Data-driven methods in application to flood defence systems monitoring and analysis

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Chapter 7. Conclusions

The problem of structural health monitoring in application to flood defence structures is investigated in this work. Application of the data-driven methods was required for on-line monitoring of levee behaviour. Only in this case the onset of the levee failure can be detected in advance. It is important to be able to detect any kind of levee failure. This can be achieved by application of the physical model but it will not provide early warning signals. Several scientific objectives were formulated and covered step-by-step in the study.

The first scientific objective was dedicated to investigation of the raw sensor data properties and selection of the required pre-processing procedures. This is an important problem because data-driven methods fully depend on measurements collected from sensors installed into the monitored objects. It was shown (Sections 3.3 and 3.4) that measurements collected from the sensors installed into the monitored object often have problems (e.g., gaps) that prevent application of most of the data-driven methods for analysis. Combination of interpolation technique (e.g., linear interpolation) with gap filling procedure (e.g., singular spectrum analysis) improved quality of data.

Several dams were analysed in this work: the Stammer dike (in the Netherlands), Zeeland dike (in the Netherlands), Rhine levee (in Germany), a retaining dam, and the Boston levee (in the United Kingdom). We considered only levees/dikes in this work (earth-fill dams).

There were two types of sensor networks installed into levees listed above (except for the Zeeland dike): Alert Solutions and GTC Kappelmeyer sensors (Chapter 2).

The Alert Solutions sensors (GeoBeads) installed in the Stammer, Rhine and Boston levees simultaneously measure the pore pressure, inclination and temperature at one point. The pore pressure values exhibit periodic behaviour in the case of river levees (Rhine levee and Boston levee) and sea levees (Zeeland dike). In Dutch canals and rivers, the water level is usually fixed at a relatively stable level. This is the reason why pore pressure values do not change significantly in the case of the Stammer dike. Inclination measurements are useful for detection of possible erosion. It is difficult to use temperature measurements for leakage detection because they provide information about the specific monitored points only. Usage of distributed temperature sensor technology is required if the levee is considered to be unstable because of piping development.

The GTC Kappelmeyer distributed fibre optic cable installed in the Rhine levee and retaining dam measures the temperature using the so-called active principle, in which the cable is heated. This cable provides detection of leakage even during the spring and autumn, when the water and ground temperature are nearly the same.

Investigation of different variants of construction of anomaly detection approach was considered as the second scientific objective. One of the most important requirements to the developed approach was ability to identify onset of failure without patterns of real collapse (levees are usually stable). That is why we interpreted condition monitoring task as the anomaly detection task. We defined an “anomaly” as a deviation from the previously
known normal conditions. Two concepts of anomaly detection were developed (Section 3.7). The first approach is based on one-side classification method (e.g., Neural Clouds (NC)): deviation from clusters of the “normal” historical measurements is interpreted as an anomaly. Training set should include only measurements related to the normal conditions only. Each NC produces the confidence values of normal behaviour: values close to 1 mean that the new measurements can be classified as “normal” data, values close to 0 mean that the received measurements are unknown (“abnormal” behaviour). The second approach assumed construction of a transfer function between sensors. Monitoring of stability of this function was interpreted as the task of anomaly detection. The detailed data analysis schemes were described in Section 3.8. These schemes are based on results of raw sensor data properties investigation. The separated methods were well known before this work, but combination of the methods is the novelty of this work.

The third scientific objective was formulated as validation of the investigated anomaly detection approach on the real-world objects. Application of the demonstrated in Section 3.8 anomaly detection processing schemes is presented in Chapter 4. The one-side classification approach has been tested on measurements collected from the Stammer dike, Zeeland dike, Rhine levee and retaining dam. Preliminary results for the Stammer dike (non-destructive macro-stability experiment) and Zeeland dike (non-destructive piping experiment) measurements analysis demonstrated the operability of this anomaly detection approach, but a feature extraction stage was required to improve the quality of the overall approach. Time-frequency methods were selected at the feature selection stage because they combine representations of the input signal in both the time and frequency domains.

Based on a comparison of several time-frequency methods for the Zeeland dike, the maximum overlap discrete wavelet transform (MODWT) method was selected as an appropriate feature extraction technique (Sub-Section 4.2.3) because the MODWT method is the most suitable method from a computational aspect in comparison with short time Fourier transform (STFT) and continuous wavelet transform (CWT). The same cascade of methods (MODWT and NC) was applied for the GTC Kappelmeyer data analysis (for the Rhine levee and retaining dam). Abnormal behaviour in the case of Rhine levee was caused by non-saturated soil, and a data set collected from the retaining dam contained a pattern of real leakage. Both anomalies were successfully detected.

Successful detection of real-world anomalies demonstrates the operability of the suggested concept. One of the weak points of the suggested anomaly detection approach is that previously unknown normal behaviour (i.e., behaviour that is not included in the training data set) will be classified as an anomaly. If the low confidence value of normal behaviour calculated by the component is evaluated by a physical model or expert as a false alarm, the training set should be extended and the component should be retrained.

The second anomaly detection (transfer function) approach was used for detection of “strange” behaviour of the pore pressure sensor at the Boston levee. This approach assumes that the dependency (or transfer function) between sensors should be stable in time. If the modelled values and real sensor measurements do not coincide, this can be interpreted as an anomaly. A nonlinear (feed-forward neural network) model and a linear (polynomial autoregressive) model were applied for this task. Both models exhibited good results. If a
good model is constructed, it provides robust detection of anomalies. The most complicated task is construction of a high-quality model which requires an expert knowledge.

The one-side classification approach turns to be more suitable for monitoring of the levees for that the external conditions do not vary significantly. Most of the levees within the UrbanFlood project had controllable water level (or controllable external parameters). That is why the one-side classification approach was selected as the basis for implementation of the anomaly detection approach within the artificial intelligence (AI) component of the UrbanFlood early warning system (EWS). Condition monitoring using the UrbanFlood EWS provided a scalable solution: the required number of virtual machines (VM) that contained the AI component could be initiated in the cloud-computing infrastructure of the EWS on demand (Chapter 5). This covered the fourth scientific objective: development of the anomaly detection approach as a component of the early warning system. Implementation of the component performing on-line computations fulfilled the goal of on-line alerting.

Investigation of combination of the data-driven anomaly detection approach with physical modelling and validation of combination of the anomaly detection approach with physical modelling are presented in Chapter 6 (the fifth scientific objective). An artificial abnormal state of the levee generated by the Virtual Dike (another component of the UrbanFlood EWS) was successfully detected by the AI component. During the full-scale IJkdijk All-in-One Sensor Validation Test organised in 2012 anomaly detection approach in combination with physical model was able to identify the onset of levee collapse in advance.

The developed in this work anomaly detection approach can be applied for monitoring various objects within the structural health monitoring domain: it can be used for artificial (e.g., bridge, concrete dam, or building) or natural (e.g., levee) construction monitoring. The only requirement is installation of sensors that provide comprehensive information about important object parameters and availability of an on-line data stream for on-line analysis. The developed AI component can be integrated into existing condition monitoring systems.

An automatic procedure for relevant feature selection is to be considered as one of the tasks for further research. The transfer function approach can be used simultaneously with the one-side classification approach to increase the robustness of the condition monitoring system.

Combination of various data-driven approaches with physical modelling provides the most robust solution: the physical model can generate pattern of normal and abnormal behaviour. The generated by the data-driven methods alarms can be validated using the physical model.

It should also be mentioned that the developed anomaly detection approach reduces the amount of data to be analysed by the expert and reduces the time needed for decision-making: an alarm will be generated if some previously unknown behaviour is registered. The final evaluation of levee behaviour should be still made by an expert and using high-accuracy physical models

The results were validated in two projects: UrbanFlood (2009 - 2012) and IJkdijk AIO SVT (2012).