2014 IEEE Congress on Evolutionary Computation (CEC)
July 6-11, 2014, Beijing, China

Particle Swarm Optimization for Integrity Monitoring in BDS/DR based Railway Train Positioning

Jiang Liu, Bai-gen Cai, Jian Wang

Abstract—**Satellite navigation system, especially the BeiDou Navigation Satellite System (BDS), has become a significant resource for many transport branches. It is strongly required that BDS is applied in modern railway transportation systems to support the rapid development of Chinese railway infrastructure and services. Currently, the BDS is still in the developing period, and the existing resources are not sufficient to support integrity assurance for many safety-related railway applications. The aim of this paper is therefore to develop a novel integrity monitoring method for the BDS-based train positioning with assistance from the additional dead reckoning system. In this method, the raw measurements of sensors are fused with the Bayesian filtering, and the self-weight adaptive particle swarm optimization with a combined objective function is involved to achieve an effective solution for the horizontal protection level which indicates the integrity capability. Field data are taken to validate effectiveness of the proposed solution and the advantages of the integrated particle fitness strategy. The implementation of this method will be positive for realizing fault detection and isolation for a series of safety-related railway applications based on BDS.**

I. INTRODUCTION

THE rapid development of computer and communication technology promises a better service level of the modern railway transportation. Current GNSS (Global Navigation Satellite System), such as GPS, GLONASS and GALILEO, is experiencing a great period in performance and capability as it is of significant value in lots of application fields. Furthermore, the progress in GNSS enables great opportunities for applying satellite navigation technology in railway systems, including train operation control, collision avoidance, centralized train control, track surveying and so forth [1, 2]. However, when used in some safety-critical applications, the performance of current Chinese BDS cannot provide sufficient support to the expected stage, due to the Signal-in-space (SIS) unavailability and signal interference issues. Integrity, which is defined as the level of ability to provide valid and timely warning to the users when misleading information from system is detected [3], is of great significance to achieve a high safety level of the BDS-based railway applications. Presently, the BDS is lack of integrity measures in the space segment. Therefore, integrity monitoring in the user segment is of great necessity because of its flexibility and autonomy. In the GPS and GALILEO-based railway applications, RAIM (Receiver Autonomous Integrity Monitoring) technique has been regarded as a very effective solution to solve the integrity monitoring problem and realize fault detection and isolation [4, 5]. Furthermore, considering the multi-sensor integrated train positioning scheme, there are also integrity monitoring strategies proposed in the literature, i.e. the LAIM (Locator Autonomous Integrity Monitoring) method [6], integrity check algorithm [7], etc. For the BDS- based train integrated positioning, the integrity monitoring for the BDS-based integrated architecture has not been highly concerned, and the existing results in other GNSS applications still need to be improved by considering multiple aspects in evaluating the key indicators for the monitoring purpose.

Jiang Liu, Bai-gen Cai and Jian Wang are with School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing 100044 China (e-mail: jiangliu@bjtu.edu.cn, bgcai@bjtu.edu.cn, wangj@bjtu.edu.cn).

This research was supported by the International Science & Technology Cooperation Program of China (2014DFA80260), National Natural Science Foundation of China (U1334211), National Key Technology R&D Program of China (2013BAG24B02), the Technological Research and Development Program of China Railway Corporation (2013X001-A-2), and Fundamental Research Funds for the Central Universities (2014JBM003).

This paper aims to address the limitations of the current integrity monitoring solutions. The objective of this paper is to develop an enhanced integrity monitoring method using the intelligent swarm optimization strategy, which is suitable to be used in the BDS/DR(Dead Reckoning)-based integrated train positioning. Field data is utilized to validate the performance of the proposed solution. The reminder of this paper is organized as follows. Section II states the problem. The proposed solution is detailed introduced in Section III, and the filed results are analyzed in Section IV. Finally, the Section V concludes this paper and shows future directions.

II. PROBLEM STATEMENT

A. BDS-based train positioning

When used in practical railway applications, especially the safety-critical systems, the risk of BDS for locating the train should be investigated and analyzed. It is well known that the satellite navigation system is usually constrained by the SIS shadowing by the different objects along the railway lines or by a landscape profile [8]. The first factor for promoting the safety risk in most of the BDS-based applications is the SIS unavailability since the system may fail in precise positioning or even lose the expected functions. Besides that, there may be unexpected interferences caused by multi-path effects or electromagnetic interference sources, which are harmful to the fulfillment of performance requirements. Furthermore, BDS constellation is still in a developing stage, where 16 satellites are currently in orbit for the Asian-Pacific coverage.

According to the current status of BDS and the features of satellite navigation system, the utilization of the multi-sensor integration-based positioning is naturally an effective solution for compensating the drawbacks of BDS-based train positioning. The existing train odometry sensors, such as the odometer and Balise, are capable of being used to assist BDS. Moreover, the MEMS (Micro-Electro-Mechanical Systems) inertial sensors provide possibilities to achieve an integrated architecture, where the DR system using the odometer, gyroscope or the accelerator makes it possible to realize effective integration solutions with lower cost, though system complexity corresponding to both the hardware construction and the software computing logics might be increased.

B. Positioning integrity monitoring

The integrity monitoring for a BDS-based train positioning system involves several aspects including Alert Limit (AL), Time-To-Alarm (TTA), Integrity Risk Rate (IRR) and the Tolerable Hazard Rate (THR) [9]. Core principle to monitor the integrity in the stage of output is to identify the situation of the error bound with the defined threshold for alert. For the 2D railway train positioning, the Horizontal Position Error (HPE) is enhanced to a Horizontal Protection Level (HPL) to verify the decision for alerting the users if it exceeds the threshold of HAL. Fig. 1 shows the relationship of HPE, HPL and HAL in the integrity monitoring process.

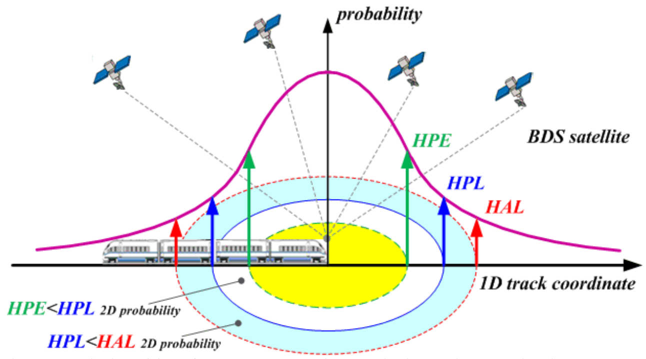

Fig. 1. Relationship of HPE, HPL and HAL in integrity monitoring.

The key problem is to calculate the HPE corresponding to the position state estimation using BDS and additional sensor data, determine a HPL that properly represents the error state we can put trust in, and make decisions with HAL.

III. Proposed Integrity Monitoring Method

A. Particle Swarm Optimization

Particle swarm optimization is inspired from the collective behavior exhibited in swarms of social insects, and is famous for its simplicity with expected optimization capabilities [10]. In the PSO solution, each particle is identified by its location and velocity. The fitness associated to a certain particle is built and updated in each iteration step to evaluate the convergence to the global best location. The procedure of the standard PSO is simple. Denote the local best location of particle i and the global best location as $p_{best}(i)$ and g_{best} respectively, the location and velocity of each particle can be updated by using the iteration equations as

$$V_i(t) = \omega V_i(t-1) + c_1 r_1 \left(p_{best}(i) - X_i(t-1)\right) + c_2 r_2 \left(g_{best} - X_i(t-1)\right) \tag{1}$$

$$X_i(t) = X_i(t-1) + V_i(t) \tag{2}$$

where $V_i(t)$ and $X_i(t)$ are location and velocity of the i th particle at step t, ω is the inertia weight, r_1 and r_2 are random value, and c_1 and c_2 are acceleration coefficients.

Based on the standard PSO, it is proved that there exists an underlying relation among the inertia weight, swarm size and dimension size of the solution space. A constant inertia weight is not sufficient to support an effective convergence, while the adaptive weight may accelerate the rate of convergence if the lower fitted particle takes a larger speed, and the better fitted one moves slow. Therefore, the self-adaptive inertia weight strategy is proposed to improve the standard PSO by updating ω with the strategy as [11]

$$\omega = \left[3 - e^{-\frac{PS}{200}} + \left(rank / 8 \cdot D\right)^2\right]^{-1} \tag{3}$$

where PS is the particle population size, $rank$ denotes the rank of particle fitness, and D indicates the dimension of the solution space. Thus, the ranked particle fitness affects the inertia weight and further improves the searching capability.

B. BDS/DR information fusion

The first step for identifying HPL is to carry out the state estimation by fusing information with the system model and sensor measurement. Assume that $\boldsymbol{x}_k$ denotes the state vector at instant k that describes the dynamic state of a train moving along the track, the system model for fusion is

$$\boldsymbol{x}_k = f\left(\boldsymbol{x}_{k-1}, k-1\right) + \boldsymbol{w}_k \tag{4}$$

$$\boldsymbol{z}_k = h\left(\boldsymbol{x}_k, k\right) + \boldsymbol{v}_k \tag{5}$$

where $f(*)$ and $h(*)$ denote the system and measurement function respectively, $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ represent the independent Gaussian noise vectors, and $\boldsymbol{z}_k$ is the observation vector with instant sensor measurement. The state vector is defined as

$$\boldsymbol{x}_k = \left(x_k, \dot{x}_k, y_k, \dot{y}_k, \theta_k, \varpi_k, a_k\right)^{\mathrm{T}} \tag{6}$$

where x_k and y_k denote the 2D coordinate location, θ_k and ϖ_k represent the heading and heading rate, and a_k is the longitudinal acceleration. Under a Bayesian filtering scheme, the state can be estimated by integrating the prediction $\hat{\boldsymbol{x}}_{k,k-1}$ and innovation $\boldsymbol{\varepsilon}_{k,k-1}$ with a gain $\boldsymbol{K}_k$, which means

$$\hat{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_{k,k-1} + \boldsymbol{K}_k \boldsymbol{\varepsilon}_{k,k-1} = \hat{\boldsymbol{x}}_{k,k-1} + \boldsymbol{K}_k \left[\boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k,k-1})\right] \tag{7}$$

In each filtering step, since the true value of the state cannot be acquired in practical operation, usually we use estimation residual $\boldsymbol{\varepsilon}_k$ to represent the status of estimator as

$$\boldsymbol{\varepsilon}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_k) \tag{8}$$

Thus, the horizontal position error is estimated by using the corresponding elements of $\boldsymbol{\varepsilon}_k$ as

$$hpe_k = \sqrt{(z_{\mathrm{x},k} - \hat{x}_k)^2 + (z_{\mathrm{y},k} - \hat{y}_k)^2} \tag{9}$$

Furthermore, the covariance $\boldsymbol{P}_k$ that is updated in every filter iteration step represents the precision level of estimation, and therefore is with potential to support the monitoring of integrity level in the BDS/DR train positioning.

C. Integrated HPL calculation

Under the single-fault hypothesis, the protection level can be calculated by projecting the test statistic of filter residual to the position domain. Considering the residual $\boldsymbol{\varepsilon}_k$ in detecting the possible fault in BDS/DR integration, equation (8) can be changed with the linearization of $h(*)$, where

$$\boldsymbol{\varepsilon}_k = \boldsymbol{z}_k - \boldsymbol{H}_k \hat{\boldsymbol{x}}_k = \boldsymbol{z}_k - \left.\frac{\partial h(\boldsymbol{x}_k, k)}{\partial \boldsymbol{x}_k}\right|_{\boldsymbol{x}_k = \hat{\boldsymbol{x}}_k} \cdot \hat{\boldsymbol{x}}_k \tag{10}$$

Combing equation (10) with the filter estimation solution in (7), the residual can be expressed as

$$\boldsymbol{\varepsilon}_k = (\boldsymbol{I} - \boldsymbol{H}_k \boldsymbol{K}_k) \boldsymbol{\varepsilon}_{k,k-1} \tag{11}$$

Then, the test statistic is formed with the residual as

$$\begin{aligned} \boldsymbol{t} &= \sqrt{\boldsymbol{\varepsilon}_k^{\mathrm{T}} \boldsymbol{\varepsilon}_k} = \sqrt{\boldsymbol{\varepsilon}_{k,k-1}^{\mathrm{T}} \boldsymbol{F}^{\mathrm{T}} \boldsymbol{F} \boldsymbol{\varepsilon}_{k,k-1}} \\ &= \sqrt{\boldsymbol{\varepsilon}_{k,k-1}^{\mathrm{T}} (\boldsymbol{I} - \boldsymbol{H}_k \boldsymbol{K}_k)^{\mathrm{T}} (\boldsymbol{I} - \boldsymbol{H}_k \boldsymbol{K}_k) \boldsymbol{\varepsilon}_{k,k-1}} \end{aligned} \tag{12}$$

Considering the situation where the fault only exists in one sensor and others are all in the fault-free state, sensitivity of horizontal position error to the i th component corresponding to the measurement $\boldsymbol{z}_k$ is evaluated by the slope as

$$slope_i = \sqrt{(\boldsymbol{K}_{1i}^2 + \boldsymbol{K}_{3i}^2) / \boldsymbol{F}_{ii}} \tag{13}$$

Hence, the horizontal protection level is calculated with the maximum slope

$$HPL_f = slope_{\max} \cdot p_{\mathrm{bias}} \tag{14}$$

where p_{bias} is the Minimum Detectable Bias (MDB) related to the probability of missed detection.

Besides the slope-based HPL solution, it is also necessary to consider the effect of measurement noise when developing the statistic for the total system error [12], and the Horizontal Uncertainty Level (HUL) is defined as

$$HUL = \gamma_k \cdot \sigma_k = \gamma_k \cdot \sqrt{\boldsymbol{P}_{k,11} + \boldsymbol{P}_{k,33} + 2\boldsymbol{P}_{k,13}} \tag{15}$$

where γ_k is the factor referring to the probability of missed detection. Calculation of σ_k considers the correlation of the noises in east and north directions, while $\sqrt{\boldsymbol{P}_{k,11} + \boldsymbol{P}_{k,33}}$ is usually taken as the one-sigma bound of the estimation error.

With different strategies for determining the HPL in train positioning integrity monitoring and fault detection, there have been several solutions proposed for integrating the two components. In order to compensate the correlation on HPL, a sigma inflation factor (SIF) α is introduced for an integrated HPL solution [13]. According to the principle for integration, the HPL_t and HUL can be combined as

$$\begin{aligned} &HPL_{\inf} = \sqrt{HPL_f^2 + (1+\alpha^2) HUL^2}, \\ &0 \le \alpha \le \frac{2HPL_f}{HUL} \end{aligned} \tag{16}$$

Under the assumption of a Gaussian statistical property for position estimation error, the integrity risk corresponding to a certain SIF value can be expressed as

$$p_r = \Phi\left(\frac{-HPL_{\inf} - \mu_{\mathrm{H}}}{\sigma_{\mathrm{H}}}\right) + 1 - \Phi\left(\frac{HPL_{\inf} - \mu_{\mathrm{H}}}{\sigma_{\mathrm{H}}}\right) \tag{17}$$

where μ_{H} and σ_{H} are the mean and variance of the position estimation error $\tilde{\boldsymbol{x}}_{\mathrm{H}}$.

According to the principle of SIF-based HPL integration, it is obvious that the performance of HPL evaluation and its effectiveness for integrity monitoring will be sensitive to the selection of α. Basically, it is expected that the derived HPL that will be used in comparison with HPE and HAL is with a lower integrity risk, since that is meaningful and significant to detect and identify the existing or potential fault in sensors or the information processing logics. With this consideration, the objective corresponding to the integrity risk is defined as

$$l_1 = \min J_1 = \min_{\alpha} p_r, 0 \le \alpha \le \frac{2HPL_f}{HUL} \tag{18}$$

However, it should also be noticed that the HPL value itself is also important to influence the integrity monitoring results, where a relatively lower and smoother HPL will benefit the adaptive capacity of integrity monitoring especially during the absence of sensor measurement. Hence, additional objectives are involved for an improvement to the balance of integrity risk and adaptability. Considering the HPL variance and the absolute HPL value, the additional objectives are defined as

$$l_2 = \min J_2 = \min_{\alpha} \sigma(HPL_{\inf}) \tag{19}$$

$$l_3 = \min J_3 = \min_{\alpha} |HPL_{\inf}| \tag{20}$$

Based on these objectives, in the iteration of sensor fusion, when the filtering-based estimation is completed, the particle swarm optimization method is applied to obtain the proper SIF value for updating HPL. The fitness function in PSO is defined with a combination of l_1, l_2 and l_3, which means that particles will be evaluated by an integrated standard to decide its importance and performance as

$$J_{\mathrm{fitness}} = \lambda_1 \frac{p_r}{\beta_1} + \lambda_2 \frac{\sigma(HPL_{\inf})}{\beta_2} + \lambda_3 \frac{|HPL_{\inf}|}{\beta_3} \tag{21}$$

where λ_i is the weight coefficient which fulfills $\sum \lambda_i = 1$, β_i is the scale coefficient, $i = 1, 2, 3$. The weight value of λ_i determines the importance of a certain factor with respect to the contribution to the overall evaluation of fitness, and the value determined by experience may benefit the efficiency for PSO computation. The scale β_i is used to make the quantity of the values (risk probability, HPL variance and the absolute HPL value) uniformly.

When using this definition of fitness function in PSO, the different particles are generated after each filtering cycle to achieve an optimal SIF α_{opt}. Only when the updated fitness is less than a given threshold $\overline{J}$ or the maximum PSO iteration step is reached, the PSO calculation will be terminated. Based on that, the optimal SIF is used for HPL update and the further integrity monitoring operation.

IV. Experimental Results

In order to validate the effectiveness of the proposed HPL calculation solution, field test data from the Wuhan-Yichang Railway line in China is collected and analyzed. The BDS data and DR measurements were recorded by an integrated train positioning unit in June 2012. The test was performed within the track section from the Zhijiang North Station to Jingzhou Station in the up track direction. The test lasted 770 seconds, and the BDS satellite condition was good, where 8 satellites were available all the time and the average HDOP (Horizontal Dilution of Precision) value is 1.4.

The geographic location of the test track section in Google Earth is shown in Fig. 2, and Fig. 3 gives raw measurement from the BDS receiver, gyroscope and the accelerator.

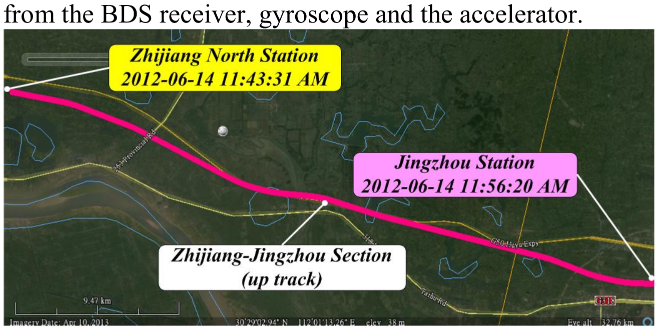

Fig. 2. The test railway track section in the Google Earth.

TABLE I
PARAMETERS USED IN PSO CALCULATION

Population size	50	***Acceleration coefficient c_2***	1.494
Maximum iteration step	50	***Maximum position***	10.0
Fitness threshold	0.01	***Minimum position***	0
Dimension D	1	***Maximum speed***	0.2
Acceleration coefficient c_1	1.494	***Minimum speed***	-0.2

For the sensor data fusion, we use a cubature Kalman filter (CKF) to solve the Bayesian filtering problem and obtain the state estimation results, since the CKF is proved a powerful tool to deal with the integral problem in the ordinary Bayesian filtering scheme. The proposed PSO-based method is used to optimize the SIF and update HPL. The configuration for PSO calculation is listed in Table 1.

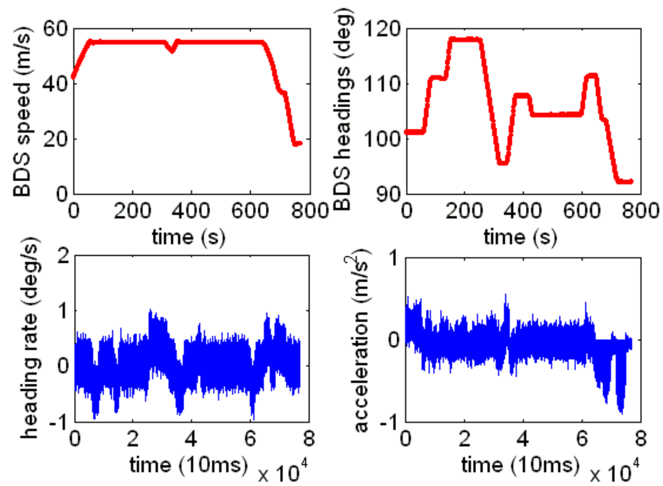

Fig. 3. Raw measurements from BDS and DR sensors.

The obtained global best fitness in each filter cycle is shown in Fig. 4. Correspondingly, the optimized SIF is indicated and compared with the upper bound that is defined as (16), which is as shown in Fig. 5.

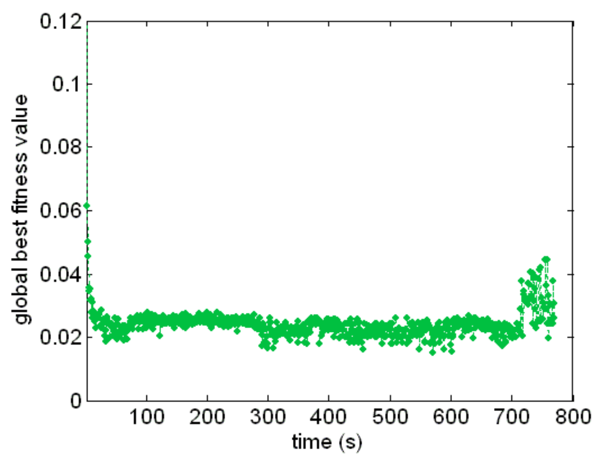

Fig. 4. Global best fitness in each filtering cycle.

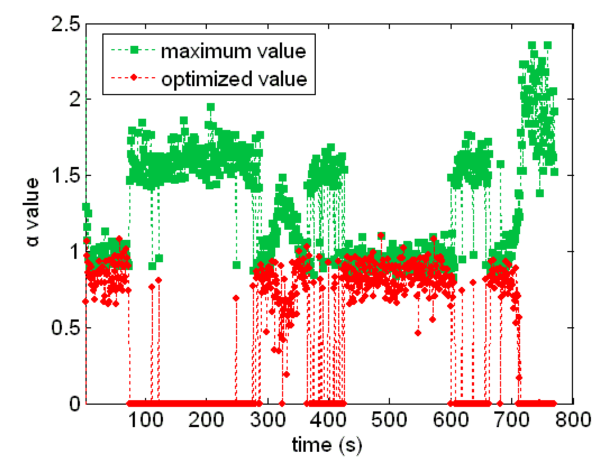

Fig. 5. Comparison of the optimized SIF value and its upper bound.

As the theoretical analysis of the horizontal protection level, five different strategies are tested and compared to validate the proposed solution, where HPL_f, HUL, and

$HPL_{\inf}$ with SIF=0, the maximum SIF and the PSO-optimized SIF are all parellelly calculated. Fig. 6 and Fig. 7 show the results of integrity risk and the derived horizontal protection level.

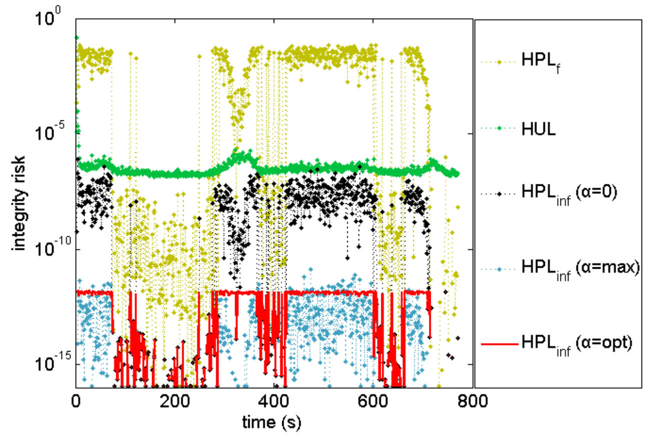

Fig. 6. Comparison of integrity risk with different strategies.

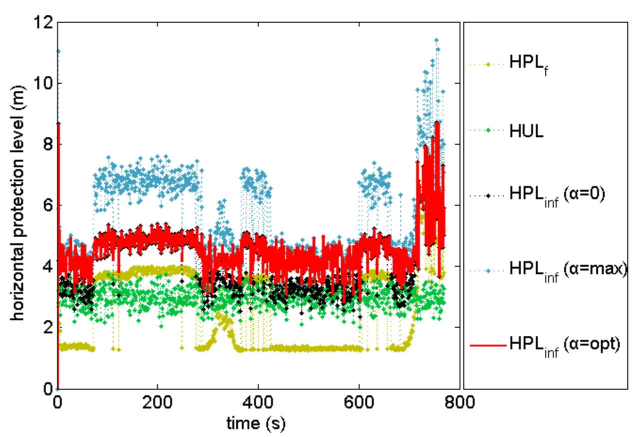

Fig. 7. Comparison of HPL value with different strategies.

Based on the HPL results, the horizontal position error and one-sigma bound are computed and compared with the HPL for integrity monitoring, which is as shown in Fig. 8. Since the horizontal alert limit is set 50 meters, the comparison results suggest a normal state of the BDS/DR integrated train positioning process.

In order to evaluate HPL performance under the integrated objective strategy, tests were carried out with single objective PSO and the integrated strategy separately. Fig. 9 and Fig. 10 show the comparison of the global best fitness value and the optimized SIF value. Accordingly, the integrity risk and the horizontal protection level from different fitness strategies are indicated in Fig. 11 and Fig. 12 respectively.

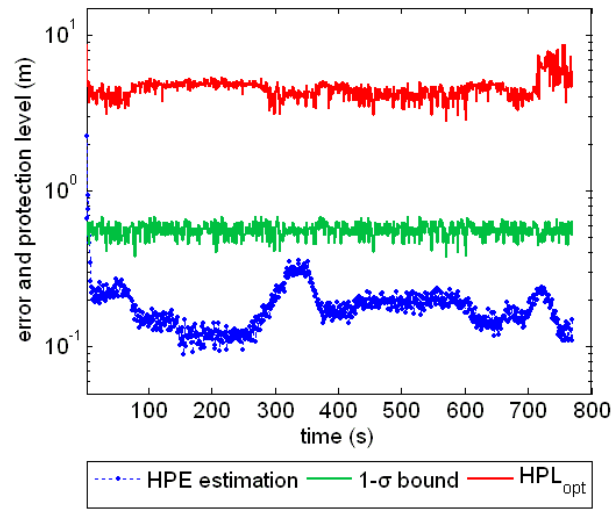

Fig. 8. Comparison of HPE with one-sigma bound and HPL.

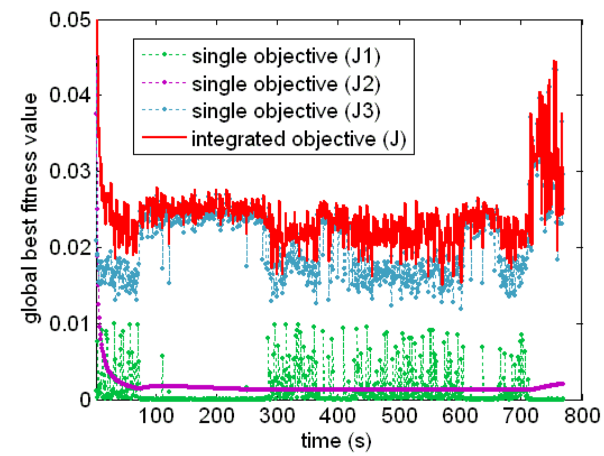

Fig. 9. Comparison of best fitness under different fitness strategies.

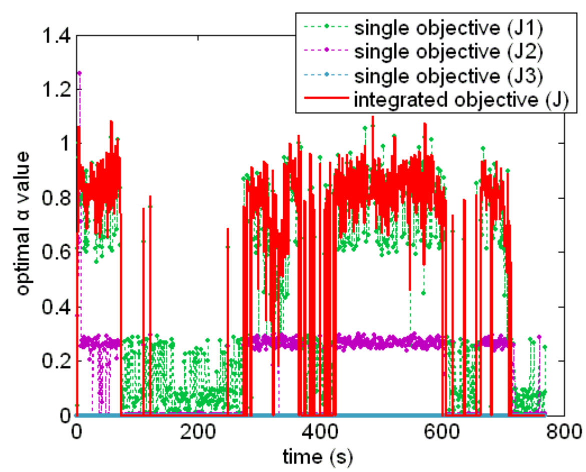

Fig. 10. Comparison of optimized α under different fitness strategies.

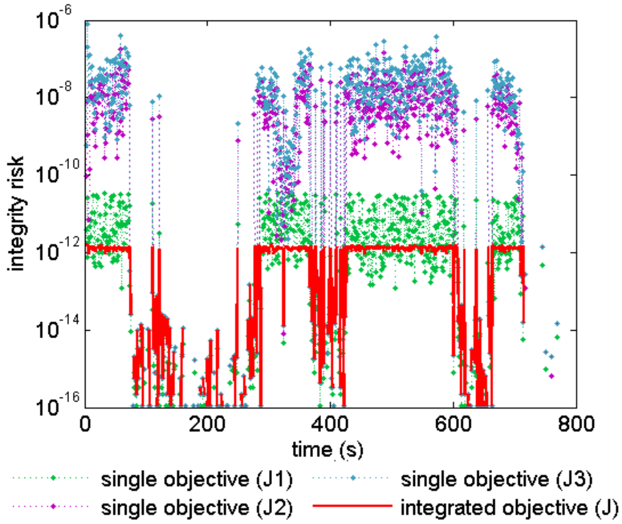

Fig. 11. Comparison of integrity risk under different fitness strategies.

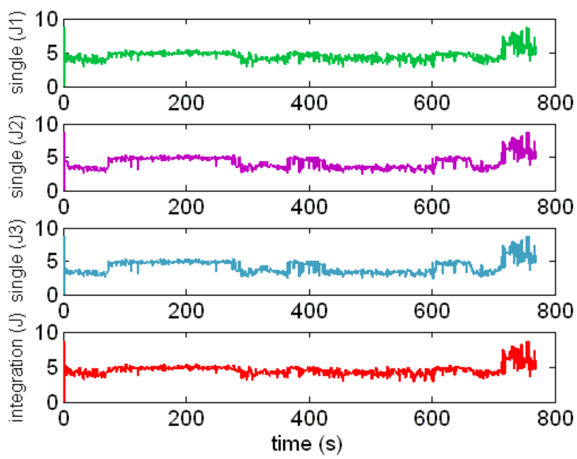

Fig. 12. Horizontal protection levels under different fitness strategies.

To clearly indicate the results from these comparisons, the mean values are summarized in Table 2.

TABLE II
UNITS FOR MAGNETIC PROPERTIES

Content	Global best fitness	Optimal α value	Integrity risk	Horizontal protection level (m)
Single J1	0.0012	0.4584	4.09E-12	4.5116
Single J2	0.0017	0.1399	6.92E-09	4.1736
Single J3	0.0206	0	1.81E-08	4.1219
Integration J	0.0240	0.4232	6.86E-13	4.5381

From the above results, it can be summarized that:

(1) The proposed method is capable of evaluating the HPL by using the results from the filter estimation and being used for the HAL comparison to identify the integrity status.

(2) Compared with the fixed SIF strategies, the PSO-based method apparently achieves a lower integrity risk level for its adjustment and therefore further improves the smoothness and adaptability, which owes much to the use of the adaptive-SIF strategy and the capability of PSO.

(3) Although the integrated fitness dose not perform best in a certain criteria such as the global best fitness, optimal FIS, integrity risk and the HPL, it promotes a balance among these indices. More than anything, the integrated fitness-based PSO strategy corresponds to a desired performance in integrity risk control, which is of great significance to assure the capability in some specific railway applications.

V. CONCLUSION

This paper develops an integrity monitoring method for the BDS/DR-based railway train positioning by considering the improvement of the determination of horizontal protection level, which is an important indicator for integrity and fault detection. The PSO technique is involved to optimize the key coefficient as sigma inflation factor, where the self-adaptive weight and integrated fitness strategy are applied to enhance the traditional solution. Based on the assurance of integrity risk, performance of HPL is improved in smoothness and adaptability. The field results demonstrate the capability and potential in future application.

The correlation of false and missed detection probability to HPL performance will be investigated. Furthermore, as the integrity indicators are designed for a fault detection purpose, the future research will focus more on the use of an enhanced HPL in fault detection, diagnosis and isolation.

REFERENCES

[1] Y. Zheng, P. Cross, “Integrated GNSS with different accuracy of track database for safety-critical railway control systems,” *GPS Solutions,* vol. 16, no. 2, 2012, pp. 169-179.

[2] S. Fabio, “Satellite application for train control systems: The Test Site in Sardinia,” *Journal of Rail Transport Planning & Management*, vol. 2, no. 4, 2012, pp. 73-78.

[3] W. Ochieng, K. Sauer, D. Walsh, G. Brodin, et al, “GPS integrity and potential impact on aviation safety,” *Journal of Navigation*, vol. 56, no. 1, 2003, pp. 51-65.

[4] S. Hewitson. J. Wang, “Extended receiver autonomous integrity monitoring (eRAIM) for GNSS/INS integration,” *Journal of Surveying Engineering*, vol. 136, no.1, 2010, pp. 13-22.

[5] C. D. Milnera, W. Y. Ochieng, “Weighted RAIM for APV: The ideal protection level,” *Journal of Navigation*, vol 64, no. 1, 2011, pp. 61-73.

[6] A. Filip, J. Taufer,H. Mocek, L. Bazant, et al, “The high integrity GNSS/ INS based train position locator,” in Proc. Ninth International Conference on Computers in Railways, Dresden, 2004, pp. 497-506.

[7] A. Albanese, L. Marradi, “The RUNE project: The integrity performances of GNSS-based railway user navigation equipment,” in Proc. ASME/IEEE Joint Rail Conference, Pueblo, 2005, pp. 211-218.

[8] M. Jonas. “GNSS integrity for railway transportation,” *Transactions on Transport Science*, vol. 4, no. 4, 2011, pp. 183-192.

[9] A. Filip , L. Bazant, H. Mocek, “Diagnostics for GNSS based train position locator,” in Proc. second international conference reliability, safety and diagnostics of transport structures and means, Pardubice, 2005, pp. 1-8.

[10] M. E. H. Pedersen, A. J. Chipperfield, “Simplifying particle swarm optimization,” *Applied Soft Computing*, vol. 10, no. 2, 2010, pp. 618-628.

[11] D. Chen, G. Wang, Z. Chen, Z. Yu, “A method of self-adaptive inertia weight for PSO,” in Proc. International Conference on Computer Science and Software Engineering, Wuhan, 2008, pp. 1195-1198.

[12] J. Diesel, S. Luu, “GPS/IRS AIME: Calculation of thresholds and protection radius using Chi-square methods,” in Proc. 8th International Technical Meeting of the Satellite Division of The Institute of Navigation, Palm Springs, 1995, pp. 1959-1964.

[13] L. Li, M. Quddus, L. Zhao, “High accuracy tightly-coupled integrity monitoring algorithm for map-matching,” *Transportation Research Part C: Emerging Technologies*, vol. 36, 2013, pp. 13-26.