

李言俊 张 科 余瑞星 © 编著

# 系统辨识 理论及应用

SYSTEM IDENTIFICATION  
THEORY AND APPLICATION

# 系统辨识理论及应用

SYSTEM IDENTIFICATION THEORY AND APPLICATION

李言俊 张科 余瑞星 编著

国防工业出版社

·北京·

**图书在版编目(CIP)数据**

系统辨识理论及应用:英文/李言俊,张科,余瑞星编  
著. —北京:国防工业出版社,2011.2

ISBN 978-7-118-07230-3

I. ①系... II. ①李... ②张... ③余... III. ①系  
统辨识—英文 IV. ①N945.14

中国版本图书馆 CIP 数据核字(2011)第 008049 号

※

**国防工业出版社** 出版发行

(北京市海淀区紫竹院南路 23 号 邮政编码 100048)

国防工业出版社印刷厂印刷

新华书店经售

\*

开本 787×1092 1/16 印张 19½ 字数 446 千字

2011 年 2 月第 1 版第 1 次印刷 印数 1—1000 册 定价 48.00 元

---

(本书如有印装错误,我社负责调换)

国防书店:(010)68428422

发行邮购:(010)68414474

发行传真:(010)68411535

发行业务:(010)68472764

## FORWORD( 前言 )

System identification, state estimation and control theory are three interconnected fields of modern cybernetics. System identification and state estimation cannot be developed without control theory, but applications of control theory are hardly done without system identification and state estimation.

System identification mainly investigates how to determine the mathematical model of a system and its parameters, it is a subject used widely, its theory is increasingly matured, and its practical applications have been extended over many fields. At present the research on theory of system identification is more and more deep, and its applications in aeronautic engineering, astronautic engineering, marine engineering, engineering control, biology, medical science, environment improvement, hydrology, social economics and so on are more and more extensive.

This book mainly introduces basic principle and applications of system identification. Whole book contains 14 chapters. Chapters 1 to 4 are introduction, commonly used input signals for system identification, classical identification methods of linear system, and canonical expression of dynamic systems. They mainly review and introduce some basic knowledge about system identification. Chapters 5 to 12 are least-squares identification, maximum likelihood identification, identification methods of time-varying parameters, identification of multi-input multi-output systems, some other kinds of identification methods, establishment of time series models, identification of system structure, and identification of closed-loop system. They introduce often-used basic methods of system identification, and they are main content of this book. Chapters 13 and 14 introduce application of system identification to parameter identification of aircraft and application of neural network to system identification.

Chapters 1 to 12 are compiled and written by professor Li Yanjun, Chapters 13 and 14 are compiled and written by professor Zhang Ke, and associate professor Yu Ruixing participates in compilation, charting, revision and others of whole book.

Heartfelt thanks to the Teaching Affairs Office, the Postgraduate School of Northwestern Polytechnic University, which have given warm support to publication of this book. If you find some inappropriate points in the book, please give us your advice.

## **Composers**

# Contents

<b>Chapter 1 Introduction</b> .....	1
1.1 Classification of Mathematic Models of System and Modelling Methods .....	2
1.1.1 Signification of Model .....	2
1.1.2 Representation Forms of Models .....	3
1.1.3 Classification of Mathematic Models .....	3
1.1.4 Basic Methods to Establish Mathematic Model .....	4
1.1.5 Basic Principles Followed for Modeling .....	5
1.2 Definition, Content and Procedure of Identification .....	5
1.2.1 Definition of Identification .....	5
1.2.2 Content and Procedure of Identification .....	6
1.3 Error Criteria Usually Used in Identification .....	7
1.3.1 Output Error Criterion .....	7
1.3.2 Input Error Criterion .....	8
1.3.3 Generalized Error Criterion .....	8
1.4 Classification of System Identification .....	9
1.4.1 Off-line Identification .....	9
1.4.2 On-line Identification .....	9
Problems .....	10
<b>Chapter 2 Commonly Used Input Signals for System Identification</b> .....	11
2.1 Selective Criteria of Input Signal for System Identification .....	11
2.2 White Noises and Its Generating Methods .....	12
2.2.1 White Noise Process .....	12
2.2.2 White Noise Sequence .....	15
2.2.3 Generating Methods of White Noise Sequence .....	15
2.3 Generation of Pseudorandom Binary Sequence—M-Sequence and Its Properties .....	18
2.3.1 Pseudorandom Noise .....	18
2.3.2 Generating Method of M-Sequence .....	22
2.3.3 Properties of M-Sequence .....	23
2.3.4 Autocorrelation Function of Two-Level M-Sequence .....	24
2.3.5 Power Spectral Density of Two-Level M-Sequence .....	28
Problems .....	31
<b>Chapter 3 Classical Identification Methods of Linear System</b> .....	32
3.1 Identify Impulse Response of Linear System by Use of M-Sequence .....	33

3.2	Obtain Transfer Function from Impulse Function .....	39
3.2.1	Transfer Function $G(s)$ of Continuous System .....	39
3.2.2	Transfer Function of Discrete System—Impulse Transfer Function $G(z^{-1})$ .....	41
	Problems .....	43
<b>Chapter 4 Canonical Expression of Dynamic Systems .....</b>		<b>45</b>
4.1	Parsimony Principle .....	46
4.2	Representations of Difference Equation and State Equation of Linear System .....	49
4.2.1	Representation of Difference Equation of Linear Time-Invariant System .....	49
4.2.2	Representation of State Equation of Linear System .....	50
4.3	Deterministic Canonical State Equations .....	50
4.3.1	Controllable Form of Canonical State Equation I .....	51
4.3.2	Controllable Form of Canonical State Equation II .....	52
4.3.3	Observable Form of Canonical State Equation I .....	52
4.3.4	Observable Form of Canonical State Equation II .....	52
4.3.5	Observable Form of Canonical State Equation I of MIMO System .....	53
4.3.6	Observable Form of Canonical State Equation II of MIMO System .....	53
4.4	Deterministic Canonical Difference Equations .....	55
4.5	Stochastic Canonical State Equations .....	57
4.6	Stochastic Canonical Difference Equations .....	58
4.7	Prediction Error Equation .....	60
	Problems .....	61
<b>Chapter 5 Least-Squares Identification .....</b>		<b>62</b>
5.1	Least Square Method .....	62
5.1.1	Algorithms of Least-Square Estimation .....	64
5.1.2	Input Signals for Least-Squares Estimation .....	65
5.1.3	Probability Properties of Least-Squares Estimation .....	68
5.2	A Kind of Least Squares Which Need Not Invert Matrix .....	74
5.3	Recursive Least Squares .....	76
5.4	Auxiliary Variable Method .....	79
5.5	Recursive Auxiliary Variable Method .....	82
5.6	Generalized Least Squares .....	83
5.7	An Alternative Generalized Least Squares Technique (Hsia Method) .....	89
5.8	Extended Matrix Method .....	93
5.9	Multistage Least Squares .....	94
5.9.1	The First Algorithm .....	94
5.9.2	The Second Algorithm .....	98
5.9.3	The Third Algorithm .....	99
5.10	Fast Multistage Least Squares .....	102
	Problems .....	108

<b>Chapter 6 Maximum-Likelihood Identification</b> .....	111
6.1 Maximum-Likelihood Method for Parameter Identification .....	111
6.1.1 Principle of Maximum Likelihood .....	111
6.1.2 Maximum-Likelihood Estimation of System Parameters .....	114
6.2 Recursive Maximum-Likelihood Method .....	121
6.2.1 Approximate Recursive Maximum-Likelihood Method .....	121
6.2.2 Recursive Newton-Raphson Maximum-Likelihood Algorithm .....	126
6.3 Achievable Precision of Parameter Estimations .....	130
Problems .....	132
<b>Chapter 7 Identification Methods of Time-Varying Parameters</b> .....	134
7.1 Forgetting Factor Method, Rectangular Window Method and Kalman Filter Method .....	134
7.1.1 Forgetting Factor Method .....	134
7.1.2 Rectangular Window Method .....	135
7.1.3 Kalman Filter Method .....	136
7.2 An Identification Method of Time-Varying Parameters with Automatically Adjusted Forgetting Factor .....	137
7.3 An Identification Method Using Broken-Line Segments to Approximate to Time-Varying Parameter .....	140
Problems .....	143
<b>Chapter 8 Identification of Multi-Input Multi-Output Systems</b> .....	144
8.1 Least-Squares Identification of Multi-Input Multi-Output Systems .....	144
8.2 Maximum-Likelihood Identification of Multi-Input Multi-Output System; Relaxation Algorithm .....	147
8.3 Use Square-Wave Pulse Function to Identify State Equation of Linear Time-Varying System .....	151
8.3.1 Expansion of State Station in Square-Wave Pulse Series .....	151
8.3.2 Identification of Matrix $A(t)$ .....	153
8.3.3 Identification of Matrix $B(t)$ .....	155
8.4 Identification of Multi-Input Multi-Output Linear Time-Varying System by Use of Piecewise Multiple Chebyshev Polynomials .....	158
8.4.1 Definition of Piecewise Multiple Chebyshev Polynomials and Their Main Properties .....	159
8.4.2 Parameter Identification of Multi-Input Multi-Output Linear Time-Varying System by Use of Piecewise Multiple Chebyshev Polynomials .....	162
Problems .....	166
<b>Chapter 9 Some Other Kinds of Identification Methods</b> .....	167
9.1 A Simple Recursive Algorithm—Method of Stochastic Approximation .....	167



9.1.1	Basic Principle of Stochastic Approximation .....	168
9.1.2	Method of Parameter Estimation by Means of Stochastic Approximation .....	170
9.1.3	Random Newton Method .....	173
9.2	Two Kinds of Recursive Least Squares Based on Different Concepts .....	175
9.2.1	Least-Squares Estimation Recuring with Number of Observation Equations .....	175
9.2.2	Recursive Least-Squares Estimation Varying with Number of Unknown Parameters .....	177
9.2.3	Error Model Best Estimation of Trajectory Derived Based on Recursive Least Squares .....	179
9.3	Recursive Generalized Extended Least Squares for Identification of Box-Jenkins Model .....	181
9.4	Innovations-Modified Least Squares for Identification of Box-Jenkins Model .....	183
9.4.1	Increasing-Parameter Recursive Formulas of Least Squares .....	184
9.4.2	Identification of CAR( $p$ ) Model .....	185
9.4.3	Elimination of Derivations and Determination of Order for MA Part .....	186
	Problems .....	187
<b>Chapter 10 Establishment of Random Time Series Models .....</b>		<b>189</b>
10.1	Regressive Model .....	189
10.1.1	First-Order Linear Regressive Model .....	190
10.1.2	Polynomial Regressive Model .....	191
10.2	Autoregressive Model of Stationary Time Series .....	192
10.3	Moving Average Models of Stationary Time Series .....	195
10.4	Autoregressive Moving Average Model of Stationary Time Series .....	197
10.5	Model of Non-Stationary Time Series .....	197
	Problems .....	199
<b>Chapter 11 Structure Identification of System .....</b>		<b>201</b>
11.1	Order Estimation of Models .....	201
11.1.1	Determine Order According to Variance of Residual Errors .....	201
11.1.2	Akaike Information Criterion For Determining Order .....	203
11.1.3	Determine Order by Use of White Residual Errors .....	206
11.1.4	Use Zero-Pole Cancellation to Check Order .....	207
11.1.5	Determine Order by Use of Ratio Between Determinants .....	207
11.1.6	Determine Order by Use of Hankel Matrix .....	208
11.2	A Non-Recursive Algorithm to Identify Order and Parameters of Model at the Same Time .....	210
11.3	A Recursive Algorithm to Identify Order and Parameters of Model at the Same Time .....	213
11.4	Structure Identification of Multivariable Carma Model .....	216

11. 4. 1	Recursive Least-Squares Estimation of Parameters .....	217
11. 4. 2	Determine the Order of Submodel .....	218
11. 4. 3	Determinations of Succinct Parameter Model, Suborder and Time-Delay .....	219
	Problems .....	223
<b>Chapter 12 Identification of Closed-Loop System .....</b>		<b>224</b>
12. 1	Discrimination Methods of Closed-Loop Systems .....	224
12. 1. 1	Method of Spectral Factor Decomposition .....	225
12. 1. 2	Method of Likelihood Ratio Test .....	226
12. 2	Identifiable Concept of Closed-Loop System .....	229
12. 3	Identification of Single-Input Single-Output Closed-Loop System .....	232
12. 3. 1	Direct Identification .....	232
12. 3. 2	Indirect Identification .....	238
12. 4	Identification of Multi-Input Multi-Output Closed-Loop System .....	240
12. 4. 1	Autoregressive Model Identification Method .....	240
12. 4. 2	Identification Method Changing Feedback Matrix .....	242
	Problems .....	244
<b>Chapter 13 Application of System Identification to Parameter Identification of Aircraft .....</b>		<b>246</b>
13. 1	Foreword .....	246
13. 1. 1	Identification of Aerodynamic Parameters .....	246
13. 1. 2	Identification of Aerothermodynamic Parameters .....	247
13. 1. 3	Parameter Identification of Structural Dynamics .....	248
13. 1. 4	Identification of Modal Parameters for Rock of Liquid .....	249
13. 1. 5	Error Coefficient Identification of Inertial Instrument .....	250
13. 2	Maximum Likelihood Identification of Noise Model for Target Seeker of Missile .....	251
13. 2. 1	Description of Seeker Noise Model .....	252
13. 2. 2	Maximum Likelihood Identification of Noise Model Parameters .....	254
13. 2. 3	Identification of Noise Model for Seeker-Target Line-of-Sight Angular Velocity .....	257
13. 2. 4	Identification of Noise Model for Target Approaching Velocity .....	259
13. 2. 5	Check of Noise Model .....	259
13. 2. 6	An Example of Maximum Likelihood Identification .....	260
13. 3	Modelling of Output Noise for Seeker System by Use of Time Series .....	261
13. 3. 1	Design of Scheme .....	261
13. 3. 2	Establishment of Noise Model .....	262
13. 3. 3	Parameter Identification of Noise Model .....	264
13. 3. 4	Example of Identification by Use of Time Series Method .....	266
13. 4	Application of System Identification to Pneumatic Parameter Identification of Aircraft .....	267

13. 4. 1	Identification of Aerodynamic Parameters for Tactical Missile .....	269
13. 4. 2	Examples of Closed-Loop Identification .....	280
<b>Chapter 14</b>	<b>Application of Neural Network to System Identification .....</b>	<b>283</b>
14. 1	Brief Introduction of Neutral Network .....	283
14. 1. 1	Development Survey of Neutral Network .....	283
14. 1. 2	Structure and Type of Neutral Network .....	283
14. 2	Identification of Linear System .....	284
14. 2. 1	Identification of Linear System Based on Single-Layer Neutral Network .....	284
14. 2. 2	Identification Methods of Linear System Based on Single-Layer Adaline Network .....	286
14. 3	Application of BP Algorithm to Neutral Network .....	287
14. 3. 1	Brief Introduction of BP Network .....	288
14. 3. 2	Mathematical Principle of BP Network .....	288
14. 4	Identification of Linear Time-Varying System .....	291
14. 4. 1	Structure of Network and Analysis of Its Approximating Ability .....	291
14. 4. 2	Learning Algorithm .....	293
14. 4. 3	Results of Simulation .....	296
<b>References</b>	.....	<b>298</b>

# Chapter 1 Introduction

System identification, state estimation and control theory are three interconnected fields of modern cybernetics. System identification and state estimation cannot be developed without control theory, but applications of control theory are hardly done without system identification and state estimation. As the complexity of controlled plant increases, the applications of control theory become more and more extensive. However, its practical applications cannot get out the mathematic model of controlled plant. When discussing the linear system theory, the optimal control theory and the optimal filtering theory in other courses, we always assume that the mathematic models of the systems are known. Some mathematic models of control systems can be derived by theoretical analysis methods, for example, the mathematic models of airplane motion and missile motion in general may be more precisely derived based on mechanical principle. Although the mathematic models of the airplane and the missile may be more precisely derived by theoretical analysis methods, their model parameters vary with flight altitude and flight velocity. In order to implement the adaptive control, parameters of the models should be continuously estimated in flight processes of the airplane and the missile. For some controlled plants, such as the chemical production process and so on, it is difficult to derive their mathematic models using the theoretical method due to their complexities. Sometimes we can know the general forms of their mathematic models and their part of parameters, sometimes we cannot know even the general forms of their mathematic models, thus the problem how to determine the mathematic models of the systems and their parameters is proposed, which is so-called the system identification problem.

System identification is a subject used widely, its theory is increasingly matured, and its practical applications have been extended over many fields. At present the controlled plants need to establish mathematic models and to use these mathematic models to determine the optimal control decisions not only in engineering but also in other fields, such as biology, ecology, medical science, astronomy, atmosphere pollution, social economics and so on. Since the systems in above fields are complicated, persons often have understood less, even hardly, the structures of the systems and the mechanism to govern the motion of the systems, so it is impossible to obtain the mathematic models by use of theoretical analysis method, and the mathematic models are determined only using observed data. Therefore, the system identification has attracted persons' attention. At present the research on the system identification theory is more and more deep,

and its applications in aeronautic engineering, astronautic engineering, marine engineering, engineering control, biology, medical science, environment improvement, hydrology and social economics are more and more extensive.

As it is to determine the mathematic model of the system according to the experimental data of the system and there must exist an actual system, so the system identification is to establish a mathematic model for an existent system. However, when we design the system, the system still does not exist, thus it is impossible to determine the mathematic model by means of the system identification method. Under this situation we have no choice but to establish the mathematic model by use of theoretical analysis method, even a very glancing mathematic model also is very necessary. Using the mathematic model established by means of theoretical analysis method, we can do some simulations by use of computer and can get many useful results, which can provide scientific basis for design of the system. Therefore, when we discuss the system identification, we cannot deny the importance of the theoretical method for establishing the mathematic model.

In this chapter we shall mainly introduce some basic concepts which include modeling method, definition of identification, error criterion, content and classification of identification and so on.

## **1.1 Classification of Mathematic Models of Systems and Modelling Methods**

### **1.1.1 Signification of Model**

So called model is that the essentially partial information of an actual system is simplified to a useful description form. It can be used to describe the motion law of the system, and it is an objective portrayal or an epitome of the system, and is a powerful tool to analyze the system, to predict and to control dynamic characteristics of the system. However, what part of an actual system ever is essential and what part is nonessential, which depends on the investigated problem. For example, when investigating the dynamic characteristics of the missile in flight process, we often neglect the affections of the high-frequency element and the nonlinear factor in the missile system, and reduce the whole system to a second-order or third-order system. When deriving the guidance law, we may also regard the missile as a particle for the convenience of implementing the guidance law in engineering. This shows that the contents reflected by model are different for its different objectives to be used.

For an actual system a model cannot consider all factors. In this sense so-called model then is an approximate description of the system according to its objective to be used. Of course, the higher the precision requirement of the model is, the more complicated the model is. In contradiction to this, if the precision requirement of the model is

suitably decreased, which only considers the main factors and neglects the subordinate factors, the model would become simple. Therefore, when model of an actual system is established, there exists contradiction between precision and complicity, so to find a compromise between them often is a key to establish model of an actual system.

### 1.1.2 Representation Forms of Models

Models usually are of the following representation forms,

(1) Intuitive model. It indicates that the character of the system is directly stored in the human brain in the non-analytic form and the variation of the system is controlled by human intuition. For example, driver drives motor, director directs fighting, which depends on this sort of intuitive models.

(2) Physical model. It indicates a replica to miniaturize an actual system based on the principle of similitude, or a kind of physical simulation for the actual system. For example, wind-tunnel model, water-tunnel model, heat-transfer model, dynamic simulation of electrical power system and others, all belong to physical models.

(3) Chart model. The behavior of the system is represented by the form of a graph or a table, such as step response, impulse response, frequency characteristic and so on, they are also called non-parametric model.

(4) Mathematic model. It reflects behaviors of an actual system in the form of mathematic structure. Usually used mathematic models are algebraic equation, differential equation, difference equation, state equation, transfer function, nonlinear differential equation, distributed parameter equation and so on. These mathematic models are also called parametric equation. After determining order and parameters of the model, the mathematic model would be also determined.

### 1.1.3 Classification of Mathematic Models

There are many classification methods for mathematic models. Familiar one is classified by continuous and discrete, time-invariant and time-varying, centralized parameter and distributed parameter, which have been much introduced in the courses such as the linear system and so on, here we do not repeat them again. They can also be classified by linear and nonlinear, dynamic and static, determinate and stochastic, macro and micro.

(1) Linear model. Linear model is used to describe the linear system. Its remarkable specialty is to satisfy the principle of superposition and the uniformity. That is, to satisfy the following operations;

$$(\alpha_1 + \alpha_2)x = \alpha_1 x + \alpha_2 x$$

$$\alpha_1(\alpha_2 x) = \alpha_2(\alpha_1 x)$$

$$\alpha_1(x + y) = \alpha_1 x + \alpha_1 y$$

where  $x$  and  $y$  are state-space variables of the system,  $\alpha_1$  and  $\alpha_2$  are operators acting on  $x$

and  $y$  respectively.

(2) Nonlinear model. Nonlinear model is used to describe the nonlinear system, and it in general does not satisfy the principle of superposition.

(3) Dynamic model. Dynamic model is used to describe relations among variables of the system located in the transient process. In general it is a function of time.

(4) Static model. Static model is used to represent relations among variables of the system located in steady state (all derivatives of variables are equal to zero). In general it is not a function of time.

(5) Determinate model. The output response of the system described by determinate model is unique and determinate after its states are determined.

(6) Stochastic model. After states of the system described by stochastic model are determined, its output response still is not determinate.

(7) Macro model. Macro model is used to investigate the macro phenomena of an object. In general it is described by simultaneous equations or integral equation.

(8) Micro model. Micro model is used to investigate the motion law of micro unit inside object. In general it is described by differential equation or difference equation.

In addition, when discussing linear and nonlinear problems, we should note the following two differences.

(1) Difference between the system linearity and the linearity with respect to parametric space: If output of the model is linear with respect to input, the model is called having system linearity. If output of the model is linear with respect to parametric space, the model is called having linearity with respect to parametric space. For example, for model  $y=a+bx+cx^2$ , output  $y$  is nonlinear with respect to input  $x$  but linear with respect to parameters  $a, b$  and  $c$ , i. e., the model is not the system linearity but the linearity with respect to parametric space.

(2) Difference between essential linearity and essential nonlinearity: If an original nonlinear model may be transformed into a linear model by suitable mathematic transformation, the original model is called the essential linearity. Otherwise the original model is called the essential nonlinearity.

#### **1. 1. 4 Basic Methods to Establish Mathematic Model**

Establishment of mathematic model usually needs to adopt two basic methods such as theoretical analysis and experiment at method.

##### **1) Theoretical analysis method**

Theoretical analysis method is also called the mechanism analysis method or the theoretical modeling. This method mainly uses mathematic methods to derive and to establish mathematic model of the system via analysis of motion law of the system based on some known laws, theorems and principles such as principle of mechanics, biological laws, Newton theorems, energy balance equation, heat transfer and mass transfer prin-

ciple and so on.

Theoretical analysis method is only applicable to modeling of simpler system, and designer should more distinctly understand the mechanism of the system. This modeling method has large restriction for a more complicated actual system, because the theoretical modeling has to propose some reasonable simplification assumptions for the investigated plant, otherwise the problem would become too complicated. However, if these simplification assumptions are wanted to accord completely with practical situations, it often is quite difficult.

## 2) Experimental method

In general input and output of a system can always be measurable. Since dynamic characteristics must be revealed in these input and output data, so information of these input and output data can be used to establish mathematic model of the system. This modeling method is exactly the system identification.

As compared with theoretical method, an advantage of the experimental method is that the mechanism of the system need not be deeply understood, and its shortage is that a suitable experiment must be designed to gain large amount of information required, but design of a suitable experiment often is difficult. Therefore, when establishing a specific model, we often combine the theoretical analysis method with the measurement method, that is, the part whose mechanism is known adopts the theoretical analysis method, but the part whose mechanism is unknown adopts the measurement method.

### 1.1.5 Basic Principles Followed for Modeling

(1) Modeling objective should be definite, because for different modeling objectives, different modeling methods would be adopted.

(2) Physical concepts of the model should be clear.

(3) System should be identifiable, i. e. , structure of the model is reasonable, the input signal is persistently exciting, and the amount of data is sufficient.

(4) The modeling should accord with the parsimony principle, namely the number of parameters of the model to be identified should be as small as possible.

## 1.2 Definition, Content and Procedure of Identification

### 1.2.1 Definition of Identification

Many scholars have defined the identification. In the following we shall introduce several typical and applicable definitions.

(1) Identification is to determine a model being equivalent to the measured system from a set of given model sorts based on input and output data.



(2) Identification problem may be summed up in a kind of calculation which uses a model to express essential characteristic of an objective system (or a system to be constructed), and this model is used to express the understanding of the objective system as a useful form.

This definition of identification emphasizes a very important concept: Final model only should express the essential characteristic of the dynamic system, and it should be expressed as a suitable form. This implies that we do not desire to acquire an exact mathematic description of a real physical system, and that what we want is only an applicable model.

(3) Identification has three factors—data, model type and criterion. Identification is to select a model best fitting to data from a set of model types according to a criterion.

### **1. 2. 2 Content and Procedure of Identification**

From above definitions we can see that the identification is to use measured input and output data (they often contain noises) to select a model best fitting with the measured data from a set of model sorts according to the selected criterion. In the following we shall introduce procedure and method of the identification.

(1) Understanding target of identification. To understand final applied target of the model is very important, because it will determine type of model, requirement of precision and identification algorithm to be used.

(2) Mastering a priori knowledge. Before identifying system, it should be as more as possible to master a priori knowledge of the system, for example, nonlinearity of the system, time-varying or time-invariant, proportional or integral characteristic, time constant, transient time, cut-off frequency, time-delay characteristic, static amplifying times, noise characteristic, operational environment and so on. The a priori knowledge will play a directive role in primary selection of mathematic model sort and design of experiment for identification.

(3) Utilizing a priori knowledge to predict and choose mathematic model sort of the identified system, and determine prior assumed model.

(4) Design of the experiment, including selecting experimental signal, sampling period, datum length and so on, and noting down input and output data. If the system is continuously operating and does not allow adding experimental signal, it has to use normal operating data for identification.

(5) Preprocessing of data. The input and output data often contain direct-current (DC) component or low-frequency component, and it is difficult to eliminate their influence on precision of identification using any identification algorithm. High-frequency components of data will have disadvantageous influence on identification. Therefore, we should do such preprocessing of the input and output data as zero-equalization and eliminating high-frequency components. Better preprocessing would obviously increase the