Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 56-2 (2023) 366–371

IFAC Papers Online CONFERENCE PAPER ARCHIVE

A Novel Globally Exponentially Stable Observer for Sensorless Control of the IPMSM via Kreisselmeier's Extension

Bowen Yi *, **Romeo Ortega** **, **Jongwon Choi** †, **Kwanghee Nam** ‡

* *Robotics Institute, University of Technology Sydney, NSW 2007, Australia*
** *Departamento Académico de Sistemas Digitales, ITAM, Progreso Tizapán 1, Ciudad de México, 04100, México*
† *Department of Electrical and Electronic Engineering, Hannam University, Daejeon 34430, Korea*
‡ *Department of Electrical Engineering, Pohang University of Science and Technology (POSTECH), Pohang 790-784, Korea*
(E-mail: b.yi@outlook.com, romeo.ortega@itam.mx, jongwon@hnu.kr, kwnam@postech.ac.kr)

Abstract: In a recent paper Ortega et al. (2021a) the authors proposed the first solution to the problem of designing a *globally exponentially stable* (GES) flux observer for the interior permanent magnet synchronous motor. However, the establishment of the stability proof relies on the assumption that the adaptation gain is sufficiently *small*—a condition that may degrade the quality of transient behavior. In this paper we propose a new GES flux observer that overcomes this limitation ensuring a high performance behavior. The design relies on the use of a novel theoretical tool—the generation of a *"virtual" invariant manifold*—that allows the use of the more advanced Kreisselmeier's regression extension estimator, instead of a simple gradient descent one. We illustrate its superior transient behavior via simulations.

Keywords: Observers Design; Nonlinear Systems; Motor Drive

1. INTRODUCTION

Sensorless control is one of the most important topics in the field of motor drives, for which we assume only access to electrical coordinates, i.e., the stator currents and voltages. It is of paramount importance in industry since sensorless control of motors can reduce hardware complexity, improve reliability, and achieve cost reduction Holtz (2002); Nam (2017); Zhang (2022); Wang et al. (2019). Meanwhile, this problem has received particular attention from the automatic control community due to its theoretical interests, i.e., the dynamical model of the permanent magnet synchronous motor (PMSM) does not belong to any observable canonical forms that have been studied comprehensively Bernard (2019). To be precise, the main constructive challenges arise from the highly nonlinear output functions.

It is widely recognized that the centrality of sensorless torque control is the high-performance algorithm to estimate angular positions. The existing estimation algorithms can be broadly classified into two classes, which make use of high-frequency and fundamental components in stator currents, respectively. The former is known as the signal injection approach, which is applicable to the low speed region; and the latter is more suitable at middle and high speeds Nam (2017). In this paper, we are limited to the (fundamental frequency) model-based approaches. Indeed, both the back-emf and flux contain the information of angular positions implicitly, thus providing distinct technical routes to reconstruct angular positions. A salient feature of flux is its *constant* magnitude regardless of rotating speeds, and this fact triggers intensive research activity on *flux observers* for PMSMs Bobtsov et al. (2015); Boldea et al. (2008); Ortega et al. (2010) in both the power electronics and control communities.

An important contribution to motor flux observers was reported in Ortega et al. (2010), where it was observed that the motor dynamics satisfies an algebraic relation that can be used to formulate an optimization criterion whose gradient can be explicitly computed for its use in a gradient descent-based observer. This observation led to the design of the first locally stable observer whose practical viability was established in Lee et al. (2010). Later on, this design was rendered global (via convexification) in Malaizé et al. (2012) and then combined with an adaptive mechanism in Bernard and Praly (2018), both achieving global asymptotic stability (GAS). Following the research line initiated in Poulain et al. (2008), a Kazantzis-Kravaris-Luenberger observer was recently proposed in Bernard and Praly (2020), which is capable of dealing with the scenario of unknown resistance. Note that above-mentioned methods are tailored for the *surface-mounted* PMSM (a.k.a. non-salient PMSM). However, in recent years the *interior* (or salient) permanent magnet synchronous motor (IPMSM)

10.1016/j.ifacol.2023.10.1595

has become widely popular in a variety of industrial applications due to its high power density, cheaper cost and reluctance torque. The dynamical model of the IPMSM is far more complicated than the one of surface-mounted PMSMs. In particular, the equivalent of the algebraic relation mentioned above, which was exploited in Ortega et al. (2010), depends now on the rotor angle—hence been unsuitable for its use in a gradient descent based observer. For this reason the design of a globally stable flux observer for IPMSMs was considered to be a wide open problem in (Ortega et al., 2010, Sec. VI), a fact also endorsed in (Bernard and Praly, 2020, Sec. VII).

This problem has been recently solved by the authors in Ortega et al. (2021a). A key observation to establish this result was to formulate the estimation objective in terms of the active, instead of the magnetic, flux Boldea et al. (2008). A similar shift of the problem formulation was (unknowingly) pursued in Malaizé and Praly (2020), leading also to a globally stable design. It is also worth noting the work of Verrelli et al. (2022) where local convergence is reported for a scheme incorporating parameter adaptation. As of this date, the observer design reported in the literature with the strongest stability property, namely GES, is the one in Ortega et al. (2021a). Its basic idea is to obtain a *nonlinear* regression equation on the active flux—which can be viewed as a perturbed linear regressor—by adopting the filtering technique in Choi et al. (2019). A potential drawback of this scheme is that to prove stability, we require a technical condition—selecting the adaptation gain *sufficiently small*. Such low adaptation gain design may limit the estimation performance, particularly in the transient stage. The aim of this paper is to propose an alternative solution, where we do not impose a restriction on the size of the adaptation gain, addressing in this way the issue of (potentially poor) transient behaviors.

In order to be able to design our new globally exponentially convergent flux observer, we add to the filtering technique of Choi and Nam (2019); Ortega et al. (2021a), a novel mathematical concept: the creation of a *virtual invariant manifold*. Thanks to this new technique we are able to replace the gradient-based observer design by the high performance Kreisselmeier's regression extension (KRE)-based estimator, reported in Kreisselmeier (1977) for the design of adaptive observers for linear time-invariant (LTI) systems. We notice that the KRE-based estimator was recently used for electromechanical systems in Li (2020)—see Aranovskiy et al. (2022) for a detailed analysis of the properties of this estimator. To evaluate performance of the proposed sensorless observer for IPMSMs we present numerous simulation results.

The remainder of the paper is organized as follows. In Section 2 we introduce the dynamical model of IPMSMs, as well as the problem formulation studied in the paper. Then, some key assumptions are made in Section 3, under which the novel flux and position observer proposed in Section 4 would admit some provable properties. We present these properties in Proposition 7. However, due to the space limitation we omit its proof, and will report it in a full version in the near future. Section 5 presents numerous simulation results of the proposed approach, which was compared to our previous result in Ortega et al. (2021a). The paper is wrapped up by some concluding remarks in Section 6.

Nomenclature

$\alpha\beta$	Stationary axis reference frame quantities
$\mathbf{v}, \mathbf{i} \in \mathbb{R}^2$	Stator voltage and current [V, A]
$\lambda \in \mathbb{R}^2$	Stator flux [Wb]
$\mathbf{x} \in \mathbb{R}^2$	Active flux [Wb]
$\theta \in \mathbb{S}$	Rotor flux angle [rad]
R	Stator winding resistance [Ω]
ψ_m	PM flux linkage constant
L_d, L_q	d and q-axis inductances [H]
L_0	Inductance difference $L_0 := L_d - L_q$ [H]
L_s	Averaged inductance $L_s := \frac{L_d+L_q}{2}$ [H]
p	Differential operator $p := \frac{d}{dt}$
$G(p)[w]$	Action of $G(p) \in \mathbb{R}(p)$ on a signal $w(t)$

2. MOTOR MODEL AND OBSERVER PROBLEM FORMULATION

According to Faraday's Law, the electrical dynamics (in the stationary $\alpha\beta$ frame) is given by

$$\dot{\lambda} = -R\mathbf{i} + \mathbf{v}. \tag{1}$$

For IPMSMs, the measurable current satisfies

$$\mathbf{i} = \mathcal{L}^{-1}(\theta)[\lambda - \psi_m \mathbf{c}(\theta)] \tag{2}$$

with the mappings

$$\begin{aligned} \mathcal{L}(\theta) &:= L_s I_2 + \frac{L_0}{2} Q(\theta) \\ Q(\theta) &:= \begin{bmatrix} \cos(2\theta) & \sin(2\theta) \\ \sin(2\theta) & -\cos(2\theta) \end{bmatrix} \\ \mathbf{c}(\theta) &:= \mathrm{col}(\cos\theta, \sin\theta). \end{aligned}$$

Following Choi and Nam (2019) we define the active flux $\mathbf{x}(t) \in \mathbb{R}^2$ as

$$\mathbf{x} := \lambda - L_q \mathbf{i}. \tag{3}$$

As shown in Choi and Nam (2019); Ortega et al. (2021a), the rotor angle can be reconstructed from $\mathbf{x}$ via the relation

$$\tan(\theta) = \frac{\mathbf{x}_2}{\mathbf{x}_1}. \tag{4}$$

The central problem in sensorless control of electric motors is to estimate the mechanical angular position $\theta(t) \in \mathbb{S}$ from the measurable signals $\mathbf{v}(t) \in \mathbb{R}^2$ and $\mathbf{i}(t) \in \mathbb{R}^2$. This is equivalent to online estimation of the active flux $\mathbf{x}$.

Observer Design Problem Consider the dynamical model (1) with the output (2). Design an observer

$$\begin{aligned} \dot{\eta} &= F(\eta, \mathbf{i}, \mathbf{v}) \\ \hat{\mathbf{x}} &= N(\eta, \mathbf{i}, \mathbf{v}) \end{aligned} \tag{5}$$

with $\eta(t) \in \mathbb{R}^{n_\eta}$, that ensures global exponential convergence of the active flux estimation error, that is,

$$\lim_{t\to\infty} |\hat{\mathbf{x}}(t) - \mathbf{x}(t)| = 0, \text{ (exp.)} \tag{6}$$

for all system and observer initial conditions. □

3. ASSUMPTIONS AND PRELIMINARY RESULTS

The success of the GES observer design in Ortega et al. (2021a) relies on the following lemma, which was established in Choi and Nam (2019); see also (Ortega et al., 2021a, Lemma 1). By introducing some LTI stable filters, we are able to obtain a perturbed linear regression equation (LRE), which is instrumental for the gradient observer design in the sequel.

Lemma 1. The electrical dynamics of the IPMSM (1), (2) satisfies the following (perturbed) linear regression equation

$$y = \Phi^\top \mathbf{x} + d + \epsilon_t, \tag{7}$$

where the active flux $\mathbf{x}$ is defined in (3), and the *measurable* signals $y(t) \in \mathbb{R}^2$ and $\Phi(t) \in \mathbb{R}^2$ are given as

$$\begin{aligned} y &:= L_0 H_2[\mathbf{i}]^\top \Omega_1 + \frac{1}{\alpha}|\Omega_1|^2 + \frac{1}{\alpha} H_2[\Omega_2^\top \Omega_1] \\ \Phi &:= \Omega_1 + \Omega_2. \end{aligned}$$

with the signals $\Omega_1(t) \in \mathbb{R}^2$ and $\Omega_2(t) \in \mathbb{R}^2$ defined as

$$\begin{aligned} \Omega_1 &:= H_2[\mathbf{v} - R\mathbf{i} - L_q p \mathbf{i}] \\ \Omega_2 &:= \Omega_1 - L_0 H_1[\mathbf{i}], \end{aligned}$$

and the filters

$$H_1(p) := \frac{\alpha p}{p+\alpha}, \quad H_2(p) := \frac{\alpha}{p+\alpha}, \tag{8}$$

where $\alpha > 0$ is a *tuning* parameter.

The (unknown) perturbing signal d is given by

$$d := -\ell H_1\left[\mathbf{i}^\top \frac{\mathbf{x}}{|\mathbf{x}|}\right], \tag{9}$$

with $\ell := \psi_m L_0$, and $\epsilon_t \in \mathbb{R}^2$ is an exponentially decaying term[1] caused by the initial condition of the filters. □

To address the observer design problem, we make the following assumptions that, as thoroughly discussed in Choi and Nam (2019); Ortega et al. (2021a), hold true in practice—see Remark 6 below.

Assumption 2. (*Motor rotating behavior*) Φ is persistently excited, namely, there exist $T > 0$ and $\delta > 0$ such that

$$\int_t^{t+T} \Phi(s)\Phi^\top(s) ds \ge \delta I_2, \quad \forall t \ge 0 \tag{10}$$

with $|\Phi|$ upper bounded.

Assumption 3. (*Boundedness*) The motor operates in a mode guaranteeing that all signals $\mathbf{i}$, $\mathbf{v}$ and λ are bounded and $|\mathbf{x}| \ge x_{\min}$ for some constant $x_{\min} > 0$.

Assumption 4. (*Small anisotropy*) The current $\mathbf{i}$ verifies $|L_0 \mathbf{i}| < \psi_m$.

Motivated by the flux dynamics (1) an observer of the following form is suggested in many works

$$\begin{aligned} \dot{\hat{\lambda}} &= \mathbf{v} - R\mathbf{i} + E \\ \hat{\mathbf{x}} &= \hat{\lambda} - L_q \mathbf{i} \end{aligned} \tag{11}$$

with a signal $E(t) \in \mathbb{R}^2$ to be defined. Invoking (3) we see that, for this observer structure, we get

$$\dot{\tilde{\mathbf{x}}} = E \tag{12}$$

with $\tilde{\mathbf{x}} := \hat{\mathbf{x}} - \mathbf{x}$. Several different correction terms E can be used to complete the observer design.

i) By leaving out the perturbation term d and applying a gradient descent to minimize the cost function

$$J_{\mathtt{tie}}(\hat{\mathbf{x}}) = \left| y - \Phi^\top \hat{\mathbf{x}} \right|^2,$$

the correction term in Choi et al. (2019)[2] is selected as

$$E_{\mathtt{tie}} = \gamma \Phi(y - \Phi^\top \hat{\mathbf{x}}), \quad \gamma > 0.$$

As shown in Choi et al. (2019) the estimation error dynamics is *practically* exponentially stable with bounded ultimate errors.

ii) The paper Ortega et al. (2021a) proposes the correction term[3]

$$\begin{aligned} E_{\mathtt{aut}} &= \gamma \Phi\Big(y - \Phi^\top \hat{\mathbf{x}} - \hat{d}\Big), \quad \gamma > 0 \\ \hat{d} &= -\ell H_1\left[\mathbf{i}^\top \frac{\hat{\mathbf{x}}}{|\hat{\mathbf{x}}|}\right]. \end{aligned} \tag{13}$$

The term in (13) can be viewed as a certainty equivalent approximation of the gradient descent to minimize the cost function

$$J_{\mathtt{aut}}(\hat{\mathbf{x}}) = \left| y - \Phi^\top \hat{\mathbf{x}} - \hat{d} \right|^2. \tag{14}$$

In Ortega et al. (2021a), to guarantee global exponential stability, we require the adaptation gain $\gamma > 0$ to be *sufficiently small*, which may have a deleterious effect on the transient performance. The main objective of this paper is to propose an alternative observer design that *removes* the requirement of a small adaptation gain.

Remark 5. In Lemma 1, we obtain a nonlinear regression model (7) via the filtering technique. It can be viewed as a linear regression model with respect to $\mathbf{x}$ with a perturbation term d. This term $d = -\ell H_1[\mathbf{i}^\top \frac{\mathbf{x}}{|\mathbf{x}|}]$ is, in nature, the filtered signal of the inner product between the current (stator flux) and the *normalized* rotor flux vector, which should be maintained to be zero for torque maximization.

Remark 6. Some remarks on the assumptions adopted in the paper are in order.

(i) The persistency of excitation condition (10) is generally satisfied when motors are operating at middle- or high-speed regions. Otherwise, it is necessary to probe high-frequency signals in low speed to impose observability (Ortega et al., 2021a, Sec. 5). Note that another way to use signal injection is to demodulate the angular information implicitly carried by the high-frequency component of stator currents Nam (2017); Yi et al. (2020); Briz and Degner (2011); Wang et al. (2019).

(ii) Assumption 3 is reasonable since the active flux $\mathbf{x}$ is not zero as far as the rotor permanent magnet is magnetized.

[1] Following standard practice, we neglect these terms in the sequel.

[2] The paper Choi et al. (2019) considers another perturbed linear regression model rather than (7), but they are exactly in the same form. Hence, we may conclude the same stability properties for the closed-loop dynamics.

[3] In Ortega et al. (2021a) a slight modification in $\hat{d}$ is introduced to guarantee $|\hat{\mathbf{x}}| > x_{\min}$ and thus avoid singularities. We omit it here for simplicity of presentation.

4. FLUX AND POSITION OBSERVER

To overcome the performance limitation imposed by the requirement to use a small adaptation gain in the gradient-based scheme of Ortega et al. (2021a) we add to the filtering technique of Choi and Nam (2019); Ortega et al. (2021a), a novel mathematical concept: the creation of a *virtual invariant manifold*. Thanks to this new technique we are able to replace the gradient-based observer design by the high performance KRE-based estimator. As explained in Ortega et al. (2020) the key step in Kreisselmeier's estimator is the construction of the KRE that, as shown in Ortega et al. (2021b), is a particular form of the more general dynamic regressor extension. For the purpose of this paper, the key feature of this estimator is that, in contrast with gradient or least-squares schemes, it is possible to make the estimator converge arbitrarily fast (after a short transient phase due to filtering) by increasing the adaptation gain—see also Aranovskiy et al. (2022) for a detailed analysis of the properties of this estimator.

Motivated by Lemma 1, Kreisselmeier's estimator Kreisselmeier (1977), the results of Li (2020), our previous work Ortega et al. (2021a) and the discussion in the previous section, we propose the following flux observer.

Flux and position observer

$$\left.\begin{aligned}\dot{Q} &= -a\big(Q - \Phi\Phi^\top\big),\ Q(0)=0\\ \dot{Y} &= -a\big(Y - \Phi e\big) + QE,\ Y(0)=0\\ E &= -\gamma Y\end{aligned}\right\}\ \text{(KRE)}$$

$$\left.\begin{aligned}\dot{\hat{\lambda}} &= \mathbf{v} - R\mathbf{i} + E\\ \hat{\mathbf{x}} &= \hat{\lambda} - L_q\mathbf{i}\\ \hat{\theta} &= \text{atan2}(\hat{\mathbf{x}}_2, \hat{\mathbf{x}}_1),\end{aligned}\right\}\ \text{(Flux-position estimate)} \tag{15}$$

with the estimate of the disturbance signal

$$\hat{d} \ = \ -\ell H_1[\mathbf{i}^\top\sigma(\hat{\mathbf{x}})], \tag{16}$$

the variable

$$e := \Phi^\top\hat{\mathbf{x}} + \hat{d} - y,$$

the mapping

$$\sigma(\hat{\mathbf{x}}) = \begin{cases}\dfrac{\hat{\mathbf{x}}}{|\hat{\mathbf{x}}|} & \text{if } \ |\hat{\mathbf{x}}| \ge \epsilon > 0\\ \text{col}(0,0) & \text{otherwise,}\end{cases}$$

where $\epsilon \in (0, x_{\mathtt{min}})$ and $a, \alpha, \gamma > 0$ are tuning parameters. □

We summarize the provable properties of the above observer as follows.

Proposition 7. Consider the model (1) with output (2). For any adaptation gains $\gamma > 0$ and $a > 0$, there always exists a scalar $\alpha_{\max} > 0$ such that the observer (15) and (16) guarantees the global exponential convergence (6) and

$$\lim_{t\to\infty}\left|\begin{bmatrix}\hat{\theta}(t) - \theta(t)\\ \hat{\mathbf{x}}(t) - \mathbf{x}(t)\end{bmatrix}\right| = 0 \quad \text{(exp.)}$$

for any[4] $\alpha \le \alpha_{\max}$.

[4] We underscore the fact that, as shown in (8), α is a free tuning parameter that determines the time constant of the low pass LTI filters $H_1(p)$ and $H_2(p)$.

Proof. We omit the proof due to the space limitation. Indeed, the proof is based on two key observations:

- After the moment $t > T$, the variable $Q(t)$ is positive definite.
- There exists a (virtual) forward invariant manifold
$$\mathcal{M} := \{(Y, Q, \xi) \in \mathbb{R}^2 \times \mathbb{R}^{2\times} \times \mathbb{R}^2 : Y = Q\tilde{\mathbf{x}} + \xi\}$$
with ξ generated by the dynamics
$$\dot{\xi} = -a\big(\xi - \Phi\tilde{d}\big),\ \xi(0) = 0, \tag{17}$$
and we have defined $\tilde{d} := \hat{d} - d$.

The full proof will be reported somewhere else. □

Remark 8. There are three positive adaptation parameters to tune, i.e., a, α and γ.

(i) The parameter α appears in the filters $H_1(p)$ and $H_2(p)$ for pre-filtering in order to generate the regression model (7). This parameter affects the convergence rate of the exponentially decaying term ϵ_t. As shown in Proposition 7, a large $\alpha > 0$ may yield instability of the closed loop.

(ii) The parameter a appears in the KRE

$$\dot{Q} = -a(Q - \Phi\Phi^\top).$$

Roughly, a small $a > 0$ means that "more past" information of $\Phi\Phi^\top$ is utilized in the matrix Q.

(iii) The parameter γ appears in the $(1,1)$-element of $A(t)$, making it closely connected to the convergence rate of the active flux estimate. In the above design we fix $Q(0) = 0$ and $Y(0) = 0$ and $\xi(0) = 0$. If we select a small $a > 0$ and a sufficiently large γ, then the estimation error $\tilde{\mathbf{x}}$ will converge to a small neighborhood of zero very fast. In contrast, in Ortega et al. (2021a) we require the adaption gain $\gamma > 0$ *sufficiently small*, thus we are unable to assign the transient performance.

Remark 9. The correction term E in the proposed flux and position observer (15) can be roughly viewed as the gradient descent of the cost function generated from the KRE, rather than the "natural" cost function (14) adopted in Ortega et al. (2021a). This idea was originally proposed in the pioneer work Kreisselmeier (1977) to improve transient performance in adaptive observers, for which the unknown parameters are *constant*. In the context of observer design, we need to take into account the dynamics of the *time-varying* states, and this is captured by the additional variable ξ in the proof.

5. SIMULATION RESULTS

In simulations, in order to make it more realistic we adopted the parameters from a real motor. They are $R = 2.5\ \Omega$, $L_d = 0.00782$ H, $L_q = 0.00782$ H, and $\psi_m = 0.10$, with the pole number equal to 8. We consider the gains $\alpha = 200\pi$ and $a = 20\pi$, and consider different adaptation gains γ. Simulations were performed using MATLAB/Simulink. The motor was rotating at 1000 rpm, and we selected the initial magnetic flux angle error as $\pi/2$. The magnitude error was set as twice as the real value, i.e.,

$$\hat{\lambda}(0) = 2\psi_m\begin{bmatrix}\cos(\theta - \pi/2)\\ \sin(\theta - \pi/2)\end{bmatrix}.$$

In Fig. 1, we present the simulation results for the observer (15) with the adaptation gain $\gamma = 1$, showing its satisfactory performance. By increasing γ to 5, we observe in Fig. 3 that the convergence rate becomes faster as expected from Proposition 7. This is compared to the position observer in our previous work Ortega et al. (2021a), with the simulation results in the same scenario are shown in Figs. 2 and 4 for the gains $\gamma = 1$ and $\gamma = 5$, respectively. Note that the approach in Ortega et al. (2021a) requires the adaptation gain γ sufficiently small to achieve global exponential stability. It is clear in Fig. 4 that when selecting $\gamma = 5$ it slows down the convergence rate and even causes the inconsistency issue. This demonstrates the key merit of tunability for the observer proposed in this paper.

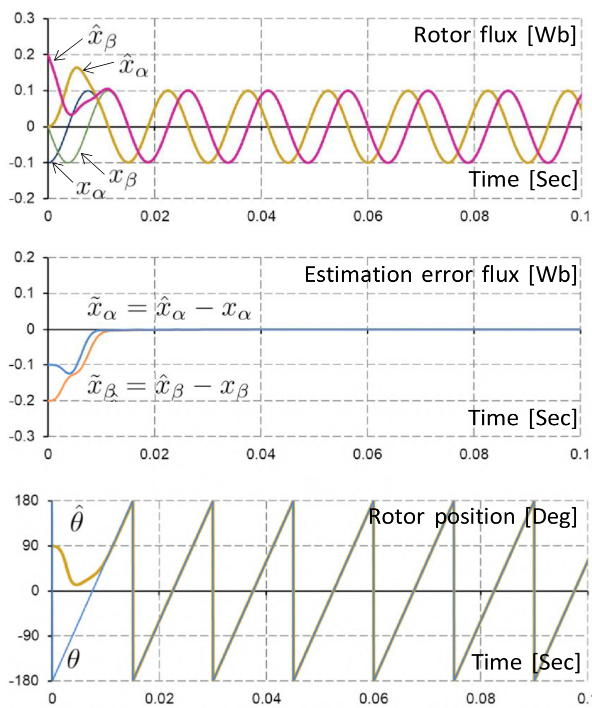

Fig. 1. Simulation results: Estimation of rotor flux from the proposed observer with $\gamma = 1$

6. CONCLUSION

In this paper, we revisited the problem of designing a GES observer for sensorless control of IPMSMs. Compared to our previous result in Ortega et al. (2021a), the new design does not impose a requirement of using a sufficiently small adaptation gain $\gamma > 0$, a restriction that may affect the transient performance of the observer. Our motivation in this paper is to remove this restriction to improve the convergence rate of the observer.

The success of the new design relies on the introduction of a virtual invariant manifold that is instrumental for the inclusion of the KRE estimator. We have also conducted comprehensive simulations to validate our theoretical development and its practical usefulness. Some real-world experiments are on the way, and we hope to report them in the near future.

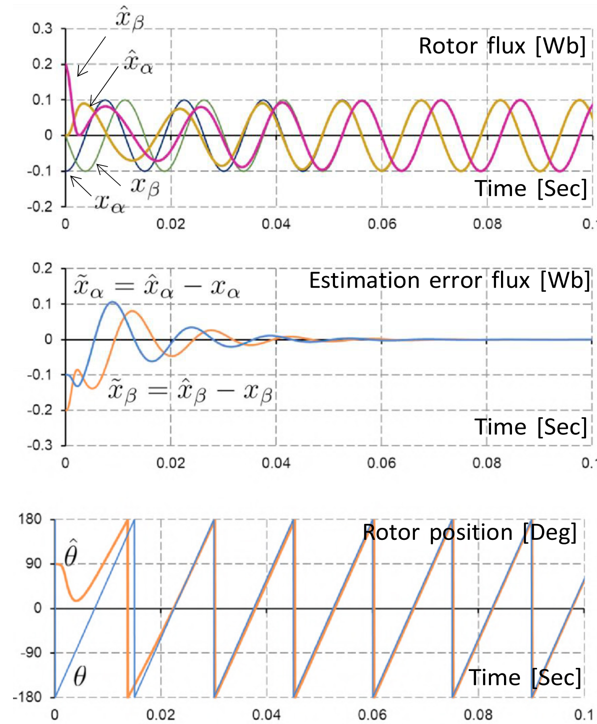

Fig. 2. Simulation results: Estimation of rotor flux from the observer in Ortega et al. (2021a) with $\gamma = 1$

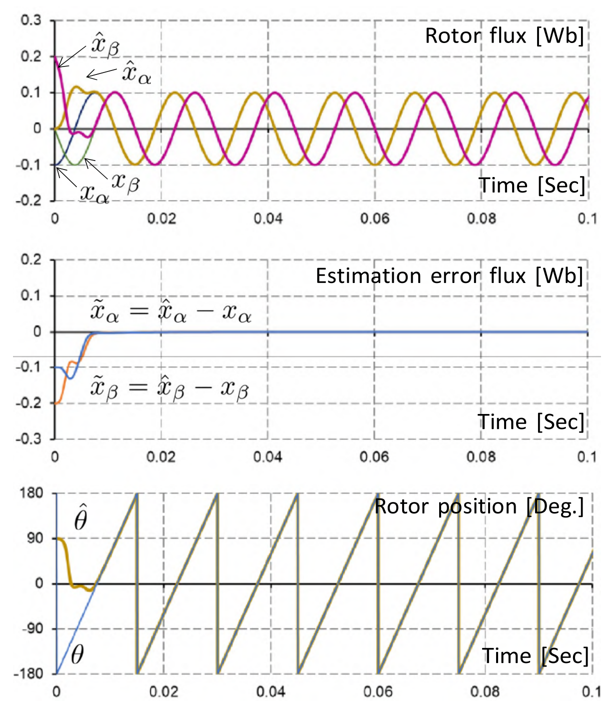

Fig. 3. Simulation results: Estimation of rotor flux from the proposed observer with $\gamma = 5$

ACKNOWLEDGEMENT

This work was partially supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (NRF-2021R1I1A3059676).

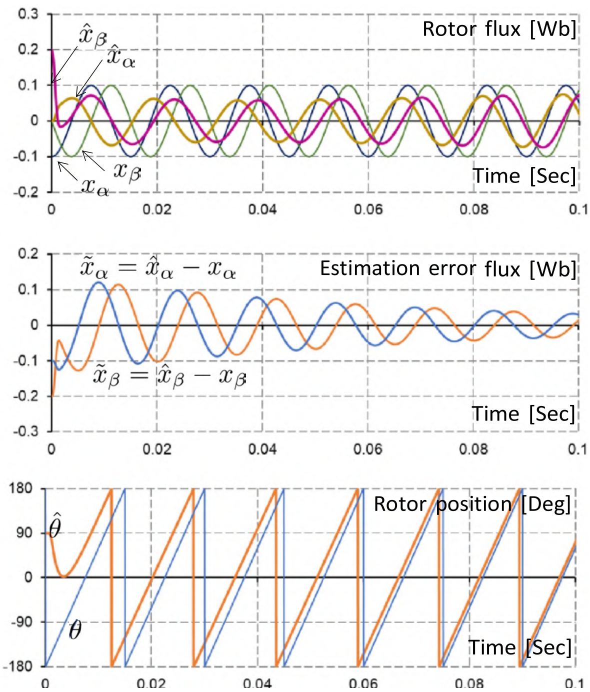

Fig. 4. Simulation results: Estimation of rotor flux from the observer in Ortega et al. (2021a) with $\gamma = 5$

REFERENCES

S. Aranovskiy, R. Ushirobira, M. Korotina and V. Vedyakov, On preserving-excitation properties of Kreisselmeiers regressor extension scheme, *IEEE Trans. Autom. Control*, vol. 68, pp. 1296–1302, 2023.

P. Bernard, *Observer Design for Nonlinear Systems*, Springer, Switzerland, 2019.

P. Bernard and L. Praly, Convergence of gradient observer for rotor position and magnet flux estimation of permanent magnet synchronous motors, *Automatica*, vol. 94, pp. 88–93, 2018.

P. Bernard and L. Praly, Estimation of position and resistance of a sensorless PMSM: a nonlinear Luenberger approach for a nonobservable system, *IEEE Trans. Autom. Control*, vol. 66, pp. 481–496, 2020.

A. Bobtsov, A. Pyrkin, R. Ortega, S. Vukosavic, A.M. Stankovic and E.V. Panteley, A robust globally convergent position observer for the permanent magnet synchronous motor, *Automatica*, vol. 61, pp. 47–54, 2015.

I. Boldea, M.C. Paicu, G.-D. Andreescu, Active flux concept for motion-sensorless unified AC drives, *IEEE Trans. Power Syst.*, vol. 23, pp. 2612–2618, 2008.

F. Briz and M.W. Degner, Rotor position estimation, *IEEE Ind. Electron. Mag.*, vol. 5, pp. 24–36, 2011.

J. Choi, K. Nam, A.A. Bobtsov and R. Ortega, Sensorless control of IPMSM based on regression model, *IEEE Trans. Power Electron.*, vol. 34, no. 9, pp. 9191–9201, 2019.

J. Choi and K. Nam, Model-based sensorless control for IPMSM providing seamless transition to signal injection method, *Tech. Report*, 2019.

J. Holtz, Sensorless control of induction motor drives, *Proc. IEEE*, vol. 90, pp. 1359–1394, 2002.

G. Kreisselmeier, Adaptive observers with exponential rate of convergence, *IEEE Trans. Autom. Control*, vol. 22, pp. 2-8, 1977.

J. Lee, J. Hong, K. Nam, R. Ortega, A. Astolfi and L. Praly, Sensorless control of surface-mount permanent magnet synchronous motors based on a nonlinear observer, *IEEE Trans. Power Electron.*, vol. 25, no. 2, pp. 290–297, 2010.

P.Y. Li, Self-sensing dual push-pull solenoids using a finite dimension flux-observer, *Proc. Am. Control Conf.*, pp. 590–595, Denver, USA, July 1-3, 2020.

P.M. Lion, Rapid identification of linear and nonlinear systems, *AIAA J.*, vol. 5, pp. 1835-1842, 1967.

J. Malaizé and L. Praly, Robust position estimation for permanent magnet synchronous electrical machines with salient poles, Archive ouverte HAL, 2020. (`hal-02568844`).

J. Malaizé, L. Praly and N. Henwood, Globally convergent nonlinear observer for the sensorless control of surface-mount permanent magnet synchronous machines, *IEEE Conf. Decis. Control*, pp. 5900–5905, 2012.

K. Nam, *AC Motor Control and Electric Vehicle Applications*, CRC Press, 2017.

R. Ortega, L. Praly, A. Astolfi, J. Lee and K. Nam, Estimation of rotor position and speed of permanent magnet synchronous motors with guaranteed stability, *IEEE Trans. Control Syst. Technol*, vol. 19, pp. 601–614, 2010.

R. Ortega, V. Nikiforov and D. Gerasimov, On modified parameter estimators for identification and adaptive control: A unified framework and some new schemes, *Annu. Rev. Control*, vol. 50, pp. 278–293, 2020.

R. Ortega, B. Yi, S. Vukosavic, K. Nam and J. Choi. A globally exponentially stable position observer for interior permanent magnet synchronous motors. *Automatica*, vol. 125, Art. no. 109424, 2021a.

R. Ortega, S. Aranovskiy, A. Pyrkin, A Astolfi and A. Bobtsov, New results on parameter estimation via dynamic regressor extension and mixing: Continuous and discrete-time cases, *IEEE Trans. Autom. Control*, vol. 66, no. 5, pp. 2265-2272, 2021b.

F. Poulain, L. Praly and R. Ortega, An observer for permanent magnet synchronous motors with application to sensorless control, *IEEE Conf. Decis. Control*, Cancun, Mexico, 9-11 December, 2008.

C.M. Verrelli, E. Carfagna, M. Frigieri, A.S. Crinto and E. Lorenzani, A new Bernard-Praly-like observer for sensorless IPMSMs, *Automatica*, vol. 140, Art. no. 110266, 2022.

G. Wang, M. Valla and J. Solsona, Position sensorless permanent magnet synchronous machine drives – A review, *IEEE Trans. Ind. Electron.*, vol. 67, pp. 5830–5842, 2019.

B. Yi and R. Ortega, Conditions for convergence of dynamic regressor extension and mixing parameter estimators using LTI filters, *IEEE Trans. Autom. Control*, vol. 68, pp. 1253–1258, 2023.

B. Yi, S.N. Vukosavić, R. Ortega, A.M. Stanković and W. Zhang, A new signal injection-based method for estimation of position in interior permanent magnet synchronous motor, *IET Power Electron.*, vol. 13, no. 9, pp. 1865–1874, 2020.

Z. Zhang, Sensorless back EMF based control of synchronous PM and reluctance motor drives – A review, *IEEE Trans. Power Electron.*, vol. 35, pp. 10290–10305, 2022.