



## Research article

## Identification of look-up tables using gradient algorithm

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## ARTICLE INFO

## Article history:

Received 25 May 2017

Revised 7 December 2017

Accepted 12 February 2018

Available online 21 February 2018

## Keywords:

Engine

Lookup tables (or Maps)

Identification

Gradient method

Persistent excitation

## ABSTRACT

In view of the relatively low computational load, look-up tables (or maps) are usually used to approximate nonlinear function or characterize operating-point-dependent system variables in typical embedded applications. Aiming at the problem of off-line identifying the look-up tables, a method based on the gradient algorithm is presented to estimate the look-up table parameters in this paper. The nonlinear function is approximated in terms of the piecewise linear interpolation model with the look-up table parameters, which can be rewritten as a dot product between the regression vector and unknown parameter vector using membership function. With the approximation error of the nonlinear function, a method for updating look-up tables using the gradient algorithm is given, and the relationship between the parameter estimation error and model approximation error is explicitly derived. To guarantee the convergence of the look-up table parameters estimation, a condition for the persistent excitation of the look-up table input is derived, which also provides a theoretical basis for the data characteristics of the look-up table input required to identify look-up table parameters offline using dynamic data. The validity of the proposed method is verified respectively by updating a one-dimensional (1D) look-up table, and the identification of the two-dimensional (2D) look-up table for the throttle discharge coefficient of a spark ignition gasoline engine from engine simulation tool eNDYNA.

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## 1. Introduction

Modern control and diagnosis systems rely upon accurate information about the system variables, in which the accurate model plays a vital role. Model-based representations for the nonlinear system are concise and able to characterize a wide range of dynamic behavior with a small set of parameters. Meanwhile, look-up tables (or maps) are useful for characterizing nonlinear systems, in which the functional relationship of nonlinear terms in equations are not known or too complex to represent analytically. As a method for the nonlinear function approximation, look-up tables providing a transparent and flexible representation are the most common type of nonlinear static models, and widely used for the machine learning, nonlinear network analysis, and nonlinear control systems [1,2].

In typical embedded applications, look-up tables with the advantage of the low computational load are by far the most common approach for handling and storing operating-point-dependent system variables. Especially in automotive applications, look-up tables are frequently used to describe relations when physical models are

unavailable [2,3]. For controller design and implementation, look-up tables can be applied as nonlinear feedforward controllers storing controller parameters to determine the manipulated variable in dependency on the different operating condition [4–7]. Meanwhile, look-up tables can also be used to store operating-point-dependent reference values and nonlinear feedback gains (for gain scheduling) for the closed-loop controller [8–10].

In model-based control and diagnosis systems applications, two problems have to be considered for updating look-up tables parameters. First, the accuracy of these tables are driven by the collection of the appropriate data and calibration of all the table parameters. This can be a time consuming task [11]. Such as the identification of engine volumetric efficiency with static data, in which every single static measure is expensive in terms of the test bench occupation and operator working time [12–14]. Second, there is also a need to adapt or update the look-up tables parameters on-line in order to cope with surrounding conditions changes, systems variations and ageing [15].

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Many algorithms are proposed to solve the problem of off-line identifying or on-line updating the look-up tables, in which the dynamic data can be used to update table parameters or reduce the calibration time and cost comparing static data. In Ref. [16], a method for updating look-up tables parameters using a proportional weighting is proposed and applied to engine adaptive knock control. In order to identify or adapt the look-up table parameters with low calculation burden and storage, a new recursive least-squares identification algorithm exploiting the sparse structure of the look-up table matrix equations is developed in Ref. [15], where the volumetric efficiency map is identified by dynamic data to reduce the calibration time and cost. In Refs. [17–19], the extended Kalman filter (EKF) with confined covariance matrix for updating sensor error map is presented to track the mass air flow (MAF) sensor aging, in which the look-up table parameters are considered as parameter states. Nevertheless, the heavy matrices from EKF must be calculated, preventing it from being implemented in commercial electronic control units (ECUs). Therefore, the new look-up tables updating method using Kalman filter framework with simplified covariance matrix are developed in Refs. [20,21], which are suitable for being implemented on commercial ECUs and applied to NOx estimation in diesel engines. Nevertheless, the convergence of the EKF with the confined or simplified covariance matrix cannot be guaranteed. Therefore, a linear parameter varying (LPV) adaptive observer with exponential convergence is proposed to estimate the one dimensional (1D) map, in which the exponential convergence of the algorithm is proved [22]. In order to improve the accuracy of the model structure for sensor error, a two dimensional (2D) map taking the operating point as inputs is used to describe the MAF sensor error in Ref. [23], in which a LPV adaptive observer for updating 2D map is designed and the convergence of the proposed algorithm is proven under the conditions of the persistent excitation and given inequalities. Furthermore, the mean-value engine model of a diesel engine with additional model biases is analyzed and employed to improve the estimation precision of the 2D map [24]. However, the relationship between the estimation error of the existing methods for off-line identifying or on-line updating look-up tables and the model error of look-up tables to approximate the nonlinear function is not given. Meanwhile, the approach for judging the convergence of the look-up table parameters estimation is still not clear.

There are two classes of important parameter estimation approaches: least squares methods and gradient methods. The gradient algorithm requires less computational effort than the recursive least squares algorithm, and can be used to estimate large number of parameters in real-time application [25,26]. In order to identify offline or update online the look-up tables using the gradient algorithm with low computational load, the nonlinear function presenting operating-point-dependent system variable is approximated in terms of piecewise linear interpolation model with look-up table parameters, which is rewritten as a dot product between regression vector and unknown parameter vector using membership function. With the approximation error for the nonlinear function, a method for updating look-up tables using the gradient algorithm is given, and the relationship between the estimation error and model approximation error is explicitly derived. To guarantee the convergence of the estimation for all look-up table parameters, a trajectory scheme of the look-up table input passed through all the interpolation regions is introduced. Furthermore, a sufficient condition for persistent excitation of the look-up table input is given, which is a condition for the convergence of look-up table parameters estimation and provides a theoretical basis for the data characteristics of the look-up table input required to identify look-up table parameters offline.

The rest of the paper is organized as follows. Section 2 gives the mathematical description of the 1D and 2D look-up tables, and presents the regression models using the piecewise linear interpolation. Section 3 and 4 present the main result of this paper. Furthermore, through a simple 1D look-up table example and the 2D look-up table identification of the throttle discharge coefficient in a gasoline engine from engine simulation tool enDYNA, Section 5 shows the verification of our results. Finally, Section 6 makes the concluding remarks.

## 2. Look-up table mathematical description

In this section, the definition of the look-up table is given first. Let  $u = (u_1, \dots, u_n) \in \mathbb{R}^n$  is a  $n$ -dimensional ( $n$ D) vector, and define a partition as:  $\left\{ (u_1^{i_1}, \dots, u_n^{i_n}) \mid u_k^{i_k} < u_k^{i_k+1}, i_k = 1, 2, \dots, p_k, p_k \in \mathbb{Z}^+, k = 1, 2, \dots, n \right\}$ . A table is defined as a  $n$ D mapping  $T: \mathbb{R}^n \rightarrow \mathbb{R}, (u_1^{i_1}, \dots, u_n^{i_n}) \mapsto \theta^{i_1 \dots i_n}$ , where  $(u_1^{i_1}, \dots, u_n^{i_n})$  is the grid point of the table  $T$ ,  $\theta^{i_1 \dots i_n}$  is the table parameter satisfying  $\theta^{i_1 \dots i_n} = T(u_1^{i_1}, \dots, u_n^{i_n})$ . Using the table  $T$  and piecewise interpolation method, a  $n$ D look-up table is defined as a  $n$ D function  $f_T: \mathbb{R}^n \rightarrow \mathbb{R}, u \mapsto y = f_T(u)$ , which satisfies  $\theta^{i_1 \dots i_n} = f_T(u_1^{i_1}, \dots, u_n^{i_n}) = T(u_1^{i_1}, \dots, u_n^{i_n}), i_k = 1, 2, \dots, p_k, k = 1, 2, \dots, n$ .

In fact, the 1D and 2D look-up tables are widely used in typical embedded applications, and the higher-dimensional relationships can be described by many low-dimensional look-up tables combined in an additive or multiplicative manner [1]. In this paper, the method for updating 1D and 2D look-up tables is studied. Therefore, the regression vectors of the 1D and 2D look-up tables are given in the following.

### 2.1. Regression structure of look-up tables

A two variable function with bounded fourth order derivative is defined as:

$$y = f(u), u = (u_1, u_2) \in [a, b] \times [c, d] \quad (1)$$

where  $a, b \in \mathbb{R}$  are the minimum and maximum values of  $u_1$ , and  $c, d \in \mathbb{R}$  are the minimum and maximum values of  $u_2$ . In order to approximate the function  $f(u)$  using the 2D look-up table, define the partition of the input  $u$  as:

$$\begin{aligned} a &= u_1^1 < u_1^2 < \dots < u_1^{p_1} = b \\ c &= u_2^1 < u_2^2 < \dots < u_2^{p_2} = d \end{aligned} \quad (2)$$

where  $p_1$  is the number of the grid points in  $[a, b]$ , and  $p_2$  is the number of the grid points in  $[c, d]$ . Assume that the function of the input grid point  $(u_1^i, u_2^j)$  is  $\theta^{ij}$ , i.e.,

$$\begin{aligned} \theta^{ij} &= f(u_1^i, u_2^j) \\ i &= 1, 2, \dots, p_1; j = 1, 2, \dots, p_2 \end{aligned} \quad (3)$$

Then, for  $\forall u \in [u_1^i, u_1^{i+1}] \times [u_2^j, u_2^{j+1}], i \in [1, 2, \dots, p_1 - 1], j \in [1, 2, \dots, p_2 - 1]$ , we can apply the piecewise bilinear interpolation using the Lagrange form to describe the 2D look-up table. The result is

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