factor for motor current measurements.

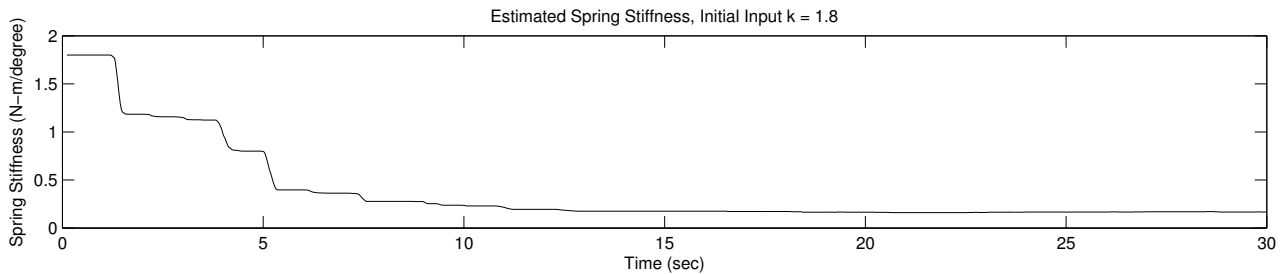


Fig. 11: The estimated spring constant over time, with a poor initialization. It quickly converges to an accurate value.

REFERENCES

- [1] G. Pratt and M. Williamson, "Series elastic actuators," *Proceedings 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems.*, pp. 399–406, 1995.
- [2] W. Lee, *Designing articulated legs for running machines*. PhD thesis, Massachusetts Institute of Technology, 1990.
- [3] D. W. Robinson, J. E. Pratt, D. J. Paluska, and G. A. Pratt, "Series elastic actuator development for a biomimetic walking robot," in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, (Atlanta, USA), 1999.
- [4] J. Hurst, D. Hobbelen, and A. Rizzi, "Series Elastic Actuation: Potential and Pitfalls," in *International Conference on Climbing and Walking Robots (CLAWAR)*, 2004.
- [5] J. W. Hurst, *The Role and Implementation of Compliance in Legged Locomotion*. PhD thesis, Carnegie Mellon University, 2008.
- [6] A. Seyfarth, H. Geyer, R. Blickhan, and S. Lipfert, "Running and walking with compliant legs," *Lecture Notes in Control and Information Sciences: Fast Motions in Biomechanics and Robotics*, vol. 340, pp. 383–401, 2006.
- [7] D. Rollinson, S. Ford, B. Brown, and H. Choset, "Design and Modeling of a Series Elastic Element for Snake Robots," in *ASME Dynamic Systems and Control Conference (DSCC) (accepted)*, (Palo Alto, USA), 2013.
- [8] S. Hirose, *Biologically Inspired Robots*. Oxford University Press, 1993.
- [9] C. Wright, A. Buchan, B. Brown, J. Geist, M. Schwerin, D. Rollinson, M. Tesch, and H. Choset, "Design and Architecture of the Unified Modular Snake Robot," in *IEEE International Conference on Robotics and Automation (ICRA)*, (St. Paul, USA), pp. 4347–4354, 2012.
- [10] B. Y. S. Hirose and H. Yamada, "Snake-Like Robots," *IEEE Robotics & Automation Magazine*, no. March, pp. 88–98, 2009.
- [11] M. Yim, W. Shen, and B. Salemi, "Modular self-reconfigurable robot systems," *Robotics & ...*, no. March, 2007.
- [12] P. Young, "Parameter estimation for continuous-time models: a survey," *Automatica*, vol. 17, no. 1, 1981.
- [13] E. Wan and R. V. D. Merwe, "The unscented Kalman filter for nonlinear estimation," in *IEEE Conference on Adaptive Systems for Signal Processing, Communications, and Control Symposium (AS-SPCC)*, (Lake Louise, Canada), pp. 153–158, 2000.
- [14] S. Julier, "The spherical simplex unscented transformation," *Proceedings of the 2003 American Control Conference*, 2003., pp. 2430–2434, 2003.
- [15] A. Stolt, M. Linderoth, A. Robertsson, and R. Johansson, "Force controlled robotic assembly without a force sensor," in *IEEE International Conference on Robotics and Automation (ICRA)*, (St. Paul, USA), pp. 1538–1543, IEEE, May 2012.
- [16] A. De Luca, A. Albu-Schaffer, S. Haddadin, and G. Hirzinger, "Collision Detection and Safe Reaction with the DLR-III Lightweight Manipulator Arm," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 1623–1630, Ieee, Oct. 2006.
- [17] A. N. Gent, "Engineering with Rubber: How to Design Rubber Components," in *Engineering with Rubber: How to Design Rubber Components*, ch. 3, Hanser Publications, 2nd ed., 2001.
- [18] F. Karlsson and A. Persson, *Modelling Non-Linear Dynamics of Rubber Bushings - Parameter Identification and Validation*. PhD thesis, Lund University, 2003.
- [19] M. Kikuchi and I. A. N. D. Aiken, "An Analytical Hysteresis Model for Elastomeric Seismic Isolation Bearings," *Earthquake Engineering and Structural Dynamics*, vol. 26, pp. 215–231, 1997.