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CONVOLUTIONAL NEURAL NETWORK FOR THE TIME-DEPENDENT PREDICTION OF FRESH CONCRETE PROPERTIES

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Introduction

To reduce $C0_2$ emissions, an increasing number of materials are being added to the concrete mix design. However, this trend leads to more complex mix designs, which can affect the robustness of the concrete (González-Taboada et al., 2018). Current quality assurance methods are inadequate for this challenge as they are carried out after production. To effectively control deviations in the fresh concrete properties, they must be detected during mixing. Also, ideally the properties should be predicted for the time of placing. As the concrete is usually not placed immediately after mixing and the properties change over time, the development of the properties over time must be predicted. If this prediction is made during the mixing process and deviations are detected, those can be counteracted during mixing by changing the mixture or adding chemical admixtures. Such a prediction of the properties can be made based on images of the mixing process. To come one step closer to this vision, in the present work, the deep learning method presented in (Meyer et al., 2024) is refined with the following contributions: an optimised loss function, a realistic data set and a detailed analysis of reasons for incorrect predictions.

Methodology

Our method consists of a Convolutional Neural Network (CNN) which generates a time-dependent prediction of the properties. The architecture of the network is shown in Fig. 1. The properties are described by the slump flow diameter δ, measured by the slump test, the yield stress τ_0 and the plastic viscosity μ, both measured in a rheometer. As input, the CNN receives an orthophoto, a depth map, optical flow images, a binary mask, temporal information Δ_t and mix design information m. To generate the orthophotos and depth maps, a camera system records stereoscopic image sequences of the concrete during the mixing process, from which the desired products are derived using photogrammetric techniques. The optical flow images are computed between orthophotos of two subsequent epochs. The binary mask indicates which areas of the orthophoto and depth map are not valid due to occlusions. The orthophoto, depth map, optical flow images (movement in x- and y-direction) and binary mask form a five-channel input image. Δ_t and m are fed into the CNN in a late fusion manner. Δ_t contains the time difference between the end of the mixing process and the point in time for which the properties should be predicted. m contains important parameters like the amount of water and cement, superplasticiser content and the means and standard deviations of the power and humidity during the mixing process. Since the reference values for training are measured at different points in time after mixing, the CNN implicitly learns to predict the properties over time. To compare and evaluate

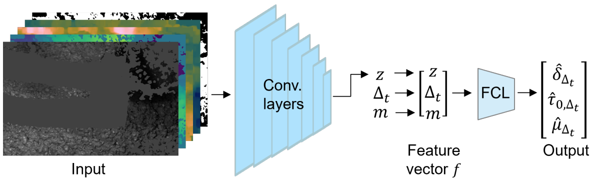

Figure 1: Our CNN architecture. The convolutional layers are extracting features z of the input image. The temporal and mix design information Δ_t and m are are concatenated to z in a late fusion manner and form the feature vector f. f is fed into the fully-connected layers (FCL) which map f to the three time-dependent output parameters.

the described method, a Multi Layer Perceptron (MLP) is created which only uses Δ_t an m as input.

Data generation

For training, an extensive data set was generated: an industrial mixer produced 20 concretes under realistic conditions, all of which differed significantly in their mix design. Images were taken through an opening in the mixer cover. After the mixing process, three slump tests and rheometer measurements were carried out over 30 minutes in intervals of 15 minutes. The experimental setup is shown in Fig. 2.

Results

In the experiments, the CNN and the MLP are each trained with a five-fold cross-validation. The concretes are divided into cross-validation sets based on the first slump flow diameter in order to obtain a less imbalanced distribution. For the training, data augmentation is used for all image channels. The cross-validation is carried out three times and the results are averaged. We can thus show that the promising results from (Meyer et al., 2024) can be reproduced using a real-world data set. The CNN performs significantly better than the MLP, which shows the importance of the images for predicting the properties. The CNN has a mean absolute error of about 3 cm for the prediction of δ. The precision of the slump test is 2.5 cm (EN 12350-5, 2019). Therefore, we argue that the prediction of δ is already in an acceptable range.

τ_0 and μ are predicted with a mean absolute error of 45 Pa and 8.5 Pa·s respectively. However, the results for the rheological parameters are more difficult to assess, as there are no comparable accuracy values for the rheometer measurement. A detailed analysis shows that the main reason for bad predictions are an imbalanced data distribution (some consistency ranges are only contained once in the data set). The results also show that the CNN has learned the time-dependent behaviour of δ. Examples of a continuous time-dependent prediction are shown in Fig. 3. However, not all concretes can yet be predicted so accurately and the data set consists of relatively few concretes and only of concretes with increasing toughness over time.

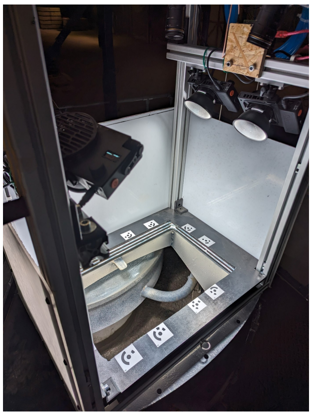

Figure 2: Experimental setup.

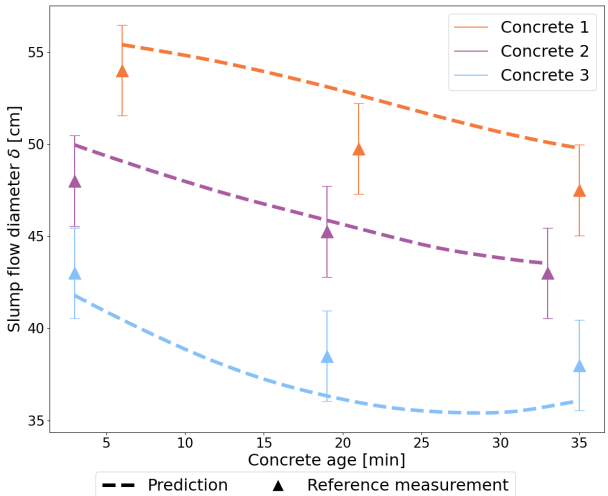

Figure 3: Exemplary results for the prediction of the slump flow diameter δ as a function of time. The precision of the slump test (used as reference measurement) is shown as an error bar.

Conclusion

Although some challenges remain open and require further investigations, the results show that this method is able to predict the properties as a function of time in a realistic environment.

References

EN 12350-5 (2019). Testing Fresh Concrete - Part 5: Flow Table Test. European Committee for Standardization.

González-Taboada, I., González-Fonteboa, B., Martínez-Abella, F., and Roussel, N. (2018). Robustness of self-compacting recycled Concrete: Analysis of Sensitivity Parameters. Materials and Structures, 51(8).

Meyer, M., Langer, A., Mehltretter, M., Beyer, D., Coenen, M., Schack, T., Haist, M., and Heipke, C. (2024). Fresh concrete properties from stereoscopic image sequences. PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 92(5):517–529.