Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Model Predictive Control of MEMS Vibratory Gyroscope

M. Hoseini Pishrobat. J. Keighobadi.

Department of Mechanical Engineering, University of Tabriz, Tabriz, Iran (e-mails:Mehranhp1369@gmail.com, Keighobadi@Tabrizu.ac.ir)

Abstract: This paper presents a MPC (Model Predictive Control) algorithm for MEMS vibratory gyroscopes based on force-balancing control strategy. In the proposed MPC method, using a set of orthonormal basis functions named *Laguerre* functions, a new prediction and optimization technique is designed. To enhance the capability of proposed MPC method for tracking time-varying reference trajectories, first a repetitive control technique is developed. Second, following representing the governing dynamical equations of the vibratory gyroscope, discrete-time Laguerre network based MPC has been developed. The effective tracking performance of the proposed control methods has been shown through computer simulations.

Keywords: MEMS, vibratory gyroscope, Force-balancing control, MPC, Laguerre functions.

1. INTRODUCTION

Technically speaking, gyroscopes are instruments for measuring the rotation rate of a rigid element. Fabrication methods of MEMS technology have made possible to construct gyroscopes in very compact sizes. Most of the MEMS gyroscopes are of *vibratory* kind gyroscopes, i.e. vibrating elements are used to detect the applied angular velocity. The main operating principle of the gyroscopes is based on *Coriolis effect* to transfer energy from one mode of vibration to the other one (Acar & Shkel 2009).

In most MEMS vibratory gyroscopes, the basic structure consists of a proof mass suspended by elastic members above a substrate. The proof mass has the capability of oscillating along two perpendicular directions; known as drive (x) and sense (y) directions. Thereby, the overall mechanical system of gyroscope can be considered as a 2DOF (two degrees of freedom) vibrating system (Acar & Shkel 2009); see Fig. 1.

In conventional mode of operation, the proof mass is driven to vibrate in x direction with its natural frequency; then, in presence of angular velocity, Coriolis acceleration causes the oscillation of proof mass in the other (sense) direction. The amplitude of second vibration mode provides information about the input angular velocity. Ideally, the vibrating modes of the gyroscope are supposed to have no mechanical coupling and their natural frequencies should be matched (Park & Horowitz 2003).

However, in practice, the fabrication imperfections and ambient noises violate the ideal conditions and therefore cause less performance and inaccurate results. Hence, using a suitable control system to compensate the imperfections and to improve the performance of the vibratory gyroscope is required (Park & Horowitz 2003). As an important control technique, in *force-balancing* strategy, the sense direction is forced to be stationary, while the other direction vibrates with a known frequency. The control effort of sense direction is used to estimate the applied angular velocity (Park & Horowitz 2003 and Bature, Sreeramreddy & Khasawneh 2006).

Model predictive control has several interesting aspects in particular the effective applicability to multi-input, multi-output systems and the ability to handle imposed constraints on system (Wang 2009). Most of classic model predictive control algorithms merely consider tracking on step-wise reference trajectories with zero steady-state error and also simultaneously rejection of fixed-value disturbances (Camacho & Bordons 2007). This accomplishes via embedding an integrator to the underlying system. However, in the case of non-step reference trajectories, for example periodic signals, the method is unable. Therefore, *Repetitive* control method based on *internal model principle*, may be used to enhance the tracking capability in the reference signals with zero steady-state error (Wang et al. 2011). The proposed technique can be considered as the generalization of the integral action.

Two key steps in a MPC, are: first, modelling of future behaviour of system including states, outputs and manipulated variables based on some describing model of the plant; and second, performing an optimization process in order to obtain the optimal control action for applying on the system. In the case of MIMO systems with complex dynamics or fast sampling times, traditional MPC methods require using too many parameters and heavy matrix computations. A new approach, which can be considered as a solution to these problems, is to use a set of orthonormal functions with exponential nature to model the future trajectory of the control input. Due to the exponential nature, using these orthonormal functions results in a fast convergence rate (Wang 2009). One appropriate choice for these function, is so-called *Laguerre function*, which has been fully discussed by Wang (2009).

Copyright © 2014 IFAC

In this paper, a new discrete-time MPC approach is proposed for MEMS vibratory rate gyroscope, based on force-balancing control scheme. In the problem of controlling vibratory gyroscopes, tracking of periodic reference signals is required. In order to adapt the MPC to track periodic reference signals with zero steady-state error, the combination of repetitive control method with predictive control is developed. In the designed discrete-time MPC method, discrete-time Laguerre network is used for prediction and optimization processes. It is assumed that in the MEMS gyroscope, sensors may only measure the displacements of proof mass in derive and sense directions. Since the proposed MPC method uses state-space model of the system, an observer should be used to estimate the unmeasured states including velocities. For the estimation purpose, *Kalman filter* is a suitable tool; especially in the case of noisy environments. Therefore, in the performed simulations Kalman filter is used to estimate the unknown velocities of proof mass in derive and sense directions.

2. DYNAMICS OF MEMS VIBRATORY RATE GYROSCOPE

An intuitive method to describe the dynamics of the MEMS gyroscope is obtaining the acceleration of proof mass by taking the second time derivative of its position vector (Acar & Shkel 2009). For this purpose, we introduce two Cartesian reference frames; the first is a ground -fixed inertial reference frame $\{XYZ\}$ and the second is a body-fixed reference frame $\{xyz\}$ which is fixed to the gyroscope table. According to *Coriolis's theorem*, the time derivatives of a given vector $\mathbf{A}$ in two reference frames $\{XYZ\}$ and $\{xyz\}$ are related by:

$$(\frac{d\mathbf{A}}{dt})_{XYZ} = (\frac{d\mathbf{A}}{dt})_{xyz} + \Omega\times\mathbf{A} \tag{1}$$

Where the subscripts stand for which reference frame the derivative is taken, and Ω is the angular velocity vector of $\{xyz\}$ frame axes with respect to $\{XYZ\}$ frame. Considering the position vector of proof mass in reference frame $\{XYZ\}$, r, the position vector of the origin of $\{xyz\}$ with respect to $\{XYZ\}$, $\tilde{r}$ and the position vector of proof mass with respect to $\{xyz\}$ ρ yields:

$$r = \tilde{r} + \rho \tag{2}$$

Now by twice differentiating (2) with respect to time and using (1) the acceleration of proof mass is obtained as:

$$a_{XYZ} = \overbrace{(\frac{d^2\tilde{r}}{dt^2})_{xyz} + \dot{\Omega}\times\tilde{r} + \Omega\times(\Omega\times\tilde{r}) + 2\Omega\times(\frac{d\tilde{r}}{dt})_{xyz}}^{a_{rel}}$$
$$+(\frac{d^2\rho}{dt^2})_{xyz} + \dot{\Omega}\times\rho + \Omega\times(\Omega\times\rho) + 2\Omega\times(\frac{d\rho}{dt})_{xyz} \tag{3}$$

Where a_{XYZ} is the acceleration of proof mass with respect to inertial frame $\{XYZ\}$ and $\dot{\Omega}$ is the time derivative of Ω (which is same in both reference frames). Coriolis term, $2\Omega\times(\frac{d\rho}{dt})_{xyz}$ play main role in characterising of vibratory MEMS gyroscope, because it provides the energy transfer mechanism between two modes of vibration. Regarding $\Omega = (\Omega_x, \Omega_y, \Omega_z)^T$ and $\rho = (x, y, z)^T$ with respect to gyroscope frame $\{xyz\}$; in the case of Z-axis gyroscope, Ω_x and Ω_y are negligible in comparison to, Ω_z. Furthermore, in a long enough period of time, $\dot{\Omega} \approx 0$ and the centrifugal and the relative acceleration terms often could be neglected. With these simplifying assumptions and using Newton's second law we can obtain the equation of motion of proof mass (with mass *m*) in the reference frame $\{xyz\}$ as follows.

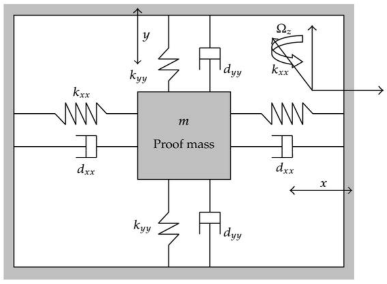

Fig. 1. Schematic of MEMS vibratory gyroscope (Fei & Ding 2010)

$$M\ddot{q} + D\dot{q} + Kq + 2\Lambda\dot{q} = u \tag{4}$$
$$M = \begin{bmatrix} m & 0 \\ 0 & m \end{bmatrix}, D = \begin{bmatrix} d_{xx} & d_{xy} \\ d_{xy} & d_{yy} \end{bmatrix}$$
$$K = \begin{bmatrix} k_{xx} & k_{xy} \\ k_{xy} & k_{yy} \end{bmatrix}, \Lambda = \begin{bmatrix} 0 & -\Omega_z \\ \Omega_z & 0 \end{bmatrix}$$

Where $q = [x, y]^T$ is the displacement vector of proof mass measured from its free position, and $u = [u_x, u_y]^T$ is applied electrostatic control force.

Note that the damping coefficient d_{xy} and the stiffness coefficient k_{xy} have been considered to model the coupling effect between x and y directions, which are mainly caused by fabrication imperfections (Fei & Ding 2010).

For the purpose of computational efficiency, non-dimensionalized governing equations are more appropriate and useful. By introducing the reference mass *m*, reference length q_0 and non-dimensional time $\tau = \omega_0 t$ (4) is re-written in the following non-dimensional form (Fei & Ding 2010);

$$\ddot{q} + D\dot{q} + Kq + 2\Lambda\dot{q} = u \tag{5}$$

Where

$$\frac{q}{q_0} \to q; \frac{D}{m\omega_0} \to D; \frac{K}{m\omega_0^2} \to K; \frac{\Lambda}{\omega_0} \to \Lambda; \frac{u}{mq_0\omega_0^2} \to u$$

3. MODEL PREDICTIVE CONTROL

In various types of MPC algorithms, different model structures of the system may be used; e.g. transfer function models, finite impulse response and etc. Here we use state-space model which is a suitable tool for description and handling of MIMO systems. The majority of traditional MPC formulations are based on *integral action*; i.e. embedding an integrator to the system. The technique ensures that the system will track step-wise reference trajectories with zero steady-state error. However, in most applications, the reference signals include periodic signal components (for instance the MEMS vibratory gyroscope) and the MPC with integral action is inapplicable to precise track of these kind of reference trajectories (Wang et al. 2011).Therefore, to solve the tracking difficulty along periodic/ sinusoidal trajectories, a new design of MPC of the MEMS gyroscope is proposed in the paper.

3.1 MPC for Tracking Periodic Reference Trajectories

Generally speaking, the reference signal, $r(t)$ with a known structure will satisfy the following type differential equation with real coefficients, α_i $(i = 0,...,n_r - 1)$.

$$\frac{d^{n_r} r}{dt^{n_r}} + \alpha_{n_r-1}\frac{d^{n_r-1} r}{dt^{n_r-1}} + \cdots + \alpha_1 \frac{d\ r}{dt} + \alpha_0 r = 0 \tag{6}$$

Taking Laplace transform of both sides of (5) yields:

$$\Gamma(s)R(s) = F(r(0), \frac{d\ r}{dt}(0),...,s)$$

$$\Gamma(s) = s^{n_r} + \alpha_{n_r-1}s^{n_r-1} + \cdots + \alpha_1 s + \alpha_0 \tag{7}$$

Where, s denotes Laplace variable and F represents some terms of the initial values of r(t). The polynomial $\Gamma(s)$ is called the *generating polynomial* of the reference signal, $r(t)$; for example, sinusoidal reference signal, $r(t) = r_0 \sin(\omega t)$ has the generating polynomial $\Gamma(s) = s^2 + \omega^2$. According to the *Internal Model Principle*, for tracking the reference signal $r(t)$ with zero steady state error; the generating polynomial must be embedded in the system (Goodwin, Graebe & Salgado 2001). Since we are dealing with discrete time systems, we replace (6) with a difference equation and use the Z-transform instead of Laplace transform to obtain the generating polynomial in discrete manner:

$$\Gamma(z^{-1}) = 1 + \beta_1 z^{-1} + \cdots + \beta_{n_r} z^{-n_r} \tag{8}$$

Where, z^{-1} is the backward shift operator. It should be noted that $\Gamma(z^{-1})$ can be obtained directly by discretizing the differential equation (6).
The following state-space description is considered for underlying plant model.

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + w(k) \\ y(k) &= Cx(k) + v(k) \end{aligned} \tag{9}$$

Where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$ and $y \in \mathbb{R}^q$ are respectively the state vector, manipulated control variable and output of system; $w(k) \in \mathbb{R}^n$ is process disturbance and $v(k) \in \mathbb{R}^q$ is measurement noise. In order to model the noises and disturbances, we assume that $w(k)$ and $v(k)$ satisfy following equations:

$$\Gamma(z^{-1})\ w(k) = \varepsilon(k)\ ,\ \Gamma(z^{-1})\ v(k) = \xi(k) \tag{10}$$

Where $\varepsilon(k)$ and $\xi(k)$ are zero-mean white noises.

Incorporating, $\Gamma(z^{-1})$ in system (9) has been proposed and discussed by Wang et al .2011; In this method, new variables are used as:

$$x_s(k) = \Gamma(z^{-1})x(k)\ ,\ u_s(k) = \Gamma(z^{-1})\ u(k)$$

By applying $\Gamma(z^{-1})$ to both sides of state equation (9), we get the *filtered* form of (9):

$$x_s(k+1) = Ax_s(k) + Bu_s(k) + \varepsilon(k) \tag{11}$$

Now, a new state vector $X(k)$ is considered as follows.

$$X(k) = [x_s(k)^T\ y(k)^T\ y(k-1)^T\ \cdots\ y(k-n_r+1)^T]^T$$

With the new state, we will obtain an augmented state-space models:

$$\begin{aligned} X(k+1) &= \mathrm{F}X(k) + \mathrm{G}u_s(k) + \Xi(k) \\ y(k) &= \mathrm{H}X(k) + v(k) \end{aligned} \tag{12}$$

Where $\Xi(k)$ denotes the augmented noise terms. The characteristics equation of the augmented state-space model (12) comprises of characteristic equation of original plant and the generating polynomial of reference signal; thus according to the internal model principle we can assure that the output will follows reference trajectory with zero steady state error (Wang et al. 2011). The method is also known as *Repetitive control* in literatures.

3.2 Prediction and Optimization Using Laguerre Functions

The next step in design of MPC is predicting the future of state and output vectors based on the chosen system model and current information of the plant. It is reasonable to set these predictions equal to their *expected* values. With this in mind, based on (12) we get:

$$\begin{aligned} X(k+p) &= \mathrm{F}^p X(k) + \sum_{i=0}^{p-1} \mathrm{F}^{p-i-1}\mathrm{G}u_s(k+i) \\ y(k+p) &= \mathrm{H}X(k+p) \end{aligned} \tag{13}$$

Note that the disturbance and noise terms were vanished, because the expectation of a white noise is zero; See Wang (2009) for more details. The main target of MPC is to find the future trajectory of control input which is *optimal*, i.e. it minimizes a function of some type of error. A new interesting and simultaneously efficient method to describe this future trajectory is use of a set of discrete-time orthonormal basis functions, named *Laguerre functions*. This method has been fully discussed in Wang (2009) and here we just briefly explain the main idea and steps.
First, portion the input vector and matrix as:

$$u_s(k) = [u_s^1(k)\ u_s^2(k)\ \cdots\ u_s^m(k)]^T$$

$$\mathrm{G} = [G_1\ G_2\ \cdots\ G_m]$$

Where $u_s^i(k)$ and G_i are the *ith* component and the *ith* column of G, respectively. Next, express each control input $u_s^i(k)$ in finite series of discrete-time Laguerre functions; so in vector form:

$$u_s^i(k) = L_i(k)^T \eta_i \tag{14}$$

Where $L_i(k)$ is the *ith Laguerre Network*, which is specified by the number of functions N_i and the pole of the network a_i, and comprises of first N_i discrete-time Laguerre functions. The vector η_i contains coefficients of Laguerre expansion. The orthonormality of discrete-time Laguerre function can be expressed as:

$$\sum_{k=0}^{\infty} L(k)L^T(k) = I_{N\times N} \tag{15}$$

Where, I stands for identity matrix. As another important property, the discrete-time Laguerre network, $L(k)$ satisfies the following recursive equation:

$$L(k+1) = A_l L(k) \tag{16}$$

$A_l \in \mathbb{R}^{N\times N}$ is a function of poles location a as:

$$A_l(i,j) = \begin{cases} 0 & i<j \\ a & i=j \\ (-a)^{i-j-1}\sqrt{1-a^2} & i>j \end{cases} \tag{17}$$

Noting that the stability of network requires $a \in [0,1)$; Equation (16) can be used for iterative computation of $L(k)$ with the following initial values.

$$L(0) = \sqrt{1-a^2}\,[1\ \ {-a}\ \ a^2\ \cdots\ (-1)^{N-1}a^{N-1}]^T \tag{18}$$

Now, substituting Laguerre network description (14) in prediction model (13) yields:

$$X(k+p) = \mathrm{F}^p X(k) + \sum_{i=0}^{p-1} \mathrm{F}^{p-i-1}[G_1 L_1(i)^T \eta_1\ \cdots\ G_m L_m(i)^T \eta_m]$$

$$\begin{aligned} X(k+p) &= \mathrm{F}^p X(k) + \phi(p)^T \eta \\ y(k+p) &= \mathrm{H}X(k+p) \end{aligned} \tag{19}$$

where:

$$\phi(p)^T = \sum_{i=0}^{p-1} F^{p-j-1}[G_1 L_1(k)^T\ \cdots\ G_m L_m(k)^T]$$

$$\eta = [\eta_1^T \cdots \eta_m^T]^T$$

Now, the design objective of searching an optimal future trajectory of manipulated variable switches to determine the optimal Laguerre coefficients, η. Let consider the following quadratic cost function:

$$\begin{aligned} J &= \sum_{i=1}^{Np}(r(k)-y(k+i))^T Q_w (r(k)-y(k+i)) \\ &+ \sum_{j=0}^{Np} u_s^T(k+j) R_w u_s(k+j) \end{aligned} \tag{20}$$

Where $r(k)$ is the reference signal, Q_w and R_w are weighting matrices on tracking error and control input, respectively. Note that we have assumed that the reference signal remains constant during prediction. By utilizing the orthonormal property of Laguerre functions the cost function can be simplified to:

$$J = \sum_{i=1}^{Np}(r(k)-y(k+i))^T Q (r(k)-y(k+i)) + \eta^T R \eta \tag{21}$$

Without any constraint, the unknown vector η can be found by minimizing the cost function *J*:

$$\eta = -\left(\sum_{i=1}^{Np}\phi(i)\ Q\ \phi(i)^T + R\right)^{-1}\left(\sum_{i=1}^{Np}\phi(i)\ Q\ F^i\right)X_{\mathrm{mod}} \tag{22}$$

Where, X_{mod} (the *modified state vector*) has been defined in order to change the problem to regulator design scheme (i.e. $r(k)=0$) as follows (Wang 2009):

$$X_{\mathrm{mod}}(k) = [x_s(k)^{\mathrm{T}}, (y(k)-r(k))^{\mathrm{T}}, \ldots, (y(k-n_r+1)-r(k))^{\mathrm{T}}]^{\mathrm{T}} \tag{23}$$

4. MPC FOR MEMS VIBRATORY GYROSCOPE

Referring to (5), by considering the state vector as $X = [x\ \dot{x}\ y\ \dot{y}]^T$, and the input vector $u = [u_x\ u_y]^T$, the following continuous-time state-space realization is obtained (Fei & Ding 2010):

$$\dot{X} = AX + Bu \tag{24}$$

Where the system matrices are:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -k_{xx} & -d_{xx} & -\omega_{xy} & -(d_{xy}-2\Omega_z) \\ 0 & 0 & 0 & 1 \\ -k_{xy} & -(d_{xy}+2\Omega_z) & -k_{yy} & -d_{yy} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}^T$$

Now, assuming that merely positions, x and y of proof mass are measured by sensors; the measurement equation is:

$$\mathbf{y} = CX,\ C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{25}$$

The other states can be estimated via an observer. By the way, we should discretize the above mentioned model using some suitable sampling time, T_s.

In force-balancing control strategy of vibratory gyroscope, we try to control the x (derive) direction displacement such that it follows a periodic reference signal and simultaneously the y (sense) axis displacement remains stationary (Bature, Sreeramreddy & Khasawneh 2006); thus the reference trajectories can now be described by differential equations $\ddot{x}_r + \omega^2 x_r = 0$ and $\dot{y}_r = 0$, respectively. The generating polynomials $\Gamma_x(z^{-1})$ and $\Gamma_y(z^{-1})$ are obtained by discretizing these differential equations. The overall generating polynomial is considered to be $\Gamma(z^{-1}) = \Gamma_x(z^{-1})\Gamma_y(z^{-1})$. After achieving the motion control of the proof mass, the control input in y direction can be used to extract the information about unknown angular velocity. Indeed, since $y_r = \dot{y}_r = \ddot{y}_r = 0$, therefore:

$$u_y - k_{xy}x_r - (d_{xy} + 2\Omega_z)\dot{x}_r = 0 \tag{26}$$

The suitable approach to estimate the angular velocity by (26) is *recursive least square* algorithm; substituting the desired value $x_r = X_0 \sin(\omega t)$; (26) yields (Bature, Sreeramreddy & Khasawneh 2006):

$$\begin{aligned} &u_y(t_k) - d_{xy}X_0\omega\cos(\omega t_k) - k_{xy}X_0\sin(\omega t_k) \\ &= 2\hat{\Omega}_z X_0 \omega\cos(\omega t_k) \end{aligned} \tag{27}$$

5. SIMULATIONS

To assess the proposed MPC method of MEMS gyroscopes, computer simulations are performed based on non-dimensioned equations. For this purpose, we use the following gyroscope parameters (Fei & Ding 2010):

$$m = 0.57e\text{-}08Kg,\ k_{xx} = 80.98\frac{N}{m},\ k_{yy} = 71.62\frac{N}{m}$$

$$k_{xy} = 5\frac{N}{m}, d_{xx} = 0.429e\text{-}06\frac{Ns}{m},\ d_{yy} = 0.678e\text{-}03\frac{Ns}{m}$$

$$d_{xy} = 0.0429e\text{-}06\frac{Ns}{m},\ \omega_0 = 1kHz,\ q_0 = 1e\text{-}06m$$

The input angular velocity is assumed 10 rad/sec in plant model simulations. The desired reference trajectories are $x_r = \sin(\omega t)$ with $\omega = 5kHz$ and $y_r = 0$. The Laguerre network parameters for each control input $u_1 = u_x$ and $u_2 = u_y$ are $a_1 = a_2 = 0.5$ and $N_1 = N_2 = 5$, respectively. The parameters of MPC cost function are set to be $R = diag\{0.001, 0.001\}$, $Q = diag\{1,0,1,0\}$ and $N_p = 60$. In order to estimate the unmeasured states, *Kalman filter* is implemented with process noise covariance $Q_f = 10^{-6} I_{4\times4}$, and measurement noise covariance $R_f = 10^{-8} I_{2\times2}$.

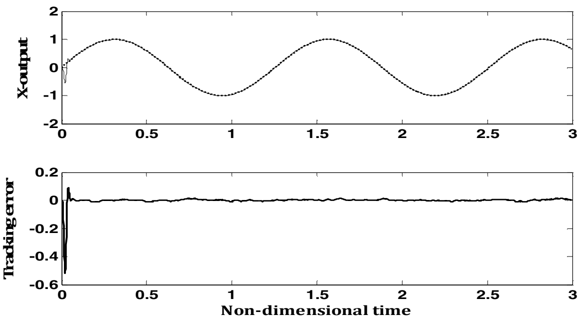

Figure. 2. top to bottom: x direction output, and x direction tracking error.

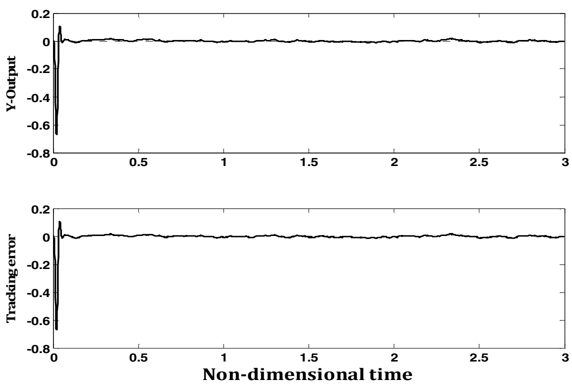

Figure. 3. top to bottom: y direction output, and y direction tracking error.

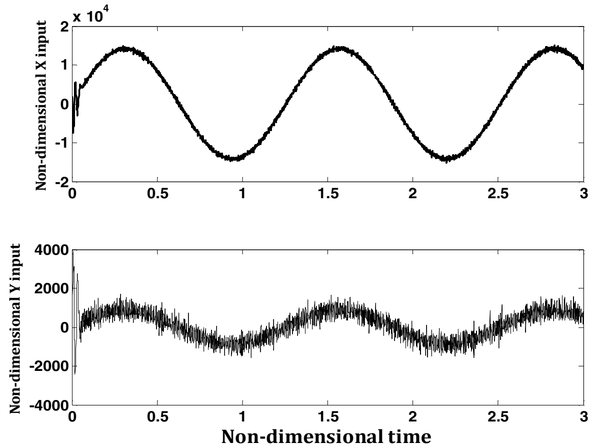

Figure. 4. top to bottom: control effort in x direction and control effort in y direction.

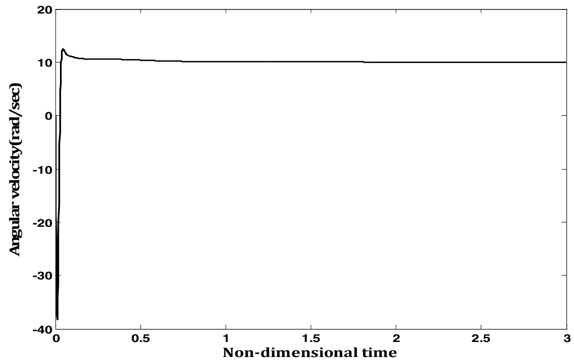

Figure. 5. estimation of unknown angular velocity

6. CONCLUSIONS

This paper presented a discrete-time MPC method for MEMS vibratory gyroscope. The main idea was using the force-balancing strategy for tracking control of the gyroscope and the estimation of input angular rate. The prediction and optimization processes have been designed based on discrete-time Laguerre functions in modelling the future trajectory of input control variables. Repetitive control method was combined with the predictive control to ensure that the system will track the periodic reference trajectories with zero steady-state error. By the way, in the proposed control system, a Kalman filter was used as the observer of unknown states. To estimate the input angular rate through the control input in the sense direction, a recursive least square method was utilized. Computer simulation has been performed in order to testify the proposed method were it was observed that the method is successful in both tracking the reference trajectories and the estimation of input angular velocity.

REFERENCES

Acar, C., Shkel, A. (2009). *MEMS Vibratory Rate Gyroscopes, Structural Approaches to Improve*

Robustness. Springer Science+Business Media, LLC, New York.

Bature, C., Sreeramreddy, T., Khasawneh, Q. (2010). Sliding Mode Control of a Simulated MEMS Gyroscope. *ISA Transactions*, Volume (45), 99-108.

Camacho, E.F., Bordons, C. (1999). *Model Predictive Control*. Springer-Verlag, London.

Fei, J., Ding, H. (2010). System Dynamics and Adaptive Control for MEMS Gyroscope Sensor. *International Journal of Advanced Robotic Systems*, Volume (7), 81-86.

Goodwin, G.C., Graebe, S., Salgado, M. (2001). *Control System Design*. Prentice Hall.

Park, S., Horowitz, R. (2003). Adaptive Control for the Conventional Mode of Operation of MEMS Gyroscopes. *Journal of Microelectromechanical Systems*, Volume (12), 101-108.

Wang, L. (2009). *Model Predictive Control System Design and Implementation Using MATLAB*. Springer-Verlag, London.

Wang, L., Freeman, C.T., Chai, S., Roger, E. (2011). Multivariable Repetitive-predictive Control of a Robot Arm with Experimental Results. *18th International Federation of Automatic Control (IFAC),* Volume (18), 7672-7677.