Terrestrial Laserscanning - Modeling of Correlations and Surface Deformations

Corinna HARMENING, Austria , Stephanie KAUKER, Germany, Hans-Berndt NEUNER, Austria, Volker SCHWIEGER, Germany

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SUMMARY

Terrestrial Laserscanning offers new possibilities to engineering geodesy in general and deformation analysis in particular. Huge amounts of measured points lead to changing modelling and analysis approaches. Within the project "Integrated spatio-temporal modelling using correlated observations for the derivation of surveying configurations and description of deformation processes" (IMKAD) modeling of correlations and surfaces will be treated among others.
The modelling of correlations within laser scanning point clouds can be realized by using synthetic covariance matrices. These are based on the elementary error model that consists of non-correlating, functional correlating and stochastic correlating error groups. This elementary error model will be applied on terrestrial laser scanning by defining three groups of error sources: instrumental, atmospheric and object based ones. All known TLS-errors have to be classified and modelled according to the model of elementary errors. This contribution presents first simulation results for the Leica HDS 7000 measuring on small test pieces made of gypsum, aluminum and rusty steel. The determined variances and the spatial correlations of the points are estimated and discussed. Hereby, the mean standard deviation of an individual point within the point cloud is up to 2.5 mm and the mean correlation is about 0.94 neglecting the object based error sources in a first approach.
In the second part of this paper the development of the trend component of a spatiotemporal continuous collocation in order to describe areal deformations is presented. This component is modelled by estimated B-spline surfaces. One set of parameters used to define B-Spline curves and surfaces are the control points. Their number and position need to be estimated from the measurements. Here the determination of the optimal number of control points is regarded as a model selection problem. Two linear model selection criteria - the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) - are investigated, compared and applied to simulated data sets. Additionally, the contribution will give an outlook with respect to the combination of the before mentioned stochastic and the deterministic approaches with the aim to detect surface deformations in a stochastically correct way.

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1. INTRODUCTION

Classical deformation modelling and monitoring requires the discretization in time and space. The definition of epochs, the time between point measurements, can be seen as a simple discretization in time. With respect to space the monitoring network points may be regarded as a discretization. Especially the last aspect has to be reconsidered in a new perspective since areal measurement techniques in terms of terrestrial laser scanning as well as photogrammetric methods can be applied for monitoring purposes nowadays (Schwieger, 2014). In this contribution the authors will focus on laser scanning.

According to Kern (2003) a surface or a body determined by terrestrial laser scanning can be modelled in three different ways: Either by using the original or filtered point cloud (meshed or not meshed), by estimating geometric primitives like cylinders or cones or by estimating freeform surfaces. The modelling using these options is well known and established within typical software packages like Cyclone or Geomagic. The problem arises when movements and deformations have to be detected. Different approaches concerning this task are currently under investigation. A very good overview is given by Ohlmann-Lauber and Schäfer (2011). Basically it has to be distinguished between two procedures: The first one is based directly on the measured point clouds; the second one realizes a model for each epoch in a first step and analyses the geometrical changes of these models in the second step. Most approaches are based on the second procedure. The most advanced idea to model surfaces is the use of freeform elements like Bézier curves and surfaces. Changes at some point of the Bézier surface influence the modelled surface as a whole. This may be a problem if local deformations have to be detected, modelled and analyzed. In contrast,B-Splines as a generalization of Bézier curves and surfaces, have a local modification property as they consist of piecewise polynomial functions, which are defined by means of base functions. At the transition points between two parts, the nodes, the *p*-order differentiability has to be assured. The number of polynomial functions, the nodes in one part and the control points defining the transition lines are required to optimally approximate the real surface. The advantage of B-spline surfaces over Bézier surfaces is the ability to model deformations locally.

Within this contribution some details of surface deformation modelling and analysis based on B-spline surfaces are investigated: One the one hand realistic variances and co-variances among the scanned object points are determined; on the other hand the possibility to estimate the optimal number of control points for a given surface is investigated. Both research topics are executed within a cooperation project between the Technical University of Vienna (TUV) and the University of Stuttgart (US).

2. PROJECT PRESENTATION

The project IMKAD deals with "integrated spatio-temporal modeling using correlated measured values for the derivation of surveying configurations and description of deformation processes" aiming at the determination of optimal scanning configurations for space-continuous kinematic deformation models of non-linear deformation processes based on realistic correlation modeling. The researchers at the US investigate the correlations using the model of elementary errors to define an appropriate synthetic covariance matrix. This matrix has to be evaluated by means of empirical measurements at test objects. In parallel the researchers at the TUV model the non-linear deformation process in a collocation based approach. The deterministic part of the collocation is modelled using B-spline surfaces. Based on the synthetic and evaluated correlation patterns, one- and multi-dimensional correlation functions will be estimated or approximated afterwards.. Exemplary reduced covariance matrices will be generated to achieve mathematical controllable correlations for the temporal and spatial analysis. The latter is of particular importance regarding the stochastic part of the final deformation model to be developed by the TUV as well as regarding the sensitivity of the scanning configurations with respect to this model to be developed by US. The separability of different models is another important part of the research project. The current paper focusses on the first working packages: the modelling of synthetic covariance matrices and special aspects of the B-spline surface modelling.

3. MODELLING OF CORRELATIONS

3.1 Model of Elementary Errors and Synthetic Covariance Matrix

Hagen (1837) and Bessel (1837) established the elementary error model. All observations are treated as random quantities; the respective random deviation is treated as a random variable with expectation value equal to zero. According to Pelzer (1985) each elementary error contains the same absolute value, and negative and positive signs are equally probable. Summing up all elementary errors the random deviation of an observation may be determined. Hence, on the assumption of an infinite number of elementary errors, their absolute values may be infinitely small. This leads to the justification of the normal distribution for one scalar observation. Handling multi-dimensional data requires the classification of elementary errors. Schwieger (1999) considers three types of elementary errors which are classified below:

- p non-correlating error vectors $\boldsymbol{\delta_k}$,
- m functionally correlating errors ξ_j ,
- q stochastically correlating error vectors $\boldsymbol{\gamma_h}$,

$$\boldsymbol{\delta_k} = \begin{bmatrix} \delta_{1k} \\ \delta_{2k} \\ \vdots \\ \delta_{nk} \end{bmatrix}, k = 1,2,\dots,p,\ \boldsymbol{\xi} = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_m \end{bmatrix},\ \text{and}\quad \boldsymbol{\gamma_h} = \begin{bmatrix} \gamma_{1h} \\ \gamma_{2h} \\ \vdots \\ \gamma_{nh} \end{bmatrix}, h = 1,2,\dots,q\,, \qquad (1)$$

where the index *n* defines the number of observations. Regarding the non-correlating errors, *k* specifies the kind of elementary errors, whereas *p* describes the number of elementary errors. The index *m* represents the number of functionally correlating elementary errors ξ_j. Additionally, the index *h* involves the type of stochastically classified elementary errors and *q* implies the number of stochastically correlating errors.

In order to model the impact of the elementary errors on the observations, influence factors are used in order to build influencing matrices. These matrices contain the linearized elementary errors' effect on the observations as well as on the covariance matrix of the observations. The influence factors can be implemented by partial derivatives, which have to be determined analytically or numerically. Schwieger (1999) induces the influences of different elementary errors on the observations by integrating the derivatives into influencing matrices.

As mentioned above, three types of errors have to be considered which can now be computed as follows:

- *p* matrices $\boldsymbol{D}_k$ for non-correlating errors,
- one matrix $\boldsymbol{F}$ for functionally correlating errors,
- *q* matrices $\boldsymbol{G}_h$ for stochastically correlating errors.

The influencing matrices differ with regard to their structures, because several elementary errors affect the measurements in different ways.. The matrices $\boldsymbol{D}_k$ and $\boldsymbol{G}_h$ are diagonally structured because each elementary error of the non-correlating and stochastically correlating classes influences exactly one measurement quantity functionally (see eq. (6)). In contrast to these cases, matrix $\boldsymbol{F}$ is not structured diagonally, since one functional correlating error may impact more than one measurement quantity (Schwieger, 1999). For details the authors refer to Kauker and Schwieger (2016).

In order to determine a synthetic vector of observations, the influences of the elementary errors have to be summed up. This leads to**:**

$$\boldsymbol{\varepsilon} = \sum_{k=1}^{p} \boldsymbol{D}_k \cdot \boldsymbol{\delta_k} + \boldsymbol{F} \cdot \boldsymbol{\xi} + \sum_{h=1}^{q} \boldsymbol{G}_h \cdot \boldsymbol{\gamma_h}\ . \qquad (2)$$

For the construction of a synthetic covariance matrix of the observations, the covariance matrices of the elementary errors have to be known:

- $\boldsymbol{\Sigma_{\delta\delta,k}}$**:** the covariance matrix for the non-correlating errors,
- $\boldsymbol{\Sigma_{\xi\xi}}$**:** the covariance matrix for the functionally correlating errors,
- $\boldsymbol{\Sigma_{\gamma\gamma,h}}$**:** the covariance matrix for the stochastically correlating errors.

The first two matrices are structured diagonally, the latter may be completely filled. The definition of variances and co-variances of all these matrices is a challenging task. Thus, they may either be specified by using manufacturers' information or by using empirical values. As an alternative they can be estimated based on maximum errors and known parametric probability distributions. In case

that the standard deviation σ_k of an error δ_{ik} is unknown, the approximation is typically based on an assumed normal distribution (Pelzer 1985):

$$\sigma_k \approx 0.3 \cdot \delta_{ik}[\max] \,. \tag{3}$$

For further details is referred to Pelzer (1985), Schwieger (1999) and Kauker and Schwieger (2015). The synthetic covariance matrix can be determined by applying the variance-covariance propagation to equation (2):

$$\boldsymbol{\Sigma_{ll}} = \sum_{k=1}^{p} \boldsymbol{D}_k \cdot \boldsymbol{\Sigma_{\delta\delta,k}} \cdot \boldsymbol{D}_k^T + \boldsymbol{F} \cdot \boldsymbol{\Sigma}_{\xi\xi} \cdot \boldsymbol{F}^T + \sum_{h=1}^{q} \boldsymbol{G}_h \cdot \boldsymbol{\Sigma}_{\gamma\gamma,h} \cdot \boldsymbol{G}_h^T \,. \tag{4}$$

By means of the covariances and the square root of the variances, the correlation coefficient ρ (e.g. Benning, 2010) and the correlation matrix $\boldsymbol{R}$ can be determined:

$$\rho = \frac{\sigma_{12}}{\sigma_1 \cdot \sigma_2} \quad \text{and} \quad \boldsymbol{R} = \frac{1}{\sqrt{diag(\boldsymbol{\Sigma}_{ll})}} \cdot \boldsymbol{\Sigma}_{ll} \cdot \frac{1}{\sqrt{diag(\boldsymbol{\Sigma}_{ll})}} \,. \tag{5}$$

3.2 Elementary Errors of Terrestrial Laserscanners

In order to apply the elementary error model to terrestrial laser scanning measurements, all fundamental sources of errors must be identified first. This error sources have to be modelled as elementary errors and classified into non-correlating, stochastically correlating and functional correlating accordingly. On the one hand, measurements are affected by the manufacturing accuracy of the instrument itself. For terrestrial laserscanning three main sources exist: instrumental, atmospheric and object-related error sources. Table 1 presents the instrumental errors including realistic values for the standard deviations of the elementary errors. The first two errors are non-correlating errors, all the others are functionally correlating. For more details regarding the influencing matrices the authors refer to Kauker and Schwieger (2016). With respect to the atmospheric errors Kauker and Schwieger (2016) present standard deviations for the atmospheric parameters based on empirical data in the vicinity of Stuttgart. Since on the one hand the spatial correlations for these stochastically correlating errors are unknown, and as on the other hand the first simulations are realized for indoor and short distance measurements, the errors may be considered as functionally correlating and with clearly reduced standard deviations: $\sigma_t = 0.01$ °C, $\sigma_p = \sigma_e = 10^{-8}$ hPa. The object related error sources are not modelled up to now. They are only classified into functionally and stochastically correlating errors. An overview is presented in Kauker and Schwieger (2015). In conclusion, the modelled covariance matrix of the observations is not complete for the time being.

Table 1: Standard deviations of instrumental errors

Error Sources	**Standard deviations**
range noise	0.5 [mm]
angle noise	125 [µrad]
scale error	0.300018[mm/km]
zero point error	1.50 [mm]
collimation axis error	5.89 [mgon]

horizontal axis error	4.38 [mgon]
vertical index error	5.31 [mgon]
tumbling error	0.09 [mm/m]
eccentricity of the collimation axis	0.60 [mm]

3.3 Simulation of a Synthetic Covariance Matrix for Short Distances

In order to evaluate and improve the model of the synthetic covariance matrix, small test objects are necessary. Taking into account the impact on the laser beam caused by the material, the investigated sample test objects consist of aluminium, gypsum, wood and rusty steel. This is the reason why the simulation presented in this contribution is adopted to the size of the test objects and to indoor conditions. It is planned to use an aluminium and a gypsum flat board with a size of 30 cm x 25 cm. Therefore, the synthetic covariance matrix is generated for an equidistant angle with a point distance of 6.283 mm at 5 m scanning distance. The standard deviations of the coordinates are displayed in Fig. 1. They reach values around 2.5 mm for the 3D-point-error. As expected, the standard deviation is best in the middle of the board and gets worse in the direction of each corner. Moreover, it is clearly visible that the range between the minimum and the maximum is 1 µm only. This small difference is caused by the small area of the test piece and the ignorance of object based impacts and can therefore be considered realistic. Nevertheless, the standard deviation values are particularly pessimistic, because the applied maximum errors for the variance determination of the elementary errors may not be well suited for the HDS 7000. The correlations are around 0.95. So the coordinates depend strongly on each other; they have a small tendency to decrease for longer distances between the points (compare Kauker and Schwieger, 2016).

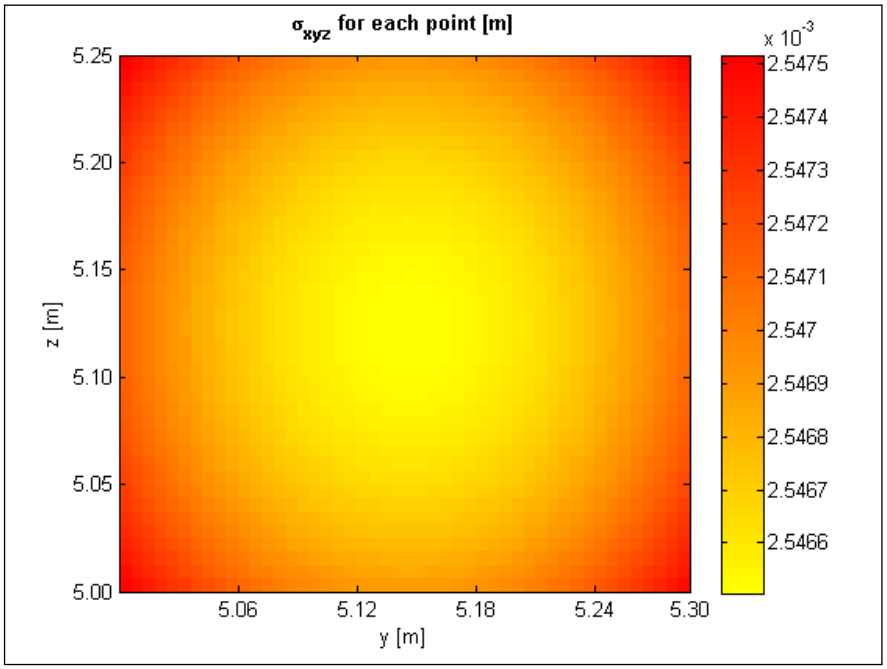

Fig. 1: Helmert's point error in 5 m scanning distance (neglecting object related sources)

4. MODELING OF AREAL DEFORMATIONS

4.1 Modelling of Surfaces Using B-Splines

One possibility to model surfaces of scanned objects is the use of B-Spline surfaces as one representative for freeform surfaces. One advantage of this technique is the ability to model local changes of the surfaces, to be interpreted as deformations, without changing the surface at the other parts of the modelled surface (e.g. Koch (2010), Schmitt et al. (2013), Harmening and Neuner (2015b)).
A B-Spline surface $\boldsymbol{S}(u,v)$ of degree p and q is defined by its $(n_B+1)*(m_B+1)$ control points $\boldsymbol{P}_{ij}$, the B-spline basis functions $N_{i,p}(u)$ and $N_{i,q}(v)$ as well as two knot vectors $\boldsymbol{U} = [u_0,\dots u_r]$ and $\boldsymbol{V} = [v_0,\dots v_s]$ (Piegl and Tiller (1997)):

$$\boldsymbol{S}(u,v) = \sum_{i=0}^{m_B}\sum_{j=0}^{n_B} N_{i,p}(u)\, N_{j,q}(v)\boldsymbol{P}_{ij} \qquad \text{, with: } u, v = [0,\dots,1]. \qquad (6)$$

When estimating a best-fitting B-Spline surface, a variety of unknown parameters has to be determined, generally leading to a nonlinear adjustment problem. A typical approach is to fix some of the parameters while estimating the other ones; e.g. the B-spline's degrees are usually set to p = 3 and q = 3, which is generally accepted as a reasonable choice and the knot vectors can be determined a priori according to (Piegl and Tiller (1997)). If the surface parameters u and v are also determined a priori (for example according to Harmening and Neuner (2015a)), a fixed number of control points can be estimated in a linear adjustment. The remaining parameter type is the number of control points n_B+1 and m_B+1, whose influence on the estimation's result is immense, as it determines substantially the B-spline's complexity. Typically, this parameter type is chosen quite arbitrary by using trial-and-error-procedures, wherefore in the following the applicability of model selection criteria to the determination of the optimal number of control points is introduced.

4.2 Determination of the Optimal Number of Control Points

To determine the optimal number of control points models of different complexity need to be compared: this means that model selection has to be applied. The optimal model from a given set of models is identified by means of the principle of parsimony, which states that a good model has to be as simple as possible while being a good approximation of the data (Burnham and Anderson (2002)). The more parameters are included into the estimation problem, the better the data is approximated, leading to a small approximation error. However, the function's variance increases, which leads to an overfitting. On the contrary, models which are too simple have a large bias.
In the following the two most popular model selection criteria, the Akaike Information Criterion (AIC) (Akaike, 1998) and the Bayesian/Schwarz Information Criterion (BIC/SIC), are compared with respect to the identification of the optimal number of control points.

Both criteria are built on maximum-likelihood theory, which choses those model parameters $\widehat{\boldsymbol{\theta}}$ as optimal, which maximize the conditional probability $\mathcal{L}(\widehat{\boldsymbol{\theta}}|\text{data})$. Further information is available in Koch (1999) and Harmening and Neuner (2016).

The AIC is an asymptotic efficient criterion. Those criteria assume that the truth is not included into the set of candidate models and aim to find asymptotically the best approximation of the truth by minimizing a certain distance measure between the truth and the candidate models. The AIC interprets the model as well as the underlying truth as probability distributions g and f respectively and minimizes the relative Kullback-Leibler (KL) distance between these two distributions (see Harmening and Neuner (2016)). The estimation of the relative KL distance leads to the general equation for the AIC, which is given in the following:

$$\begin{aligned} \text{AIC} &= -2\log\left(\mathcal{L}\left(\widehat{\boldsymbol{\theta}}\middle|\text{data}\right)\right) + 2\text{K}, \\ \text{with K} &= 3\big((n_B+1)(m_B+1)\big)+1 \quad \text{in case of a B-spline surface.} \end{aligned} \tag{7}$$

The log-likelihood attempts to choose the model producing the smallest approximation error, whereas the model's complexity in terms of the number of parameters is penalized by means of the second term in equation (7) (Claeskens and Hjort (2008)).

The BIC was introduced by Schwarz (1978) and is an asymptotic consistent criterion, which assumes, that the truth is included into the set of candidate models and which aims to identify this true model for infinite sample sizes. According to Bayes' theorem, the posteriori probabilities of the models are given by the prior probabilities of the models $P(M_j)$, the unconditional likelihood of the data f(data) and the marginal likelihood $\lambda_{n,j}(\text{data})$ (Claeskens and Hjort (2008)), which results in the final equation:

$$\text{BIC} \approx -2\log\left(\mathcal{L}\left(\widehat{\boldsymbol{\theta}}\middle|\text{data}\right)\right) + \log(n)K. \tag{8}$$

Comparing equations (7) and (8) it can be seen, that the two criteria differ only slightly. AIC and BIC are both penalized by log-likelihood criteria, with BIC imposing a stronger penalty on the models' complexity than AIC for $n \geq 8$.

4.3 First Results

Starting point is a B-spline surface with 5 * 7 control points ($n_B + 1 = 5$, $m_B + 1 = 7$), which is superimposed by white noise. In the following the two criteria are investigated with regard to the repeatability and their behavior in case of varying sample sizes, what may be related to larger monitored object or to higher laser scanning resolution. For this reason, five data sets (Rep. 1 to Rep. 5) with varying sample sizes are generated. For each sample size, the noise generating is repeated five times, resulting in 25 data sets which are different realizations of the same phenomenon.

Table 2: Optimal number of surface control points according to AIC.
(The surface was generated with $n_B+1=5$, $m_B+1=7$.)

Sample size	**900**	**1600**	**2500**	**3600**	**4900**
Rep. 1	8,11	10,11	10,11	6,10	7,9
Rep. 2	11, **7**	7,11	6,11	**5**,10	7,11
Rep. 3	**5**,11	11,10	9,9	11,11	11,11
Rep. 4	11,11	7,11	7,11	8,11	**5**,9
Rep. 5	**5**,9	6,11	9,**7**	11,10	**5**,11

Table 3: Optimal number of surface control points according to BIC.
(The surface was generated with $n_B+1 = 5$, $m_B+1 = 7$.)

Sample size	**900**	**1600**	**2500**	**3600**	**4900**
Rep. 1	**5,7**	**5,7**	7,**7**	6,10	8,10
Rep. 2	**5,7**	**5,7**	**5**,9	**5,7**	**5**,9
Rep. 3	**5,7**	**5,7**	**5**,10	**5,7**	**5**,10
Rep. 4	**5,7**	6,**7**	7,**7**	7,**7**	**5**,9
Rep. 5	**5,7**	**5**,8	6,**7**	**5,7**	**5**,11

The sample sizes, which were used, vary between n_1=900 and n_5=4900. B-spline surfaces are fitted through all those data sets while varying the number of control points in a range from $n_B + 1 = m_B + 1 = [4,\ldots,11]$. The resulting residuals are used to compute the AIC- and BIC-scores (equations (7) and (8)) and the number of control points producing the smallest score is marked to be optimal in bold letters.
The results are presented in tables 2 and 3. For the major parts of the data sets, the number of control points chosen by AIC is significantly larger than the actual number of control points. Only few data sets exist, for which the AIC identifies at least one of the two parameters correctly; the correct combination, however, is never identified. The results which are yielded by BIC are much more satisfying: Especially, for the sample sizes l=900 and l=1600, the number of parameters, which is chosen to be optimal, is identical to the actual one. However, this result becomes instable with growing sample sizes. Nevertheless, in the major part of the data sets, at least one of the parameters is identified correctly.
Altogether it can be stated, that BIC identifies the actual model complexity better than AIC does. Theoretically AIC is based on an idea which seems to be much more suitable for the concrete problem: The surface estimation is not based on the surface parameters u and v or on the knot vector U and V, which were used to simulate the data, but are determined independently. As a consequence, the truth is not contained in the set of candidate models and the concrete goal of model selection in this context should be to find a model which approximates the truth in an optimal manner (AIC) and not to identify the true model (BIC). Nevertheless, as not the asymptotic properties, but those of finite sample sizes are important in practice, the BIC is recommended in order to identify the optimal number of control points.

5. SUMMARY AND FURTHER RESEARCH

In summary the authors have presented two intermediate results for modelling aerial deformations as a whole. At first co-variances or correlations of the scanned object points are of importance for a correct spatial (within a deformation epoch) and temporal (between two or more deformation epochs) stochastic model. In this contribution the general model for a synthetic covariance matrix was introduced and adopted for terrestrial laser scanning. Hereby, different error sources like instrumental errors referred to the Leica HDS7000 and atmospheric errors were already considered; object related errors were neglected for the time being. For first calculations the atmospheric impact was simplified due to laboratory scanning conditions. It could be shown that the modelled standard deviations of the point cloud are about 2.5 mm which primarily depends on the value of the instrumental error variances and the resolution of the scanning. The correlations reach more than 0.95 and depend on the point distances to each other. In the future, object based impacts have to be integrated and the synthetic covariance matrix has to be evaluated by means of empirical values.
At second a model for the deterministic part of the time-related deformations was developed based on B-spline surfaces. B-spline surfaces depend on multiple parameters. In this paper the authors concentrated on the optimization of the number of control points. Two criteria, AIC and BIC, were used to compute the optimal number of control points that should coincide with the given truth that was randomized before by white noise. Based on the simulated data, the BIC put out to be the more appropriate method to determine the optimal number of control points. Nevertheless the results were not completely satisfying. This yields to the task of identifying additional criteria which are based on the Vapnik-Chervonenski dimension (Vapnik, 1998). Additionally it has to be mentioned that correlated data, that is really available, will cause problems with respect to the optimization so that additional research e.g. with respect to the adoption of decorrelation techniques is required.
These intermediate results are cornerstones on the way towards a complete deformation model that includes deterministic and stochastic parts. The next steps will be the completion of the synthetic covariance matrix as well as the deformation model. For the second part correlation pattern have to be extracted from the evaluated data. These patterns will additionally lead to the support of a sensitivity analysis with respect to expected deformation models for e.g. barrages and dams.

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BIOGRAPHICAL NOTES

M.Sc. **Corinna Harmening**

2008 – 2013	Studies of Geodesy at Leibniz University Hannover
2011	Bachelor of Science (Leibniz University Hannover)
2013	Master of Science (Leibniz University Hannover)
Since 2014	FWF-Project Assistant at the TU Vienna

Dipl.-Ing. **Stephanie Kauker**

2008 - 2014	Studies of Geodesy at University of Stuttgart
2014	Dipl.-Ing. Geodesy (University of Stuttgart)
Since 2014	Research Associate (DFG) at Institute of Engineering Geodesy, University of Stuttgart

Prof. Dr.-Ing. **Hans-Berndt Neuner**

1993 – 1999	Studies of Geodesy at Faculty of Geodesy Bucharest, Romania
1999	Dipl.-Ing. Geodesy (Faculty of Geodesy Bucharest, Romania)
2008	Dr.-Ing. Geodesy (Leibniz University of Hannover, Germany)
2013	Professor and Head of Research Group Engineering Geodesy, TU Vienna, Austria

Prof. Dr.-Ing. habil. **Volker Schwieger**

1983 – 1989	Studies of Geodesy in Hannover
1989	Dipl.-Ing. Geodesy (University of Hannover)
1998	Dr.-Ing. Geodesy (University of Hannover)
2004	Habilitation (University of Stuttgart)
Since 2010	Professor and Head of Institute of Engineering Geodesy, University of Stuttgart

CONTACTS

M.Sc. Corinna Harmening
TU Wien
Department of Geodesy and Geoinformation, Research Group Engineering Geodesy
Gusshausstr. 25-29
1040 Vienna
AUSTRIA
Tel. +43 (1) 58801 - 12839
Email: corinna.harmening@tuwien.ac.at

Website: http://info.tuwien.ac.at/ingeo/

Dipl.-Ing. Stephanie Kauker
University of Stuttgart
Institute of Engineering Geodesy
Geschwister-Scholl-Str. 24 D
D-70174 Stuttgart
GERMANY
Tel. + 49/711-685-84068
Email: stephanie.kauker@ingeo.uni-stuttgart.de
Website: http://www.uni-stuttgart.de/ingeo/

Prof. Dr.-Ing.Hans-Berndt Neuner
TU Wien
Department of Geodesy and Geoinformation, Research Group Engineering Geodesy
Gusshausstr. 25-29
1040 Vienna
AUSTRIA
Tel. +43 (1) 58801 - 12839
Email: hans.neuner@tuwien.ac.at
Website: http://info.tuwien.ac.at/ingeo/

Prof. Dr.-Ing. habil. Volker Schwieger
University of Stuttgart
Institute of Engineering Geodesy
Geschwister-Scholl-Str. 24 D
D-70174 Stuttgart
GERMANY
Tel. + 49/711-685-84040
Email: volker.schwieger@ingeo.uni-stuttgart.de
Website: http://www.uni-stuttgart.de/ingeo/