A Test Method for the Static/Moving State of Targets Applied to Airport Surface Surveillance MLAT System

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Abstract: Due to the particularity of its location algorithm, there are some unique difficulties and features regarding the test of target motion states of multilateration (MLAT) system for airport surface surveillance. This paper proposed a test method applicable for the airport surface surveillance MLAT system, which can effectively determine whether the target is static or moving at a certain speed. Via a normalized test statistic designed in the sliding data window, the proposed method not only eliminates the impact of geometry Dilution of precision (GDOP) effectively, but also transforms the test of different motion states into the test of different probability density functions. Meanwhile, by adjusting the size of the sliding window, it can fulfill different test performance requirements. The method was developed through strict theoretical extrapolation and performance analysis, and simulations results verified its correctness and effectiveness.

Key words: multilateration (MLAT); hypothesis testing; motion state detection; sliding window; geometric Dilution of precision (GDOP)

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0 Introduction

Multilateration (MLAT) is a novel positioning technology, and the fundamental principle is to identify locations using time difference of arrival (TDOA)[1]. MLAT system is featured with high positioning accuracy, strong anti-interference capability and good redundancy, which is a basic component of the next generation airport surface surveillance system proposed by International Civil Aviation Organization (ICAO)[2-3].

Airport surface surveillance refers to the process of detecting, positioning, correlating and tracking aircraft and service vehicles in civil airports. The localization signal of airport surface surveillance system based on MLAT technology may come from the transponder and automatic broadcasting signal of aircraft and vehicles[4]. When designing a complete airport surface surveillance system, it not only requires to accurately determine the positions of aircraft and vehicles, but also to detect and determine their motion states, for instance, whether the target is static or moving at a certain speed[5-6].

Detecting target motion state is ultimately a decision-making process or a hypothetic testing problem[7]. Traditional test methods of motion states construct the test statistics according to the target moving model and noise characteristics, then compare the statistics value with selected thresholds, and thus determine the motion state of targets. In general, noise is considered as stationary white Gaussian noise, which also coincides with many practical conditions[8-9].

MLAT location algorithm is based on TDOA, which means the related localization equation is nonlinear. Many processing techniques

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have been proposed with different complexity and restrictions. Linearizing the nonlinear equation by Taylor-series expansion and then solving iteratively is one possible way[10]. Chan adopted two liner approximate equations and the corresponding weighted least squares method to estimate target position. Thanks to its linear closed-form solution, Chan algorithm has been widely used in practical engineering[11]. In 2006, Chan proposed approximate maximum likelihood (AML) method, which can attain the theoretical lower bound, but is unable to fulfill the requirements of practical engineering due to its complex calculations[12]. Huang analyzed the influence of target height difference on three stations positioning accuracy[13]. Sharp and Hahn proposed location method of a three-station with auxiliary height difference. However, this method can only be applied when the geometric relationship between the satellite and the Earth is special[14-15]. A novel method is proposed by Yang et al. that uses known pressure altitudes to improve positioning accuracy in MLAT. But there is no in-depth analysis of the theoretical positioning accuracy and robustness of the method[16].

Due to the particularity of MLAT location algorithm, the errors of estimated target position are related to TDOA measurement accuracy, layout of receiving stations, as well as the relative geometric positions between the target and the set of receiving stations, meaning the location noise of MLAT is related to multiple error variables[17-18]. The application of traditional detection algorithms of target motion state may lead to the degradation of detection performance and even to the failure. Regarding this problem, there is little research at home and abroad and no effective solutions. Yuan and Chen propose a detection algorithm of static state using the features of positioning error and ant colony algorithm[19]. However, this algorithm is rather complex and the calculation is heavy, which therefore is not suitable for the implementation of engineering applications.

This paper proposed a detection method of motion states of airport surface targets based on MLAT systems. The detection method combines the characteristics of MLAT location algorithm, and implements the detection through the designed normalized test statistic within a sliding data window. The proposed method works on the principle that when the target remains static or moving, the normalized test statistic obeys different distributions (central Chi square or non-central Chi square distribution). Through normalization and adjusting the size of sliding window, the proposed method not only eliminates the effects of geometry dilution of precision (GDOP) on detection performance, but also is able to fulfill different detection requirements.

The context of this paper is organized as below: Section 0 is introduction, and Section 1 describes the detailed derivation and performance analysis of the proposed method. Section 2 provides the details of simulation verification. Finally, we draw the conclusion.

1 Theoretical Derivation and Performance Analysis

In the following derivation process, we first presented the formula of static/moving state based on binary hypothesis test, and used the data within a sliding window to implement linear transformation in order to develop a normalized test statistic. The goal is to eliminate the effects of GDOP, and to transform the test of target motion state into the test of the probability density functions.

1.1 Motion state test based on binary hypothesis test

Based on binary hypothesis test, the formula in terms of a target motion state (static/moving) can be represented as

$$\begin{cases} H_0:\{x_{tk}=x^0_{t(k-1)}+\eta_{xk}\}\&\&\{y_{tk}=y^0_{t(k-1)}+\eta_{yk}\} \\ H_1:\{x_{tk}=x^0_{t(k-1)}+v_{xk}(t_k-t_{k-1})+\eta_{xk}\}\parallel\{y_{tk}=y^0_{t(k-1)}+v_{yk}(t_k-t_{k-1})+\eta_{yk}\} \end{cases} \tag{1}$$

where H_0 and H_1 denote the target is static and moving, respectively; $x^0_{t(k-1)}$, $y^0_{t(k-1)}$, x_{tk}, y_{tk} the target′s true and estimated value on x axis and y axis at time t_{k-1}, t_k respectively; v_{xk} and v_{yk} the velocity of the target on x axis and y axis over the interval $[t_{k-1}, t_k]$ (this paper only discusses the case that a target remain state of uniform motion); η_{xk} and η_{yk} the MLAT location errors on x axis and y axis at time t_k, & and ‖ the logic ″and″ and ″or″, respectively.

In the following processes, we will define a sliding window consisting of N position samples of a target (the positions of N samples is estimated by MLAT system), and use the Nth sample(x_N, y_N) to subtract the rest samples (x_i, y_i), respectively ($i=1,\cdots,N-1$), thus we can obtain the difference d_{xNi}, d_{yNi} ($i=1,\cdots,N-1$) corresponding to x, y axis

$$\begin{cases} d_{xN1} = x_N - x_1 \\ d_{xN2} = x_N - x_2 \\ \quad\vdots \\ d_{xNN-1} = x_N - x_{N-1} \end{cases} \qquad \begin{cases} d_{yN1} = \eta_{yN} - \eta_{y1} \\ d_{yN2} = \eta_{yN} - \eta_{y2} \\ \quad\vdots \\ d_{yNN-1} = \eta_{yN} - \eta_{yN-1} \end{cases} \tag{2}$$

When the target remain static, namely $v_{xk}=v_{yk}=0$ in Eq. (1), then the concrete form of Eq. (2) is

$$\begin{cases} d_{xN1} = \eta_{xN} - \eta_{x1} \\ d_{xN2} = \eta_{xN} - \eta_{x2} \\ \quad\vdots \\ d_{xNN-1} = \eta_{xN} - \eta_{xN-1} \end{cases} \qquad \begin{cases} d_{yN1} = \eta_{yN} - \eta_{y1} \\ d_{yN2} = \eta_{yN} - \eta_{y2} \\ \quad\vdots \\ d_{yNN-1} = \eta_{yN} - \eta_{yN-1} \end{cases} \tag{3}$$

Here we construct difference vector $\boldsymbol{d}_{wx} = [d_{xN1}, d_{xN2}, \cdots, d_{xNN-1}]^{\mathrm{T}}$, $\boldsymbol{d}_{wy} = [d_{yN1}, d_{yN2}, \cdots, d_{yNN-1}]^{\mathrm{T}}$ for x axis and y axis with $N-1$ values in Eq. (3), respectively, and where $[\,\cdot\,]^{\mathrm{T}}$ represents transposition.

Therefore, we can use vector $\boldsymbol{d}_{wx}$ to construct the test statistics in order to perform motion test on x axis (without losing the generality, the procedure and conclusion of $\boldsymbol{d}_{wy}$ is similar to $\boldsymbol{d}_{wx}$). The specific steps for deciding whether a target is static or moving are as follows:

Step 1 Derive the covariance matrix of $\boldsymbol{d}_{wx}$ based on MLAT location algorithm characteristic when the target is static.

Step 2 $\boldsymbol{d}_{xy}$ is normalized using the covariance matrix, and to obtain appropriate test statistics.

Step 3 Obtain the detection threshold $M_{x\xi}$ according to the distribution of test statistics and performance requirement.

Step 4 Determine the motion state of the target using the test statistic and properly chosen threshold in step 2 and 3.

The detailed descriptions of those steps above is as follow. When the state of target is H_0 (namely the state of target is static), the covariance matrix of $\boldsymbol{d}_{wx}$ could be expressed as follows according to Eq. (3).

$$\boldsymbol{D}_{xx} = E\{\boldsymbol{d}_{wx}\boldsymbol{d}_{wx}^{\mathrm{T}}\} = E\left\{\begin{bmatrix} (\eta_{xN}-\eta_{x1})(\eta_{xN}-\eta_{x1}), (\eta_{xN}-\eta_{x1})(\eta_{xN}-\eta_{x2}), \cdots, (\eta_{xN}-\eta_{x1})(\eta_{xN}-\eta_{xN-1}) \\ (\eta_{xN}-\eta_{x2})(\eta_{xN}-\eta_{x1}), (\eta_{xN}-\eta_{x2})(\eta_{xN}-\eta_{x2}), \cdots, (\eta_{xN}-\eta_{x2})(\eta_{xN}-\eta_{xN-1}) \\ \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ (\eta_{xN}-\eta_{xN-1})(\eta_{xN}-\eta_{x1}), (\eta_{xN}-\eta_{xN-1})(\eta_{xN}-\eta_{x2}), \cdots, (\eta_{xN}-\eta_{xN-1})(\eta_{xN}-\eta_{xN-1}) \end{bmatrix}\right\} \tag{4}$$

Since η_{xi} is usually assumed to be Gaussian white noise with zero mean, then, $E\{\eta_{xi}\}=0$ ($i=1,\cdots,N$) and $E\{\eta_{xi}\eta_{xj}\} = \begin{cases} E\{\eta_{xi}\}E\{\eta_{xj}\}=0, & i\neq j \\ E\{(\eta_{xi})^2, & i=j \end{cases}$, so that in Eq. (4) $E\{(\eta_{xN}-\eta_{xi})(\eta_{xN}-\eta_{xj})\} = \begin{cases} E\{(\eta_{xN})^2\} & i\neq j \\ E\{(\eta_{xN})^2\}+E\{(\eta_{xi})^2\} & i=j \end{cases}$, and thus $\boldsymbol{d}_{wx}$ is a $(N-1)$ dimensional Gaussian random vector, then Eq. (4) might be simplified as

$$\boldsymbol{D}_{xx} = E\{\boldsymbol{d}_{wx}\boldsymbol{d}_{wx}^{\mathrm{T}}\} = \begin{bmatrix} E\{(\eta_{xN})^2\}+E\{(\eta_{x1})^2\}, E\{(\eta_{xN})^2\}, E\{(\eta_{xN})^2\}, \cdots, E\{(\eta_{xN})^2\} \\ E\{(\eta_{xN})^2\}, E\{(\eta_{xN})^2\}+E\{(\eta_{x2})^2\}, E\{(\eta_{xN})^2\}, \cdots, E\{(\eta_{xN})^2\} \\ \vdots \qquad\qquad \vdots \\ E\{(\eta_{xN})^2\}, E\{(\eta_{xN})^2\}, E\{(\eta_{xN})^2\}, \cdots, E\{(\eta_{xN})^2\}+E\{(\eta_{xN-1})^2\} \end{bmatrix} \tag{5}$$

According to Chan and Sharp[12,14], $E\{(\eta_{xi})^2\}, i=1,\cdots,N$ in Eq. (5) not only relates to receiver thermal noise, but also to the relative positions between target and stations, and the relationship between them is

$$\boldsymbol{\Phi}_{xy}=c^2\left(\frac{\partial \boldsymbol{r}^{\mathrm{T}}}{\partial \boldsymbol{z}_{\mathrm{p}}}\boldsymbol{Q}^{-1}\frac{\partial \boldsymbol{r}}{\partial \boldsymbol{z}_{\mathrm{p}}}\right)^{-1}\sigma_{\mathrm{TOA}}^2 \tag{6}$$

where $\boldsymbol{r}=[r_{2,1}^0,r_{3,1}^0,\cdots,r_{M,1}^0]^{\mathrm{T}}$ denotes $M-1$ noise free values of range difference between the first station with respect to the others, namely $r_{i,1}^0=r_i^0-r_1^0, i=2,\cdots,M$, and $r_i=\sqrt{(x_t-x_i)^2+(y_t-y_i)^2+(z_t^0-z_i)^2}$, where (x_i,y_i,z_i) is known location of station; c is the electromagnetic wave speed; $\boldsymbol{z}_{\mathrm{p}}=[x_t,y_t]^{\mathrm{T}}$ the position of the target (for the height of target z_t^0 at airport surface is known, it can be ignored in z_{p}), $\boldsymbol{Q}$ the covariance matrix of estimated TDOA, σ_{TOA}^2 is the variance of measured time of arrival (TOA). Set $\boldsymbol{G}_t=\frac{\partial \boldsymbol{r}}{\partial \boldsymbol{z}_{\mathrm{p}}}$, the following could be derived[11]

$$\boldsymbol{G}_t=\begin{bmatrix}(x_t-x_2)/r_2-(x_t-x_1)/r_1, & (y_t-y_2)/r_2-(y_t-y_1)/r_1\\(x_t-x_3)/r_3-(x_t-x_1)/r_1, & (y_t-y_3)/r_3-(y_t-y_1)/r_1\\ \vdots & \vdots\\(x_t-x_M)/r_M-(x_t-x_1)/r_1, & (y_t-y_M)/r_M-(y_t-y_1)/r_1\end{bmatrix} \tag{7}$$

To calculate the value of $\boldsymbol{\Phi}_{xy}$ in Eq. (6), getting the true position of target is needed, namely (x_t, y_t), which is unknown in practice. Nevertheless, $\boldsymbol{\Phi}_{xy}$ can be approximated by means of estimated target position $(\hat{x}_t, \hat{y}_t)$. According to Ref. [13], $E\{(\eta_{xi})^2\}=[\boldsymbol{\Phi}_{xy}^i]_{11}$, where, $\boldsymbol{\Phi}_{xy}^i$ is the error covariance matrix of the i th sample in sliding window (which can be considered approximately as CRLB of the i th sample), and $[\boldsymbol{\Phi}_{xy}^i]_{pq}$ expresses element at the p th row and the q th column in matrix $\boldsymbol{\Phi}_{xy}^i$, and then, $\boldsymbol{D}_{xx}$ in Eq. (5) could be expressed as follows

$$\boldsymbol{D}_{xx}=\begin{bmatrix}[\boldsymbol{\Phi}_{xy}^N]_{11}+[\boldsymbol{\Phi}_{xy}^1]_{11}, & [\boldsymbol{\Phi}_{xy}^N]_{11}, & [\boldsymbol{\Phi}_{xy}^N]_{11}, & \cdots, & [\boldsymbol{\Phi}_{xy}^N]_{11}\\ [\boldsymbol{\Phi}_{xy}^N]_{11}, & [\boldsymbol{\Phi}_{xy}^N]_{11}+[\boldsymbol{\Phi}_{xy}^2]_{11}, & [\boldsymbol{\Phi}_{xy}^N]_{11}, & \cdots, & [\boldsymbol{\Phi}_{xy}^N]_{11}\\ \vdots & \vdots & \vdots & & \vdots\\ [\boldsymbol{\Phi}_{xy}^N]_{11}, & [\boldsymbol{\Phi}_{xy}^N]_{11}, & [\boldsymbol{\Phi}_{xy}^N]_{11}, & \cdots, & [\boldsymbol{\Phi}_{xy}^N]_{11}+[\boldsymbol{\Phi}_{xy}^{N-1}]_{11}\end{bmatrix} \tag{8}$$

When the state of target is static, and all the samples of receiving stations set are the same (in actual situation it could be usually met), namely $\boldsymbol{\Phi}_{xy}^1=\boldsymbol{\Phi}_{xy}^2=\cdots=\boldsymbol{\Phi}_{xy}^N$, so $\boldsymbol{D}_{xx}$ could be simplified as

$$\boldsymbol{D}_{xx}=[\boldsymbol{\Phi}_{wxy}]_{11}\begin{bmatrix}2 & 1 & 1 & \cdots & 1\\1 & 2 & 1 & \cdots & 1\\ \vdots & \vdots & \vdots & \ddots & \vdots\\1 & 1 & 1 & \cdots & 2\end{bmatrix}=[\boldsymbol{\Phi}_{wxy}]_{11}\boldsymbol{P} \tag{9}$$

where $\boldsymbol{\Phi}_{wxy}=\boldsymbol{\Phi}_{xy}^1=\boldsymbol{\Phi}_{xy}^2=\cdots=\boldsymbol{\Phi}_{xy}^N$,

$$\boldsymbol{P}=\begin{bmatrix}2 & 1 & 1 & \cdots & 1\\1 & 2 & 1 & \cdots & 1\\ \vdots & \vdots & \vdots & \ddots & \vdots\\1 & 1 & 1 & \cdots & 2\end{bmatrix}$$

To deal with d_{wx} through normalization processing as follows, the influence on test process caused by relative localization geometry between target and stations can be eliminated. Then normalized statistic quantity $\boldsymbol{\xi}_{xk}$ for test process can be gotten

$$\boldsymbol{\xi}_{xk}=\boldsymbol{d}_{wx}^{\mathrm{T}}\boldsymbol{D}_{xx}^{-1}\boldsymbol{d}_{wx} \tag{10}$$

Substitut Eq. (9) into Eq. (10) gives

$$\boldsymbol{\xi}_{xk}=\boldsymbol{d}_{wx}^{\mathrm{T}}\boldsymbol{D}_{xx}^{-1}\boldsymbol{d}_{wx}=\boldsymbol{d}_{wx}^{\mathrm{T}}\boldsymbol{P}^{-1}\boldsymbol{d}_{wx}/[\boldsymbol{\Phi}_{wxy}]_{11} \tag{11}$$

It is well known that $\|y-\bar{y}\|_{\sum^{-1}}^2=(y-\bar{y})^{\mathrm{T}}\sum^{-1}(y-\bar{y})$ is χ^2 distributed with n degrees of freedom for any n-dimensional Gaussian random vector $y\sim N(\bar{y},\sum)$[20]. In this, when the state of target is static, $\boldsymbol{d}_{wx}$ is $(N-1)$-dimensional Gaussian random vector with $\boldsymbol{d}_{wx}\sim N(0,\boldsymbol{D}_{xx})$ and thus the probability density function (PDF) of $\boldsymbol{\xi}_{xk}$ in Eq. (10) is Chi-square distributed with $(N-1)$ degree of freedom, and when the state of target is moving, according to Eq. (1), then $E\{\boldsymbol{d}_{wx}\}=[v_{xk}(t_N-t_1),v_{xk}(t_N-t_2),\cdots,v_{xk}(t_N-t_{N-1})]^{\mathrm{T}}$, where, $t_i, i=1,\cdots,N$ expresses TOA of the ith sample within the window, and ξ_{xk} can be considered as a non-central Chi-square, with the non-central parameters being a function of window size N, target velocity v_{xk}, and TOA $t_i, i=1,\cdots,N$. In this sense, Chi-square test provides a check of the goodness of fit to judge target motion state. Therefore, the test for motion state could be converted into test for probability density function.

1.2 Motion state test based on probability density function

By properly choosing the level of confidence, the threshold value $M_{x\xi}$ can be determined, and hypothesis testing for static or moving target could be made as

$$\begin{cases} H_0 : \boldsymbol{\xi}_{xk} < M_{x\xi} \\ H_1 : \boldsymbol{\xi}_{xk} \geq M_{x\xi} \end{cases} \tag{12}$$

In conclusion, the concrete steps of the test method proposed in this paper applied to judge whether a target is static or moving state are as follows:

(1) Determine the sliding window size N according to performance requirements, and determine threshold $M_{x\xi}$ and $M_{y\xi}$ according to level of confidence. Calculate $\boldsymbol{d}_{wx}$ and $\boldsymbol{d}_{wy}$ in sliding window, respectively.

(2) Calculate $\boldsymbol{D}_{xx}$, $\boldsymbol{D}_{yy}$, $\boldsymbol{D}_{xx}^{-1}$ and $\boldsymbol{D}_{yy}^{-1}$ according to Eq. (8) or Eq. (9).

(3) Calculate normalized statistic $\boldsymbol{\xi}_{xw} = \boldsymbol{d}_{wx}^{\mathrm{T}} \boldsymbol{D}_{xx}^{-1} \boldsymbol{d}_{wx}$ and $\boldsymbol{\xi}_{yw} = \boldsymbol{d}_{wy}^{\mathrm{T}} \boldsymbol{D}_{yy}^{-1} \boldsymbol{d}_{wy}$, when both $\boldsymbol{\xi}_{xw} < M_{x\xi}$ and $\boldsymbol{\xi}_{yw} < M_{y\xi}$ exist, it can be deduced that the state of target is static, otherwise, it is moving.

(4) To make repetitive judgment according to the steps described above as the next sample slides into the window.

Note: When the condition of Eq. (9) is met, namely $\boldsymbol{D}_{xx}^{-1} = \boldsymbol{P}^{-1} / [\boldsymbol{\Phi}_{wxy}]_{11}$ and $\boldsymbol{D}_{yy}^{-1} = \boldsymbol{P}^{-1} / [\boldsymbol{\Phi}_{wxy}]_{22}$, in practice the matrix $\boldsymbol{P}^{-1}$ applied could be calculated in advance so as to decrease computational complexity.

2 Simulation

Simulation was carried out to verify the validity of the proposed method. Chan algorithm was applied to simulation to estimate the target location. There were 8 stations and the (x, y, z) coordinates of each station were (−114.199 28, 2 913.697 04, −3.489 79), (−331.837 08, −240.138 36, −5.383 16), (586.891 45, 1 854.460 46, 28.302 10), (683.941 72, 3 116.517 55, 18.578 23), (556.024 14, 1 166.376 65, −4.601 39), (−331.926 47, 422.073 61, −4.512 67), (0, 0, 0), and (−0.098 85, 3 527.896 14, −5.710 45) (these coordinates also are the actual station coordinates of MLAT at Guilin Liangjiang International Airport). The target coordinates was (−360, 300, −10), the time interval of samples was 1 s, the TOA noise was set as Gaussian white noise with standard deviation 3 ns. The experimental PDFs came from 10 000 independent Monte Carlo trials.

The simulation generated the PDFs when the target was static or moving at a certain speed, in order to validate the correctness of the proposed method, as well as to assess its performance. The simulation consisted of the following two parts:

(1) By comparing the degree of coincidence of simulated PDFs and theoretical PDFs (in static state), we verifed the correctness of theory analysis;

(2) We generatd the PDFs when the target was static and moving at different speeds and in different sizes of sliding window. The PDF when target remained static was overlapped with those when target moved at different speed with different sliding window size. The comparisons of the overlaps showed the effects of target speed and window size on test performance which could be quantitatively assessed (since false detecting and leaking detecting probabilities were related to the overlap extent of the PDFs).

2.1 Comparison of simulated and theoretical PDFs

Fig. 1 shows the theoretical and simulated values of PDFs when target was static and the sizes of sliding window were 3, 5 and 7, respectively (in that case the theoretical PDFs were central χ^2 PDFs with 2, 4, 6 degrees of freedom). As shown in the Fig. 1, the simulated results fit well with the theoretical values. It proves the correctness of previous derivation.

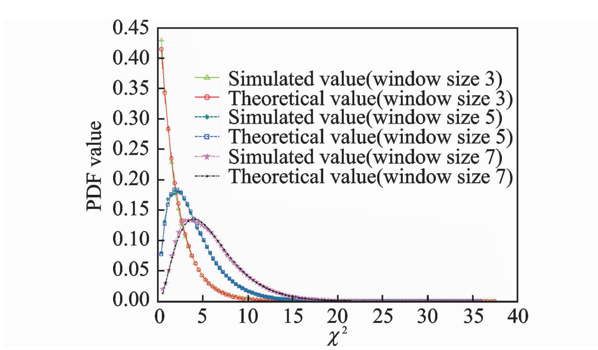

Fig. 1 Simulated and theoretical PDFs in different sizes of sliding window (target is static)

2.2 Performance comparisons

Let P_{fd} denotes the probability of false detection, i. e., when target is moving but is determined to be static. Let P_{ld} denotes the probability of leaking detection; i. e., when target is static but the decision is moving. To improve the test performance (i. e. reduce P_{fd} and P_{ld} at the same time), it requires the overlapping area of the PDF for static target and the PDFs for moving target to be as small as possible.

We simulated the PDFs, when the target was static and moving at different velocities and in different sizes of sliding window, in order to assess the effects of target speed and window size on test performance.

The selected parameters in the simulation were as follows:

(1) The size of sliding window was 3, and the velocity of target was 0.5 m/s, 1 m/s, and 1.3 m/s, respectively.

(2) The size of sliding window was 5, and the velocity of target was 0.5 m/s, 0.6 m/s, and 1.0 m/s, respectively.

(3) Both significance level and false detection probability P_{fd} were set as 0.05.

Figs. 2, 3 show the simulation results As x axis was similar to y axis, only x axis was simulated.

From above analysis we can see that, with the static target and window size of 3, the distribution of test statistics was centralized χ^2 distribution with 2 degrees of freedom. In that case the corresponding detection threshold was obtained to be 6 (namely $M_{x\xi}=6$) from the distribution. In Fig. 2, when the target velocity was 0.5 m/s, 1 m/s and 1.3 m/s, the corresponding PDF was non-centralised χ^2 distribution (2 degrees of freedom). By calculation, the simulated non-central Chi-square areas to the left of $M_{x\xi}$ were 0.693, 0.145, 0.023 successively when the target velocity values were 0.5 m/s, 1m/s and 1.3 m/s, respectively (namely corresponding P_{fd} were 0.693, 0.145, 0.023, respectively). Obviously, it indicates that only when the target is moving at 1.3 m/s and the size of sliding window is 3, the proposed method is able to fulfill the performance requirements of P_{fd}.

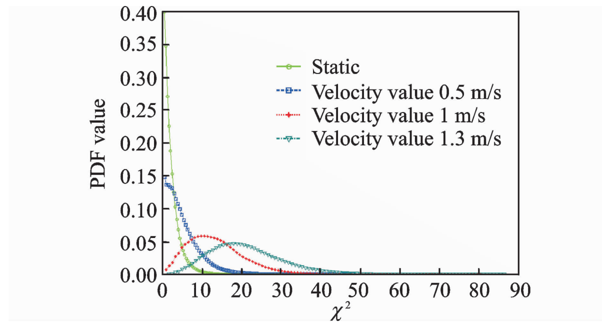

Fig. 2 PDFs with different speed when the size of sliding window is 3

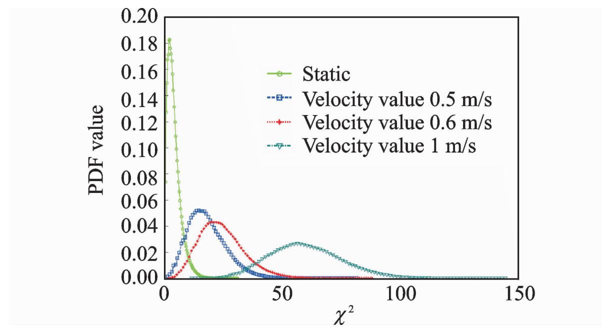

Fig. 3 PDFs with different speed when the size of sliding window is 5

With the static target and window size of 5, the distribution of test statistics was centralized χ^2 distribution with 4 degrees of freedom. In the same way above, we obtained detection threshold ($M_{x\xi}=9.49$). The data in Fig. 3 indicate that, when the velocity of target was 0.5 m/s, 0.6 m/s and 1 m/s, the simulated non-centralized χ^2 distribution (4 degrees of freedom) areas to the left of $M_{x\xi}$ were 0.133, 0.039 and 0.0, respectively (i. e. corresponding P_{fd} are 0.133, 0.039 and 0.0, respectively).

Apparently, it indicates that when the window size is set to 5, the target with velocity of 0.6 m/s is able to fulfill the requirements of P_{fd}.

Known in Figs. 2, 3, along with the increasing window size and target velocity, the overlapping area of centralized χ^2 distribution (target remain static) and non-centralized χ^2 distribution (target is moving) would be decreased. This will reduce the probability of false detection and the probability of leaking detection at the same time, with the disadvantage of increasing amount of calculation.

From above simulation results we can see that, the window size and target velocity significantly affect the test performance. In practice, it may choose properly size of window according to the system performance requirements.

3 Conclusions

This paper proposed a method of determining the static/moving state of targets, which is applied to MLAT system for airport surface surveillance. Using designed test statistics, this method constructs different PDFs to represent the static/moving state of targets, and uses it as the basis of binary hypothesis test. The main characteristics of this method are as follows:

(1) It eliminates the effects of GDOP on estimation error in MLAT system, which enables the test performance to have no connection with the relative geometric location between targets and stations;

(2) The size of sliding data window can be adjusted to fulfill different requirements of test performance.

As the theoretical basis of the state judging module in A-SMGCS, the proposed method has already been applied to the demonstration project of MLAT experimental system at Guilin Liangjiang International Airport.

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