

# The Effect of Measurement Distribution on System Identification and Detection of Behavior of Nonlinearities of Data

Mohammad Javad Mollakazemi, Farhad Asadi, Aref Ghafouri

**Abstract**—In this paper, we considered and applied parametric modeling for some experimental data of dynamical system. In this study, we investigated the different distribution of output measurement from some dynamical systems. Also, with variance processing in experimental data we obtained the region of nonlinearity in experimental data and then identification of output section is applied in different situation and data distribution. Finally, the effect of the spanning the measurement such as variance to identification and limitation of this approach is explained.

**Keywords**—Gaussian process, Nonlinearity distribution, Particle filter.

## I. INTRODUCTION

SYSTEM identification has many applications and are used for many engineering applications [1]. Commonly, a state-space model is used for the linear dynamical system and a Gaussian process model is applied to the static nonlinearity also for statistical application. In this modeling approach, stochastic disturbances with some predefined distribution are entered in both measurement noise and process noise [2]. Gaussian process modeling allows us to model a wide range of nonlinearities in system because when group of noise with different ranges and distributions are inputted to system according to central limit theorem these noises can considered as Gaussian function [3].

Generally, decomposition of system in linear and nonlinear section are common method in control application and many nonlinear dynamical systems can be modeled by this approach and many attentions are attracted to system identification method with this method [4], [5]. Generally, in this modeling the overall system is constructed with interconnection of linear dynamical system and static nonlinearities as block diagram or any other relations.

In this modeling we use the Bayesian approach for modeling the unknown parameters of the system as random variables that evolve in time.

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However, the overall idea behind this method is to use a particle filter for generating trajectory of measurements [6], [7] Also, there is other methods such as maximum likelihood approach for solving this identification [4], [8]. It should be said that inputting of process noise in the model significantly complicates the estimation and in some references this effect is ignored.

In this paper, we use this approach with Markov chain for estimation. The overall important note about this modeling is expressed in next section and then with using different measurements and distributions of data the performance of this method for spanning the region of nonlinearity and characteristics of a good identification is simulated. Besides, important parameter that affects this approach is defined and explained.

## II. METHOD AND APPROACH

In this work, a mixed model for evaluation and approximation of data is considered that linear dynamical system has state space form and static nonlinearity have Gaussian process form. The overall schematic of these equations is expressed by (1)–(3):

$$\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{w}_t, \mathbf{w}_t \sim \mathcal{N}(0, \mathbf{Q}), \quad (1)$$

$$\mathbf{y}_t = \mathbf{C}\mathbf{x}_t, \quad (2)$$

$$\mathbf{y}_t = \mathbf{h}(\mathbf{z}_t) + \mathbf{e}_t, \mathbf{e}_t \sim \mathcal{N}(0, \mathbf{r}). \quad (3)$$

In these relations linear system is assumed to be observable. There is no unobservable mode in the dynamical system which is important as a limitation assumption in this modeling but it has common application in mechanical engineering because the quality characteristics of observable or unobservable mode in dynamical systems have important influence on controlling the systems.

In this study, Bayesian approach is used and parameters of the model are considered as random variables. Management and definition of different matrix in this method is reported well in [6] and we don't enter to the detail in this paper. For the nonlinear mapping we apply a GP function on static nonlinearity modeling in system. The important notice to this modeling is the nonparametric nature of this function; this modeling is flexible and can express a wide range of nonlinear mapping.

In fact, we don't select any specific form of this function and the particle filter in structure of algorithm can smooth this

function and we can apply and model different nonlinearities in function of our system [7], [4]. For example, the nonlinear mapping can take as a saturation form or other discontinuity nonlinear form. In experimental data that we have simulated in this paper we obtain it in different sample periods and use  $n=4$  particles in the sample. The algorithm appears to do a well identifying both for linear dynamical system and nonlinear mapping [9]-[11].

region of this validation in system is showed in two different iterations. Firstly, we show the output of measurement in Fig. 1 with  $n=20$  observable of output and sampling time for all of these measurements is constant and same. Then, the identification of nonlinear region with fitting the best of data is plotted in Figs. 2, 3. The difference between Figs. 2 and 3 is the iteration step of algorithm. We plotted this issue for representing better the spanning of algorithm and also the variation of the shape of the nonlinearity with step. This is because of the completion and convergence of algorithm in particle filter and we can decide the smoothness of nonlinearity in system with variation of these figures during the algorithm runtime.

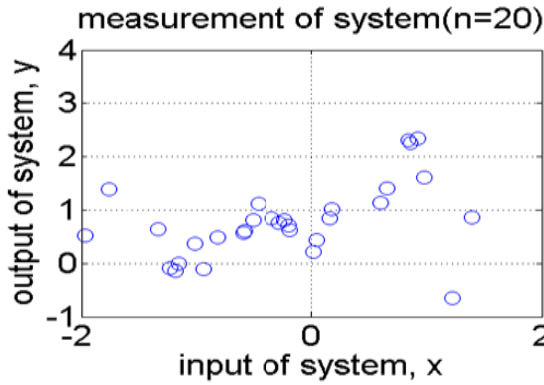


Fig. 1 Measurement of system

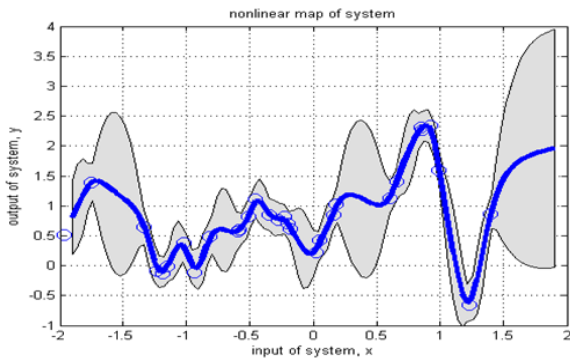


Fig. 2 Nonlinear distribution of system in middle of titration

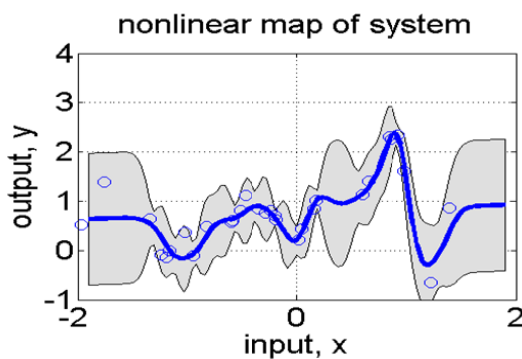


Fig. 3 Nonlinear distribution of system in last of iteration

### III. SIMULATION RESULTS FOR DIFFERENT DATA

In this section, we observe the output of system with design of linear state space and nonlinear section in control of system. In each of these measurements, we changed the distribution of output such as distribution or number of measurements and then we plotted the nonlinear shape of system. Also, the

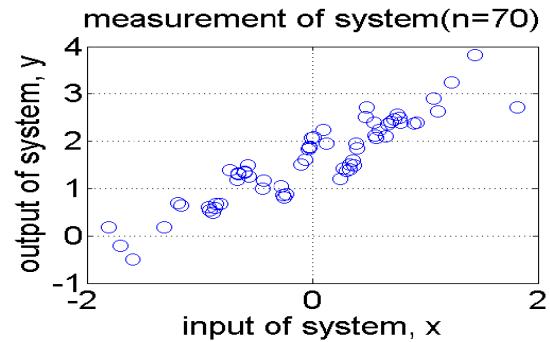


Fig. 4 Measurement of system

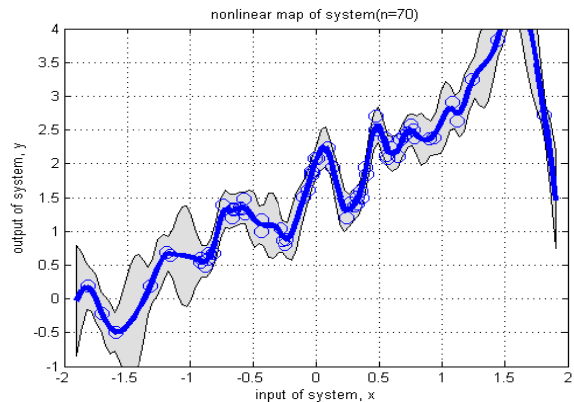


Fig. 5 Nonlinear distribution of system in middle of titration

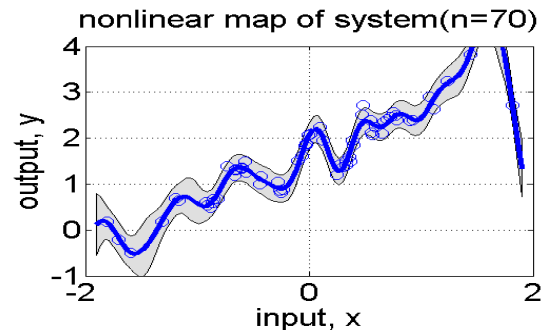


Fig. 6 Nonlinear distribution of system in last of iteration

In Fig. 4 we plotted other measurement of system with adding noise and changing number of measurements and

nonlinear mapping of system are plotted in Figs. 5 and 6. This noise have less covariance and in the figure it is evident that the shape of region of nonlinearity is less but in Fig. 7 we plotted the output measurement with some more noise variance and in Fig. 8 and 9 the nonlinear mapping of system at two different iterations is plotted and influence of variance of nonlinearity is evident from the shape of the validity of our modeling.

uncertainty in nonlinearity gets larger and different phenomena of nonlinear dynamics is existed in system, the power of this method is reduced even with increasing the particle number that makes the response goes to instability.

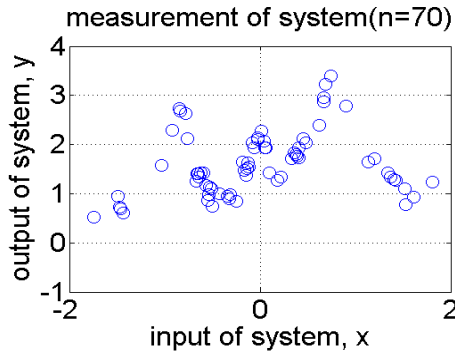


Fig. 7 Measurement of system

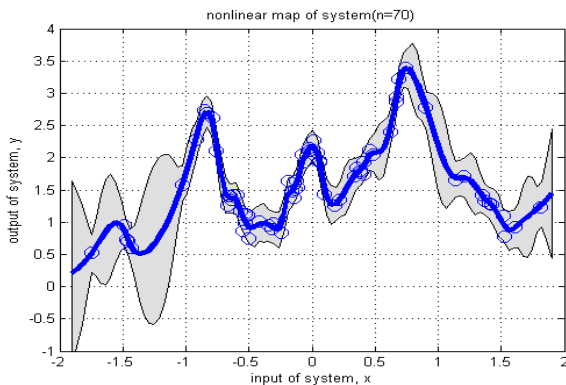


Fig. 8 Nonlinear distribution of system in middle of titration

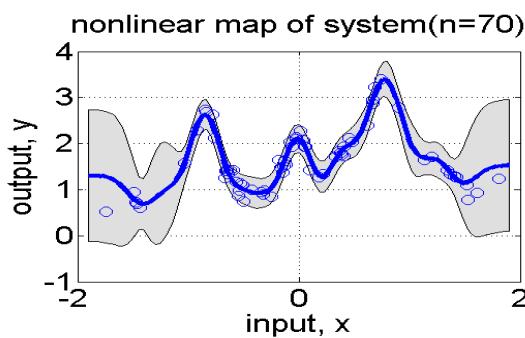


Fig. 9 Nonlinear distribution of system in last of iteration

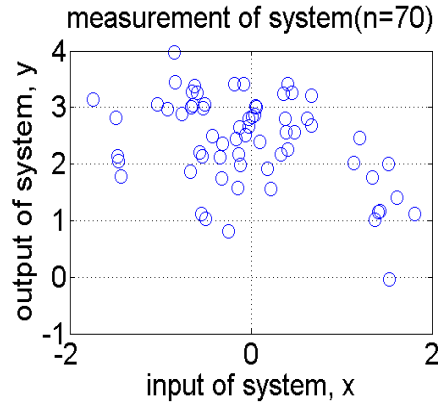


Fig. 10 Measurement of system

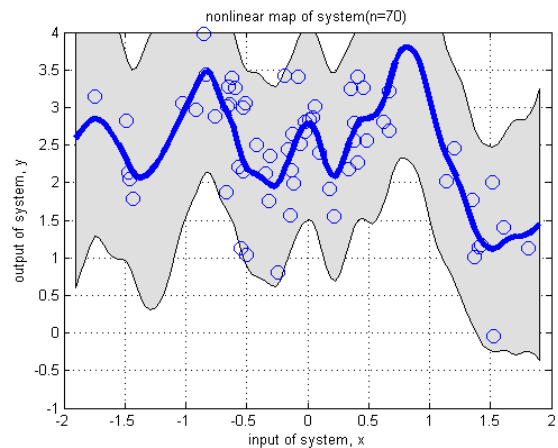


Fig. 11 Nonlinear distribution of system in middle of titration

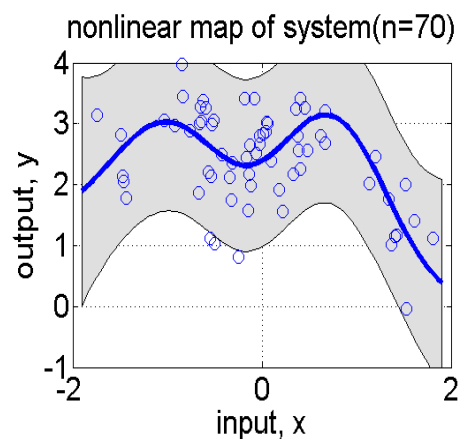


Fig. 12 Nonlinear distribution of system in last of iteration

#### IV. THE INFLUENCE OF NONLINEARITY IN THIS MODELING

In this section we changed the nonlinear section of our modeling and we considered the non-smoothness nonlinearity. Then, we evaluated the change of shape of the model. Generally, the importance of this algorithm is that with observing the posterior PDF of output we can obtain and identify the shape of the nonlinearity in system. But, when the

In Fig. 10 we plotted the measurement with  $n=70$  data and also in Figs. 13 and 16 we plotted another two measurements of system. It should be said here with changing the parameter of noise or dynamics of model these figures are captured.

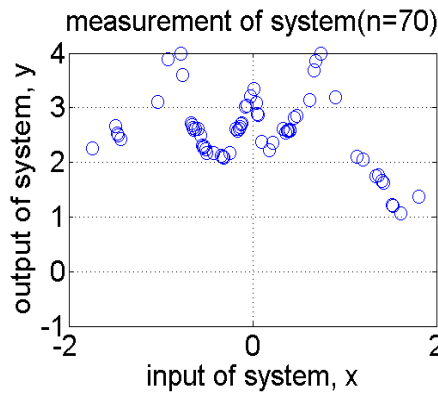


Fig. 13 Measurement of system

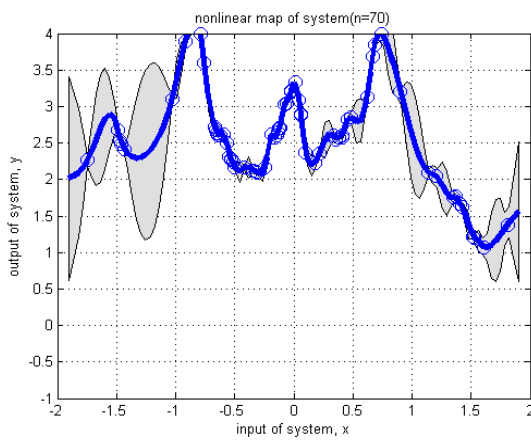


Fig. 14 Nonlinear distribution of system in middle of titration

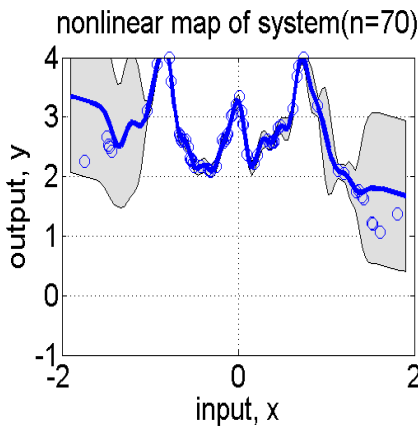


Fig. 15 Nonlinear distribution of system in last of iteration

Then nonlinear map of Figs. 11 and 12 are plotted for the first measurement. It is evident due to the no smoothness of nonlinearity the variation of shape of the model is very high and in Fig. 12 this method cannot be used for identification of system because of data is outside of the region of validity of model. Then, in Figs. 14 and 15 we plotted nonlinear map for another measurement and finally the nonlinear map of third measurement is plotted in Figs. 17 and 18. Another point for this identification is when the distribution of output is irregular

such Fig. 17 and model has high noise but spanning the region is well. We can conclude from this figure that the covariance dependent and structure of variance in nonlinearity in model is well and less so we can deduce that nonlinearity in model has smooth behavior and it is important identification that can find and applying this method.

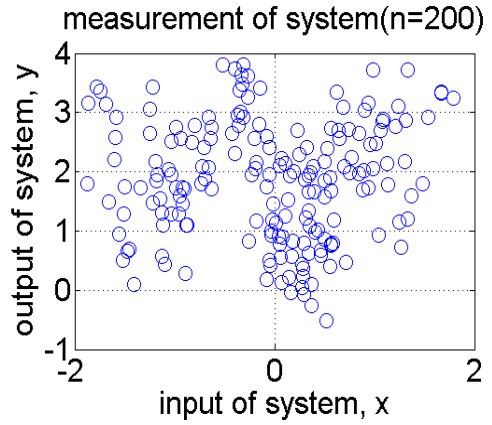


Fig. 16 Measurement of system

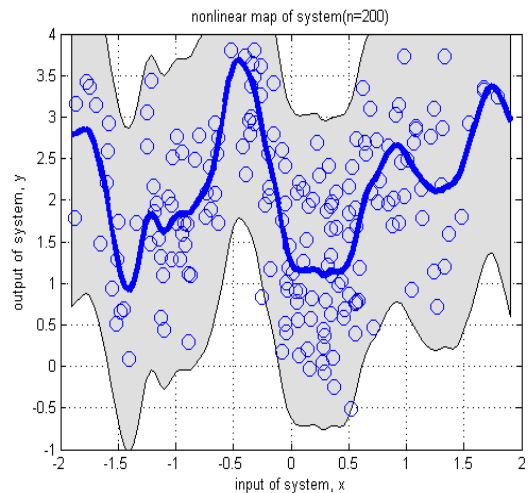


Fig. 17 Nonlinear distribution of system in middle of titration

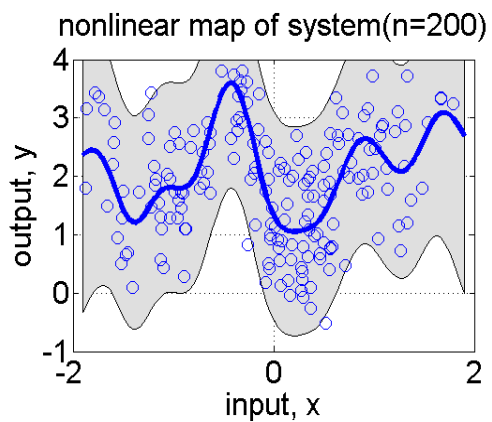


Fig. 18 Nonlinear distribution of system in last of iteration

## V.CONCLUSION

We have considered a Bayesian model of nonlinear with linear model. In this paper, the influence of variance and nonlinearity on shape of the model is simulated. Finally, the deduction about the behavior and smoothness of nonlinearity with help of the shape of region is explained.

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