

GNSS Modernization and its Consequences for Reference Station Network Solutions

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BIOGRAPHY

Xiaoming Chen is a senior engineer at Trimble Terrasat responsible for R&D in the area of network solutions. He holds a Ph.D. in Geodesy from Wuhan Technical University of Surveying and Mapping. His primary interests are in the field of network solutions for RTK positioning systems and tropospheric modeling.

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Jan Köhler is a quality assurance engineer at Trimble Terrasat. He received his engineering degree in surveying and geoinformatics from the Munich University of Applied Sciences in 2005. Jan joined Trimble in April 2004. He is mainly working in the field of reference station network and RTK testing.

Herbert Landau received a Ph.D. in Satellite Geodesy from the University FAF Munich, Germany in 1988. At Trimble he is acting as Managing Director of Trimble Terrasat GmbH, Germany and as Director of the Trimble GNSS Algorithms and Infrastructure Software group. He has many years of experience in GPS and has been involved in a large variety of GPS and GLONASS developments. His professional interest is focused on high-precision real-time kinematic positioning and reference station network processing.

Ulrich Vollath received a Ph.D. in Computer Science from the Munich University of Technology (TUM) in 1993. At Trimble Terrasat - where he has worked on GPS algorithms for more than thirteen years - he is responsible for the RTK development team. His professional interest is focused on high-precision real-time kinematic positioning and reference station network processing.

INTRODUCTION

Modernization plans for the US Global Positioning System GPS and the Russian GLONASS system are actively pursued. The first GPS-IIR-M satellites with L2C support have been launched and more will come in the near future. The first launch of a GPS-IIF satellite with L5 support is announced for spring 2008. Russia has started to launch GLONASS-M satellites with an extended life-time and a civil L2 signal and has announced to build up a full 18 satellite system by 2007 and a 24 satellite system by 2009. The European Union together with the European Space Agency and other partnering countries are going to launch the new European satellite system Galileo, which will also provide worldwide satellite navigation service at some time after 2011.

Today a large number of reference station networks with several thousands of GPS receivers exist all over the world and provide correction services for network-based DGPS and RTK type of positioning. Operators of these networks have started to upgrade reference stations with GNSS receiver hardware gradually to support L2C, L5 and in many cases also GLONASS. Deployment of Galileo capable receivers into these networks is also expected to start in a few years when Galileo satellites are becoming operational.

As a consequence we expect there will be a transition period during which the reference station networks have very heterogeneous receiver hardware and the network server software computing network corrections will have to deal with the heterogeneity of the available data from an increased number of signals and satellites. The complexity but also the CPU load for this server software will increase dramatically.

To verify the approach a network in Germany with 123 stations was processed in real-time and post-processing. From these 123 stations, we selected 50, 60, 70 up to 100 stations to run network processing with both approaches. The total processing time on a 3 GHz Intel Pentium processor (including data preparation, ionosphere modeling and network ambiguity fixing) of each process for one day of data is summarized in figure 3. For a 50 station network, the centralized approach requires 100 msec while the federated approach requires less than 15 msec. For a 100 station network, the centralized approach requires more than 800 msec while the federated filter approach uses approximately 60 msec. This test proved that the federated filter approach is highly computationally efficient for large networks.

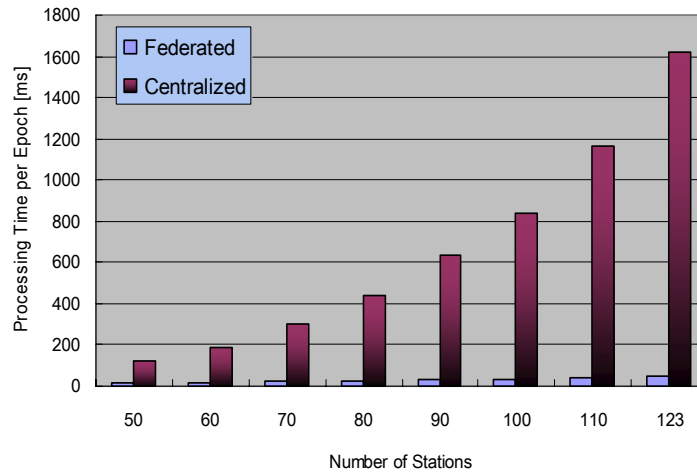


Fig. 3: Required CPU time for the processing of one epoch with both methods

It was also shown by Landau et al. (2007) that the performance and accuracy provided in a network operating with the federated filter approach is comparable to the classical centralized approach.

SUPPORTING SPARSE GLONASS NETWORKS

Due to the fact that an increasing number of GLONASS satellites are becoming available and the Russian Federation is promising a more stable GLONASS system, providers of VRS™ network services have started to introduce GLONASS capable receivers into existing “GPS only” networks. Especially in existing VRS™ networks GLONASS receivers are not deployed on all reference stations for organizational or financial reasons. This is resulting in situations with dense GPS networks and sparse GLONASS coverage. This is demanding solutions in which the network corrections for GPS are actually derived from the dense network while the GLONASS corrections are computed from the more sparse network stations. We will show in the following that our VRS™ in GPSNet™ is able to handle such mixed networks and providing high quality GPS corrections in combination with acceptable GLONASS corrections. A typical example for such a scenario is shown in the following figure.

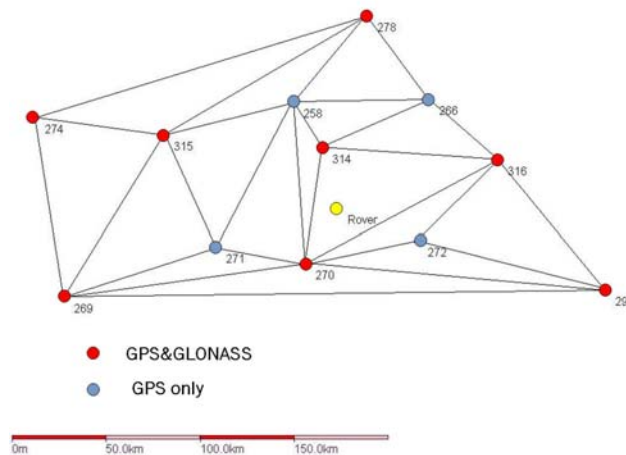


Fig. 4: “Dense” Network with GPS+GLONASS stations (red) and “GPS only” stations (light blue) and the rover location (yellow)

In the network described above we have a reasonable dense GLONASS coverage. In the analysis we have done we have compared this network with a more sparse one. We have created this sparse network by disabling the availability of GLONASS data in the real-time data streams from some of the stations. The sparse network looks like described in the following figure.

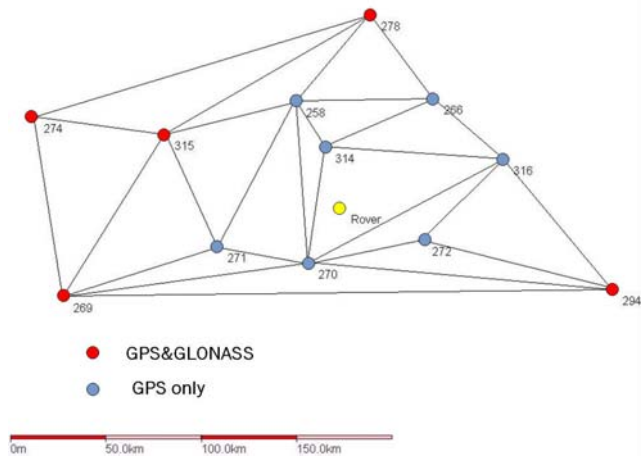


Fig. 5: “Sparse” Network with GPS+GLONASS stations (red) and “GPS only” stations (light blue) and the rover location (yellow)

To create a third configuration from the same physical network we were feeding the same station data into a third GPSNet™ server but disabled GLONASS data completely.

On the rover location we were running three rovers of the same type connected to the same antenna and are measuring initialization performance and positioning accuracy over a time period of 24 hours. The distance of the rover from the nearest reference station is more than 30 km. The RTK initialization results are summarized in the following table 1.

Network Type	68% [sec]	95% [sec]	Number of Inits
GPS Only	14	18	2643
Dense GPS+GLONASS	12	15	2645
Sparse GPS+GLONASS	13	16	2644

Table 1: Initialization Performance of RTK systems in three different network types

The table shows best performance for the dense GPS+GLONASS network. However, the sparse network is not performing significantly worse but better than the “GPS only” system. It should be noted that none of the more than 2640 RTK initializations produced wrong ambiguity sets in any network type. Eleven GLONASS satellites were healthy during the test and could be used for the performance evaluation. The positioning accuracy was derived by comparison with true values.

Network Type	RMS North [mm]	RMS East [mm]	RMS Height [mm]
GPS Only	12	7	25
Dense GPS+GLONASS	12	6	23
Sparse GPS+GLONASS	12	6	23

Table 2: RTK positioning accuracy derived from 86400 positions in three different network types

The positioning accuracy does not significantly differ between the three networks. All of the three rovers provided excellent RTK positioning accuracy.

While the presented method works fine we still want to point out that the tests we have performed were done during a period of low ionospheric activity. In preparation for the next ionospheric maximum in 3-4 years VRS™ network service providers should prepare for this scenario by deploying GLONASS enabled GNSS receivers on all network stations.

ON THE USE OF NETWORK CORRECTION QUALITY INFORMATION AT THE ROVER

The models used in network RTK (e.g. for ionospheric, orbital and tropospheric errors) are reducing error sources dramatically but they are unable to eliminate the errors completely. Applying specific methods as described by Chen et al. (2003) the predicted variance of the geometric and ionospheric correction for each rover location can be computed from the available data for each satellite individually. These predicted values can be used in the rover to derive an optimum position solution using specific weighting mechanisms. The application of this approach is described below and results are presented showing the positioning performance due to the use of the computed statistical information.

The VRS™ method generates “optimized” corrections for individual rover locations. However, errors cannot be completely eliminated. Based on the available data, density of the network and irregularities in atmospheric conditions, different residual errors are affecting the solution. Our VRS™ network server software GPSNet™ is able to predict variances of residual errors at the individual rover location for each satellite in view. These parameters characterize the expected geometric and ionospheric errors at the rover. The proposed parameters and relations are for the ionospheric error

$$\sigma_i^2 = \sigma_{ic}^2 + \sigma_{id}^2 \times d^2$$

where σ_{ic} = Constant term of standard deviation for dispersive prediction error
 σ_{id} = Distance dependent term of standard deviation for dispersive prediction error
 d = Distance to nearest reference station

For the non-dispersive error we use

$$\sigma_0^2 = \sigma_{0c}^2 + \sigma_{0d}^2 \times d^2 + \sigma_{0h}^2 \times \Delta h^2$$

where σ_{0c} = Constant term of standard deviation for non-dispersive prediction error
 σ_{0d} = Distance dependent term of standard deviation for non-dispersive prediction error
 σ_{0h} = Height dependent term of standard deviation for non-dispersive prediction error
 d = Distance to nearest physical reference station
 h = Height difference to reference station

The distance dependent part was introduced to describe the error growth with the distance to the nearest physical reference station. The height dependent part is used to describe the error growth due to tropospheric effects. Typically the errors grow with distance from reference stations, i.e. the estimates for the dispersive and non-dispersive errors at the rover location will be dependent on the rover location in the network. As we can see in figure 6 the error is small for some areas around the reference stations and increasing with the distance. An alternative approach, which is desirable, is to continuously compute the error statistics in the network server software for the current rover position. In that case the distance and height dependent parts of the equations describing the errors will be zero. The following figure 6 shows a typical error behavior for the ionospheric effect.

The RTCM SC104 committee is currently discussing the potential creation of RTCM version 3 messages to transmit these parameters from the network server to the user in the field for GPS and GLONASS satellites. These new messages will allow us to improve our RTK accuracy in future systems. In preparation of these standardized messages a dataset was selected allowing the comparison of quality information with real RTK processing residuals and potentially the comparison between different server software. In the following we will describe the dataset briefly and compare the computed “one-sigma” standard deviations with the true residual errors as observed in rover data processing. The dataset is using 24 hours of 1 Hz reference station data of 5 reference stations and a rover. The distance from the rover to station 0272 is 33 km.

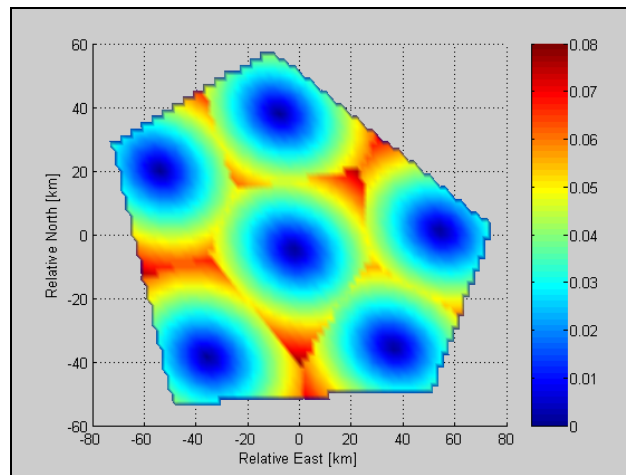


Fig. 6: Typical ionospheric error distribution in a VRSTM network in time periods of strong ionosphere [values in meters]

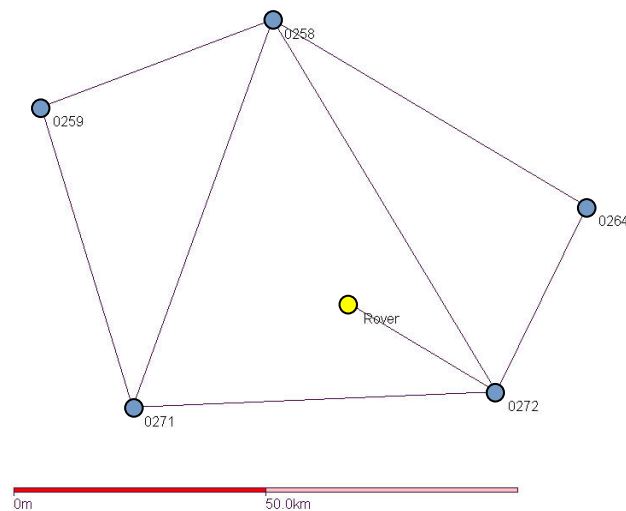


Fig. 7: Network used for the analysis of the derived network quality parameters

Virtual reference station data and associated predicted standard deviations were computed for the rover location. The rover data was then processed together with the virtual reference station data to compute positions and double difference residuals. In the following figures we show the predicted standard deviations for the geometric and the ionospheric corrections, which are reflecting the quality of the network corrections. We also show the double difference residuals in geometry (ionosphere-free) and ionosphere (geometry-free). Although these double difference residuals are influenced by the reference satellite we can expect that the residuals should correlate with the predicted standard deviations.

As an example we show the ionospheric double difference residuals and the associated predicted standard deviations for one pass of GPS satellite PRN 1.

The figure shows nicely the high degree of correlation of the estimated quality information with the real double difference residuals. The geometric information shows similar behavior.

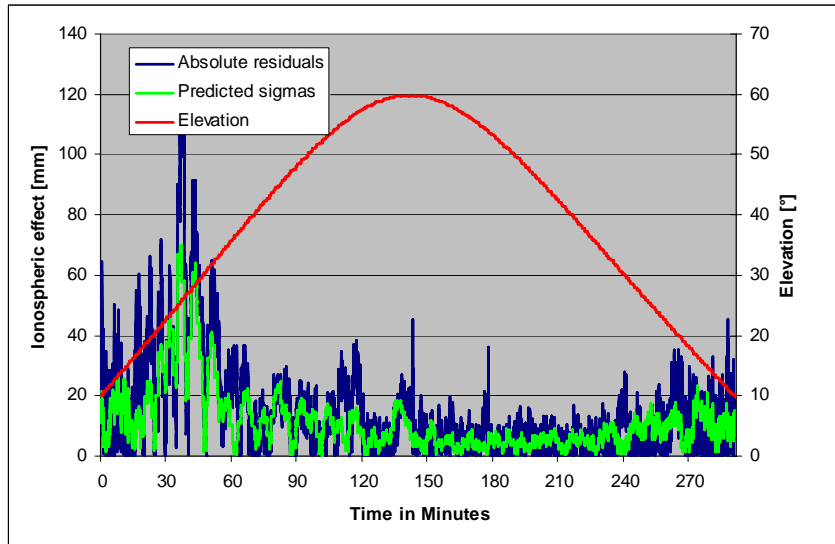


Fig. 8: Absolute double difference residuals and predicted sigmas for the ionospheric effect on GPS satellite 1 (62% of the predicted sigmas are less than the absolute residual)

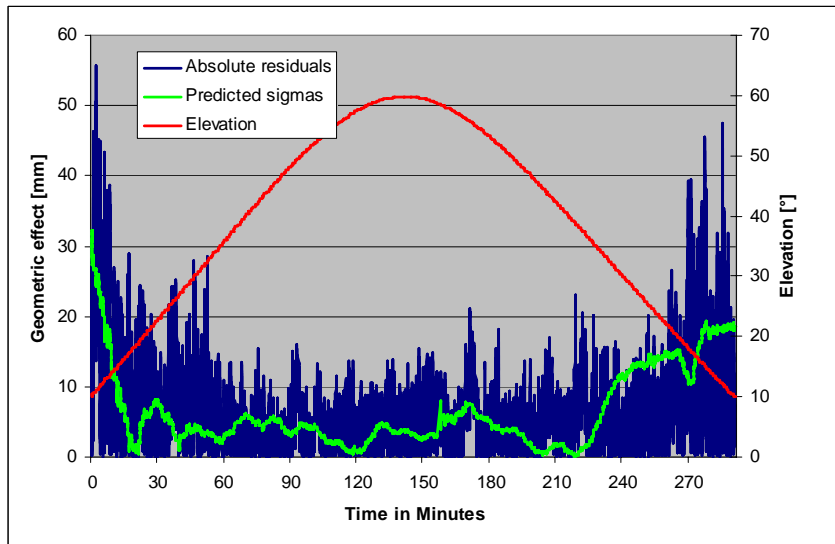


Fig. 9: Absolute double difference residuals and predicted sigmas for the geometric effect on GPS satellite 1 (55% of the predicted sigmas are less than the absolute residual)

For comparison we show the effects for GPS satellite PRN 22 below .

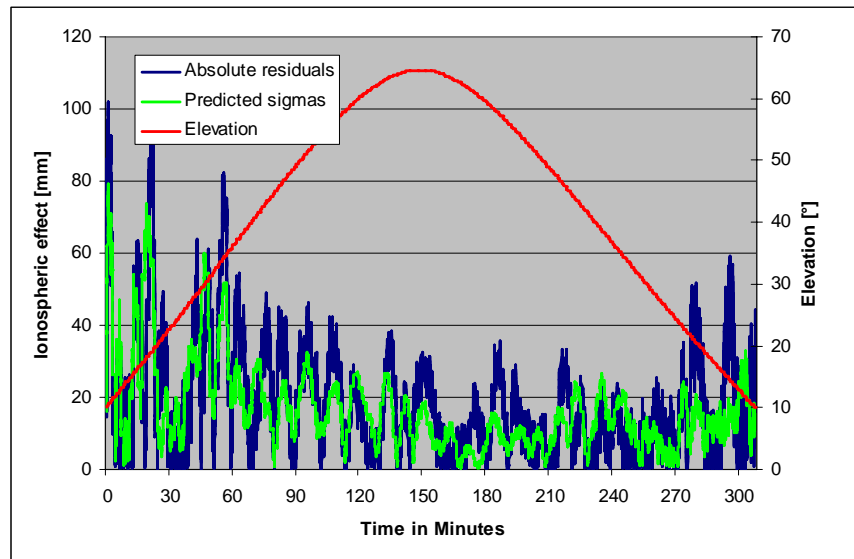


Fig. 10: Absolute double difference residuals and predicted sigmas for the ionospheric effect on GPS satellite 22 (55% of the predicted sigmas are less than the absolute residual)

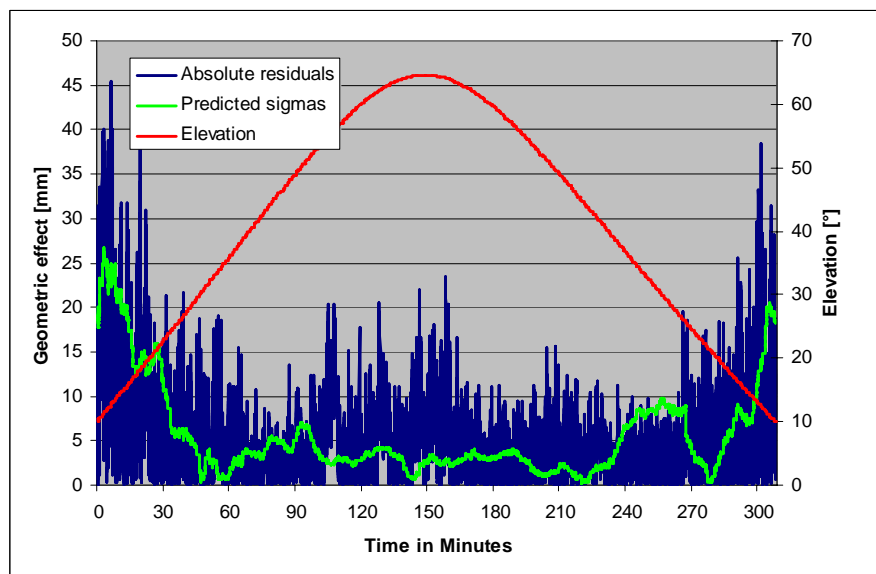


Fig. 11: Absolute double difference residuals and predicted sigmas for the geometric effect on GPS satellite 22 (47% of the predicted sigmas are less than the absolute residual)

The predicted sigmas for the network corrections are one-sigma values and therefore from a statistical viewpoint 68% of the estimates should be less than the true residuals. Given the fact that we actually do not compare with the raw residuals but with the double difference residuals the computed percentages are within the expected range (55% / 62% for PRN 1 and 47% / 55% for PRN 22).

The above parameters can be used in the rover to control the optimum weighting of Virtual Reference Station data for the individual satellites in the position solution and thus lead to increased position accuracy. It can also be used to support the ambiguity search process and the optimum combination of L1 and L2 observations to derive a “minimum-error” position estimate.

The idea was verified earlier by using data from a Terrasat network (Trimble NetRS and NetR5 receivers) in the surrounding of Munich, Germany (Landau et al., 2007).

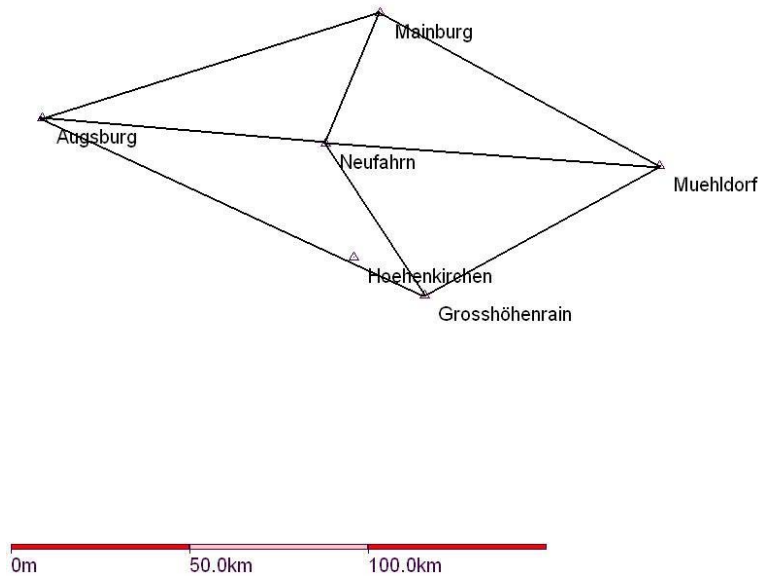


Fig. 12: Reference station network in the surrounding of Munich

The station Hoehenkirchen was not part of the network processing, it was used as a rover station only. The nearest reference station is Grosshoehenrain, which is approximately 16 km away. An optimum VRSTM data stream was generated for a full day and this data stream was used to position the rover Hoehenkirchen with the Trimble RTK engine. The RTK engine was run in the standard mode and in a modified mode, in which the RTK engine made use of the statistical information on ionospheric and geometric residual errors in the VRSTM data stream. In order to visualize the accuracy improvement the complete day was cut in 48 ½ hour parts and the 3D RMS for each ½ hour slot was computed and visualized. The green bars in figure 13 represent the RMS values for the standard procedure previously used in the RTK engine while the red bars represent errors for the optimized solution. The cyan bars are showing the average predicted ionospheric errors. The graph shows that in almost all cases the optimized solution was able to reduce the position errors by up to a factor of 2. For some of the ½ hour slots no improvement was reached, which will need to be the topic for further research. The problematic times are mainly the ½ hour periods with higher ionospheric residual errors. This would be consistent with an ionosphere-free carrier phase providing the best solution here.

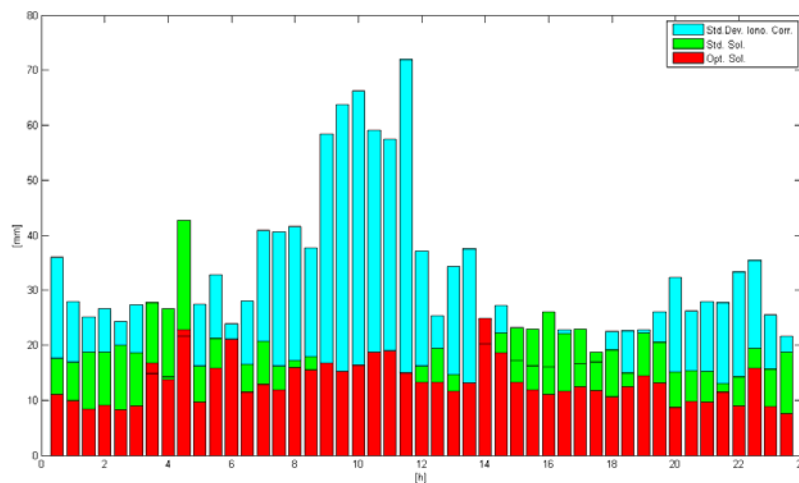


Fig. 13: 3D-RMS values for ½ hour slots for the optimized solution in red, standard solution in green (iono correction sigmas in cyan)

To show the individual errors in detail a ½ hour period was selected and the following figures show the errors for the standard solution in blue and the optimized solution in red in North, East and Height. It can be easily seen that the optimized solution provides much better accuracy in all three components.

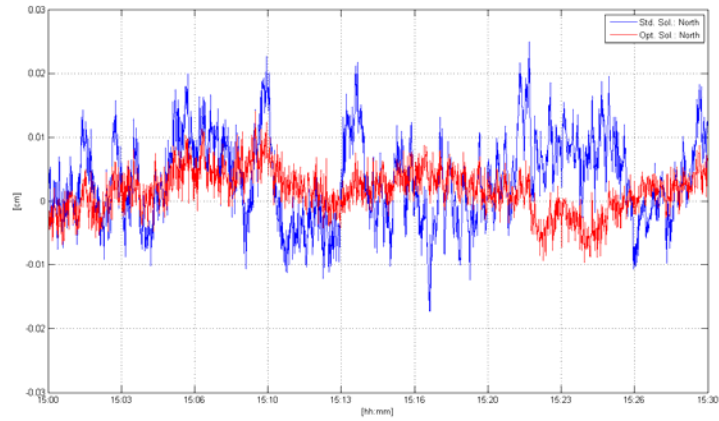


Fig. 14: Position errors in North direction for the optimized solution in red (5 mm RMS) and the standard solution in blue (9 mm RMS)

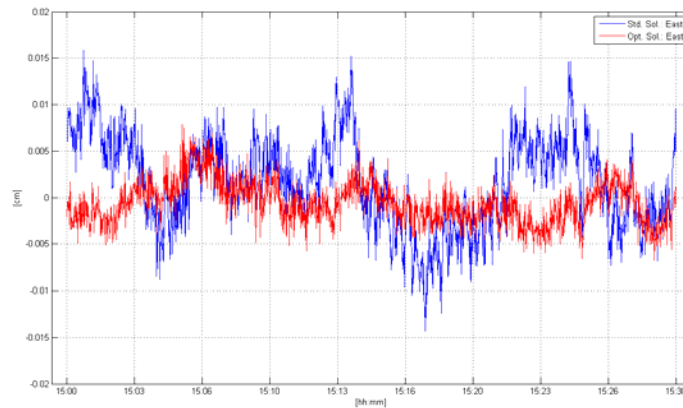


Fig. 15: Position errors in East direction for the optimized solution in red (2 mm RMS) and the standard solution in blue (6 mm RMS)

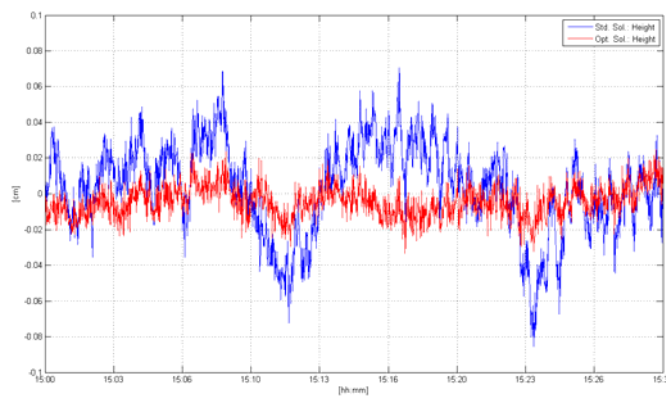


Fig. 16: Position errors in Height direction for the optimized solution in red (13 mm RMS) and the standard solution in blue (21 mm RMS)

All our tests so far have shown that the use of the error estimates from the network have been able to improve the positioning accuracy considerably. The analysis we have done until now is a pure offline post-processing one, which allowed us to verify the usefulness of the approach.

Initialization Performance

Besides the RTK positioning accuracy the RTK initialization performance can also be improved. First analysis of the “Time To Fix” performance for the VRS™ networks analyzed above show that the initialization time can be reduced by a factor of approximately 30% compared to the already excellent ambiguity resolution performance typically seen in networked RTK.

SUMMARY

Continuing R&D on VRS™ technology allows us to provide solutions, which can process larger networks with more satellites and signals and support multiple satellite systems. Performance analyses for the federated filter approach show that availability and reliability of network processing are comparable and the rover performance stays the same compared to the centralized filter approach.

New technology in the VRS™ server software provides a practical and accurate solution for so called sparse GLONASS networks, i.e. networks with dense GPS coverage (50 km between stations) and longer distances like 100 km between GPS/GLONASS reference stations. While this method works satisfactorily during low to medium periods of ionospheric activity, we recommend strongly providing GLONASS tracking capability on all network stations for optimum GLONASS correction quality in VRS™ networks.

Using predicted dispersive and non-dispersive quality information computed from GPSNet™ for the rover location and all GPS and GLONASS satellites improves the rover positioning performance considerably when using the VRS™ technology. We hope that this technology will be accepted soon by the industry and will be available in almost all the existing VRS™ networks.

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