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Unscented Particle Filtering Algorithm for Optical-Fiber Sensing Intrusion Localization Based on Particle Swarm Optimization

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Abstract

To improve the convergence and precision of intrusion localization in optical-fiber sensing perimeter protection applications, we present an algorithm based on an unscented particle filter (UPF). The algorithm employs particle swarm optimization (PSO) to mitigate the sample degeneracy and impoverishment problem of the particle filter. By comparing the present fitness value of particles with the optimum fitness value of the objective function, PSO moves particles with insignificant UPF weights towards the higher likelihood region and determines the optimal positions for particles with larger weights. The particles with larger weights results in a new sample set with a more balanced distribution between the priors and the likelihood. Simulations demonstrate that the algorithm speeds up convergence and improves the precision of intrusion localization.

Keywords*: optical-fiber sensor, intrusion localization, UPF, PSO*

1. Introduction

Optical-fiber sensor-based intrusion detection technologies are widely used in perimeter security protection systems. Recently, the optical fiber sensing technologies available for intrusion detection include the interferometer-based optical fiber sensors and the optical time domain reflectometry (OTDR)-based optical fiber sensors, and each of which has characters [1]-[8]. Among the technologies, the interferometer-based optical-fiber sensors are preferred in intrusion detection for their high sensitivity to vibrational signals and low cost. As is known, it is important to localize the intruder when an intrusion signal is detected in a perimeter protection system. Generally, the underground intrusion signals to be detected are acoustic (or vibrational) signals generated by the intruder. When an intrusion occurs, the time of arrival (TOA) of the intrusion signal is used to locate the position of the intruder approximately [9].

As the interferometer-based systems use consecutive laser pulses, the interval between the laser being sent out and the intrusion signal arriving at the receiver cannot be determined. Thus, the TOA of the intrusion signal cannot be accurately measured, which affects the precision of intrusion localization. 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 fiber, the errors of the time limit the precision of the intrusion localization to tens of meters [12]. Many researchers have worked on this problem and various signal processing algorithms have been employed to obtain a precise TOA in optical-fiber sensing localization [13],[14]. To improve the precision of intrusion localization, we have previously used the geometrical positions of the distributed sensors and the differences in relative *TOAs to estimate the position of the intruder* [15]-[16]*. State estimation-based methods demonstrate high precision.* However, as the measurement equation is nonlinear, the convergence speed is poor and the precision is subject to measurement errors.

In this paper, a particle filter is used to handle the problem of nonlinearity in optical-fiber sensing intrusion localization. To avoid the degeneracy problem and sample impoverishment after resampling, we employ the unscented particle filter (UPF) and use particle swarm optimization (PSO) to maintain diversity in the particles. A series of simulations demonstrate that the proposed algorithm improves precision and convergence when there is no prior intruder location.

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2. Intrusion localization in optical-fiber sensing perimeter protection

In optical-fiber sensing perimeter protection systems, intruders generate vibrational signals that can be detected by the optical-fiber sensors. After the detected signals have been processed and analyzed, the time intervals between the laser pulse being sent and the 0-phase of the intrusion signal waveforms being received can be calculated. This interval is the time that the vibrational signals take to propagate from the intruder to the sensor, and is called the TOA of the intrusion signal.

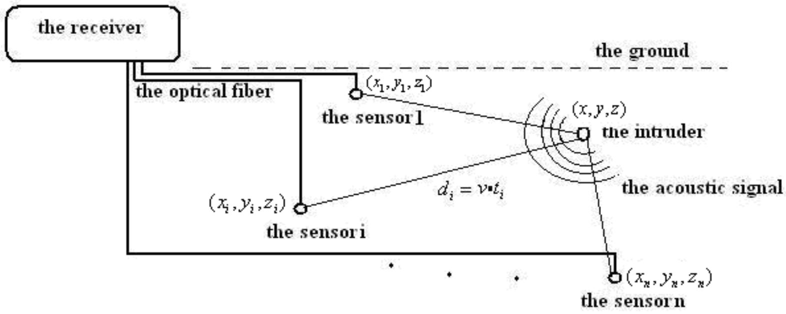

Figure 1. Distances from intruder to sensors are equal to the distance that the acoustic signals travels from intruder to sensors

Figure 1 illustrates a distributed optical-fiber sensing perimeter protection system. Let the moment at which the intruder generates the vibrational signal be t_0, and the TOA be t. The time interval (t-t0) includes the time taken by the vibrational signal to arrive at the sensor and the time for the laser to propagate along the optical fiber. As the sensor locations are fixed, the propagation time of the laser in the optical fiber is almost constant and can be pre-calibrated. Thus, the geometrical relationship between the i*th* sensor and the intruder is:

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

where (x_i, y_i, z_i) is the location of the i*th* sensor and (x, y, z) is the location of the intruder. v_I is the speed at which the vibrational signal generated by the intruder is transported, t_0 is the moment at which the intruder generates the vibrational signal, T_i is the time taken by the laser to propagate along the optical fiber of the i*th* sensor, and t_i is the moment at which the intrusion signal in the i*th* sensor is detected by the receiver.

As the precise moment at which the intruder generates the vibrational signal and the propagation speed of the vibrational signal are unknown (i.e., t_0 and v_I are unknown), the position of the intruder cannot be computed directly by solving Equation (1). In previous work, we used optimal estimation and state estimation methods to obtain the best estimate of the intruder's location $(\hat{x}, \hat{y}, \hat{z})$.

2.1. Optimal estimation-based localization

If the intrusion signal is detected by more than two sensors, t_0 can be ignored by considering the distances between the sensors:

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

where $\|(\cdot)\|$ returns the absolute value. Then, (x, y, z) and v_I can be computed by optimal estimation techniques such as the least-squares (L-S) method [15]. However, the determinate relationship in Equation (2) does not consider noise in the parameters, resulting in imprecise estimates. In particular, when no more than four sensors detect the intrusion signal, the error in the location estimation increases considerably.

2.2. State estimation-based localization

To use state estimation methods to estimate and track an intruder's location, the state equations and measurement model are deduced as follows. The location and speed of the intruder, the unknown speed of the vibrational signal, and the moment at which the intruder generated the vibrational signals are considered as the state parameters, i.e., $X = [x \quad y \quad z \quad v_x \quad v_y \quad v_z \quad v_I \quad t_0]^T$. To simplify the problem, we assume that the speed at which the intruder is moving is almost constant, i.e., the variation in speed is zero, and that the speed of the vibrational signal is constant. Zero-mean Gaussian noise is added to both the intruder speed and the vibrational signal. The state equation is then,

$$\dot{X} = AX + W \tag{3}$$

Where

$$A = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4}$$

and W is the noise vector of the state parameters, which have means of zero and covariance matrix $\mathrm{R{=}diag}(\sigma_1 \quad \sigma_2 \quad . \quad . \quad . \quad \sigma_8)$.

The measurement parameters are the points at which the intrusion signals arrive at the sensors, i.e., $Y = [t_1 \quad t_2 \quad . \quad . \quad t_n]^T$. From Equation (1), we have

$$t_i = \frac{1}{v_I} \cdot \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} + t_0 + T_i \tag{5}$$

Then, the measurement model can be written as:

$$Z = G(X) + V \tag{6}$$

where $G(\cdot)$ denotes the measurement function vectors noted in Equation (5) and V is the measurement noise vector, which has mean m and covariance matrix $\mathrm{Q{=}diag}(\sigma_{t_1} \quad \sigma_{t_2} \quad . \quad . \quad . \quad \sigma_{t_n})$.

As the measurement equations in Equation (6) are nonlinear, the unscented Kalman filter (UKF) is used to obtain high precision [16]. The algorithm yields good performance in tracking the intruder. However, when there is no prior knowledge of the intrusion location, the algorithm is slow to converge.

3. PSO-based UPF Algorithm for Intrusion Localization

UPF is a popular state estimation algorithm for nonlinear systems. In UPF, UKF is used to generate sophisticated proposed distributions that seamlessly integrate the current observation [18]. The combination of UKF with a particle filter outperforms existing particle filters, albeit at the cost of computational complexity. UPF also suffers from the degeneracy problem and the loss of particle diversity. As PSO is simple, fast, and efficient, it can be used to improve the performance of the UPF algorithm.

3.1. PSO algorithm

PSO is an evolutionary computation technique based on the behavior of individuals within a swarm [17]. The individuals find the optimum solution using their own previous experience and that of their neighbors. Each individual in the swarm tracks the coordinates in the problem space that are associated with the best solution achieved so far. In the realization process of a PSO algorithm, each particle corresponds to a candidate solution to the optimization problem. The direction and distance that the particles move within the solution space are determined by their speed, and the objective function determines the fitness value of each initial population. The particles follow the current optimal particle, and an optimal solution is achieved after each generation. In each generation, the particles follow the optimal solution p_{best} of the particle itself, denoted as $P_{bi}=(p_{bi1},p_{bi2},\dots,p_{biN})^T$, as well as the optimal solution g_{best} of the whole population, denoted as $G_b=(g_{b1},g_{b2},\dots,g_{bN})^T$.

For a random particle swarm containing M particles, the positions and velocities of the i*th* particle in N-dimensional space are $X_i=(x_{i1},x_{i2},\dots,x_{iN})^T$ and $V_i=(v_{i1},v_{i2},\dots,v_{iN})^T$. After determining p_{best} and g_{best}, each particle updates its position and velocity according to the following equations:

$$v_i(\mathrm{k}+1)=w(\mathrm{k})v_i(\mathrm{k})+c_1r_1(\mathrm{k})(\mathrm{p}_{bi}-x_i(\mathrm{k}))+c_2r_2(\mathrm{k})(g_b-x_i(\mathrm{k})) \tag{7}$$

$$x_i(\mathrm{k}+1)=x_i(\mathrm{k})+v_i(\mathrm{k}) \tag{8}$$

where $r_1(\mathrm{k})$~U(0, 1) and $r_2(\mathrm{k})$~U(0, 1) are used to give the algorithm a stochastic nature, $w(\mathrm{k})$ is the inertial weight, and c_1, c_2 are acceleration factors used to adjust the maximum step size of p_{best} and g_{best}.

3.2. PSO-optimized UPF for optical-fiber sensing intrusion localization

In the PSO process, the particle swarm searches for optimal solutions and determines the optimal location by updating the particle velocities. When UPF is applied to the estimation of the intrusion location, the PSO algorithm is used to optimize the particles in UPF. In the algorithm, the particle population in the PSO supplies the particles for UPF. PSO quickly finds the target region, which ensures that the particle set searches regions with a high likelihood of containing the optimal solution. The algorithm proceeds as follows:

Step 1: Initialization

Initialize the PSO parameters. Set up the PSO parameters, such as the number of particles N, acceleration coefficients C_1 and C_2, and the maximum number of iterations.

Step 2: Initial sampling

Sample N particles $\{x_0^i$, i = 1, 2, …, N} from the prior distribution with initial weights $\{w_i(k+1)=1/N, i=1,2,\dots,N\}$.

Step 3: Importance sampling

Sample particles $x_i(\mathrm{k})$ from the proposed distribution:

$$q(\mathrm{x}(\mathrm{k})/\mathrm{x}_i(\mathrm{k}-1),\mathrm{Z}_\mathrm{k})=N(\hat{x}_i(\mathrm{k}),\bar{x}_i(\mathrm{k}),\hat{\delta}_{x(\mathrm{k})}(\mathrm{k})) \tag{9}$$

Step 4: Update weights

a. Obtain system measurements.

b. According to the new measurements, calculate and normalize particle weights according to:

$$\tilde{w}_i(\mathrm{k}) = \tilde{w}_i(\mathrm{k}-1)\frac{p(z(\mathrm{k})/x_i(\mathrm{k}))p(x_i(\mathrm{k})/x_i(\mathrm{k}-1))}{q(x_i(\mathrm{k})/x_i(\mathrm{k}-1),Z(\mathrm{k}))} \quad (10)$$

Step 5: Optimize the particles by PSO

a. Resample the weighted particles to obtain particles $\{x_k^i, w_k^i\}$ with equal weights $\{x_k^i, N^{-1}\}$. Particles with smaller weights are eliminated, and the number of particles with larger weights increases.

b. The majority of particles move towards the high-likelihood region and are assigned a new weight by comparing the current positions with the fitness value of the optimal particles $\Delta p = p(z_k^{i*}/x_k^{i*}) - p(z_k^i/x_k^i)$.

c. Set the minimum movement threshold α for the particles. If $\Delta p < \alpha$, the filter particles remain stationary; otherwise, the filter particles adjust their speed according to Equation (7):

$$v_i^k(\mathrm{k}+1|\mathrm{k}) = w(\mathrm{k})v_i(\mathrm{k}|\mathrm{k}-1) + c_1r_1(\mathrm{k}-1)(x_p^*(\mathrm{k}-1) - x_i^*(\mathrm{k}|\mathrm{k}-1)) + c_2r_2(\mathrm{k}-1)(x_g^*(\mathrm{k}-1) - x_i^*(\mathrm{k}|\mathrm{k}-1)) \quad (11)$$

where $v_i^k(\mathrm{k}+1|\mathrm{k})$ is the value of $v_i(\mathrm{k}+1|\mathrm{k})$ after k iterations. The speed determines the direction and distance moved by the particles

d. Redetermine the particle positions according to Equation (8) to obtain a new particle set $\{x_k^i, w_k^i\}$.

Step 6: State estimation

Compute the posterior probability estimation of the target state at time k using $x_k^{i*} = \sum_{i=1}^{N} x_k^i w_k^i$.

Step 7: Set k = k+1, return to Step 3, and continue to estimate the posterior probability of the target state at the next time step.

In the above processes, PSO moves the particles in the UPF towards areas of high likelihood. Thus, the optimal position is determined in the resampling process by comparing the present fitness value with the optimum fitness value of the objective function. Modifying the prior sample weights such that the resulting particles have larger weights results in a new sample set that assumes a more balanced distribution between the priors and the likelihood.

4. Simulations and Analysis

To verify the performance of the proposed algorithm, the convergence speed and precision of the proposed algorithm were compared with that of the UKF algorithm and an L-S algorithm [15]-[16]. The simulation data in [15] are used, where the sensors are located in lines and rows as shown in Figure 2, and the intervals between every pair of the neighboring sensors are 50 meters. The propagation speed of the vibrational signal generated by the intruder was assumed to be a constant 1000 m/s. The errors in TOAs were assumed to be below 0.1 ms, and the measurement noise was assumed to have zero mean and a covariance of 0.1. The intruder was considered to be moving with a speed of 1 m/s, and the initial R = diag(1,1,1,1,1,1,1,1). In our simulations, the likelihood function is defined as the objective function, and this was assumed to have the posterior probability function $p(z_k^i/x_k^i) = \frac{1}{(2\pi\delta_v^2)^{1/2}}\exp[-\frac{1}{2\delta_v^2}(z_k - z_{k|k-1}^i)]$, where z_k is the latest observation and $z_{k|k-1}^i$ is the predicted observation.

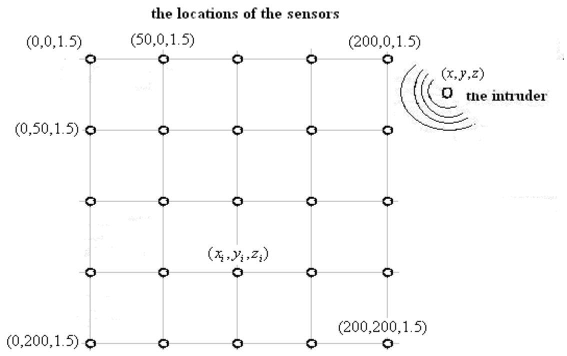

Figure 2. The locations of the sensors for simulation [15]

4.1. The convergence speed and precision of the algorithms

Figure 3 depicts the simulation results and the statistical results of the algorithms are listed in table 1. As shown in the simulations, the PSO algorithm optimizes the particles in efficiency and the particle population in the PSO supplies the particles for UPF. As PSO quickly finds the target region, the particle set searches regions with a high likelihood of containing the optimal solution. As shown in Table 1, the proposed algorithm converges within 50 iterations.

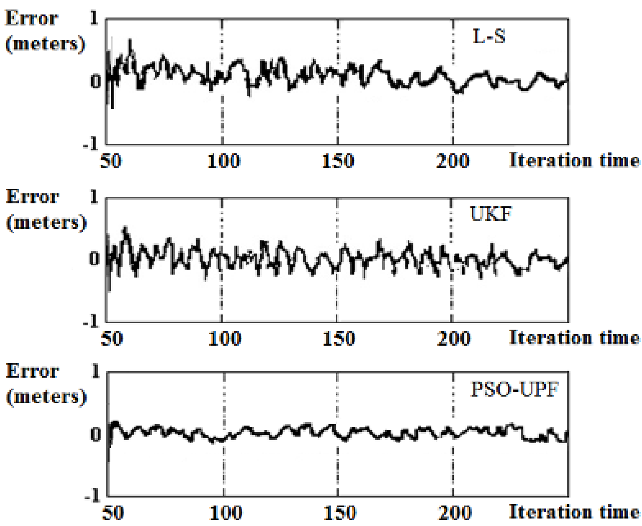

Figure 3 Simulation results for each algorithm

Where as the L-S and UKF algorithms require more than 200 iterations. Thus, the proposed algorithm has a reduced computational burden, which makes it suitable for real-time applications. The errors given by the different algorithms are approximately the same, although those from the proposed algorithm are less than 0.1 m after 50 iterations. This demonstrates that the algorithm can also improve the precision of detection. The simulations demonstrate that the proposed algorithm outperforms the others in terms of both precision and convergence speed.

Table 1. The statistics of the algorithms

Algorithms	Error of the location estimation(meters)	Number of iterations(times)
L-S[15]	0.23	>200
UKF[16]	0.21	>200
The proposed algorithm	0.07	<50

4.2. The robustness of the algorithm to the number of the sensors

As in state-estimation based algorithms, the precision is subject to the number of the sensors and the errors of the location estimation under various numbers of the sensors which detected the intrusion are listed in Table 2. As shown in Table 2, to get higher precision, the intruder should be detected by more than 5 sensors simultaneously for L-S algorithm. The number for the same precision in the UKF algorithm and the proposed algorithm are 3. Even when there is only one sensor which can detect the intruder, the proposed algorithm can track the intruder precisely. It demonstrates that the proposed algorithm is robust to the number of the sensors used for location estimation.

Table 2. The statistical errors with various numbers of sensors detecting the intrusion signals

Algorithms	Number of the sensors	Errors of the location estimation(meters)
L-S	1	-
	3	3.29
	5	0.24
UKF	1	2.12
	3	0.29
	5	0.11
The proposed algorithm	1	1.53
	3	0.15
	5	0.07

5. Conclusion

To improve the convergence and precision of intrusion localization in optical-fiber sensing perimeter protection applications, we have proposed an algorithm based on PSO-optimized UPF. In the proposed algorithm, PSO is employed to mitigate the sample degeneracy and impoverishment problem of the particle filter. By comparing the present fitness value of the particles with the optimum fitness value of the objective function, PSO ensures particles that have insignificant UPF weights move towards higher likelihood regions and determines the optimal position of particles with larger weights. Simulations have demonstrated that the proposed algorithm speeds up convergence and improves the intrusion localization precision compared with previous methods.

Acknowledgements

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