SmartRTK: A Novel Method Of Processing Standardised RTCM Network RTK Information For High Precision Positioning

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Technical Literature

SmartRTK

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SmartRTK: A Novel Method Of Processing Standardised RTCM Network RTK Information For High Precision Positioning

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BIOGRAPHY

Frank Takac received an MSc from RMIT University, Melbourne, Australia in 2001. He joined Leica Geosystems in 2002 and has been involved in developing algorithms for a range of high-precision GNSS field products and infrastructure solutions. He is currently leading the GNSS positioning algorithms group.

Werner Lienhart received an MSc from Graz University of Technology, Austria in 2001 and a PhD in 2006. After working as research associate for the Austrian Academy of Science he was involved in several monitoring projects including GPS as University assistant at Graz University of Technology. He joined Leica Geosystems in 2006 where he is working in the GPS Product Management group.

1. ABSTRACT

Network RTK is a maturing technology that overcomes range limitations of conventional RTK by modelling distance dependent atmospheric effects. However, correction information might not be available for all satellites observed in a network. Traditional RTK algorithms do not process raw observations without corrections in the position solution. Nevertheless, these observations still contain valuable information for positioning.

In this paper we present a SmartRTK solution that considers all of the available observation information in the position solution. The results demonstrate that uncorrected observations can be effectively included in order to improve the precision of the position solution and to yield more fixed rover positions. In addition, the SmartRTK approach employs an atmospheric decorrelator that uses optimal combinations of the L1 and L2 observations and atmospheric stochastic modelling to mitigate the effects of residual model errors. The result is more homogeneous positioning accuracy throughout the network.

2. INTRODUCTION

Real-time kinematic (RTK) positioning is an effective tool for applications that require high precision (centimetre level) coordinate accuracy. A conventional RTK positioning system typically comprises of a single reference station which transmits formatted information such as code and carrier phase observations to one or more mobile rover units in the field. The reference station data is combined with local measurements collected at the rover using proprietary differential processing techniques to yield precise relative coordinate estimates. The accuracy of conventional RTK decreases as the distance to the reference increases due to the spatial decorrelation of dispersive and non-dispersive errors induced by the ionosphere and troposphere respectively. Depending on the prevailing atmospheric conditions, the operating range of conventional RTK positioning is usually limited to a few tens of kilometres.

Network RTK is a maturing technology that has the potential to overcome several limitations of conventional RTK. The typical network RTK model comprises of three or more permanent reference stations connected to a central processing facility that estimates the distance dependent errors across the network. Corrections for these errors are combined with raw reference station observations and distributed to users in the field as depicted in Figure 1.

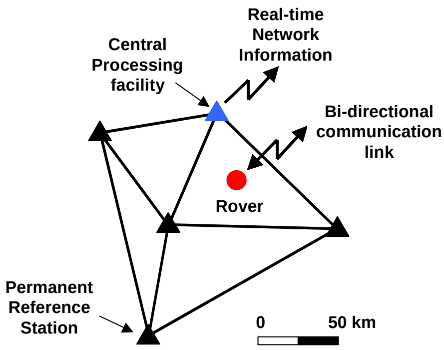

Figure 1. The generalized network RTK model. The central processing facility collects real-time data from three or more reference stations, estimates distance dependent errors for the network and distributes the precise correction information to *n* rovers in the field.

The network information helps to mitigate the distance dependent errors observed at the rover resulting in more homogeneous position accuracy within the region bounded by the reference stations. The concept of network RTK has been proven commercially. There are currently several competing solutions including the Master-Auxiliary Concept (MAC), Virtual Reference Station (VRS), individualised Master-Auxiliary corrections (iMAX), Pseudo-reference Station (PRS) and Flächenkorrekturparameter (FKP). Despite the proven benefits of network RTK, the technology still has limitations.

In order to meet the accuracy demands of RTK applications, the network information is derived using unambiguous (fixed ambiguity) carrier phase observations and associated models for the dispersive and non-dispersive effects. In addition to the measurement errors inherent in the carrier phase observations, imperfect modelling of the distance dependent errors can degrade the accuracy of the corrections. As these residual errors grow, the effectiveness of network RTK diminishes.

The performance of RTK is dependent, in part, on the number of available satellites (Takac and Walford, 2006). However, the network software may not be able to provide corrections for all satellites in view. A typical case is low elevation satellites for which the network software has not resolved the corresponding ambiguities. Nevertheless, the raw reference observations still contain valuable information that can be useful for RTK positioning. However, network RTK is traditionally considered as an all-or-nothing solution (Alves, 2004). That is, raw and corrected observations should not be mixed in the position solution.

In an optimal solution, the rover software should consider all of the available observation information and account for any residual observation errors remaining after modelling. In this contribution, the novel concept of combining raw and corrected observations is examined using the MAC network RTK approach. The effects of residual observation errors are mitigated using combinations of dual frequency measurements and stochastic modelling. The practical benefit of this new approach for RTK positioning is tested using real-time data. The results demonstrate increased availability of position, better precision and more homogeneous accuracy throughout the network. Finally, the application of this approach to other network RTK solutions is also examined.

3. NETWORK RTK TECHNOLOGY

In practice, network RTK is realised in several ways; for example, MAC, VRS and FKP. Each approach has associated advantages and disadvantages but they all share a common goal, which is to provide accurate correction information for high-precision positioning. A detailed critique of the various network RTK solutions is beyond the scope of this paper. Instead, a brief description of each method is provided as a basis for discussion.

VRS, PRS and iMAX are all variations of the same theme and can be broadly categorised as non-physical reference stations. In each case, the network software computes dispersive and non-dispersive corrections optimised for the position of the user. The individualised corrections are applied to raw reference station observations to form virtual observations, which are then broadcast to the user. For VRS and PRS, the physical reference station is also displaced so that the virtual observations refer to a non-physical reference station located in the vicinity of the approximate rover location. Typically, the baseline length is several metres for VRS and several kilometres for PRS.

In contrast to non-physical network solutions, MAC and FKP broadcast raw reference station observations and network information separately. In the MAC approach, the network information is represented as single-difference dispersive and non-dispersive corrections for all auxiliary reference stations relative to a master (Euler et al, 2001). The FKP solution represents the network information using the coefficients of a plane surface centred at the location of a physical reference station (Wübbena and Bagge, 2006). In both cases, the rover software decides how the network information is applied in the position solution.

Generally, estimates of the dispersive and non-dispersive effects in the network are derived from unambiguous carrier phase observations. Typically, corrections for the distant dependent effects at the rover are computed using linear approximation models, although higher order surfaces can also be employed. The effectiveness of network RTK depends, in part, on the accuracy of the computed corrections. Figure 2 shows the relationship between the modelled information and the true distance dependent errors for a fictitious network of two reference stations. For simplicity, the discussion is limited to the linear case.

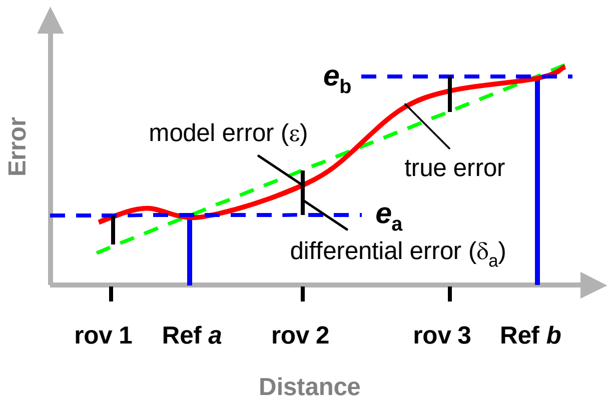

Figure 2 Relationship between the modelled distance dependent effects and the true errors. The true error is shown in red and the linear approximation in green. The symbol δ is the differential error associated with the conventional baseline solution and ε is the model error (Adapted from Wübbena et al., 2005).

In Figure 2, the network software receives precise carrier phase observations from reference stations *a* and *b* and estimates the true errors e_a and e_b. The true error shown in red could be dispersive, non-dispersive or a combination of both. The distance dependent errors are modelled using a linear approximation shown in green. The linear approximation is not perfect and differences to the true error ε represent the model error. The differential error δ is the difference between the true errors observed at the reference station and some other point in the network. Network information is expected to improve the conventional (single base) RTK solution if the model errors are less than the corresponding differential errors at the rover location.

For a rover operating in the vicinity of a reference station, the benefit of network information is minimal since the distance dependent errors effectively cancel in conventional differential processing schemes. As the user moves away from the reference towards rov 2, the magnitude of the differential error increases. In this example, the linear model is a reasonable approximation of the errors at this point; therefore, network information should is expected to improve the position solution. However, the impact network corrections at rov 3 will be less significant because the model and differential errors are of similar magnitude. The same situation is also evident at rov 1 which is located outside the network boundary.

Estimates of the dispersive and non-dispersive effects for a given satellite can only be derived once the associated integer ambiguities have been resolved. Generally, it is more problematic to resolve ambiguities for satellites at low elevations. Therefore, network corrections may only be available for a subset of the tracked satellites. Traditionally, raw and corrected observations are not mixed in the same solution. This is not optimal because the raw reference observations still contain valuable information that is useful for positioning. For example, a user located at rov 2 could still make use of the raw reference observations in the absence of network corrections.

In order to combine all of the available information in the position solution correctly, the rover software needs to have a detailed understanding of the processes applied to the data received from the network. Standardisation is a means of ensuring that the network information is generated in a consistent and understandable manner. The MAC approach is realised in v3.1 of the RTCM SC-104 standard for differential services (RTCM, 2007). The procedure for generating MAC data is clearly defined in the standard and the format is used to verify the concepts presented in this paper.

4. THE MASTER -AUXILIARY CONCEPT

A brief overview of MAC is presented in this section. For a detailed review, the reader is referred to Euler et al (2001) and RTCM v3.1 (2007). In essence, MAC data comprises the raw observations of all reference stations in a network minus nuisance parameters such as clock errors and integer ambiguities. In the context of MAC, a network comprises one master station m and k auxiliary reference stations as depicted in Figure 3.

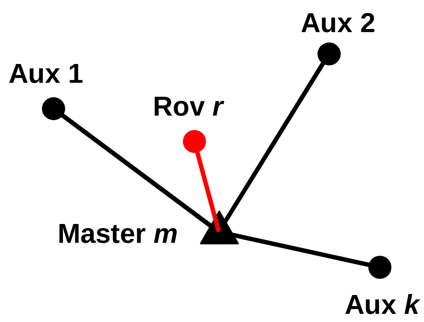

Figure 3. The definition of a network in the context of MAC. Station m is the master and stations $1\ldots k$, ($k \geq 2$) represent auxiliary reference stations.

Let $\phi^q_{m,i}$ be the raw carrier phase observation between station m and satellite q in units of metres such that:

$$\phi^q_{m,i} = \rho^q_m + cdt_m - cdt^q - I^q_{m,i} + T^q_m + \lambda_i n^q_{m,i} + \varepsilon^q_{m,i} \qquad (1)$$

where:

ρ^q_m is the geometric range

c is the speed of light.

dt_m, dt^q are the receiver and satellite clock errors respectively.

$I^q_{m,i}$ is the frequency dependent ionospheric delay.

T^q_m is the tropospheric delay

λ_i is the carrier wavelength for frequency f_i

$n^q_{m,i}$ is the true integer cycle ambiguity

$\varepsilon^q_{m,i}$ is the random measurement error.

Introducing an auxiliary station k, the between station single difference observable can be written as:

$$\begin{aligned}\phi^q_{mk,i} &= \phi^q_{k,i} - \phi^q_{m,i} \\ &= \rho^q_{mk} + cdt_{mk} - I^q_{mk,i} + T^q_{mk} + \lambda_i n^q_{mk,i} + \varepsilon^q_{mk,i}\end{aligned} \qquad (2)$$

where $\rho^q_{mk} = \rho^q_k - \rho^q_m$ and so forth for the remaining terms in (2).

The correction difference observable is generated by subtracting computed quantities for the geometric range, receiver clock error and integer cycle ambiguity from the single-difference observable given in (2) such that:

$$\delta\phi^q_{mk,i} = s^q_{mk} - \phi^q_{mk,i} + c\,\tau_{mk} + \lambda_i a^q_{mk,i} \qquad (3)$$

where:

$\delta\phi^q_{mk,i}$ is the correction difference observable for master station *m*, auxiliary station *k* and satellite *q*

s^q_{mk} is the computed geometric range

τ_{mk} is the computed receiver clock error

$a^q_{mk,i}$ is the computed integer ambiguity in units of cycles.

Finally, the raw correction differences given by (3) are factored as dispersive and non-dispersive observables. The dispersive observable, denoted by the subscript γ, is given by:

$$\delta\phi^q_{mk,\gamma} = \frac{f_2^2}{f_2^2 - f_1^2}\delta\phi^q_{mk,1} - \frac{f_2^2}{f_2^2 - f_1^2}\delta\phi^q_{mk,2} \quad (4)$$

while the non-dispersive observable, denoted by the subscript χ, is given by:

$$\delta\phi^q_{mk,\chi} = \frac{f_1^2}{f_1^2 - f_2^2}\delta\phi^q_{mk,1} - \frac{f_2^2}{f_1^2 - f_2^2}\delta\phi^q_{mk,2} \quad (5)$$

In (4) and (5), *f* is the frequency of the L1 or L2 carrier denoted by the subscripts *1* and *2* respectively. The dispersive and non-dispersive network errors are precisely determined using fixed single-difference ambiguity values. However, it is well known that absolute integer ambiguities can only resolved correctly on the double-difference level. Therefore, the expanded single-difference ambiguity term in (3) is given by:

$$a^q_{mk,i} = n^q_{mk,i} - \Delta a^p_{mk,i} \quad (6)$$

where:

$n^q_{mk,i}$ is the true ambiguity for satellite *q*.

$\Delta a^p_{mk,i}$ is the difference between the true ambiguity and the estimated ambiguity for a reference satellite *p*.

The ambiguity bias, also referred to as the ambiguity level, is common to all estimated ambiguities for the baseline *mk*. Therefore, the bias will be estimated as a modified clock term in single-difference processing schemes or cancel in the double-difference solution.

The network software transmits dispersive and non-dispersive correction differences together with the raw observations of the master station. The rover software is then free to decide how the network information is applied in the position solution. If correction differences are only available for a subset of the observed satellites, the rover software has three options. First, only process observations for the satellites that have corrections; second, ignore all of the network information and only process raw observations; thirdly, mix raw and corrected observations in the solution. The next section will examine the practical applications of this flexibility.

5. COMBINING NETWORK INFORMATION AND RAW OBSERVATIONS

In standard network RTK positioning solutions, observations without corresponding network information are not processed. As discussed in 3, this is an arbitrary approach that excludes valuable information from the solution. When treated properly, raw and corrected observations can be combined in a *SmartRTK* solution to improve positioning accuracy. To demonstrate the effect of combining all the available information, static data was collected from the network depicted in Figure 4.

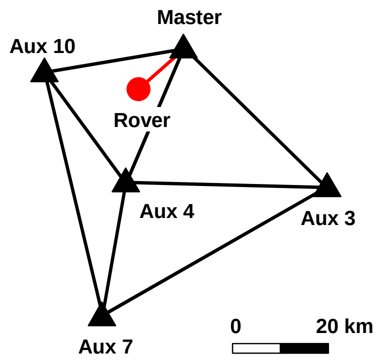

Figure 4. The rover in network A is located approximately 15km from the master, which is also the closest reference station.

The data was first processed using a conventional *single base RTK* solution followed by a *standard network RTK* solution, which only considers corrected observations. The data was processed a third time using the SmartRTK solution that combines all of the available information. In all tests, the data was processed in a simulated RTK mode. Figure 5 shows the number of available satellites with and without network corrections.

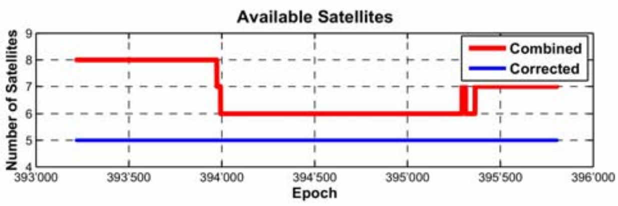

Figure 5. The number of available satellites with and without network corrections (network A).

The number of available satellites peaks at 8 during the first quarter of the session and never drops below 6. In comparison, there are only 5 available satellites with network corrections. The horizontal position errors for each solution are compared in Figure 6. The standard network RTK and SmartRTK solutions have both been plotted against the single base results.

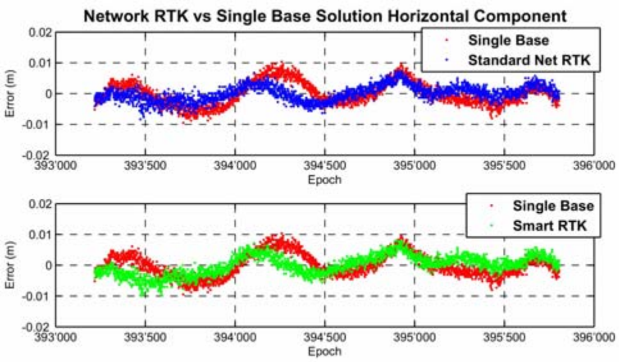

Figure 6. Horizontal position errors for the single base, standard network RTK and SmartRTK solutions (network A). The performance of each solution is comparable.

All of the solutions show similar horizontal positioning performance. Indeed, the precision of the horizontal component in all cases is sub-centimetre as shown in Table 1.

Table 1. Horizontal position statistics (1σ) (network A).

Solution	σ Hz
Single Base	0.004
Standard Net RTK	0.003
SmartRTK	**0.003**

In this example, applying network corrections does not yield a significant improvement in terms of horizontal position accuracy. This result suggests that the dispersive and non-dispersive errors at the reference and rover are highly correlated. In such cases, conventional RTK is still an effective positioning tool.

It is well known that the precision of the height component derived from GNSS positioning is typically 1-2 times less than horizontal precision. This is due an inherent weakness in satellite geometry caused by a lack of observed satellites below the local horizon.
Figure 7 compares the precision of the height component for the single base and standard network RTK solutions.

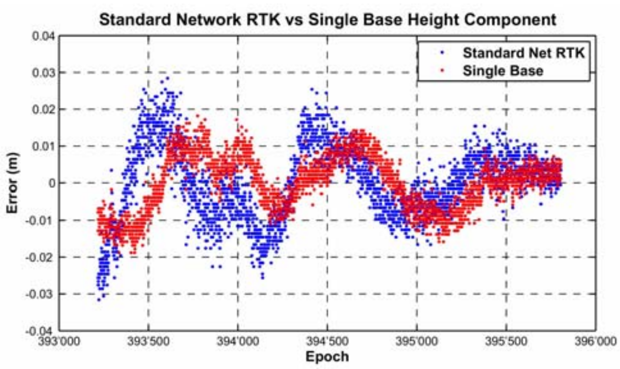

Figure 7. Height position errors for the single base and standard network RTK solutions (network A). The standard network RTK solution is less precise as a consequence of less satellites and weaker geometry.

In this example, the single base solution is more precise than standard network RTK, especially in the first half of the data set. This is a consequence of weak satellite geometry rather than poor quality network information. In fact, the vertical dilution of precision (vdop) is approximately three times higher than the single base solution at the beginning of the test. The availability of more satellites in the single base solution improves the geometry. These extra satellites are also considered in the SmartRTK solution. The height positioning performance of SmartRTK is compared to the single base results in Figure 8.

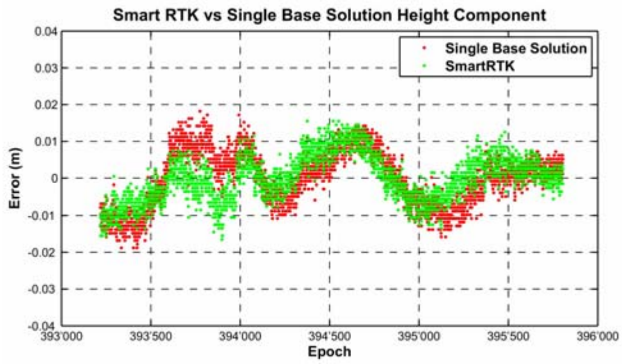

Figure 8. Height position errors for the single base and SmartRTK solutions (network A). The combination of all available information yields the most precise solution.

The combination of all available satellites and network information yields the most precise solution. This inference is supported by the height position statistics for all solutions presented in Table 2.

Table 2. Height position statistics (1σ) (network A).

Solution	σ Ht
Single Base	0.007
Standard Net RTK	0.010
SmartRTK	**0.006**

Statistically, the standard network RTK solution is the least precise, as depicted in
Figure 7, The SmartRTK solution is the most precise; however, the improvement is only marginal due to the high quality of the raw data.

One disadvantage of the standard network RTK solution arises when the number of available satellites with corrections is less than the critical threshold needed for positioning. In Figure 9, the number of satellites that have corrections falls below 5 after epoch 395805. However, there are at least 6 satellites observed at the master and rover stations during the whole period.

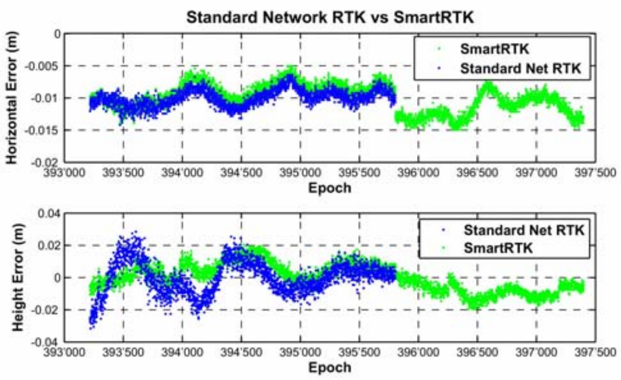

Figure 9. Position errors for the standard network and SmartRTK solutions (network A). SmartRTK maintains a fixed solution even when the number of available satellites with corrections falls below 5.

The consequence of ignoring uncorrected satellites is the loss of the fixed position. In contrast, SmartRTK maintains the solution without the need for re-initialisation. The results presented in this section serve as proof-of-concept for the SmartRTK approach of combining raw and corrected observations in the position solution. However, the data was collected during a quiet period of atmospheric activity where the distance dependent errors effectively cancel in single base RTK processing. In practice, this is not always the case and distance dependent errors for uncorrected satellites can become significant. Furthermore, corrected observations may also be affected by residual model errors. It is imperative to treat residual errors properly for the best overall performance.

6. ATMOSPHERIC DECORRELATION

Raw and corrected differential observations can be biased by residual errors. In the case of raw measurements, the residual errors grow as the reference-rover baseline length increases. For corrected observations, imperfect modelling of the distance dependent effects is the cause of residual biases (see section 3). To illustrate the effect of residual errors, data was collected from the network depicted in Figure 10.

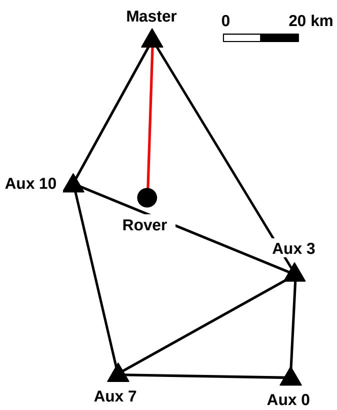

Figure 10 In network B the rover is located approximately 43km from the Master. The closest reference station is Aux 10, approximately 21km from the rover.

In this network, the closest reference station is Aux 10 while the master station is located approximately 43km from the rover. The position errors for the single base and standard network RTK solutions are shown in Figure 11.

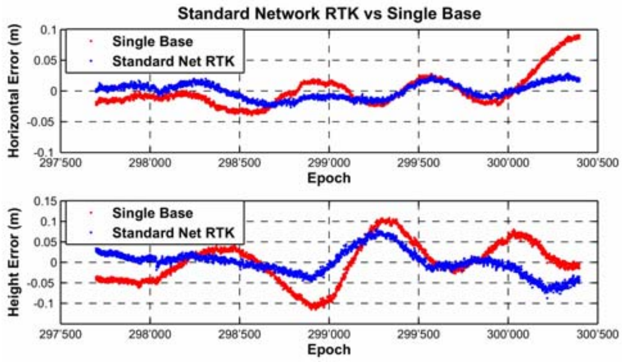

Figure 11 Position errors for the single base and standard network RTK solutions (network B). Despite the availability of network information, the standard network RTK solution is still affected by significant residual distance dependent errors.

In the first test, the precision of the horizontal position for the single base solution was sub-centimetre. In this experiment, position errors as large as 0.09 m are evident indicating that significant residual distance errors are present in the data. The position statistics for the single base and standard network RTK solutions are presented in Table 3.

Table 3. Position error statistics (1σ) (network B).

Solution	σ Hz	σ Ht
Single Base	0.027	0.050
Standard Net RTK	0.013	0.030

The impact of applying network corrections cannot be properly assessed in this case. Although the precision of the standard network RTK solution is better than the single base, the results can't be compared directly because the master station is not the closest reference station.

The magnitude of the position errors for the standard network RTK solution are significantly larger compared to results recorded in the first experiment (Table 1 and Table 2), despite the relatively close proximity of the nearest reference station (21km). It is evident that the standard network RTK solution is still affected by residual biases. An analysis of the observation residuals reveals that residual ionosphere is the dominant error source. An example plot for PRN 14 is shown in Figure 12.

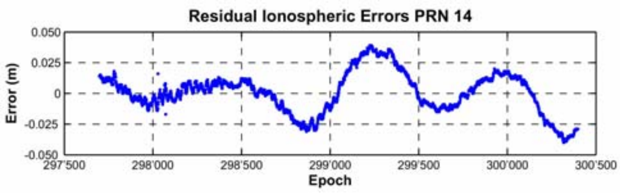

Figure 12 Residual model errors can still remain in the data after network corrections have been applied. This chart is an example of the residual ionospheric errors for PRN 14.

It is well known that the first order ionospheric effect can be removed by a forming a linear combination of the L1 and L2 observables. Unfortunately, the noise of the iono-free observable (L3) is approximately 3 times greater than L1. In conventional RTK, the decision to switch to an L3 solution is usually a function of the baseline length. However, network RTK tries to model the distance dependent errors so baseline length is a less meaningful metric for predicting residual errors. In fact, the typical baseline length in a VRS solution is in the order of only a few metres. A more robust approach of assessing the residual distance dependent errors is needed for network RTK.

If the network consists of four or more stations, then the precision of the predicted corrections can be used to assess the quality of the network information (Chen et al., 2003). The precision of the computed corrections will be high if the approximation model used for the distance dependent effects matches the spatial shape of the actual errors and vice versa. An example of the precision of the ionospheric corrections computed by the rover software for PRN 14 is given in Figure 13.

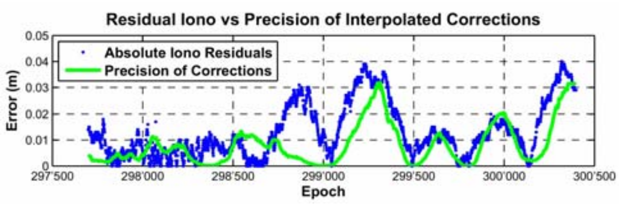

Figure 13 The precision of the interpolated ionospheric corrections for PRN 14. Note that the ionospheric residuals are absolute. The precision of the computed corrections can be used to assess the quality of the network information.

In Figure 13, the precision of the computed corrections correlates well with the actual ionospheric residuals. The quality information can be used for observation weighting or for selecting optimal combinations of the L1 and L2 observables. However, this information can only be generated for satellites that have correction information. When combining uncorrected observations, the algorithm must also account for the distance dependent errors affecting these measurements, which can have different stochastic properties compared to corrected observations. The SmartRTK *atmospheric decorrelator* treats residual distance dependent errors using optimal combinations of the L1 and L2 observables and ionospheric residual stochastic modelling. The result of the SmartRTK solution is compared to the standard network RTK solution in Figure 14.

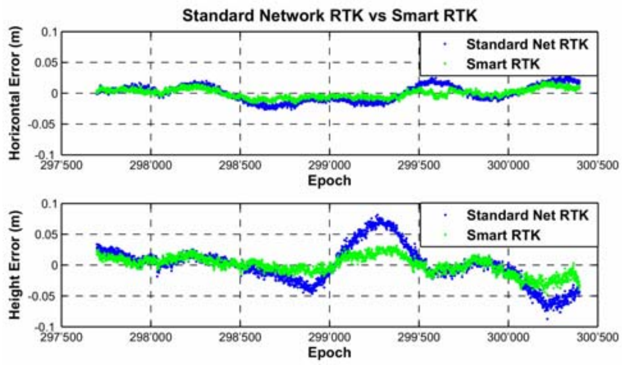

Figure 14 Position errors for the SmartRTK and standard network RTK solutions (network B). The combination of all available information and the atmospheric decorrelator yields the most precise results.

The precision of the SmartRTK solution is visibly more precise than the standard network RTK solution. The large position errors around epoch 299250 have been successfully mitigated, which is reflected in the position statistics given in Table 4. SmartRTK typically makes use of one or two extra satellites in the position solution as shown in Figure 15.

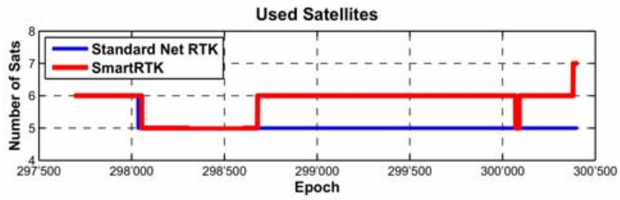

Figure 15 The number of satellites contributing to the standard network and SmartRTK position solutions. SmartRTK typically uses one extra satellite in this example.

Table 4. Position error statistics (1σ) (network B).

Solution	σ Hz	σ Ht
Standard Net RTK	0.013	0.030
SmartRTK	**0.007**	**0.014**

SmartRTK reduces the standard deviation of horizontal and vertical position errors by a factor of two. The solution is achieved without switching to an L3 solution. The result is more homogeneous position accuracy throughout the network even in disturbed atmospheric conditions.

7. APPLICABILITY TO OTHER NETWORK RTK APPROACHES

The advantage of combining raw and corrected observations has been demonstrated using the MAC network RTK approach. Theoretically, the idea of combining observations can also be applied to other types of network RTK solutions. However, there are several factors that limit the general application of this approach in practice.

For non-physical network RTK solutions such as iMAX and VRS, it is the network service and not the rover software that applies individualised network information to the raw reference data. This is problematic in practice because the processes applied by the network software are not fully described and the rover software has no way of identifying uncorrected measurements. Mixing these observations in the position solution could bias the results and degrade performance. To illustrate the problem, consider the virtual observation for a non-physical reference station v to satellite p as given by:

$$\phi_{v,i}^{p} = \phi_{m,i}^{p} + \rho_{mv}^{p} + d_{mv,i}^{p} \tag{7}$$

where:

$\phi_{m,i}^{p}$ is the raw observation from a physical reference station m to satellite p

ρ_{mv}^{p} is the geometric displacement between stations m and v.

In the formation of the virtual observation, a computed single-difference correction term d is applied to the undifferenced observation of the physical reference station. The distance dependent term in (7) is given by:

$$d_{mv,i}^{p} = \kappa_{mv,i}^{p} + b_{mv,i} \tag{8}$$

The correction consists of the true value κ relative to a physical reference station m and a single-difference bias term b, which is described in section 4. Since the bias term is not satellite dependent, it cancels in the double-difference if only corrected observations are used. If uncorrected observations ($d = 0$) are mixed with corrected observations in the double-difference, then only the single-difference correction is applied and the bias term will not cancel in conventional processing schemes.

A second problem arises for uncorrected observations of non-physical reference stations. The geometry of the observations is related to some virtual point in the network due to the displacement of the physical reference station. However, these observations no longer have any physical meaning because the distance dependent errors still refer to the location of the physical reference station. Data processing algorithms often use baseline length for observation weighting and building optimal combinations of L1 and L2 observations. It would be invalid to apply these algorithms to the uncorrected observations. This particular problem does not affect the iMAX solution since the non-physical reference station is not displaced ($\rho = 0$).

In the case of FKP, the rover receives the raw observations of the physical reference station and network information separately. The problems identified for non-physical reference stations do not apply. Therefore, it is also possible to mix corrected and uncorrected observations in FKP mode.

The SmartRTK solution also consists of an atmospheric decorrelator to deal with residual model errors as described in section 6. This technology is employed when only corrected observations are processed and also in combination with uncorrected measurements. Therefore, the solution is applicable to all types of network RTK solutions.

8. CONCLUSION

Dispersive and non-dispersive observation errors induced by the ionosphere and troposphere limit the operating range of conventional RTK. The goal of Network RTK is to model the distance dependent effects in order to provide homogeneous position accuracy within the region bounded by the reference stations. Despite the proven benefits of this technology, Network RTK still has limitations.

If the approximation models used for the distances dependent effects do not match the spatial shape of the actual errors, the effectiveness of network RTK will diminish to the point where at best it no longer provides any benefit over conventional RTK or, worse, degrades the single base solution.

To meet the accuracy demands of high-precision RTK applications, estimates of the dispersive and non-dispersive errors are derived from a fixed ambiguity solution. Therefore, correction information might only be available for a subset of satellites observed in the network. Traditionally, raw observations without corrections are not included in the position solution. In many cases, these observations still contain valuable information for positioning.

A SmartRTK solution was presented in this paper that combines all of the available observation information in the position solution. The results demonstrate that uncorrected observations can be effectively included in order to improve the precision of the position solution. An atmospheric decorrelator, which uses optimal combinations of the L1 and L2 observations and atmospheric stochastic modelling, was effective at mitigating the effects of residual modelling errors. The result of SmartRTK is more homogeneous positioning accuracy throughout the network.

The SmartRTK solution was demonstrated using the MAC network RTK approach. MAC is realised in the RTCM v3.1 standard for differential services. There is also provision for non-physical reference station observations in the standard; however, the methods applied in the generation of the network information are not clearly described. This limits the general application of SmartRTK to non-physical network RTK technology.

The SmartRTK solution is implemented in the latest release of the Leica System 1200 firmware.

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