Performance Enhancement of GNSS/MEMS-IMU Tightly Integration Navigation System Using Multiple Receivers

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ABSTRACT Global Navigation Satellite System (GNSS) and Inertial Navigation System (INS) are the most commonly used navigation systems. They both have unique advantages and disadvantages. GNSS is capable of generating precise navigation solutions while enough satellites are in view. However, the GNSS signals are sensitive to the environment. While the signals is attenuated, the GNSS receiver will fail to provide reliable navigation solutions. INS is an advanced navigation system built based on Newton’s law. Due to the random noises contained in the Inertial Measurement Unit (IMU), the INS navigation solutions errors diverge over time. Therefore, effective integration of the two common systems can obtain better navigation results than any individual system. In this paper, for enhancing the GNSS/INS tightly integration system with low cost, multiple receivers were employed in the tight integration. Pseudo-range and Pseudo-range rates from the multiple receivers were employed to compose the measurement vector of the integration filter. In order to reduce the computation load, a measurement difference method was proposed. The state vector dimension could be reduced with the measurement difference scheme. Both simulation and field test were carried out for evaluating the performance of the proposed method. Since it was hard to obtain GNSS raw measurements from commercial receivers, self-developed DSP+FPGA (Digital Signal Processor, DSP; Field Programmable Gate Array, FPGA) based GNSS receivers were employed in the field test. The statistical analysis of the results showed that the positioning errors decreased with the receiver’s amount increasing. In addition, a measurement difference method was proposed to reduce the state vector dimension for saving the computation load with the identical navigation solutions accuracy.

INDEX TERMS GNSS, INS, tight integration, multiple receivers.

I. INTRODUCTION
With the autonomous and unmanned systems development, reliable position and location information are becoming increasingly important and crucial [1]–[3]. Global Navigation Satellite System (GNSS) receiver is the most popular positioning device providing precise position information [3]–[5]. With carefully designed constellation, the satellites covering the earth continuously broadcast navigation signals towards the ground. Receivers around the world available to enough satellites are capable of generating precise position, velocity and time information [6]–[8].

Strap-down Inertial Navigation System (SINS) is a self-contained navigation system built on Newton Law [9], [10]. In the SINS, angular and acceleration measurements from an Inertial Measurement Unit (IMU) are processed using the SINS algorithm. Position, Velocity and Attitude (PVA) are generated without receiving or transmitting signals from or to outside [9], [10]. However, due to the complicated noises contained in the IMU measurements, the SINS PVA errors diverge dramatically over time.
GNSS and SINS both have its unique advantages and disadvantages [6]–[10]. GNSS is able to provide precise PVT information without diverging over time. However, the navigation signals is weak while approaching the ground. INS is a totally self-constrained navigation system, and it works independent on the outer environment [6]–[10]. GNSS and SINS are highly complementary, integration of GNSS and SINS have been demonstrated a better method to provide more reliable navigation solutions.

In the integration, the GNSS can calibrate the SINS errors while there are available satellites in view [8]–[12]. While the GNSS fail to provide reliable navigation solutions, the SINS can provide moderate navigation solutions during short time [8]–[12]. In addition, the SINS has higher navigation solutions updating frequency than GNSS, which can smooth the GNSS information and fill the gap between GNSS navigation solutions.

Generally, the GNSS and SINS integration has three different models: loose, tight and ultra-tight [6], [11]–[15]. The three methods are different in the measurement model of the integration filter. In loose integration, position and velocity information from GNSS and SINS are directly employed as the measurement vector in the integration filter [6], [11]–[15]. In the tight integration model, pseudo range and pseudo-range rates are employed in the integration filter [6], [11]–[15]. Ultra-tight model utilizes the baseband signal processing results to construct the measurement vector of the integration filter [6], [11]–[15]. Loose and tight models are comparatively easier to be implemented compared with ultra-tight model. Therefore, loose and tight integration were commonly utilized in various applications [6], [11]–[15].

In aspects of the loose and tight integration, Falco assessed their performance in real urban scenarios [13]. Tight integration was able to output moderate navigation solutions while the less than four satellites in view [13]. Tight integration was superior to loose integration under signal challenging condition. Scientists are devoted to develop new algorithms to enhance the performance of the tight integration model. High-precision GNSS receiver and high-grade IMU would help improving the accuracy [16]–[24]. However, high-precision GNSS receiver and high-grade IMU might be out of budget. For improving the navigation accuracy, scientists employed redundant sensors in the navigation information estimation. Grace proposed a multi-receiver-based Vector Tracking Loop for vehicle positioning [25]. IMU array was designed and calibrated to improve the navigation accuracy [26]. Inspired by this, in this paper, a tight integration method utilizing multiple receivers was proposed for enhancing the positioning accuracy. Three self-developed DSP+FPGA based GNSS receivers and a MEMS IMU (MSI3200) was employed in the field test for evaluating the performance. The position and velocity accuracy were compared between the multiple receivers based tight integration (MR-TI) and single receiver based tight integration. Numeric and statistical analysis of the results were presented for demonstrating effectiveness of the proposed method. The contribution of this paper was summarized as:

1) this paper proposed a low-cost method for enhancing the performance of the tight integration method;
2) a difference method was proposed in the multiple receivers based tight integration for reducing the state vector dimension, which could reduce the computation load brought by the multiple receivers.

The remainder this paper is organized as follows: the section 2 gives integration model in detail including state model and the measurement model. Section 3 presents the field testing results; then the paper is concluded.

II. MULTIPLE RECEIVERS/MEMS-IMU TIGHT INTEGRATION MODEL

Fig. 1 gives the structure of the multiple receivers based GNSS/INS tight integration system (MR-TI). In this method, these receivers and the INS provide pseudo range and pseudo-range rates to the integration filter. The integration filter estimates the INS errors and feeds them back to compensate INS. The compensated INS navigation solutions are output as the ultimate MR-TI information.

In this method, each receiver’s raw measurements are directly conveyed to the integration filter. The measurement vector is consisted of the measurements from the receivers and the INS. In fact, the state model of the integration filter is almost the same as the single receiver based tight integration system. However, each receiver has its unique clock error and clock bias. More clock bias and drift variables are included in the state model. The difference is that more measurements are added to the measurement vector. Following Section 2.1 gives the detailed description of the state model and the measurement model.

A. STATE MODEL

Kalman filter is the commonly employed fusion algorithm in the tight integration. Therefore, state model and measurement model are necessary. The state model is built based on IMU...
device error model. The state variables usually include position errors, velocity errors, attitude errors, gyroscope drift, accelerometer bias and clock bias/drift. Assuming there are $N$ receivers employed in the MR-TI. The MR-TI state vector $X$ is defined as

$$X = \left[ \delta p \; \delta v \; \Phi \; \nabla \; \delta R_{bias}^1 \; \Delta t_{bias}^1 \; \cdots \; \delta R_{bias}^N \; \Delta t_{bias}^N \right]$$

(1)

The MR-TI model is built in E-N-U coordinates. In the state vector, the detailed of the related variables are as,

$\delta p = [\delta \phi \; \delta \lambda \; \delta h]$ : INS latitude, longitude and altitude errors;

$\delta v = [\delta v_E \; \delta v_N \; \delta v_U]$ : INS east, north, and up velocity errors;

$\Phi = [\alpha \; \beta \; \gamma]$ : INS pitch, roll and yaw attitude errors;

$\nabla = [\nabla_x \; \nabla_y \; \nabla_z]$ : bias of the three-axis accelerometer;

$\varepsilon = [\varepsilon_x \; \varepsilon_y \; \varepsilon_z]$ : drift of the three axis gyroscope.

$\Delta t_{bias}$ : clock bias of the first receiver.

$\Delta t_{drift}$ : clock drift of the first receiver.

$\Delta R_{bias}$ : clock bias of the $N_{th}$ receiver.

$\Delta R_{drift}$ : clock drift of the $N_{th}$ receiver.

The state equation of the navigation filter can be written as:

$$\dot{X} = A \cdot X + W$$

(2)

where, $A$ is the state transformation matrix and $W$ is noise matrix, which is composed of INS state model and the clock state model.

$$F = \begin{bmatrix} F_{INS} & 0 & 0 & \cdots & 0 \\ 0 & F_{r_1} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & F_{r_N} \end{bmatrix}$$

(3)

where, the $F_{INS}$ is the INS state transformation matrix, and the $F_{r_1} \ldots F_{r_N}$ are the clock errors transformation matrix for different receivers.

The SINS transformation matrix is [20]–[22]:

$$\begin{bmatrix} \delta \phi_{3 \times 1} \\ \delta v_{3 \times 1} \\ \delta \phi_{3 \times 1} \\ \widetilde{\delta} \phi_{3 \times 1} \\ \nabla_{3 \times 1} \end{bmatrix} = \begin{bmatrix} F_{pp} & F_{pv} & 0_{1 \times 3} & 0_{1 \times 3} & 0_{1 \times 3} \\ F_{vp} & F_{ww} & F_{v\phi} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & F_{\phi \phi} & C_{b}^{n} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & F_{\phi \phi} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & F_{\phi \phi} \end{bmatrix} \begin{bmatrix} \delta p_{3 \times 1} \\ \delta v_{3 \times 1} \\ \delta \phi_{3 \times 1} \\ \widetilde{\delta} \phi_{3 \times 1} \\ \nabla_{3 \times 1} \end{bmatrix} + \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ C_{b}^{n} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & C_{b}^{n} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & F_{\phi \phi} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & F_{\phi \phi} \end{bmatrix} \begin{bmatrix} w_{3 \times 1} \\ w_{3 \times 1} \\ w_{3 \times 1} \\ w_{3 \times 1} \\ w_{3 \times 1} \end{bmatrix}$$

(4)

The clock transformation matrix is [23], [24]:

$$F_{r_i} = \begin{bmatrix} 0 & 1 \\ 0 & -\beta_{r_i} \end{bmatrix}, \quad i = 1 \ldots N$$

(5)

where, $\beta_{r_i}$ is related to the clock drift [23], [24].

**B. MEASUREMENT MODEL**

As previously illustrated, a common TI system employs the pseudo-range and pseudo-range difference between GNSS and the INS as the measurements. For the $i_{th}$ receiver, the pseudo-range is as:

$$Z_{R_i}^p = H_{R_i}^p \cdot X + V_{R_i}^p$$

$$= [0_{M \times 6} \; H_{R_i}^{p1} \; 0_{M \times 6} \; H_{R_i}^{p2}] \cdot X + V_{R_i}^p$$

(6)

$$Z_{R_i}^d = [\delta \rho_{R_i}^{1} \ldots \delta \rho_{R_i}^{k} \cdots \delta \rho_{R_i}^{M}]_{M \times 1}^T$$

(7)

$$H_{R_i}^{p1} = F_{R_i}^{p1} \cdot D_{LLH}^{XYZ}$$

(8)

$$H_{R_i}^{p2} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 \end{bmatrix}_{M \times 4}$$

(9)

where, $Z_{R_i}^p$ is the pseudo-range measurement vector, and the $E_{R_i}^{p1}$ is the relative position projected onto a unit Line-Of-Sight (LOS) vector [20], and the $D_{LLH}^{XYZ}$ is the position conversion matrix from E-N-U coordinates to ECEF (earth-centered-earth-fixed) coordinates. $V_{R_i}^p$ is the pseudo-range measurement noise. Equation (6) is the linearized version of the measurement model, the details are given in the references [23], [24].

Similarly, the

$$Z_{R_i}^d = H_{R_i}^d \cdot X + V_{R_i}^d$$

$$= [0_{M \times 3} \; H_{R_i}^{d1} \; 0_{M \times 9} \; H_{R_i}^{d2}] \cdot X + V_{R_i}^d$$

(10)

$$Z_{R_i}^{d1} = [\delta \hat{\rho}_{R_i}^{1} \cdots \delta \hat{\rho}_{R_i}^{k} \cdots \delta \hat{\rho}_{R_i}^{M}]_{M \times 1}^T$$

(11)

$$H_{R_i}^{d1} = E_{R_i}^{d1} \cdot D_{ENU}^{XYZ}$$

(12)

$$H_{R_i}^{d2} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & 0 & 0 \end{bmatrix}_{M \times 4}$$

(13)

where, $Z_{R_i}^d$ is the pseudo-range rates measurement vector, and the $E_{R_i}^{d1}$ is the relative velocity projected onto a unit Line-Of-Sight (LOS) vector [20], and the $D_{ENU}^{XYZ}$ is the velocity conversion matrix from the E-N-U coordinates to the ECEF (earth-centered-earth-fixed) coordinates. $V_{R_i}^d$ is the pseudo-range rate measurement noise, and the Equation (10) is the linearized version of the measurement models, more details are illustrated in the references [23], [24]. Combining the pseudo-range measurement vector and the pseudo-range rates measurement vector, the measurement vector of the MR-TI system is:

$$Z = \begin{bmatrix} Z_{R_1} \\ \vdots \\ Z_{R_N} \end{bmatrix} = H \cdot X + V$$

(14)
C. MEASUREMENT DIFFERENCE MODEL

As aforementioned in Section 2.2, with more receivers included in the tight integration system, clock bias and drift are included in the state vector. The dimension of the state vector increases with the amount of the receivers. Higher dimension of the state vector will contribute heavier computation load of the integration filter. According to the GNSS pseudo-range errors model, the equation is

\[
\dot{\rho}_R^k = d_{\text{real}}^k - c \cdot \delta t_R^k + \epsilon_\rho^k
\]

where, \(d_{\text{real}}^k\) is the distance between the satellite and the user, \(c\) is the light speed, \(\delta t_R^k\) is the clock bias, and the \(\epsilon_\rho^k\) is the measurement noise.

Therefore, the difference between the GNSS pseudo-range and SINS pseudo-range is as:

\[
\delta \rho_R^k = \rho_{\text{INS}}^k - \rho_R^k = -\frac{x_k - x_{\text{real}}}{r_{\text{real}}} \delta x - \frac{y_k - y_{\text{real}}}{r_{\text{real}}} \delta y - \frac{z_k - z_{\text{real}}}{r_{\text{real}}} \delta z - c \cdot \delta t_R^k + \epsilon_\rho^k
\]

Similarly, the pseudo-range rates measurement can be written as:

\[
\delta \dot{\rho}_R^k = \dot{\rho}_{\text{INS}}^k - \dot{\rho}_R^k = -\frac{x_k - x_{\text{real}}}{r_{\text{real}}} \delta \dot{x} - \frac{y_k - y_{\text{real}}}{r_{\text{real}}} \delta \dot{y} - \frac{z_k - z_{\text{real}}}{r_{\text{real}}} \delta \dot{z} - c \cdot \delta \dot{t}_R^k + \epsilon_{\dot{\rho}}^k
\]

With the clock bias and clock drift exclusion, the state vector dimension is reduced.

\[
X_D = [\delta \rho \delta v \Phi \nabla \epsilon]
\]

Compared with Equation (1), clock bias and clock drift of the receiver are eliminated for reducing the computation load. The measurement model after the difference is presented in the following Equations.

In the \(i_{th}\) receiver \((i = 1 \ldots N)\), selecting one channel as the reference, the pseudo-range model of the \(i_{th}\) receiver after difference is as:

\[
Z_{\rho R_i}^p = [0_{M \times 3} \ H_{\rho R_i}^{i,1} \ 0_{M \times 9} \ H_{\rho R_i}^{i,2} ] \cdot X_D + V_{\rho R_i}^p
\]

Similarly, the pseudo-range model of the \(i_{th}\) receiver after difference is as:

\[
Z_{\dot{\rho} R_i}^p = [0_{M \times 3} \ H_{\dot{\rho} R_i}^{i,1} \ 0_{M \times 9} \ H_{\dot{\rho} R_i}^{i,2} ] \cdot X_D + V_{\dot{\rho} R_i}^p
\]
TABLE 1. Pseudo-range and pseudo-range rate accuracy comparison.

|            | Mean   | STD   |
|------------|--------|-------|
| One        | 2.51   | 3.14  |
| Pseudo-range (m/s) | 0.10   | 0.13  |
| Two        | 1.76   | 2.20  |
| Pseudo-range (m/s) | 0.07   | 0.09  |
| Four       | 1.27   | 1.60  |
| Pseudo-range (m/s) | 0.05   | 0.06  |
| Eight      | 0.89   | 1.12  |
| Pseudo-range (m/s) | 0.04   | 0.05  |

III. EXPERIMENTAL RESULTS AND ANALYSIS

For demonstrating the effectiveness and quantitatively analyzing the improvements of utilizing multiple receivers, a simulation experiment and a field test were carried out in this section. In Section III.A, eight receivers were simulated for demonstrating the benefits of improving the pseudo-range accuracy and pseudo-range rate accuracy. Based on this, in Section III.B, a field test with four receivers placed on the top of the car was conducted for further evaluating the proposed method.

A. SIMULATION

In the simulation, we assumed the pseudo-range error model as following:

\[ \rho_{R_k} = d_{R_k} + \text{Gauss}^\rho_{R_k} \quad (24) \]

where, \( d_{R_k} \) is the real distance and the \( \text{Gauss}^\rho_{R_k} \) is the noise subject to Gaussian distribution. Similarly the pseudo-range rate model was as:

\[ \dot{\rho}_{R_k} = \dot{d}_{R_k} + \text{Gauss}^\dot{\rho}_{R_k} \quad (25) \]

where, \( \dot{d}_{R_k} \) is the real pseudo-range rate and the \( \text{Gauss}^{\dot{\rho}}_{R_k} \) is the noise subject to Gaussian distribution. The parameters of the pseudo-range noise and pseudo-range rate noise were as:

\[ \text{Gauss}^\rho_{R_k} \sim N \left(0, 10^2\right) \quad (26) \]

\[ \text{Gauss}^{\dot{\rho}}_{R_k} \sim N \left(0, 0.1^2\right) \quad (27) \]

Fig. 2 presented the pseudo-range and pseudo-range rate errors comparison, which was calculated by averaging the multi-receivers’ measurements. Statistical analysis of the results was listed in Table 1. Compared with the one receiver, the mean values of the two-receiver, four-receiver and eight-receiver decreased by 29.8%, 49.4% and 64.5%; the standard deviation values (STD) decreased by 29.9%, 49.0% and 64.3%. In aspects of the pseudo-ranges, the mean values of the two-receiver, four-receiver and eight-receiver decreased by 30.0%, 50.0% and 60.0%; the standard deviation values (STD) decreased by 30.8%, 53.8% and 61.5%. The errors decreased along with the receivers’ amount increasing. The simulation results provided a preliminary proof of the benefits employing multiple receivers.

B. FIELD TEST SETTING

Apart from the simulation in Section III.A, this sub-section carried out a field test for fully evaluating the performance.
of the proposed method. Since it was hard to obtain pseudorange and pseudo-range rates from low-cost commercial receivers, three self-developed DSP + FPGA receivers were employed in the field test. Fig. 3 presented the employed receiver and the MEMS IMU (MSI3200) in the laboratory. The blue rectangle marked was the DSP+FPGA based receiver. Another three receivers were the copies of this one. The red rectangle marked was the MEMS IMU. Table 2 gave the specifications of the MEMS IMU. The Allan stability of the gyroscope was 2°/h, and the accelerometer bias stability was 0.5mg. The sampling rate was 400 Hz. Fig. 4 plotted the trajectory of the field test, and the Fig. 5 was the amount of the satellite amount in view during the testing. Amount of the available satellites were more than 8 during the trajectory. The testing time length was approximately 4 minutes. During the field testing, the four receivers’ antennas were placed together closely, and the shared a common MEMS IMU. A commercial UBL0X with RTK operation was employed as the reference. The trajectory was plotted using the trajectory files.

Following Fig. 6 presented the navigation solutions errors curves. Fig. 6(a), Fig. 6(b) and Fig. 6(c) were the latitude, longitude and altitude errors. In these Figures, red line represented the position errors of one-receiver based TI, the blue line represented the position errors of two-receiver based TI and the green line represented the position errors of four-receiver based TI. Table 3, Table 4 and Table 5 listed the statistical analysis of the position and velocity errors. In aspects of the latitude errors, mean values of the two-receiver TI and four-receiver TI obtained 19.3% and 25.0% decrease, and the STD values decreased by 19.3% and 32.4%; mean values of the longitude errors decreased by 43.1% and 51.4%, the STD values decreased by 21.6% and 35.1%; mean values of the altitude decreased by 8.8% and 27.1%, the STD values of the altitude errors gained 11.8% improvement.

Fig. 7 presented the velocity errors, and the statistical results were listed in Table 3, Table 4 and Table 5. The east velocity errors mean values of the two-receiver and four-receiver TI reduced by 9.1% and 18.2% compared with the

| TABLE 3. Latitude errors and east velocity errors. |
|-----------------------------------------------|
| One   | Position(m) | Mean | STD  |
|       | East Velocity(m/s) | 0.88  | 1.09  |
|       | East Velocity(m/s) | 0.022 | 0.031 |
| Two   | Position(m) | 0.71  | 0.88  |
|       | East Velocity(m/s) | 0.020 | 0.030 |
| Four  | Position(m) | 0.66  | 0.75  |
|       | East Velocity(m/s) | 0.018 | 0.027 |
|       | East Velocity(m/s) | 0.017 | 0.031 |

| TABLE 4. Longitude errors and north velocity errors. |
|-----------------------------------------------|
| One   | Position(m) | Mean | STD  |
|       | East Velocity(m/s) | 1.32  | 1.11  |
|       | East Velocity(m/s) | 0.031 | 0.030 |
| Two   | Position(m) | 0.75  | 0.87  |
|       | East Velocity(m/s) | 0.024 | 0.028 |
| Four  | Position(m) | 0.51  | 0.72  |
|       | East Velocity(m/s) | 0.024 | 0.020 |

| TABLE 5. Altitude errors and up velocity errors. |
|-----------------------------------------------|
| One   | Position(m) | Mean | STD  |
|       | East Velocity(m/s) | 1.81  | 1.52  |
|       | East Velocity(m/s) | 0.032 | 0.042 |
| Two   | Position(m) | 1.65  | 1.49  |
|       | East Velocity(m/s) | 0.020 | 0.034 |
| Four  | Position(m) | 1.23  | 1.34  |
|       | East Velocity(m/s) | 0.017 | 0.031 |

| TABLE 6. Latitude errors and east velocity errors. |
|-----------------------------------------------|
| One   | Position(m) | Mean | STD  |
|       | East Velocity(m/s) | 2.61  | 1.68  |
|       | East Velocity(m/s) | 0.027 | 0.037 |
| Two   | Position(m) | 1.03  | 1.47  |
|       | East Velocity(m/s) | 0.026 | 0.034 |
| Four  | Position(m) | 0.75  | 1.21  |
|       | East Velocity(m/s) | 0.020 | 0.027 |
one-receiver TI, the corresponding STD values reduced by 3.2% and 12.9%; the north velocity errors also were suppressed, as listed in the table 4, the mean values of the north velocity errors reduced by 22.6% and 22.6%, the STD values decreased by 6.7% and 33.3%. It seemed that the mean values kept the same from the two-receiver to four-receiver; however, the STD values preformed some reduction. In addition, the up velocity errors mean values also decreased by 37.5% and 46.8%, and the STD values reduced by 19.0% and 26.2%.

Following Fig. 8 presented the navigation solutions errors of the multiple receivers based tight integration system (MR-TI) using measurement difference. Fig. 8(a), Fig. 8(b) and Fig. 8(c) were the latitude, longitude and altitude errors. Similarly, statistical analysis results were listed in Table 6, Table 7 and Table 8. For the latitude errors, mean values of the two-receiver TI and four-receiver TI decreased by 60.5% and 70.1%, and the STD values decreased by 12.5% and 30.0%; mean values of the longitude errors decreased by 23.5% and 53.9%, the STD values decreased by 23.5% and 48.5%; mean values of the altitude decreased by 12.7% and 21.8%, the STD values of the altitude errors reduced by 15.3% and 26.1%.

Fig. 9 presented the velocity errors of the one-receiver, tow-receiver and four-receiver TI, the means values of the east velocity errors decreased by 3.7% and 25.9%, the STD values decreased by 8.1% and 27.0%; the north velocity errors...
mean values reduced by 67.3% and 73.1%, and the STD values decreased by 63.3% and 68.3%; the up velocity errors
reduced by 67.3% and 73.1%, and the STD values also decreased by 43.4% and 45.3%.

IV. CONCLUSION

This paper proposed multiple receivers based GNSS/SINS tight integration system. Three self-developed DSP+FPGA receivers were employed in the field testing. Compared with the single receiver based GNSS/SINS tight integration system, the navigation solutions errors obtained improvement at different degrees. For reducing the dimension of the state vector, a measurement difference method was proposed and the clock bias and drift variables were excluded from the state vector for reducing the computation load of the integration filter. The simulation and filed testing results demonstrated the effectiveness of the proposed method.

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