Sampled Data High Gain Observer Design Combined with State Predictor For Synchronous PMSMs

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To cite this version:


HAL Id: hal-01465330
https://hal.archives-ouvertes.fr/hal-01465330
Submitted on 18 Feb 2017

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Introduction

- This work is devoted to Sampled Data High Gain Observer design for a class of uniformly observable systems.
- The design of nonlinear observers with sampled measurements has received a great attention.
- This interest is motivated by many applications such as Networks Communication Systems.
- Recently, a hybrid sample data observer dedicated to a class of nonlinear systems has been presented.
- This approach is based on an inter - sample time predictor, which estimates the output between two sampling instants.
- The advantage of this algorithm is in the fact that the state estimates remain continuous time model.
- At each sampling instant, the predictor is reset to the actual output .
- This work presents observer with sampled data measurements and his application to a surface permanent magnet synchronous motor.

Modelling and Observability Study of Synchronous PMS Machines

Because the rotor position is not supposed to be available, the PMSM model is considered in the (α - β) frame : 

The objective is to determine under what conditions all the state of the SPMSM motor, is \( τ_s, ω_m \) and \( T_C \) can be determined from the output and input measurements, namely the current and the voltage measurements \( i_s \) and \( u \), respectively.

\[
\frac{dθ}{dt} = \frac{1}{p} \tan^{-1} \left( \frac{\dot{θ}}{\ddot{θ}} \right)
\]

Now, let us consider the following change of state variables.

\[
Φ : \mathbb{R}^6 \rightarrow \mathbb{R}^6, x \rightarrow z = \begin{pmatrix} Z_1 \\ Z_2 \\ Z_3 \end{pmatrix} = Φ(x) = \begin{pmatrix} Φ_1(x) \\ Φ_2(x) \\ Φ_3(x) \end{pmatrix}
\]

Let \( J_Φ \) be the Jacobian of \( Φ(x) \). According to (6), one has:

\[
J_Φ(x) = \begin{bmatrix} I_2 & 0_2 & 0_2 \\ 0_2 & \frac{dΦ_2(x)}{dx_2} & \frac{dΦ_3(x)}{dx_1} \\ \frac{dΦ_2(x)}{dx_1} & \frac{dΦ_3(x)}{dx_2} & \frac{dΦ_3(x)}{dx_3} \end{bmatrix}
\]

It is clear that the matrix \( J_Φ(x) \) is of full rank if and only if the following square matrix is also of full rank:

\[
G_Φ(x) = \begin{bmatrix} \frac{dΦ_2(x)}{dx_1} & \frac{dΦ_2(x)}{dx_3} \\ \frac{dΦ_3(x)}{dx_1} & \frac{dΦ_3(x)}{dx_2} \\ \frac{dΦ_3(x)}{dx_3} & \frac{dΦ_3(x)}{dx_2} \end{bmatrix} \triangleq \begin{bmatrix} G_2(x) \\ G_3(x) \\ G_3(x) \end{bmatrix}
\]

\[
\det G_Φ(x) = \det(G_1G_2 \cdot G_3G_2) \cdot \det G_Φ(x) = \frac{e}{I_2} (1 + \frac{2πJ}{T}) x_1^2 x_2^2
\]

Then, the considered transformation has a full rank in each x as soon as:

\[
x_{31} x_2^2 x_2 \neq 0 \quad \text{or in the original motor variables,} \quad θs, ω_m \neq 0
\]

The following dynamical system is an observer

\[
\hat{x} = f(x, u) - θp^{-1}(x) θ^{-1} (C(x) - w(t))
\]

\[
w(t) = y(t) + v(t)
\]

Maximal Observability Sampling Period

\[
T_{MSP} = \lim _{p \rightarrow 0} \left( \int _{0}^{\pi} (\tan(x) - \tan(\theta)) \right)
\]

Theorem 1: Under assumptions (A1- A2), system (22) is a sampled data observer for system (16) with the following property: For sufficiently large values of parameters \( p \) and \( ki = 1:2:3 \), there exists a real positive bounded \( T_{MSP} \) such for all \( t \rightarrow 0 \), the observation error is ultimately bounded and the corresponding ultimate bound can be made as small as desired by choosing values of \( p \) high enough.

- We derive a condition on the maximum allowable sample period that ensures a convergence of the observation error.

\[
T_{MSP} = \lim _{p \rightarrow 0} \left( \int _{0}^{\pi} (\tan(x) - \tan(\theta)) \right)
\]

Then, the observer is exponentially stable whatever the initial conditions. The error vector \( \epsilon(t) = 2(t) - x(t) \) converges exponentially to a compact neighborhood of the origin and the size of this compact set can be made small by choosing the design parameters \( p \) sufficiently large.

Mathematical Results:

- The simulation results illustrate that the proposed SDHGO algorithm has fast transient response, good external load torque rejection response accurate tracking response and accurate recovery from any external disturbance.

Simulation Results:

- The following plots illustrate the results of the observers for SPMSM drives.

1. **Simulation Results:**
   - **Figure 1:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 2:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 3:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 4:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 5:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 6:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 7:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 8:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 9:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).
   - **Figure 10:** Real rotor flux \( \psi \) (black), estimated flux \( \hat{\psi} \) (blue).