UKF-based underground intrusion localization algorithm for optical-fibre sensing perimeter protection

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Abstract

To improve the precision of the underground intrusion localization in the optical-fibre sensing perimeter protection application, an intrusion localization algorithm based on the Unscented Kalman Filter (UKF) is presented. The geometrical relationships of the sensors and the intruder are analysed and the state equation and the measurement model are deduced. Then the UKF algorithm is used to estimate and track the location of the intruder. The simulations demonstrate that the algorithm improves the intrusion localization precision and the intruder can be tracked even if no enough sensors detect the intrusion signal.

Keywords: Optical-Fibre Sensor, Underground Intrusion Detection, State Estimation, Unscented Kalman Filter

1 Introduction

The optical fibre sensing-based intrusion detection technologies have been widely used in perimeter security protection systems, with the characters of high vibrational sensitivity together with electromagnetic interference immunity. The optical fibre sensing technologies used for intrusion detection include the interferometer-based optical fibre sensors and the optical time domain reflectometry (OTDR)-based optical fibre sensors [1-9]. The OTDR-based optical sensors are sensitive to very low vibrations and can be used in intrusion detection. However, it is subject to the quality of the laser and costly [8]. The Sagnac interferometer-based optical fibre sensing system is of high sensitivity to vibrational disturbances and low cost [2, 3]. The Mach-Zehnder interferometer based optical fibre sensing technologies have the same property of high phase-sensitivity as the OTDR-based technologies and have been studied widely [4]. To improve the performance of the perimeter security system, the distributed optical fibre sensing system has been used in intrusion detecting systems [1].

In a perimeter protection system, it is important to localize the intruder when an intrusion signal is detected. The need for intrusion localization is more necessary for an underground perimeter protection system to reduce the rate of false alarm. Generally, the underground intrusion signals to be detected are acoustic (or vibrational) signals generated by the intruder. When an intrusion occurs, the waveforms sampled in the sensors are processed and analysed in amplitudes, phases and frequencies to judge the intrusion, and the time of arrival (TOA) of the intrusion signal is used to locate the position of the intruder approximately [9]. Actually, the properties of the received intrusion signals are studied to localize the intruder by many researchers [10]. As in the interferometer-based optical-fibre sensor system, the time interval between the moment the laser was sent out and the moment the intrusion signal arrives at the receiver can not be got where the consecutive laser pulses are used. To get the precise TOAs of the intrusion signals, many signal-processing algorithms were employed [11]. However, the approaches suffer from the measurement errors for the fast speed of the laser propagating in the optical fibre, the errors of the time limit the precision of the intrusion localization to tens of meters [12].

In this paper, a state estimation based intrusion localization algorithm is proposed to get high precise underground intrusion localization estimation. The geometrical relationships of the distributed sensors and the intruder are analysed and the state equation and the measurement model are deduced. Then the Unscented Kalman Filter (UKF) is used to estimate and track the location of the intruder. The simulation demonstrates that the algorithm improves the intrusion localization precision and the intruder can be tracked even if no enough sensors detect the intrusion signal.

2 Intrusion Localization Algorithm based on the Geometric Relationship of the Sensors and the Intruder

As mentioned above, the optical-fibre sensor-based intrusion detecting technologies include the interferometer-based methods and the OTDR-based methods. Although the principles of the two methods are distinct, to detect the underground intrusion signals, both methods use the optical fibre sensors to detect the

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acoustic signals generated by the intruder. The acoustic signals may be generated by the excavating or ambulating actions of the intruders. As the acoustic signals are detected by the optical fibre sensors, the signals are processed and the TOAs are got. Then the geometrical equations can be deduced from the locations of the distributed sensors and the differences of the TOAs. For convenience, a Sagnac interferometer-based optical fibre sensing system is used to detect the underground intrusion in our work.

When the underground intrusion signal occurs, the resultant vibrations or acoustic signals can be detected by the optical-fibre sensors. The detected signals may be of the different phases or be of various light intensities. As the sensing light signals are converted to the electric signals and then converted into digital signals, the digital signals are processed and analysed in amplitudes and frequencies. And the signals with certain amplitudes and waveforms are judged as the markers of the intrusion. Then the time intervals between the moment the laser pulse was sent out and the moment the 0-phase of the intrusion signal waveform can be got. The time interval is the time the acoustic signal costs in propagating from the intruder to the sensor. So it is called time of arrival (TOA) of the intrusion signal.

When an intrusion signal is detected, the moment t which is called TOA can be gotten by signal processing. If the moment the intruder generated the vibrational signal is t_0, the time interval $(t\text{-}t_0)$ includes the time for the acoustic signal arriving at the sensor and the time for the laser propagating in the optical fibre. As shown in Figure 1, the distance from the intruder to the sensor is equal to the distance the acoustic signal transports in TOA of the intrusion signal. As the locations of the sensors are fixed, the time for the laser is almost constant and can be calibrated previously. Then the geometrical relationship between the sensor i and the intruder is:

$$\sqrt{\left(x-x_i\right)^2+\left(y-y_i\right)^2+\left(z-z_i\right)^2}=v_I\left(t_i-t_0-T_i\right), \qquad (1)$$

where, (x_i, y_i, z_i) is the location of the i^{th} sensor, (x, y, z) is the location of the intruder, and v_I is the transporting speed of the vibrational signal generated by the intruder, t_0 is the moment the intruder generated the vibrational signal, T_i is the time for the laser propagating in the optical fibre of the i^{th} sensor, and t_i is the moment at which the intrusion signal in the i^{th} sensor is detected in the receiver.

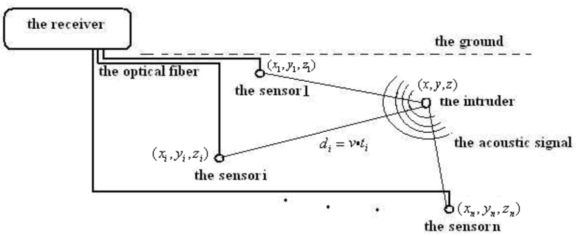

FIGURE 1 In an underground perimeter protection system, the distances from the intruder to the sensors are equal to the distance which the acoustic signals transport from the intruder to the sensors.

As in the Equation (1), the parameters t_0 and v_I are unknown, the parameters can be ignored by using the different distances of the sensors,

$$\sqrt{(x\text{-}x_i)^2+(y\text{-}y_i)^2+(z\text{-}z_i)^2}-\sqrt{(x\text{-}x_j)^2+(y\text{-}y_j)^2+(z\text{-}z_j)^2} = v_I \cdot \left\|(t_i\text{-}t_j\text{-}(T_i\text{-}T_j))\right\| , \qquad (2)$$

where $\left\|(\cdot)\right\|$ is the absolute value sign.

As long as the intrusion signal is detected by enough sensors, the parameters (x, y, z) and v_I can be computed with optimal estimation methods such as the Least-Square methods. The Least-Square based intrusion localization algorithm is as follows:

Firstly, the equation (2) can be written as,

$$\begin{aligned}&\sqrt{\left(x-x_i\right)^2+\left(y-y_i\right)^2+\left(z-z_i\right)^2}\\&-\sqrt{\left(x-x_j\right)^2+\left(y-y_j\right)^2+\left(z-z_j\right)^2}\ .\\&-v_I\left\|\left(t_i-t_j-\left(T_i-T_j\right)\right)\right\|=0\end{aligned} \qquad (3)$$

Then the left side of the equation (3) can be denoted by a function,

$$\begin{aligned}&f_{ij}\left(x,y,z,v\right)=\sqrt{\left(x-x_i\right)^2+\left(y-y_i\right)^2+\left(z-z_i\right)^2}\\&-\sqrt{\left(x-x_j\right)^2+\left(y-y_j\right)^2+\left(z-z_j\right)^2}\ .\\&-v_I\left\|\left(t_i-t_j\left(T_i-T_j\right)\right)\right\|\end{aligned} \qquad (4)$$

To solute the equation (3), use the linearization about the nominal value $(\hat{x},\hat{y},\hat{z},\hat{v})$,

$$x=\hat{x}+\Delta x, y=\hat{y}+\Delta y, z=\hat{z}+\Delta z, v=\hat{v}_I+\Delta v\,. \qquad (5)$$

Substitute equation (5) to equation (4), we get

$$\begin{aligned}&f_{ij}\left(x,y,z,v\right)=f_{ij}\left(\hat{x},\hat{y},\hat{z},\hat{v}\right)\\&+\begin{bmatrix}\dfrac{\partial f_{ij}}{\partial x}&\dfrac{\partial f_{ij}}{\partial y}&\dfrac{\partial f_{ij}}{\partial z}&\dfrac{\partial f_{ij}}{\partial v}\end{bmatrix}\begin{Bmatrix}\Delta x\\\Delta y\\\Delta z\\\Delta v\end{Bmatrix}\ .\end{aligned} \qquad (6)$$

From equation (3),

$$R_{ij}=0-f_{ij}\left(\hat{x},\hat{y},\hat{z},\hat{v}\right)=\begin{bmatrix}\dfrac{\partial f_{ij}}{\partial x}&\dfrac{\partial f_{ij}}{\partial y}&\dfrac{\partial f_{ij}}{\partial z}&\dfrac{\partial f_{ij}}{\partial v}\end{bmatrix}\begin{Bmatrix}\Delta x\\\Delta y\\\Delta z\\\Delta v\end{Bmatrix}. \qquad (7)$$

If there are n sensors, which detected the intrusion, for $(i=1,2,...,n-1)$ and $(j=2,3,...,n)$ the equation (7) can be written as,

$$\{R\}=\{A\}\bullet\{\Delta E\}, \tag{8}$$

where,

$$R=\begin{Bmatrix} R_{12} \\ R_{13} \\ \cdot \\ \cdot \\ R_{n-1,n} \end{Bmatrix}, A=\begin{Bmatrix} \frac{\partial f_{12}}{\partial x} & \frac{\partial f_{12}}{\partial y} & \frac{\partial f_{12}}{\partial z} & \frac{\partial f_{12}}{\partial v} \\ \frac{\partial f_{13}}{\partial x} & \frac{\partial f_{13}}{\partial y} & \frac{\partial f_{13}}{\partial z} & \frac{\partial f_{13}}{\partial v} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \frac{\partial f_{n-1,n}}{\partial x} & \frac{\partial f_{n-1,n}}{\partial y} & \frac{\partial f_{n-1,n}}{\partial z} & \frac{\partial f_{n-1,n}}{\partial v} \end{Bmatrix} \tag{9}$$

and

$$\Delta E=(\Delta x \quad \Delta y \quad \Delta z \quad \Delta v)^T. \tag{10}$$

Then the method of least squares can be used to get the optimal estimation of the nominal value $(\hat{x},\hat{y},\hat{v})$. Here we use the minimal residual method of least squares by solving ΔZ,

$$\{\Delta E\}_k=\left[A_k^T A_k\right]^{-1}\cdot A_k^T\cdot\{R\}_k, \tag{11}$$

where k=1, 2… is the number of iterations, and the estimation in k-step iteration is

$$\begin{Bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \\ \hat{v} \end{Bmatrix}_k=\begin{Bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \\ \hat{v} \end{Bmatrix}_{k-1}+\begin{Bmatrix} \Delta x \\ \Delta y \\ \Delta z \\ \Delta v \end{Bmatrix}_{k-1}. \tag{12}$$

The partial derivative terms in equation (7), (9) are given by

$$\begin{cases} \frac{\partial f_{ij}}{\partial x}=\frac{(x\text{-}x_i)}{\sqrt{(x\text{-}x_i(^2+(y\text{-}y_i)^2+(z\text{-}z_i)^2}}-\frac{(x\text{-}x_j)}{\sqrt{(x\text{-}x_j)^2+(y\text{-}y_j)^2+(z\text{-}z_j)^2}} \\ \frac{\partial f_{ij}}{\partial y}=\frac{(y\text{-}y_i)}{\sqrt{(x\text{-}x_i)^2+(y\text{-}y_i)^2+(z\text{-}z_i)^2}}-\frac{(y\text{-}y_j)}{\sqrt{(x\text{-}x_j)^2+(y\text{-}y_j)^2+(z\text{-}z_j)^2}} \\ \frac{\partial f_{ij}}{\partial z}=\frac{(z\text{-}z_i)}{\sqrt{(x\text{-}x_i)^2+(y\text{-}y_i)^2+(z\text{-}z_i)^2}}-\frac{(z\text{-}z_j)}{\sqrt{(x\text{-}x_j)^2+(y\text{-}y_j)^2+(z\text{-}z_j)^2}} \\ \frac{\partial f_{12}}{\partial v}=\text{-}\left|(t_i\text{-}t_j\text{-}(T_i\text{-}T_j))\right| \end{cases} \tag{13}$$

The algorithms from equation (4) to (13) above are repeated recursively, the iteration is going on until ΔE is less than a set tolerance. However, as the geometrical relationship in Equation (2) does not consider the noises in the parameters, the number of the iterations of the algorithm may be too large and the algorithm results in bad precision. Especially, when the number of the distributed sensors, which detected the intrusion signal is less than 4, the errors of the location estimation increase remarkably.

3 UKF-based Intrusion Localization Algorithm

To improve the accuracy of the location estimation of the intruder, the state estimation methods can be used to track the location of the intruder when the measurement noises and the system noises are considered. The state equations and the measurement model are deduced from the geometric relationship in equation (2) and the UKF algorithms are used for state estimation.

3.1 THE SYSTEM EQUATION AND THE MEASUREMENT MODEL FOR INTRUSION LOCALIZATION

As in equation (2), the speed of the vibrational signals propagating underground is unknown. To improve the precision of the location estimated, the unknown speed of the vibrational signals and the moment the intruder generated the vibrational signals as well as the location of the intruder and the moving speed of the intruder, are considered as the state parameters, i.e., $X=\left[x\,y\,z\,v_x\,v_y\,v_z\,v_l\,t_0\right]^T$. For simplification, the moving speed of the intruder is considered almost constant, i.e. the variation of the moving speed is zero, and a zero-mean Gaussian noise is added. Moreover, the speed of the vibrational signal is considered constant and the zero-mean Gaussian noise is added. Then we get the state equations as:

$$\dot{X}=AX+W, \tag{14}$$

where,

$$A=\begin{bmatrix} 0&0&0&1&0&0&0&0 \\ 0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0 \end{bmatrix}. \tag{15}$$

And W is the noise vector of the state parameters, the means of which are considered zero and the covariance matrix $R=diag\left(\sigma_1\,\sigma_2\,...\sigma_8\right)$.

The measurement parameters are the moments when the intrusion signal arrives at the sensors, t_i, i.e., $Y=\left[t_1 t_2 \dots t_n\right]^T$. From Equation (1), we get

$$t_i=\frac{1}{v_I}\cdot\sqrt{(x-x_i)^2+(y-y_i)^2+(z-z_i)^2}+t_0+T_i\,. \quad (16)$$

Then the measurement model can be written as:

$$Y=G(X)+V\,, \quad (17)$$

where, $G(\cdot)$ is the measurement function vectors as noted in Equation (5), and V is the measurement noise vector, with the mean m and the covariance matrix $Q=diag\left(\sigma_{t_1}\sigma_{t_2}\dots\sigma_{t_n}\right)$.

3.2 THE UKF ALGORITHM

As the measurement equation in (17) is nonlinear, the original Kalman Filter cannot be used for state estimation directly. If the equation is linearized, the extended Kalman Filter (EKF) can be used to estimate the location of the intruder. However, the errors in the linearization may result in state estimation errors [13, 14]. As the unscented Kalman Filter (UKF) algorithm is excellent in nonlinear system, it is adopted in our work [15, 16]. The algorithm can be described as follows:

3.2.1 Initiation

At first, the initial mean and covariance of the 8-dimensional state sector can be computed as:

$$\hat{X}_0=E(X_0)\,, \quad (18)$$

$$P_0=E[(X_0-\hat{X}_0)(X_0-\hat{X}_0)^T]\,. \quad (19)$$

3.2.2 Sigma Point Sample and the Weight

The symmetric sampling method is used and (2n+1) points $\left\{x_i\left(k\middle|k\right)\middle|i-0,1,\dots,2\mathrm{n},\mathrm{k}\geq 1\right\}$ are sampled. The points and the weight are selected as follows:

$$\chi_0\left(k-1\right)=\hat{X}\left(k-1\right), \quad (20)$$

$$\chi_1\left(k-1\right)=\hat{X}\left(k-1\right)+\left(\sqrt{(n+\lambda)P_{xx}\left(k-1\right)}\right)_i,\ i=1,\dots,n, \quad (21)$$

$$\chi_i\left(k-1\right)=\hat{X}\left(k-1\right)-\left(\sqrt{(n+\lambda)P_{xx}\left(k-1\right)}\right), i=n+1,\dots,2n, \quad (22)$$

where, n is the dimension of feature state, $\lambda=\alpha^2(n+\kappa)-n$ is a scale parameter. The α is constant which determines the spread of the sigma points around $\hat{X}(k-1)$ and is usually set to a small positive value. In addition, the constant κ is another scale parameter, which is set to (3-n). β is used to incorporate prior knowledge of the distribution of the system states.

In addition, two weights ω_i^m and ω_i^c are used to compute the mean and covariance of the state estimation:

$$\omega_0^m=\frac{\lambda}{n+\lambda}\,, \quad (23)$$

$$\omega_0^c=\frac{\lambda}{n+\lambda}+(1-\alpha^2+\beta)\,, \quad (24)$$

$$\omega_i^m=\omega_i^c=\frac{1}{2(n+\lambda)}, i=1,\dots,2n\,. \quad (25)$$

3.2.3 Time Update

The predicted mean and covariance are computed as follows:

$$\chi_i\left(k\middle|k-1\right)=tA\chi_i\left(k-1\right), \quad (26)$$

$$\hat{X}(k\mid k-1)=\sum_{i=0}^{2n}\omega_i^m\chi_i(k\mid k-1)\,, \quad (27)$$

$$P_{xx}(k\mid k-1)=\sum_{i=0}^{2n}\omega_i^m[\chi_i(k\mid k-1)-\hat{X}(k\mid k-1)][\chi_i(k\mid k-1)-\hat{X}(k\mid k-1)]^T\,, \quad (28)$$

$$Y_i(k\mid k-1)=G(\chi_i(k\mid k-1))\,, \quad (29)$$

$$\hat{Y}(k\mid k-1)=\sum_{i=0}^{2n}\omega_i^c Y_i(k\mid k-1)\,. \quad (30)$$

3.2.4 Measurement Update

Moreover, the predicted observation mean, innovation covariance and the cross relation matrix are computed as follows:

$$P_{yy}(k)=\sum_{i=0}^{2n}\omega_i^c[Y_i(k\mid k-1)-\hat{Y}(k\mid k-1)][Y_i(k\mid k-1)-\hat{Y}(k\mid k-1)]^T\,, \quad (31)$$

$$P_{xy}(k)=\sum_{i=0}^{2n}\omega_i^c[\chi_i(k\mid k-1)-\hat{X}(k\mid k-1)][Y_i(k\mid k-1)-\hat{Y}(k\mid k-1)]^T, \quad (32)$$

$$K(k)=P_{xy}(k)P_{yy}^{-1}(k), \quad (33)$$

$$\hat{X}(k)=\hat{X}(k\mid k-1)+K(k)[Y(k)-\hat{Y}(k\mid k-1)], \quad (34)$$

$$P_{xx}(k)=P_{xx}(k\mid k-1)-K(k)P_{xy}(k)K^T(k). \quad (35)$$

The algorithms above are repeated from equation (20) to (35), the iteration is going on to estimate and track the location of the intruder.

4 Simulations and Experiments

To test the precision of the intrusion localization algorithm proposed, simulations are performed in given data. In the simulations, the distributed Sagnac-based optical-fibre sensors are used and the sensors assumed to be located in lines and rows as shown in Figure 2, and the distance between each pair of the neighbouring sensors is 50 meters, and all the sensors are assumed to be buried 1.5 meters below the ground. The propagating speed of the vibrational signal the intruder generated underground is assumed to be constant, i.e. 1000m/S. Generally, the sampling rate of the receiver is above 10k times per second. So the errors of the TOAs are considered below 0.1mS and the measurement noise is considered zero mean and the covariance 0.1. The intruder is considered moving in a speed 1m/S, and the initial R=diag(1,1,1,1,1,1,1,1). The number of sigmal points is set to 21 in simulation.

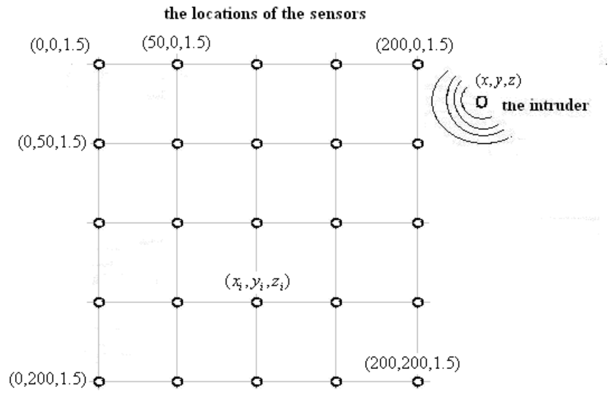

FIGURE 2 The locations of the sensors for simulation

Figure 3 depicts the result of the simulations. The error of the locations is below 0.5 meters and the locations of the intruder can be tracked precisely. Moreover, the errors of the estimation under various numbers of the sensors, which detected the intrusion are listed in table 1. It demonstrates that even if only one sensor detects the intruder, the algorithm can track the intruder precisely.

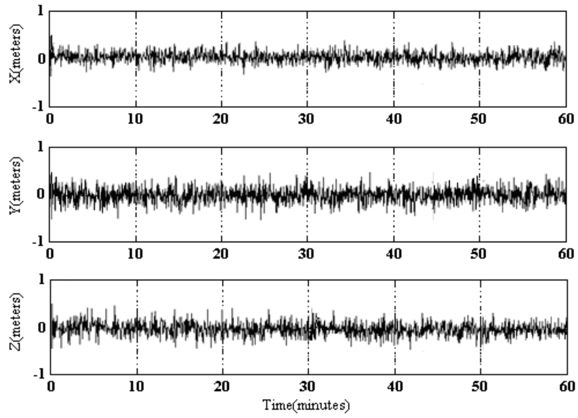

FIGURE 3 The Simulation of the Intruder Localization Estimation

TABLE 1 The statistical errors with various number of sensors, which detected the intrusion

Number of the sensors	The parameters	Errors of estimation (meters)
1	x	1.46
1	y	1.722
1	z	2.21
3	x	0.73
3	y	0.92
3	z	0.88
5	x	0.18
5	y	0.22
5	z	0.3

5 Conclusions

To improve the precision of the underground intrusion localization in the optical-fibre sensing perimeter protection application, an UKF-based intrusion localization algorithm is proposed in the paper. The state equation and the measurement model are deduced from the geometrical relationship of the sensors and the intruder, and the UKF algorithm is used to estimate and track the location of the intruder. The simulation demonstrates that the algorithm improves the intrusion localization precision and the intruder can be tracked even if no enough sensors detect the intrusion signal.

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References

[1] Juarez J C, Maier E W, et al 2005 Distributed Fiber-Optic Intrusion Sensor System *Journal of Lightwave Technology* **23**(6) 2081-87

[2] Szustakowski M, Yczkowski M, et al 2004 Sensitivity of perimeter sensor based on Sagnac interferometer *Light guides and Their Applications* **5576** 319-23

[3] Culshaw B 2006 The optical fibre Sagnac interferometer: An overview of its principles and applications *Measurement Science and Technology* **17** 1-16

[4] Jahed N M S, Nurmohammadi T, et al 2009 Enhanced resolution fiber optic strain sensor based on Mach-Zehnder interferometer and displacement sensing principles *Proc. ELECO International Conference on Electrical and Electronics Engineering* Turkish/American IEEE: Bursa p II-302

[5] Linze N, Mégret P, et al 2012 Development of an Intrusion Sensor Based on a Polarization-OTDR System *IEEE Sensors Journal* **12**(10) 3005-09

[6] Li X L, Sun Q Z, et al 2012 Hybrid TDM/WDM-Based Fiber-Optic Sensor Network for Perimeter Intrusion Detection *Journal of Lightwave Technology* **30**(8) 1113-20

[7] Zyczkowski M, Szustakowski M, et al 2004 Fiber optic perimeter protection sensor with intruder localization *Proc. SPIE on Unmanned/Unattended Sensors and Sensor Networks* **5611** UK/American SPIE: London p 71

[8] Park J 2003 Fiber optic intrusion sensor using coherent optical time domain reflectometer *Japanese Journal of Applied Physics* **42**(6a) 3481-82

[9] Mcaulay A D, Wang Jian 2004 A Sagnac interferometer sensor system for intrusion detection and localization *Proc. SPIE on Enabling Photonic Technologies for Aerospace Applications* **5435** American SPIE: Orlando FL p 114

[10] Kondrat M, Szustakowski M, et al 2006 Two-interferometer fiber optic sensor with disturbance localization *Proc. SPIE on Unattended Sensors and Sensor Networks* **6394** Sweden/ American SPIE: Stockholm p 0T-1

[11] Zhang Y, Chen J M 2012 Location method of Distributed Fiber-optic Perimeter Security System Based on Mach-Zehnder Interferometer *Chinese Journal of Lasers* **39**(6) 0605005-1-4

[12] Zyczkowski M, Ciurapinski W 2007 Fiber optic sensor with disturbance localization in one optical fiber *Proc. SPIE, on Optical Sensing Technology and Applications* **6585** Czech Republic/ American SPIE: Prague p 1K-1

[13] Belkacem S, et al 2010 Robust Non-Linear Direct Torque and Flux Control of Adjustable Speed Sensorless PMSM Drive Based on SVM Using a PI Predictive Controller *Journal of Engineering Science and Technology Review* **3**(1) 168-75

[14] Su S C, Zhang W 2013 Fault Prediction of Nonlinear System Using Time Series Novelty Estimation *Journal of Digital Information Management* **11**(3) 207-12

[15] Juliet S J, Uhlmann J K, et al 2000 A New Method for the Nonlinear Transformation of Means and Covariances in Filters and Estimators *IEEE Transactions on Automatic Control* **AC-45**(3) 477-82

[16] Crassidis J L, Markley F L 2003 Unscented Filtering for Spacecraft Attitude Estimation *Journal of Guidance and Dynamics* **26**(4) 536-42

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