Adaptive Parameter Estimation and Anomaly Detection while Cutting Insulation during Telerobotic Satellite Servicing

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***Abstract*— For satellite servicing, it is necessary to remove a patch of multi-layer insulation (MLI) that covers the access panel. We consider the case where this patch is secured by tape and desire to use ground-based teleoperation to carefully cut the tape on three sides of the patch. Communication delays of several seconds motivate the development of an online method to enable failure detection by the remote (on-orbit) robot system. This method is based on a model that predicts the force in the direction of cutting. The model parameters are provided by a recursive least squares estimator, with vector-like forgetting factors, that also includes a throttling mechanism to ensure that the estimator is used only when operating conditions and measurements enable reasonable outcomes. During cutting, the predicted force is compared to the measured force to detect various types of failures. Experiments are conducted on a ground-based platform to demonstrate that the proposed estimation system can reliably detect these failures.**

I. INTRODUCTION

NASA's Satellite Servicing Capabilities Office (SSCO) has been exploring technology to enable ground-based telerobotic servicing of satellites on-orbit [1]. One challenge is that delay in the video and telemetry feedback is on the order of seconds, which makes it difficult for an operator to stop an action when unexpected events occur before any damage takes place. In this paper, we consider the task of telerobotically cutting the tape that fastens the Multi-Layer Insulation (MLI) patch over the satellite access panel. Possible failure modes include bunching, tearing of the tape, slipping out of the tape seam, and blockage by hard surfaces or wires.

We assume the model-based telemanipulation approach described in our previous work [2], where the ground-based operator interacts with a local task model (simulation) and the remote robot uses sensor-based control to attempt to replicate the results of the simulation (a few seconds later) in the real environment. Thus, it is advantageous to implement a Task Monitor on the remote robot that can detect when it has failed to replicate the simulation. In this case, the remote system can abort the current action rather than waiting several seconds for the operator to observe and react to the failure. The Task Monitor is based on a previously-developed model of the expected force in the direction of cutting, which consists of a coefficient of kinetic (Coulomb) friction and a constant cutting force [3]. During cutting, the Task Monitor compares the measured force to the force predicted by the model and stops the task if the discrepancy is greater than a specified threshold (indicating a failure). One limitation of the prior work is that these two parameters were based on off-line experimental measurements and therefore do not consider variations in the material properties of the MLI (e.g., due to long-term exposure in space). This paper builds on that work by introducing an adaptive estimator that updates the model parameters during the task. This introduces several design challenges. One challenge is that there is a tradeoff between the responsiveness of the estimator and the ability to detect anomalies. For example, bunching of the tape causes a sudden increase in the measured force, but this should be detected as an anomaly and should not allow the estimator to adapt the parameters based on that measurement. A second challenge is that the two model parameters are not observable unless there is sufficient variability in the applied normal force.

Previous efforts have been made to accurately estimate interaction forces at the cutting interface. Most of the interaction force modelling techniques are developed under the context of machining operations (e.g., turning, milling). However, due to the fact that cutting and shearing processes with metal on metal contact are relatively uniform both at the interface as well as in material properties, modelling usually assumes constant geometric and material parameters which is not the case here. Cutting of biological materials with scissors has been modeled as a sequence of deformation and fracture phases, utilizing energy-based fracture mechanics [4], [5]. Others have used a more geometric approach to model the cutting force of scissors in general [6]. Needle insertion force during surgical procedures was estimated by a disturbance observer that estimated variations in friction force; a recursive least squares formulation converts this variation into changes in the friction parameters and hence obtains estimates of the force parameters [7].

The remainder of the sections are structured as follows. Section II introduces the task model and the adaptive estimator. Section III describes the experimental setup, which consists of a da Vinci master console and a Barrett Whole Arm Manipulator (WAM); further details can be found in [2], [3], [8]. This section also presents definitions and values for the various tunable estimator parameters. Section IV presents results followed by a discussion of their significance. Section V concludes the paper.

II. FORCE MODEL AND ADAPTIVE ESTIMATOR

Because the cutting phase of interest disregards the initial step of inserting the cutter into the tape, the force model is taken to be a simple linear model given by:

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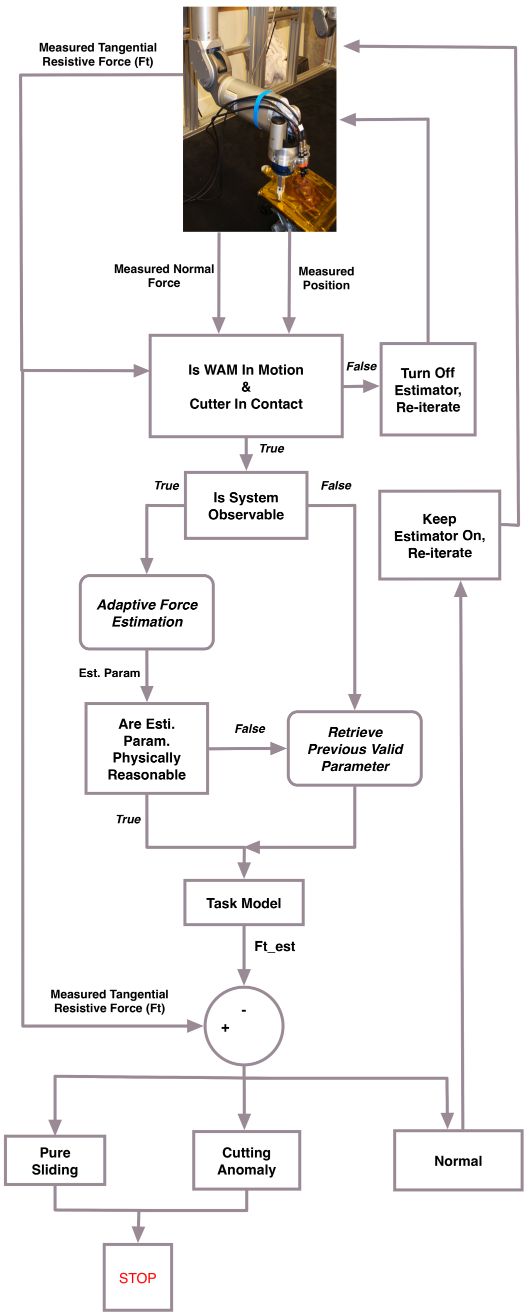

Fig. 1. Estimator Flowchart

$$F_t = \mu_k |F_n| + F_c \tag{1}$$

where F_t is the total tangential force in the direction of motion (cutting), μ_k is the coefficient of kinetic friction, F_n is the contact normal force, and F_c is the cutting force due to shearing of the tape (both are measured from the force sensor). Here we assume that the positive F_t and F_c direction opposes the manipulator's direction of motion (while cutting, F_t is always greater than zero). Previous experiments [3] have verified that this simple model can adequately predict the force, so we can avoid the use of a more complex model that would require an estimator of a higher dimension and greater computational resources to execute the estimator online. Maintaining an acceptable failure detection accuracy while minimizing the computational complexity is especially important for space hardware that is limited in its computing capabilities. We have taken the absolute value of F_n to account for the two cutting strategies (compression-based and tension-based) that were presented in [3]; the main difference between these strategies is the sign of F_n.

The goal is to design an adaptive estimator such that for given measurements $\boldsymbol{y} = [F_t, F_n]^T$, parameters $\boldsymbol{x} = [\mu_k, F_c]^T$ can be recursively updated (denote the estimated parameters as $\hat{\boldsymbol{x}} = [\hat{\mu}_k, \hat{F}_c]^T$) and that $\hat{\boldsymbol{x}}$ will adapt to small changes in the cutting environment (material properties, cutter contact conditions, etc.) but the estimated force given by $\hat{F}_t = \hat{\mu}_k F_n + \hat{F}_c$ will be significantly different from the measured F_t when a cutting abnormality occurs. This adaptive parameter update step can be illustrated by figure 2 below.

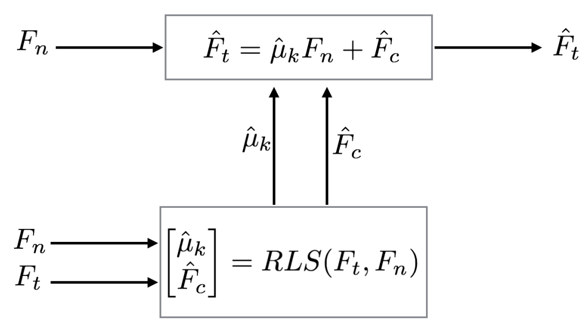

Fig. 2. Estimator Flowchart (note that variables with hat are those estimated and variables without hat are measured from the force sensor)

The proposed approach utilizes a Recursive Least Squares (RLS) Estimator with vector-like forgetting factors. The choice of an RLS estimator is based on the fact that a least squares estimator in its recursive form is the least computationally demanding. The vector-like forgetting factors enable us to individually adjust the variational rates of the parameters, as discussed below.

Equation 1 can be rewriten as

$$F_t = \begin{bmatrix} |F_n| & 1 \end{bmatrix} \begin{bmatrix} \mu_k \\ F_c \end{bmatrix} := H^T \boldsymbol{x} \tag{2}$$

Let P_k be the covariance of the estimated parameters. The adaptive estimation at step k can be formulated as (according to [9]):

$$K_k = P_{k-1} H_k (H_k^T P_{k-1} H_k + 1)^{-1} \tag{3}$$

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_{k-1} + K_k(\boldsymbol{y}_k - H_k^T \hat{\boldsymbol{x}}_{k-1}) \tag{4}$$

$$P_k = \Lambda^{-1}(I - K_k H_k^T) P_{k-1} \Lambda^{-1} \tag{5}$$

where $\Lambda = diag(\lambda_{\mu_k}, \lambda_{F_c})$ contains the forgetting factor for each parameter ($0 < \lambda_i < 1$). The smaller λ_i is, the more weight is put on recent data. By incorporating forgetting factors, the estimator can be controlled such that the coefficient of kinetic friction (μ_k) is updated taking into account more historic data and the cutting force (F_c) updated with more emphasis on recent data. This aligns with the expectation that if the material properties of the cutter and MLI do not change abruptly, μ_k should vary in a small range. Mild variations in the measured tangential force are likely due to varied cutting conditions, such as slight wrinkling of the tape, and generally do not indicate cutting failures. To handle cases like these, we choose a lower forgetting factor for F_c so that it can take more responsibility for adapting to the changes.

In addition to forgetting factors, the method checks situations where the estimator would give inaccurate results and employs throttling (i.e., disables the adaptation) to ensure reasonable outcomes, as shown in Fig. 1. The first situation is when the observability is low, which occurs when there is insufficient variation in the input vector $[|F_n| 1]^T$. This is more likely to occur when force control is used to maintain contact with the surface, as proposed in [2]. To find a measure for variation, a *Moving Window Least Squares* is imposed on the measured normal force and a line $F_n = at+b$ is fit to the data within each fixed size window. At time $t(n)$, the estimation is given by:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left[\sum_{i=n-w}^{n} u(i)u(i)^T \right]^{-1} \sum_{i=n-w}^{n} u(i)F_n(i) \quad (6)$$

Where $u(i) = [t(i), 1]^T$ and w is the window size. The slope of that line is used as a measure for variation. A threshold is then set on a and if $a(t) < threshold$ the adaptive estimator is turned off and failure identification is executed with the previous set of valid estimates. During our experiments, we also observed cases where the estimator produced negative $\hat{\mu}_c$ and/or $\hat{F}_c$; since these are physically unreasonable values, they are discarded and the previous valid estimates are used to compute the $\hat{F}_t$ that is used for failure detection.

III. Experiment and Estimator Setup

The experimental system consists of a da Vinci master console and a Barrett WAM. Data from nine users was collected with approval from the Johns Hopkins University Homewood Institutional Review Board (HIRB00000701). These users performed a number of trials, where each trial consisted of cutting through one vertical strip of tape as illustrated in Fig. 3 [10]. For some trials, the system controlled the normal force, F_n, whereas for other trials the operator had control over this direction and could apply any desired normal force. Video, joint encoder and force sensor data are recorded for analysis.

The goal of the estimator is to accurately identify cutting anomalies, which are separated into the following three categories: (1) cutter motion obstruction, (2) MLI tearing, and (3) cutter slippage (sliding without cutting). Figure 4 shows examples of these anomalies that were recorded during the experiments; note that MLI bunching and cutter sinking (Fig. 4 top right and bottom left) are box examples of cutter motion obstruction.

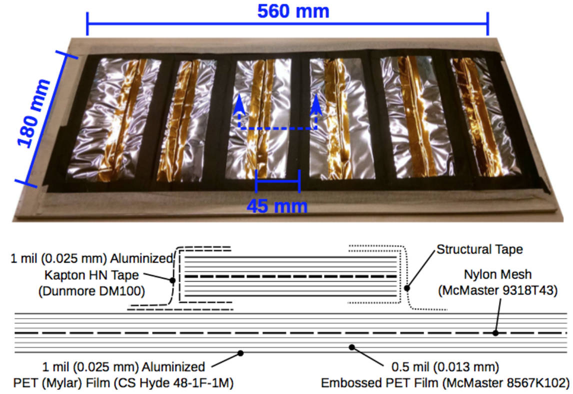

Fig. 3. Mock MLI Samples (image courtesy of Steve Vozar)

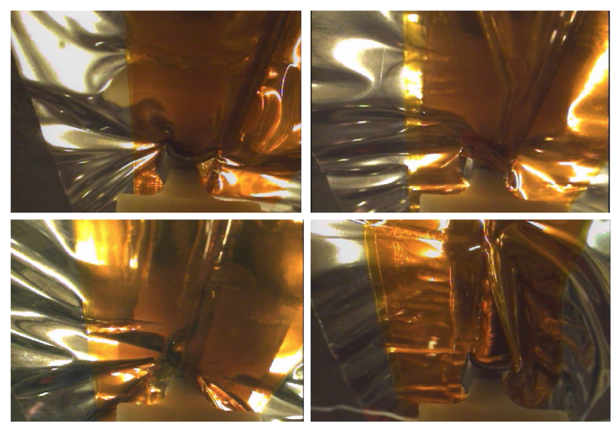

Fig. 4. Illustration of cutting anomalies (top left) normal cutting condition, (top right) MLI bunching, (bottom left) cutter sinking into MLI, (bottom right) MLI tearing

TABLE I
Evaluation Criteria for Cutting Anomaly Identification

	Evaluation Criteria
Cutter Motion Obstruction	$F_t > \hat{F}_t$ + threshold
MLI Tearing	$F_n > 0$ and $F_t < \hat{F}_t$ + threshold
Cutter Sliding Without Cutting	$F_n < 0$ and $F_t < \hat{F}_t$ + threshold

Table I lists the evaluation criteria for detecting each cutting anomaly. Recall that F_t is the measured force in the direction of cutting, F_n is the measured normal force (positive in compression and negative in tension), and $\hat{F}_t$ is the estimated force (in the direction of cutting). We define a false positive to be an identification of failure when there is no failure and a false negative to be the opposite. There are a number of parameters that must be set to achieve an acceptable tradeoff between false positives (indicating failure during normal cutting) and false negatives (not detecting a cutting failure). These parameters, and the values used for this experiment, are given in Table II. In this table, the same force threshold value was used for detecting cutter motion obstruction, MLI tearing, and cutter sliding, but in general these values could be different. The observability threshold and window size are used by the moving window least squares estimator that determines whether there is sufficient variation in the normal force to enable estimation of both parameters. The window size of 130 samples corresponds to 1.3 seconds. To avoid false positives due to the static friction at the start of each cutting motion, we define a motion threshold to indicate when the cutter is in motion (note that the operator often stops motion during the task, so this threshold is applied in any such case). Finally, when a failure occurs, the estimator is turned off and the previous valid estimate is used until the cutting condition becomes normal again.

TABLE II
ESTIMATOR PARAMETER VALUES

Est. Parameters	Value Used	Brief Description
Obstruction threshold	1.8 (N)	For detection of cutter motion obstruction
Tearing threshold	1.8 (N)	For detection of MLI tearing
Slippage threshold	1.8 (N)	For Detection of cutter sliding without cutting
Observability Threshold	0.30 (N/s)	Threshold placed on slope of the line fitted through a section of the most recent input signal F_n used to throttle the estimator at low observability level
Window Size	130	Number of samples in the moving window least squares estimator used for observability identification
Motion Threshold	0.001 (m/s)	Threshold on joint velocities used to identify if cutter is in motion
λ_{μ_k}	0.99	Forgetting factor for μ_k
λ_{F_c}	0.98	Forgetting factor for F_c

A graphical interface is implemented in ROS/rviz as panel plugins (see Fig. 5) to enable the user to monitor and interact with the estimator during the task. In addition to the video streamed from cameras mounted on the cutter (bottom left), the interface provides real-time plots that show (in order from top to bottom) the measured and estimated force in the direction of cutting, the measured normal force, the difference between the measured and estimated forces that is used to indicate cutting anomaly, and the variation in normal force that indicates the observability of the estimator. The dashed lines in the third and fourth plot are visualizations of the user-specified thresholds that determine the occurrences of cutting anomalies and the observability of the parameters, respectively. The value of these dashed lines can be controlled with the slidebars on the upper right of the interface. This feature enables the operator to tune the estimator during the task, for example to decrease the number of false positives or false negatives. The slidebar panel also enables tuning of other estimator parameters, such as the forgetting factors and the window size for the normal force least square estimator. The panel below the tuning slidebars shows a text representation of the estimator's evaluation of the current cutting condition, which can be NORMAL, BUNCHING, TEARING, or SlIDING.

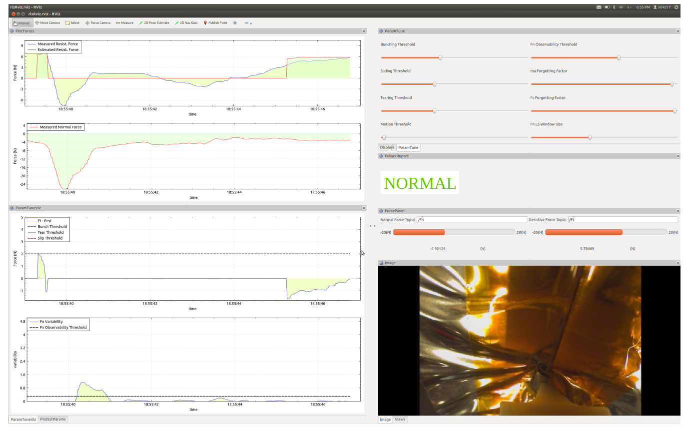

Fig. 5. Estimator User Interface

IV. RESULTS AND DISCUSSION

A total of 22 experimental trials are used to assess the performance of the estimator. Some trials included the force controller, which attempted to keep the normal force F_n at -3N, whereas other trials did not include force control. Figure 6 illustrates a sample outcome of the estimator. The first subplot shows the time series of the measured and estimated resistive force (i.e., force in direction of cutting). The bars that intermittently reach 10 Newtons are binary indicators that a cutting anomaly has occurred (which is also shown in the UI). The pictures at the top are sample screenshots of the video stream when specific failures occurred (in this case, two occurrences of tearing). The last three subplots show the measured normal force, the estimated coefficient of kinetic friction, and the estimated cutting force. The figure shows a clear strip-like pattern for these estimated values. This is the result of estimator throttling under situations including cutter at rest, cutter not in contact, low observability of the system, unreasonable estimated values as well as occurrences of cutting anomalies (as mentioned above). We can observe from the third and forth subplots that the estimated parameters start out with large variations but gradually stabilize over time indicating that, under normal cutting conditions, the coefficient of kinetic friction and the cutting force are relatively constant.

To further assess the effectiveness of this estimator, the recorded video from the 22 trials was visually analyzed to find occurrences of cutting anomalies. Table III compare the visually identified anomalies to the ones reported by the estimator. Note that since anomalies usually occur over a period of time, we consider that the estimator has detected the anomaly if it is reported within this time or within three seconds prior to the start of the visually identified failure. This takes into account the possibility that the failure may have started before there was a visual cue. It is seen that

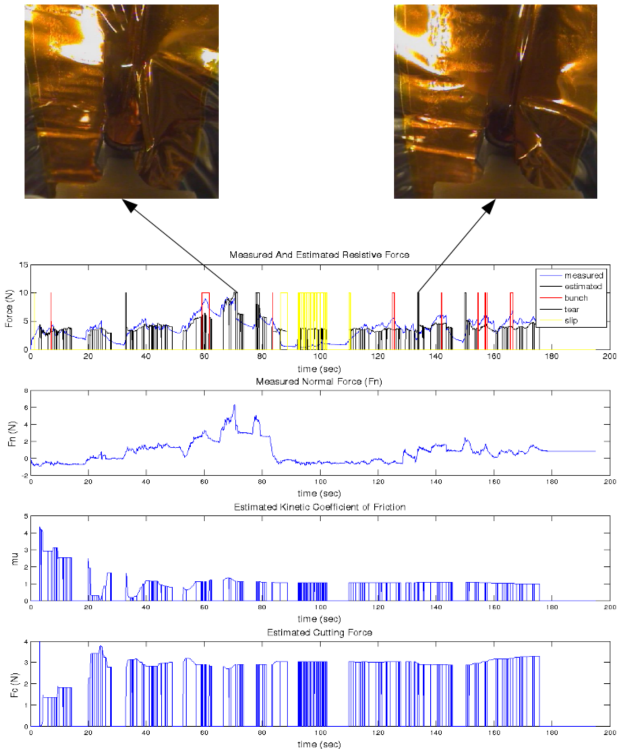

Fig. 6. Sample Estimator Output

the majority of visually identified anomalies are detected. Adding the false positives for all cases of cutting anomaly and dividing the result by the sum of all visually identified anomalies gives us a rate of 10% false positives. Doing the same results in a rate of 4% false negatives. Most importantly, we noted 17 cases in the video where the cutting motion was significantly obstructed and required the operator to perform a recovery action; all of these cases were reported by the Task Monitor.

TABLE III
ESTIMATOR PERFORMANCE

	Visually Identified	**False Positives**	**False Negatives**
Bunching	56	5	2
Tearing	21	2	1
Slipping	22	3	1

We have determined that two of the false negatives (one bunching and one tearing) occurred due to the motion threshold described in the previous section (which is used to determine when the cutter is moving). In those two cases, the actual motion of the cutter was so slow that the Task Monitor did not compute an estimated force. One solution may be to include static friction in the model, so that estimated forces can be computed even in these cases.

In addition, detection of failure relies on a sudden change in the measured force that results in a significant difference with the estimated force, due to the lag in the adaptive estimator that is updating the parameter values. There is the possibility that the bunched MLI accumulates gradually, which gives the estimator enough time to adapt to this abnormal condition without reporting an anomaly. This explains the bunching false negative. Because the tape and MLI is deformable and relatively ductile, the cutting interface is unpredictable and relying on a single threshold to detect failure is simple, but not the most reliable, which causes the majority of the false positives. However, there is also the possibility that failure may be happening underneath the surface and not be visible in the video; we have considered this to be a false positive, but further investigation is necessary to obtain a more thorough assessment.

Of the 22 recorded trials, 9 trials were conducted under force control. Fortunately (for this work), the force controller was not perfect and so 4 of those trials had sufficient normal force variation to enable adaptive parameter updates. The remaining 13 trials were performed without force control and therefore contained sufficient force variation. The cutting task completed without major failure in 6 of these trials. Tables IV and V present the steady state estimates of μ and F_c for the 4 force control trials with sufficient force variation and the 6 completed trials without force control. The values of these parameters show considerable variation (more than a factor of two between the minimum and maximum values). But, we note that it is possible for the estimator to trade off between changes to these parameters, especially if there is small variation in the normal force, F_n. We therefore normalize by comparing the estimated force in the direction of cutting at F_n = -3 (N), which corresponds to the desired force in the force control cases. Specifically, we compute $F_{t_{steady}} = -3(N) \times \mu_{steady} + F_{c_{steady}}$ and display the results in Tables IV and V. It can be seen that there is less variation in the steady-state value of F_t, which suggests that estimator did, in fact, trade off between μ and F_c. We are currently working to reduce this variation, but we note that our goal is to detect cutting anomalies, rather than to accurately estimate μ and F_c. Our results indicate that we can successfully detect most cutting anomalies even though the adaptive estimator may not always converge to the physically correct values of the parameters. As a point of comparison, our prior offline modeling [3], based on a large amount of collected data (though with a different type of MLI and tape), estimated μ to be 0.56 and F_c to be 4N, which are both within the range of the values presented in Tables IV and V.

TABLE IV
ESTIMATION RESULTS FOR TRIALS WITH FORCE CONTROL

μ_{steady}	$F_{c_{steady}}$	$F_{t_{steady}}$
0.27	6.0	6.81
0.26	5.2	5.98
0.79	3.8	6.17
0.78	2.4	4.74

V. CONCLUSIONS

An online adaptive estimation system is proposed to estimate the model parameters used by a task monitor that is designed to detect tape cutting failures during telerobotic satellite servicing. This estimator is formulated as a recursive

TABLE V

ESTIMATION RESULTS FOR TRIALS WITHOUT FORCE CONTROL

μ_{steady}	$F_{c_{steady}}$	$F_{t_{steady}}$
0.3	5.4	6.3
0.72	2.0	4.16
0.45	3.5	4.85
0.60	6.1	7.90
0.70	4.4	6.5
0.62	4.0	5.86

least squares with vector-like forgetting factors. Efforts have been made to identify situations when the adaptive estimator is not valid, which includes cutter not in motion, cutter not in contact, and low observability due to insufficient variation in normal force. Under these circumstances, the adaptive estimator is throttled and the task monitor uses the previous valid parameter estimates for failure detection. This throttling process is important to ensure steady performance of the estimator. We have shown through a number of experiments that the estimator is able to detect failures with an acceptable accuracy and performs consistently across different trials of the same experiment. For future work, finding an optimal set of the tunable estimator parameters (and/or a systematic way of tuning the parameters) is crucial for improving the estimator's accuracy. In addition, we currently cannot consistently estimate the parameters when force control is active; this suggests that we may wish to intentionally introduce occasional variations in the applied force.

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