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# State and Unknown Inputs Estimation for a Class of Discrete-time Takagi-Sugeno Descriptor Models

Karim Bouassem[1,2], Jalal Soulami[1,2], Abdellatif El Assoudi[1,2], El Hassane El Yaagoubi[1,2]

[1]Laboratory of High Energy Physics and Condensed Matter, Faculty of Science
Hassan II University of Casablanca, B.P 5366, Maarif, Casablanca, Morocco
[2]ECPI, Department of Electrical Engineering, ENSEM
Hassan II University of Casablanca, B.P 8118, Oasis, Casablanca Morocco.
Email: jalal.soulami@gmail.com

***Abstract*—In this paper, the design problem of simultaneous estimation of unmeasurable states and unknown inputs (UIs) is investigated for a class of discrete-time Takagi-Sugeno descriptor models (DTSDMs) with measurable premise variables. The UIs affect both state and output of the system. The approach is based on the separation between dynamic and static relations in the considered DTSDM. First, the method permitting to separate dynamic equations from static equations is exposed. Next, an augmented fuzzy explicit model which contains the dynamic equations and the UIs is constructed. Then a fuzzy unknown inputs observer (FUIO) design in explicit structure is developed. The exponential convergence of the state estimation error is studied by using the Lyapunov theory and the stability conditions are given in terms of linear matrix inequalities (LMIs). Finally, an illustrative example is given to show the good performances of the proposed method.**

**Keywords**: Discrete-time Takagi-Sugeno descriptor model, unknown inputs, fuzzy unknown inputs observer, LMI.

In this paper, some notations used are fair standard.
For example, $X > 0$ means the matrix $X$ is symmetric and positive definite. $X^T$ denotes the transpose of $X$.
The symbol $I$ (or 0) represents the identity matrix (or zero matrix) with appropriate dimension.
$\sum_{i,j=1}^{q}\mu_i\mu_j = \sum_{i=1}^{q}\sum_{j=1}^{q}\mu_i\mu_j$, $\begin{pmatrix} X & * \\ Z & Y \end{pmatrix} = \begin{pmatrix} X & Z^T \\ Z & Y \end{pmatrix}$.

## I. Introduction and Problem Statement

Descriptor dynamic models, known as a generalization of standard dynamic models, constitute a powerful modeling tool allowing to describe the dynamic behavior of processes governed by both dynamic and static equations. They represent physical phenomenas that can not be described by standard models, see [1], [2], [3] for some real applications of descriptor models. Moreover, the ordinary T-S fuzzy model [4], [5] has been successfully developed to study nonlinear control systems, see e.g. [6], [7] and the references therein. In [8], [9], a fuzzy descriptor system is defined by extending the T-S fuzzy model [4]. Notice that, UIs can result either from uncertainty in the model or from the presence of unknown external excitation. Thus, due to the increasing demand for reliability and maintenability of the automatic control process, unknown inputs observer design is widely used in the area of fault detection and design of fault tolerant control strategy. This is one of the most attractive research areas in both theoretical and practical fields during these last two decades, see e.g. [10], [11], [12] for works using different approaches. In this paper, the following class of DTSDMs subject to UIs which affect both state and output of the system is considered:

$$\begin{cases} MZ_{k+1} = \sum_{i=1}^{q}\mu_i(\eta_k)(A_iZ_k + B_iu_k + C_id_k) \\ y_k = \sum_{i=1}^{q}\mu_i(\eta_k)(D_iZ_k + E_iu_k + F_id_k) \end{cases} \quad (1)$$

where $Z_k^T = [Z_k^{1T} \; Z_k^{2T}] \in \mathbf{R}^n$ is the state vector with $Z_k^1 \in \mathbf{R}^{n_1}$ is the vector of difference variables, $Z_k^2 \in \mathbf{R}^{n_2}$ is the vector of algebraic variables with $n_1+n_2 = n$, $u_k \in \mathbf{R}^m$ is the control input, $d_k \in \mathbf{R}^r$ is the unknown control input, $y_k \in \mathbf{R}^p$ is the measured output. $A_i \in \mathbf{R}^{n\times n}$, $B_i \in \mathbf{R}^{n\times m}$, $C_i \in \mathbf{R}^{n\times r}$, $D_i \in \mathbf{R}^{p\times n}$, $E_i \in \mathbf{R}^{p\times m}$, $F_i \in \mathbf{R}^{p\times r}$, $M \in \mathbf{R}^{n\times n}$ such that $rank(M) = n_1$ are real known constant matrices with:

$$M = \begin{pmatrix} I & 0 \\ 0 & 0 \end{pmatrix}; \quad A_i = \begin{pmatrix} A_{11i} & A_{12i} \\ A_{21i} & A_{22i} \end{pmatrix} \quad (2)$$

$$B_i = \begin{pmatrix} B_{1i} \\ B_{2i} \end{pmatrix}; C_i = \begin{pmatrix} C_{1i} \\ C_{2i} \end{pmatrix}; D_i = \begin{pmatrix} D_{1i} & D_{2i} \end{pmatrix} \quad (3)$$

where constant matrices $A_{22i}$ are supposed invertible. $q$ is the number of sub-models. $\eta_k$ is the premise variable which is supposed here to be real-time accessible and the $\mu_i(\eta_k)$ ($i = 1, \ldots, q$) are the weighting functions that ensure the transition between the contribution of each sub model:

$$\begin{cases} MZ_{k+1} = A_iZ_k + B_iu_k + C_id_k \\ y_k = D_iZ_k + E_iu_k + F_id_k \end{cases} \quad (4)$$

They verify the so-called convex sum properties:

$$\begin{cases} \sum_{i=1}^{q}\mu_i(\eta_k) = 1 \\ 0 \leq \mu_i(\eta_k) \leq 1 \quad i = 1, \ldots, q \end{cases} \quad (5)$$


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The aim of the paper consists in investigating the problem of FUIO design for the class of systems (1). Notice that, this problem design for T-S explicit or descriptor systems has received considerable attention and is still an active area of research in both continuous-time and discrete-time cases. Indeed, for T-S fuzzy systems described by ordinary dynamic equations subject to UIs, various developments on fuzzy observer and its application to fault detection exist in the literature, see for instance [13], [14], [15], [16], [17] for continuous-time systems and [18], [19], [20], [21] for discrete-time systems. Likewise, for T-S fuzzy descriptor systems subject to UIs several works are discussed in the literature see e.g. [22], [23], [24], [25], [26], [27], [28]. It should be noted that, generally, an interesting way to solve the various FUIO raised previously is to write the convergence conditions on the LMI form [29].

Before giving the main result, let us make the following assumption [1], [24]:

*Assumption 1:* : Suppose that:

- $(M,\ A_i)$ is regular, i.e. $det(zM - A_i) \neq 0\ \forall z \in \mathbf{C}$
- All sub-models (4) are impulse observable and detectable.

In order to investigate the FUIO design for system (1), we proceed as mentioned above to the separation of the dynamic equations from static equations of the model (1). Indeed, from (2)-(3), sub-model (4) can be rewritten as follows:

$$\left\{\begin{array}{rcl} Z^1_{k+1} & = & A_{11i}Z^1_k + A_{12i}Z^2_k + B_{1i}u_k + C_{1i}d_k \\ 0 & = & A_{21i}Z^1_k + A_{22i}Z^2_k + B_{2i}u_k + C_{2i}d_k \\ y_k & = & D_{1i}Z^1_k + D_{2i}Z^2_k + E_iu_k + F_id_k \end{array}\right. \tag{6}$$

Since $A_{22i}$ is inversible, it follows:

$$Z^2_k \quad = \quad J_iZ^1_k + K_iu_k + L_id_k \tag{7}$$

where

$$\left\{\begin{array}{rcl} J_i & = & -A^{-1}_{22i}A_{21i} \\ K_i & = & -A^{-1}_{22i}B_{2i} \\ L_i & = & -A^{-1}_{22i}C_{2i} \end{array}\right. \tag{8}$$

Thus, combining (6) and (7) we have:

$$\left\{\begin{array}{rcl} Z^1_{k+1} & = & M_iZ^1_k + N_iu_k + P_id_k \\ Z^2_k & = & J_iZ^1_k + K_iu_k + L_id_k \\ y_k & = & R_iZ^1_k + S_iu_k + T_id_k \end{array}\right. \tag{9}$$

where

$$\left\{\begin{array}{rcl} M_i & = & A_{11i} + A_{12i}J_i \\ N_i & = & B_{1i} + A_{12i}K_i \\ P_i & = & C_{1i} + A_{12i}L_i \\ R_i & = & D_{1i} + D_{2i}J_i \\ S_i & = & E_i + D_{2i}K_i \\ T_i & = & F_i + D_{2i}L_i \end{array}\right. \tag{10}$$

So, by aggregation of the resulting sub-models (9), the following global fuzzy model is obtained:

$$\left\{\begin{array}{rcl} Z^1_{k+1} & = & \sum_{i=1}^{q} \mu_i(\eta_k)(M_iZ^1_k + N_iu_k + P_id_k) \\ Z^2_k & = & \sum_{i=1}^{q} \mu_i(\eta_k)(J_iZ^1_k + K_iu_k + L_id_k) \\ y_k & = & \sum_{i=1}^{q} \mu_i(\eta_k)(R_iZ^1_k + S_iu_k + T_id_k) \end{array}\right. \tag{11}$$

*Assumption 2:* : Suppose that $d_k$ is considered as a constant unknown control input per time interval i.e.:

$$d_{k+1} \quad = \quad d_k \qquad k \in [T_1 \quad T_2], \qquad \forall\ T_1, T_2 \in \mathbf{R}^+ \tag{12}$$

Let us define the augmented state vector $\xi^1_k = [Z^{1^T}_k\ d^T_k]^T$ and $\xi^2_k = Z^2_k$. Thus, the system (11) can be represented as:

$$\left\{\begin{array}{rcl} \xi^1_{k+1} & = & \sum_{i=1}^{q} \mu_i(\eta_k)(\tilde{M}_i\xi^1_k + \tilde{N}_iu_k) \\ \xi^2_k & = & \sum_{i=1}^{q} \mu_i(\eta_k)(\tilde{J}_i\xi^1_k + K_iu_k) \\ y_k & = & \sum_{i=1}^{q} \mu_i(\eta_k)(\tilde{R}_i\xi^1_k + S_iu_k) \end{array}\right. \tag{13}$$

where

$$\left\{\begin{array}{rcl} \tilde{M}_i & = & = \begin{pmatrix} M_i & P_i \\ 0 & I \end{pmatrix} \\ \tilde{N}_i & = & = \begin{pmatrix} N_i \\ 0 \end{pmatrix} \\ \tilde{J}_i & = & = \begin{pmatrix} J_i & L_i \end{pmatrix} \\ \tilde{R}_i & = & = \begin{pmatrix} R_i & T_i \end{pmatrix} \end{array}\right. \tag{14}$$

The rest of the paper is structured as follows. The main result about FUIO design permitting to estimate simultaneously unmeasurable states and UIs for the considered class of systems (1) is stated in Section 2. The observer gains are found directly from LMI formulation. In Section 3, a numerical example to show the good performance of the proposed technique is given. Finally, a conclusion is given in section 4.

## II. State and unknown inputs estimation

Systems (1) and (13) are equivalent. For the design of the fuzzy observer permitting to estimate simultaneously the unmeasurable states and UIs, we will use the second structure. So, the proposed FUIO takes the following form:

$$\left\{\begin{array}{rcl} \hat{\xi}^1_{k+1} & = & \sum_{i=1}^{q} \mu_i(\eta_k)(\tilde{M}_i\hat{\xi}^1_k + \tilde{N}_iu_k - G_i(\hat{y}_k - y_k)) \\ \hat{\xi}^2_k & = & \sum_{i=1}^{q} \mu_i(\eta_k)(\tilde{J}_i\hat{\xi}^1_k + K_iu_k) \\ \hat{y}_k & = & \sum_{i=1}^{q} \mu_i(\eta_k)(\tilde{R}_i\hat{\xi}^1_k + S_iu_k) \end{array}\right. \tag{15}$$

where $(\hat{\xi}^1_k,\ \hat{\xi}^2_k)$ and $\hat{y}_k$ denote the estimated augmented state vector and the output vector respectively. The activation functions $\mu_i(\eta_k)$ are the same than those used in the T-S model (13). $G_i$, $i = 1, \ldots, q$ are the gains of FUIO which are determined such that $(\hat{\xi}_k^1,\ \hat{\xi}_k^2)$ asymptotically converges to $(\xi_k^1,\ \xi_k^2)$.

In order to establish the conditions for the asymptotic convergence of the observer (15), we define the state estimation error:

$$\varepsilon_k = \begin{pmatrix} \varepsilon_k^1 \\ \varepsilon_k^2 \end{pmatrix} = \begin{pmatrix} \hat{\xi}_k^1 - \xi_k^1 \\ \hat{\xi}_k^2 - \xi_k^2 \end{pmatrix} \tag{16}$$

It follows from (13) and (15) that the estimated error equation can be written as:

$$\begin{cases} \varepsilon_{k+1}^1 &= \displaystyle\sum_{i,j=1}^{q} \mu_i(\eta_k)\mu_j(\eta_k)\Omega_{ij}\varepsilon_k^1 \\ \varepsilon_k^2 &= \displaystyle\sum_{i=1}^{q} \mu_i(\eta_k) Q_i \varepsilon_k^1 \end{cases} \tag{17}$$

where

$$\Omega_{ij} = \tilde{M}_i - G_i\tilde{R}_j \tag{18}$$

To prove the convergence of the estimation error $\varepsilon_k$ toward zero, it suffices to prove from (17), that $\varepsilon_k^1$ converges toward zero. The main result is stated in the following Theorem.

*Theorem 1:* : There exists an FUIO (15) for DTSDM (1) if given $0 < \alpha < 1$ there exist matrices $Q > 0$, $W_i$, $i = 1, \ldots, q$ verifying the following LMIs:

$$\begin{pmatrix} -\alpha^2 Q & * \\ Q\tilde{M}_i - W_i\tilde{R}_j & -Q \end{pmatrix} < 0 \quad \forall\, i, j \in \ \{1, \ldots, q\} \tag{19}$$

The fuzzy local observer gains $G_i$, $i = 1, \ldots, q$ are given by:

$$G_i = Q^{-1}W_i \tag{20}$$

**Proof of Theorem 1** : Let us consider the following quadratic Lyapunov function as follows:

$$V_k = (\varepsilon_k^1)^T Q \varepsilon_k^1 \ , \qquad Q > 0 \tag{21}$$

Estimation error convergence is exponentially ensured if the following condition is guaranteed ([30] as cited in [6]):

$$\begin{array}{rcl} V_{k+1} - V_k &=& (\varepsilon_{k+1}^1)^T Q \varepsilon_{k+1}^1 - (\varepsilon_k^1)^T Q \varepsilon_k^1 \\ &<& (\alpha^2 - 1)V_k \end{array} \tag{22}$$

with $0 < \alpha < 1$.

By using (17), the condition (22) can be written as:

$$\begin{array}{l} V_{k+1} - V_k = \displaystyle\sum_{i,j=1}^{q} \mu_i(\eta)\mu_j(\eta)(\varepsilon_k^1)^T(\Omega_{ij}^T Q \Omega_{ij} - Q)\varepsilon_k^1 \\ \qquad\qquad < (\alpha^2 - 1)V_k \end{array} \tag{23}$$

which is equivalent to the following stability conditions:

$$\Omega_{ij}^T Q \Omega_{ij} - \alpha^2 Q < 0 \qquad i, j = 1, \ldots, q \tag{24}$$

Letting $W_i = QG_i$, from (18) it follows that (24) is equivalent to (19) by using the Schur complement [29]. From the Lypunov stability theory, if the LMI conditions (19) are satisfied, the error dynamic equation (17) is exponentially asymptotically stable.

## III. Numerical illustration

In order to show the performance of the proposed method of FUIO design, the following DTSDM is considered:

$$\begin{cases} MZ_{k+1} &= \displaystyle\sum_{i=1}^{2} \mu_i(\eta_k)(A_i Z_k + Bu_k + Cd_k) \\ y &= DZ \end{cases} \tag{25}$$

where $Z_k = (z_{1k},\ z_{2k},\ z_{3k},\ z_{4k})^T \in \mathbf{R}^4$, $u_k \in \mathbf{R}$, $d_k \in \mathbf{R}$ and $y_k \in \mathbf{R}$ are the state vector, known input, UI and output, respectively. The matrices numerical values are:

$$A_1 = \begin{pmatrix} 1 & 0.0100 & 0 & 0 \\ -0.0250 & 0.9925 & 0 & 0.0003 \\ 0 & 0.0100 & -0.0040 & 0 \\ -0.0250 & -0.0075 & 0 & 0.0008 \end{pmatrix}$$

$$A_2 = \begin{pmatrix} 1 & 0.0100 & 0 & 0 \\ -0.0270 & 0.9925 & 0 & 0.0003 \\ 0 & 0.0100 & -0.0040 & 0 \\ -0.0270 & -0.0075 & 0 & 0.0008 \end{pmatrix}$$

$$M = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}; \quad B = \begin{pmatrix} 0 \\ 0 \\ 0 \\ -0.0013 \end{pmatrix}$$

$$C = \begin{pmatrix} 0 \\ 0.01 \\ 0 \\ 0 \end{pmatrix}; \quad D = \begin{pmatrix} 1 & 0 & 0 & 0 \end{pmatrix}$$

The weighting functions are:

$\mu_1(\eta_k) = 1 - 12.76 * z_{1k}^2$ and $\mu_2(\eta_k) = 12.76 * z_{1k}^2$.

Therefore to apply the proposed FUIO (18) for the model (38), as stated in Theorem 1, it suffices to rewrite the model (25) into its equivalent form (13) as mentioned above.

Thus, by Theorem 1 with $\alpha = 0.92$ the following observer gains $G_1$ and $G_2$ are obtained:

$$G_1 = \begin{pmatrix} 1.3621 \\ 29.2238 \\ 190.0753 \end{pmatrix}, \quad G_2 = \begin{pmatrix} 1.3620 \\ 29.2208 \\ 190.0639 \end{pmatrix}$$

The expression of unknown input signal $d_k$ is defined as in Figure 1 and the input signal $u_k$ is defined as:

$$u_k = \begin{cases} 2 & 0 \leq k \leq 2 \\ 0 & otherwise \end{cases} \tag{26}$$

Simulation results with initial conditions:

$$\begin{array}{ll} \xi_k^1 = [0.10 \ \ 0.30 \ \ 2.00]^T, & \xi_k^2 = [0.75 \ \ 3.03]^T \\ \hat{\xi}_k^1 = [0.10 \ \ 0.45 \ \ 4.00]^T, & \hat{\xi}_k^2 = [1.13 \ \ 4.53]^T \end{array}$$

are given in Figures 1 to 5. These simulation results show the performances of the proposed FUIO (15) with the gains $G_1$, $G_2$ where the dashed lines denote the state variables and UI estimated by the FUIO. They show that the FUIO gives a good estimation of unmeasurable states and UI of the considered DTSDM.

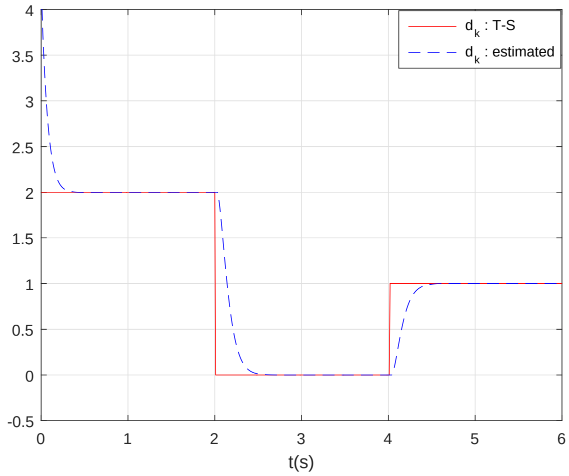


Fig. 1. Unknown input $d_k$ and its estimate

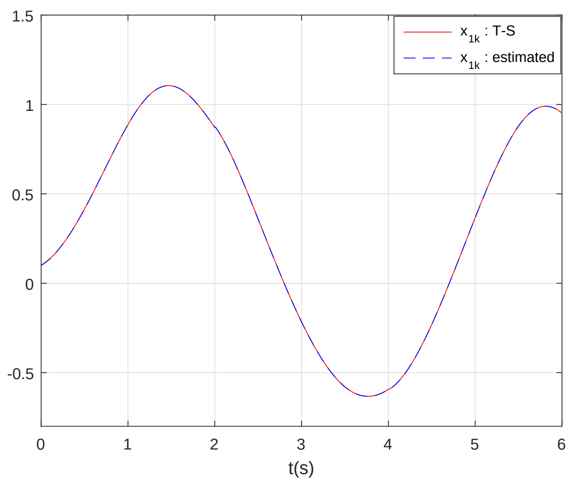


Fig. 2. State variables $x_{1k}$ and its estimate

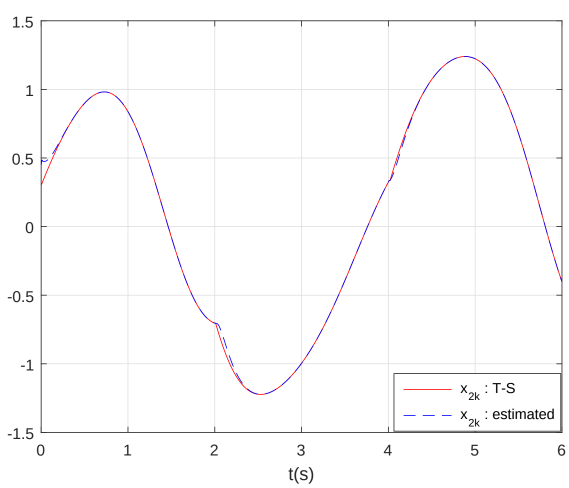


Fig. 3. State variables $x_{2k}$ and its estimate

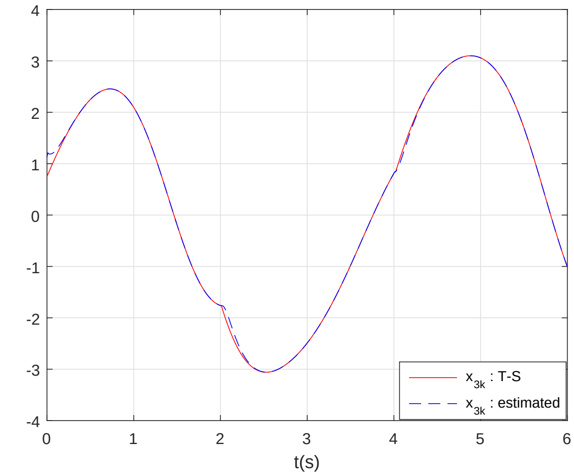


Fig. 4. State variables $x_{3k}$ and its estimate

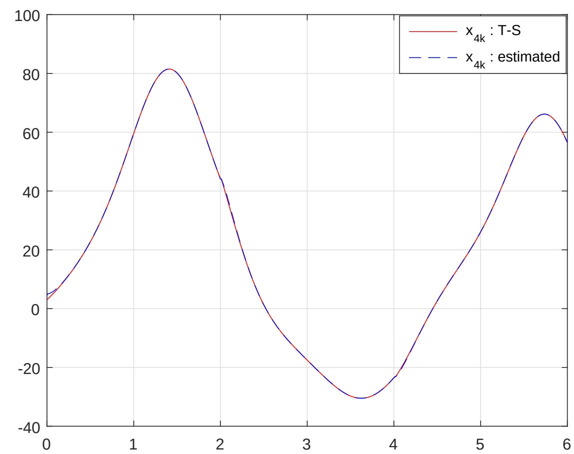


Fig. 5. State variables $x_{4k}$ and its estimate

## IV. Conclusion

A novel method of fuzzy observer design for a class of DTSIMs with measurable premise variables and subject to UIs which affect both state and output of the model is presented in this paper. The proposed result permitting to estimate simultaneously the system state and the UIs is based on the separation between dynamic and static equations in the considered fuzzy descriptor model and the use of an augmented system structure formed by the dynamic equations and the UIs. The exponential convergence of the state estimation error is studied by using the Lyapunov theory and the existence of the condition ensuring this convergence is expressed in term of LMIs. To show the good performance of the proposed method, a DTSDM subject to UI variable is proposed. The effectiveness of the proposed FUIO design for the on-line simultaneous estimation of unknown states and UI of the considered model is illustrated by numerical simulation, since both state and UI are well estimated.

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