Optimal Filtering for Humanoid Robot State Estimators

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Abstract— In controlling a humanoid robot, state estimators are used to estimate condition of motion and orientation of the body part which will be feedbacked to control systems to regulate level of the body along with controlling trajectory of center of gravity (C.G.) of the robot. In this research, an algorithm for state estimators is developed by applying the *H2-norm* optimal filtering technique to a linearized dynamic model of the body part of the robot.

Key Words: Dynamic system filtering, State estimator, Humanoid robot

1. Introduction

In controlling a humanoid robot, the body should be regulated to be horizontal all times while its C.G. is being controlled along a planned trajectory. For this purpose, there must be a state estimator for estimating states of motion of the C.G. and orientation of the body part to be feedbacked to control systems.

Estimating states of the body part can be analyzed by treating it as a rigid body. Up till now, there has been much research concerning state estimation of rigid bodies. Most of them are used in the field of vehicle navigation where position and/or orientation of vehicles are determined. Generally, angular rate sensors incorporating with accelerometers are used and sensor data is fused together by using the Kalman filter or complementary filters[1, 2, 3, 4)]. In most research, only kinematic equations of rigid bodies are used in developing filters due to unknown input forces and moments. For example, in head tracking systems [2)], the forces and moments exerted by muscles can not be determined. However, not using the equations of motion results in missing information about inertia of the objects. To obtain more accurate estimation, the equations of motion of the object being tracked should be included in developing filters such as in [4] where input forces and moments of an aircraft can be calculated from the position of aileron.

In case of humanoid robot systems, total forces and moments on the body part can be determined by using whole body dynamic equations of the robot because information of joint angles, forces and moments on both feet are available from encoders and force-moment sensors respectively. However, the whole body equations are very complex and require long computational time hence not practical to be solved in real-time.

In this paper, we develop a state estimator by using both kinematic equations and equations of motion of rigid bodies without trying to calculate input forces and moments. Instead, we design it as a filter that estimates states from sensor data in the presence of external disturbance. In this case, the Kalman filter would not be appropriate because it requires the assumption that noises are white with zero means which is too restrictive. In order to design a filter that is more robust to noise characteristics, we approach by the H_2-norm optimal filtering technique.

2. Linearized Dynamic Equations

The dynamic equations of the body part and measurement equations can be written as follows[5)]

$$\left.\begin{aligned} m\dot{\boldsymbol{v}}^b + \boldsymbol{\omega}^b \times m\boldsymbol{v}^b = \boldsymbol{f}^b \\ \boldsymbol{J}\dot{\boldsymbol{\omega}}^b + \boldsymbol{\omega}^b \times \boldsymbol{J}\boldsymbol{\omega}^b = \boldsymbol{\tau}^b \end{aligned}\right\} \tag{1}$$

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \dfrac{\sin\phi}{\cos\theta} & \dfrac{\cos\phi}{\cos\theta} \end{bmatrix} \boldsymbol{\omega}^b \tag{2}$$

$$\left.\begin{aligned} \boldsymbol{a}_{\text{sensor}} &= \frac{1}{m}\boldsymbol{f}^b + \boldsymbol{\omega}^b \times (\boldsymbol{\omega}^b \times \boldsymbol{r}^b) + \boldsymbol{g}^b \\ &\quad + [\boldsymbol{J}^{-1}\boldsymbol{\tau}^b - \boldsymbol{J}^{-1}\boldsymbol{\omega}^b \times \boldsymbol{J}\boldsymbol{\omega}^b] \times \boldsymbol{r}^b \\ \boldsymbol{\omega}_{\text{sensor}} &= \boldsymbol{\omega}^b \end{aligned}\right\} \tag{3}$$

Eq.(1) is the Newton-Euler equations in body coordinates. Eq.(2) represents the kinematic equation of rigid bodies that relates angular rate to euler angles and their derivatives. Eq.(3) is the measurement equations that relate measured data from accelerometers and gyroscopes to states parameters where r^b is the vector pointing from C.G. to the point that an accelerometer is mounted relative to the body frame.

Because the body part is to be controlled at the horizontal position, changes in orientation are very small under normal operation. Equations (1)(2)(3) can be linearized about the horizontal and stable position.

$$\left.\begin{aligned} \ddot{\boldsymbol{x}}^b \simeq \frac{1}{m}\boldsymbol{f}^b \\ \dot{\boldsymbol{\omega}}^b \simeq \boldsymbol{J}^{-1}\boldsymbol{\tau}^b \end{aligned}\right\} \tag{4}$$

$$\dot{\boldsymbol{\Omega}} = \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \simeq \boldsymbol{\omega}^b \tag{5}$$

$$\boldsymbol{a}_{\text{sensor}} \simeq \frac{1}{m}\boldsymbol{f}^b - \boldsymbol{r}^b \times \boldsymbol{J}^{-1}\boldsymbol{\tau}^b + \boldsymbol{g}^b \qquad (6)$$

By choosing $\boldsymbol{q} = [\boldsymbol{x}^b\ \dot{\boldsymbol{x}}^b\ \boldsymbol{\Omega}\ \boldsymbol{\omega}^b]^T$ as states; $u = [\boldsymbol{f}^b\ \boldsymbol{\tau}^b]^T$ as inputs; and $y = [\boldsymbol{a}_{\text{sensor}}\ \boldsymbol{\omega}^b]^T$ as measurements, we can write the dynamic equations in state-space form.

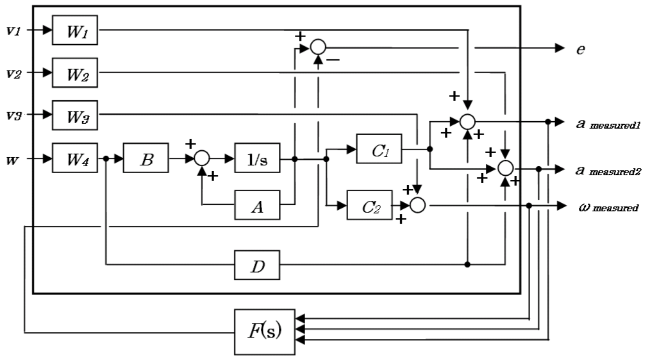

Fig.1 Generalized control system for designing the H_2 optimal filter

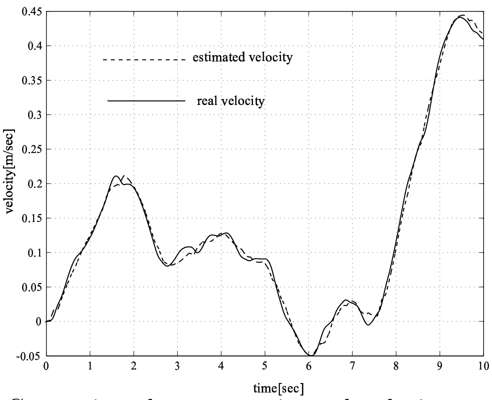

Fig.2 Comparison between estimated velocity and actual velocity from simulation

3. Sensor Unit

The sensor unit consists of two bi-axial gyroscopes (placed perpendicularly to form a tri-axial one), and two tri-axial accelerometers with different frequency response characteristics (one in low frequency region, the other in high frequency region). Sensor signals are filtered and amplified by analog op-amp circuits before entering A/D to the computer.

4. Filter Design

Fig.1 illustrates the block diagram used for designing the filter. The dynamic equations in state-space form are separated into blocks A, B, C_1, C_2, and D. W_4 represents model of force-moment inputs. Acceleration and angular velocity of the system governed by force-moment input w are measured by two accelerometers and a gyroscope $a_{measured1}$, $a_{measured2}$, $\omega_{measured}$. Measurement is corrupted by noises v_1, v_2, v_3 entering the system through the blocks representing noise models W_1, W_2 and W_3 respectively. $F(s)$ is the filter that receives sensor signals and outputs estimates of the states. The difference between actual states and estimated states is designated as state errors e. The design policy is "design a filter $F(s)$ that minimizes the H_2-norm of the transfer matrix of inputs (v_1, v_2, v_3, w) to the state errors e ". It is important to note that W_1, W_2, W_3, and W_4 must be defined so that all conditions for existence of an optimal $F(s)$ are satisfied [6]. The MATLAB command h2syn is used to obtain the optimal filter.

5. Simulation results

We defined W_1, W_2, and W_3 as complements in frequency response of each sensor (approximated by information from manufacturers) in order to emulate frequency characteristic of noises entering during measurement. W_4 was modeled as a low-pass filter according to the assumption that low frequency inputs dominate motion of the body part. The effectiveness of the designed filter was tested by simulation on MATLAB and SIMULINK. In the simulation, we used the white noise of power 0.1 to generate noises v_1, v_2, v_3 and of power 1 to generate the force-moment input signal w. The filter estimated states (euler angle, angular velocity, and position as well as velocity) from signals of angular velocity and acceleration corrupted by noises. The estimated velocity and actual velocity obtained from simulation is shown in figure Fig.2 as one example. Small error can be noticed.

6. Conclusions

We have developed a preliminary algorithm for the state estimator based on the linearized model. To implement it on the real humanoid robot, we need tuning some parameters in design process and refining models of inputs and disturbance to closely match the reality. Some trial and error and extensively testing on the real system are inevitable.

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