

ANOMALY DETECTION FOR DIKE MONITORING USING SYSTEM IDENTIFICATION

Neha Thakre, Christian Debes, Roel Heremans

AGT International
Darmstadt, Germany

Abdelhak Zoubir

Signal Processing Group,
Technische Universität Darmstadt, Germany

ABSTRACT

Structures such as seawalls, levees and dikes prevent low lying land from flooding. The structural health of these constructions is critical and needs to be maintained. In this paper, we present a data-driven approach that uses the information of different in-situ measurements to detect structural anomalies at an early stage. Our approach is based on system identification, in which the dike is modeled as a single-input, multiple-output, linear system whose parameters can be learned based on training data. A statistical test is then deployed to perform a systematic detection of anomalies. We demonstrate the performance of the proposed approach on real data from an experimental dike setup.

Index Terms— Dike monitoring, anomaly detection, system identification

1. INTRODUCTION

The loss of dry land due to rising water levels (upto 3.1 mm/year [1]) originating from climate change can be prevented or slowed down by building water infrastructure, such as seawalls, levees and dikes. The exposure to a variety of harsh weather conditions such as extremely high and extremely low temperatures, drought, wind and rain affect the stability of the structures and can lead to dike breach [2]. A protection of the dike from flooding requires regular monitoring of the dikes whereby two main types of dike breaches can be identified: the first class is dike weakening, e.g. due to external erosion from the outside layers towards the inside, whereas in the second class, weakening takes place from the inside towards the outside (e.g. piping, internal erosion) [3]. The first type can be easily detected by external dike inspection, but in the second case, the failure remains invisible from the outside. At present, various models characterizing a specific failing type have been suggested. The process of piping was described by Bligh and Lane's empirical rule [4], [5]. Other models include the Sellmeijer model [6], Bishop [7], Spencer [8], Janbu [9] and Morgenstern-Price [10]. Although these models can accurately describe the characteristics of various failure types, linking them with real dike situations is not straightforward and depends on several parameters, such as exact composition of the soil, the load acting on the dike

at a given time, the kind of vegetation on the dike, dike repair works, weather conditions, etc. The problem of predicting a dike failure is, therefore, far from solved. The increasing advances in sensor design and sensor data analysis [11] have paved the way to automatically monitor the dike stability and predict the failing types and failing time. First attempts to apply signal processing methods for environmental monitoring and flood protection were neural networks and clustering methods [12]. The concept of abnormal behavior detection for early warning systems has been applied for the first time in [2] where seasonal training was performed to learn normal dike behavior.

The contribution of this paper is the presentation of a data-driven approach to detect dike anomalies. In this approach, a healthy dike model is learned using system identification concepts. In order to estimate the dike parameters an ordinary and a regularized least-squares estimator are compared. The newly observed data, after the training duration, is validated against the learned model to detect deviations of the current data from a normal dike behavior, or in other words, to detect an anomaly. Finally, a statistical test is used for automatic anomaly detection. The paper is structured as follows. Section 2 describes the experimental setup considered in this paper. In Section 3 the system and signal model are presented followed by the details of our proposed approach in Section 4. Results using experimental data for dike anomaly detection are shown in Section 5; conclusions are drawn in Section 6.

2. EXPERIMENTAL SETUP AND USED DATA SET

In August and September, 2012, a series of tests called *All-In-One Sensor Validation Test (AIO-SVT)*, also known as the *IJkdijk experiment* were conducted in Booneschans, the Netherlands [13][14]. Test dikes were built as can be seen in Fig. 1. Multiple sensors were embedded into the dike at strategic locations to monitor dike stability. The main purpose of the experiment was to test the power of signal processing methods to draw conclusions about the state of the dike in terms of its stability and predict dike failures through continuous sensor monitoring and analysis of the generated sensor data. This paper will focus on the data taken from the west dike which was designed to breach towards the end of the experiment due to a piping that developed due to soil erosion

underneath the dike. Of all the sensors installed in the west



Fig. 1: Aerial view of the IJkdijk experiment showing the west dike. Courtesy: Stichting IJkdijk.

dike during the experiment, the ones that are considered here are a water level sensor in the reservoir (corresponding to the left side on Fig. 2) and five GeoBead (GB) sensors installed at the ground level of the dike at the dry land side, measuring pore pressure.

3. SYSTEM AND SIGNAL MODEL

In this section we introduce the signal model used throughout the rest of the paper. We hereby consider the dike as a linear, single- input, multiple-output system that has water level as the input and pore pressure at different locations inside the dike as the outputs. The sampled pore pressure signal at a given location i is denoted by $y_i(m)$, $m = 1, 2, \dots, M$, with M being the total number of samples and $i = 1, 2, \dots, L$, where L denotes the total number of pore pressure sensors. Similarly, the water level signal is denoted by $x(m)$, with $m = 1, 2, \dots, M$. Their vector notations are considered as follows:

$$\mathbf{y}_i = [y_i(1), y_i(2), \dots, y_i(M)]^T. \quad (1)$$

$$\mathbf{x} = [x(1), x(2), \dots, x(M)]^T. \quad (2)$$

All pore pressure and water level signals are sampled uniformly at the same time intervals. In a first-order approach, dikes can be assumed to behave in an approximately linear manner in normal conditions [15]. Therefore we consider the relationship between the pore pressure and the water level to be linear. In the case of localized failure types like piping, the pressure outputs can be considered uncorrelated to each other. We hereby consider a grey-box model [16] to represent the relations between the input and each of the outputs shown in Fig. 2. The water level on the reservoir side, when raised to a considerable level, seeps through the various soil types in the dike, and raises the pore pressure at locations throughout the dike. The pressure at a given location, observed by

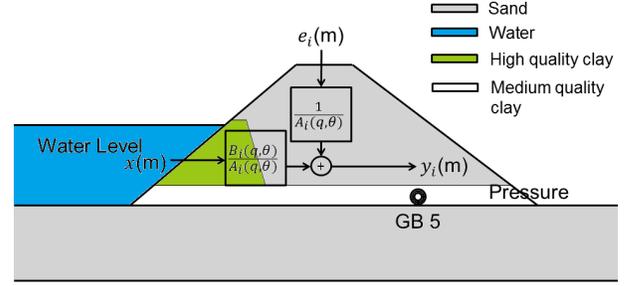


Fig. 2: Symbolic representation of the dike as a grey-box system, considering one of the outputs.

one of the GeoBead (GB) sensors, like GB 5, in the Fig. 2, at a sample m would depend on $m, m - 1, \dots, m - n_b + 1$ current and past water level samples and $m - 1, \dots, m - n_a$ pressure samples. We propose representing this input-output relationship by an Auto Regressive Model with Exogenous Input (ARX) [17] in a single- input, multiple- output structure as seen in Fig. 3. Thus, the system equation between the water level $x(m)$, observed at the water side of the dike, and the pore pressure $y_i(m)$ is given by

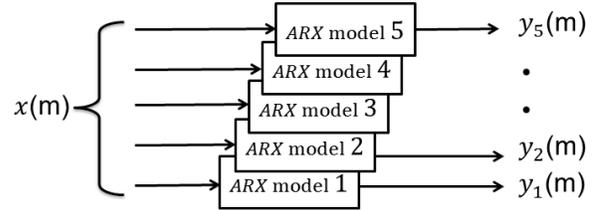


Fig. 3: The dike as a single input, multiple output system.

$$A_i(q, \theta)y_i(m) = B_i(q, \theta)x(m - n_k) + e_i(m) \quad (3)$$

where A and B are polynomials, with q being the shift operator, $\theta = [1, a_1, \dots, a_{n_a}, b_1, \dots, b_{n_b+1}]^T$, n_k is the input output delay in the system, $e_i(m)$ is zero mean, white noise.

4. PROPOSED ANOMALY DETECTOR

This section details our proposed approach for dike anomaly detection that is also depicted in Fig. 4. The process of anomaly detection consists of three major steps, namely, system identification, prediction, and a statistical test.

4.1. System Identification

A section of the data for which the dike is under healthy operation is selected as the training interval. This training interval

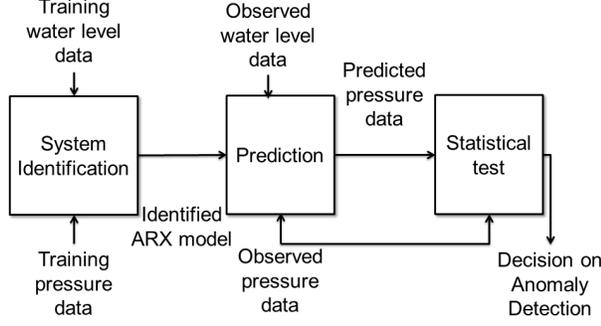


Fig. 4: Proposed anomaly detection process.

is supposed to be representative for the typical (healthy) situations a dike will encounter. Given a training set of the input and output observation data $\{y_i(m); x(m), m = 1, \dots, N\}$, the objective is to find the polynomials $A_i(q, \theta)$ and $B_i(q, \theta)$ for the assumed ARX model (3). The predictor for the system model is the output estimate $\hat{y}_i(m|\theta)$. The least-squares estimation technique is used for model estimation with the cost function

$$V_N(\theta) = \frac{1}{N} \sum_{m=1}^N |y_i(m) - \hat{y}_i(m|\theta)|^2 \quad (4)$$

and parameter estimate

$$\hat{\theta}_N = \arg \min_{\theta} V_N(\theta) \quad (5)$$

where the subscript N denotes the number of samples in the training set. The estimation of the model practically is always erroneous with the two sources being bias and variance. Bias is introduced if the model structure is not flexible enough to contain a correct description of the system whereas variance is a result of the measurement noise in the data [18]. With an increase in the number of parameters, the flexibility of the model increases, the bias of the estimate decreases and the variance of the estimate increases. We propose to not directly use Equation (5) but to consider regularization to manage a bias-variance trade off. Consider the case of linear regression,

$$\mathbf{y} = \mathbf{g}\theta + \mathbf{e} \quad (6)$$

where \mathbf{y} is the output vector and \mathbf{g} is the regression vector. The regularized least-squares solution is

$$\hat{\theta}^R = \arg \min_{\theta} |\mathbf{y} - \mathbf{g}\theta|^2 + \theta^T P^{-1} \theta \quad (7)$$

where P is a positive semi-definite matrix. Considering $R_N = \mathbf{g}^T \mathbf{g}$, Equation (7) becomes

$$\hat{\theta}^R = (R_N + P^{-1})^{-1} R_N \hat{\theta}^{LS}. \quad (8)$$

There are many methods available to estimate the appropriate kernel P . Extending this to the ARX modeling problem, the ARX model, using Equation (3), (ignoring the input - output delay, n_k) can be rewritten as

$$\begin{aligned} y_i(m) &= -a_1 y_i(m-1) - \dots - a_{n_a} y_i(m-n_a) + b_1 x(m) \\ &\quad + b_2 x(m-1) + \dots + b_{n_b} x(m-n_b+1) \\ &= \mathbf{g}_a^T(m) \theta_a + \mathbf{g}_b^T(m) \theta_b \\ &= \mathbf{g}^T(m) \theta. \end{aligned} \quad (9)$$

Thus the ARX model is a linear regression, to which the same idea of regularization can be applied. For the results described below, a tuned/correlated (TC) kernel is used to find an appropriate P . More details about this kernel can be found in [19].

4.2. Prediction

Given the parameter estimate $\hat{\theta}$ as obtained per Equation (7) it is used to estimate the current $\hat{y}_i(m|\theta)$ taking into account a total of n_b past samples and the current sample of the input signal and a total of n_a past samples of the output signal as

$$\hat{y}_i(m|\hat{\theta}^R) = \frac{B_i(q, \hat{\theta}^R)}{A_i(q, \hat{\theta}^R)} x(m) + \frac{1}{A_i(q, \hat{\theta}^R)} e_i(m). \quad (10)$$

4.3. Statistical Test

We propose testing for a dike anomaly using a statistical test based on the residual power between the observed and predicted pressure data, which is denoted as $r_i(m)$:

$$r_i(m) = (y_i(m) - \hat{y}_i(m))^2. \quad (11)$$

Consider the following composite hypotheses:

$$\begin{aligned} H_0 &: \text{Dike is in a healthy state} \\ H_1 &: \text{Dike is in an unhealthy state} \end{aligned} \quad (12)$$

As it is practically infeasible to obtain data to construct the conditional distribution $p(r_i(m)|H_1)$; a simple test based only on $p(r_i(m)|H_0)$ with threshold τ_i is formulated as

$$p(r_i(m)|H_0) \stackrel{H_1}{\underset{H_0}{\leq}} \tau_i. \quad (13)$$

The test is done for all i and all m .

5. RESULTS

In this section, we will present the results using system identification techniques for dike anomaly detection with the experimental setup described in Section 2. First, a comparison between the ordinary (5) and regularized least-squares solution (7) will be made to estimate the parameter vector θ of the ARX model. Second, the output of the statistical test

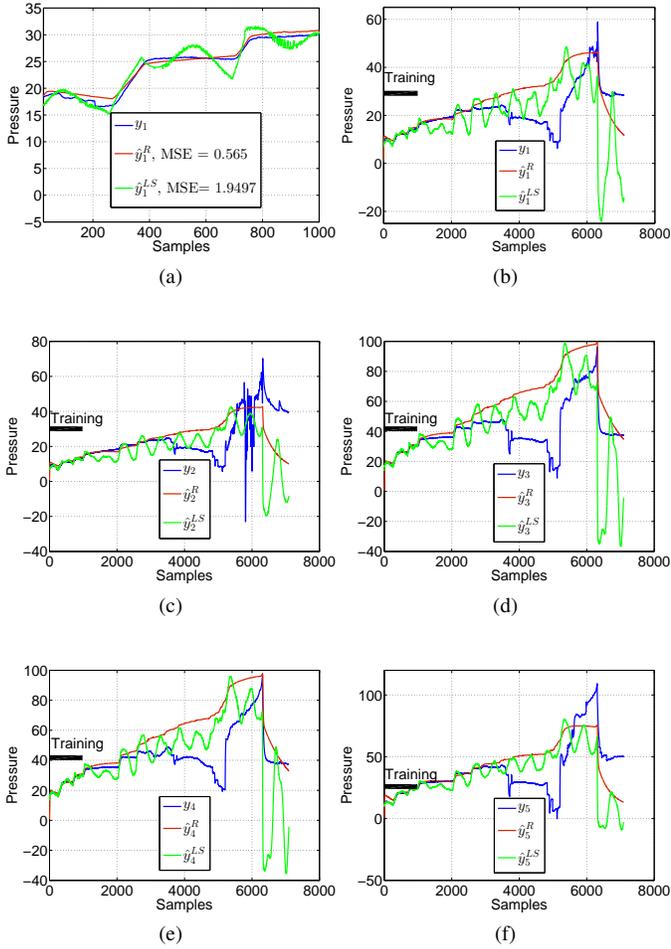


Fig. 5: (a) Pressure estimate over the training period for an ARX model estimated via least-squares and regularized least-squares (b)-(f) The predicted outputs over the whole duration using ARX modeling with regularization \hat{y}_i^R and without regularization $\hat{y}_i^{L,S}$ for GB 1 to 5

as per Equation (13) will be shown. The data from each of the five pressure sensors is processed independently of the other sensors. Fig. 5(a) exemplary shows the pressure estimate in the training duration ($N = 1000$ samples). As expected, the model estimated using the ordinary least-squares estimator has a higher variance. On the other hand, the regularized least-squares estimator results in a lower mean-square error (MSE) at the cost of introducing a small bias. In the Figs. 5 (b) - (f) the estimated θ , obtained from the $N = 1000$ training samples is used for prediction. Again, it can be seen that the regularized least-squares estimator has smaller MSE and follows the actual system output more closely than the ordinary least-squares estimator. Further, both predicted outputs start deviating from the actual output starting at around

$3000 < m < 4000$. A systematic test as per (13) is considered and depicted in Figs. 6 (a) - (e). Here, the threshold τ_i was chosen based on a p-value of 1%. The tests show an anomalous behavior around sample 3297 (averaged over different sensors), which matches the physical anomalous behavior observations during the experiment.

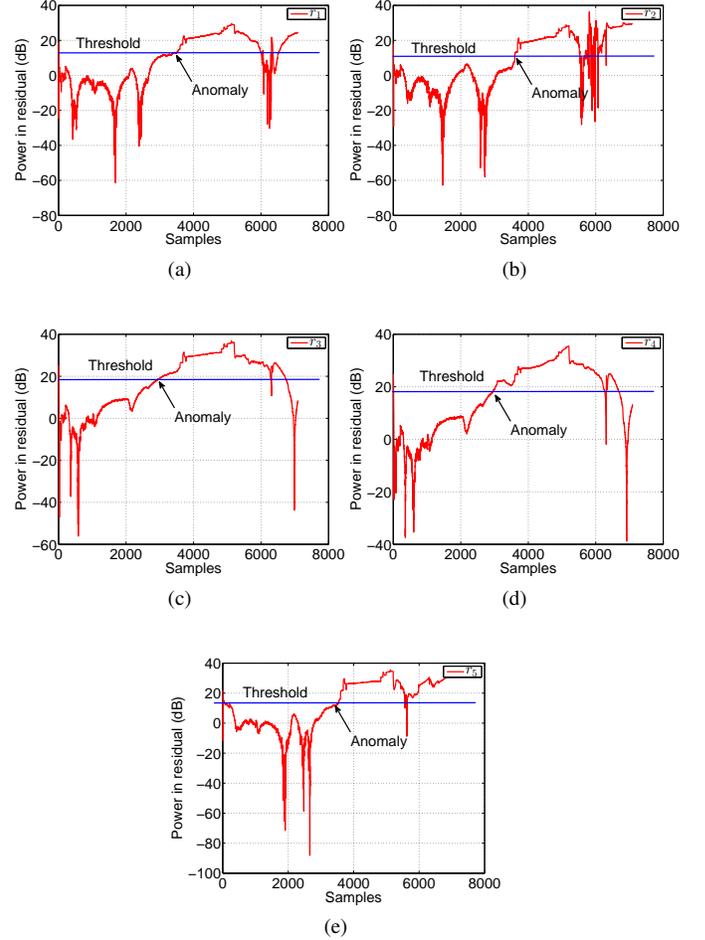


Fig. 6: (a)-(e) Residual power and thresholds for the sensors.

6. CONCLUSION

We have presented a method for dike anomaly detection that is purely data-driven, where no geological and/or hydrological knowledge is needed. It is based on system identification and learns the system parameters of a healthy dike situation and detects deviations from them. We have demonstrated that regularized methods for estimating the parameters of an ARX model improve accuracy and allow for a bias-variance trade off. Experimental results have shown that the proposed approach was able to detect failure due to piping.

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