Moy de Vitry, M, Kramer, S, Villez, K, Wegner, J D, Leitao, J P (2018). Calibrating urban flood models with qualitative probabilistic flooding information extracted from CCTV footage. 11th International Conference on Urban Drainage Modelling (UDM2018), Palermo, Italy, September 23-26, 2018, Oral presentation

UDM 2018

11th International Conference on Urban Drainage Modelling
23-26 Sep | Palermo - Italy

Calibrating urban flood models with qualitative probabilistic flooding information extracted from CCTV footage

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It is of common agreement that urban flood modelling should be supported with monitoring data, be it for validating the simulation results or for calibrating the model parameters. Nevertheless, many practitioners develop and apply flood models on the basis of only limited monitoring data. This failure can largely be attributed to the lack of suitable sensing technology for urban floods. CCTV systems are an already existing source of flooding information that in recent years has been starting to be used for flood modelling. However, privacy concerns and the sheer volume of potentially available data call for automated data interpretation and assimilation techniques. In this work, we will demonstrate an automated methodology by which qualitative CCTV-sourced information can be used to calibrate a flood model, thus improving the model's predictive performance. First, a deep learning algorithm based on convolutional neural networks is trained to detect flood water in CCTV images. Second, the qualitative evolution of flood depth is then estimated with an dimensionless index. Third, trend periods of rising and falling water are identified with quantified certainty. Finally, a flood model is calibrated with a novel objective function that takes into account the uncertainty of the trend information. The method will be demonstrated with experimental flash flood data, by which we hope to quantify the value of qualitative flooding information for modelling. If successful, the methods developed could pave the way to a new paradigm in urban flood model calibration.

Keywords: Calibration, Flood modelling, Big data, Deep learning, Trend analysis, CCTV

1. Introduction

Around the world, cities are under increasing pressure from population that continues to grow and concentrate in urban areas. At the same time, weather patterns in certain regions are becoming more extreme and the risk of pluvial, fluvial, and coastal flooding is increasing. In these conditions, urban drainage managers must plan and construct infrastructure in order to maintain flood risk within an acceptable range.

Today, the assessment of flood risk and evaluation of risk mitigation measures is often done with numerical flood models. The importance of calibrating these flood models is well recognized. This is highlighted by the amount of research invested into the algorithms, selection of objective functions, input and monitoring data for model calibration. Specifically, Tscheikner-Gratl et al. (2016) showed that model calibration allows systematic flood model errors to be reduced. Also among practitioners, model calibration is given increasing importance and included in certain water management guidelines. Nevertheless, model calibration is often neglected (Tscheikner-Gratl et al., 2016), a fact that can be attributed to the cost and complexity of measurement campaigns, and intermittency of flood events. In general, conventional sensors are not suited for measuring surface flooding in urban areas and the need for new methods is well-known (Hunter et al., 2008). In this context, some researchers have started looking beyond conventional sensors and started considering crowd sourcing, social media and surveillance cameras as potential sources of flood monitoring information (Le Boursicaud et al., 2016; Lo et al., 2015; Yu et al., 2016).

On a new front, we have recently proposed extracting qualitative water level information from CCTV footage, using a fully automated approach based on deep learning (Moy de Vitry et al., submitted). It is imperative, however, that the uncertainties and limited information content be considered when assimilating qualitative flooding data. In the current work, we aim to show that despite the challenges, urban flood models can indeed be calibrated with qualitative information derived from CCTV footage when appropriate methods are used. This work builds on previous work in order to complete the method toolbox. First, we introduce a method for extracting trend information from noisy dimensionless time series. The method also provides a certainty level for the estimated trend for each time step. Second, we propose an objective function that enables the calibration of flood models with qualitative and probabilistic monitoring data.

2. Methods

2.1. Flood water detection with convolutional neural networks

Deep convolutional neural networks (DCNN) are the current go-to methods for advanced computer vision problems. In this work, we use a deep convolutional neural network for the segmentation (i.e. pixel-wise annotation) of images into wet, flooded, and dry classes. In particular, the DCNN architecture used is that of U-Net (Ronneberger et al., 2015). This architecture is composed of an equal number of encoding and decoding layers which allow the extraction and interpretation of complex patterns and visual features in the image. Additionally, U-Net has skip connection that short-circuit the network, allowing high-resolution information to inform the segmentation prediction.

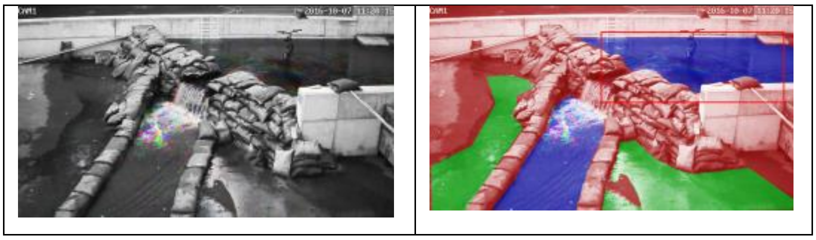

Figure 1: CCTV footage frame of flooding (left), and manually segmented image (right).

To interpret CCTV footage, frames are extracted at regular intervals and segmented with the DCNN. The result is a large number of images with time stamps in which flooded areas, if present, are highlighted. This procedure is documented in (Moy de Vitry et al., submitted).

2.2. Qualitative estimation of water level evolution

The next step is estimate the temporal evolution of flooding visible in the video frames over time. This is done with the Static Observer Flooding Index (SOFI), as presented in (Moy de Vitry et al., submitted). This index is designed to reduce sensitivity to segmentation errors thanks to an area-averaging approach. By estimating the SOFI index for each segmented frame, a time series describing the evolution of visible water surfaces can be generated (Figure 2, black line). In (Moy de Vitry et al., submitted), we showed with a series of examples that the SOFI index is positively correlated with the water level.

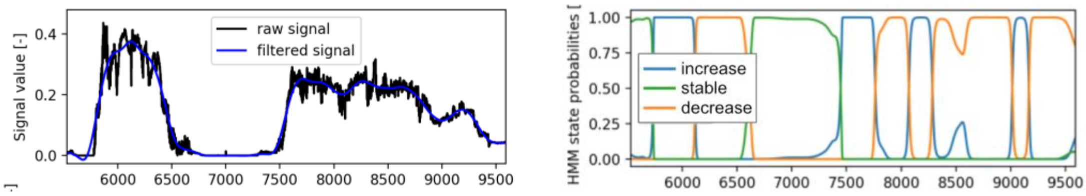

Figure 2: Flood index time series (left) and estimated trends (right)

2.3. Water level trend extraction from qualitative noisy time series

Due to the nature of the flooding index computed in the previous step, the only concrete insight about the flooding that can be gathered from the time series is whether the water level is increasing, decreasing, or stable. This information is extracted in a multi-step process inspired from the Qualitative State Estimator (QSE) (Villez, 2015), as follows. First, a first-order regression is performed on a sliding window of the data, providing at each step an estimate of the regression coefficients. The regression coefficients are then used to assign the system an instantaneous state, or “primitive”. Finally, a Markov chain is applied estimate system state probabilities with consideration of previous system states and prior knowledge about the system (Figure 2, right). A core advantage of this approach is that it explicitly extracts relevant information from the signal while carrying over uncertainty due to noise.

2.4. Objective function for qualitative probabilistic monitoring data

The final component required for model calibration is an objective function that is suited to probabilistic qualitative data. This part of the work is still in progress, but the function could be based on metrics commonly used to evaluate classification performance.

2.5. Model calibration

The flood model will be calibrated with a standard parameter optimization routine, implemented in python. To assess the value of trend extraction for calibration, the model will also be calibrated directly with SOFI index data using the Spearman rank correlation coefficient (Spearman, 1904), which evaluates the correlation between two signals.

3. Experiments

3.1. Data and model

The data supporting this research was collected from real-world experiments at a flood response training facility rented for this purpose and equipped with conventional sensors as well as CCTVs. The facility is documented by (Moy de Vitry et al., 2017). A SWMM model will be used to simulate flooding, since the flows of the experimental flood events can be assumed to be one-dimensional.

4. Conclusions

As the work is still underway, no general conclusions can be made. The initial trend extraction results, as shown in Figure 2, are promising.

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