

Online Contact Impedance Identification for Robotic Systems

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Abstract—In this paper, we study the performance of various algorithms for fast online identification of environment impedance during robotic contact tasks. In particular, we evaluate and compare algorithms with regard to their convergence rate, computational complexity and sensitivity to noise for different environments using a single degree-of-freedom experimental setup. The results provide some guidelines for choosing an appropriate identification algorithm for a specific application.

I. INTRODUCTION

Robotic tasks often contain constant or intermittent physical contacts with different environments and the availability of an accurate description of contact dynamics is necessary in contact control problems. For instance, environment parameter estimation has been used in the design of indirect adaptive impedance controllers [2], [3] or model reference adaptive controllers [4]. Online identified environment impedance has also been used for transparency in teleoperation systems [1], [5] or the identified range of the environment can be used to analyze robust stability of teleoperation systems [6].

In situations where environment estimation is used in an adaptive controller, in addition to performance degradation, instability could also result in the absence of accurate and fast estimation [3], [5], [7]. These problems are more severe when environment displays sudden changes in its dynamic parameters which cannot be tracked by the identification process. For instance, it was found in [5] that in order to faithfully convey to the operator the sense of high frequency chattering of contact between the slave and hard objects, faster identification and structurally modified methods were required.

The identification methods that are widely used for environment estimation are mainly limited to *Recursive Least Squares* (RLS) and *Exponentially Weighted Recursive Least Squares* (EWRLS) [7], [8], [9], [11], or Lyapunov-based methods [2], [7] which do not have the ability to rapidly estimate the parameters in the presence of *abrupt changes*. Considerable effort has been put towards the development of modified versions of RLS for tracking abrupt changes in system dynamic parameters. *Block Least Squares* (BLS) has also been shown to be fast in the presence of abrupt changes in parameters [15]. Among these Covariance Resetting and Self-Perturbing are the most common methods [10], [11].

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Steepest Descent (SD) optimization method has also been used to update the online estimated parameters with the goal of minimizing Mean Square Error (MSE) cost function [12], [13]. These methods show faster initial convergence rates as reported in [13]. Cost functions with high powers have been reported to have faster convergence rate since the sudden large errors are significantly magnified resulting in the optimization algorithm to spend more effort to reduce the corresponding error. Recently an optimal *Block Least Mean Fourth* (BLMF) parameter estimation method has been proposed and its superiority has been compared to a similar method with second-order cost function, *i.e.* *Block Least Mean Square* (BLMS) [14].

In this paper, the problem of fast online parameter identification, in the presence of abrupt changes in the environment dynamics is addressed. We will implement and evaluate four different identification methods for their convergence rate, computational complexity and sensitivity to noise in various contacts. The paper is organized as follows: in Section II fast identification methods are presented and discussed. Section III describes the experimental setup and data collection. The results of experiments on different environments is then presented in IV. Implementation challenges are discussed in Section V. Section VI draws conclusions and lays out the future work.

II. ENVIRONMENT IDENTIFICATION METHODS

A. Environment Model

Different models have been proposed in order to provide a continuous representation of the contact phenomenon at microscopic and macroscopic levels [8]. The simplest and the most common model that we use throughout this paper is the Kelvin-Voigt linear model, which is the dynamics of a linear damper-spring system

$$F(t) = \begin{cases} Kx(t) + B\dot{x}(t) & x(t) \geq 0 \\ 0 & x(t) < 0 \end{cases} \quad (1)$$

where $x(t)$ represents penetration in the environment, K the environment stiffness and B the environment damping.

In discrete domain, the environment dynamics can be written as

$$F_k = \phi_k^T \theta_k + n_k, \quad \forall x_k > 0 \quad (2)$$

where the subscript k denotes the time instant, $\phi_k^T = [x_k \ v_k]$ the regressor vector, $\theta_k = [K_k \ B_k]^T$ the vector of dynamic parameters, n_k the modeling error and measurement noise,

x_k the penetration at sample time $t = k.T$ and v_k the contact velocity computed from

$$v_k = \dot{x}_k = L\left(\frac{x_k - x_{k-1}}{T}\right). \quad (3)$$

Here, the parameter T is the sampling period and $L(\cdot)$ is a low-pass filter operator.

B. Least Squares Based Methods

Variations of the Least Squares method are based on the block-wise MSE cost function

$$J[\hat{\theta}_k] = \frac{1}{2} \sum_{j=k-W+1}^k \lambda^{k-j} [y_j - \phi_j^T \hat{\theta}_k]^2, \quad (4)$$

where W is the data window length considered in each method and λ is the forgetting factor which satisfying $0 < \lambda \leq 1$. Obviously, small values for λ puts greater emphasis on recent data.

B1. Exponentially Weighted Recursive Least Squares (EWRLS)

EWRLS estimation method has been widely employed for environment estimation applications in robotic systems. This method is particularly used for tracking gradual changes in system parameters. Therefore, EWRLS has been selected as a benchmark method for evaluation in this paper. EWRLS update equations can be written as follows

$$\begin{aligned} \mathbf{L}_{k+1} &= \frac{\mathbf{P}_k \phi_{k+1}}{\lambda + \phi_{k+1}^T \mathbf{P}_k \phi_{k+1}} \\ \mathbf{P}_{k+1} &= \frac{1}{\lambda} [\mathbf{P}_k - \mathbf{L}_{k+1} \phi_{k+1}^T \mathbf{P}_k] \\ \hat{\theta}_{k+1} &= \hat{\theta}_k + \mathbf{L}_{k+1} [F_{k+1} - \phi_{k+1}^T \hat{\theta}_k] \end{aligned}$$

where \mathbf{P}_k is the covariance matrix at time instant k . For $\lambda = 1$, EWRLS and regular RLS methods are identical.

B2. Self Perturbing Recursive Least Squares (SPRLS)

In the regular RLS method, once the estimated parameters converge, the covariance matrix \mathbf{P} reaches a small value and thus the matrix \mathbf{L} diminishes. Therefore, the parameter estimates $\hat{\theta}$ do not track any changes. A few algorithms have been proposed in order to overcome this problem by modifying the covariance matrix update law. One of these methods is Self-Perturbing Recursive Least Squares (SPRLS) [10].

In SPRLS, the adaptation gain is automatically adjusted through perturbations imposed by the estimation error on the covariance update dynamics

$$\mathbf{P}_{k+1} = \mathbf{P}_k - \mathbf{L}_{k+1} \phi_{k+1}^T \mathbf{P}_k + \beta \text{NINT}(\gamma e_{k-1}^2) \mathbf{I}$$

where $e_{k-1} := F_k - \phi_k^T \hat{\theta}_{k-1}$ and \mathbf{I} is an identity matrix of the same size of the matrix \mathbf{P} . Therefore, whenever an abrupt change occurs and error increases, the adaptation gain increases automatically. Here **NINT** is a roundoff operator, and β and γ are design constants that can be adjusted according to the system measurement noise. The

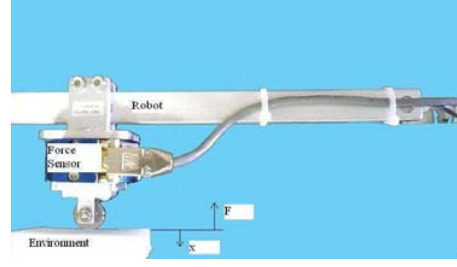


Fig. 1. Experimental Setup

function **NINT**(\cdot) grounds the self-perturbing term when $\gamma e_{k-1}^2 < 0.5$, thus implementing regular RLS algorithm. Therefore, parameter γ controls the minimum error band for the self-perturbing action, and thus in effect it determines a dead zone for noise rejection.

B3. Block Least Squares (BLS)

Block Least Squares (BLS) identification method, applies batch LS to a floating window of data at each sample time. With the recent advancements in computing technology, the computational complexity of BLS has become less and less an issue for real-time applications.

The key to tracking time-varying parameters is the use of some type of forgetting techniques to discard old data. By changing the size of window we can easily discard any number of data points that we need in the case of parameter changes. Therefore, theoretically the method can be as fast as we want. However, in practice lower window size increases sensitivity to measurement noise. In addition, the input signal must be rich enough in the period of the short window length. By defining regressor matrix and force vector for W observations as:

$$\Phi_k = \begin{pmatrix} \phi_k^T \\ \phi_{k-1}^T \\ \vdots \\ \phi_{k-W+1}^T \end{pmatrix}, \quad \mathbf{F}_k = \begin{pmatrix} F_k \\ F_{k-1} \\ \vdots \\ F_{k-W+1} \end{pmatrix} \quad (5)$$

the BLS update equation can be written as

$$\hat{\theta}_k = [\Phi_k^T \Phi_k]^{-1} \Phi_k^T \mathbf{F}_k. \quad (6)$$

C. Steepest Descent Based Methods

In the identification methods based on Steepest Descent (SD) optimization technique, the parameter estimates are updated according to the incremental rule

$$\hat{\theta}_{k+1} = \hat{\theta}_k + \lambda_k \mathbf{u}_k, \quad (7)$$

where λ_k is the correcting gain, and \mathbf{u}_k is a unit vector in the opposite direction of gradient of the cost function, i.e.

$$\mathbf{u}_k = -\frac{\mathbf{g}_k}{\|\mathbf{g}_k\|}. \quad (8)$$

The optimum parameter λ_k is found such that the cost function of interest is minimized.

C1. Block Least Mean Fourth (BLMF)

For block-wise MSE cost function, there exists a closed-form solution for λ_k . However, as mentioned before, higher order cost functions set higher cost on error caused by abrupt changes in system dynamic parameters; thus, they tend to spend more effort in faster reduction of the error. In general, there is no closed-form solution for the general problem of Least Mean Pth Error (MPE) and thus numerical optimization or constant values for λ_k have been used for various applications [17]. However, an *optimal* and analytical closed-form solution has been found in [14] for Block Least Mean Fourth (BLMF) problem with the block-wise LMF cost function

$$J_k = \frac{1}{4} \sum_{j=k-W+1}^k [y_j - \phi_j^T \hat{\theta}_k]^4, \quad (9)$$

As shown in [14], there exists one and only one real λ_k satisfying the following 3rd-order algebraic equation

$$A_k \lambda_k^3 + B_k \lambda_k^2 + C_k \lambda_k + D_k = 0, \quad (10)$$

where the coefficients are derived from

$$A_k = \sum_{j=k-W+1}^k (\phi_j^T \mathbf{u}_k)^4 \quad (11)$$

$$B_k = -3 \sum_{j=k-W+1}^k (\phi_j^T \mathbf{u}_k)^3 (y_j - \phi_j^T \hat{\theta}_k) \quad (12)$$

$$C_k = 3 \sum_{j=k-W+1}^k (\phi_j^T \mathbf{u}_k)^2 (y_j - \phi_j^T \hat{\theta}_k)^2 \quad (13)$$

$$D_k = - \sum_{j=k-W+1}^k (\phi_j^T \mathbf{u}_k) (y_j - \phi_j^T \hat{\theta}_k)^3 = -\|\mathbf{g}_k\|. \quad (14)$$

The scaling factor can be obtained by solving (10) numerically using optimization or from or explicitly as described in [14]. A rigorous proof of uniqueness of λ_k can also be found in the same reference.

III. EXPERIMENTAL SETUP AND PROCEDURE

A. Experimental Setup

The performance of the above four impedance identification methods are evaluated with three different environments using a single degree-of-freedom experimental test bed as shown in Figure 1. The test bed consists of a DC motor connected to an aluminum bar via a cable mechanism with ratio of 4:1. A JR3 wrist force sensor is mounted on the bar and its location along the bar can be adjusted. The resolution of the motor encoder is 4096 PPR, which maps to 0.08 degree. Considering the transmission ratio and the length of the bar, the resolution of the linear penetration of the end-effector tool (poking device) is 0.1 mm. The resolution of force sensing with a 14 bit D/A converter is 0.05 N. The control system was implemented at the rate of 1KHz and the collected data was down sampled by a factor of 10.

The three different environments that were used for the experiments were sponge, bubble-wrap sheet and a hard plastic foam representing soft contact, soft contact with varying impedance, and medium contact.

B. Inputs to the System - Persistency of Excitation

The above-mentioned manipulator arm is commanded to follow the desired reference trajectory

$$x_d(t) = f(t) + a \sin(20\pi t), \quad (15)$$

where $f(t)$ is a periodic function of square pulses smoothed by low-pass filters, which has been designed to establish intermittent contact between the arm and the environment. Since the number of parameters to estimate is two, a minimum of one sinusoidal excitation is enough for true estimation of the system parameters as long as the environment dynamics can be approximated by a first-order linear system [16]. As we use block windows of data, the frequency of excitation (in our case 10 Hz) should be high enough to make sure that the block of data is rich enough considering the sampling period and the block length. The scaling factor a is chosen to have non-zero velocity in soft and moderate environments, needed to identify damping of the environment. The amount of penetration and the amplitude of oscillations depend on the stiffness of the environments. For the medium contact, the end-effector is not able to penetrate into the body. Therefore, only stiffness which is in fact the dominant component of the environment impedance can be estimated.

IV. EXPERIMENTAL RESULTS

The performance of the four online identification methods for three different environments are evaluated and compared, on a 3.2 GHz Pentium IV computer using MATLAB.

A. Soft Contact

Figure 2 shows the actual position, velocity and force profiles of the manipulator arm for the experiment with soft environment, in which positive position implies contact penetration. Once the end-effector makes contact with the environment, impact forces that are built up at contact push the end-effector off the contact. Afterwards, a long-term contact is made until the robot is commanded to disconnect at $t = 30$ s. The oscillations in position and especially in force after contact are due to the high frequency sinusoidal position input. In this experiment and all future ones, the identification algorithms are performed only when the measured contact force is non-zero, that is when the end-effector is in contact. At other times the stiffness and damping estimates are reset to zero.

Figure 3 shows the estimated stiffness and prediction error of the four algorithms for soft contact. Estimated damping for soft contact as well as soft contact with time varying impedance, which will be discussed in IV-B, are shown in Figure 4. A window length of 300 is considered for the block of data. For EWRLS a forgetting factor $\lambda = 0.9967$ was chosen, which tends to put substantial weight on the past $1/(1 - \lambda) = 300$ samples. The results show that EWRLS has much slower convergence rate compared to the other methods. This is due to the fact that the estimation is incremental and that all past data contribute to the current estimate algorithm, which makes it slower than the BLS

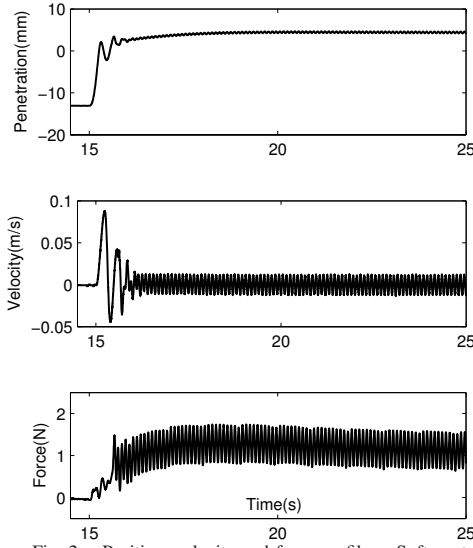


Fig. 2. Position, velocity and force profiles - Soft contact.

method that uses only a specific number of data points. Thus, if the sliding window with length 200 samples covers the data points after the change, the old data that includes the change do not have any effect on the identification result. This is one of the reasons of fast convergence rate in BLS method.

The fast convergence rate of BLMF method is the result of using higher power for the prediction error e_k in the cost function. Therefore, after a sudden change, a higher effort is spent to minimize the cost function. It is important to note that although a window of data is used to derive the correcting gain in BLMF, the effect of old data is not zero, as seen in equation (7) where θ_{k+1} is derived iteratively from θ_k . Therefore older data points indirectly affect current estimates.

The SPRLS method with $\beta = 100$ and $\gamma = 2$, that are chosen for both fast convergence and robustness to noise, shows relatively faster response to the abrupt changes compared to EWRLS. This is because of the effect of higher gain in the identification process resulting from external perturbations in the covariance matrix as sudden jumps happen. The estimation gain approaches a small value in EWRLS method, once the parameters converge to a value. Therefore, as expected from the above analysis and verified by experiments, BLS and BLMF show the fastest convergence rates. For large window sizes, e.g. over 300 (not shown in figures), BLS convergence rate reduces significantly, since more data points collected before parameter change are included in the identification process, which have no information of the parameter variations.

B. Soft Contact with Time-Varying Impedance (TVI)

The environment chosen for this section is a bubble-wrap sheet, which is a soft object with an impedance that changes with time after compression, due to the deflation of the bubbles. This effect can be seen in Figure 5, where the amount of contact force is larger at the beginning and

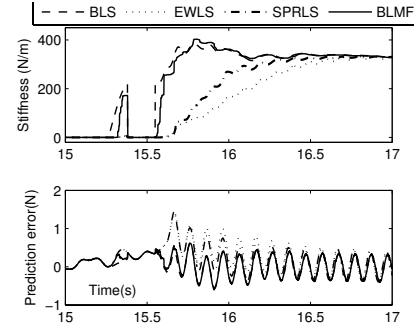


Fig. 3. Estimated stiffness and prediction error using four identification methods - Soft contact.

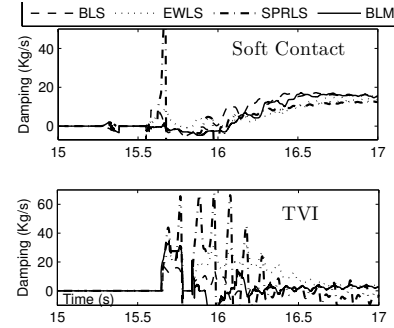


Fig. 4. Estimated damping for soft contact and soft contact with time-varying impedance (TVI).

subsidies later on for almost constant contact position and velocity. The identification methods verify this effect in Figure 6, where the contact stiffness gradually reduces during contact. Figure 7 provides a detailed view of the estimated stiffness for a short duration of time around the contact time. In this Figure BLS and BLMF are responsive and capture initial high stiffness of the object with extra overshoot. The estimated damping for this type of the environment is shown in Figure 4. The two recursive methods almost miss the high stiffness period and converge in over 1 second.

C. Medium Contact

Figure 8 shows the position, velocity and force profiles for medium contact. Since penetration into the environment is significantly resisted, the force actuated manipulator cannot faithfully track the desired position trajectory. As a result the end-effector velocity is substantially reduced to almost zero as shown in Figure 8. Thus the velocity profile is not rich enough to allow proper estimation of damping. This may not

TABLE I
RMSE% FOR DIFFERENT ENVIRONMENTS (W=300)

Method	Soft	Soft - TVI	Medium
BLS	9.27	5.97	2.79
BLMF	8.99	8.315	1.72
SPRLS	16.02	18.04	4.24
EWLS	12.96	15.33	6.29

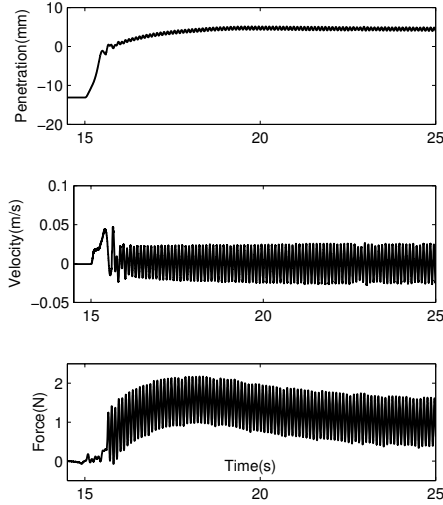


Fig. 5. Position, velocity and force profile - Soft contact with time-varying impedance.

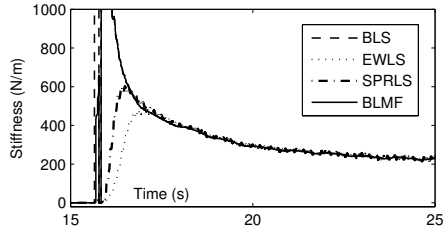


Fig. 6. Estimated stiffness - Soft contact with time-varying impedance (view of full contact interval).

create any severe problem as the impedance of the harder objects can be dominated by stiffness. Figure 9 illustrates the results of identification methods for stiffness and the prediction error. In this case, the amount of sudden jump in environment dynamics is significantly higher than that of the previous cases. Therefore, EWRLS converges much slower than the other methods. As before, BLMF and BLS show much faster convergence rate even compared to SPRLS.

Table I compares the the percent root-mean-square of prediction error (RMSE%) resulted from different identification methods for different environments. In order to make the analysis independent of experiment conditions, all table entries present the average of RMSE% for 5 different trials. This table shows that BLS and BLMF methods predict contact force with more accuracy than SPRLS and EWRLS. This result is also expected from much faster convergence rate of BLS and BLMF as can be seen in Figures 3, 7 and 9. On the other hand, although EWRLS seems to be slower than SPRLS in all cases, it shows lower average RMSE% for both soft contacts. One reason for this discrepancy is that the RMSE% is also affected by identified damping as well.

V. IMPLEMENTATION CONSIDERATIONS

In this section, the effect of window size on convergence rate, sensitivity to noise and computational complexity for the window-based methods BLS and BLMF are investigated. As increase in forgetting factor in EWRLS puts more

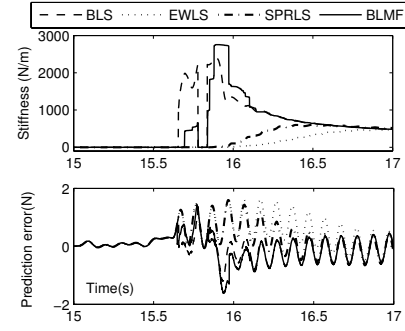


Fig. 7. Estimated stiffness and force prediction error - Soft contact with time-varying impedance.

weight on larger number of sample points, EWRLS can also be viewed as a method with variable window. Therefore, EWRLS is also used as a benchmark for comparison.

A. Convergence Rate and Sensitivity to Noise

Figure 10 shows the estimated stiffness and the force prediction error using the BLS method with window sizes 50 and 300. It is clear that the smaller the window length (W), the more sensitive the BLS method is to noise. On the other hand as shown in Figure 11, the BLMF method is more robust to noise than BLS method, especially for small window sizes. Theoretically, due to the incremental change in its estimates in (7), BLMF unlike BLS, takes into account the old data rather than just a window of data, which makes it more robust to noise.

In terms of force prediction accuracy, Table II shows RMSE% for BLS and BLMF methods in soft contact for two different window lengths. The values of the table are the average RMSE% from 5 different trials. RMSE% is measured from the beginning of the identification process and thus it is expected to be affected by convergence rate and noise. From Figures 10 and 11 the convergence rates almost remains flat; as a result, the slightly higher RMSE% for both BLS and BLMF in Table II after reduction in window size can be attributed to the increased effect of noise.

For the EWRLS method, an increase in forgetting factor to 0.98 causes higher weight on the past 50 data points than the past 300 (i.e. practically equivalent to reduction in window size). This reduction in window size in EWRLS, as shown in Figure 12, has significant effect on increasing its convergence rate, while demonstrating more robustness to noise than BLS and BLMF. This higher robustness to noise in EWRLS is due to the fact that the exponential weights of data points are not zero outside of the window of 50. Therefore, old data points still have some effect on estimation, which causes higher robustness to noise at the cost of lower convergence rate compared to other methods.

Table II shows that RMSE% for EWRLS, as opposed to BLS and BLMF, increases when its window length increases. To explain the cause of this difference in behavior, a better understanding of the effect of noise for various window sizes and identification methods is needed. Table III compares

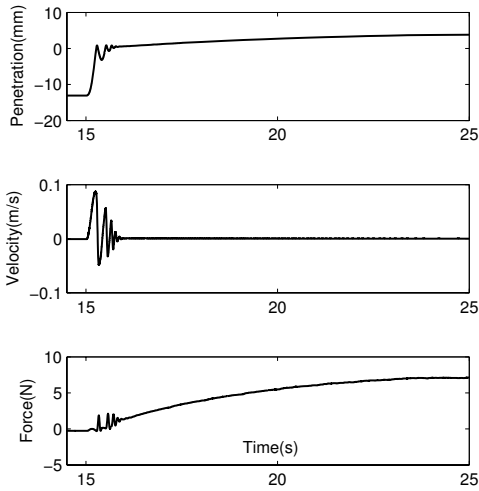


Fig. 8. Position, velocity and force profile profile - Medium contact.

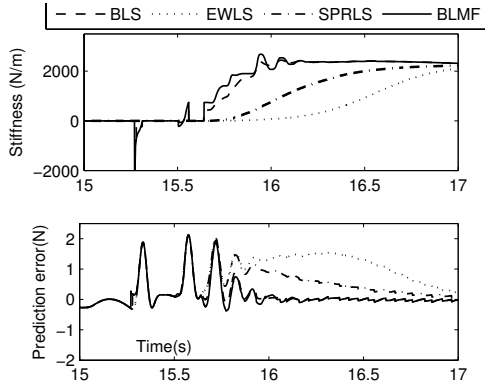


Fig. 9. Stiffness and force prediction error - Medium contact.

the standard deviation (STD) of parameter θ_1 for different methods in different window sizes, when the environment is soft. STD is measured after the parameter converges to the 90% of its final value. This table shows that increasing the window size decreases the effect of noise, at different rates for different methods. This result along with Figure 12 reveals that the decrease in RMSE% for EWRLS with decreasing window length in Table II, is due to the fact that the effect of increase in convergence rate is more apparent than that of increase in noise effect for EWRLS method. It can also be seen from Table III that BLMF is slightly more robust to noise than BLS method for smaller window size; yet similar for large window sizes.

B. Computational Complexity and Real-Time Implementation

The main drawback of block-wise methods is their computational load. The computational complexity of the BLS method is in the order of $\max(P^3, kP^2)$, where P is the number of parameters and k is the number of measurement

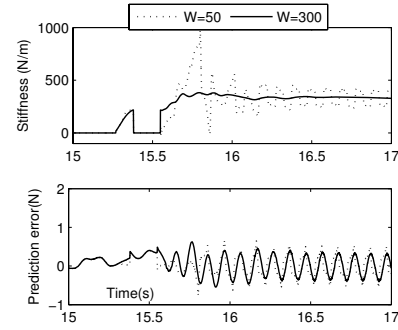


Fig. 10. Estimated stiffness and prediction error using BLS with different window lengths - Soft contact.

TABLE II
EFFECT OF WINDOW SIZE: RMSE% FOR SOFT CONTACT IDENTIFICATION

Method	W=50	W=300
BLS	10.10	9.27
BLMF	10.32	9.35
EWRLS	11.49	13.14

points [15]. It is clear that the computational load grows continuously with the number of measurement. Due to its recursive nature, the computational load of EWRLS is only in the order of $O(P^2)$. Computational complexity of BLMF is higher than that of the BLS method, due to the heavy computations involved in finding the coefficients of the cubic polynomial in 10. However, with the advancements in computer technologies, the computational complexity of block-wise methods becomes less and less an issue real-time applications.

Table IV shows the elapsed time for a single iteration of soft contact identification, which is an indication of the minimum possible sampling time for BLS, BLMF and EWRLS to identify a system of 2 parameters, on a 3.2 GHz Pentium IV computer using MATLAB. All the experiments are performed with the same computer for window sizes of 10 and 300 for BLS and BLMF methods in order to study the effect of window size on the computational load. It can be seen from Table IV that BLMF has the highest computational complexity. The highest sampling frequency for the BLMF method with $W = 10$ is about 2.4 KHz and 200 Hz for $W = 300$. For BLS method the maximum sampling frequency is about 4.2 KHz and 2.5 KHz for $W = 10$ and $W = 300$, respectively, and for EWRLS the maximum sampling frequency can go up to 5 KHz. Therefore, in practical applications, BLMF can only be used when lower sampling frequency is acceptable or when shorter window size can be selected.

VI. CONCLUSIONS

This paper experimentally evaluated and compared the performance of three fast online least squares-based and steepest descent-based identification methods (SPRLS, BLS,

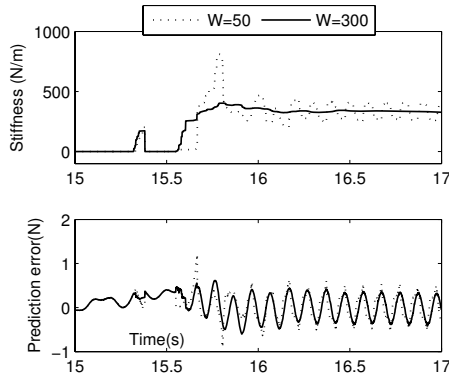


Fig. 11. Estimated stiffness and prediction error using BLMF with different window lengths - Soft contact.

TABLE III

EFFECT OF WINDOW SIZE: STANDARD DEVIATION (STD) OF θ_1 FOR SOFT CONTACT IDENTIFICATION.

Method	W=50	W=300
BLS	28.38	8.92
BLMF	25.01	8.91
EWRLS	11.2	6.00

BLMF) with a benchmark method (EWRLS) commonly used for the identification of environments with varying dynamic parameters. The results of a number of intermittent contact experiments with different environments revealed that EWRLS has the slowest convergence rate (over 1 sec) and BLS as well as BLMF resulted in the lowest average RMSE%. Although SPRLS shows faster convergence rate (over 0.5 sec) and is more robust to noise than EWRLS, it is not as fast as BLS and BLMF methods with their quick initial rise time and less than 300 ms of convergence rate for window size 300. The BLS method is very sensitive to noise for small window size of 50. Compared to BLS, BLMF shows more robustness even with smaller window size and displays almost the same convergence rate for the same window size. The experiment and analysis shows that BLMF has the highest computational complexity, which grows drastically with increase in window size. Therefore, for real-time implementations, BLMF is more suitable for small window sizes if the effect of noise remains small; or for applications where high sampling rate is not necessary. Future work will aim towards the generalization of the above online techniques to other dynamic models of environment and incorporation of the above identification techniques in adaptive control of robotic systems.

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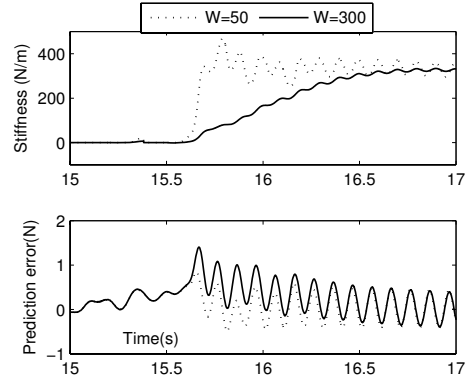


Fig. 12. Estimated stiffness and prediction error using EWRLS with different window lengths - Soft contact.

TABLE IV

EFFECT OF WINDOW SIZE: MINIMUM SAMPLING TIME (ms.).

Method	W=10	W=300
BLS	0.24	0.40
BLMF	0.41	4.92
EWRLS	0.21	0.21

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