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Identification of Behavior of Anti–Vibration Gloves by ARMAX Model

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Case Report

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Abstract

In the literature many researches propose models of biodynamic responses of the human hand–arm system to identify mechanical characteristics. In this paper the Authors suggest a method for the time domain identification of modal parameters of a vibrating structure using Z–transformation sequences. This identification proceeds using the Z–transfer function of a vibrating structure coming from the ARMAX model of the vibrating structure. The modal parameters can be identified by this ARMAX model in time domain data. To demonstrate the application and efficiency of the method, it is proposed a test on human hand and arm exposed to mechanical vibrations. [DOI:10.12866/J.PIVAA.2013.09.001] [1]

Keywords: System identification, Z–transfer function, ARMAX model, Residual Analysis

1 Introduction

The human hand–arm system is belonged to highly nonlinear systems. Perfect knowledge of parameters of human hand–arm system is unattainable by conventional modelling techniques because of the time varying inertia, stiffness, damping, hysteresis and other joint friction model uncertainties. To guarantee a good prediction of modal behavior of the human hand–arm system, we propose an ARMAX model. The model has been validated using laboratory measured data on vibration transmitted on different locations of the hand–arm system.

Nowadays, system stability and reliability are extremely important in some applications, such as aircraft, nuclear plants and chemical processes [Moore et al., 2007a]. A modal parameter estimation scheme, based on the identification of parameters in an autoregressive moving average

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with exogenous excitation (ARMAX) model, introduces modelled sources of unmeasured excitation [Moore et al., 2007b]. Fassois introduces a critical assessment of the LMS–ARMAX method under various noise conditions [Fassois, 2001]. The study continues with a critical assessment of the MIMO LMS–ARMAX method, along with comparisons with a pure ARX version and the Eigensystem Realisation Algorithm (ERA) based upon two-input three output vibration data [Florakis et al., 2001]. A critical comparison of four stochastic (PEM, 2SLS, LMS, IV) and three deterministic (LS, Prony, ERA) methods for the parametric time–domain identification of vibrating structures from random excitation and noise–corrupted response signals is presented in the paper [Petsounis and Fassois, 2001]. Fung et al. estimate the parameters of the ARMAX and NARMAX structures, respectively, by the recursive extended least square (RELS) method and the neural network (NN) method [Fung et al., 2003]. Important research concerns experimental assessment of several stochastic identification methods with respect to their ability in capturing the structural uncertainty [Michaelides and Fassois, 2013].

Within modelling of biodynamic responses of the human handarm system, the parameters of the proposed four- and five degrees–of–freedom models are identified through minimization of an rms error function of the model and measured responses under different hand actions, namely, fingers pull, push only, grip only, and combined push and grip [Dong et al., 2007].

By this paper the Authors present a method for the time domain identification of modal parameters of a vibrating structure using Z–transformation sequences. This identification proceeds using the Z–transfer function of a vibrating structure coming from the ARMAX model of the vibrating structure. The modal parameters can be identified by this ARMAX model in time domain data. To demonstrate the application and efficiency of the method, it is proposed a test on human hand and arm exposed to mechanical vibrations.

Time domain methods are essentially discrete modal identification methods. The Z–transform of a discrete time signal defined as a power series in z^{-1} whose coefficients are the amplitude of the discrete time signals [Ljung, 2007]. The Z–transform is suitable for the analysis of practical vibration test data and identification of modal parameters. In this paper the Z–transform function of the vibrating structure is used to derive an autoregressive and moving–average model of the system. The relationship between the eigenvalues of the structure and the poles of the ARMAX model is derived on the basis that the eigenvalues of the structure can be determined through the identification of the poles of the ARMAX model.

2 ARMAX model

The current observation $y\left(t\right)$ is the sum of its own past (the autoregressive part) plus a linear combination of uncorrelated terms (the moving–average) (Fig. 1). The input–output relationship is the following relation

$$\begin{aligned} y\left(t\right) +&a_1 y\left(t-1\right) + \ldots + a_{n_a} y\left(t-n_a\right) \\ =&b_1 u\left(t-1\right) + \ldots + b_{n_b} u\left(t-n_b\right) + e\left(t\right) + c_1 e\left(t-1\right) + \ldots + c_{n_c} e\left(t-n_c\right) \ . \end{aligned} \tag{1}$$

The white–noise term $e\left(t\right)$ is a direct error in the difference equation. The input $u\left(t\right)$ and output $y\left(t\right)$ histories are supposed to be known. Parameters a_i $\left(i=1,\ldots,n_a\right)$, b_j $\left(j=1,\ldots,n_b\right)$ and c_k $\left(k=1,\ldots,n_c\right)$ are unknown. Introducing the operator q, the model description becomes

Figure 1: The ARMAX model structure

$$A(z)\,y(t) = B(z)\,u(t) + C(z)\,e(t)\ . \tag{2}$$

with

$$\begin{aligned} A(z) &= 1 + a_1 z^{-1} + \ldots + a_{n_a} z^{-n_a} \\ B(z) &= b_1 z^{-1} + \ldots + b_{n_b} z^{-n_b} \\ C(z) &= 1 + c_1 z^{-1} + \ldots + c_{n_c} z^{-n_c} \end{aligned} \tag{3}$$

and

$$G(z,\vartheta) = \frac{B(z)}{A(z)} \quad H(z,\vartheta) = \frac{C(z)}{A(z)}\ . \tag{4}$$

The parameters produce the following vector

$$\boldsymbol{\vartheta} = \left[\begin{array}{ccccccccc} a_1 & a_2 & \ldots & a_{n_a} & b_1 & \ldots & b_{n_b} & c_1 & \ldots & c_{n_c} \end{array}\right]^T\ . \tag{5}$$

The parameters $\boldsymbol{\vartheta}$ can be estimate by least–squares method. In view of the moving average (MA) part $C(z)\,e(t)$, the model (2) will be called ARMAX.

3 Residual Analysis

The part of the data that the model could not reproduce are the residuals $\epsilon(t)$. Residuals $\epsilon(t)$ are differences between the one–step–predicted output from the model and the measured output from the validation data set. Thus, residuals represent the portion of the validation data not explained by the model. Residual analysis consists of two tests: the whiteness test and the independence test.

According to the whiteness test criteria, a good model has the residual autocorrelation function inside the confidence interval of the corresponding estimates, indicating that the residuals are uncorrelated.

According to the independence test criteria, a good model has residuals uncorrelated with past inputs. Evidence of correlation indicates that the model does not describe how part of the output relates to the corresponding input. For example, a peak outside the confidence interval for lag k means that the output $y(t)$ that originates from the input $u(t-k)$ is not properly described by the model.

It is reasonable to study the covariance between residuals and past inputs

$$R_{\epsilon u}^{N}\left(\tau\right)=\frac{1}{N}\sum_{n=0}^{t=1}\epsilon\left(t\right)u\left(t-\tau\right)\ . \tag{6}$$

If the numbers are small, we have some reason to believe that the measure could have relevance also the model is applied to other inputs. Another way to express the importance of $R_{\epsilon u}^{N}$ being small it as follows: If there are traces of past inputs in the residuals, then there is a part of $y\left(t\right)$ that originates from the past input and that has not been properly picked up by the model m. Hence, the model could be improved. Similarly, if we find correlation among the residuals themselves, i.e., if the numbers

$$R_{\epsilon}^{N}\left(\tau\right)=\frac{1}{N}\sum_{n=0}^{t=1}\epsilon\left(t\right)\epsilon\left(t-\tau\right)\ . \tag{7}$$

are not small for $\tau\neq 0$, then part of $\epsilon\left(t\right)$ could have better predicted from past data, which again is a sign of deficiency of the model. This means that $y\left(t\right)$ could have been predicted, which again is a sign of the deficiency of the model.

The confidence interval corresponds to the range of residual values with a specific probability of being statistically insignificant for the system.

3.1 Whiteness Test

The numbers $\hat{R}_{\epsilon}^{N}\left(\tau\right)$ carry information about whether the residuals can be regarded as white. To get an idea of how large these numbers may be if indeed $\epsilon\left(t\right)$ are white, we reason as follows: suppose $\left[\epsilon\left(t\right)\right]$ is a white noise sequence with zero mean and variance λ. Then it follows that

$$\frac{1}{\sqrt{N}}\sum_{N}^{t=1}\left[\begin{array}{c}\epsilon\left(t-1\right)\\ \vdots\\ \epsilon\left(t-M\right)\end{array}\right]^{T}\epsilon\left(t\right)\qquad As\left(0,\lambda^{2}\cdot I\right)\ . \tag{8}$$

The k–th row of this vector $\sqrt{N}R_{\epsilon}^{N}\left(k\right)$. Under the assumption that the ϵ are white, the consequently means that

$$\frac{N}{\lambda^{2}}\sum_{M}^{t=1}\left[R_{\epsilon}^{N}\left(\tau\right)\right]^{2}\ . \tag{9}$$

should be asymptotically $\chi^{2}\left(M\right)$–distributed. Replacing the unknown λ by the obvious estimate does not change this, asymptotically. The test for whiteness will thus be if

$$\zeta_{N,M}=\frac{N}{\left[R_{\epsilon}^{N}\left(0\right)\right]^{2}}\sum_{M}^{t=1}\left[R_{\epsilon}^{N}\left(\tau\right)\right]^{2}\ . \tag{10}$$

will pass a test of being $\chi^{2}\left(M\right)$ distributed, by checking if $\zeta_{N,M}<\chi_{\alpha}^{2}\left(M\right)$, the α level of the $\chi^{2}\left(M\right)$–distribution. If the value of $\chi^{2}\left(M\right)$–test assumes a value close to 0, we consider to be valid the model ARMAX. The difference between the observed values and the values, obtained by the ARMAX model, increases the value of $\chi^{2}\left(M\right)$–test: model ARMAX is not appropriate.

In addition to this whiteness test, histogram test for the distribution of ϵ can be performed.

3.2 Independence between Residuals and Past Inputs

The independence between residuals and past inputs is an important step of the investigation in order to validate the statistical model. When examining plots of $R_{\epsilon u}^{N}(\tau)$, note the following points

1. Correlation between $u(t-\tau)$ and $\epsilon(t)$ for negative τ is an indication of output feedback in the input, note that the model structure is deficient

2. The least–squares method construct $\hat{\vartheta}_N$ so that $\epsilon\left(t, \hat{\vartheta}_N\right)$ is uncorrelated with the regressors. We thus have $\hat{R}_{\epsilon u}^{N}(\tau)$ for $\tau = 1, \ldots, n_b$ automatically for the model structure (1), when the analysis is carried out on estimation data.

4 Results

Anti–vibration (AV) gloves can help to reduce hand–transmitted vibration exposure. The International Organization for Standardization (ISO) has set forth a standard for the evaluation of the AV gloves (ISO 10819, 1996). It is based on the measurement of the vibration transmissibility of the glove at the palm using an adapter. Briefly, the method requires three adult subjects with hand sizes in the range of 7–9 (En 420, 2003). The test utilizes an instrumented handle, capable of measuring the grip force and acceleration due to vibration along the forearm direction (Z_h–axis), mounted on a single–axis vibration excitation system capable of generating the required vibration [Welcome et al., 2012].

A lightweight cusp–shaped palm–held adapter, containing a single–axis accelerometer oriented along the Z_h–axis, is placed between the subject's palm and the glove. It is applied a grip force ($=30$ N) and a push force ($=50$ N) on the handle with a specified arm posture. The push force is measured using either a force transducer installed on the handle or a force plate where the subject stands. The method also defines a medium–frequency excitation spectrum and a high-frequency spectrum to evaluate the vibration isolation effectiveness of the glove. The M–frequency range is 31.5–200 Hz; and H–frequency range is 200–1250 Hz. The frequency–weighted root–mean square (rms) acceleration due to vibration measured at the handle and palm–held adapter are computed using the weighting function defined in ISO 5349–1 (2001). The vibration transmissibility of the glove is evaluated as the ratio of the rms acceleration of the adapter (Fig. 3) to that of the handle (Fig.2). The AV gloves must satisfy the following two criteria:

1. the transmissibility values of the glove in the M- and H–frequency ranges must be below 1.0 and 0.6, respectively (Fig.5);

2. the fingers of the glove have the same properties (materials and thickness) as the part of the glove covering the palm of the hand (ISO 10819, 1996).

The vibration isolation of the glove depends on the dynamic properties of a glove and on the biodynamic properties of the hand–arm (ISO 13753, 1999). The biodynamic properties are also functions of some factors, such as hand force, arm posture, and physical properties of the glove wearer.

We have estimated many different models of ARMAX model $A(q)\, y(t) = B(q)\, u(t) + C(q)\, e(t)$ by least–squares method. We can also compare how well the models are able to predict the output. Making connections between model output and measured output, the best model has $n_a = 10$, $n_b = 10$ and $n_c = 10$. The values of parameters $A(q)$, $B(q)$ and $C(q)$ are presented in

Table (Table 1). The result of model output is plotted together with the corresponding measured output (Fig.4). The percentage of the output variation is about 90%.

As previously mentioned, residual analysis can be used to evaluate the residues both in the time and the frequency domains. First, we obtain the residuals for the output error model in the time domain. The autocorrelation function of $e(t)$ and the cross correlation between $e(t)$ and the input are computed and displayed. The 99% confidence intervals for these values are also computed and shown as a yellow region (Fig.7).

In time domain and frequency domain, we see that the cross correlation between residuals and input lies in the confidence region (yellow region), indicating that there is no significant correlation (Fig.6 and Fig.7).

Therefore, we obtain a good agreement between the results of simulated output, obtained by ARMAX model, and ones of measured output. It shows that the ARMAX $(10, 10, 10)$ model gives residuals that pass whiteness and independence tests. The value of $\chi^2(M)$–test assumes a value close to 0.

	Parameters of ARMAX model
$A(q) =$	$1 - 2.076 \cdot q^{-1} + 1.423 \cdot q^{-2} - 0.7295 \cdot q^{-3} + 0.7788 \cdot q^{-4} - 0.826 \cdot q^{-5}$ $+0.9966 \cdot q^{-6} - 1.757 \cdot q^{-7} + 1.732 \cdot q^{-8} - 0.2838 \cdot q^{-9} - 0.259 \cdot q^{-10}$
$B(q) =$	$-0.003993 \cdot q^{-1} + 0.006237 \cdot q^{-2} - 0.001395 \cdot q^{-3} - 0.009223 \cdot q^{-4} + 0.01563 \cdot q^{-5}$ $-0.015 \cdot q^{-6} + 0.01332 \cdot q^{-7} - 0.01081 \cdot q^{-8} + 0.00672 \cdot q^{-9} - 0.002118 \cdot q^{-10}$
$C(q) =$	$1 - 1.558 \cdot q^{-1} + 1.063 \cdot q^{-2} - 0.8261 \cdot q^{-3} + 0.7441 \cdot q^{-4} - 0.7373 \cdot q^{-5}$ $+0.8302 \cdot q^{-6} - 1.51 \cdot q^{-7} + 1.249 \cdot q^{-8} - 0.316 \cdot q^{-9} + 0.06823 \cdot q^{-10}$

Table 1: Values of parameters

5 Conclusions

This paper has presented a time domain modal parameter identification method. The Z–transform is used to develop an ARMAX model. The time domain excitation and response data are used to estimate the coefficients of the ARMAX model. The modal parameters are determined from the coefficients of the ARMAX model. Measured data used in identification are in form of impulse or free decay responses. An experimental test is shown to indicate the effectiveness and accuracy of the method.

Figure 2: Time history input

Figure 3: Time history output

Figure 4: Time history reconstruction via ARMAX model

Figure 5: Bode of ARMAX model

Figure 6: Residual Analysis in Time Domain

Figure 7: Residual Analysis in Frequency Domain

References

R.G. Dong, J.H. Dong, J.Z. Wu, and S. Rakheja. Modeling of biodynamic responses distributed at the fingers and the palm of the human handarm system. *Journal of Biomechanics*, 40:23352340, 2007.

S.D. Fassois. Mimo lms-armax identification of vibrating structures - part i: The method. *Mechanical Systems and Signal Processing*, 15(4):723–735, 2001.

A. Florakis, S.D. Fassois, and F.M. Hemez. Mimo lms-armax identification of vibrating structures - part ii: A critical assessment. *Mechanical Systems and Signal Processing*, 15(4):737–758, 2001.

E. H.K. Fung, Y.K. Wong, H.F. Ho, and M.P. Mignolet. Modelling and prediction of machining errors using armax and narmax structures. *Applied Mathematical Modelling*, 27:611627, 2003.

L. Ljung. *System Identification. Theory for the User*. Prentice Hall PTR, 2007.

P.G. Michaelides and S.D. Fassois. Experimental identification of structural uncertainty an assessment of conventional and non-conventional stochastic identification techniques. *Engineering Structures*, 53:112121, 2013.

S.M. Moore, J.C.S. Lai, and K. K. Shankar. Armax modal parameter identification in the presence of unmeasured excitation - ii: Numerical and experimental verification. *Mechanical Systems and Signal Processing*, 21:16161641, 2007a.

S.M. Moore, J.C.S. Lai, and K. Shankar. Armax modal parameter identification in the presence of unmeasured excitation - i: Theoretical background. *Mechanical Systems and Signal Processing*, 21:16011615, 2007b.

K.A. Petsounis and S.D. Fassois. Parametric time-domain methods for the identification of vibrating structures - a critical comparison and assessment. *Mechanical Systems and Signal Processing*, 15(6):1031–1060, 2001.

D.E. Welcome, R.G. Dong, S.X. Xueyan, C. Warren, and T.W. McDowell. An evaluation of the proposed revision of the anti-vibration glove test method defined in iso 10819 (1996). *International Journal of Industrial Ergonomics*, 42:143–155, 2012.

NOMENCLATURE

$u(t)$	input variable at time t
$y(t)$	output variable at time t
ϑ	vector used to parametrize models
$\hat{y}(t\|\vartheta)$	predicted output at time t using a model $\mathcal{M}(\vartheta)$
$e(t)$	disturbance at time t
$\epsilon(t,\vartheta)$	$= y(t) - \hat{y}(t\|\vartheta)$ prediction error
z, z^{-1}	forward and backward shift operators z
λ	variance
T_s	sampling interval