# Disturbance State Distinction Algorithm and its Application to Estimation of Time Delay with Inertia Error

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*Abstract*— **This paper proposes a novel algorithm to detect information of time delay and inertia errors of the nominal model in the disturbance observer. The proposed method adopts the Hidden Markov Model to relate the states causing disturbances with the observed disturbances. Output distribution of the hidden disturbance state can be defined based on the relationship between the observed disturbance and time delay/inertia errors. The proposed algorithm is compared with the Interacting Multiple Model algorithm. Simulation results verify effectiveness and properties of the proposed algorithm.**

## I. INTRODUCTION

Disturbance observers[1] have been a practical control design in many industrial applications especially for disturbance rejection and sensitivity design. In addition to the linear disturbance rejection property, some learning algorithms have been utilized to make use of the estimated disturbance by the disturbance observer for identification of properties of target plants.

Identification of parameters such as inertia and stiffness is one significant application of the learning algorithm to the disturbance observer[2],[3]. There is also research which uses the short-time Fourier transform[4] or wavelet transform[5]. Prediction using attractors of chaotic systems embedded in the disturbances has also been applied to disturbance observers[6]. These learning or identification algorithms deal with parameter variation as continuous value changes, and they need some inverse calculation which requires considerable computation and leads to sensitivity to undesired factors.

The use of disturbance observers as force sensors was suggested more than 10 years ago[7]. Recently, however, the force estimation using the disturbance observer has again started to receive attention as a design method of force control without force sensors so that the disturbance observer has come to attract considerable attention as a base technology of force sensor-less power assist control [8].

For this usage of the disturbance observer for the force sensor-less control, the force to be assisted needs to be extracted from the external forces observed by the disturbance observer, since the observed disturbance includes not only the external force to be assisted but also all the other disturbances such as modeling error and friction force. This is the reason why the disturbance observer requires a discerning function to extract the force to be assisted.

This is not only for the application to force sensor-less power assist control; if the disturbance discerning function can detect the type of modeling error that causes disturbance, that information can be utilized to achieve more precise motion control. For example, a modified disturbance observer control [9] that can stabilize a plant with a variable time delay leaves steady state tracking errors with modeling errors in the nominal plant of the disturbance observer. If the controller can distinguish such causes of disturbance as modeling error or time delay and the amount of the errors, it can achieve more precise tracking control performance.

In this paper, these kinds of causes which lead to disturbances to the controller are stated as disturbance states, and a novel algorithm is suggested to discern these disturbance states based on the Hidden Markov Model. This is a new learning approach using disturbance observers. As a practical application of the suggested algorithm, distinction between inertia error and time delay in the disturbance observer is addressed in this paper.

This paper is organized as follows. In Section II, some fundamental preliminaries for the suggested algorithm are introduced. Section III suggests a novel algorithm based on the relationship between the measured data and Hidden Markov Model. In Section IV, the effectiveness of the proposed method is validated by simulation.

## II. Fundamental Preliminaries for Disturbance States Discernment

### A. Disturbance Observation as System Output

Disturbance states such as external forces, modeling error in nominal inertia value and time delay that cause disturbances to a system should be represented in the measured system output. We need to specify what can be used for this measurement which includes the disturbance state information.

In the disturbance observer the standard form of which is described in Figure 1, the control input ($u$) and observed disturbance ($\hat{d}$) can be used as the measurements which include information on disturbance states. If the nominal values of parameters such as the inertia, the damping or

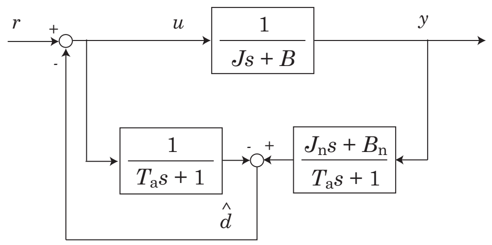



Fig. 1. Standard Disturbance Observer Control System

the time delay have modeling error, the measured data will show some characteristics related to those disturbance states.

Methodology to describe the relationship between the measurements and the disturbance states is one significant issue. This paper describes this relationship using the Hidden Markov Model.

### *B. Introduction of the Hidden Markov Model*

The Hidden Markov Model is generally used to estimate hidden states based on measured limited data. Estimation of a driver's intent based on the measured data of the steering angle and detection of human mistakes based on the monitors of human behavior are examples of this Hidden Markov Model [13]. In these examples, human inner states are the hidden states and the measured data are the numerical data obtained by sensors.

Figure 2 is an illustration of the Hidden Markov Model. $S_1$ to $S_3$ are the hidden Markov model, $y_1$ to $y_4$ are the possible output symbols of all states, and $b_1$ to $b_3$ are the probabilities of the output symbols in each state. $a_{11}$ to $a_{33}$ are the state transition probabilities.

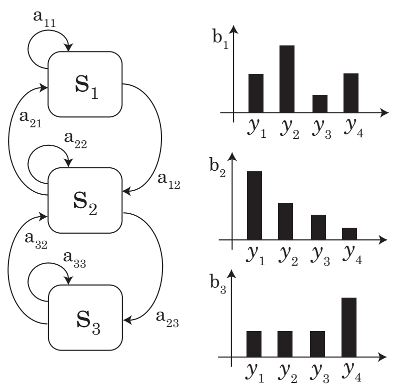



Fig. 2. Probabilities in a Hidden Markov Model

The Hidden Markov Model finds the most likely sequence of the states ($S_1$ to $S_3$) using the output observation sequence (sequence consisting of $y_1$ to $y_4$) based on the probability parameter, $b_1$ to $b_3$ and $a_{11}$ to $a_{33}$. The probability parameters are defined as follows;

$$\boldsymbol{\pi} = \{\pi_i\}, \pi_i = P(S_1 = i) \tag{1}$$

$$\boldsymbol{A} = \{a_{ij}\}, a_{ij} = P(S_{t+1} = j | S_t = i) \tag{2}$$

$$\boldsymbol{B} = \{b_j(k)\}, b_j(k) = P(\text{output} = y_k | S_t = j) \tag{3}$$

In Equations (2) and (3), the index $i, j$ represents the state number, $t$ represents the time, $k$ represents the index of the output symbols ($k$ is 1 to 4 in Figure 2). Equation (1) is the probabilities of the states at initial time ($t = 1$).

Given these parameters $\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{B}$, the Hidden Markov Model algorithm can determine the most likely hidden state sequence based on the probability. Note that a discrete output symbols are used in Figure 2. There also is a continuous output version of Hidden Markov Model which we will adopt in this paper.

### *C. Disturbance States as Hidden Markov States*

Here, the disturbance states which cause disturbances are modeled as Hidden Markov models and the measured data $u, \hat{d}$ in Figure 1 and their derivatives $\dot{u}, \dot{\hat{d}}$ are defined as output symbols of those hidden disturbance states.

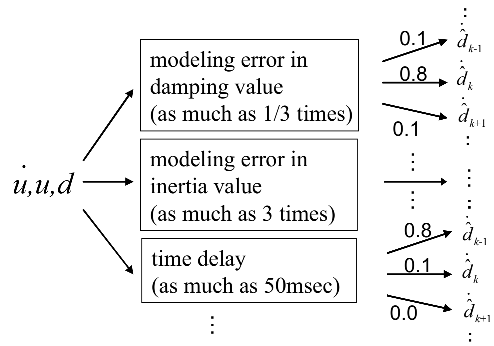



Fig. 3. Output Probabilities of Disturbance States

Figure 3 illustrates how the output probability distributions of the measured output $u, \dot{u}, \hat{d}, \dot{\hat{d}}$ are defined according to the hidden disturbance states. Modeling errors such as errors in the nominal inertia or damping values or unmodeled time delay with a particular amount of the error can be defined as the hidden disturbance states, which means only a finite discrete numbers of error amounts are modeled as the disturbance states, not continuous and infinite numbers of errors.

Definition of output distribution of each hidden disturbance states is not straightforward even though it is most important in this application of Hidden Markov Model to the disturbance states. What makes this output distribution definition complicated is that the disturbance states have multi-dimensional outputs: $u, \dot{u}, \hat{d}$, and $\dot{\hat{d}}$. However, we do not need four probability distributions for four outputs. One output probability distribution defined on the relationship between these four measured data can characterize a particular disturbance state.

We can use a signal space composed of $u, \dot{u}, \hat{d}, \dot{\hat{d}}$ and define the output probability using distance of a measurement from hyperplanes specifying by disturbance states. A particular disturbance state can specify a hyperplane in the signal space based on model dynamics, and it is identified with a function of the measurements $u, \dot{u}, \hat{d}$, and $\dot{\hat{d}}$. This hyperplane can be a one-dimensional output symbol of the

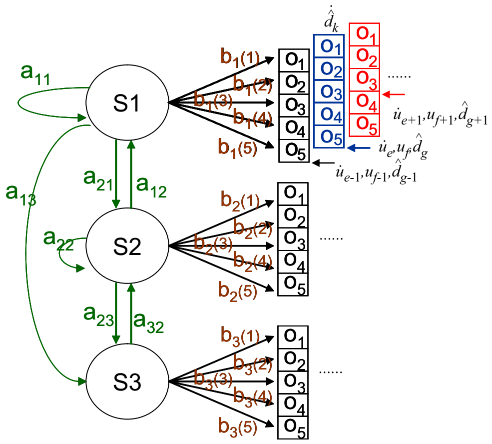



Fig. 4. Proposed Output Distribution for Distinction of Disturbance States

disturbance states.

Figure 4 illustrates this definition of output distribution as a function as discrete outputs. By defining the probability distribution of $\dot{\hat{d}}$ as a function of $u, \dot{u}, \hat{d}$ with regard to each disturbance state, the Hidden Markov Model could be applied to a damping parameter identification problem [10].

## III. Detection of Disturbance States based on Statistical Inference

### A. Definition of Probability Distribution and its Extension to General Disturbance States

In order to apply the Hidden Markov Model to this case, the probability parameter $\lambda = (\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\pi})$ in Equations (1) to (3) need to be defined. The parameters, generally, are defined statistically using the Baum-Welch algorithm [14].

However, in this disturbance states distinction, the output probability of each disturbance state can be defined based on the mathematical model of the system since the relationship between the disturbance states such as parametric errors and the output signals can be described in a mathematical way. Equations (4),(5) are our suggested output definition for disturbance states.

$$\boldsymbol{B} = N(\hat{d}; f(u, \dot{u}), \rho^2) \tag{4}$$

$$b_i = \frac{1}{\sqrt{2\pi}\rho} \exp\left(-\frac{\left(\hat{d} - f_i(u, \dot{u})\right)^2}{2\rho^2}\right) \tag{5}$$

Normal distribution is adopted here with a mean calculated based on each disturbance states, and the variance $\rho^2$ is a tuning parameter making the detection more robust to the noise in measured signals. The mean value of observed disturbance $\hat{d}$ in Figure 1 can be calculated based on a disturbance state modeling described by $f(u, \dot{u})$ in Equations (4) and (5). The function $f_i(u, \dot{u})$ is decided by the characteristic of a disturbance state $S_i$.

In [10], errors in the damping were dealt with as the disturbance states, and the output distribution was defined as the followings:

$$b_i(t) = \frac{1}{\sqrt{2\pi}\rho} \exp\left(-\frac{\left(\dot{\hat{d}}(t) - \frac{\Delta B_i u(t) - B\hat{d}(t)}{J}\right)^2}{2\rho^2}\right), \tag{6}$$

where several errors $\Delta B_i$ in the damping define the disturbance states $S_i$ with $\dot{\hat{d}}$ used as the outputs instead of $\hat{d}$ as a function of $u(t)$ and $\hat{d}(t)$.

The freedom in definition of the output symbol allows the suggested algorithm to detect various disturbance states. This will lead us to the detection of more arbitrary disturbance states not restricted to the linear function of the parametric error.

It can include nonlinear parametric error or exterior information such as the temperature and so on. In this paper, time delays with errors in the inertia which cannot be described in a linear way are estimated using the proposed algorithm.

The disturbance observer implementing the proposed detection algorithm can be called an “intelligent disturbance observer” since they can distinguish the way of feedback according to the disturbance states.

### B. Development of Distinction Algorithm

The most popular algorithm for determination of the hidden Markov states is the Viterbi algorithm. However, the Viterbi algorithm is not favorable for real-time states detection, since it considers the probability of the whole sequence from the start to the end.

Although the evaluation of the likelihood of instantaneous state transition from time $i$ to $(i+1)$ is significant enough for real-time state detection, the Viterbi algorithm evaluates the transition with regard to the whole sequence and determines the most likely sequence, not the most likely instantaneous states at time $i$; the Viterbi algorithm is more suitable for off-line detection.

This paper proposes a novel definition of the likelihood of the state which needs short calculation time so as to make it suitable for on-line determination of the disturbance states.

$$p_i(t) = a_{\hat{D}(t-1)i} b_i(t) \tag{7}$$

$$p_i^N(t) = \frac{1}{N}\sum_{n=0}^{N-1}\left(a_{\hat{D}(t-N)i} b_i(t-n)\right) \tag{8}$$

$$\hat{D}(t) = \operatorname*{argmax}_i p_i^N(t) \tag{9}$$

Equations (7) to (9) are the proposed definition where $i$ is the index indicating a disturbance state, $\hat{D}$ is the index indicating the most likely state, $p_t(i)$ is the likelihood of being in the state $i$ at the time $t$. To decrease the sensitivity to noise and increase the robustness to noise in the signal, the likelihood is calculated as in Equation (8), averaging the likelihood over $N$ samples. This averaged likelihood is described as $p_t^N(i)$ with $N$ as the size of time range.

$b_i(t)$ is the output distribution defined in Equation (5) attributed to a disturbance state $i$. The state transition probability $a_{ij}$ (or $a_{\hat{D}(t-1)i}$ in Equation (7)) is another tuning parameter that can represent the characteristic of the target system. For an example, the parameter $\boldsymbol{A}$ with large diagonal elements and small diagonal elements can represent a system in which the disturbance states will not change so easily.

Note that this $\boldsymbol{A}$ is not introduced to represent the Markov property of disturbance states. It is employed here as a tuning parameter to provide the proposed algorithm with reluctance to change, as said above. In other words, linearity in the transition probability is not necessary, and even nonlinear transition probability can be introduced as a substitute of $\boldsymbol{A}$.

Based on the proposed likelihood $p_t^N(i)$, the most likely disturbance state $\hat{D}(t)$ is determined as Equation (9). Note that this determination makes full use of the two parameters $\boldsymbol{A}$ and $\boldsymbol{B}$ of the Hidden Markov Model, which means not only the output likelihood of a disturbance states is utilized but also the probability of the state transition is utilized for this determination.

### *C. Comparison with Interacting Multiple Model Algorithm*

The proposed algorithm has some characteristics in common with the interacting multiple model (IMM [15]) algorithm: multiple parallel calculations of model outputs, evaluation of likelihood of each modes based on measurements. Similar and different points between the suggested algorithm and the IMM algorithm should be made clear.

The IMM algorithm is similar to the proposed algorithm in a point that it includes multiple dynamics which can describe modes of a target system; the modes in the IMM correspond to the disturbance states in the proposed algorithm, and both the modes and the disturbance states are considered to have the Markov property. The mode, however, is a general concept that deals with all parameter variations in systems while the disturbance state focuses more on the dynamics of disturbance.

The purpose of the IMM algorithm is to estimate the system states correctly using likelihood of modes as weightings. In the proposed algorithm, the likelihood of the disturbance states is a criterion for decision of the most likely disturbance state. Equations (10) to (11) explain this.

$$\mu_j(t) = \frac{b_j(t)}{c}\sum_i a_{ij}\mu_i(t-1) \quad (10)$$

$$\hat{x}(t) = \sum_j \hat{x}_j(t)\mu_j(t) \quad (11)$$

$\mu_j$ in Equation (10) where $c$ is a normalizing factor, is the mode probability in the IMM which means probability for a real system to be in the mode $j$ at time $t$ and corresponds to $p_i(t)$ in Equation (7) in the proposed algorithm. Using this mode probability, the IMM estimates the accurate system state $\hat{x}$ as Equation (11) while the proposed algorithm determines the most likely disturbance state as Equation (9) using $p_i(t)$.

The proposed algorithm, indeed, can also adopt the combination process in the IMM algorithm to identify accurate parameters in a target system. It, however, will be for improvement of precision of disturbance state distinction not system state. If a parameter $k_i$ specifies a disturbance states $D_i$, then a linear combination of $k_i$ with the mode probabilities as weightings (Equation (12)) can improve the identification of true $k$, but only in the case where the outputs of the disturbance states and the parameters $k_i$ have monotonic relationship.

$$\hat{k}(t) = \sum_j k_j p_j^N(t) \quad (12)$$

Even this linear combination is different from Equation (11) in a sense that it is for estimation of the disturbance state, not system state value.

## IV. Novel Identification of Time Delay and Inertia Errors

In [10], the disturbance states were defined based on the error in the damping and some simulations were performed verifying the followings about the proposed algorithm.

1. Correct disturbance state is discerned with the input signal having low richness.
2. An unconsidered disturbance state located between two considered disturbance states is detected as a disturbance state closer to the true state.

Although the result is likely to show some oscillation between two states, the sensitivity causing this can be adjusted by the parameters in the proposed algorithm: the variation $\rho$ and the transition matrix $\boldsymbol{A}$.

3. By the Markov property specified by the matrix $\boldsymbol{A}$, the proposed algorithm shows good distinction performance robust to external forces that is not related to any considered disturbance state.

The simulations achieved in [10] was on the disturbances caused by the errors in the damping which are linear modeling errors in a system. In this paper, time delay and inertia error that cannot be described in a linear way is considered as disturbance states.

### *A. Disturbance Distinction for Identification of Time Delay and Inertia Error*

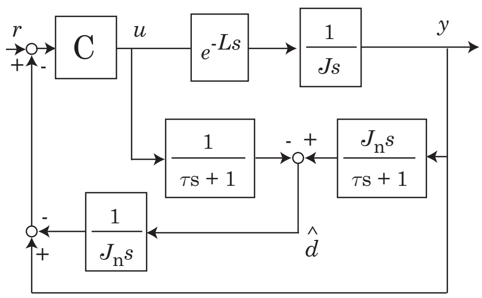



Fig. 5. System with Time Delay and Disturbance Observer

Figure 5 is the a system with time delay controller by a disturbance observer based controller. For a plant with time delay $L$, network disturbance observer based stabilizing controller is designed. This stabilization controller is designed based on Natori's algorithm [9], which guarantees the stability robust to the amount of time delay. Although this controller is robust to time delays in terms of stabilization, it leaves constant tracking error under errors in nominal inertia $J_n$, which makes the proposed algorithm necessary to discern the disturbance states if the disturbance is caused by the time delay or an inertia error.

This section suggests an algorithm to detect time delay and the errors in the inertia simultaneously based on the disturbance state distinction algorithm suggested in Section III.

A novel definition of the output distribution is necessary for this distinction of time delay and inertia error. To this end, the way the time delay and the inertia error are represented in the disturbance observer should be explored. The observed disturbance under time delay and inertia error is given as Equation (13)[9].

$$\hat{d}(t) = \frac{J_n}{J} u(t-L) - u(t) \tag{13}$$

This disturbance equation is utilized as a definition of output distribution in this paper. Several numbers of time delays and inertia values are chosen to specify disturbance states. Let the numbers of chosen time delays and inertia values be $G$ and $H$ respectively, then the $G \times H$ numbers of disturbance states are considered as possible disturbance states. The proposed algorithm will determine the most likely state from the $G \times H$ states.

Let $L_g$ and $J_h$ be values of time delay and inertia that specifies a possible disturbance state $D_{gh}$, then the average output, i.e., the disturbance $d_{gh}$ by the state $D_{gh}$ is given as

$$d_{gh}(t) = \frac{J_n}{J_h} u(t-L_g) - u(t), \tag{14}$$

and the output distribution can be given as $N(d_{gh}, \rho^2)$. Note that one parameter set will specify one disturbance state, that is, a disturbance state $D_{gh}$ denotes a parameter set consisting of $J_h$ and $L_g$.

The probability of being in a state $D_{gh}$ is evaluated based on the similarity of $d_{gh}$ to the actual $\hat{d}$ measured by the disturbance observer. The output likelihood for the disturbance state $D_{gh}$ is given as

$$b_{gh}(t) = \frac{1}{\sqrt{2\pi}\rho} \exp\left( - \frac{\left(\hat{\boldsymbol{d}}(t) - \boldsymbol{d}_{gh}(t)\right)^T \cdot \left(\hat{\boldsymbol{d}}(t) - \boldsymbol{d}_{gh}(t)\right)}{2\rho^2} \right). \tag{15}$$

The distance is evaluated using $M$ points of $\hat{d}$ and $d_{gh}$. The distance between two vectors,

$$\hat{\boldsymbol{d}}(t) = \left(\hat{d}(t), \hat{d}(t-1), \ldots, \hat{d}(t-M+1)\right)^T \tag{16}$$

$$\boldsymbol{d}_{gh}(t) = \left(d_{gh}(t), d_{gh}(t-1), \ldots, d_{gh}(t-M+1)\right)^T \tag{17}$$

is used to make the distinction robust.

The state transition probability $\boldsymbol{A}$ and the variance $\rho^2$ are adjustable parameters to make the distinction more robust and tune distinction sensitivity. With these settings, the probability of being in a disturbance state $D_{gh}$ is given as

$$p_{gh}(t) = a_{\hat{D}(t-1)gh} b_{gh}(t), \tag{18}$$

where $a_{\hat{D}(t-1)gh}$ is an element of the matrix $\boldsymbol{A}$ meaning the probability of transition from the state $\hat{D}(t-1)$ to $D_{gh}$.

Based on this probability definition, the most likely disturbance state $\hat{D}(t)$ is determined as

$$\hat{D}(t) = \underset{gh}{\operatorname{argmax}}\, p_{gh}(t). \tag{19}$$

## B. Verification by Simulations

To see the performance of the proposed algorithm, a system illustrated in Figure 5 is simulated with $J_n = 1, \tau = 0.01$ and the controller $C$ consisting of a PD controller; PD gains are designed based on the coefficient diagram method[16] with the time constant 2.5 and using $J_n$ as a inertia value of the plant in the design.

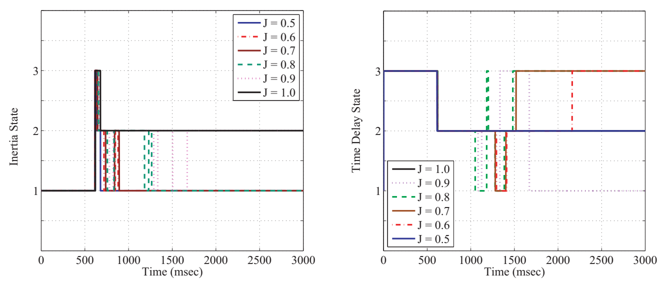
Three time delays and three inertia values (9 sets of parameters) are selected: $L_1 = 0.2$s, $L_2 = 0.3$s, and $L_3 = 0.4$s for time delay and $J_1 = 0.5$, $J_2 = 1$, and $J_3 = 2$ for the inertia. The disturbance states are specified according to the parameter sets as possible disturbance states. The number of samples $M$ used in the calucation of the distance in Equation (15) is set to 100.

TABLE I

Parameters used in Simulations

| | |
|---|---|
| Inertias in Disturbance States | $J_1 = 0.5, J_2 = 1, J_3 = 2$ |
| Actual Inertias in Simulations | $J = 0.5, 0.6, 0.7, 0.8, 0.9, 1.0$ |

The state transition probability $\boldsymbol{A}$ is set to have the same value in all elements just to make sure the effectiveness of the output distribution definition in Equation (15), and the variance $\rho$ is set to 0.3.




(a) Inertia State Distinction (b) Time Delay Distinction

Fig. 6. Disturbance Distinction under Inertia Variation w/ Step $r$

Figure 6 is the simulation result with step input $r$; the value of $r$ becomes 1 at the time of 0.3s. The initial states in the distinction algorithm are 1 for the inertia and 3 for the time delay. In order to explore the performance of the proposed algorithm, six kinds of $J$ (0.5,0.6,0.7,0.8,0.9,1.0) are used as the actual inertia $J$ in six simulations, and time delay is set to 0.3s. Note that only $J_1 = 0.5$ and $J_2 = 1.0$ are considered in disturbance states. 1 in Figure

6 (a) represents that the most likely inertia state is 1, which means the actual inertia is likely to have the value of $J_1 = 0.5$. As for 2 and 3 in the inertia state, and the time delay state in Figure 6 (b) have the same meaning corresponding to the values set previously.

When actual inertia has the same values with the values of the possible states (e.g., $J = 0.5$ or $J = 1.0$), the distinction of time delay and inertia shows correct result identifying the true values. With $J$ other than 0.5 and 1.0, although inertia distinction shows some oscillatory result between two states, a closer state is more likely to be chosen. This vibration can be attenuated by choosing appropriate $\rho$ in Equation (15).

The problem is with the time delay distinction. When actual $J$ has the value from 0.6 to 0.9, the estimated time delay state shows wrong result after 1.5s in particular. This is due to the characteristic of $r$; around 0.6s to 1s, there is excitation in $r$ enough to affect the distinction process to have correct time delay estimation. Equation (13) explains this deterioration in distinction. When $r$ has a constant value, information on $L$ cannot be detected in $\hat{d}$.

We can also say that information on the inertia and time delay are so related with each other that it is difficult to detect them correctly at the same time; when there is some error between the real $J$ and the $J_h$ considered in the algorithm, it will affect the distinction of time delay, too. This problem should be addressed to develop the proposed algorithm in a more practical way.

Figure 7 is the result with the sinusoidal $r$ with a frequency of 20 rad/sec. Even though $J$ is varied from 0.5

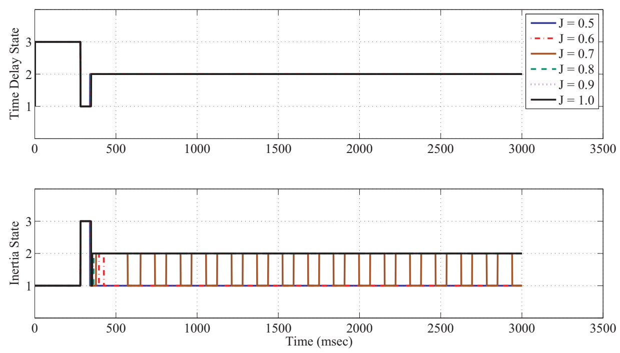



Fig. 7. Disturbance Distinction (sinusoidal $r$ w/ freq. 20 rad/sec)

to 1.0, with this sinusoidal $r$, the time delay is correctly detected.

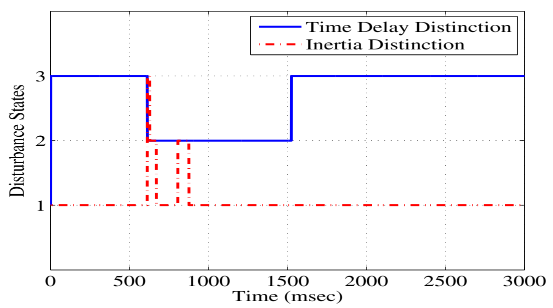



Fig. 8. Distinction under Time Delay Variation ($L = 0.3\text{s} \rightarrow 0.4\text{s}$)

The proposed method is applied to a time varying system, and Figure 8 is the result with step $r$. At 1.5 second the time delay changes from 0.3s to 0.4s which means the time delay state changes from 2 to 3. The result shows the proposed algorithm can quickly detect the change.

## V. Conclusion

This paper proposed a novel algorithm that can distinguish the cause of disturbances: the time delay and inertia error at the same time. The simulation results show the proposed algorithm can distinguish these causes of disturbance and the amounts of them with adequate sensitivity of detection.

Development of control design to reflect the detected disturbance state to controllers is to be researched.

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