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Chapter 1 : Control theory - Wikipedia

Indirect identification of linear stochastic systems with known feedback dynamics of linear stochastic systems with known feedback stochastic systems with.

 Abstract A robust adaptive tracking control design for nonlinear stochastic systems with both Brownian motion and Poisson jumps is proposed, which is based on Takagiâ€"Sugeno T-S type fuzzy techniques. Because the state of to-be-controlled systems cannot be known exactly, to overcome this difficulty, the state estimation systems and error estimation systems are introduced to obtain an augmented system. By using the fuzzy systems to approximate the nonlinear systems, an adaptive fuzzy control is employed to achieve the desired tracking performance for stochastic systems with exogenous disturbance. A simulation example is presented to illustrate the tracking performance of the proposed design method. Introduction Adaptive control theory is a powerful methodology which has been widely applied to design feedback control for systems with parametric uncertainties or for plants with unknown structure or changing operating conditions [1 , 2]. The robust tracking control theory is a powerful methodology to design feedback controllers where the system parametric uncertainties are seen as the exogenous disturbance [7 â€" 9]. This methodology is widely applied in networked control systems [10], mobile robots [11], etc. The objective of the robust tracking control design is to construct an adaptive controller which guarantees the tracking control performance. However, it is very difficult to solve the Hamilton-Jacobi equalities or inequalities [13 , 14]. In practice, to overcome this difficulty, the fuzzy methods have been applied to the robust control design of nonlinear systems where the Takagiâ€"Sugeno T-S type fuzzy is widely used [15 â€" 17]. Stochastic systems are applied in economics [18], biology [19], and natural science to describe the randomness in models [20 â€" 23]. The linear stochastic theory has been developed since s via the linear matrix inequalities LMI approach [31]. The nonlinear stochastic problems are solved by means of Hamilton-Jacobi equations [25]. In practice, there exist sudden shifts in the systems. The main complication in the tracking control design problem studied here is due to the presence of both deterministic, stochastic perturbations and Poisson jumps terms in the system. Nonlinear tracking theory and fuzzy control design are combined together to construct the adaptive fuzzy-based controller which guarantees the tracking control performance. This paper is organized as follows: In Section 2 , some lemmas about stochastic differential equations with Poisson jumps are reviewed, which will be used in the latter theoretical analysis and deductions. In Section 3 , the theories of tracking control are extended to the case of linear stochastic systems with Poisson jumps. In Section 4 , the tracking control design methods based on the Takagiâ€"Sugeno type fuzzy techniques are applied to the nonlinear stochastic systems with Poisson jumps, and the tracking controller is obtained. In Section 5 , the air-to-air missile pursuit systems are presented to show the effectiveness of the proposed method. For convenience, we adopt the following notations:

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An algorithm is presented for identifying a state-space model of linear stochastic systems operating under known feedback controller. In this algorithm, only the reference input and output of closed-loop data are required.

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Chapter 3 : Adaptive Neural Output Feedback Control of Stochastic Nonlinear Systems with Unmodeled Dy

An algorithm is presented for identifying a state-space model of linear stochastic systems operating under known feedback controller. In this algorithm, only the reference input and output of.

The Wright brothers made their first successful test flights on December 17, and were distinguished by their ability to control their flights for substantial periods more so than the ability to produce lift from an airfoil, which was known. Continuous, reliable control of the airplane was necessary for flights lasting longer than a few seconds. By World War II , control theory was becoming an important area of research. A Centrifugal governor is used to regulate the windmill velocity. For example, ship stabilizers are fins mounted beneath the waterline and emerging laterally. In contemporary vessels, they may be gyroscopically controlled active fins, which have the capacity to change their angle of attack to counteract roll caused by wind or waves acting on the ship. The Space Race also depended on accurate spacecraft control, and control theory has also seen an increasing use in fields such as economics. Open-loop and closed-loop feedback control[edit] A block diagram of a negative feedback control system using a feedback loop to control the process variable by comparing it with a desired value, and applying the difference as an error signal to generate a control output to reduce or eliminate the error. Example of a single industrial control loop; showing continuously modulated control of process flow. Fundamentally, there are two types of control loops: In open loop control, the control action from the controller is independent of the "process output" or "controlled process variable" - PV. A good example of this is a central heating boiler controlled only by a timer, so that heat is applied for a constant time, regardless of the temperature of the building. In closed loop control, the control action from the controller is dependent on feedback from the process in the form of the value of the process variable PV. In the case of the boiler analogy, a closed loop would include a thermostat to compare the building temperature PV with the temperature set on the thermostat the set point - SP. This generates a controller output to maintain the building at the desired temperature by switching the boiler on and off. A closed loop controller, therefore, has a feedback loop which ensures the controller exerts a control action to manipulate the process variable to be the same as the "Reference input" or "set point". For this reason, closed loop controllers are also called feedback controllers. The controller is the cruise control, the plant is the car, and the system is the car and the cruise control. A primitive way to implement cruise control is simply to lock the throttle position when the driver engages cruise control. However, if the cruise control is engaged on a stretch of flat road, then the car will travel slower going uphill and faster when going downhill. As a result, the controller cannot compensate for changes acting on the car, like a change in the slope of the road. The difference, called the error, determines the throttle position the control. Now, when the car goes uphill, the difference between the input the sensed speed and the reference continuously determines the throttle position. As the sensed speed drops below the reference, the difference increases, the throttle opens, and engine power increases, speeding up the vehicle. The central idea of these control systems is the feedback loop, the controller affects the system output, which in turn is measured and fed back to the controller. Classical control theory[edit] Main article: Classical control theory To overcome the limitations of the open-loop controller , control theory introduces feedback. A closed-loop controller uses feedback to control states or outputs of a dynamical system. Its name comes from the information path in the system: Closed-loop controllers have the following advantages over open-loop controllers: In such systems, the open-loop control is termed feedforward and serves to further improve reference tracking performance. A common closed-loop controller architecture is the PID controller. Closed-loop transfer function[edit] Further information: The controller C then takes the error e difference between the reference and the output to change the inputs u to the system under control P. This is shown in the figure. This kind of controller is a closed-loop controller or feedback controller. In such cases variables are represented through vectors instead of simple scalar values. For some distributed parameter systems the vectors may be infinite- dimensional typically functions. If we assume the controller C, the plant P, and the sensor F are linear and time-invariant i. This gives the following relations:

Chapter 4 : Robust Tracking Control of Stochastic T-S Fuzzy Systems with Poisson Jumps

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Advanced Search Abstract Motivation: Identification of regulatory networks is typically based on deterministic models of gene expression. Increasing experimental evidence suggests that the gene regulation process is intrinsically random. To ensure accurate and thorough processing of the experimental data, stochasticity must be explicitly accounted for both at the modelling stage and in the design of the identification algorithms. We propose a model of gene expression in prokaryotes where transcription is described as a probabilistic event, whereas protein synthesis and degradation are captured by first-order deterministic kinetics. Based on this model and assuming that the network of interactions is known, a method for estimating unknown parameters, such as synthesis and binding rates, from the outcomes of multiple time-course experiments is introduced. The method accounts naturally for sparse, irregularly sampled and noisy data and is applicable to gene networks of arbitrary size. The performance of the method is evaluated on a model of nutrient stress response in Escherichia coli. Supplementary data are available at Bioinformatics online. Stochasticity can be attributed to the randomness of the transcription and translation processes intrinsic noise , as well as to fluctuations in the amounts of molecular components that affect the expression of a certain gene extrinsic noise Elowitz et al. The behaviour of gene regulatory networks also displays stochastic characteristics which, in several cases, can lead to significant phenotypic variation in isogenic cell populations Ozbudak et al. In Samad et al. A related model of random dynamics of gene networks is discussed in Hespanha and Singh In practice, the stochastic dynamics of a regulatory network must be inferred from experiments. To this aim, deterministic models are not suitable, since they are unable to capture the randomness of the network. On the other hand, currently available stochastic models are typically too detailed and hardly tractable by analytic means. In this work, we present a stochastic approach to modelling and parameter identification of gene regulatory network dynamics and test it on a model for a procaryotic cell. The aim of our modelling framework is to provide a convenient tradeoff between model accuracy and analytic tractability that is typically not offered by more complex models. In Cinquemani et al. In Koutroumpas et al. Both these contributions were Taylor-made for the specific form of the example. Here, we extend the concepts to establish a general genetic network modelling and identification methodology. In contrast, the description of the transcription and translation processes is simplified by assuming that they can be approximated by deterministic first-order kinetics. A similar approach is taken in Zeiser et al. The co-existence of discrete and continuous-type events as well as of deterministic and stochastic dynamics makes the model a stochastic hybrid one Kouretas et al. Based on this modelling formalism, genetic network identification is addressed in Section 2. The overall problem can be seen as a sequence of three tasks, each posing its own challenges: Here, we concentrate on Task 2, assuming that Task 1 has been accomplished. Parameter estimation for regulatory networks has traditionally been studied in a deterministic setting. The literature on identification of stochastic regulatory network models is quite recent. In Reinker et al. A similar approach is taken in Tian et al. A Markov chain Monte Carlo method relying on an approximate diffusion model is considered in Golightly and Wilkinson Based on our modelling framework, we develop a method for the estimation of the unknown parameters of the model from observations of the evolution of protein concentrations in a single cell. The method deals naturally with sparse and noisy observations. It reduces the identification problem to several subproblems. In each subproblem, the estimation of the dynamics of a single gene is performed based on the concentration profiles of the proteins that regulate its expression. To demonstrate the effectiveness of the proposed identification algorithm, we apply it to the estimation of the parameters of a stochastic model of the Escherichia coli carbon starvation response network. The model is inferred from Ropers et al. Estimation is performed on simulated data from the same model with realistic parameter values personal communication G. Results are discussed in Section 3. In light of the current rapid progress of single-cell protein level measurement techniques Cai et al. Of the many steps that transcription comprises, gene activation and inactivation is one of the key events that contribute to random fluctuations of protein production. Collectively called TFs, repressors and activators are composed of proteins that may be produced by other genes, or by the regulated gene itself, thus creating feedback loops among genes. Consider a network with n genes, each encoding one protein. Let xi t denote the concentration of protein i at time t. More specifically, gi is modelled as follows: Finally, different summation terms i. This model may encode quite complicated activation rules and is illustrated in Figure 1. Graphical conventions follow Kohn, Expression of gene 4 is activated by TF2. Conversely, expression of gene 1 is inhibited by TF2. Gene 3 has a single promoter but is controlled simultaneously by the activating TF4 and by the inhibiting TF1. Finally, gene 2 has two independent promoters, one for the activating TF1 and one for the inhibiting TF4. More generally, one may think of 2 as abstract rules governing the expression of a gene. In this case, variable ui,k t may not express the binding of TF k to the operator of gene i, but a different discrete event whose outcome is the regulation of gene i by TF k, such as formation of complexes, translocation, etc. The following is a basic underlying assumption of our model framework. We shall focus on the biologically relevant case where each transition probability pi,k is a sigmoidal function of xk Hill function. While this function cannot represent a binding probability, it is well suited to express the influence of a TF on the expression of a gene. Examples of a decreasing and an increasing sigmoidal function can be found in Figure 4 subfigures C2 and C4. View large Download slide The bar plots compare the estimation results from Monte Carlo repetitions of the two independent identification tests under four different experimental conditions 25 trajectories with and without measurement noise and trajectories with and without measurement noise. The normalized mean values i. For each parameter estimate, the green bar represents results from 25 trajectories without measurement noise, red 25 trajectories with measurement noise, blue trajectories without measurement noise and yellow trajectories with measurement noise from left to right. A Results from the first identification test. Steepness A1 and threshold A2 coefficients of all sigmoids are identified. Those coefficients deemed unidentifiable see Supplementary Material are saturated at 2. B Results from the second identification experiment. Steepness B1 and threshold B2 coefficients explored by the dataset are considered along with all synthesis B3 and degradation B4 rates. The parameters deemed unidentifiable see Supplementary Material are saturated at 2. C An example of scatter and sigmoidal estimation plots from one explored C3 and C4 and one unexplored C1 and C2 sigmoid in the first test case only sigmoid coefficients identified with a dataset of 25 trajectories. The scatter plots compare the sigmoid coefficient estimates with blue crosses with mean represented by black dashed lines and without red dots with mean represented by black dotted lines measurement noise to the true parameter values black solid lines. The sigmoid curves visually convey the variance and mean of the estimates with cyan dotted lines with mean represented by a red dashed line and without yellow dotted lines with mean represented by a red dotted line measurement noise versus the true sigmoid curves blue solid line and the sigmoid curve representing the initial estimates green solid line. Vertical gray lines indicate the location of the measurements. C An example of scatter and sigmoidal estimation plots from one explored C3 and C4 and one unexplored C1 and C2.

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Chapter 5 : Jen-Kuang Huang - Old Dominion University

Indirect identification of linear stochastic systems with known feedback dynamics: Authors: Journal of Guidance, Control, and Dynamics, vol. 19, issue 4, pp.

 Abstract An adaptive neural output feedback control scheme is investigated for a class of stochastic nonlinear systems with unmodeled dynamics and unmeasured states. The unmeasured states are estimated by K-filters, and unmodeled dynamics is dealt with by introducing a novel description based on Lyapunov function. The neural networks weight vector used to approximate the black box function is adjusted online. The unknown nonlinear system functions are handled together with some functions resulting from theoretical deduction, and such method effectively reduces the number of adaptive tuning parameters. Simulation results are provided to verify the effectiveness of the proposed approach. Introduction During the past decades, backstepping in [1] and dynamic surface control DSC in [2] have become two most popular methods for adaptive controller design. In the existing literature, three types of uncertainties were commonly considered, which included unknown system functions and parameter uncertainties and unmodeled dynamics. Unmodeled dynamics was dealt with by introducing an available dynamic signal in [3]. In addition, it was handled by a description method of Lyapunov function in [4]. In [4 , 5], adaptive tracking control schemes were developed by backstepping and DSC for a class of strict-feedback uncertain nonlinear systems, respectively. In [7 â€” 10], adaptive control schemes were presented for a class of pure-feedback nonlinear systems. In [11 â€” 13], the adaptive tracking approaches for single-input single-output SISO nonlinear systems were extended to uncertain large-scale nonlinear systems. When system states are assumed to be unmeasurable, output feedback adaptive control based on filters or observers has attracted much attention. In [14], K-filters were firstly proposed, and adaptive output feedback control was developed using K-filters. Inspired by the work in [14], robust adaptive output feedback control schemes were studied for SISO uncertain nonlinear systems in [15 , 16]. In [17], combining backstepping technique with small-gain approach, indirect adaptive output feedback fuzzy control was developed. In [18], decentralized adaptive output-feedback control was designed based on high-gain K-filters and dynamic surface control method for a class of uncertain interconnected nonlinear systems. In the past decade, much effort has focused on the study of adaptive control schemes for uncertain stochastic nonlinear systems and the proof of the control system stability in probability sense. In [22], by employing the stochastic Lyapunov-like theorem, adaptive backstepping state feedback control was developed for a class of stochastic nonlinear systems with unknown backlash-like hysteresis nonlinearities. In [23], the problem of decentralized adaptive output-feedback control was discussed for a class of stochastic nonlinear interconnected systems. In [24 , 25], output feedback adaptive fuzzy control approaches were considered using backstepping method for a class of uncertain stochastic nonlinear systems. In [26], by combining stochastic small-gain theorem with backstepping design technique, an adaptive output feedback control scheme was presented for a class of stochastic nonlinear systems with unmodeled dynamics and uncertain nonlinear functions. In [27], a concept of stochastic integral input-to-state stability SiISS using Lyapunov function was first introduced, and output feedback control was developed for stochastic nonlinear systems with stochastic inverse dynamics. In [28], two linear output feedback control schemes were studied to make the closed-loop system noise-to-state stable or globally asymptotically stable in probability. In [29], by using the homogeneous domination technique and appropriate Lyapunov functions, an output-feedback stabilizing controller was designed to be globally asymptotically stable in probability. In [30], the small-gain control method was investigated for stochastic nonlinear systems with SiISS inverse dynamics. In [31], based on a reduced-order observer, small-gain type condition on SiISS and stochastic LaSalle theorem, an output feedback controller was developed for stochastic nonlinear systems. In [32], an adaptive output feedback control scheme was investigated by combining K-filters with DSC for a class of stochastic nonlinear systems with dynamic uncertainties and unmeasured states. In [33], adaptive control was developed using the backstepping method for a class of stochastic nonlinear systems with time-varying state delays and unmodeled dynamics. Motivated by the above-mentioned results [4 , 14 , 32], in this paper, adaptive neural stochastic output feedback control is developed by combining K-filters with dynamic surface control to guarantee the stability of the closed-loop system. The main contributions of the paper lie in the following. The advantage of the design is that once the local system constructed by the filter signals is stabilized, all the signals in the closed-loop system are bounded in probability. The novel description, which provides an effective method for dealing with unmodeled dynamics in output feedback adaptive controller design, is the development of original idea about handling unmodeled dynamics in [4]. Therefore the design effectively reduces the order of filters and the number of adjustable parameters of the whole system, without estimating in [32]. Therefore, the difficulty, that the transfer function cannot be used in a stochastic system while it was widely used to analyze the boundedness of the K-filters signals in the deterministic systems in [4 , 14 , 16 â€" 18], is solved by the proposed stability analysis approach in this paper. The rest of the paper is organized as follows. The problem formulation and preliminaries are given in Section 2. The neural filters are designed, and adaptive stochastic output feedback control is developed based on dynamic surface control method. The stability in the closed-loop system in probability sense is analyzed in Section 3. Simulation results are presented to illustrate the effectiveness of the proposed scheme in Section 4. Section 5 contains the conclusions. Problem Statement and Preliminaries Consider the following uncertain stochastic nonlinear systems with unmodeled dynamics:

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Chapter 6 : System identification - Wikipedia

() Indirect identification of linear stochastic systems with known feedback dynamics. Journal of Guidance, Control, and Dynamics , Online publication date: 1-Jul

Overview[edit] A dynamical mathematical model in this context is a mathematical description of the dynamic behavior of a system or process in either the time or frequency domain. One of the many possible applications of system identification is in control systems. For example, it is the basis for modern data-driven control systems , in which concepts of system identification are integrated into the controller design, and lay the foundations for formal controller optimality proofs. Input-output vs output-only[edit] System identification techniques can utilize both input and output data e. Typically an input-output technique would be more accurate, but the input data is not always available. Optimal design of experiments[edit] Main article: Therefore, systems engineers have long used the principles of the design of experiments. In recent decades, engineers have increasingly used the theory of optimal experimental design to specify inputs that yield maximally precise estimators. A much more common approach is therefore to start from measurements of the behavior of the system and the external influences inputs to the system and try to determine a mathematical relation between them without going into the details of what is actually happening inside the system. This approach is called system identification. Two types of models are common in the field of system identification: This model does however still have a number of unknown free parameters which can be estimated using system identification. The model contains a simple hyperbolic relationship between substrate concentration and growth rate, but this can be justified by molecules binding to a substrate without going into detail on the types of molecules or types of binding. Grey box modeling is also known as semi-physical modeling. No prior model is available. Most system identification algorithms are of this type. In the context of nonlinear system identification Jin et al. Parameter estimation is relatively easy if the model form is known but this is rarely the case. Alternatively the structure or model terms for both linear and highly complex nonlinear models can be identified using NARMAX methods. Another advantage of this approach is that the algorithms will just select linear terms if the system under study is linear, and nonlinear terms if the system is nonlinear, which allows a great deal of flexibility in the identification. Identification for control[edit] In control systems applications, the objective of engineers is to obtain a good performance of the closed-loop system, which is the one comprising the physical system, the feedback loop and the controller. This performance is typically achieved by designing the control law relying on a model of the system, which needs to be identified starting from experimental data. If the model identification procedure is aimed at control purposes, what really matters is not to obtain the best possible model that fits the data, as in the classical system identification approach, but to obtain a model satisfying enough for the closed-loop performance. This more recent approach is called identification for control, or I4C in short. The idea behind I4C can be better understood by considering the following simple example.