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Latest Developments in Network RTK Modeling to Support GNSS Modernization

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Abstract. Global Navigation Satellite Systems like the US Global Positioning System GPS and the Russian GLONASS system are currently going through a number of modernization steps. The first satellites of the type GPS-IIR-M with L2C support were launched and from now on all new GPS satellites will transmit this new civil L2 signal. 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. Independently of that 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. As a consequence we can expect to have very heterogeneous receiver hardware in these reference station networks for a transition period which could last until 2015. Network server software computing network corrections will have to deal with an increased number of signals, satellites and heterogeneity of the available data. The complexity but also the CPU load for this server software will increase dramatically. With the increasing number of signals and satellites the demands for the network server software is growing rapidly. The progress on the satellite system side is going hand in hand with the tendency of the customers to operate growing numbers of reference station receivers resulting in higher demands for CPU power. The paper presents a new approach, which allows us to process data from a large number of reference stations and multiple signals via a new federated Kalman filter approach. With the newest improvements in the GLONASS satellite system, more and more Network RTK service providers have started to use GLONASS capable receivers in their networks. Today, practically all service providers, who are using GLONASS, are applying the Virtual Reference Station (VRS) technique to deliver optimized correction streams to the users in the field. Different satellite systems and generations require different weighting in network server processing and receiver positioning. The network correction quality depends very much on the satellite and signal type. New message types have been recently developed providing individualized statistical information for each rover on unmodeled residual geometric and ionospheric errors for GPS and GLONASS satellites. The use of this information leads to RTK performance improvements, which is demonstrated in practical examples.

Keywords: GPS, GNSS, GNSS Modernisation, Network RTK.

INTRODUCTION

After its introduction in the late 90s, Network RTK technology based on the Virtual Reference Station (VRS) approach became an accepted and proven technology, which is widely used today in a large number of installations all over the world. Developments over the past years (Chen et al., 2003, 2004, 2005; Kolb et al., 2005, Landau et al., 2002; Vollath et al., 2000, 2001) have resulted in a solution, which is marketed under the name GPSNetTM since 1999 (Vollath et al., 2000). Comparing with traditional single base RTK technology, network RTK removes a significant amount of spatially correlated errors due to the troposphere, ionosphere and satellite orbit errors, and thus allows performing RTK positioning in reference station networks with distances of 40 km or more from the next reference station while providing the performance of short baseline positioning.

Currently more than 2500 reference stations are operating in networks in more than 30 countries using the Trimble GPSNet solution. Data processing in GPSNet utilizes the mathematically optimal Kalman filter technique to process data from all network reference stations. This comprehends modelling all relevant error sources, including satellite orbit and clock errors, reference station receiver clock errors, multipath and particularly ionospheric and tropospheric effects.

To optimize real-time computational performance, the Trimble patented FAMCAR (Factorized Multi-Carrier Ambiguity Resolution) methodology has been used to factorize uncorrelated error components into a bank of smaller filters, i.e. “Geometry Filter” and “Geometry-free Filters” and “Code-carrier Filters” (Vollath et al., 2004, Kolb et al., 2005). This approach results in significantly higher computational efficiency. However, due to the fact that the geometry filter still contains a large number of states (several hundreds to thousand states depending on the number of stations in the network), GPSNet until recently was able to process 50 reference stations on a single PC server only, larger networks were divided into sub-networks and operated by multi-server solutions.

In recent years, more and more service providers have setup reference networks to provide nation-wide or region-wide RTK services. Many of them contain more than 50 reference stations, i.e. JENOBA, Japan (338 stations), E.ON Ruhrgas AG ASCOS, Germany (more than 180 stations); Ordnance Survey, United Kingdom (86 stations), and many existing network operators intend to extend their network to serve larger areas. In order to allow the processing of larger networks on one single PC, an efficient approach – Federated Geometry Filter – has been developed and implemented in Trimble’s latest infrastructure software (GPSNet version 2.5).

Speeding up the GeOMETRY FILTER

Centralized Geometry Filter

The geometry filter plays an important role in the GNSS network data processing. It provides not only the float estimation of ionosphere-free ambiguities for later network ambiguity fixing, but also provides tropospheric zenith total delay (Vollath et al, 2003). This filter is usually running as a centralized Kalman filter. The typical state vector in the filter consists of:

- Tropospheric zenith total delay (ZTD) per station
- Receiver clock error per station
- Satellite clock error per satellite
- Ionosphere-free ambiguity per station per satellite
- Orbit errors

Table 1 shows the number of states in the filter with given number of stations and number of satellites observed at each station. For a 20 station network and 12 satellites observed in each station, the filter has 328 states; for a 120 station network and 18 satellites observed in each station, the filter has 2472 states. With the increase in the number of stations in the network and number of satellites observed on each station, the number of states thus processing time will increase dramatically.

Table 1: Number of states in the centralized geometry filter

Stations	Satellites	States
20	12	328
	15	400
	18	472
40	12	608
	15	740
	18	872
80	12	1168
	15	1420
	18	1672
120	12	1728
	15	2100
	18	2472

Fig. 1 shows the number of multiplications required for one filter step (one epoch of data sent through the filter) for a given number of stations with the assumption that 12 satellites are observed on each station. As the most expensive operation in the filter is the multiplication, this figure can be approximately interpreted as the relationship between number of stations and computational load of the filter. In Fig. 1, the blue bars give the number of multiplications in billions for number of station from 10 up to 120. The pink line in the figure represents the function $(36x)^3$, which fits perfectly to the required multiplications. So, it is clear that the computational time increases cubically with the number of stations in the network.

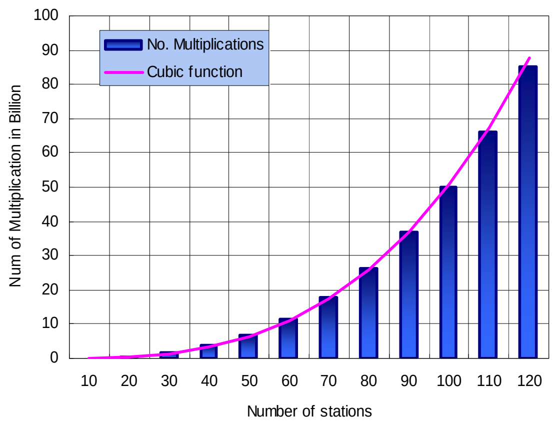

Fig. 1: Relation between number of reference stations and required multiplications in one filter step

Federated Geometry Filter

The Federated Kalman filter was introduced by N.A. Carlson (1990). The basic idea of federated filter is that:

- A bank of local Kalman filters runs in parallel. Each filter operates on measurements from one local sensor only. Each filter contains unique states for one local sensor and common system states for all the local sensors.
- A central fusion processor computes an optimally weighted least-square estimate of the common system states and their covariance.
- Then the result of the central fusion processor is fed back to each local filter to compute better estimates for the local unique states.

The main benefit of this approach is that each local filter runs with reduced number of states and the computation time for the whole system increases only linearly with the increase of the number of local sensors. This significantly reduces the computational load compared to the centralized filter approach.

For GNSS network processing, each reference station can be treated as a local sensor with unique states like ZTD, receiver clock error and ionosphere-free ambiguities (2+n, where n is number of satellites in the system), and common states like satellite clock errors and orbit errors (n + m x n, where n is number of satellites in the system and m is number of orbit error parameter per satellite). Therefore the federated filter approach can be applied. As there are still too many common states, a further step can be taken to further reduce the computational load. The satellite orbit error states are estimated with a frame filter. This frame filter uses only a subset of the reference stations in the network to estimate the orbit error parameters. Then the estimated orbit errors are applied directly to observation processed in the local filters.

Fig.2 illustrates the block diagram of a Federated Geometry Filter for GNSS network processing. This approach contains one frame filter, a bank of single station geometry filters (one per reference station) and one central fusion master filter.

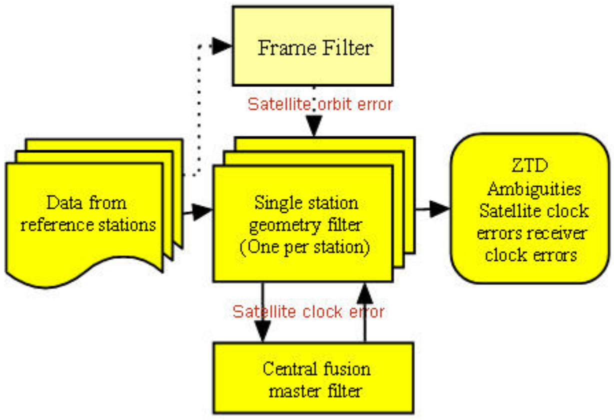

Fig. 2: Block diagram of a Federated Geometry Filter

Performance Analysis

Our performance analysis includes two parts. One is the post-processing performance comparison between the centralized geometry filter approach and federated geometry filter approach. It is focusing on the server performance – availability, reliability of the network processing and processing time. The other part is the real-time performance analysis focusing on the RTK rover positioning and fixing performance in the network.

Post-processing Performance

The post-processing performance study uses a post-processing version of GPSNet. The first test performed is to check the availability (percentage of fixed ambiguities) and reliability (percentage of correctly fixed ambiguities) with both the centralized geometry filter approach and the federated geometry filter approach. Four days of data (days 289, 290, 291 and 322 of the year 2003) from the Bavarian Land Survey Department BLVG network (45 GPS stations, Germany) were used in the test. Table 2 summarizes the test results. For the GPS only network (BLVG), both approaches give similar results in terms of availability and reliability.

Table 2: Post-processing performance test (availability and reliability)

Network	Centralized Approach		Federated Approach	
	Availa-bility	Relia-bility	Availa-bility	Relia-bility
BLVG289	98.86	100	99.05	100
BLVG290	99.05	100	99.06	100
BLVG291	98.99	100	98.98	100
BLVG322	97.79	100	97.40	100

The second analysis is to check the processing time needed by the centralized and federated geometry filter approaches. In this test, one day data of 123 reference stations from five German states [Bayern, Nordrhein-Westfalen, Hessen, Thüringen and Niedersachsen] was used as shown in Fig. 3.

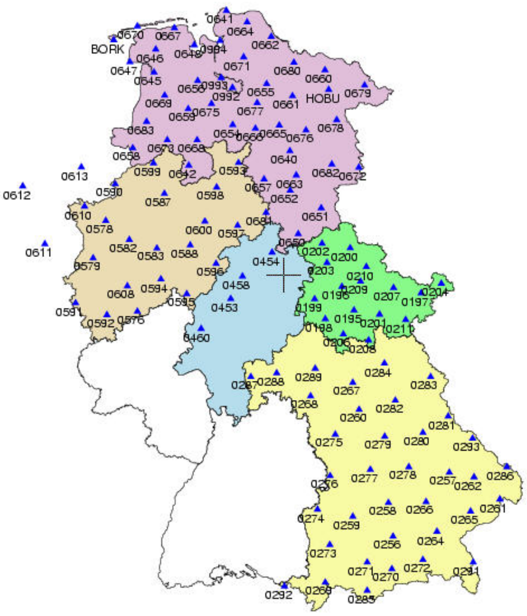

Fig. 3: Test Network in Germany

From these 123 stations, we selected 50, 60, 70 up to 100 stations to run network processing with both approaches. The total processing time (including data preparation, ionosphere modeling and network ambiguity fixing) of each process for one day of data is summarized in Table 3. For a 50 station network, the federated filter approach uses 20 minutes to process the data, while the centralized filter uses 173 minutes. For a 100 station network, the federated filter approach uses 57 minutes, while the centralized filter approach used 3581 minutes (nearly 2.5 days) to process one day of data, which means it is impossible to process data in real-time. Table 3 also gives the ratio of processing time between centralized filter and federated filter approach. For a 50 station network, the federated filter approach is 8 times faster and for a 100 station network, the federated filter approach is 63 times faster than the centralized filter approach. This test proves that the federated filter approach is highly computationally efficient for large networks (Table 3).

Table 3: Processing time comparison

Number of Stations	Centralized [Minute]	Federated. [Minute]	Ratio
50	173.35	20.57	8.4
60	280.83	25.56	11.0
70	455.03	31.28	14.5
80	697.83	38.23	18.2
90	1152.47	53.15	21.7
100	3581.46	56.85	63.0

Real Time Performance

For the real time test, two GPSNet systems were set up in parallel. One was running with the centralized filter approach. Real time data streams of 45 stations from the BLVG network were used in this configuration. Another system was running with the federated filter approach. Real-time data streams of more than 100 stations from the German SAPOS network were used in this configuration. Two Trimble 5700 rovers located in Trimble Terrasat office were used to verify the rover positioning and fixing performance. The VRS data streams generated from these two systems were streamed to both rovers respectively. The nearest reference station was 16 km away in both cases.

Table 4: Position error statistics

		Centralized [m]	Federated [m]
Mean	North	0.001	0.002
	East	-0.006	-0.006
	Height	0.001	0.005
1-Sigma	North	0.008	0.007
	East	0.005	0.005
	Height	0.013	0.013
RMS	North	0.007	0.007
	East	0.008	0.008
	Height	0.013	0.013

Table 4 summarizes the statistics of position errors over one day, which indicate that the positioning performances from both systems are the same from a statistical point of view.

Another test conducted in real time is to check the RTK fixing performance. The test setup is the same as the positioning performance test. Table 5 summarizes the RTK fixing performance during one day in terms of mean fixing time, 68%, 90%, 95% quantiles and minimum, maximum fixing time. Though the minimum and maximum fixing times for the rover in the system running the federated filter approach are longer than the centralized filter approach, other statistics are very much the same.

Table 5: RTK fixing performance

	Mean [s]	68% [s]	90% [s]	95% [s]	Min [s]	Max [s]
Centralized	25	27	30	34	13	508
Federated	25	27	29	35	16	561

IMPROVING ROVER PERFORMANCE USING NETWORK CORRECTION QUALITY INFORMATION

Latest developments have shown that it is possible to improve the rover positioning performance by using statistical information for the predicted residual error at the rover location. The models used in network RTK (e.g. ionospheric, orbit 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

Δh = 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. 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 4 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 4 shows a typical error behavior for the ionospheric effect.

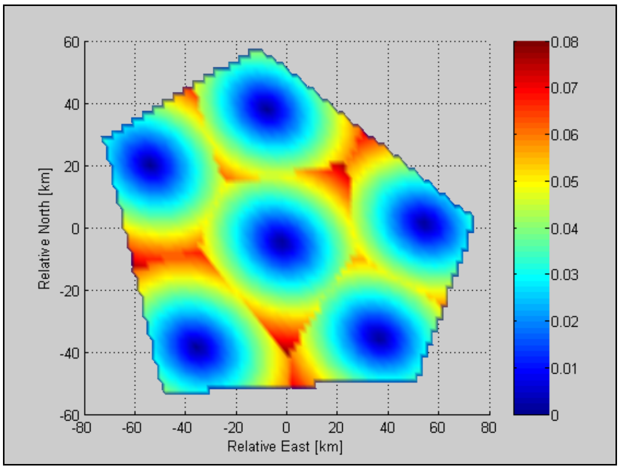

Fig. 4: Typical ionospheric error distribution in a VRS network in time periods of strong ionosphere [values in meters]

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.

To verify this idea data from two different networks were used. The first network is based on Terrasat owned reference stations (Trimble NetRS and NetR5 receivers) in the surrounding of Munich, Germany.

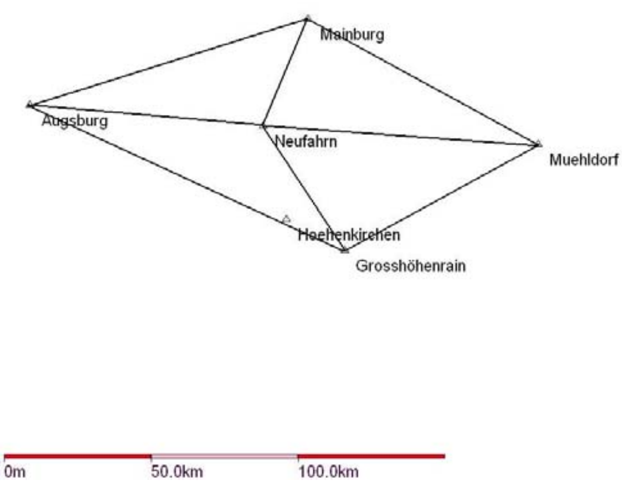

Fig. 5: Reference station network in the surrounding of Munich

The station Hoehenkirchen was not part of the network processing, it was used as a rover station only. The nearest reference station is Grosshöhenrain, which is approximately 16 km away. An optimum VRS 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 VRS 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 6 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.

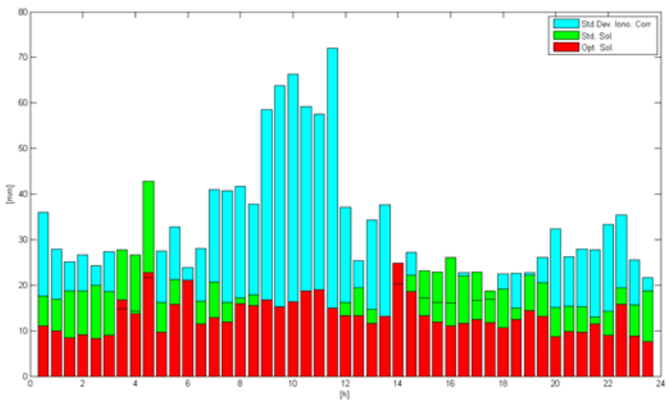

Fig. 6: 3D-RMS values for ½ hour slots for the optimized solution in red, standard solution in green (iono correction sigmas in cyan)

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.

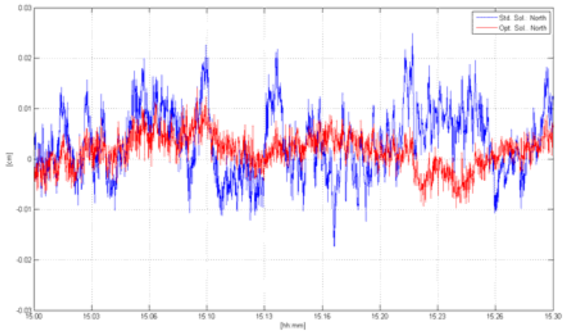

Fig. 7: Position errors in North direction for the optimized solution in red (5 mm RMS) and the standard solution in blue (9 mm RMS)

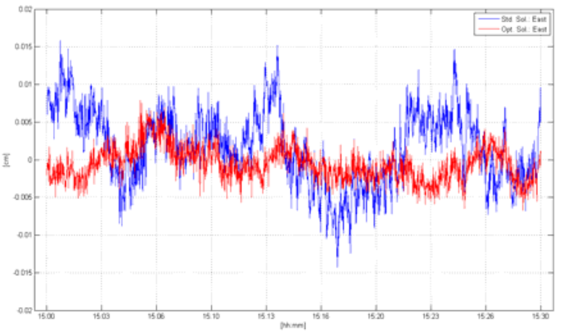

Fig. 8: Position errors in East direction for the optimized solution in red (2 mm RMS) and the standard solution in blue (6 mm RMS)

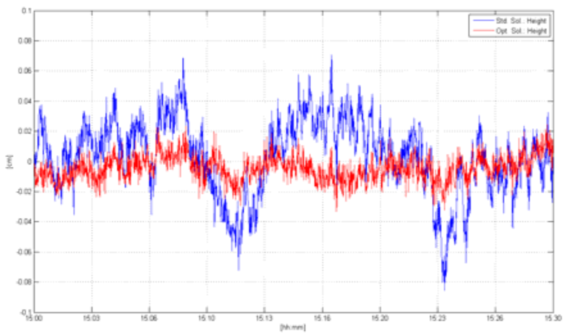

Fig. 9: Position errors in Height direction for the optimized solution in red (13 mm RMS) and the standard solution in blue (21 mm RMS)

The second network is using stations of the Bavarian Land Survey Department network (Mainly non-Trimble receivers) and a rover location at the Terrasat office in Hoehenkirchen (Trimble R8 GNSS). The distance between the reference station is typically about 50 km.

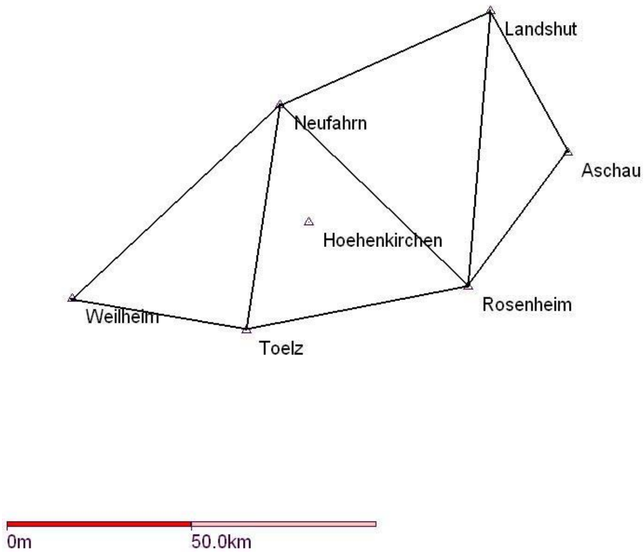

Fig. 10: Reference station network in the surrounding of Munich (mainly Land Survey Dept. network stations)

The distance to the nearest reference station is approximately 30 km. A virtual reference station was generated for the position of Hoehenkirchen while receiver data from station Hoehenkirchen was not used in the network as in the previous example. Then the VRS data was used to position the rover. The resulting position errors are shown in the figures below.

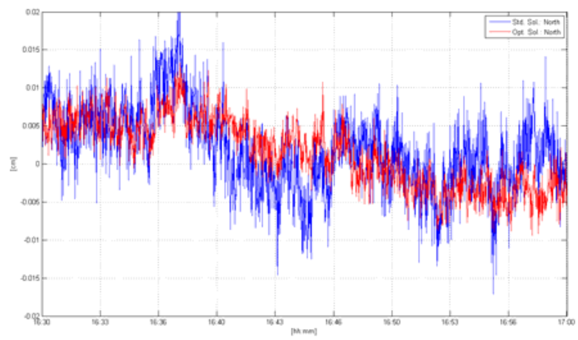

Fig. 11: Position errors in North direction for the optimized solution in red (5 mm RMS) and the standard solution in blue (6 mm RMS)

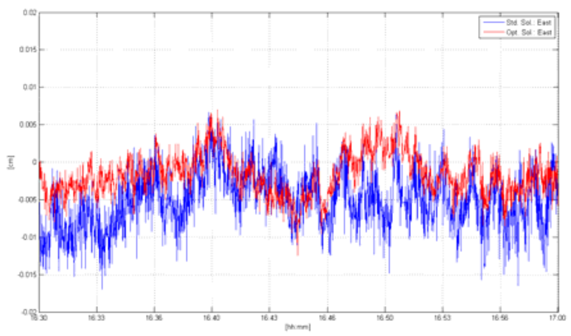

Fig. 12: Position errors in East direction for the optimized solution in red (3 mm RMS) and the standard solution in blue (6 mm RMS)

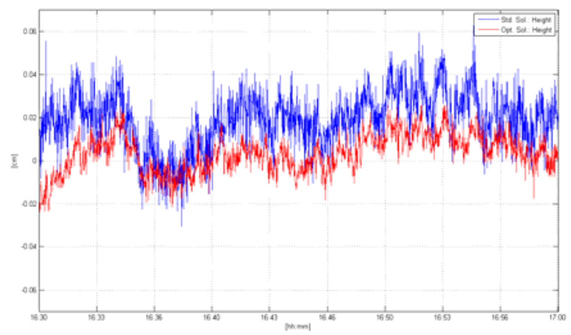

Fig. 13: Position errors in Height direction for the optimized solution in red (9 mm RMS) and the standard solution in blue (23 mm RMS)

Again it can be easily seen that the position errors are very much smaller for the optimized case, in which we are using the predicted residual error information from the network.

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.

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.

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.

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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