



Combined Evaluation of Geodetic and Geotechnical Data during Tunnel Excavation by Use of a Knowledge-Based System

Klaus Chmelina ¹, Heribert Kahmen ²

¹ *Geodata ZT GmbH Wien, Geyschlägergasse 14, A-1150 Vienna, Austria*

² *Vienna University of Technology, Institute of Geodesy and Geophysics, Departement of Applied and Engineering Geodesy, Gusshausstraße 27-29, A-1040 Vienna, Austria*

VGI – Österreichische Zeitschrift für Vermessung und Geoinformation **91** (1), S. 85–91

2003

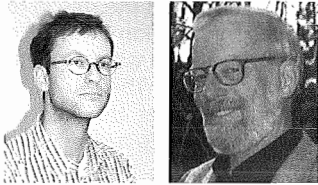
BibT_EX:

```
@ARTICLE{Chmelina_VGI_200312,  
  Title = {Combined Evaluation of Geodetic and Geotechnical Data during Tunnel  
    Excavation by Use of a Knowledge-Based System},  
  Author = {Chmelina, Klaus and Kahmen, Heribert},  
  Journal = {VGI -- {"0}sterreichische Zeitschrift f{"u}r Vermessung und  
    Geoinformation},  
  Pages = {85--91},  
  Number = {1},  
  Year = {2003},  
  Volume = {91}  
}
```



Combined Evaluation of Geodetic and Geotechnical Data during Tunnel Excavation by Use of a Knowledge-Based System

Klaus Chmelina and Heribert Kahmen, Wien



Abstract

The paper presents how geotechnical knowledge can be used for the analysis of geodetic deformation data. With this contribution the application field of NATM-tunnelling (New Austrian Tunnelling Method) is addressed. The deformation analysis is based on heuristic rules which are implemented in a knowledge-based system.

Kurzfassung

In diesem Beitrag wird dargestellt, wie geotechnisches Wissen für die Analyse geodätisch hergeleiteter Deformationen genutzt werden kann. Der Beitrag behandelt eine wichtige Thematik der Neuen Österreichischen Tunnelbaumethode. Die Deformationsanalyse stützt sich auf heuristische Regeln, welche in ein Wissensbasiertes System implementiert wurden.

1. Introduction

The geodetic monitoring of 3-d displacements during tunnel excavation has become a standard procedure for tunnel projects. In NATM-projects (New Austrian Tunnelling Method, [3]), the immediate geotechnical interpretation of the periodically observed displacements must be seen as an integral part of the tunnelling method. As a consequence, qualified and experienced geotechnical experts are needed on site.

Currently, geotechnical interpretation is based mainly on the daily analysis of numerous types of sophisticated displacement diagrams together with many other listings and graphics showing further project data – a time consuming manual work. For realizing up to date analysis of large data volumes or online analysis of automatically monitored data, e.g. when robotic tachometer systems are used, this manual procedure is obviously unpracticable. Until now, there exists no means by which these tasks are managed quickly, automatically and sufficiently reliable.

A knowledge-based approach is presented which shall assist interpretation work through an automatic analysis of the displacements by use of heuristic rules. These rules thus provide expert knowledge for the detection and interpretation of specific deformation phenomenas thus building the core of a knowledge-based system [1]. Three different examples using geotechnical

knowledge to evaluate geodetic data, are presented.

2. Example ONE: How to Find an Explanation for Reactivated Deformations

In general any *unexplainable* deformation behaviour leads to an uncertainty which must be solved quickly (the causes of the deformations must be found) in order to ensure safe continuation of the project. Such a case can occur when deformations that have been consolidated in the past suddenly become reactivated. Whether such a reactivation is really *unexplainable* depends on the current situation on site. In case of NATM-tunnelling, deformations must be analysed together with the excavation progress. If e.g. an excavation face (e.g. bench, invert) approaches or passes the deformation area (situated in or above a tunnel) the reactivation of deformations usually is expected and explainable. On the other hand, any reactivation that can not be explained (e.g. by excavation activities) is alarming and perhaps critical for the construction progress. Fig. 1 characterizes the geotechnical interpretation steps which handle this problem.

Modelling these steps by conventional programming would lead to a complex code consisting of numerous interlocked IF - THEN statements, logical expressions (AND, OR, NOT) and loop commands. Therefore a rule-based system

was chosen here. With this system the interpretation process can be modeled in a modular, transparent and much more flexible way. With respect to a better understanding of rule based inferencing the use of WHENEVER instead of IF is more appropriate. The decisive difference and advantage is that by use of rules the interpretation must not necessarily be processed top-down. The developed rule-based system can ask all the questions shown in fig. 1 dynamically at the same time but does not have to ask them sequentially (as with IF-THEN). Further, the questions can remain permanently active in memory but do not have to be repeatedly asked (as with loops). To elucidate let's transfer the problem into heuristic rules:

Rule 1: WHENEVER deformation data match the pattern "Reactivation"
THEN produce a fact that marks this data as "reactivated"

The precondition of the rule consists of a representation of an abstract deformation pattern

called „Reactivation“. At implementation level this pattern is defined in a more or less empirical way as a time series of deformation data showing increasing deformation velocities during the last 3, 4 or 5 epochs. The action of the rule is to add (assert) a meaningful information (a fact) to the working memory describing which point, which epoch, etc. is concerned. This is completed for all such incidents thus the knowledge-based system becomes aware and mindful of them.

Rule 2: WHENEVER 1. there is a fact that marks data as "reactivated"
 2. excavation data match the pattern "Close Enough"
THEN produce a fact that describes this link

The rule consists of two preconditions to be regarded as connected by the logical AND-statement. The first is fulfilled if there exists at least one of the previously mentioned facts pro-

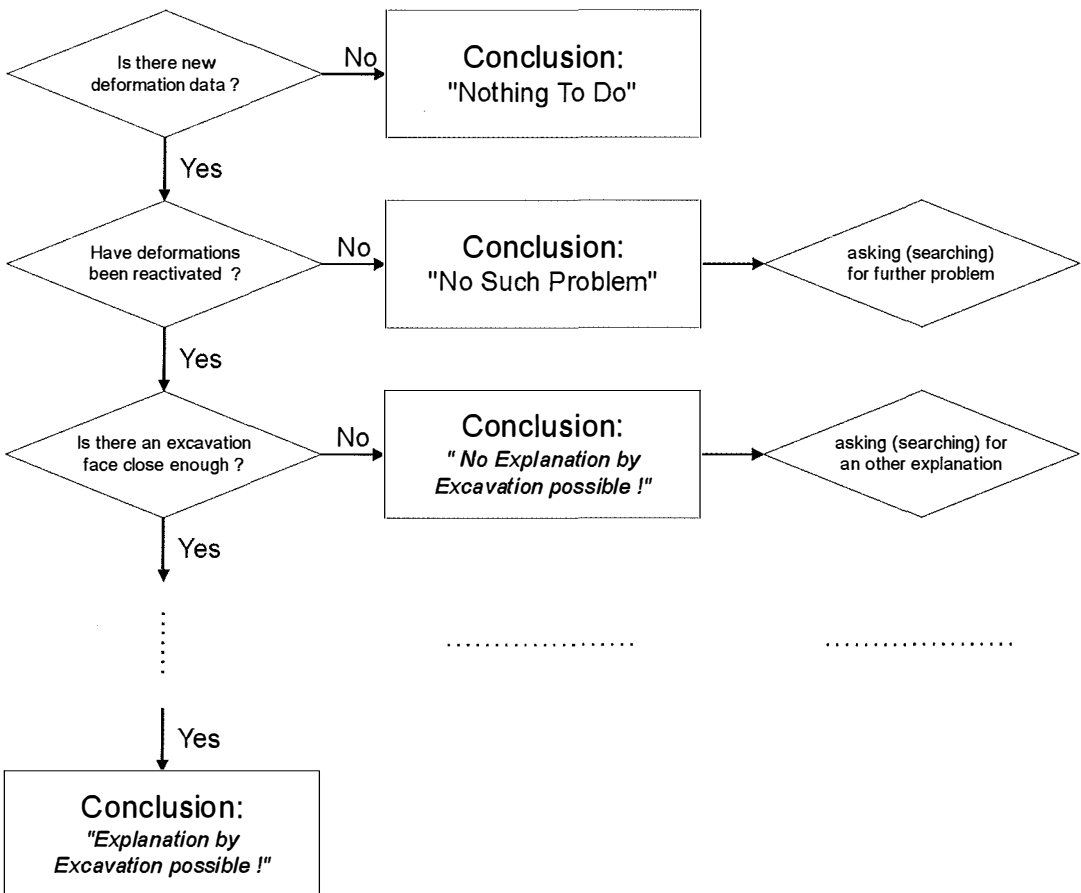


Fig. 1: Interpretation steps

duced by rule 1. The second consists of another abstract pattern "Close Enough" specifying that excavation data prove excavation activities to be a possible cause for a detected reactivation incident. For that certain distances in space as well as time constraints must be considered which are defined according to assumptions of the expert. If both conditions are fulfilled the rule adds a meaningful fact to the working memory expressing that there is (possibly) a connection between reactivation and excavation. The rule fires for each excavation activity meeting "close enough" and links it to the reactivation incident (e.g. a reactivation can be explained by more than one excavation activity). As can be seen, linking is performed whenever new excavation data or new deformation data is accessible. So rule 1 and rule 2 together keep track of both data.

For continuing interpretation (fig. 1) rule 3 could be specified by simply modifying the second precondition of rule 2 now assuming the opposite case that there is no excavation data matching the pattern "close enough". Thus the corresponding "No Explanation" - conclusion could be processed and stored. This somehow would mean that the normally large volume of excavation data has to be checked twice for each reactivation incident. To speed up runtime performance rule 3 is alternatively designed as follows:

Rule 3: WHENEVER 1. there is a fact that marks data as "reactivated"
 2. there is no fact describing a link to excavation data
THEN conclude (display and store) that there is no explanation

Adopting this method, the system must know that it cannot begin applying rule 3 before rule 2 has been used which serves as an example that asking all questions at the same time is not always efficient. This meta-knowledge was implemented by an appropriate hierarchical structuring of rules. The majority of rules were kept at equal level.

By additional rules the knowledge-based system is able to continue forward-reasoning down to a theoretical final conclusion:

"The phenomena could have been caused by the excavation,"

which in case might be reached or not. At the same time further (either independent or de-

pending) interpretational problems can be handled by other rules allowing for similar *horizontal* and *vertical* conclusions. If the user is not really interested in all problems he/she can pre-select the desired ones in a configuration dialog. The selection is then transferred into facts triggering only the relevant heuristic rules.

The system can be called heuristic as the arrangement and composition of the rules was mainly driven by common sense, efficiency aspects and some good advices of experts. System tests proved that the software can process even large data volumes within acceptable times. What has to be observed more critically is the error budget. Wrong conclusions might be drawn especially when there are inaccuracies, errors and/or missing data. This problem was realized at an early stage and as a consequence, a knowledge-based error detection method also based on heuristic rules was implemented (see example 2 below).

With regard to the problem of wrong conclusions it is emphasized that the original intention was to develop a support system where the human expert still has the last comment. All final conclusions of the system are therefore reported in the form of insecure statements ("could").

3. Example TWO: How to Find and Analyse an Error in Deformation Data

As mentioned, the knowledge-based system must reason over actual measuring results. In order to avoid wrong conclusions due to bad quality of input data, error detection is needed in advance. (In practice the geotechnical expert does not consider error detection as a separate interpretational task - in other words: "It's not their job to find errors".) So as long as data quality problems are seldom he/she apriori trusts in the data provided. He/She is however able to recognize (possibly) incorrect data by specific characteristics or signs mostly driven by experience and common sense. Further, to become sure, he/she begins to investigate the problem in detail. A typical error investigation strategy is briefly described as follows:

1. Discovering of a characteristic error sign (e.g. an unexpected deformation) more or less by accident.
2. Determining of its relevance for the interpretation. If the sign is rather small it might be considered irrelevant and neglected by the expert.
 If the sign is strong it still might be irrelevant

(e.g. if the corresponding data has no influence on the interpretation at all).

- Deriving of a hypothesis (of a possible error cause, error type) from a known correlation between the sign and a cause.

If various causes could be responsible the best one is chosen first (the most obvious, frequent or probable, the easiest to be checked, etc.). Now the sign becomes a symptom.

- Searching for further symptoms supporting the hypothesis

The search is driven by the distinct intention to prove the hypothesis.

- Searching for signs, facts, hints, features, etc. contradicting the hypothesis

Now the search is driven by the opposite intention to disprove the hypothesis. Which kind of search is started first depends on efficiency criterias. Investigations show that for psychological reasons experts usually try to verify (especially their own) assumptions first even if their falsification would mean less effort.

- Evaluating of all gathered aspects for deriving a verification certainty.

The question is: "Can the hypothesis be established as a diagnose?"

We may decide to stop and establish the hypothesis as a diagnose or to go back to point 3 deriving and evaluating an alternative hypothesis. If none of these can finally be verified sufficiently (better: satisfactory) either the initial error assumption is cancelled or the investigation result remains a list of possible but uncertain causes.

A knowledge-based system for handling this complex strategy needs an appropriate way to represent and propagate uncertainty – a problem which leads to the various concepts of probabilistic reasoning. Among those, the Certainty Factor Method [4] was chosen because it represents a pure heuristic approach especially developed for rule-based expert systems.

Certainty Factors – a brief introduction:

Each premise (condition) P_1, P_2, \dots, P_n of a rule (e.g. the statement: "there is an error sign") is attributed with a numeric parameter (a certainty factor) cf_1, cf_2, \dots, cf_n describing its degree of membership to the concept true. The parameter interval lasts from -1 (not true) to $+1$ (true). A certainty factor $cf_x = 0$ means that there is nothing known about the truth of P_x . Also, each rule R_1, R_2, \dots, R_n itself (e.g. the statement: "from the error sign can be concluded an error cause") has a

certainty factor $cf_{r_1}, cf_{r_2}, \dots, cf_{r_n}$ expressing the strength (the truth) of the relation between the premises and the conclusion. When a rule R_x is executed, all involved certainty factors cf_1, cf_2, \dots, cf_n of its n premises and cf_{r_x} are processed to obtain a certainty factor cf_{c_x} for the conclusion C_x . In rule based expert systems a common way is to calculate:

$$cf_{c_x} = \min(cf_1, cf_2, \dots, cf_n) * cf_{r_x}. \quad (1)$$

If by two different rules R_1, R_2 the same conclusion is drawn the now concurring different values of cf_{c_1} and cf_{c_2} must consequently be processed to a final cf_c which can be completed as follows:

$$cf_c = \begin{cases} cf_{c_1} + cf_{c_2} - cf_{c_1} * cf_{c_2} & \text{if : } cf_{c_1}, cf_{c_2} \geq 0 \\ cf_{c_1} + cf_{c_2} + cf_{c_1} * cf_{c_2} & \text{if : } cf_{c_1}, cf_{c_2} \leq 0 \\ \frac{cf_{c_1} + cf_{c_2}}{1 - \min(|cf_{c_1}|, |cf_{c_2}|)} & \text{if : } cf_{c_1} * cf_{c_2} < 0 \end{cases} \quad (2)$$

If further rules lead to the same conclusion the algorithm is applied sequentially. The mathematical operations for processing the certainty factors are thus chosen intuitively. They heuristically approximate the human way of propagating uncertainty.

An example is now given to imitate the above interpretation strategy by applying the Certainty Factor Method. It shall be analysed if there is a systematic height error of the instrument station in the measured vertical deformations. At first rule 4 is designed for detecting an abstract pattern "Strong Settlement". Its conclusion (fact) is considered to be an initial and relevant error sign for a specific cause (steps 1, 2 and 3 of the strategy).

Rule 4: WHENEVER

1. deformation data match the pattern "Strong Settlement"
2. there is no fact so far that marks the related epoch and station as suspicious

THEN

produce a fact that marks the related epoch and station as suspicious

The rule fires exactly one time for all measuring epochs and instrument stations having at least one measurement showing the pattern. The system now knows all suspicious epochs and stations that have to be further investigated. Now (and only for them) there is applied the Certainty Factor Method. The following initial certainty factors for the following three statements (rules) are defined as:

$cfr_1 = 0.3 e^{-(b_{ew_diff})^2}$: From one strong settlement incident there can be concluded the error.

If there is only one measurement available (which shows the sign) the error is concluded with a certainty of 0.3 thus staying rather uncertain. If there are more measurements showing the sign the certainty of concluding the error from one such sign becomes a function of the similarity of all signs. The function models the expectation that a height error of the station should be visible in all measurements in the same size. The less that one sign meets this expectation the less there can be concluded the error from it. This aspect is implemented by multiplying 0.3 with an exponential term considering the difference between the size of the sign to the mean size of all signs. The rule models step 4 of the strategy producing a list of positive certainty factors.

$cfr_2 = -0.1$: From an inconspicuous measurement there can be concluded the error.

If a measurement from the suspicious station appears as normal it is treated as if it would slightly contradict the hypothesis with a negative certainty of -0.1.

$cfr_3 = -0.5$: From a measurement showing a strong heave there can be concluded the error.

If a measurement shows a strong heave which indicates an opposite than initially expected direction of deformation, the case is regarded as a strong irritation. As a consequence, it contra-

dicts the hypothesis with a high negative certainty of -0.5. The last two rules model step 5 of the strategy producing a list of negative certainty factors.

Finally, all certainty factors were processed by eq. 2 giving a final certainty of the hypothesis. Fig. 2 shows an example of the vertical deformations of 7 points measured at Oct. 27 for which the system states: "A systematic height error of the station could have happened. For this kind of error a certainty of 0.87 was derived." By studying fig. 2 the reader is invited to compare this result with his/her own assumptions.

By applying this method, the knowledge-based system is now able to offer an additional explanation for the interpretational problem discussed in chapter 2 (fig. 1) which says:

"The phenomena could be caused by an error."

4. Example THREE: How to Find Remarkable Deformations by use of Rating Knowledge

During tunnel design deformations are prognosed by use of diverse techniques (e.g. numerical simulations) providing the knowledge of how the planned tunnel (the rock) is expected to deform under certain conditions. Besides these official prognoses, the expert also has his/her own individual and much more extended expectations (usually derived from experience). During tunnel excavation the measured deformations are compared with the prognosed and expected ones. Unexplainable big differences between

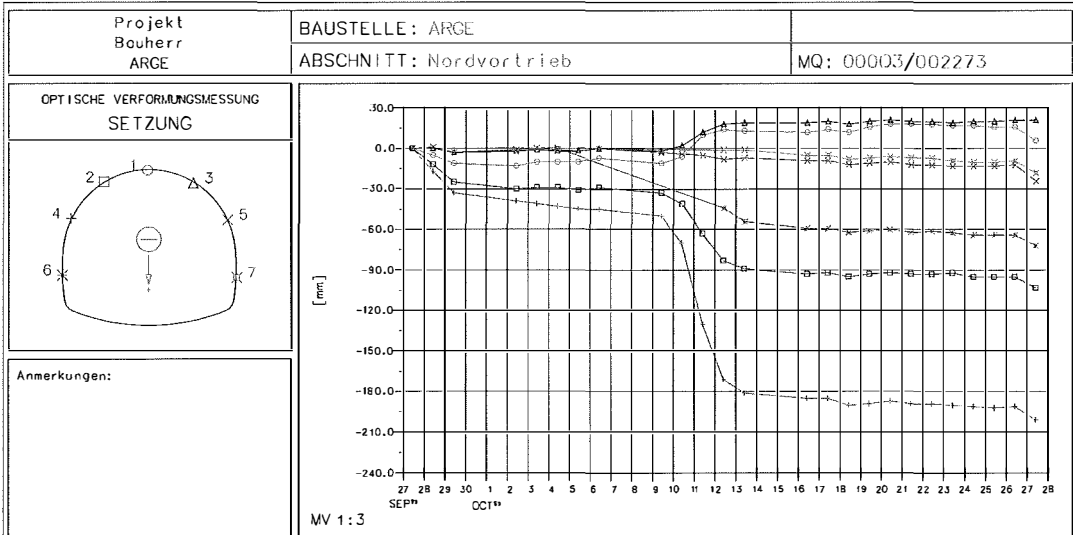


Fig. 2: Measured vertical deformations of 7 points

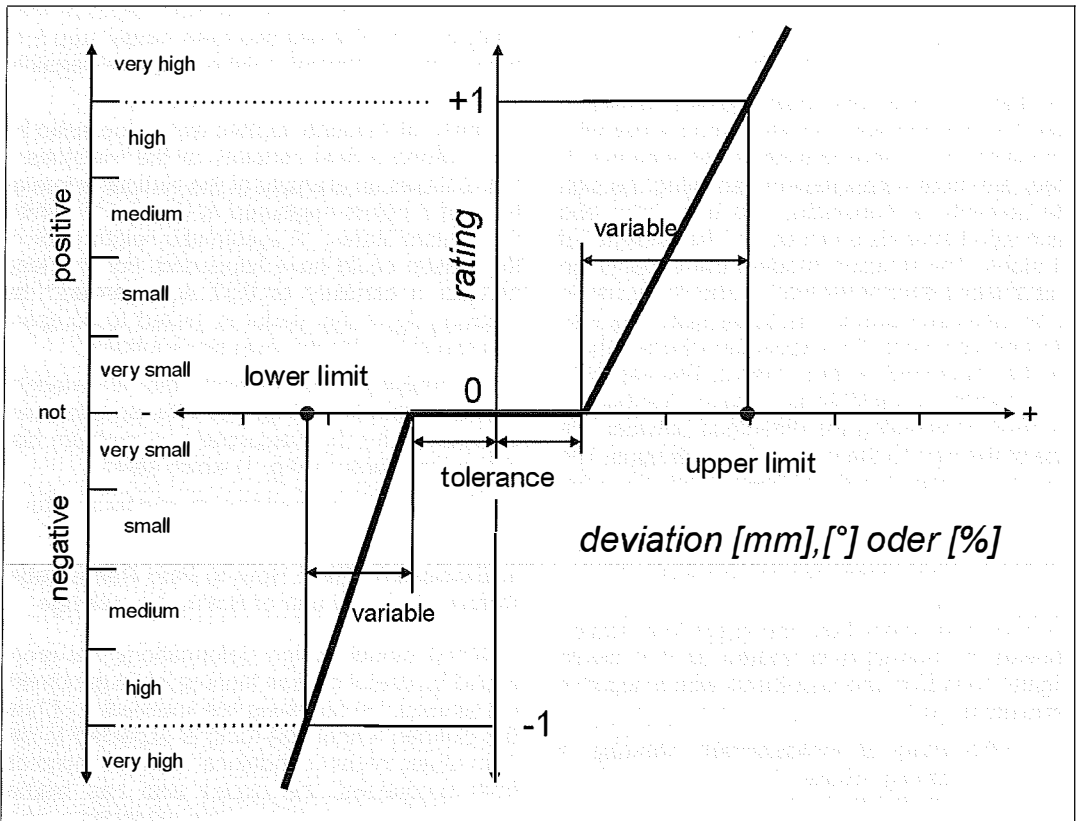


Fig. 3: Empirical rating model

them can be an alarming sign for the geotechnical expert on site. An automatic detection of such a situation makes necessary the representation of the prognoses and expectations as well as the expert knowledge of how to rate their deviation(s) from reality. In the developed knowledge-based system, prognoses and expectations can be specified by defining deformation curves, vectors, values, etc. and assigning them to distinct measuring objects (points, sections, areas). The rating knowledge is represented by empirical rating models (fig. 3) which can be selected, configured and assigned to a prognosis or expectation.

The rating model allows us to transfer the difference between a real and prognosed (expected) measuring result (e.g. the difference in settlement [mm], the difference in vector orientation [°], the difference in deformation velocity [mm/d], etc.) into a numeric rating value and an associated linguistic variable. The transfer function might either be linear (as exemplified in fig. 3), exponential, logarithmic or determined by any other mathematic equation that best serves

to approximate the users way (wish) of rating. In addition, a rating tolerance can be specified for maintaining the rating value equal to zero in case of small differences and an empirical measuring accuracy for putting the rating value to a worst-case value by simply adding the measuring accuracy to the difference before rating.

As soon as we input the knowledge into the system heuristic rules apply it to the incoming deformation data. The rules ensure that all deviations which exceed user-definable evidence limits (e.g. all deviations reaching the *very high* – level) are detected and reported automatically. Rule 5 below shows the principle structure:

- Rule 5: WHENEVER**
1. there is deformation data
 2. there is a prognosis for this data
 3. there is a rating model for this prognosis
 4. the calculated rating value exceeds an evidence limit
- THEN** produce a fact

As can be seen, more than one prognose may exist (e.g. from different numerical simulations) as well as more than one rating model (e.g. from different experts). However the rule evaluates all of them thus becoming aware of all evident cases. Alternatively, by a simple modification of the rule the knowledge-based system becomes able to offer another answer to the interpretational problem discussed in chapter 2 which says:

“The phenomena was prognosed, maybe there is no problem at all.”

In order to provide more information about this kind of answer the system additionally outputs context information to the prognose (prognosed by whom, when, based on what, etc.) which has to be input in advance (together with the prognose).

5. Conclusion

It is shown how interpretation of deformations, occurring during the construction of a tunnel, can be based on a knowledge-based system. The system is thought to support the geotechnical expert on site by reducing his/her interpretation time and effort which is necessary in case deformation monitoring is done frequently with automatic monitoring systems. Classical deformation analysis methods, only based on geometrical data, can not be used here, as in addition,

information such as geological data, data about the excavation progress, data from simulation calculations, etc. have to be included in the evaluation process. This paper shows with three examples how heuristic rules can be developed and used in such a knowledge-based system. With the developed rules, deformations reactivated by the construction process, measurement errors and differences between prognosed and measured deformation data can be analysed.

References

- [1] *CHMELINA, K.*: Wissensbasierte Analyse von Verschiebungsdaten im Tunnelbau, Dissertation, Inst. of Geodesy and Geophysics, TU-Vienna, 2002.
- [2] *BONISONE, P., DECKER, K.*: Selecting uncertainty calculi and granularity: an experiment in trading-off precision and complexity. In: Proc. of Workshop on Uncertainty and Probability in Artificial Intelligence, S. 57–66, Los Angeles, CA, 1985.
- [3] *MÜLLER, L., FECKER, E.*: Grundgedanken und Grundsätze der ‚Neuen Österreichischen Tunnelbauweise‘. Clausthal, Trans Tech Publications, 1978
- [4] *SHAPIRO, St.C.*: Encyclopedia of Artificial Intelligence. John Wiley & Sons, Inc. Publishers - New York, 2nd edition, 1992.

Contact

Dipl.-Ing. Dr. Klaus Chmelina: Geodata ZT GmbH Wien, Geyschlägergasse 14, A-1150 Vienna, Austria, email: chmelina@geodata.at

Univ.-Prof. Dr. Heribert Kahmen: Institute of Geodesy und Geophysics, TU-Vienna, Gusshausstrasse 27–29, A-1040 Vienna, Austria, email: hkahmen@pop.tuwien.ac.at