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基于异步航迹融合的乱序数据处理算法

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摘要：针对集中式融合系统中从传感器到融合中心的传输延迟时间存在差异而导致融合中心出现乱序数据的问题，提出了一种能够处理单步延迟和多步延迟的乱序数据处理（ATFOOSM）算法.首先利用乱序时刻（乱序数据的采样时刻）前的滤波结果，通过卡尔曼滤波来获取乱序时刻的目标状态，再采用异步航迹融合的方式实现对当前时刻目标状态的更新.仿真中采用ATFOOSM算法和重新排序算法对单步延迟和多步延迟下的乱序数据进行处理，结果表明ATFOOSM算法能够获得与重新排序算法相近的滤波精度.

关键词：集中式融合；异步航迹；乱序数据；航迹融合
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Asynchronous Track Fusion Based Out-of-Sequence-Measurement Algorithm

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Abstract: For processing out-of-sequence measurements in the fusion center of a centralized fusion system which arise because of different time delays in transmitting measurements from various sensors to the center, an out-of-sequence measurement (ATFOOSM) algorithm for one-step-lag and multiple-step-lag out-of-sequence measurements is given. In ATFOOSM, the target state of out-of-sequence time (sampling time of out-of-sequence measurement) is obtained by applying Kalman filter to the results filtered before out-of-sequence time. Then, the current target state is updated by using asynchronous track fusion. In simulation, one-step-lag and multiple-step-lag out-of-sequence measurements are processed with both the ATFOOSM and repeated filtering algorithm. Simulation results show that the filtering performance of ATFOOSM is close to that of repeated filtering algorithm.

Keywords: centralized fusion; asynchronous track; out-of-sequence-measurement; track fusion

在集中式融合系统中，当从传感器到融合中心的传输延迟时间存在差异时，同一目标的、来自于不同传感器的测量数据到达融合中心的先后顺序，可能与相应的采样时刻的先后顺序有所不同，从而融合中心最新获得的测量数据的采样时刻，可能小于当前状态数据的生成时刻，即出现乱序数据.

已有的乱序数据处理算法[1-7]可以分成以下3类.

（1）重新排序法：按照采样时刻的先后顺序对相关的测量数据重新进行滤波计算.

（2）状态扩维法：将多个时刻的目标状态信息加入到状态数据中，以实现乱序数据的处理.

（3）状态回退法：利用基于状态回退方程的滤波算法来实现乱序数据下的目标状态更新.

重新排序法完全放弃了已有的滤波结果，计算量太大，难于在实际中应用；状态扩维法需要采用高维的状态数据，滤波计算较为复杂；状态回退法需要

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采用状态回退方程才能实现乱序数据处理.

本文将乱序数据下的目标状态更新问题转换为不同时刻间的航迹数据融合问题,以此提出了基于异步航迹融合的乱序数据处理(ATFOOSM)算法.

1　ATFOOSM 算法

设连续时间下的目标状态方程为 $\dot{\boldsymbol{X}}(t)=\boldsymbol{A}\boldsymbol{X}(t)+\boldsymbol{G}\overline{\boldsymbol{W}}(t)$,$E[\overline{\boldsymbol{W}}(\tau)^{\mathrm{T}}\overline{\boldsymbol{W}}(\tau)]=\bar{\boldsymbol{q}}(t)\delta(t-\tau)$,传感器的测量方程为 $\boldsymbol{Z}(t_k)=\boldsymbol{H}(t_k)\boldsymbol{X}(t_k)+\boldsymbol{V}(t_k)$,$E[\boldsymbol{V}(t_k)\cdot\boldsymbol{V}^{\mathrm{T}}(t_l)]=\boldsymbol{R}(t_k)\delta(t_k-t_l)$,则离散时刻下的目标状态方程为

$$\left.\begin{aligned}\boldsymbol{X}(t_k)&=\boldsymbol{\Phi}(t_k,t_{k-1})\boldsymbol{X}(t_{k-1})+\boldsymbol{W}(t_k,t_{k-1})\\ \boldsymbol{\Phi}(t_k,t_{k-1})&=\boldsymbol{e}^{\boldsymbol{A}(t_k-t_{k-1})}\\ \boldsymbol{W}(t_k,t_{k-1})&=\int_{t_{k-1}}^{t_k}\boldsymbol{\Phi}(t_k,\tau)\boldsymbol{G}\overline{\boldsymbol{W}}(\tau)\mathrm{d}\tau\end{aligned}\right\}\quad(1)$$

$$E[\boldsymbol{W}(t_k,t_{k-1})\boldsymbol{W}^{\mathrm{T}}(t_k,t_{k-1})]=\boldsymbol{Q}(t_k,t_{k-1})=\int_{t_{k-1}}^{t_k}\boldsymbol{\Phi}(t_k,\tau)\boldsymbol{G}\bar{\boldsymbol{q}}(\tau)\boldsymbol{G}^{\mathrm{T}}\boldsymbol{\Phi}^{\mathrm{T}}(t_k,\tau)\mathrm{d}\tau\quad(2)$$

且乱序数据 $Z(t_i)$ 的采样时刻 t_i 满足

$$t_{k+1-l}<t_i<t_{k+1-(l-1)}\leqslant t_{k+1},\quad l\geqslant 1\quad(3)$$

式中:t_{k+1} 是当前状态数据的生成时刻;l 是乱序数据的延迟步数.

1.1　单步延迟下的乱序数据处理

当 $l=1$ 时,由式(3)可得 $t_k<t_i<t_{k+1}$.

设 t_k 时刻的状态数据为 $\boldsymbol{X}(t_k|t_k)=E[\boldsymbol{X}(t)|\boldsymbol{Z}(k)]$($\boldsymbol{Z}(k)=\{Z(t_0),\cdots,Z(t_k)\}$为测量数据累积集合),滤波偏差为 $\widetilde{\boldsymbol{X}}(t_k|t_k)=\boldsymbol{X}(t_k|t_k)-\boldsymbol{X}(t_k)$,则 $Z(t_i)$ 出现前 t_{k+1} 时刻的状态数据、滤波偏差分别为

$$\boldsymbol{X}(t_{k+1}\mid t_k)=\boldsymbol{K}(t_{k+1},t_k)[\boldsymbol{H}(t_{k+1})\boldsymbol{X}(t_{k+1})+\boldsymbol{V}(t_{k+1})]+[\boldsymbol{I}-\boldsymbol{K}(t_{k+1},t_k)\boldsymbol{H}(t_{k+1})]\cdot\boldsymbol{\Phi}(t_{k+1},t_k)\boldsymbol{X}(t_k\mid t_k)$$

$$\widetilde{\boldsymbol{X}}(t_{k+1}\mid t_k)=[\boldsymbol{I}-\boldsymbol{K}(t_{k+1},t_k)H(t_{k+1})]\cdot[\boldsymbol{\Phi}(t_{k+1},t_k)\widetilde{\boldsymbol{X}}(t_k\mid t_k)-\boldsymbol{W}(t_{k+1},t_k)]+\boldsymbol{K}(t_{k+1},t_k)\boldsymbol{V}(t_{k+1})$$

$Z(t_i)$ 出现后,由卡尔曼滤波可得 t_i 时刻的状态数据、滤波偏差分别为

$$\boldsymbol{X}(t_i\mid t_k)=\boldsymbol{K}(t_i,t_k)[\boldsymbol{H}(t_i)\boldsymbol{X}(t_i)+\boldsymbol{V}(t_i)]+[\boldsymbol{I}-\boldsymbol{K}(t_i,t_k)\boldsymbol{H}(t_i)]\boldsymbol{\Phi}(t_i,t_k)\boldsymbol{X}(t_k\mid t_k)$$

$$\widetilde{\boldsymbol{X}}(t_i\mid t_k)=[\boldsymbol{I}-\boldsymbol{K}(t_i,t_k)\boldsymbol{H}(t_i)][\boldsymbol{\Phi}(t_i,t_k)\widetilde{\boldsymbol{X}}(t_k\mid t_k)-\boldsymbol{W}(t_i,t_k)]+\boldsymbol{K}(t_i,t_k)\boldsymbol{V}(t_i)$$

设 $\boldsymbol{P}(t_i|t_k,t_{k+1}|t_k)=E[\widetilde{\boldsymbol{X}}(t_i|t_k)\widetilde{\boldsymbol{X}}^{\mathrm{T}}(t_{k+1}|t_k)]$,则有

$$\boldsymbol{P}(t_i\mid t_k,t_{k+1}\mid t_k)=[\boldsymbol{I}-\boldsymbol{K}(t_i,t_k)\boldsymbol{H}(t_i)]\cdot[\boldsymbol{\Phi}(t_i,t_k)\boldsymbol{P}(t_k\mid t_k)\boldsymbol{\Phi}^{\mathrm{T}}(t_{k+1},t_k)+E[\boldsymbol{W}(t_i,t_k)\cdot\boldsymbol{W}^{\mathrm{T}}(t_{k+1},t_k)]][\boldsymbol{I}-\boldsymbol{K}(t_{k+1},t_k)\boldsymbol{H}(t_{k+1})]^{\mathrm{T}}=\boldsymbol{P}^{\mathrm{T}}(t_{k+1}\mid t_k,t_i\mid t_k)$$

由式(1)可知,$\boldsymbol{W}(t_{k+1},t_k)=\boldsymbol{\Phi}(t_{k+1},t_i)\boldsymbol{W}(t_i,t_k)+W(t_{k+1},t_i)$,则有

$$E[\boldsymbol{W}(t_i,t_k)\boldsymbol{W}^{\mathrm{T}}(t_{k+1},t_k)]=\boldsymbol{Q}(t_i,t_k)\boldsymbol{\Phi}^{\mathrm{T}}(t_{k+1},t_i)$$

设 $Z(t_i)$ 出现后 t_{k+1} 时刻的状态数据 $\boldsymbol{X}_f(t_{k+1})$ 满足

$$\boldsymbol{X}_f(t_{k+1})=\boldsymbol{L}_1\boldsymbol{X}(t_i\mid t_k)+\boldsymbol{L}_2\boldsymbol{X}(t_{k+1}\mid t_k)\quad(4)$$

则有

$$\widetilde{\boldsymbol{X}}_f(t_{k+1})=\boldsymbol{L}_1\widetilde{\boldsymbol{X}}(t_i\mid t_k)+\boldsymbol{L}_2\widetilde{\boldsymbol{X}}(t_{k+1}\mid t_k)+[\boldsymbol{L}_1\boldsymbol{\Phi}(t_i,t_{k+1})+\boldsymbol{L}_2-\boldsymbol{I}]\boldsymbol{X}(t_{k+1})-\boldsymbol{L}_1\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{W}(t_{k+1},t_i)$$

由 $E[\widetilde{\boldsymbol{X}}_f(t_{k+1})]=0$,可得

$$\boldsymbol{L}_2=\boldsymbol{I}-\boldsymbol{L}_1\boldsymbol{\Phi}(t_i,t_{k+1})\quad(5)$$

$$\widetilde{\boldsymbol{X}}_f(t_{k+1})=\boldsymbol{L}_1[\widetilde{\boldsymbol{X}}(t_i\mid t_k)-\boldsymbol{\Phi}(t_i,t_{k+1})\widetilde{\boldsymbol{X}}(t_{k+1}\mid t_k)-\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{W}(t_{k+1},t_i)]+\widetilde{\boldsymbol{X}}(t_{k+1}\mid t_k)\quad(6)$$

$$\begin{aligned}\boldsymbol{P}_f(t_{k+1})=&\boldsymbol{L}_1[\boldsymbol{P}(t_i\mid t_k)-\boldsymbol{P}(t_i\mid t_k,t_{k+1}\mid t_k)\cdot\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})-\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{P}(t_{k+1}\mid t_k,t_i\mid t_k)+\\&\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{P}(t_{k+1}\mid t_k)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})+\boldsymbol{\Phi}(t_i,t_{k+1})\cdot\boldsymbol{Q}(t_{k+1},t_i)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})]\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{L}_1[\boldsymbol{P}(t_i\mid t_k,t_{k+1}\mid t_k)-\\&\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{P}(t_{k+1}\mid t_k)]+[\boldsymbol{P}(t_{k+1}\mid t_k,t_i\mid t_k)-\boldsymbol{P}^{\mathrm{T}}(t_{k+1}\mid t_k)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})]\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{P}(t_{k+1}\mid t_k)\end{aligned}\quad(7)$$

设

$$\begin{aligned}\boldsymbol{M}_1=&\boldsymbol{P}(t_i\mid t_k)-\boldsymbol{P}(t_i\mid t_k,t_{k+1}\mid t_k)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})-\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{P}(t_{k+1}\mid t_k,t_i\mid t_k)+\\&\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{P}(t_{k+1}\mid t_k)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})+\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{Q}(t_{k+1},t_i)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,t_{k+1})\end{aligned}$$

$$\boldsymbol{N}=\boldsymbol{P}(t_i\mid t_k,t_{k+1}\mid t_k)-\boldsymbol{\Phi}(t_i,t_{k+1})\boldsymbol{P}(t_{k+1}\mid t_k)$$

$$\boldsymbol{M}_2=\boldsymbol{P}(t_{k+1}\mid t_k)$$

则式(7)可简化为

$$\boldsymbol{P}_f(t_{k+1})=\boldsymbol{L}_1\boldsymbol{M}_1\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{L}_1\boldsymbol{N}+\boldsymbol{N}^{\mathrm{T}}\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{M}_2$$

由 $\dfrac{\partial\mathrm{tr}[\boldsymbol{P}_f(t_{k+1})]}{\partial\boldsymbol{L}}=0$ 可得

$$\boldsymbol{L}_1=-\boldsymbol{N}^{\mathrm{T}}\boldsymbol{M}_1^{-1}\quad(8)$$

1.2　多步延迟下的乱序数据处理

当 $l>1$ 时,由式(3)可得 $t_{k+1-l}<t_i<t_{k+1-(l-1)}\leqslant t_k<t_{k+1}$.

设 t_{k+1-l} 时刻的状态数据为 $\boldsymbol{X}(t_{k+1-l}|t_{k+1-l})$,滤波偏差为 $\widetilde{\boldsymbol{X}}(t_{k+1-l}|t_{k+1-l})$,且 $Z(t_i)$ 出现前 t_{k+1} 时刻的状态数据为 $\boldsymbol{X}(t_{k+1}\mid t_{k+1-l})$,滤波偏差为 $\widetilde{\boldsymbol{X}}(t_{k+1}|t_{k+1-l})$.

$Z(t_i)$ 出现后,由卡尔曼滤波可得 t_i 时刻状态数据、滤波偏差分别为

$$\boldsymbol{X}(t_i\mid t_{k+1-l})=\boldsymbol{K}(t_i,t_{k+1-l})[\boldsymbol{H}(t_i)\boldsymbol{X}(t_i)+\boldsymbol{V}(t_i)]+$$

$$[\boldsymbol{I}-\boldsymbol{K}(t_i,\ t_{k+1-l})\boldsymbol{H}(t_i)]\boldsymbol{\Phi}(t_i,\ t_{k+1-l})\boldsymbol{X}(t_{k+1-l} \mid t_{k+1-l})$$

$$\widetilde{\boldsymbol{X}}(t_i \mid t_{k+1-l}) = [\boldsymbol{I}-\boldsymbol{K}(t_i,\ t_{k+1-l})\boldsymbol{H}(t_i)][\boldsymbol{\Phi}(t_i,\ t_{k+1-l})\cdot \widetilde{\boldsymbol{X}}(t_{k+1-l} \mid t_{k+1-l})-\boldsymbol{W}(t_i,\ t_{k+1-l})]+\boldsymbol{K}(t_i,\ t_{k+1-l})\boldsymbol{V}(t_i)$$

设 $\boldsymbol{P}(t_i|t_{k+1-l},\ t_{k+1}|t_{k+1-l})=E[\widetilde{\boldsymbol{X}}(t_i|t_{k+1-l})\cdot \widetilde{\boldsymbol{X}}^{\mathrm{T}}(t_{k+1}|t_{k+1-l})]$,则有

$$\boldsymbol{P}(t_i \mid t_{k+1-l},\ t_{k+1} \mid t_{k+1-l}) = [\boldsymbol{I}-\boldsymbol{K}(t_i,\ t_{k+1-l})\cdot \boldsymbol{H}(t_i)]\boldsymbol{\Phi}(t_i,\ t_{k+1-l})E[\widetilde{\boldsymbol{X}}(t_{k+1-l} \mid t_{k+1-l})\cdot \widetilde{\boldsymbol{X}}^{\mathrm{T}}(t_k \mid t_{k+1-l})]\boldsymbol{\Phi}^{\mathrm{T}}(t_{k+1},\ t_k)[\boldsymbol{I}-\boldsymbol{K}(t_{k+1},\ t_k)\cdot \boldsymbol{H}(t_{k+1})]^{\mathrm{T}} = \boldsymbol{P}^{\mathrm{T}}(t_{k+1} \mid t_{k+1-l},\ t_i \mid t_{k+1-l})$$

$$E[\widetilde{\boldsymbol{X}}(t_{k+1-l} \mid t_{k+1-l})\widetilde{\boldsymbol{X}}^{\mathrm{T}}(t_k \mid t_{k+1-l})] = \boldsymbol{P}(t_{k+1-l} \mid t_{k+1-l})\prod_{d=1}^{l-1}\boldsymbol{\Phi}^{\mathrm{T}}(t_{k+1-d},\ t_{k-d})[\boldsymbol{I}-\boldsymbol{K}(t_{k+1-d},\ t_{k-d})\boldsymbol{H}(t_{k+1-d})]^{\mathrm{T}}$$

设 $Z(t_i)$出现后 t_{k+1}时刻的状态数据 $\boldsymbol{X}_f(t_{k+1})$满足

$$\boldsymbol{X}_f(t_{k+1}) = \boldsymbol{L}_1\boldsymbol{X}(t_i \mid t_{k+1-l})+\boldsymbol{L}_2\boldsymbol{X}(t_{k+1} \mid t_{k+1-l}) \tag{9}$$

则有

$$\widetilde{\boldsymbol{X}}_f(t_{k+1}) = \boldsymbol{L}_1\widetilde{\boldsymbol{X}}(t_i \mid t_{k+1-l})+\boldsymbol{L}_2\widetilde{\boldsymbol{X}}(t_{k+1} \mid t_{k+1-l})+[\boldsymbol{L}_1\boldsymbol{\Phi}(t_i,\ t_{k+1})+\boldsymbol{L}_2-\boldsymbol{I}]\boldsymbol{X}(t_{k+1})-\boldsymbol{L}_1\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{W}(t_{k+1},\ t_i)$$

由 $E[\widetilde{\boldsymbol{X}}_f(t_{k+1})]=0$,可得

$$\boldsymbol{L}_2 = \boldsymbol{I}-\boldsymbol{L}_1\boldsymbol{\Phi}(t_i,\ t_{k+1}) \tag{10}$$

$$\widetilde{\boldsymbol{X}}_f(t_{k+1}) = \boldsymbol{L}_1[\widetilde{\boldsymbol{X}}(t_i \mid t_{k+1-l})-\boldsymbol{\Phi}(t_i,\ t_{k+1})\widetilde{\boldsymbol{X}}(t_{k+1} \mid t_{k+1-l})-\boldsymbol{\Phi}(t_i,\ t_{k+1})\cdot \boldsymbol{W}(t_{k+1},\ t_i)]+\widetilde{\boldsymbol{X}}(t_{k+1} \mid t_{k+1-l}) \tag{11}$$

$$\begin{aligned}\boldsymbol{P}_f(t_{k+1}) = {}& \boldsymbol{L}_1[\boldsymbol{P}(t_i \mid t_{k+1-l})-\boldsymbol{P}(t_i \mid t_{k+1-l},\ t_{k+1} \mid t_{k+1-l})\boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})-\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{P}(t_{k+1} \mid t_{k+1-l},\ t_i \mid t_{k+1-l})+\\&\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{P}(t_{k+1} \mid t_{k+1-l})\boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})+\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{Q}(t_{k+1},\ t_i)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})]\boldsymbol{L}_1^{\mathrm{T}}+\\&\boldsymbol{L}_1[\boldsymbol{P}(t_i \mid t_{k+1-l},\ t_{k+1} \mid t_{k+1-l})-\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{P}(t_{k+1} \mid t_{k+1-l})]+\\&[\boldsymbol{P}(t_{k+1} \mid t_{k+1-l},\ t_i \mid t_{k+1-l})-\boldsymbol{P}^{\mathrm{T}}(t_{k+1} \mid t_{k+1-l})\boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})]\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{P}(t_{k+1} \mid t_{k+1-l})\end{aligned} \tag{12}$$

设

$$\begin{aligned}\boldsymbol{M}_1 = {}& \boldsymbol{P}(t_i \mid t_{k+1-l})-\boldsymbol{P}(t_i \mid t_{k+1-l},\ t_{k+1} \mid t_{k+1-l})\cdot \boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})-\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{P}(t_{k+1} \mid t_{k+1-l},\ t_i \mid t_{k+1-l})+\\&\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{P}(t_{k+1} \mid t_{k+1-l})\boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})+\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{Q}(t_{k+1},\ t_i)\boldsymbol{\Phi}^{\mathrm{T}}(t_i,\ t_{k+1})\end{aligned}$$

$$\boldsymbol{N}=\boldsymbol{P}(t_i \mid t_{k+1-l},\ t_{k+1} \mid t_{k+1-l})-\boldsymbol{\Phi}(t_i,\ t_{k+1})\boldsymbol{P}(t_{k+1} \mid t_{k+1-l})$$

$$\boldsymbol{M}_2 = \boldsymbol{P}(t_{k+1} \mid t_{k+1-l})$$

则式(12)可简化为

$$\boldsymbol{P}_f(t_{k+1}) = \boldsymbol{L}_1\boldsymbol{M}_1\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{L}_1\boldsymbol{N}+\boldsymbol{N}^{\mathrm{T}}\boldsymbol{L}_1^{\mathrm{T}}+\boldsymbol{M}_2$$

由$\dfrac{\partial \mathrm{tr}[\boldsymbol{P}_f(t_{k+1})]}{\partial \boldsymbol{L}}=0$ 可得

$$\boldsymbol{L}_1 = -\boldsymbol{N}^{\mathrm{T}}\boldsymbol{M}_1^{-1} \tag{13}$$

综上,ATFOOSM 算法的执行步骤描述如下.

(1)利用 $Z(t_i)$进行滤波计算得到状态数据 $\boldsymbol{X}(t_i|t_k)$和 $\boldsymbol{P}(t_i|t_k)$.

(2)由式(8)、式(5)或式(13)、式(10)计算最优加权系数 $\boldsymbol{L}_1$ 和 $\boldsymbol{L}_2$.

(3)由式(4)或式(9)得到更新后的当前状态数据 $\boldsymbol{X}_f(t_{k+1})$.

2 仿真结果

下面通过仿真计算来验证 ATFOOSM 算法的有效性.

设传感器 S_1 和 S_2 同时对目标 T 进行跟踪,采样起始时间分别为 0.2 s 和 0.4 s,采样周期 T_{s} 均为 0.4 s,传感器 S_1 到融合中心的传输延迟时间为 0,目标 T 的运动方程为 $x(t)=vt$,$v=10$ m/s,$0\leqslant t\leqslant 30$ s,融合中心的滤波方程为

$$\boldsymbol{X}=[x,\ \dot{x}]^{\mathrm{T}}$$

$$\boldsymbol{\Phi}=\begin{bmatrix}1 & T_{\mathrm{s}}\\ 0 & 1\end{bmatrix}$$

$$\boldsymbol{Q}=\begin{bmatrix}T_{\mathrm{s}}^4 & 2T_{\mathrm{s}}^3\\ 2T_{\mathrm{s}}^3 & 4T_{\mathrm{s}}^2\end{bmatrix}$$

$$\boldsymbol{H}=[1\quad 0]$$

$$R=25$$

下面采用 3 种方式对滤波过程中的乱序数据进行处理:①所有的乱序数据一律舍弃;②采用 ATFOOSM 算法;③采用重新排序算法,并且采用下述设置条件进行仿真.

(1)传感器 S_2 到融合中心的传输延迟时间为 0.3 s,融合中心利用传感器 S_1 和 S_2 的测量数据进行目标跟踪,传感器 S_2 的测量数据为单步延迟的乱序数据,由此得到的目标位置误差分布如图 1 所示.

(2)传感器 S_2 到融合中心的传输延迟时间为 0.8s,融合中心利用传感器S_1和S_2的测量数据进

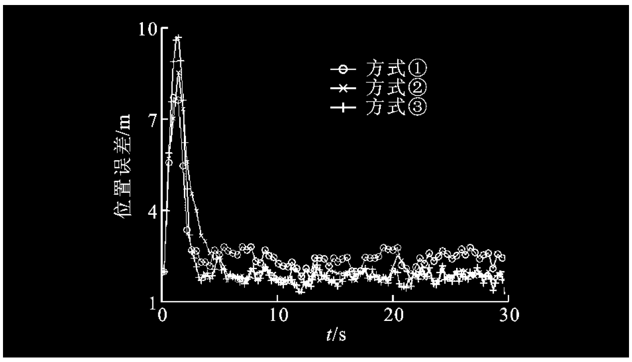

图 1 单步延迟下的乱序数据处理结果

行目标跟踪，传感器 S_2 的测量数据为多步延迟的乱序数据，由此得到的目标位置误差分布如图 2 所示.

由图 1、图 2 可知：方式①的滤波精度最低，方式③的滤波精度最高；方式②的滤波精度高于方式①，略低于方式③.

方式①在滤波过程未处理乱序数据，虽然浪费了部分测量数据，但数据处理速度最快；方式③需要对排序后的测量数据重新滤波，在改善滤波精度的同时大大降低了数据处理的速度；方式②仅对乱序数据进行滤波处理，与方式③相比，具有更好的实时性能.

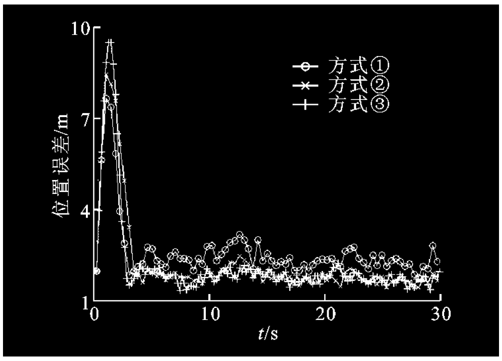

图 2　多步延迟下的乱序数据处理结果

综上，ATFOOSM 算法具有较高的滤波精度和较好的实时性能，是一种有效的乱序数据处理算法.

3　结束语

本文将乱序数据下的目标状态更新问题转换为不同时刻间的航迹数据融合问题，以此提出了基于异步航迹融合的乱序数据处理算法. 仿真结果验证了所提算法是有效的.

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