Parameter Estimation Algorithm and Application in Industry Design

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Abstract. The paper presents parameter estimation algorithm and application in industry design, it proposes low order autoregressive algorithm, and it presents the parameter estimation model. Experiments show that the proposed algorithm can make parameter estimation effective. The parameter estimation algorithm can be used in more industry design cases.

1. Introduction

One of the most important objectives of statistical inference is to estimate unknown model parameters based on an observed data. There are many applications of industry design involves parameter estimation algorithm [1-6]. Syed Shahnawazuddin [7] has explored the Spectral Moment time-frequency distribution Augmented by features in severe pitch mismatch task. The estimation only can realize the frequency estimation of the stationary process, and the adaptive kernel function is used to improve the algorithm in time-frequency domain, it can realize time-frequency distribution under stable distribution noise environment, and has a certain practical significance.

Parameter estimation is a kind of statistical inference. The process of estimating unknown parameters in the population distribution based on random samples extracted from the population. From the form of estimation, it can be divided into point estimation and interval estimation: from the method of constructing estimators, there are moment estimation, least square estimation, likelihood estimation, Bayesian estimation and so on. There are two problems to be solved: (1) finding the estimators of unknown parameters; (2) pointing out the accuracy of the estimators under certain reliability. Reliability is generally expressed by probability, such as 95% credibility; accuracy is measured by the proximity or error between the estimator and the estimated parameters (or parameters to be estimated).

2. The Parameter Estimation Algorithm of Model

Parameter distribution can use Gaussian distribution, the process variable, and its characteristic function is:

$$\theta(t) = \exp\{n - n[1 + \text{sign}(t)\alpha(t, \alpha)]\}$$

(1)

Where, $$\alpha(t, \alpha) = \begin{cases} \tan(\alpha) & \text{if } \alpha \neq 1 \\ \log|t| & \text{if } \alpha = 1 \end{cases}$$, $\text{sign}(t) = \begin{cases} 1 & t > 0 \\ 0 & t = 0 , \text{ when } 0 < \alpha < 2 . \\ -1 & t < 0 \end{cases}$
When the system model structure is known, then the process of calculating the parameters of the system model will use the input and output data of the system. At the end of the 18th century, the German mathematician C.F. Gauss first proposed the method of parameter estimation. He used the least square method to calculate the orbit of celestial bodies. In the 1960s, with the popularity of computers, parameter estimation has developed rapidly. There are many methods for parameter estimation, such as moment estimation, maximum likelihood method, uniform minimum variance unbiased estimation, minimum risk estimation, covariant estimation, least squares method, Bayesian estimation, maximum posteriori method, minimum risk method and minimum maximum entropy method. The most basic methods are least square method and maximum likelihood method.

The covariance of distribution does not exist because its variance is not limited. It is similar to covariance of Gaussian random process. In probability theory and statistics, Gaussian process is a stochastic process, it makes every finite collection of those random variables has a multivariate normal distribution. Optimisation software will be used to fit the Gaussian process. The distribution random variable \( X \) and distribution random variable \( Y \) can be defined as [8]:

\[
[X,Y]_\alpha = \int x y \mu(d) , \quad 1 < \alpha \leq 2
\]  

The least squares method and the maximum likelihood method have recursive forms. In addition, the recursive generalized least squares method, the recursive auxiliary variable method and the recursive extended least squares method are all improved forms of the recursive least squares method.

It can be used to estimate the system with noise interference. In addition, stochastic approximation algorithm, Kalman filter method and Landau recursive estimation are recursive parameter estimation methods from different starting points (see recursive estimation algorithm). The consistency of most recursive parameter estimation algorithms can be proved by martingale convergence, stability of ordinary differential equation, positive and real respectively.

The parameter estimation variable \( x[n] \) is defined,

\[
x[n] = -\sum_{i=1}^{M} \sum_{l=-L}^{L} a_{i,l} e x[n-i] = -\sum_{i=1}^{M} \sum_{l=-L}^{L} a_{i,l} (x)[n]
\]  

(3)

It also defines parameter estimation variable as

\[
X[n] = -\sum_{i=1}^{M} \sum_{l=-L}^{L} a_{i,l} e = -\sum_{i=1}^{M} \sum_{l=-L}^{L} a_{i,l} (x)[n]
\]  

(4)

Where it is stationary distribution process, it define the effective of parameter estimation process as

\[
\gamma[n] = \sum_{i=0}^{m} x_i e^{n/}
\]  

(5)

It can get the coefficient \( \gamma[n] \) of the parameter estimation. It uses minimum mean square error estimation algorithm for the solution.

The parameter estimation variable \( X[n] \) is:

\[
T_\alpha(e^f) = \frac{m}{1 - \sum_{i=1}^{M} a_i e^{-f}}
\]  

(6)
3. Experiment Results
It will formulate algorithm for comparing the performance of the model method. The model parameters estimation are analysed, the specific simulations are as follows.

![Figure 1. The parameter estimation in time domain](image)

4. Conclusions
The performance of the time-frequency model parameter estimation algorithm and spectrum estimation algorithm degenerate under stable distribution environment. Experiment shows that the proposed parameter estimation algorithm is effective; the proposed algorithm has wider applicability. In future, we will apply the parameter estimation algorithm in industry design cases.

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References
[1] Duy C. Huynh ; Bach H. Dinh ; Matthew W. Dunnigan ; Thu A. T. Nguyen ; Nam H. Le. Parameter estimation of a single-phase induction machine using a dynamic particle swarm optimization algorithm[C]. 2011 IEEE Power Engineering and Automation Conference. 8-9 Sept. 2011.Wuhan, China.
[2] Nasar Aldian Ambark Shashoa ; Mohamed A. Hassan ; Abdulmunem Mohammed Almukhtar.Parameter estimation and residual generation for (CARARMA) algorithm model depend on D-RGELS[C]. 2018 Electric Electronics, Computer Science, Biomedical Engineering's Meeting (EBBT).18-19 April 2018.Istanbul, Turkey.
[3] Shengyu Pei ; Yongquan Zhou ; Qifang Luo.A Hybrid Particle Swarm Algorithm for Nonlinear Parameter Estimation[C].2009 Second International Conference on Intelligent Computation Technology and Automation.10-11 Oct. 2009, Changsha, Hunan, China.
[4] Zhong Lu ; You-chao Sun.Point Estimation Optimization Model of Life Distribution Parameters Based on Genetic Algorithm[C]. 2009 Second International Conference on Information and Computing Science.21-22 May 2009. Manchester, UK.
[5] Xiaolong Li ,Guolong Cui, Wei Yi , Lingjiang Kong.A Fast Maneuvering Target Motion Parameters Estimation Algorithm Based on ACCF[J].IEEE Signal Processing Letters ,Volume: 22 , Issue: 3 , March 2015 ,Page(s): 270 - 274.
[6] Wang Feng, Wang Shaotong.Impact of missing data on parameter estimation algorithm of normal distribution[C]. 2013 2nd International Symposium on Instrumentation and Measurement, Sensor Network and Automation (IMSNA).23-24 Dec. 2013,Toronto, ON, Canada.
[7] Syed Shahnawazuddin; Rohit Sinha; Gayadhar Pradhan. Pitch-Normalized Acoustic Features for Robust Children's Speech Recognition[J]. IEEE Signal Processing Letters, Volume: 24, Issue: 8, Aug. 2017, Page(s): 1128 - 1132.

[8] LONG Junbo, WANG Haibin, ZHA Daifeng. Fractional Low-order Adaptive Time-frequency Distribution Based on Stable Distribution Noise[J], Computer Engineering, 2011,37 (18): 81-83