

A Fast Algorithm of Dynamic Weighing Based on Weighted Least Square Method



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Abstract. In dynamic weighing, the measurement accuracy is poor because of the jitter of dynamic data and noise interference. In this paper, through two aspects of filtering and data fitting, a fast algorithm of dynamic weighing based on weighted least square method is proposed, and the experimental verification of filtering and linear fitting algorithm of dynamic weighing data of living body is carried out, and compared with three traditional algorithms. The experimental results show that the proposed algorithm is better than the above algorithm in error.

Keywords: data denoising, dynamic weighing, filtering, fitting

1 Purpose and Significance of the Study

In a scientific research project of intelligent feeding system of a science and technology company, it is necessary to carry out high-precision dynamic weighing of living animals. Due to the motion of the measured object in the process of dynamic weighing, there are large interference signals and data jitter, so that the measurement result error is large, and it is difficult to achieve the ideal accuracy requirements. There have been relevant researches on vehicle dynamic weighing, such as Shu-Wei Qin, Jian-Jun Wang and so on, who put forward the solution of using optimization algorithm [1-2], but the algorithm is complex, the calculation is large, and the weighing accuracy needs to be further improved. For the dynamic weighing of living body, the interference of data jitter and noise is greater, and the measurement accuracy is worse. For example, the dynamic weighing error of smart sort intelligent feeding management system in the United States is 1%. In view of the above shortcomings, we plan to find out the rules of data characteristics by studying and analyzing the original data collected by the weight sensor in the dynamic weighing of living body. We use data filtering, fitting and interpolation methods to establish the algorithm model, and find a high-precision dynamic weighing fast algorithm, which can be realized on PLC with small amount of calculation, and the weighing error is within the acceptable range.

2 The Process of the Fast Algorithm of Dynamic Weighing

In this paper, a large number of weight data of the experimental object in the weighing platform are studied. It is found that the dynamic weighing data generally have large noise interference, and the weight data fluctuate up and down near the real weight, so it is necessary to eliminate the noise when calculating the weight. Clipping filtering, moving average filtering and median filtering are the traditional methods to remove noise, but the single application smoothing effect is poor. Kalman filtering [3], Wiener filtering [4], filter Newton interpolation method [5] and other algorithms have high complexity and large amount of operation. Inspired by Guo's improved clipping filtering method [6], this paper studies and improves the filtering, adopts the algorithm combining clipping filtering and median filtering

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for filtering processing, and then uses the weighted least square method for data fitting to obtain high-precision weighing data, and the flow is shown in Fig. 1. Based on python, this paper studies the algorithm and compares the experimental data with other dynamic weighing methods.

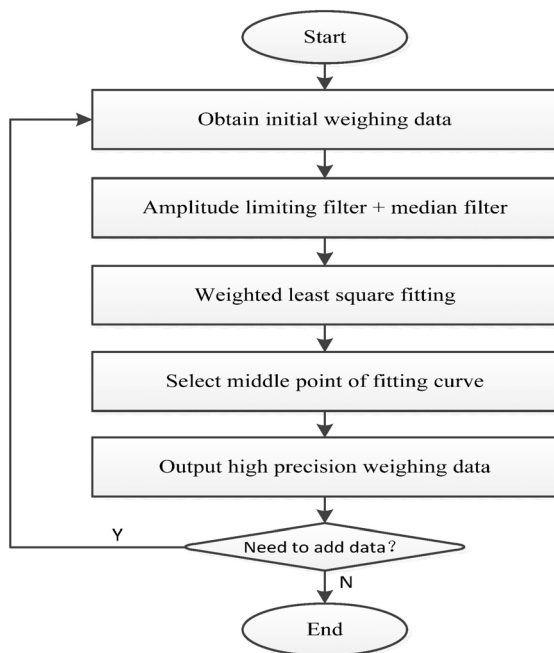


Fig. 1. Process chart of the fast algorithm of dynamic weighing

3 Filtering Processing

The purpose of filtering is to filter out the maximum and minimum values that affect the accuracy. Considering the complexity of the algorithm, the operation ability of PLC and the acceptable response time, this paper excludes the Kalman filtering, Wiener filtering and other complex algorithms, and considers the simple and efficient algorithm of limiting filter to remove the maximum and minimum.

3.1 Clipping Filtering

Although we choose the dynamic experimental object with a mass of 30-500kg, but for clipping filtering, this range is still not small enough. We need to dynamically extract the fluctuation range of each weighing and calculate its threshold value in real time. Moreover, this algorithm cannot suppress the periodic pulse interference, has poor smoothness and fails to meet the accuracy requirements. The experimental data is shown in Fig. 2.

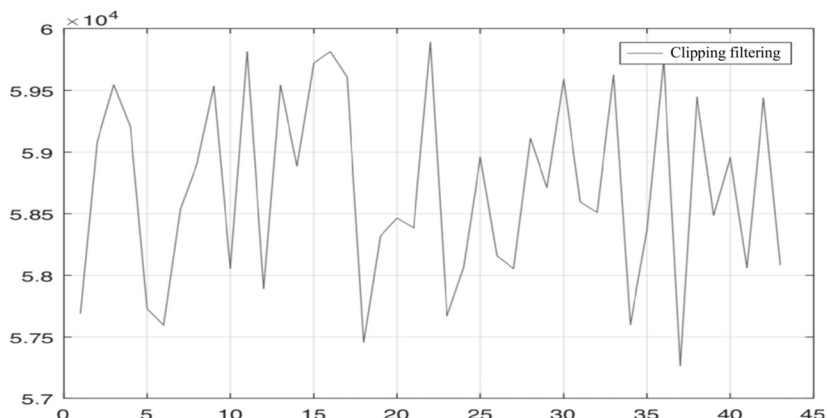


Fig. 2. Weight data function after clipping filtering

Therefore, we consider further filtering improvement, choose the median filtering or moving average filtering as the secondary filter algorithm to eliminate the function bulge and make the whole waveform smoother.

3.2 Moving Average Filtering

In this algorithm, the n-bit value is fixed and the average is calculated by moving backward in turn. This paper implements the slicing of data list in Python. Set the slice length of the data list to N, then calculate the arithmetic average of the slice part, and use the sliding average data to replace the original data as the data of the fitting curve; every time you do a step backward, an iteration is carried out until the end of the data list. The specific principle is shown in Formula 1:

$$F(x) = \frac{1}{N} \sum_{i=0}^{N-1} F(x-i) \tag{1}$$

In this formula, F (x) is the function value when the number of samples is x, N is the sliding digit, that is, the length of the selected chain list, and F (x-i) is the function value when the number of samples is x.

3.3 Median Filtering

This is a non-linear smooth filtering signal processing algorithm based on sorting theory, which can eliminate the noise interference of signal to a large extent. Its characteristic is to determine a square field first, which is centered on signal. For one-dimensional data, determining a fixed length of distance is called domain, and then sorting the values of each signal in the domain, that is, taking the middle value as the new value, which is also called window. When it moves, the signal can be smoothed by median filtering.

When filtering x_i ($-\infty < J < \infty$), because it is a digital signal, it is necessary to define an L-long window first, and it is an odd number, which is recorded as: $L = 2N + 1$, N is a positive integer. If the signal sample at a certain time point is $x_{i-N}, \dots, x_i, \dots, x_{i+N}, x_i$ is the sample value of each signal. If these sample values are sorted from small to large, the sample value at point I is the output value of the median filter, as shown in Formula 2:

$$g(i) - median[f(j-r), f(j-r+1), \dots, f(j), f(j+r)] \tag{2}$$

In this paper, if N is 5, then L= 11, use the above two algorithms to test the collected data and verify the accuracy. Randomly use one group of fifty data collected for testing, and its value is shown in Table 1.

Table 1. Experimental weighing data sheet

Nu.	Weight (g)	Nu.	Weight (g)	Nu.	Weight (g)	Nu.	Weight (g)	Nu.	Weight (g)
1	57690	11	59535	21	59607	31	58158	41	58367
2	59083	12	58056	22	57455	32	58054	42	59748
3	59546	13	59812	23	58318	33	59112	43	57266
4	59201	14	57891	24	58465	34	57005	44	59447
5	57729	15	59543	25	58385	35	58713	45	57020
6	57594	16	56884	26	59888	36	59591	46	58487
7	58538	17	58887	27	57671	37	58596	47	58959
8	60114	18	56832	28	58067	38	58510	48	58061
9	56647	19	59720	29	60139	39	59627	49	59438
10	58906	20	59813	30	58960	40	57600	50	58083

The waveform change after filtering is shown in Fig. 3, where the blue line represents the original data, the red line represents the data after median filtering, and the orange line represents the data after sliding average filtering.

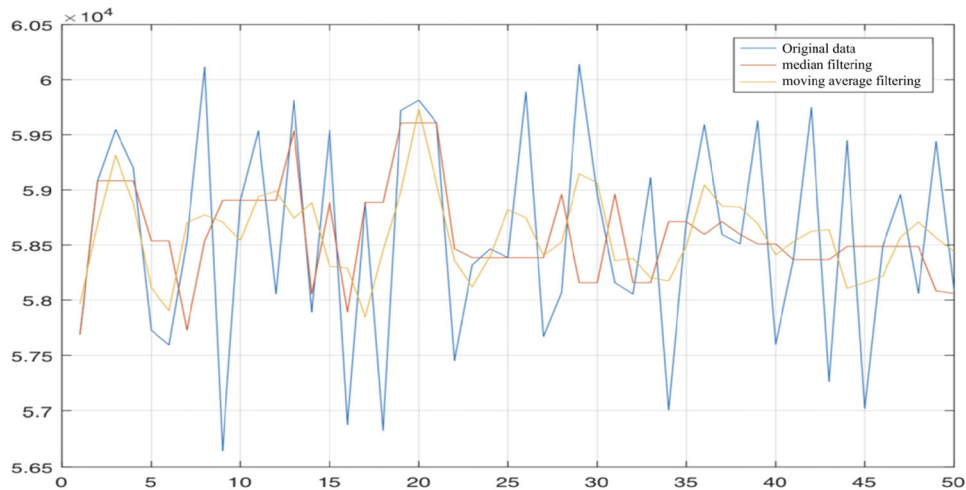


Fig. 3. Weight data change after moving average filtering and median filtering

3.4 Clipping Filtering Combined with Median Filtering

It can be seen from the above study that both the moving average filtering and the median filtering can basically eliminate the singular points of the data. But the two filtering algorithms are different. Moving average filtering will change the original data, while median filtering will not. In the case of high accuracy requirements, we obviously do not want to lose the original data. At the same time, through comparison, we can find that the median filtering can not only effectively filter out the noise, but also protect the signal edge from being blurred. In addition, the algorithm of median filter is simple and easy to implement in hardware. After comprehensive analysis, we choose the combination of clipping filtering and median filtering as the final filtering method. The pre-processing of the data is completed by clipping filtering and median filtering, which makes the data more stable, and the data table after filtering in Table 2 is obtained.

Table 2. Filtered data of clipping filtering combined with median filtering

Nu.	Weight (g)	Nu.	Weight (g)	Nu.	Weight (g)	Nu.	Weight (g)	Nu.	Weight (g)
1	57690	10	58906	19	58385	28	58713	37	58487
2	59083	11	59535	20	58385	29	58713	38	58959
3	59083	12	58887	21	58385	30	58713	39	58487
4	59083	13	59543	22	58385	31	58713	40	58959
5	58538	14	59543	23	58385	32	58596	41	58487
6	58538	15	59607	24	58158	33	58510	42	58083
7	58538	16	59607	25	58067	34	58510	43	58061
8	58538	17	59607	26	58158	35	58367		
9	58906	18	58465	27	58713	36	58367		

4 Weighted Least Square Data Fitting

In this paper, linear fitting method is used to fit the filtered data. When using the ordinary least square method for fitting, there may be abnormal points, so that the function we fit and the reality still have some errors. Therefore, we consider using a robust regression method for data fitting. The main idea of robust regression is to modify the objective function of classical least square regression, which is very sensitive to outliers. Robust regression can fit the structure of most of the data, and identify potential outliers and strong influence points. When the error obeys the normal distribution, its estimation is almost as good as the least square estimation, and when the least square estimation condition is not satisfied, its result is better than the least square estimation. As shown in Fig. 4, there is an abnormal point in the data. If the point is not removed, if the ordinary least square method is used for regression,

the red line in the figure will be obtained; if the abnormal point is removed, the green line in the figure will be obtained. Obviously, the green line is more explanatory of the data than the red line.

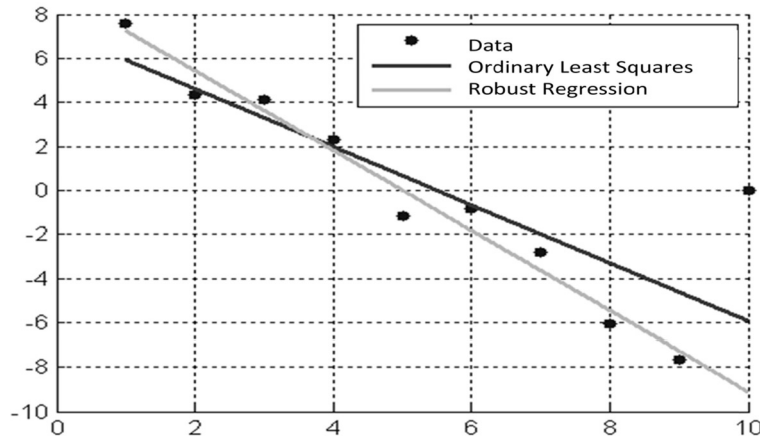


Fig. 4. Comparison of least square method and robust regression

The weighted least square method introduces the concept of weight number on the basis of the ordinary least square method. The weighted least square uses the exponential weight W^{n-i} , $0 < w < 1$, and the parameters estimated value after weighting should meet the following requirements:

$$S = \sum_{i=1}^n W^{n-i} (y_i - \hat{y}_i)^2 = \min, (i = 1, 2, \dots, n) \tag{3}$$

The weighted residual square sum of the linear model is:

$$S = \sum_{i=0}^n W^{n-i} (y_i - a - bt)^2 \tag{4}$$

The partial derivatives of a and b are calculated for the above formula, and the standard equations are obtained

$$\begin{cases} \sum W^{n-i} y_i = a \sum W^{n-i} + b \sum W^{n-i} t \\ \sum W^{n-i} ty = a \sum W^{n-i} t + b \sum W^{n-i} t^2 \end{cases} \tag{5}$$

By solving a and b, the weighted least square method is obtained to fit the linear equation

$$y = a + bt \tag{6}$$

We use the data in Table 3, set weight $W = 0.9$, and bring in formula (4) and (5) to get:

$$a = 58986.82, b = -3.94 \tag{7}$$

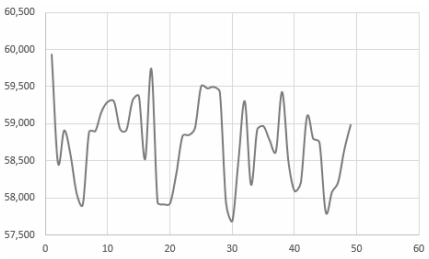
Table 3. Data comparison of four algorithms in the same experiment

Number	Weight function diagram	Clipping average method error	least square filtering method error	Newton interpolation filtering method error	This paper algorithm error
1		0.563%	0.153%	0.157%	0.099%

Table 3. (continue)

Number	Weight function diagram	Clipping average method error	least square filtering method error	Newton interpolation filtering method error	This paper algorithm error
2		0.264%	0.136%	0.223%	0.136%
3		0.117%	0.267%	0.784%	0.261%
4		0.360%	0.119%	1.122%	0.115%
5		0.254%	0.242%	0.037%	0.104%
6		0.346%	0.109%	1.148%	0.154%
7		0.478%	0.110%	3.301%	0.172%

Table 3. (continue)

Number	Weight function diagram	Clipping average method error	least square filtering method error	Newton interpolation filtering method error	This paper algorithm error
8		0.305%	0.063%	1.958%	0.148%

The new fitting line equation is obtained as follows:

$$y = -13.94t + 58986.82 \tag{8}$$

According to the fitting line equation, the weighted least square fitting curve of Fig. 5 can be obtained:

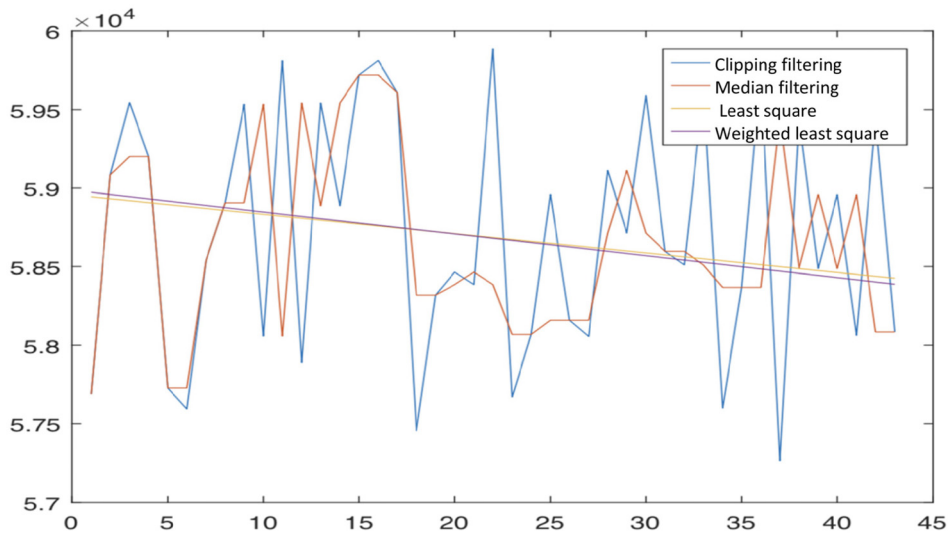


Fig. 5. Weighted least square weight algorithm fitting weight curve

Taking the middle point of the fitting line as our final calculation data, i.e. $y = 58694.08$ when $t = 21$, and the error rate is 0.016%, we can see that it is closer to the standard weight than the ordinary least square method.

Therefore, this paper uses the weighted least square method as the data regression algorithm, which can further improve the accuracy of the dynamic weighing data.

5 Comparison and Analysis of Experiment Results

In this paper, the data of the original weight sensor are obtained in the living weighing platform, and the data are preprocessed by median filtering, clipping filtering and the combined filtering method proposed in this paper, then the final experimental data are obtained by the weighted least square method.

According to the experimental results, the error of the fast algorithm of dynamic weighing proposed in this paper is kept within 150g for the experiment of 58kg, which meets the accuracy requirements. In order to further prove the stability and accuracy of the algorithm, we collected a large number of data, and compared the error rate of the limiting average method, filter least square method, filter Newton interpolation method and the dynamic weighing fast algorithm proposed in this paper. The specific

comparison data is shown in Table 3.

As can be seen from Table 3, compared with other algorithms, the error rate of the algorithm in this paper is smaller, and the overall average error rate is kept below 0.2%, which is also better than the 1% error of dynamic weighing of smart sort intelligent feeding management system in the United States.

In this paper, through the analysis of the original data of live dynamic weighing, it is found that although the original measurement data is greatly affected by noise and dynamic disturbance, they all fluctuate around the real weight data, and individual data deviate greatly. The influence of this factor can be eliminated effectively by using clipping filtering. Then, the median filtering is used for secondary filtering, which can approach the real weight data more effectively. And these two algorithms have small computation, which are suitable for fast implementation on PLC. Then, by using the weighted least square method as the data regression algorithm, we can effectively reduce the impact of possible outliers and strong influence points on the real results. Finally, by taking the calculation data of the middle point of the fitting line as the final measurement result, the measurement error can be further reduced and the higher measurement accuracy can be obtained.

The experimental results verify the correctness of the research and analysis in this paper, and also verify the effectiveness of the algorithm in this paper. The algorithm in this paper has also been successfully run in a company's intelligent feeding system's live weighing system PLC, the speed of response and measurement accuracy meet the requirements of the project.

In practical application, the complexity is still large, the accuracy needs to be further improved, and there is still room for optimization. Therefore, the next work will try to combine the pattern decision-making research to further reduce the complexity of the algorithm and improve the measurement accuracy.

References

- [1] S.-W. Qin, B.-H. Ma, J. Chen, Research on the application of dynamic weighing system in the off-site law enforcement of overload and overrun, *Weighing Instrument*, 2019-11.
- [2] J.-J. Wang, X.-Y. Liu, Discussion on WIM, *Weighing Instrument*, 2019-11.
- [3] N.H. Beni; R. Foodeh; V. Shalchyan, M.R. Daliri, Force decoding using local field potentials in primary motor cortex: PLS or Kalman filter regression? *Physical and Engineering Sciences in Medicine: The Official Journal of the Australasian College of Physical Scientists and Engineers in Medicine* 43(10)(2020) 175-186.
- [4] H.-X. Zhang, Research and analysis of image denoising technology based on Wiener filter in wavelet domain, *Information & Communications*, 2019-11.
- [5] J.-C. Zhang, P.-X. Zhou, P. Liu, A filter evaluation method of SAR image based on Newton interpolation iteration, *Geography and Geo-information Science*, 2019-06.
- [6] J.-Z. Guo, F. Cheng, B. Xie, J.-L. Wu, G. Tian, The application of the improved limited amplitude recursive average filtering method in the fuel gauge, *Science Technology and Engineering*, 2018-16.