Journal of Engineering Science and Technology Review 9 (5) (2016) 44 - 50

Research Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Translation Registration Algorithm for Multi-source Time Series Data Based on the Sliding Window

Lu Huimin[1,*], Di Tianyi[1], Song Jingjing[1], Sun Hongyang[2], Han Xuming[1] and Liu Gang[1]

[1]*School of Computer Science and Engineering, Changchun University of Technology, Changchun 130012, China*
[2]*School of Computer Engineering, Nanyang Technological University, Singapore 639798, Singapore*

Received 28 April 2016; Accepted 21 October 2016

Abstract

Most of the existing integration and mining methods of multi-source time series assume that the data has been calibrated, which avoids the problem of time series registration. However, the inconsistent sampling frequency, different time references, and transmission delay make time and frequency mismatch in multi-source time series data, resulting in an unsatisfactory integration and mining and an even poorer effect than that of the single-source data. Time series registration has becoming an important research point in the pre-processing stage of time series integration and mining. To improve the overall integration performance and data mining accuracy, a new translation registration algorithm for multi-source time series data based on the sliding window was proposed. Firstly, the demands for time series big data mining was clarified, and the disadvantages of existing time series registration approaches was analyzed, then a structural model for the translation registration based on the sliding window was presented. Secondly, by using the slide window and the nearest neighbourhood principle, the real-time intervals offset was calculated, the low-frequency sampling of time data was translated to high-frequency, and then the proposed translation registration algorithm based on the sliding window was designed and implemented. Finally, the experimental analysis and verification of the typical algorithms for time series was completed. The experimental results demonstrated that the nearest neighbourhood method can provide a targeted time registration strategy, and the sliding window approach which does not dwell on the starting moment of time series can satisfy the registration requirements of dynamic time series big data. The experiments show that the proposed algorithm's goodness-of-fit is 96.7%, and it is slightly influenced by missing data and is easy to operate. It cannot only improve the accuracy and timeliness of multi-source time series registration, but also has important theoretical and practical values to the dynamic time series data integration and mining.

Keywords: Time series, Time registration, Sliding window, Data mining

1. Introduction

With the continuous development of the sensor, network, and information technologies, big data analysis and mining have becoming a popular research topic. The integration and mining [1], [2] of time series data [3], [4] also has becoming one of the important research points of big data analysis [5]. Time series data are stored according to the sequence of time nodes and the data variation trends. It can predict future development trends through time series analysis and data mining [6], [7]. For the time series data or the data of the same variables are usually come from heterogeneous data sources, an inconsistency between the data sampling frequency and the time references, and a delay in data transmission will cause time and frequency mismatch in multi-source time series data [8], [9]. Currently, most multi-source time series integration and mining methods are based on calibrated time series, which avoids the time series registration problem. However, the absence of time registration causes an unsatisfactory mining results and an even poorer effect than that of single-source data, which do not favor the performance and robustness of comprehensive judgment and decision-making, thereby further influencing the final performance of time series integration and mining. Therefore, data registration and multi-source time series integration are required [10], [11]. Measured asynchronous data with different sensors to the same target should be synchronized through a specific method to achieve consistency on time and frequency [12], which aims to ensure the time and space consistency of multi-source time series and satisfies the requirements of data consistency and matching. Improving the accuracy and timeliness of time series registration has becoming an urgent concern in multi-source time series data analysis and mining that needs to be addressed immediately.

In this study, a translation registration algorithm for multi-source time series data based on the sliding window was proposed. This algorithm makes space and time registration before the multi-source time series data integration and mining, and achieves the time and frequency synchronization of multi-source time series data. It calculates the offset interval based on the sliding window and the nearest neighborhood principle and realizes the time registration of multi-source time series through translation, thus ensuring the quality of multi-source time series data in the integration and improving the overall integration performance and the data mining accuracy.

* E-mail address: luhm.cc@gmail.com
ISSN: 1791-2377

2. State of the Art

With the continuous development of the information integration and data mining technologies, time series, an important data type, has become one of the primary research contents in data mining. The time and space mismatching of time series intensifies analysis errors and influences the quality of data integration and mining significantly. Therefore, the time series registration problem has attracted significant attention from researchers. In addition to azimuth and positional deviations to the same object, time series spatial mismatch caused by the different coordinate systems or transform error was observed. To solve these problems, a real-time quality control method based on the data mean was proposed by Burke [13], and Leung processed measurement data using the least square method [14]. Moreover, a weighted processing based on the least square method and a generalized least squares method was implemented by Dana [15]. These three methods transform measured values into a local coordinate plane of several measured values through stereoscopic projection, and then transform them into zone flatness, causing a significant noise effect on registration. Zhou and Henry applied the maximum likelihood method of two-step regression in the spatial registration to improve the registration accuracy [16]. However, this is still a projection-based registration method, which uses an inaccurate registration model and faces possible misdescription of data. To solve the shortcomings of stereoscopic projection, Zhou and Heung et al. transformed measured values into an earth-centered earth fixed coordinate system and estimated the errors of different measured values using the least square method [17]. Helmick and Rice solved the compensation for online error estimation using the Kalman filtering algorithm, which can estimate attitude error and calibrate error simultaneously [18]. However, the Kalman filtering algorithm is only applicable to single-platform. At that time, Karniely [19] applied the neural network in space registration. Although a neural network can estimate the system deviations without knowledge on the source of systematic bias, the training time is long, making the timeliness requirements difficult to satisfy.

Several scholars explored the time mismatch caused by time reference, sampling frequency, and transmission delay further. For the time mismatch caused by time reference, time is often adjusted using a standard time clock or uniform GPS time. Sampling moment label is added in the data to solve the time mismatch caused by transmission delay. Most research focus on the time mismatch caused by the inconsistency of the sampling time or frequency. The core of such time mismatch is the registration algorithms, including interpolation-extrapolation algorithm, the least squares rule registration, Lagrange interpolation method, curve fitting method, and Kalman filtering algorithm. Wang implemented the interpolation-extrapolation algorithm to multi-source data in the same time slice using interpolation and extrapolation and projected the data on a high-accuracy observation time point to a low-accuracy time point, thus realizing the synchronization of time series [20]. Blair realized time registration by the least squares method and virtualized synchronous sampling data. He was the first to propose the least squares method [21]. Furthermore, a Lagrange interpolation method was presented by Li et al. It estimated the function expression using the Lagrange interpolation polynomial, and acquired data at time registration points in accordance with the function expression [22]. Liang et al. constructed an overall law curve of sampling data points using the curve fitting method, which ensured a minimum fitting error. They sampled according to the sampling interval and achieved the target time registration [23]. In addition, Arasaratnam, Haykin, and Wang collected filtered outputs of observation data and predicted data using the Kalman filter, which was used for cubic spline interpolation, thus obtaining observation data on the current registration and realizing real-time registration [24], [25]. The performances of these time series registration algorithms are listed in Table 1.

Table 1. Performances of main registration algorithms for time series

Name	Advantages	Disadvantages
Interpolation - extrapolation algorithm	Few application restrictions Simple calculation	Synchronous data frequency is the lowest sampling frequency in multi-source sequence. Only applicable to uniform or slow-changing motion models.
Least squares method	Simple operation Extensive use	Synchronous data frequency is the lowest sampling frequency in multi-source sequence. Start sampling times of all the time series are the same. Sampling frequency ratio of different time series is an integer.
Lagrange interpolation method	Strong logistics High registration accuracy	Interpolation is only made within the sampling period. Low timeliness.
Curve-fitting method	Strong mathematical theoretical basis High registration accuracy	Difficult selection of fitting orders. Violent fluctuation at the left and right ends of the fitting interval, and big fitting error.
Kalman filtering algorithm	High registration accuracy High timeliness	Increasing error upon abundant data missing. Poor timeliness upon large object movement.

The table above shows that the existing common interpolation–extrapolation algorithm, least squares rule registration, Lagrange interpolation method, curve-fitting method, and Kalman filtering algorithm [26] have several disadvantages, such as the synchronous data frequency equal to the lowest sampling frequency in a multi-source sequence and the poor registration timeliness. Therefore, this study employed sliding window and nearest neighborhood principle for the time series registration based on the relative registration strategy and matched data to a high-accuracy time point, aiming to establish an accurate, simple, and widely used time series registration algorithm. It can guarantee high-quality data in time series integration and mining.

The rest of this paper is organized as follows. Chapter III presents the basic flowchart for the time registration of multi-source time series, the constructed translation registration structural model and the designed and realized translation algorithm based on the sliding window. Chapter IV discusses the experimental verification of the proposed structural model and algorithms using the measurement data. Chapter V contains the conclusion.

3. Methodology

3.1 Flowchart of Time Registration

Multi-source time series registration refers to the time calibration of multiple data groups of the same object in one period to realize data synchronization on the time axis. The general flowchart of the multi-source time series registration is shown in Figure 1.

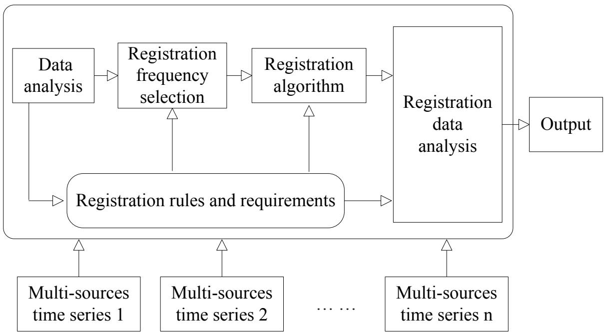

Fig. 1. Flowchart of multi-source time series registration

The flowchart mainly includes data analysis, registration frequency selection, registration algorithm, registration rules and requirements, and registration data analysis.

Data analysis: Exception handling of multi-source data and acquisitions the number of time series, type of data collection devices, sampling frequency, and interval between time series.

Registration frequency selection: According to the registration demands or default rules, the appropriate registration frequency is selected and the registration frequency of the time series is restricted while satisfying the registration requirement.

Registration algorithm: An appropriate algorithm is selected for the registration of the multi-source time series, obtaining the time series with data synchronization.

Registration data analysis: The error and timeliness of the registered time series are analyzed and the results are fed back to the registration requirements.

3.2 Translation Registration Model Based on the Sliding Window

Multi-source time series registration is the selection of appropriate registration frequency and algorithm to calibrate multi-source time series according to the registration demands or default rules based on the number of time series, type of collection devices, sampling frequency, and time interval between the time series, thus obtaining time series with data synchronization. Subsequently, it analyzes the registration error and timeliness of the registered time series and feedbacks the results to the registration requirements.

The translation registration algorithm based on sliding window divides the multi-source time series into several partition sub-sequences using the sliding window division mechanism and calculates the time difference between two time series through contrastive analysis of the collected data of related sub-sequences. According to the time difference between the two time series, the collected data are translated using the high-frequency time series as the reference, thus realizing the time registration of different time series.

The translation registration model based on sliding window is presented in Figure 2.

Data preprocessing: Processing of abnormal values and missing input of multi-source time series to reduce the measurement error of data collection, and improve the time registration accuracy.

Data analysis: Acquisition of information on the number of time series, sampling frequency of each time series, and time intervals between the time series, and formation of a binary data structure is as follows (Eq. 1),

$$S = (v, t) \tag{1}$$

where, v is the sampling data value and t is the sampling time.

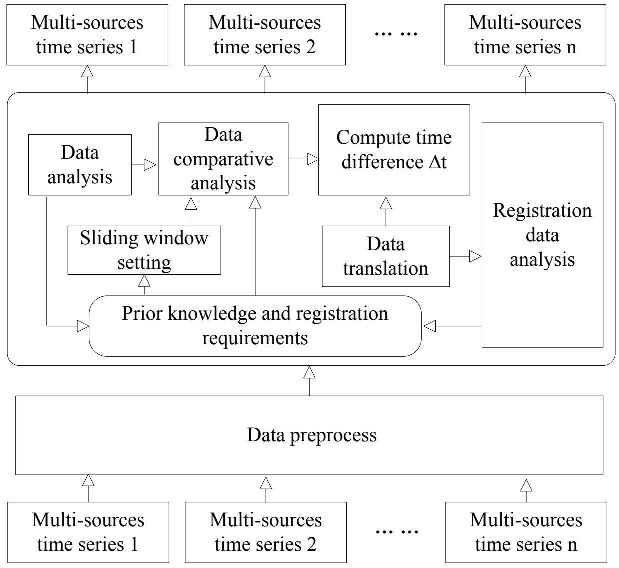

Fig. 2. Translation registration model based on sliding window

Sliding window setting: Determinate the sliding window size of a partition sub-sequence according to the Priori knowledge and registration requirements and provision of data space for data analysis.

Data comparative analysis: It is the core of the algorithm. Using the highest frequency time as the time series reference, the time difference between the multi-source-time series is analyzed and calculated, thus obtaining the amount of time for time series translation.

Data translation of time series: Time series data are translated by the calculated time difference (Δt) to achieve the time registration of series.

Registration data analysis: The collected registration time series are integrated and the error is analyzed. According to the analysis results, the registration requirements are adjusted and the registration parameters are corrected to improve the registration accuracy continuously.

3.3 Translation Registration Algorithm Based on the Sliding Window

3.3.1 Selection of Registration Frequency

In view of the time series characteristics, registration frequency is a frequency interval (Eq. 2),

$$\begin{aligned} &\max\{f_t^{\min}(T_{\max}), f_s^{\min}\} = f_t^{\min}(T_{\max}, f_s) \\ &\le f_t \le f_t^{\max}(T_{\max}, f_{\max}, f_s) \\ &= \min\{f_t^{\min}(T_{\max}, f_{\max}), f_s^{\max}\} \end{aligned} \tag{2}$$

where, f_t is the registration frequency, $f_t^{\max}$ is the maximum synchronous frequency, $f_t^{\min}$ is the minimum synchronous frequency, and $f_{\max}$ is the highest sampling frequency. Registration frequency shall be selected according to the requirements of the integration system and data mining. It is generally chosen using the following two methods.

(1) Mean of the sampling frequencies of all time series (Eq. 3)

$$f_t = \frac{1}{N}\sum_{i=1}^{N} f_i \tag{3}$$

(2) Weighted mean of the sampling frequencies of all time series (Eq. 4)

$$f_t = \frac{1}{N}\sum_{i=1}^{N} a_i f_i \ , \quad a_i = \frac{p_i}{\sum_{i=1}^{N} p_i} \tag{4}$$

where, the weighted value $a_i(i=1,2,\ldots,N)$ is determined by the sampling precision of each time series $p_i(i=1,2,\ldots,N)$.

The translation registration algorithm based on the sliding window solves the relative registration between the time series, but not the time registration in the strict sense. The data analysis on time series, especially the correlation analysis, focuses on the mutual relationship between the numerical values of corresponding time regardless of whether match the standard clock. Therefore, the proposed algorithm matches low-frequency time series onto high-frequency ones. However, it uses $f_{\max}$ as the registration frequency, making full use of the high-frequency time series data.

3.3.2 Translation Registration Algorithm Based on the Sliding Window

The core of the translation registration algorithm based on the sliding window acquires the time difference between the time series (Δt) through contrastive analysis and then matches the time reference of low-frequency time series onto the highest frequency time series according to Δt , thus realizing time registration.

This algorithm includes the following processes:

(1) Sliding window size
The key of this algorithm is to calculate Δt . Therefore, any time slice can be selected as the data source for the data analysis. To simplify the calculation, sliding window size (ΔT) was determined as follows (Eq. 5),

$$\Delta T = k\frac{1}{f_{low}} \tag{5}$$

where, f_{low} is the lower sampling frequency between the time series and k is the multiples.
(2) Data normalization
Data normalization of a time slice is performed to unify data from different sources into the same reference system for convenient follow-up data contrastive analysis. In this study, data normalization was implemented to the mean, and standard deviation of the collected data using the Z-score standardization method. The processed data conformed to the normal distribution.

The normalization formula is as follows (Eq. 6),

$$X^* = \frac{X-\mu}{\sigma} \tag{6}$$

where, μ is the mean of the sampling data (Eq. 7),

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{7}$$

σ is the standard deviation of all collected data (Eq. 8),

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2} \tag{8}$$

(3) Data contrastive analysis
Nearest neighborhood principle: For two multi-source time series (A and B) of the same object, if the measured value of A at T is V_t , the measured value of B at T (V_t) has a time interval centered at T $[T-\alpha, T+\alpha]$.

If A and B collect data for the same object, the collected time series in the same time slice is as showed in Figure 3.

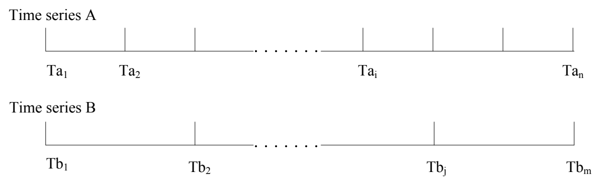

Fig. 3. Time series A and B in the time slice

The collected data of A in the time slice is as follows (Eq. 9, 10),

$$D_a = \{(Va_i, Ta_i) \mid i = 1,2,...,n\} \tag{9}$$

$$n = \Delta T * f_a \tag{10}$$

where, f_a is the sampling frequency of A.

The collected data of B in the time slice is as follows (Eq. 11, 12),

$$D_b = \{(Vb_j, Tb_j) \mid j = 1,2,...,m\} \tag{11}$$

$$m = \Delta T * f_b \tag{12}$$

where, f_b is the sampling frequency of B.

If $f_a > f_b$ and f_a / f_b is the data contrastive analysis, the sampling frequency of B at a certain time is compared with that of A (Eq. 13),

$$(Vb_j - Va_{\frac{fa}{fb}j-1}) \le \Delta \tag{13}$$

If the contrastive analysis result is within the allowable error range, the time difference between the time series is believed to be $\Delta t = 0S$.

If all the analysis results in the time slice are maintained at $\Delta t = 0S$, A and B match in time. If two groups of analysis results are out of the allowable error range, a sliding window using $Ta_{\frac{fa}{fb}j+1}$ as the center standard moment is established, and the sliding window size is $k\frac{1}{f_{high}}$. The Vb_j of B is compared with Va_i of A in the sliding window. If the calculation of time difference is $Vb_j = Va_i$, then $\Delta t_j = Ta_i - Tb_j$.

(4) Translation of time series

If Δt_j in the time slice Δt satisfies the following conditions, Δt_j is the offset interval of two time series (Eq. 14).

$$\sigma_{\Delta tj} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(\Delta t_j - \mu)^2} < \Delta \quad (14)$$

The reference time of B is translated according to Δt_j and then matched with the time of A.

(5) Registration data analysis

Considering the accuracy of the translation registration algorithm for multi-source time series based on sliding window, the translated time series are analyzed using goodness-of-fit on the nonlinear regression equation. The algorithm formula for goodness-of-fit is as follows (Eq. 15),

$$1 - \sqrt{Q/\sum y^2} \quad (15)$$

where $Q = \sum(y - y^*)^2$ (y is the measured value and y^* is the calculated value of the algorithm).

A higher goodness-of-fit reflects a high degree of matching between the calculated results and the actual situations, indicating a high registration precision.

The proposed translation registration algorithm based on the sliding window works as follows:

Input:
Ta and Tb : time series for registration;
k : the sliding window size;

Output: registered time series TS_a and TS_b.

Step 1) $\Delta T = k\frac{1}{f_{low}}$; $\Delta t = 0$; $sum = 0$; // ΔT is sliding window size and Δt is the relative translation time of the two time series.

Step 2) $D_a = \{(Va_i, Ta_i) \mid i = 1,2,...n\}$,
$D_b = \{(Vb_j, Tb_j) \mid j = 1,2,...m\}$ // sampling frequencies of the two time series in the time slice

Step 3) for $j = 1$ to $D_b.length$ do
 if $(Vb_j - Va_{\frac{f_a}{f_b}j-1}) \le \Delta$ then // Δ is the allowable error
  $\Delta t_j = (Tb_j - Ta_{\frac{f_a}{f_b}j-1})$;
 else
  for $p = (j - k\frac{1}{2f_{high}})$ to $D_c.length$ do // D_c is the sliding window dataset.
   if $(Vb_j - Va_{j-k\frac{1}{2f_{high}}}) \le \Delta$ then
    $\Delta t_j = (Tb_j - Ta_{j-k\frac{1}{2f_{high}}})$;
   end if
  end for
 end if
 if $j > 1$ and $\Delta t_j = \Delta t_{j-1}$ then
  $sum = sum + 1$;
 end if
 if $sum > T_h$ then // T_h is the threshold;
  $\Delta t = \Delta t_j$;
 end if
 end for

Step 4) for $j = 1$ to $T_b.length$ do
  $TS_b = \{(Vb_j, (Tb_j + \Delta t))\}$;
  $TS_a = T_a$;
 end for
return TS_a, TS_b

4 Result Analysis and Discussion

4.1 Collection of Experimental Data

In this study, an integrated haze monitoring equipment was designed for the multi-source collection of air quality data in one region. Data collection equipment on air pollutants often requires electricity. The integrated monitoring equipment optimizes the design through a reasonable layout, which realizes a low-power operation and ensures the continuity of data collection. It makes a uniform layout of multiple sensing devices for a centralized power supply and uses a solar energy power supply to address the monitoring device arrangement in remote regions. The integrated haze monitoring equipment is shown in Figure 4.

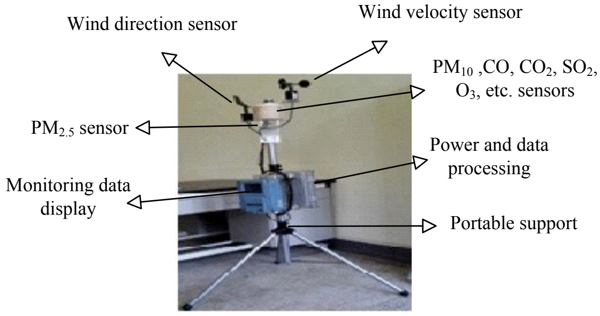

Fig. 4. Integrated haze monitoring equipment

The haze data collection system realizes accurate and timely data collection and visual display, and timely data storage and organization, which provides reliable data for multi-source time series registration, and lays the foundation for data integration and mining.

4.2 Experimental Analysis

Experimental data: Three groups of $PM_{2.5}$ sensors of air quality monitoring device in one region collect data of $PM_{2.5}$ concentrations at one place. The sampling periods of S_1, S_2, and S_3 are 15 min, 30 min, and 1 h, if the selected sliding window size (unit: hour) is as follows (Eq 16),

$$\Delta T = k\frac{1}{f_{low}} = 15\,\text{min} \tag{16}$$

When S_3 selected the sliding window starting time of 8:50-20:50, the partial data collected by S_1, S_2, and S_3 in this window are listed in Table 2.The time series before the registration is shown in Figure 5.

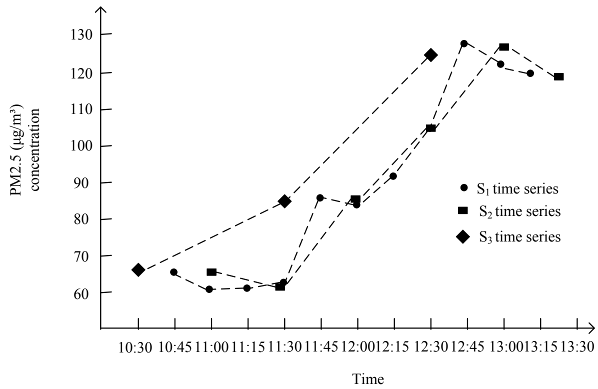

Fig. 5. Before registration of multi-source time series

After translating registration based on the sliding window, low-frequency series S_2 and S_3 were matched onto the high-frequency time series S_1 (Figure 6).

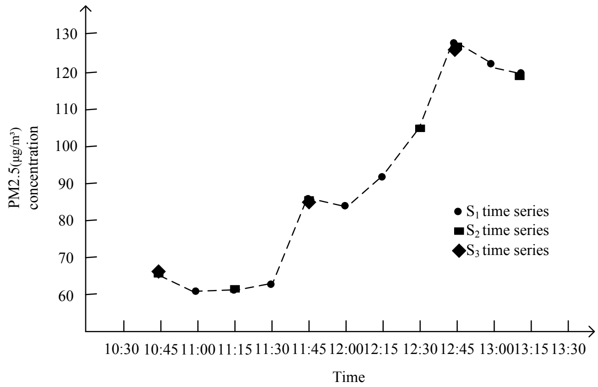

Fig. 6. After registration of multi-source time series

The proposed algorithm calculated $\Delta t = -15\,\text{min}$ between S_2 and S_1, thus the corresponding time of S_2 shall be translated 15min units leftward. It calculated $\Delta t = +15\,\text{min}$ between S_3 and S_1, thus the corresponding time of S_3 shall be translated 15min units rightward. Therefore, it realized the time registrations of S_1, S_2, and S_3.

The measured and calculated data of the algorithm is shown in Table 3.

The goodness-of-fit of the algorithm was calculated as $1\text{-}\sqrt{Q/\sum y^2} = 96.7\%$, indicating the high precision of the proposed algorithm. The goodness-of-fit of the interpolation-extrapolation algorithm and the least squares rule registration is displayed in Figure 7.

Table 2. Partial data collected by S_1, S_2, and S_3 in ΔT

S_1	**t**	…	10:45	11:00	11:15	11:30	11:45	12:00	12:15	12:30	12:45	13:00	13:15	…
	V (μg/m³)		66	61	61	63	86	83	105	128	125	122	120	…
S_2	**t**	…	11:00		11:30		12:00		12:30		13:00		13:30	…
	V (μg/m³)		65		61		85		107		126		118	…
S_3	**t**	…	10:30				11:30				12:30			…
	V (μg/m³)		68				85				126			…

Table 3. Measured data and calculated data of the algorithm

Measured	**t**	…	10:45	11:00	11:15	11:30	11:45	12:00	12:15	12:30	12:45	13:00	13:15	…
data	**V (μg/m³)**	…	68	65	62	65	88	85	108	128	120	122	125	…
Calculated	**t**	…	10:45	11:00	11:15	11:30	11:45	12:00	12:15	12:30	12:45	13:00	13:15	…
data	**V (μg/m³)**	…	67	61	61	63	85	83	106	128	126	122	119	…

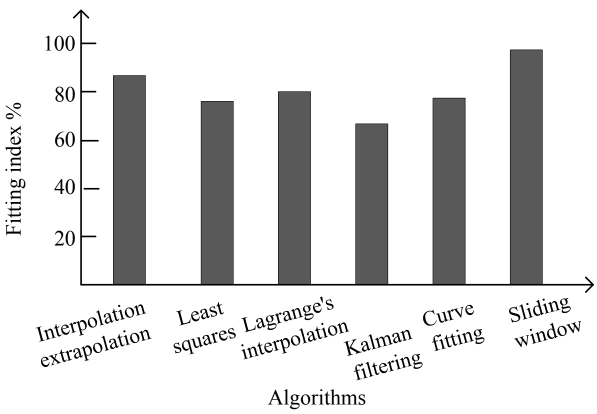

Fig. 7. Goodness of fit of different algorithms

The translation registration algorithm for the multi-source time series based on sliding window has the following advantages and characteristics in terms of data mode, timeliness, and simplicity.

Synchronous data frequency is the highest sampling frequency in the multi-source time series, making full use of the data in analysis.

It adopts a real-time data comparison based on sliding window and can perform data acquisition and analysis in a certain window with the data stream.

Missing data do not influence the algorithm significantly, thus preventing large errors.

The algorithm is applicable to multi-source time series, whose sampling frequency ratio is an integer.

5. Conclusions

Space and time registrations are the problems that need to be solved during the preprocessing stage of the time series data integration and mining. Mismatching time series cause unsatisfactory data integration and mining results and an even poorer effect than that of single-source data. To offset the effects of the time and frequency inconsistencies of multi-source time series on overall data integration and mining, many theoretical and practical studies on time registration algorithms for time series have been performed. On the basis of the analysis of existing registration algorithms, a translation registration structural model based on the sliding window was constructed according to the functional requirements and flowchart analysis of the time series registration to increase registration precision and timeliness. A translation registration algorithm based on the sliding window was designed and implemented. Finally, the following conclusions were formed:

(1) Time reference, sampling frequency, and transmission delay is the main causes of the time series data mismatch. Time registration determines the overall data integration performance and influences the data mining effect.
(2) The proposed time registration algorithm based on the sliding window does not restrict the initial time reference and is more convenient for processing dynamic data. It can satisfy the registration requirements of the dynamic time series and improve the real-time registration performance. The verification results demonstrated that the sliding window shall be chosen 3-5 times that of $1/f_{\text{low}}$. A contrastive analysis of related data is implemented by the nearest neighborhood method, which can increase operation efficiency and timeliness of the registration algorithm to the maximum extents.
(3) The registration data acquisition based on the sliding window achieves better performance than the other algorithms, and its goodness-of-fit can reach as high as 96.7%. It is slightly influenced by missing data and is easy to operate.

In this study, experimental and theoretical studies were combined to propose a new understanding of the time series registration. The established translation registration algorithm based on sliding window is simpler and closer to the application practices. Research results provide significant guidance in increasing the overall performance and precision of time series data integration and mining. Future research should combine big data and the proposed registration algorithm with correction to improve the precision of time series data registration because the current study is lacking in terms of the actual monitoring of large datasets.

Acknowledgements
This study was supported by the Science and Technology Development Plan of Jilin Province under the project No. 20150204005GX, the Significant Science and Technology Plan of Changchun City under the project No. 14KG082, the Industrial Technology Research and Development Special Project of Jilin Province under Grant No. 2011006-9, the National Natural Science Foundation of China under the project No.U1304603, No. 11301488, and No. 61472049.

References

1. Kuremoto, T., Kimura, S., Kobayashi, K., Obayashi, M., “Time series forecasting using a deep belief network with restricted Boltzmann machines”. *Neurocomputing*, 137(15), 2014, pp. 47-56.
2. Längkvist, M., Karlsson, L., Loutfi, A., “A review of unsupervised feature learning and deep learning for timeseries modeling”. *Pattern Recognition Letters*, 42(1), 2014, pp. 11-24.
3. Brockwell, P. J., Davis, R. A., “Introduction to time series and forecasting”. *Technometrics*, 39(4), 2012, pp. 426.
4. Esling, P., Agon, C., “Time-series data mining”. *ACM Computing Surveys* (*CSUR*), 45(1), 2012, pp. 7.
5. Zhang, N. F., “Forecasting and time series analysis”. *Technometrics*, 19(3), 2012, pp. 344-347.
6. Fu, T. C., “A review on time series data mining”. *Engineering Applications of Artificial Intelligence*, 24(1), 2011, pp. 164-181.
7. Aghabozorgi, S., Shirkhorshidi, A. S., Wah, T. Y., “Time-series clustering - a decade review”. *Information Systems*, 53(1), 2015, pp. 16-38.
8. Livera, A. M. D., Hyndman, R. J., Snyder, R. D., “Forecasting time series with complex seasonal patterns using exponential smoothing”. *Journal of the American Statistical Association*, 106(1), 2012, pp. 513-527.
9. Fang, F., Cai, Y. L., “Research on passive multi-sensor real-time time registration algorithm”. *System Simulation Technology & Application*, 16(1), 2015, pp. 334-338.
10. Ranjan, R., Wang, M., Perera, C., Jayaraman, P. P., Zhang, M., Strazdins, P., Shyamsundar, R. K., “City data fusion: sensor data fusion in the internet of things”. *International Journal of Distributed Systems and Technologies*, 7(1), 2016, pp. 15-36.
11. Alouani, A. T., Theodore, R., “On optimal synchronous and asynchronous track fusion”. *Optical Engineering,* 37(2), 1998, pp. 427-433.
12. Shi, L. T., “*Study on time registration technology for multi-sensor information fusion*”. Master thesis of National University of Defense Technology, China, 2010.
13. Burke, J., “The SAGE real quality control fraction and its interface with BUIC II/BUIC III”. *MITRE Technical*, 1(1), 1996, pp. 1-18.
14. Leung, H., Blanchette, M., Harrison, C., “A least squares fusion of multiple radar data”. In: *Proceedings of Radar*, Paris, France: IEEE, 1994, pp. 364-369.
15. Dana, M. P., “Registration: a prerequisite for multiple sensor tracking in multi-target multi-sensor tracking”. *Multitarget-Multisensor Tracking: Advanced Applications*, 1(1), 1990, pp. 155-185.
16. Zhou, Y. F., Henry, L., “An exact maximum likelihood registration algorithm for data fusion”. *IEEE Transactions on Signal Processing*, 45(6), 1997, pp. 1560-1572.
17. Zhou, Y. F., Leung, H., Blanchette, M., “Sensor alignment using the earth-centered earth-fixed (ECEF) coordinate system”. *IEEE Transactions on Aerospace & Electronic Systems*, 35(2), 1999, pp. 410-418.
18. Helmick, R. E., Rice, T. R., “Removal of alignment errors in an integrated system of two 3D sensor”. *IEEE Transactions on Aerospace and Electronic Systems*, 29(4), 1993, pp. 1333-1343.
19. Karniely, H., Siegelmann, H. T., “Sensor registration using neural networks”. *IEEE Transactions on Aerospace & Electronic Systems,* 36(1), 2000, pp. 85-101.
20. Wang, B. S., Li, F. S., “The research on multiple targets tracking based on the data fusion technique”. *Journal of XIDIAN University, China*, 25(3), 1998, pp. 269-272.
21. Alouani, A. T., Blair, W. D., “Use of a kinematic constraint in tracking constant speed, maneuvering targets”. *IEEE Transactions on Automatic Control*, 38(7), 1993, pp. 1107-1111.
22. Li, X. Y., Zhou, J., “A systematic model of organization conflict factors on equipment management”. *Journal of Air Force Radar Academy, China*, 21(4), 2007, pp. 252-254.
23. Liang, K., Pan, Q., Song G. M., Zhang, X. G., Zhang, Z. L., “The study of multi-sensor time registration method based on curve fitting”. *Fire Control and Command Control*, 31(12), 2006, pp. 51-53.
24. Arasaratnam, I., Haykin, S., “Cubature kalman filters”. *IEEE Transactions on Automatic Control*, 54(6), 2009, pp. 1254-1269.
25. Wang, L. N., Peng, Y. X., “Time registration algorithm based on adaptive kalman filtering”. *Computer Engineering*, 39(10), 2013, pp. 199-200.
26. Wang, W., “Temporal and spatial alignment for multi-sensors technology”. Master thesis of China institute of electronics, 2014.