BANG-BANG CONTROL OF SERVO-HYDRAULIC TESTING MACHINES USING LEARNING TECHNIQUES

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Abstract— For a given material resistance and magnitudes of alternate and mean stresses, the fatigue life depends essentially on the number of applied load cycles on the tested material. For this reason, working with a materials testing machine at high frequencies brings advantages of time and cost reduction, without altering the results. To achieve such frequencies, it is necessary to use an efficient control system. The present work shows learning control techniques developed and implemented in a materials testing machine, allowing the application of constant or variable amplitude loads at high frequencies. The proposed methodology consists of implementing a bang-bang type control to restrict the system servo-valve to permanently work at its extreme limits of operation, always completely opened in either direction. As the servo-valve works at its operating limits, the learning algorithm tries to obtain the optimal instants for the valve reversions, associating them to a non-dimensional variable, stored in a specific table. The table values are constantly updated for the learning law during the test execution, improving the system response. The experimental validation of this method is performed with a 100kN servo-hydraulic testing machine. A control system is especially developed to operate the machine, with real time control software implemented in a CompactRIO computational system. The experimental results show that the test frequency can be significantly increased with the proposed learning control technique.

Keywords— frequency increase, learning control, bang-bang control, servo-hydraulic system.

Resumo— A vida à fadiga para uma dada resistência de material e magnitudes de cargas médias e alternadas depende essencialmente do número de ciclos de carregamentos aplicados ao material testado. Por este motivo, trabalhar com uma máquina de ensaios de fadiga a altas frequências traz a vantagem de reduzir o tempo e custo do ensaio, sem a alteração dos resultados. Para atingir tais frequências é necessário um sistema de controle eficiente. O presente trabalho apresenta técnicas de controle por aprendizado desenvolvidas e aplicadas em máquinas de ensaios de materiais, permitindo a aplicação de carregamentos de amplitude variável ou constante a altas frequências. A metodologia proposta consiste na aplicação de um sistema de controle do tipo bang-bang que restrinja a servo-válvula a trabalhar em seus limites extremos de operação. O algoritmo de aprendizado irá obter os instantes ótimos de reversão da válvula, associando-os a variáveis adimensionais, armazenadas em uma tabela específica. Os valores da tabela são constantemente atualizados mediante as leis de aprendizado durante o teste, melhorando a resposta do sistema. A validação experimental deste método é feita em uma máquina servo-hidráulica de ensaios com capacidade de 100 kN. O sistema de controle é especialmente desenvolvido para operar a máquina, com um software de controle em tempo real implementado em um sistema computacional CompactRIO. Os resultados experimentais mostram que a freqüência dos testes pode ser significativamente aumentada com as técnicas de controle propostas.

Palavras chave— Aumento de frequência, controle por aprendizado, controle bang-bang, sistemas servo-hidráulicos.

1 Introduction

Hydraulic systems are widely used in industrial systems in applications such as automated plants, robotics, motion simulators, metal processing plants, mineral exploration, presses, heavy machinery and materials fatigue test systems (Merritt, 1967). In general, hydraulic systems are used in applications where relatively high forces, torques and accelerations are required. Machinery used in materials fatigue testing is based on servo-hydraulic systems, to provide useful information about the material's life in service by applying load cycles. The applied load may be repeated millions of times in typical frequencies up to one hundred times per second for metals. To achieve these relatively high frequencies in a typical fatigue test, it is necessary to have an efficient control system.

In traditional control methods, all information from the process is known in advance, deterministically, as described by (Doebelin, 1976). If the initial information is unknown, a controller may be designed to estimate the information during the operation. This information could be used for future control decisions, a process known as learning control. The literature related to the control of servo-hydraulic systems presents many developments applied to industrial manipulators used to perform repetitive tasks (Sun and Chiu, 1999). One of these works is based on a Lyapunov controller, where an adaptive law is also proposed to remove uncertainties in the hydraulic parameters (Sirouspour and Salcudean, 2000). A second work uses a non-linear controller that presents a better performance in both simulations and experiments than the results obtained using the proportional-derivative controller (Jelali and Kroll, 2003). Another work uses a robust controller and disturbance rejection for servo-hydraulic systems (Ching Lu and Wen Chen, 1993). In this case, the results of simulations and experiments show that this controller has the ability to maintain the load accuracy in the presence of very large variations of the plant parameters and/or external disturbances.

In the present work, a learning control technique is developed to increase the frequency of the applied load cycles in fatigue tests. An experimental control system is developed and applied to a fatigue test machine in order to assess and evaluate the performance of the proposed methodology.

2 Learning Control

The learning process can be seen as a problem of estimation or successive approximations of unknown quantities or an unknown function (King-Sun, 1970). In this case, the unknown quantities that are estimated or learned by the controller are parameters that are governed by the control laws.

The block diagram shown in Fig. 1 represents the learning control process. In each cycle, the system uses the information of the variables U_{IJ} stored in its memory for feedback control. The errors measured during each cycle are used to update the parameters U_{IJ} through a learning law. The learning law is applied only at the end of each learning cycle k, which updates the values $U_{IJ}(k)$ with $U_{IJ}(k+1)$ based on the errors e(k). In the present application in fatigue testing, each learning cycle is associated with each reversal of the controlled parameter, e.g., after one peak and one valley of the applied force history.

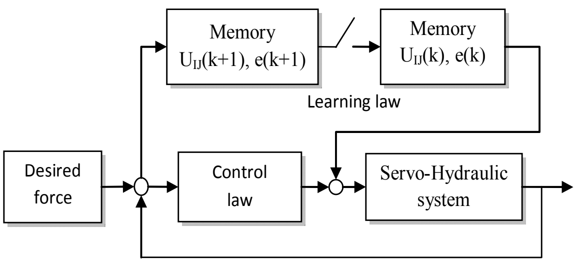

Figure 1. Block diagram of the learning control

The learning control methodology presented in this work aims to maintain the servo-valve working in its extreme operation limits, keeping the valve most of the time in the fully open position in either direction. This type of control is known as bang-bang (O' Brien, 2006). Due to the system dynamics, the servo-valve reversion instants must be chosen to happen before the desired peaks and valleys of force or stress.

This instant of reversion is represented by a non-dimensional variable U_{IJ}, which is defined as the fraction of the peak-valley (or valley-peak) path where the valve should be reversed. For instance, when controlling a force cycle from 10 to 110kN, a value $U_{IJ} = 0.8$ would be equivalent to reversing the valve when 80% of the path between 10 and 110kN has passed, i.e., when the measured force is equal to $10 + 0.8\times(110-10) = 90$kN. In this same example, when returning from 110 to 10kN, the same value $U_{IJ} = 0.8$ would be equivalent to reversing the valve at $110 - 0.8\times(110-10) = 30$kN.

This U_{IJ} is a parameter that depends on several factors such as the amplitude and mean value of the applied load, and it is also influenced by dead zones caused in some cases by slack in the test specimen fixtures. The objective of the proposed approach is to learn the values of U_{IJ} as a function of the load amplitude, mean, and direction (either from peak to valley or from valley to peak), as described next.

2.1 Learning tables

Figure 2 shows a table that stores non-dimensional numbers $U_{i,j}$ (with the indexes in lowercase) associated with the learning process. These numbers are the discrete values of U_{IJ} for several combinations of load amplitude and mean. The columns show the values of the gamma (or range, equal to twice the amplitude) of the physical variable to be controlled, while the rows show the minimum value of the peak-valley half-cycle. Note that this table can be divided into two parts, one associated to when the system is going from a valley to a peak, and another when it is going from a peak to a valley. In order to join both tables, the concept of negative gamma is used, which indicates the transition from a peak to a valley.

Columns (gamma)

Rows (minimum)	-25	-15	-5	5	15	25
-25	0,9810	0,9602	0,8795	0,8016	0,8712	0,9475
-15	0,9688	0,9415	0,8854	0,8245	0,9005	0,9516
-5	0,9520	0,9230	U_{ij}	0,8429	0,9005	0,9712
5	0,9256	0,8910	0,7415	0,9038	0,9406	0,9856
15	0,9086	0,8723	0,6879	0,9312	0,9688	0,9901
25	0,8865	0,8549	0,6218	0,9537	0,9765	0,9936

Figure 2. Learning table

As a result, $U_{i,j}$ is defined as an element associated with the row i (minimum value "min_i") and the column j (associated with the gamma "$gama_j$"). For a loading with a minimum value min_i and gamma equal to $gama_j$, then $U_{IJ} = U_{i,j}$. If the minimum and gamma values are between two consecutive values in the table, i.e., $min_i < min < min_{i+1}$ and $gama_j < gama < gama_{j+1}$, then U_{IJ} is obtained from an interpolation (see Figure 3):

$$U_{IJ} = a + (b-a)\cdot\frac{(gama - gama_j)}{\left(gama_{j+1} - gama_j\right)} \quad (1)$$

where

$$a = U_{i,j} + (U_{i+1,j} - U_{i,j})\cdot\frac{(min - min_i)}{\left(min_{i+1} - min_i\right)} \quad (2)$$

$$b = U_{i,j+1} + (U_{i+1,j+1} - U_{i,j+1})\cdot\frac{(min - min_i)}{\left(min_{i+1} - min_i\right)} \quad (3)$$

Columns (gamma)

Rows (minimum)

			$gama_j$	$gama_{j+1}$		
	0,9810	0,9602	0,8795	0,8016	0,8712	0,9475
min_i	0,9688	0,9415	$U_{i,j}$	$U_{i,j+1}$	0,9005	0,9516
min_{i+1}	0,9520	0,9230	$U_{i+1,j}$	$U_{i+1,j+1}$	0,9005	0,9712
	0,9256	0,8910	0,7415	0,9038	0,9406	0,9856
	0,9086	0,8723	0,6879	0,9312	0,9688	0,9901
	0,8865	0,8549	0,6218	0,9537	0,9765	0,9936

Figure 3. Procedure for interpolation when the values of gamma and minimum are between two cells

Once the value of U_{IJ} is calculated from Eqs. (1-3), the servo-valve reversal point can be calculated from

$$reversal = \begin{cases} min + U_{IJ}\cdot gama & (\textit{from}\ \text{valley to peak}) \\ (min + gama) - U_{IJ}\cdot gama & (\textit{from}\ \text{peak to valley}) \end{cases} \quad (4)$$

2.2 Learning law

The learning law governs how the $U_{i,j}$ values are updated after each load reversion in the test. Thus, the new value of U_{IJ} is calculated using the error between the measured peak (or valley) x and the desired peak (or valley) x_d:

$$e = \frac{x_d - x}{x_d - x'} \quad (5)$$

where x' is the valley or peak measured in the last reversion. Note that the defined error is dimensionless, and that x can be any variable to be controlled in the tests, such as applied force, test specimen deformation, or hydraulic piston displacement.

In the case where x and x_d are peaks, x' will be a valley, and the difference (x_d – x') will be positive. Thus, if there is an undershoot in this event, then $x < x_d$, resulting in $e > 0$. Analogously, if an overshoot happens, then $e < 0$.

On the other hand, if x and x_d are valleys, then x' will be a peak, and the difference (x_d – x') will be negative. In the case of an undershoot when the loading decreases, then $x > x_d$, and therefore $e > 0$. Similarly, for an overshoot, $e < 0$.

As a result, positive errors are always associated with undershoots, and negative ones with overshoots, no matter if the transition is from a valley to a peak or from a peak to a valley. Clearly, if an overshoot happens, then the approach is to reverse the valve sooner in future similar events, which implies in decreasing U_{IJ} for that combination of (*min*, *gamma*). On the other hand, in the case of an undershoot, it would be necessary to increase U_{IJ}.

Assuming that any undershoot or overshoot will remain below 100%, then $-1 < e < 1$, and a learning law can be proposed:

$$U_{IJ} := U_{IJ}\cdot(1+e) \quad (6)$$

The above learning law does not need adjustable gains. It is associated with an increment of U_{IJ} by a factor (1+e) in the case of an undershoot ($e > 0$), and a decrease in its value for an overshoot ($e < 0$). It is possible to introduce a gain to multiply the error in equation (6), in order to tune the learning rate. Nevertheless, a unitary gain was enough in this work to achieve a stable and fast learning law.

Since the learning table only stores discrete values of U_{IJ}, the values $U_{i,j}$, $U_{i,j+1}$, $U_{i+1,j}$, $U_{i+1,j+1}$ that generated U_{IJ}(*min, gamma*) by interpolation must also be updated according to the learning law, where $min_i < min < min_{i+1}$ and also $gama_j < gama < gama_{j+1}$. This update process is also made using weight factors, i.e., the neighboring cell closer to U_{IJ} shall be updated in a greater degree than the other three neighbor cells. This process is easily implemented with the learning law:

$$U_{i,j} := U_{i,j}\cdot\left[1+(1-\alpha)\cdot(1-\beta)\cdot e\right] \quad (7)$$

$$U_{i,j+1} := U_{i,j+1}\cdot\left[1+(1-\alpha)\cdot\beta\cdot e\right] \quad (8)$$

$$U_{i+1,j} := U_{i+1,j}\cdot\left[1+\alpha\cdot(1-\beta)\cdot e\right] \quad (9)$$

$$U_{i+1,j+1} := U_{i+1,j+1}\cdot\left[1+\alpha\cdot\beta\cdot e\right] \quad (10)$$

where

$$\alpha = \frac{min - min_i}{min_{i+1} - min_i},\ 0<\alpha<1 \quad (11)$$

$$\beta = \frac{gama - gama_j}{gama_{j+1} - gama_j},\ 0<\beta<1 \quad (12)$$

Note that Eqs. (1-3) may be rewritten in terms of the above defined α and β as follows:

$$U_{IJ} := U_{i,j}\cdot(1-\alpha)\cdot(1-\beta) + U_{i+1,j}\cdot\alpha\cdot(1-\beta) + U_{i,j+1}\cdot(1-\alpha)\cdot\beta + U_{i+1,j+1}\cdot\alpha\cdot\beta \quad (13)$$

3 Simulations

Simulations of the proposed control system applied to a servo-hydraulic testing machine were performed in MATLAB^{TM}. The simulation includes the modeling of a 100kN servo-hydraulic machine, including detailed models for the servo-valve (Viersma, 1980; Thayer, 1965). The system model is too lengthy to be included in this work; however, its full description can be seen in Alva (2008).

The simulations for the servo-hydraulic machine, performed for constant and variable amplitude load histories, show excellent results for the proposed learning control law. Figures 4 and 5 show how the controller learns by changing the location of the servo-valve reversion points (represented by an “x”) at each load cycle. The learning process starts assuming U_{IJ} equal to 0.5 for any value of (min, gama).

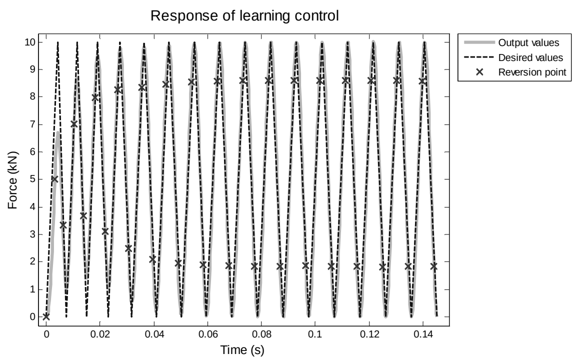

Figure 4. Learning control responses for a constant amplitude history from 0 to 10kN

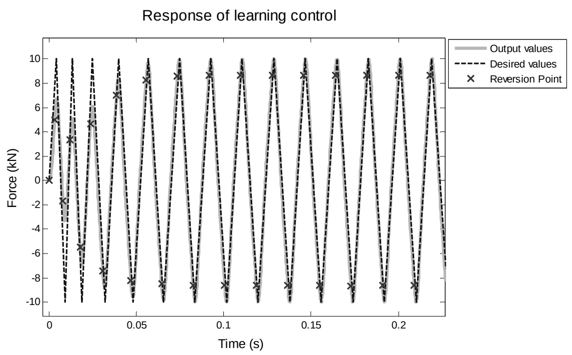

Figure 5. Learning control responses for a constant amplitude history from −10 to 10kN

As shown in Fig. 6, the learning process also presents good results for variable amplitude histories. In this example, three blocks with different (min, gama) values were applied to the specimen. In the first block, the learning process takes about 5 to 6 cycles to converge. The second block also needs 6 blocks to converge, because its (min, gama) is very different from the one from the first block, updating a very different section of the learning table. But the learning in the third block converges in only 2 cycles, because it could benefit from the updated U_{ij} values learned from the second block, which had similar (min, gama) values.

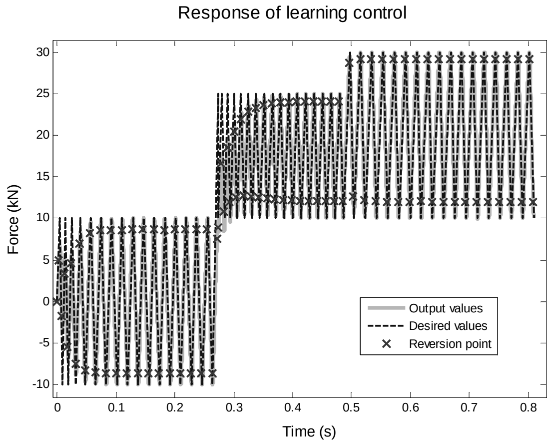

Figure 6. Learning control responses for a variable amplitude input.

Note also from Fig. 6 that the frequency of the system response depends on the desired amplitude. The blocks 1 and 3, which have the same amplitude [10 – (–10)]/2 = [30 – 10]/2 = 10kN, result in a higher frequency than block 2, with a lower amplitude [25 – 10]/2 = 7.5kN. This variable frequency is not an issue in fatigue testing, because the fatigue life of most materials under room temperature depends only on the load amplitude and mean, not on its frequency. These frequencies, on the other hand, are the highest achievable for a given system and load history, since the servo-valves are always operating at their operational limits and their reversion has been optimized due to the learning law.

4. Experiments

The proposed methodology is applied to a fatigue test machine INSTRON model 8501, with a servo-valve MOOG D562 and a current signal command of ±40 mA, see Figure 7.

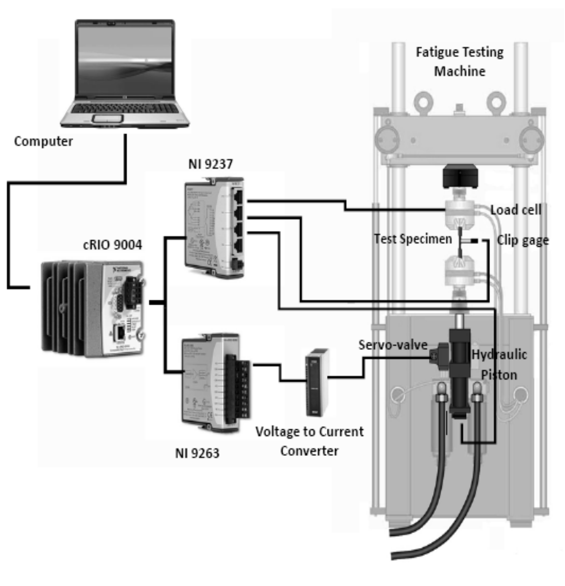

Figure 7. Experimental system

The piston from this machine can generate forces up to 100 kN with a displacement amplitude of ±50 mm (from a central position). The fatigue test machine has a force sensor (load cell) to control force histories, and a LVDT for displacement commands. A strain-gage or clip-gage attached to the test specimen also allows the control of a deformation history. The hydraulic fluid is supplied by a hydraulic pump at the pressure of 190 bar.

The learning control is implemented in a CompactRIO cRIO9004 computational system, from National Instruments. This system includes modules for analog outputs (NI9263), analog inputs, exciter module for strain gages (NI9237), and a voltage-to-current converter, see Figure 7.

The tests are run for zero mean loads and force amplitudes of 10 kN, 20 kN, 30 kN and 40 kN, all of them using ±20mA of current in the servo-valve. The tests are performed using εN test specimens with 12mm in diameter in its thinnest section.

Figure 8 compares the performance of the proposed learning control implemented at the CompactRIO using lower ±20mA currents and the traditional one from the Instron controller hardware using ±40mA, for the servo-hydraulic machine under several load amplitudes. It is possible to observe a better performance of the learning control for low amplitudes and an equal performance for high amplitudes, even though the learning control only needs half the current to operate the servo-valve. The traditional control is only able to outperform the proposed learning control when it is allowed to use currents beyond 40mA in the servo-valve (overdrive).

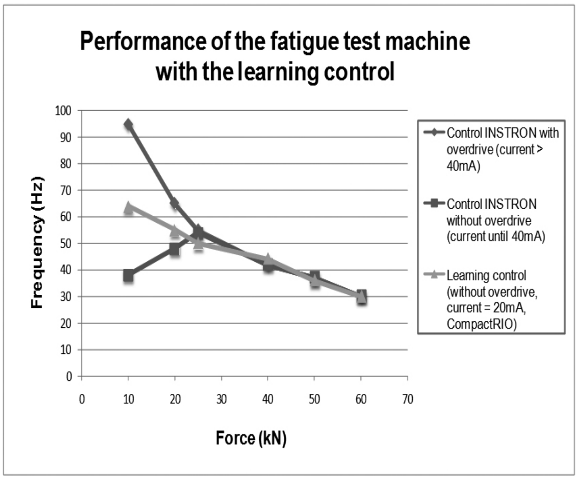

Figure 8. Performance comparison between the proposed learning control limited to ±20mA with the traditional Instron Controller at ±40mA or beyond 40mA limits

It is expected that using a current of ±40mA in the proposed learning control process it will be possible to obtain even better results. Learning control with currents beyond 40mA (overdrive) will also be investigated in future work. The use of only ±20mA for the learning control was due to a limitation of the voltage-to-current system of the CompactRIO.

5. Conclusions

In this work, it was shown that it is possible to increase the work frequency of a fatigue test machine using a learning control technique applied to servo-hydraulic systems. Both the bang-bang control and proposed learning laws do not need adjustable gains, simplifying their implementation. The proposed control system was simulated and applied to a fatigue testing machine, implemented in a CompactRIO computational system. The results showed that the proposed control was capable to generate frequencies higher than those obtained with the original controller from the testing machine manufacturer, even using lower currents for the servo-valve triggering.

Acknowledgments

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References

Alva J.G.C., "Controle por Aprendizado de Sistemas Servo-Hidráulicos de Alta Frequência," M.Sc. thesis, Pontifical Catholic University of Rio de Janeiro, in Portuguese, 2008.

Ching Lu H., Wen Chen L., "Robust Controller with Disturbance Rejection for Hydraulic Servo Systems," IEEE Transactions on Industrial Electronics, vol. 40, pp. 152-162, 1993.

Doebelin, E.O., System Dynamics: System Modeling and response. Prentice Hall, 1976.

King-Sun F., "Learning Control System," IEEE Transactions on Automatic Control, pp. 210-221, 1970.

Jelali M., Kroll A., Hydraulic servo-systems: modeling, identification and control. New York. Springer, 2003.

Merritt H.E., Hydraulic Control Systems. John Wiley and Sons, 1967.

O' Brien R.T., "Bang Bang Control for Type-2 Systems," 38th Southeastern Symposium System Theory, Tennessee, USA, 2006.

Sirouspour M., Salcudean S., "On the Nonlinear Control of Hydraulic Servo-Systems," IEEE International Conference on Robotics and Automation, San Francisco, 2000.

Sun H., Chiu G., "Nonlinear Observer Based Force Control of Electro Hydraulic Actuators," American Control Conference. San Diego, CA, USA, 1999.

Thayer W.J., "Transfer Functions for MOOG Servovalves," Technical Bulletin. New York, NY, USA, 1965.

Viersma T.J., Analysis, Synthesis and Design of Hydraulic Servosystems and Pipelines. Elsevier, 1980.