Monte-Carlo Simulation of Profile Scans from Kinematic TLS

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Key words: terrestrial laser scanning, uncertainty, simulation, structural monitoring

SUMMARY

Kinematic terrestrial laser scanning (k-TLS) has proved to be a suitable tool for geodetic monitoring of structures such as bridges or wind energy plants as it allows determine object deformations rapidly with high precision as well as temporal and spatial resolution. As the k-TLS observation process is not fully understood yet, simulation strategies can be applied in order to better model the characteristics of the observations and the time series generated within a monitoring project such as their uncertainty. This contribution focuses on the use of Monte-Carlo techniques which allow a very flexible modeling and propagation of observation uncertainty. It is consistent with the *Guide to the Expression of Uncertainty in Measurement (GUM)* which represents an international standard. The study is treating the 2D case of k-TLS where vertical profiles are repeatedly observed with a high frequency up to 50 profiles per second. After the presentation of the general simulation procedure uncertainty measures are derived for profile scans beneath an Autobahn bridge in Southern Germany. The simulation results are discussed and validated based on a comparison with a sequence of actually observed vertical profiles.

ZUSAMMENFASSUNG

Das kinematische terrestrische Laserscanning (k-TLS) gestattet die schnelle und präzise sowie räumlich und zeitlich hochaufgelöste Erfassung von Objektverformungen. Damit eignet sich das Verfahren hervorragend für die geodätische Überwachung von Tragwerken wie Brücken oder Windenergieanlagen. Der Messvorgang beim TLS, speziell k-TLS, ist derzeit jedoch noch nicht vollständig verstanden. Deshalb ist es sinnvoll, die Eigenschaften der Messungen und der aus ihnen abgeleiteten Zeitreihen wie z. B. ihre Unsicherheit zu simulieren und auf die Zielgrößen des geodätischen Monitorings zu übertragen. In diesem Beitrag werden dazu Monte-Carlo-Verfahren eingesetzt, die eine flexible Modellierung und Übertragung von Messunsicherheiten erlauben. Dies ist in Einklang mit dem *Leitfaden für die Angabe der Unsicherheit beim Messen (GUM)*, einem internationalen Standard. In den vorgestellten Untersuchungen wird der 2D-Fall des k-TLS behandelt, bei dem Vertikalprofile mit einer Wiederholfrequenz von bis zu 50 Profilen pro Sekunde gemessen werden. Zunächst wird das Simulationsverfahren allgemein beschrieben. Anschließend werden Profilscans für eine bestimmte Autobahnbrücke in Süddeutschland simuliert und tatsächlich gemessenen Werten gegenüber gestellt.

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1. INTRODUCTION

In the last decade, terrestrial laser scanning (TLS) has proved to be a useful observation technique for a variety of engineering applications in geodesy and in other disciplines. It has been used for documentation purposes such as, e. g., 3D city models, cultural heritage, forestry, and forensics. It has also been used for the monitoring of structures such as bridges, locks and dams, and of infrastructure such as roads, tunnels and railroads. All these applications benefit from the combination of several important properties within TLS. It is fast and rapid, it is precise in the range of centimeters up to distances of several hundred meters, it works without reflecting prisms or other artificial targets, it has a high spatial resolution, and it provides its results directly in 3D. The interested reader is referred to Vosselman and Maas (2009) for a present-day overview on laser scanning.

In this study precise object monitoring based on immediately repeated terrestrial laser scans is considered. Note that the short observation time of TLS allows monitoring on rather short time scales: today – depending on the particular device – a full 3D scan is completed within a few minutes only; repeated profile scans are even faster. Regarding possible geometry changes, the dedicated modeling of the observations and of their uncertainty is the essential prerequisite for the assessment of the significance. Both for observation modeling and for the planning of a sensitive observation configuration, Monte-Carlo simulation techniques can be applied effectively. As a consequence, data analysis techniques can be adapted or refined as well. The goal of this study is twofold: to provide a simulation method for the uncertainty of repeated TLS profile scans and to discuss the validity of simulation results exemplarily based on a real monitoring project. In this project the Geodetic Institute (GIH) and the Institute of Solid Construction of the Leibniz University Hannover are cooperating.

The paper is organized as follows. In Section 2 kinematic terrestrial laser scanning is shortly introduced and characterized with respect to geodetic monitoring. Monte-Carlo simulations for uncertainty assessment are presented in Section 3. The application example is given and discussed in the following sections. Due to the limited space the theoretical background is presented in a compact form without mathematical derivations. Instead, the focus of the presentation is put on the description and discussion of the given example.

2. KINEMATIC TERRESTRIAL LASER SCANNING

An observation procedure is called kinematic if the sensor (system) is in motion or the geometry of the observed object is varying with time. Thus, the expression "kinematic terrestrial laser scanning" – abbreviated as k-TLS – is used ambiguously in the literature. The first case is also known as mobile mapping; it is not considered here. Instead, the second case is studied where changes of the object geometry are observed from one or more fixed control points. Here, the discussion is limited to relative geometry changes which refer to the spatial reference system defined by the scanning device; this affects the object's position as well as its orientation and shape. A survey on k-TLS and its application mainly in monitoring is given in Kutterer et al. (2009); it is shortly summarized here.

In k-TLS-based monitoring the observation repetition frequency is mainly controlled by the chosen spatial observation mode. There are three such modes which are distinguished by the supplied dimension: 3D mode, 2D mode, and 1D mode. Whereas the 3D mode is standard – available in case of both time-of-flight and phase-shift distance measurements – the 2D and 1D modes require the deactivation of particular servo-motors; then the distance observations are based on the phase-shift principle. If the rotation about the vertical axis of the device is stopped, one particular vertical profile is repeatedly observed (2D mode). Modern scanning devices such as the Z+F Imager 5006 allow observing up to 50 profiles per second. If additionally the beam deflection unit is stopped, only distances in a constant spatial direction are observed (1D mode); up to 500.000 distances per second are possible.

In case of geodetic monitoring the supply of consistent reference frames is mandatory. In the 2D mode treated here, a temporal reference is either defined relatively by the rotation of the beam deflection unit in terms of equidistant epochs or – in case of outdoor applications – it is absolutely induced by an additional GNSS sensor. A unique spatial reference is defined through the (absolute or relative) orientation of the scanner axes. Coordinates within the considered profile are given through two observed quantities: distance and vertical angle. As it is not possible in practice to repeatedly position the identical vertical angle in subsequent epochs, a persistent spatial correspondence between the epochs is required. Therefore, the definition and use of classes of vertical angles is convenient. This is the basic idea of the k-TLS data modeling and analysis concept applied at GIH; see, e. g., Kutterer and Hesse (2006). In 2D mode, time series are generated based on equidistant vertical angle classes or height sections at the object. All observed object points are uniquely assigned to the classes; all points within a particular class are aggregated either using the arithmetic mean or the median value of the corresponding z-coordinates with the z-axis of the sensor coordinate system aligned along the vertical direction. Hence, deviations of the height coordinates are studied. Note that lower degree polynomial approximations can be used for wider classes.

3. MONTE-CARLO SIMULATION OF OBSERVATION PROCESSES

The assessment and propagation of uncertainty is an important issue in all disciplines which rely on measurements such as geodesy. In a refined model the observations are related to some basic influence parameters which depend – in case of TLS – on the scanning device, on the scanning process and on the environmental conditions. It is common practice to model observable quantities as random vectors. In the standard case such random quantities are assumed as normally distributed; from this it follows their stochastic properties are uniquely determined by the expectation vector and the variance-covariance matrix. In case of a different distribution the probability density function has to be formulated explicitly. For numerical calculations the values of all model parameters have to be quantified. For this purpose dedicated experiments can be performed; long-term experience or expert knowledge can also be used.

If the observations are processed and analyzed by mathematical means, the uncertainty of the derived quantities has to be calculated as well. In case of non-linear functional relations a linearization is typically applied. Then, the propagation of expectation vectors and variance-covariance matrices in linear mappings is straightforward; the latter is known as the law of error propagation or variance propagation, respectively. For complete distributions the convolution of probability densities is required; moments such as the expectation vector or the variance-covariance matrix are then derived using the well-known integral relations. Such approaches are also used in international standards (ISO, 1995; ISO, 2007).

In general, the functional relations between the basic influence parameters, the observations and the parameters of interest are non-linear, and the normal distribution is not the adequate probability density function. In such as case, Monte-Carlo simulation is a suitable way to approximately derive the stochastic properties of the quantities of interest (output quantities). It is assumed that the functional model is completely formulated relating the output quantities with the input quantities – the observations and the basic influence parameters, respectively. It is further assumed that the probability densities of the considered input quantities are a priori known. Then, a sample vector of the input quantities can be drawn repeatedly using random number generators. For each input sample vector the corresponding values of the output quantities are calculated by using the corresponding functional relation. The set of output sample vectors yields an empirical distribution which can be used to approximate the correct random distribution of the output quantities. All required measures (expectation values, variances and covariances) as well as higher order central moments such as skewness and kurtosis can then be derived.

Obviously, this approach is straightforward. Koch (2008) discusses Monte-Carlo simulation in case of TLS uncertainty assessment. Alkhatib et al. (2009) apply it to k-TLS vertical profile scans and they merge it with a set-theoretical approach based on fuzzy sets. Here, pure Monte-Carlo simulation is considered but it is extended to the discussion of the properties of the derived time series and of their validation using real k-TLS observation data.

4. OBJECT AND SETUP

For the simulation runs an Autobahn bridge was considered which is located in the southern part of Germany. In August 2008, the Geodetic Institute and the Institute of Solid Construction of the Leibniz University Hannover participated in several loading tests. Paffenholz et al. (2008) give a detailed description of the bridge, of the loading tests with different trucks, of the applied observation procedures and of the derived data; see Fig. 1 for a graphical representation of the object and the location of the laser scanner. The horizontal section in along-track direction of the bridge (y-axis) considered here had a length of 20 m with a shortest distance between scanner and bridge of about 9.5 m. Vennegeerts et al. (2010) show new analysis results of the k-TLS observations. Moreover, they compare these results with strain gauge observations and with numerical simulations based on finite-element models. Note that the consistency of all three kinds of data is better than 1 mm.

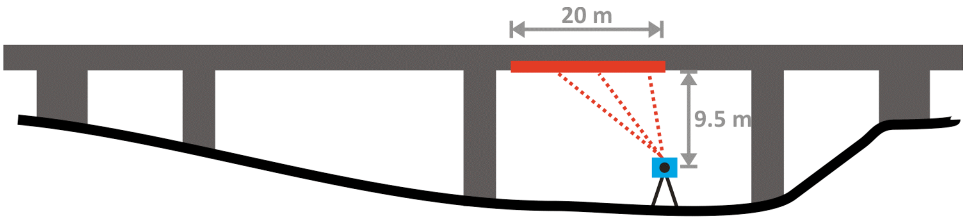

Fig. 1: Bridge and scanner

Here, the unloaded state of the Autobahn bridge is studied which was repeatedly observed in order to get a reference geometry for the analysis of the load-induced deformations. For the k-TLS measurements in 2D a Zoller+Fröhlich Imager 5006 scanner was used. For the observation of the vertical profiles a repetition rate of 12.5 profiles per second was used while the repetition frequency of the distance measurements was 500 kHz. For the vertical angle this yields an increment of 10 mgon. There are 7216 points per epoch within the observed section; 500 profiles representing the unloaded state were considered in total.

The profile data were processed according to the procedure outlined in Section 2. In order to prepare a meaningful model for the Monte-Carlo simulations the observed and processed data were roughly checked regarding the level of variance and with respect to possible quantities of influence. Within this analysis also an effect in the original data was detected which seems to be due to a different temporal resolution of distance and vertical angle observation; it is indicated in Fig. 2. This effect has been modeled accordingly for the simulations.

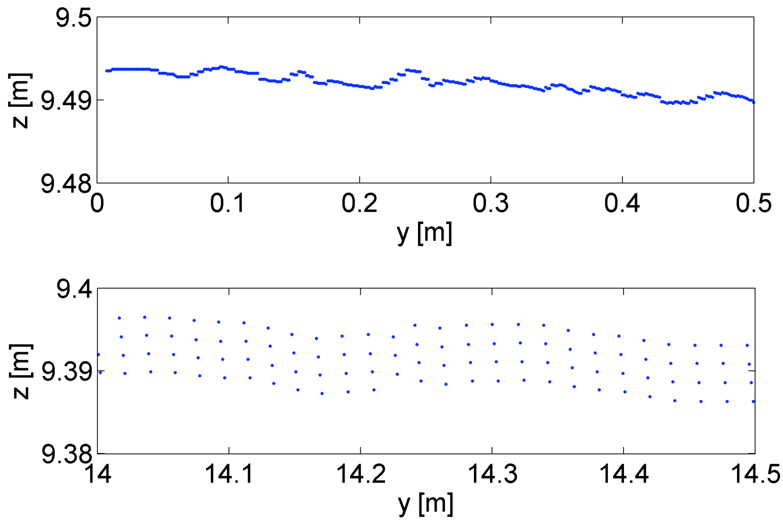

Fig. 2: Two zooms into a representative profile scan – y-coordinate (along bridge) and z-coordinate (height with inflated scale); upper figure: section directly above the laser scanner in a spatial distance of about 9.5 m with orthogonal angle of incidence; lower figure: section in a spatial distance of about 17 m with oblique angle of incidence.

5. SIMULATION OF k-TLS PROFILES

For the simulations the functional model described in Alkhatib et al. (2009) was used as a basis. In this previous study seven uncertainty components were modeled. However, during various simulation runs this number could be reduced to a subset of only three to four essential parameters which induce uncertainty. The remaining parameters are: the observed distance *d* between laser scanner and object point which induces a constant and a distance-proportional effect, the observed zenith angle ζ_0 with a constant angular effect, and the discretization term $\Delta\zeta$ which is induced by the angular increment of the vertical servo-motor. The first three parameters are considered as normally distributed whereas the last parameter is assumed as uniformly distributed. The mathematical model for the derivation of the target variable height coordinate z is straightforward:

$$z = d \cos(\zeta_0 + \Delta\zeta) \tag{1}$$

with $d \sim N(\mu_d, \sigma_d^2)$ and $\zeta_0 \sim N(\mu_{\zeta_0}, \sigma_{\zeta_0}^2)$ and $\Delta\zeta \sim U(\Delta\zeta_l, \Delta\zeta_u)$. The symbols μ and σ^2 denote the expectation value and the variance of the random variable, respectively; the uniform distribution is defined by the lower bound $\Delta\zeta_l$ and the upper bound $\Delta\zeta_u$ of the interval with positive values of the density function. Note that the effect of the angle of incidence on the uncertainty of the profile points was not considered in this study although its presence is well-known. This is due to the strong correlation of this effect with the distance-proportional effect in the considered observation configuration. More refined configurations and uncertainty models will be discussed in a following study.

In the following, the results of two different Monte-Carlo simulation runs are shown and discussed which were calculated for the bridge section described in Section 4. In both cases 500 samples were drawn for each random quantity; the obtained values were processed according to the model described in Eq. (1). Afterwards, the data processing strategy for generating k-TLS time series was applied which was explained in Section 2. Three different class widths were selected for the simulations: one / five / ten observation values per class and epoch. As representative value for each class and epoch the respective arithmetic mean of the single class values was used; this is reasonable because of the yet small class widths. Thus, only a minor spatial filtering was applied but not a temporal filter. The temporal sequences of these representative class values define the time series or data series, respectively, which are analyzed further.

Due to the unloaded state of the bridge all these time series can be considered as stationary. Therefore – and without considering any auto- or cross-correlation – three central moments of the underlying probability density functions are derived empirically: standard deviation (of the single value), skewness and kurtosis. Note that expectation value and standard deviation are necessary and sufficient in order to uniquely define a normal distribution. The skewness of a normally distributed random variable equals 0, and the kurtosis equals 3 (NB: In order to refer the kurtosis of an arbitrary density to the normal distribution the value 3 can be subtracted; then the kurtosis of the normal distribution equals 0). Hence, skewness and kurtosis are well-suited to detect violations of the normal distribution assumption.

For the first simulation (Simulation I) three input quantities were considered for uncertainty modeling: the constant and distance-proportional effect of the distance observation, and the constant angular effect of the zenith angle observation. The input quantities for Simulation I are defined in the left three columns of Table 1. The three central moments of the empirical distributions of the respective representative class values obtained as results of the Simulation I are presented in Fig. 3. For the second simulation (Simulation II) the same input quantities were used as in the first simulation; in addition, the uncertainty induced by the angular increment of the vertical servo-motor was modeled.

The idea behind Simulation II was the observation of a possible deviation from the normal distribution in the kurtosis of the real-data series during the first checks. The numerical input values for the second simulation are given in the right three columns of Table 1; the corresponding results are presented in Fig. 4. Note that in Simulation II mixed densities are obtained through the convolution of normal and uniform distributions. If the effect of the vertical motor increment was modeled using a normal distribution, it just would superpose the uncertainty of the vertical angle yielding a still normally distributed random variable with an accordingly increased variance. As the type of distribution is kept in this case, the result is in full analogy to Simulation I; for this reason it is not shown here.

Table 1: Monte-Carlo simulation: input quantities for the uncertainty models (type of probability densities and numerical values of the standard deviations)

Simulation I: without vertical increment		
Input quantity	Density type	Num. value (std. dev.)
Distance: constant	Normal	0.5 mm
Distance: proportional	Normal	30 ppm
Zenith angle	Normal	10 mgon

Simulation II: with vertical increment		
Input quantity	Density type	Num. value (std. dev.)
Distance: constant	Normal	0.3 mm
Distance: proportional	Normal	30 ppm
Zenith angle	Normal	5 mgon
Vertical increment	Rectangular	20 mgon

Looking at the standard deviations shown in Fig. 3 and Fig. 4, the distance-proportional effect on the standard deviations of the representative profile points is obvious. Moreover, the square-root law $\sigma_{\bar{x}} = \sigma / \sqrt{n}$ for the standard deviation of the mean value $\bar{x}$ with respect to the standard deviation of the single values by the number n of sample values can clearly be seen. In addition, the skewness is insignificant in both simulations. The difference lies in the kurtosis. Whereas in Fig. 3 the normal distribution assumption seems to hold, it is clearly violated in Fig. 4. Note that for a rigorous mathematical assessment this discussion has to be referred to suitable hypothesis tests; however, the tendency is clear. Due to the convolution of two different probability distributions – normal and uniform, respectively – the resulting distribution is not a normal distribution. Moreover, the kurtosis values decrease from 3 (which is valid for observations directly in vertical direction and which does not contradict to the normal distribution assumption) to about 2 in a horizontal distance of about 20 m. There are two effects which superpose each other: one from the uniform distribution and the other from the (non-linear) cosine function. In case of increasing the class width, the effect on the kurtosis is significantly mitigated – possibly due to the central limit theorem of probability theory.

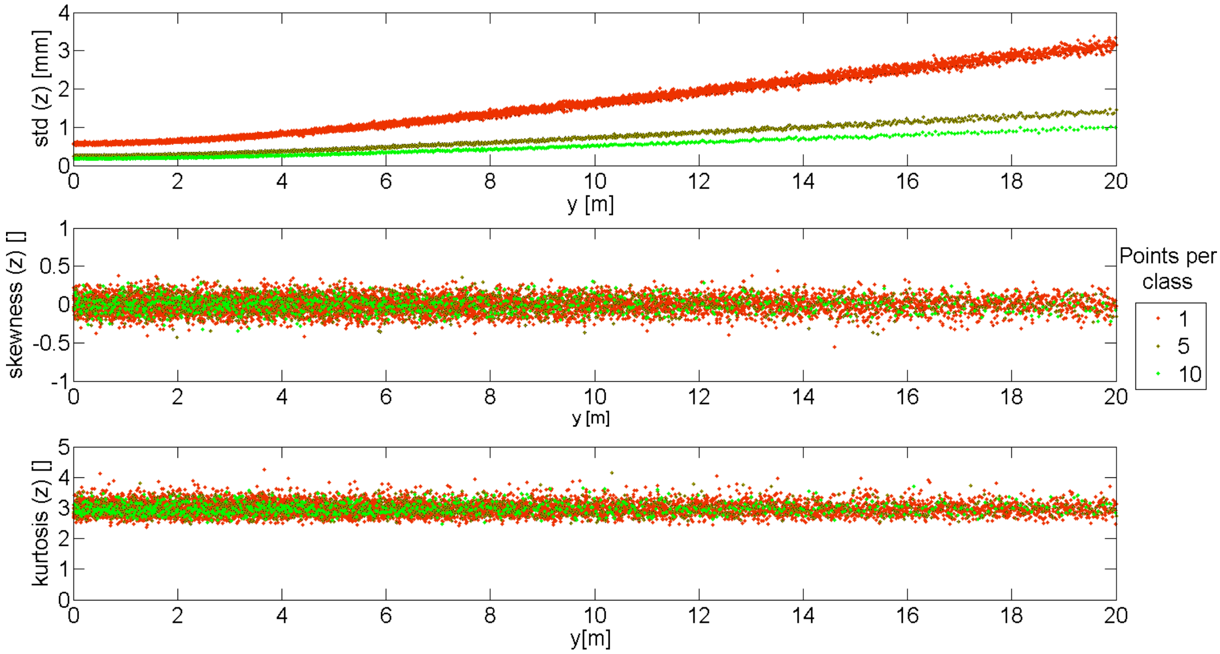

Fig. 3: Simulation I – without vertical motor increment uncertainty: analysis of the simulated k-TLS profiles for three different class widths – standard deviations, skewness, and kurtosis

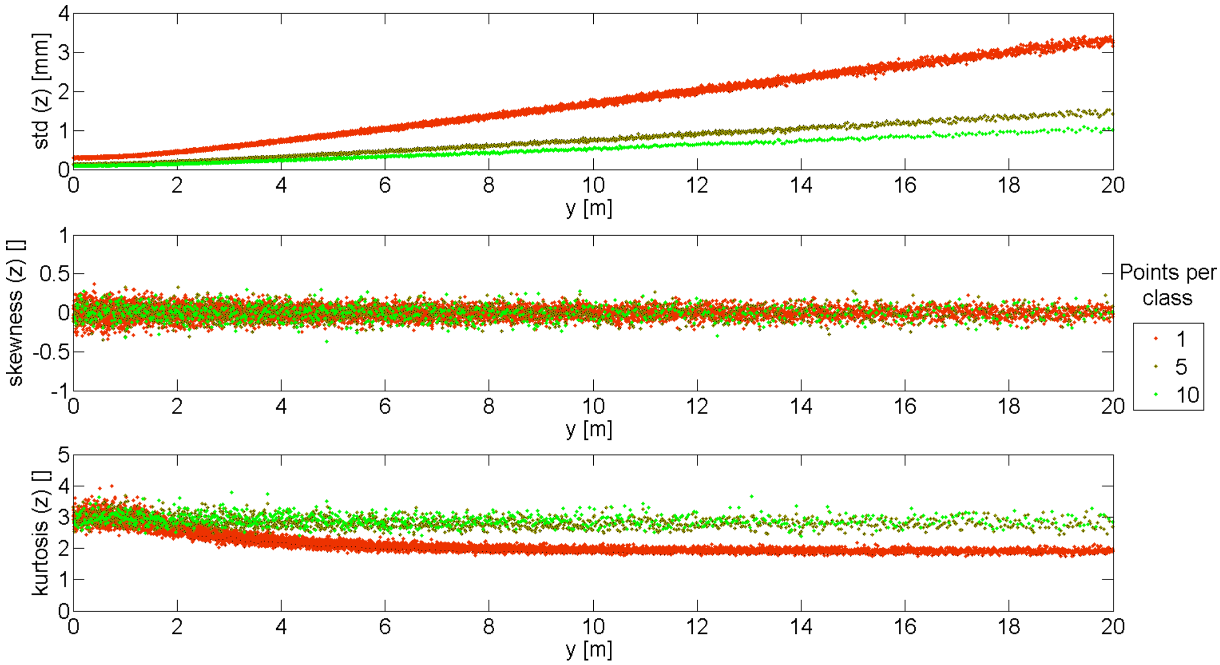

Fig. 4: Simulation II – with vertical motor increment uncertainty: analysis of the simulated k-TLS profiles for three different class widths – standard deviations, skewness, and kurtosis.

6. VALIDATION OF THE SIMULATION RESULTS

In order to assess and to validate the simulation results, actually observed profile data were processed and analyzed as well in full accordance with the procedure applied for the two simulation runs. Fig. 5 shows the obtained results; like in Section 5 the standard deviations, the skewness and the kurtosis of the individual classes of height coordinates are given. The standard deviations show again a clear dependence on the horizontal distance between the scanner and the profile points; this dependence is reduced when the class width is increased. However, in contrast to the simulated data, the mentioned square-root law does not fully apply – neither for small values of the y-coordinate nor for large values. For small values the reduction of the variance induced by averaging is smaller than expected, for large value the reduction effect is larger than expected.

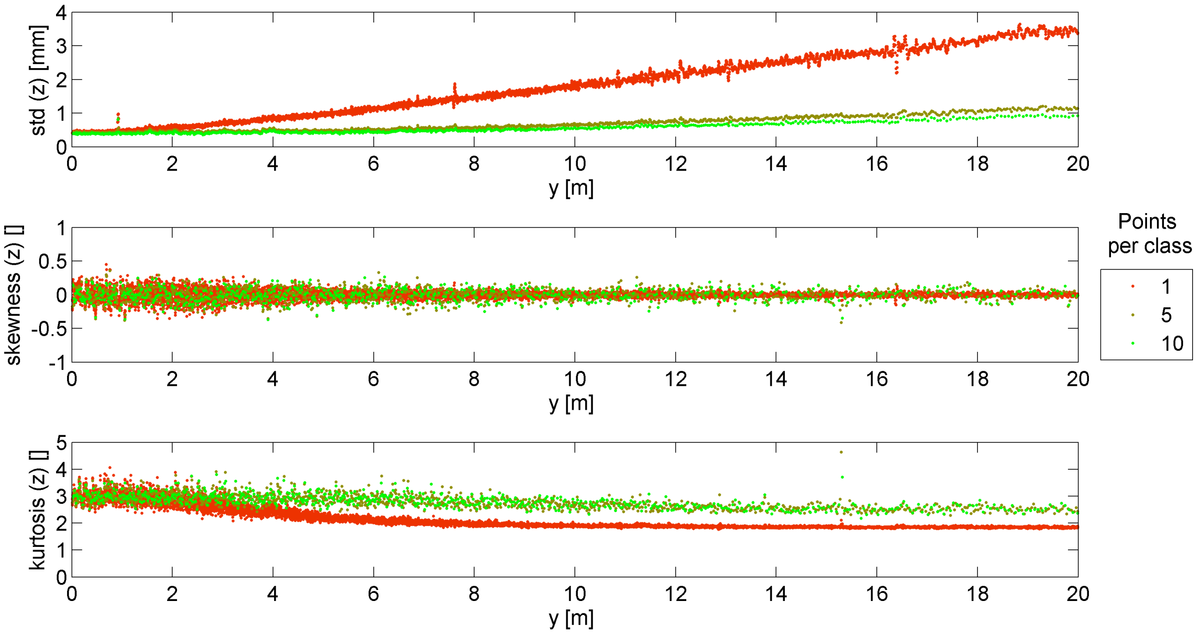

Fig. 5: Real data: analysis of the observed k-TLS profiles for three different class widths – standard deviations, skewness, and kurtosis

Like in the simulations, the skewness of the empirical distributions of the individual classes does not significantly differ from 0; note that the visible variability of the values decreases when y increases. Hence, the empirical distributions are symmetric – independent of the class width. However, the decrease of the kurtosis with respect to increasing values of y is remarkable. On the one hand, there is a systematic and significant decrease of the values from 3 (what is expected in case of normal distribution) to a value slightly below 2. This indicates clearly the violation of the normal distribution assumption. On the other hand however, this effect is mitigated in case of wider classes. Both effects were also obtained in Simulation II shown in Fig. 4 by modeling of a uniformly distributed uncertainty component for the angular increment of the vertical servo-motor. Note that the visible variability of the values decreases when y increases.

Obviously, the real-data results fit quite well to the results of Simulation II which could be obtained using a rather basic uncertainty model with a few input parameters only. In addition to the simulations there are some further effects in the real data which could not be modeled up to now. Looking, e. g., at the subfigures of Fig. 5 in total, some regions of horizontal distances y can be identified where the values of the central moments are obviously disturbed. This holds in particular for the standard deviations like, e. g., between 16 m and 17 m; there are also some periodic characteristics. A following study is required which aims at a refined statistical modeling and analysis of the k-TLS profile time series.

7. CONCLUSIONS

In this paper the 2D case of kinematic TLS was studied where repeated profile scans are observed from a fixed station with a high repetition frequency for monitoring purposes. The focus was put on a refined modeling of the uncertainty of both the observations and the derived positions of the profile points. In order to take into account the complete data processing chain, the strategy for generating and analyzing time series was considered which is presently used at GIH. Monte-Carlo simulation techniques were applied to provide numerical results for discussion and validation. It turned out that a rather small number of input parameters for the uncertainty model are required to obtain simulation results which fit quite well to actually observed data. These real data were observed on the occasion of loading tests at an Autobahn bridge in southern Germany.

Further work has to address two main topics: the more refined simulation of more complex configurations by taking more parameters for the uncertainty model into account, and the rigorous and thorough statistical analysis of the real data in order to improve the physical observation models in case of k-TLS. The solution of both problems is essential for the highly sensitive and physically meaningful application of k-TLS techniques for monitoring of, e. g., large structures such as bridges.

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BIOGRAPHICAL NOTES

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