

Time Registration Algorithm of Multi Sensors Based on Spline Interpolating

ZHIMIN CHEN

China Satellite Maritime Tracking and Controlling Department
214431 Jiangyin, Jiangsu
CHINA
chenzhimin@188.com

YUMING BO, WENHUA ZHAO, LIANG PAN, JIAHONG CHEN
China Satellite Maritime Tracking and Controlling Department
214431 Jiangyin, Jiangsu
CHINA

Abstract: The time registration algorithm applicable to modern high-accuracy target tracking system is designed based on cubic spline interpolation. This algorithm can perform time registration for any quantity of sensors, the sensor measurement short of data, and the measurement of the sensor with non-uniform sampling period. The sampling rates obtained through registration can be selected according to system requirements to provide effective time registration methods for modern high-accuracy target tracking system.

Key-Words: Spline interpolating, multi sensors, data fusion, time registration, target tracking, sampling rates

1 Introduction

Modern high-accuracy target tracking system has varieties of sensors [1]. Every unit is likely to be furnished with radar searching and tracking equipment and infrared tracking system simultaneously [2]. It is possible that tracking systems differ from each other in scan cycle and speed of detection. The center can not only track the target detected by multi-sensor equipment in the unit, but also obtain the measured information of neighboring units. Time registration is a process that pushes the status information at the previous moment into current moment, and processes the repeatedly measured information between two updates [3, 4] to acquire the synchronous measured information that has been processed.

If there is an integrated fusion system which consists of multiple sensors, the sampling mode of every sensor may be either periodic sampling or aperiodic sampling. Every sensor can derive corresponding measured value as well as detect a measurement vector during sampling time [5]. However, since each sensor has its own observational period and its data acquisition time is different, the direct measurement fusion of sensor will lead to the fused information with obvious errors as a result of time deviation [6, 7]. Thus, the primary concern that target tracking system data integration center needs to address is how to perform time registration for multi-sensor

measurement to ensure the accuracy and consistency of fusion centers information measurement time.

The time registration method applicable to modern high-accuracy target tracking system is designed based on cubic spline interpolation, which aims to provide guarantee for fusion center to process data accurately.

2 Time Registration Principle

A vast number of the studies on multi-sensor information integration attach importance to synchronous fusion. That is, these studies hypothesize that sensors track targets synchronously and meanwhile send data to system's infusion center [8, 9, 10]. However, in practice, asynchronous fusion problem occurs frequently, which usually leads to different sampling periods of every sensor in system. Meanwhile, the difference in the intrinsic delay time (such as pretreatment time) of every sensor and that of communication [11] may cause the result that sensor information cannot reach fusion center synchronously, i.e., the asynchronous problem takes place [12].

See figure 1 for schematic diagram of time registration:

In multi-sensor fusion system, time registration method can be divided into three types according to actual condition. Firstly, in normal state, the time

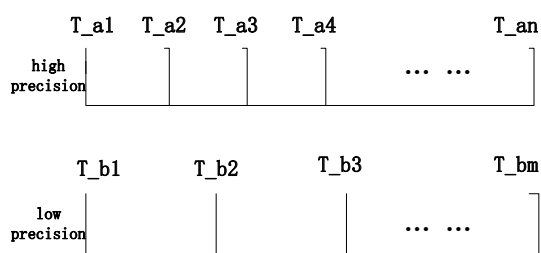


Figure 1: schematic diagram of time registration

clock of information source is set according to standard time [13]. Secondly, the clocks of other sensors need to be calibrated based on the clock of system's command center. Thirdly, during information fusion, the asynchronous measured data of every site within an information processing period are unified into the same time [14, 15]. Thus, there usually are three problems: (1) the time reference point of every sensor should remain consistent (i.e., time synchronization); (2) the communication delay during the transfer of measured information; and (3) the difference in the processing methods of data sampling time caused by the different sampling periods of sensor measurement.

3 Time registration method based on Cubic Spline Interpolation

3.1 Analysis on the Demand of Modern High-accuracy Target Tracking System for Time Registration

1. To ensure the accuracy of tracking data, modern high-accuracy tracking system tends to track multiple sensors, and perform time registration for no less than 2 sensors at a time.
2. The periodic ratio between different sensors of modern high-accuracy target tracking system is possibly not $1:n$. It is necessary to perform time registration for multisensory measurement in which the ratio of sampling period is not the integral number.
3. In terms of sampling period, the sensor of modern high-accuracy target tracking system is uncertain to rely on uniform sampling [16], and sensor's sampling interval is not surely constant. Thus, there is a need to implement time registration for multisensory without constant sampling interval.
4. Due to the factors such as system and equipment problem or detection interference, some measurements sampled by sensor may be false, and

thus cannot be used as fusion data, or sometimes, no measurements can be received. Therefore, it is necessary to perform time registration for the sensors facing the lack of measured data.

5. Given its own equipment or the computing time and accuracy, modern high-accuracy target tracking system may select appropriate sample rates after registration. Thus, the sampling rates after registration are not absolutely required to be the minimum or maximum sample rate in system sensor [17, 18].

Many typical registration algorithms are unable to meet the need of modern high-accuracy target tracking system effectively as a result of system complexity and environmental variability [19, 20]:

Least squares method has a strict demand on registration cycle, requiring that the periodic ratio between different sensors should be integral number. The sampling accuracy of least square method must be sensor's minimum sampling rates in the system, and it hypothesizes that the target remains in the state of uniform linear motion within the registration period. Thus, there will be obvious errors if the time registration is implemented when target moves under complex condition.

Interpolation and extrapolation algorithm also hypothesizes that the target moves uniformly in a straight line within the interval of every processing time, and the velocity of working target changes significantly within the interval of different processing time. Thus, interpolation and extrapolation algorithm applies to the circumstances where target's moving velocity remains unchanged or the velocity changes slowly. However, this algorithm also shows some deficiencies. For instance, the synchronous data frequency after time registration is not higher than the minimum sampling frequency of all sensors. As a consequence, the measured data obtained by the high-accuracy sensors that can achieve high sampling frequency cannot be fully used.

Lagrange's interpolation algorithm is convenient for theoretical analysis due to its well-structured formula and compactness. However, in practical use, this algorithm has rather high demands on stability of measured data. As one interpolation point is decreased or increased, corresponding fundamental polynomials will be required to be re-calculated, which will lead to significant changes in the whole formula and complicated operations. In addition, if there are a large number of interpolation points, Lagrange interpolating polynomial will have a high number of powers. In this case, Lagrange interpolating polynomial will face numerical instability, easily leading to severe Runge phenomenon.

According to the analysis above, Least squares method, interpolation and extrapolation algorithm, and Lagrange’s interpolation algorithm cannot meet the requirements above simultaneously, only able to satisfy the time registration under specific conditions.

To address the problems above, this paper designs the time registration method applicable to the data fusion of modern high-accuracy target tracking system based on cubic spline interpolation from the perspective of the demands of high-accuracy target tracking system.

3.2 Cubic Spline Interpolation Principle

3.2.1 Definition and Form of Cubic Spline Interpolation Function

(1) Let the subdivision of $[a, b]$ be $\Delta : a = x_0 < x_1 < \dots < x_n = b$; if function $S(x)$ meets the two conditions below,

(a): $S(x) \in C^2[a, b]$, i.e., there is continuous first-order and second-order derivatives;

(b): $S(x)$ is the polynomial with the number of power no greater than 3 in every small interval $[x_j, x_{j+1}] (j = 0, 1, \dots, n - 1)$;

$S(x)$ is the cubic spline function of subdivision Δ .

(2) Let function table of $y = f(x)$ be $(x_i, f(x_i)), (i = 0, 1, \dots, n)$;

If the cubic spline function $S(x)$ also meets the interpolation condition:

$$S(x_i) = f(x_i), (0, 1, \dots, n) \tag{1}$$

$S(x)$ can be understood as the cubic spline function of $f(x)$ about the subdivision Δ .

Cubic spline function has following forms:

$$S(x) = \begin{cases} S_0(x), & x \in [x_0, x_1], \\ S_1(x), & x \in [x_1, x_2], \\ \vdots \\ S_{n-1}(x), & x \in [x_{n-1}, x_n]. \end{cases} \tag{2}$$

And meets following conditions:

$$\begin{cases} S_{i-1}(x_i) = S_i(x_i), & i = 1, 2, \dots, n - 1, \\ S'_{i-1}(x_i) = S'_i(x_i), & i = 1, 2, \dots, n - 1, \\ S''_{i-1}(x_i) = S''_i(x_i), & i = 1, 2, \dots, n - 1. \end{cases} \tag{3}$$

3.2.2 Principle and Construction Methods of Cubic Spline Interpolation Function

Within the subinterval $[x_{i-1}, x_i]$, $S(x) = S_i(x)$ is a polynomial with the number of powers smaller than 3. Thus, its second-order derivative $S''(x)$ will be surely the linear function. Assuming $S''(x_i) = M_i (i = 0, 1, 2, \dots, n)$, there will be:

$$S''_i(x) = M_{i-1} \frac{x - x_i}{x_{i-1} - x_i} + M_i \frac{x - x_{i-1}}{x_i - x_{i-1}}, \tag{4}$$

$$x \in [x_{i-1}, x_i]$$

Assuming $h_i = x_i - x_{i-1}$, there will be formula (5):

$$S''_i(x) = M_{i-1} \frac{x_i - x}{h_i} + M_i \frac{x - x_{i-1}}{h_i}, \tag{5}$$

$$x \in [x_{i-1}, x_i]$$

The formula below is obtained after continuous quadratic integral operations.

$$S_i(x) = M_{i-1} \frac{(x_i - x)^3}{6h_i} + M_i \frac{(x - x_{i-1})^3}{6h_i} \tag{6}$$

$$+ A_i(x - x_{i-1}) + B_i$$

where A_i and B_i are integral constants.

The following formulas can be obtained when the interpolation condition $S_i(x_{i-1}) = y_{i-1}, S_i(x_i) = y_i$ is put in formula (6):

$$A_i = \frac{y_i - y_{i-1}}{h_i} - \frac{h_i}{6} (M_i - M_{i-1}) \tag{7}$$

$$B_i = y_{i-1} - \frac{1}{6} M_{i-1} h_i^2 \tag{8}$$

$$S_i(x) = M_{i-1} \frac{(x_i - x)^3}{6h_i} + M_i \frac{(x - x_{i-1})^3}{6h_i} \tag{9}$$

$$+ (y_{i-1} - \frac{M_{i-1} h_i^2}{6}) \frac{x_i - x}{h_i}$$

$$+ (y_i - \frac{M_i h_i^2}{6}) \frac{x - x_{i-1}}{h_i}$$

$$(x \in [x_{i-1}, x_i]; i = 1, 2, \dots, n)$$

Thus, the cubic spline interpolation function $S(x)$ can be constructed only when $n + 1$ unknown numbers M_0, M_1, \dots, M_n are made certain.

According to the continuity condition of $S_i(x) (i = 0, 1, \dots, n - 1)$, i.e., $S'(x_i - 0) = S'(x_i + 0)$ which is equal to $S'_i(x_i - 0) = S'_{i+1}(x_i + 0)$.

The following formula is obtained through formula (9):

$$S'_i(x) = -M_{i-1} \frac{(x-x_i)^2}{2h_i} + M_i \frac{(x-x_{i-1})^2}{2h_i} + \frac{y_i - y_{i-1}}{h_i} - \frac{h_i}{6}(M_i - M_{i-1}) \quad (10)$$

Thus, there is:

$$S'_i(x_i - 0) = \frac{y_i - y_{i-1}}{h_i} + \frac{h_i}{6}M_{i-1} - \frac{h_i}{3}M_i \quad (11)$$

When the i in formula (10) is replaced with $i + 1$, the formula of $S'(x)$ in the subinterval $[x_i, x_{i+1}]$ can be expressed as $S'_{i+1}(x)$.

$$S'_{i+1}(x_i + 0) = \frac{y_{i+1} - y_i}{h_{i+1}} + \frac{h_{i+1}}{6}M_i - \frac{h_{i+1}}{3}M_{i+1} \quad (12)$$

Following equation can be obtained when formulas (10) and (12) are put in $S'_i(x_i - 0) = S'_{i+1}(x_i + 0)$:

$$\frac{h_i}{6}M_{i-1} + \frac{h_i + h_{i+1}}{3}M_i + \frac{h_{i+1}}{6}M_{i+1} = \frac{y_{i+1} - y_i}{h_{i+1}} - \frac{y_i - y_{i-1}}{h_i} \quad (13)$$

Following result can be obtained when the two sides of the formula are multiplied by $\frac{6}{h_i + h_{i+1}}$:

$$\frac{h_i}{h_i + h_{i+1}}M_{i-1} + 2M_i + \frac{h_i}{h_i + h_{i+1}}M_{i+1} = \frac{6}{h_i + h_{i+1}} \left(\frac{y_{i+1} - y_i}{h_{i+1}} - \frac{y_i - y_{i-1}}{h_i} \right) \quad (14)$$

Assuming there is:

$$\begin{cases} \mu_i = \frac{h_i}{h_i + h_{i+1}} \\ \lambda_i = \frac{h_{i+1}}{h_i + h_{i+1}} = 1 - \mu_i \\ g_i = \frac{6}{h_i + h_{i+1}}(f[x_i, x_{i+1}] - f[x_{i-1}, x_i]) \end{cases} \quad (15)$$

The obtained equation can be simplified as:

$$\mu_i M_{i-1} + 2M_i + \lambda_i M_{i+1} = g_i \quad (16)$$

$(i = 1, 2, \dots, n - 1)$

$$\begin{cases} \mu_1 M_0 + 2M_1 + \lambda_1 M_2 = g_1 \\ \mu_2 M_1 + 2M_2 + \lambda_2 M_3 = g_2 \\ \vdots \\ \mu_{n-1} M_{n-2} + 2M_{n-1} + \lambda_{n-1} M_n = g_{n-1} \end{cases} \quad (17)$$

Under the boundary condition $S'(x_0) = y'_0$, $S'(x_n) = y'_n$, the derivative of $S(x)$ in the subinterval $[x_0, x_1]$ is:

$$S'_1(x) = -M_0 \frac{(x_1 - x)^2}{2h_1} + M_1 \frac{(x - x_0)^2}{2h_1} + \frac{y_1 - y_0}{h_1} - \frac{h_1}{6}(M_1 - M_0) + \frac{y_1 - y_0}{h_1} - \frac{h_1}{6}(M_1 - M_0) \quad (18)$$

Following result can be obtained when $S'(x_0) = y'_0$:

$$2M_0 + M_1 = \frac{6}{h_1} \left(\frac{y_1 - y_0}{h_1} - y'_0 \right) \quad (19)$$

Likewise, following result can be obtained when $S'(x_n) = y'_n$:

$$2M_{n-1} + M_n = \frac{6}{h_1} \left(-\frac{y_n - y_{n-1}}{h_n} + y'_n \right) \quad (20)$$

Following system of linear equations concerning M_0, M_1, \dots, M_n can be obtained when formulas (19), (20) and (17) are calculated together.

$$\begin{bmatrix} \mu_1 & 2 & \lambda_1 & & & \\ & \ddots & \ddots & \ddots & & \\ & & \mu_{n-1} & 2 & \lambda_{n-1} & \\ & & & 1 & & 2 \end{bmatrix} \begin{bmatrix} M_0 \\ M_1 \\ \vdots \\ M_{n-1} \\ M_n \end{bmatrix} = \begin{bmatrix} g_0 \\ g_1 \\ \vdots \\ g_{n-1} \\ g_n \end{bmatrix} \quad (21)$$

$$\begin{cases} g_0 = \frac{6}{h_1}(f[x_0, x_1] - y'_0) \\ g_n = \frac{6}{h_n}(-f[x_{n-1}, x_n] - y'_n) \end{cases} \quad (22)$$

Under the boundary condition $S''(x_0) = y''_0 = M_0$, $S''(x_n) = y''_n = M_n$, the equation only contain $n - 1$ unknown numbers M_1, M_2, \dots, M_{n-1} , and thus, it can be re-written as:

$$\begin{bmatrix} \mu_2 & \lambda_1 & & & & \\ \mu_2 & 2 & \lambda_2 & & & \\ & \ddots & \ddots & \ddots & & \\ & & \mu_{n-2} & 2 & \lambda_{n-2} & \\ & & & \mu_{(n-1)} & 2 & \end{bmatrix} \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_{n-2} \\ M_{n-1} \end{bmatrix} = \begin{bmatrix} g_1 - \mu_1 y''_0 \\ g_2 \\ \vdots \\ g_{n-2} \\ g_{n-1} - \lambda_{n-1} y''_n \end{bmatrix} \quad (23)$$

Under the boundary condition $S'(x_0 + 0) = S'(x_n - 0)$, $S''(x_0 + 0) = S''(x_n - 0)$. Following result can be obtained when $S''(x_0 + 0) = S''(x_n - 0)$:

$$M_0 = M_n \quad (24)$$

Following formula can be obtained when $S'(x_0 + 0) = S'(x_n - 0)$:

$$-M_0 \frac{h_1}{2} + \frac{y_1 - y_0}{h_1} - \frac{h_1}{6}(M_1 - M_0) = M_n \frac{h_n}{2} + \frac{y_n - y_{n-1}}{h_n} - \frac{h_n}{6}(M_n - M_{n-1}) \quad (25)$$

Formula (25) can be rewritten as follows when $y_0 = y_n, M_0 = M_n$:

$$\begin{aligned} & \frac{h_1}{h_1 + h_n} M_1 + 2M_n + \frac{h_n}{h_1 + h_n} M_{n-1} \\ &= \frac{6}{h_1 + h_n} \left(\frac{y_1 - y_0}{h_1} - \frac{y_n - y_{n-1}}{h_n} \right) \end{aligned} \quad (26)$$

$$\lambda_n M_1 + \mu_n M_{n-1} + 2M_n = g_n \quad (27)$$

In combination with the derivations above, the system of linear questions concerning M_1, M_2, \dots, M_n is represented as follows:

$$\begin{bmatrix} 2 & \lambda_1 & & & \mu_1 \\ \mu_2 & 2 & \lambda_2 & & \\ & \ddots & \ddots & \ddots & \\ & & \mu_{n-1} & 2 & \lambda_{n-1} \\ \lambda_n & & & \mu_n & 2 \end{bmatrix} \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_{n-1} \\ M_n \end{bmatrix} = \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_{n-1} \\ g_n \end{bmatrix} \quad (28)$$

3.3 Design and Steps of Time Registration Fitting Function based on Cubic Spline Interpolation

Assuming the sensor has measured the tracking target $h + 1$ times within the time interval $[a, b]$, the entire time zone can be divided into $a = t_i(0) < t_i(1) < \dots < t_i(h) = b$. In this formula, ($i = 1, \dots, M$); t_i is not surely the sampling time and sometimes it can be the synchronous time after time registration. At a given time, the corresponding measured value will be $f(t_i(n)) = y_n$, where ($n = 0, 1, \dots, h$). The spline interpolation function $F(x)$ is constructed to satisfy following conditions:

- (1) $F(t_i(n)) = y_i, i = 0, 1, \dots, M, n = 0, 1, \dots, h$.
- (2) It is cubic polynomial within every subinterval $[t_i(n), t_i(n + 1)]$, where $n = 0, 1, \dots, h - 1$.
- (3) $F(t)$ has second-order continuous derivative within the interval $[a, b]$: $F^{(K)}(t_i^-(n)) = F^{(K)}(t_i^+(n)), K = 0, 1, 2, n = 0, 1, \dots, h - 1$.

The core of the fitting function based on cubic spline interpolation is to find the best approximation of field norm $\|\cdot\|$ concerning $f(t)$ within the space $F_k(\Delta)$ of spline function, i.e., to find $F^*(t)$ to derive the equation below:

$$\|f - F^*\| = \min\|f - F\|, F \in F_k(\Delta) \quad (29)$$

The operational formula of interpolation function $F(t)$ can be obtained through derivation process of cubic spline interpolation function and final formula (28) within each subinterval $[t_i(n), t_i(n + 1)]$, where

($n = 0, 1, 2, \dots, h - 1$). After cubic spline interpolation fitting, a smooth curve can be calculated. The measured value of every sensor at any time can be figured out by way of this curve.

Let the data set obtained through registration processing time interval $[T_f(t - 1), T_f(t)]$ be $\{D_i(t), i = 1, \dots, M\}$, and $m_i(t)$ be the number of the measured data received within the processing time interval $[T_f(t - 1), T_f(t)]$. System's fusion center implements registration for the set $\{D_i(t)\}$ according to the sampling frequency of one of sensors, and the synchronous data of every sensor are $\bar{D}_i(t_q^t)$.

Below are the major steps of the algorithm used by system's fusion center to perform time registration for the set $\{D_i(t), i = 1, \dots, M\}$ at the time $T_f(t)$.

- 1 The registration frequency is set as f_t ; the set of the measured data obtained within the interval $[T_f(t - 1), T_f(t)]$ set as $\{D_i(t), i = 1, \dots, M\}$; and the measured data of sensor S_i at the time t as $D_i(t)$.
- 2 Let the minimum number of the effective measured data required by spline interpolation fitting operation be r . If $m_i(t) \geq r$, the fitting operation will be completed by way of the measured data within the data set $D_i(t)$. Assuming there is $j \in \{1, 2, \dots, M\}, i \neq j$, and the fitting formula obtained through the measured data of sensor S_i is $F_i(t)$, the measured data of sensor i at the sampling time of sensor j should be obtained through the operation of fitting formula; otherwise, turn to next step.
- 3 As for the set of measured data $D_i(t)$, when $m_i(t) < r$, spline interpolation fitting calculation is completed through the set of measured data $D_i(t)$ and the measured data collected at the time before $D_i(t)$. Assuming there is $j \in \{1, 2, \dots, M\}, i \neq j$, and the fitting formula obtained through the measured data of sensor S_i is $F_i(t)$, the measured data of sensor i at the sampling time of sensor j should be obtained through the operation of fitting formula.

4 Simulation Experiment

Assuming Sensor A and Sensor B measure target's x coordinate azimuth with their tracking time set as 80 s and their sampling periods set as 5s and 2s, respectively, Sensor A can get 16 data and sensor B can obtain 40 data.

Let T_A be the time when Sensor A receives measurements; X_A be the measurements received by Sensor A, T_B be the time when Sensor B receives measurements; and X_B be the measurements

received by Sensor B in simulation environment. The time when Sensor A receives measured data and the measurements received by Sensor A can be seen in table 1.

Table 1: Sampled data of Sensor A

Sampling time of Sensor A/s	Measurements of Sensor A/km
1	1.200000
6	1.403361
11	1.534848
16	1.682288
21	1.820745
26	2.011228
31	2.222307
36	2.454183
41	2.744035
46	3.049046
51	3.267804
56	3.412980
61	3.569790
66	3.670560
71	3.686546
76	3.696737

The time when Sensor B receives measured data and the measurements received by Sensor B can be seen in table 2.

Table 2: Sampled data of Sensor B

Sampling time of Sensor B/s	Measurements of Sensor B/km	Sampling time of Sensor B/s	Measurements of Sensor B/km
1	1.311882	41	2.747136
3	1.385733	43	2.883558
5	1.349095	45	2.981772
7	1.410158	47	3.143425
9	1.453231	49	3.214657
11	1.506949	51	3.260788
13	1.541677	53	3.339364
15	1.638661	55	3.361732
17	1.697034	57	3.421582
19	1.771375	59	3.525656
21	1.886078	61	3.561142
23	1.815779	63	3.548971
25	1.925430	65	3.708741
27	2.069396	67	3.667130
29	2.140200	69	3.650585
31	2.207879	71	3.714767
33	2.329597	73	3.663589
35	2.448531	75	3.680962
37	2.490406	77	3.697945
39	2.686102	79	3.696326

As shown by the data above, the measured data received by Sensor A and Sensor B are completely d-

ifferent due to the difference in sampling time. Thus, the direct fusion processing will lead to huge errors and the result that accuracy will be far lower than that of single-sensor tracking. The difference in the measured data received by Sensor A and Sensor B can be seen in figure 2:

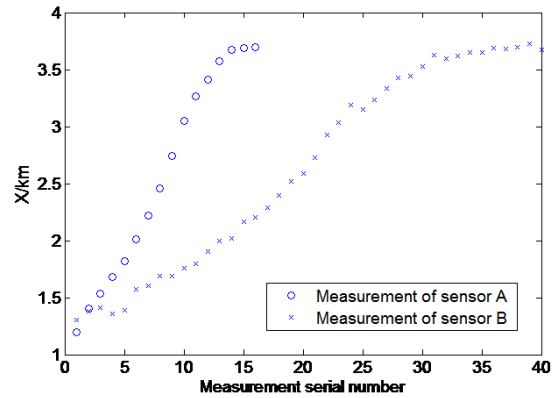


Figure 2: Sensor A's measurements received by fusion

The method proposed in this paper is used to implement the curve fitting of sensor A, as shown by figure 3:

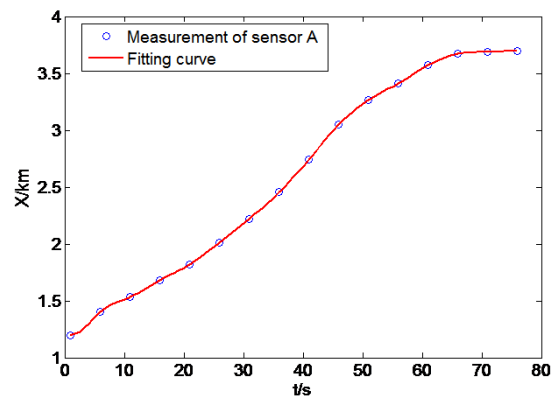


Figure 3: Measurement fitting curve of Sensor A

Sensor A's measurement fitting curve is interpolated at the sampling time of Sensor B, as shown by figure 4:

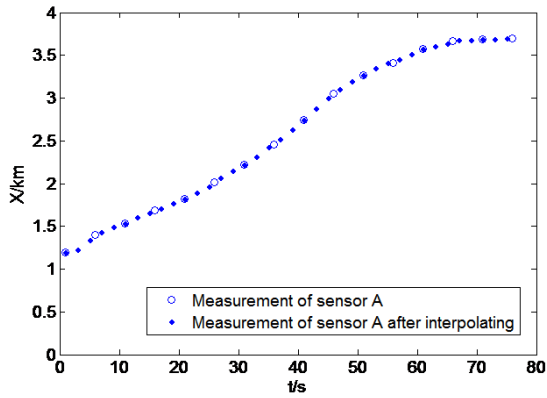


Figure 4: Sensor A's measurement after interpolation

The measurements of Sensor A and Sensor B after time registration are shown as follows:

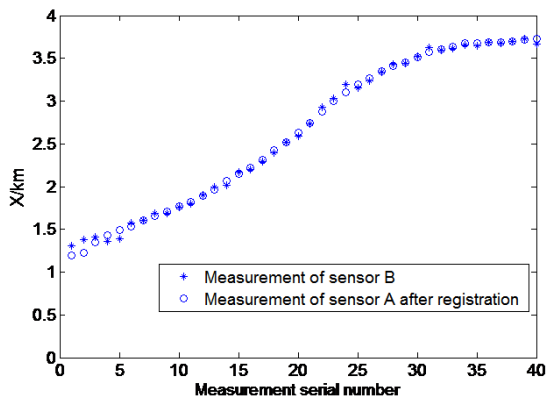


Figure 5: Measurements of Sensor A and Sensor B after time registration

As demonstrated by simulation result, the ratio of sampling proportion between Sensor A and Sensor B in this model is not an integral number. Thus, the least squares registration method is not applicable to time registration. However, the time registration method based on cubic spline interpolation in this paper can ensure the effective time registration of Sensor A and Sensor B, and the measured data of Sensor A and Sensor B at the same time point after registration can be fused, able to provide accurate and reliable information for the measurement fusion of system's fusion center.

Meanwhile, the time registration of this model can also fit the measurements of Sensor B and interpolate sampling period of Sensor A by the method proposed in this paper. The proper period after registration can be selected according to the demand of target tracking system.

Apart from this, the method proposed in this paper is applicable to the time registration of three and

Table 3: Matrix elements of fitting polynomial coefficients

Three degree term	Two degree term	One degree term	Constant term
-0.00148	0.015532	0	1.2
0.00061	-0.00666	0.044358	1.403362
-0.00026	0.002484	0.023476	1.534849
0.000216	-0.00136	0.029095	1.682289
-0.00012	0.001877	0.031683	1.820745
8.38E-06	9.37E-05	0.041538	2.011228
8.70E-05	0.000219	0.043103	2.222308
-5.90E-05	0.001525	0.051823	2.454184
-0.00019	0.00064	0.062643	2.744035
2.18E-05	-0.00226	0.054524	3.049047
0.000208	-0.00194	0.033524	3.267804
-0.00017	0.00118	0.02974	3.412981
-6.49E-05	-0.00139	0.028707	3.56979
0.000201	-0.00236	0.009979	3.670561
-0.00011	0.00065	0.001432	3.686547

more sensors: to implement time registration for Sensors A, B and C according to the sampling time of Sensor B, it is only necessary to calculate the fitting curves Sensor A and Sensor C for the measurements of Sensor A and Sensor C according to the method described above; then, the data of Sensor A and Sensor B after registration can be obtained when the sampling time of Sensor B is put into fitting curve equations Sensor A and Sensor C.

The method proposed in this paper can not only implement time registration for Sensor A and Sensor B which are short of data, but also supplement the time measurements that Sensor B lacks with the measurements of Sensor A after registration to improve registration accuracy.

5 Conclusion

This paper has analyzed the complexity and environmental variability of modern high-accuracy target tracking system as well as the reasons for the inability of common time registration methods to meet system demands to propose the time registration method based on spline interpolation. This registration method has changed the limitations of the common time registration methods such as least square time registration and maximum likelihood time registration. This registration method is able to implement time registration for the complete and incomplete measurements of any quantity of sensors as well as for

the measurement of the sensor with uniform sampling period. In addition, it is capable of selecting sampling rates according to system's specific demands to meet the demand of modern high-accuracy target tracking system for time registration. Thus, this time registration method is of high application value.

Acknowledgements: This work is partially supported by the National Natural Science Foundation of China (61501521); National Natural Science Foundation of China (U1330133); National Natural Science Foundation of China (61473153); National Natural Science Foundation of China (61403421); National Natural Science Foundation of China (61203266); Thanks for the help.

References:

- [1] Z. Zhang and G. Shan, Sensor Scheduling for Target Tracking Using Approximate Dynamic Programming, *Wseas Transactions on Systems & Control*, vol.8, no.4, 2013, pp. 121-130.
- [2] A. Morrison, V. Renaudin, J. B. Bancroft, et al., Design and testing of a multi-sensor pedestrian location and navigation platform, *Sensors*, vol.12, no.3, 2012, pp. 3720-3738.
- [3] A. A. Fathima, S. Vasuhi, T. M. Treesa, et al., Person Authentication System with Quality Analysis of Multimodal Biometrics, *WSEAS Transactions on Information Science & Applications*, vol.10, no.6, 2013, pp. 179-194.
- [4] J. Q. Lu, P. Wei, Z. Chen, A Scheme to Counter SSDF Attacks based on Hard Decision in Cognitive Radio Networks, *WSEAS Transactions on Communications*, vol.13, 2014, pp. 242-248.
- [5] J. A. Rodger, Toward reducing failure risk in an integrated vehicle health maintenance system: A fuzzy multi-sensor data fusion Kalman filter approach for IVHMS, *Expert Systems with Applications*, vol.39, no.10, 2012, pp. 9821-9836.
- [6] J. Jiao, Z. Deng, B. Zhao, et al, A Hybrid Method for Multi-sensor Remote Sensing Image Registration Based on Saliency Region, *Circuits, Systems, and Signal Processing*, vol.33, no.7, 2014, pp. 2293-2317.
- [7] S. Abdikan, F. Balik Sanli, F. Sunar, et al., A comparative data-fusion analysis of multi-sensor satellite images, *International Journal of Digital Earth*, vol.7, no.8, 2014, pp. 671-687.
- [8] T. Schenk, B. Csatho, C. van der Veen, et al., Fusion of multi-sensor surface elevation data for improved characterization of rapidly changing outlet glaciers in Greenland, *Remote Sensing of Environment*, vol.149, 2014, pp. 239-251.
- [9] L. Hegarat, S. Bloch S, Application of dumpster-Shafer evidence theory to unsupervised classification in multisource remote sensing, *IEEE Transactions on Geoscience and Remote Sensing*, vol.35, no.4, 1997, pp. 1018-1031.
- [10] M. Datcu, F. Melgani, A multisource data classification with dependence trees, *IEEE Transactions on Geoscience and Remote Sensing*, vol.40, no.3, 2002, pp. 609-617.
- [11] F. Franceschini, M. Galetto, D. Maisano, et al., Large-scale dimensional metrology (LSDM): from tapes and theodolites to multi-sensor systems, *International Journal of Precision Engineering and Manufacturing*, vol.15, no.8, 2014, pp. 1739-1758.
- [12] H. Karniely, T. H. Siegelmann, Sensor registration using neural networks, *IEEE Transactions on Aerospace and Electronic Systems*, vol.35, no.1, 2000, pp. 85-101.
- [13] X. Lin, Y. Bar-shalom, T. Kirubarajan, Multisensor-multitarget bias estimation for general asynchronous sensors, *IEEE transactions on aerospace and electronic systems*, vol.41, no.1, 2005, pp. 899-921.
- [14] Y. Jin, Y. Ding, K. Hao, et al., An endocrine-based intelligent distributed cooperative algorithm for target tracking in wireless sensor networks. *Soft Computing*, vol.19, no.5, 2015, pp. 1427-1441.
- [15] Y. E. M. Hamouda, C. Phillips, Adaptive sampling for energy-efficient collaborative multi-target tracking in wireless sensor networks, *I-ET wireless sensor systems*, vol.1, no.1, 2011, pp. 15-25.
- [16] D. Janczak, M. Sankowski, Data fusion for ballistic targets tracking using least squares, *International Journal of Electronics and Communications*, vol.66, no.6, 2012, pp. 512-519.
- [17] N. Nabaa and R. H. Bishop, Solution to a Multisensor tracking problem with sensor registration errors, *IEEE Transactions on Aerospace and Electronic Systems*, vol.35, no.1, 1999, pp. 354-363.
- [18] W. Tian, Y. Wang, X. Shan, et al., Track-to-track association for biased data based on the reference topology feature. *IEEE Signal Processing Letters*, vol.21, no.4, 2014, pp. 449-453.
- [19] W. Li, H. Leung and Y. Zhou, Space-Time Registration of Radar and ESM Using Unscented Kalman Filter, *IEEE Transaction on Aerospace and Electronic Systems*, vol.40, no.3, 2004, pp. 824-836.

- [20] Y. Fu, Q. Ling and Z. Tian, Distributed sensor allocation for multi-target tracking in wireless sensor networks, *IEEE Transaction on Aerospace and Electronic Systems*, vol.48, no.4, 2012, p-p. 3538-3553.