DIGITIZATION OF THE CONCRETE PRODUCTION CHAIN USING COMPUTER VISION AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

The production of concrete currently goes along with pronounced CO_2-emissions and an enormous consumption of (mineral) resources. In response to sustainability requirements, concretes thus are increasingly produced using recipes containing six to ten different raw materials including recycled materials and industrial wastes. This increasing complexity results in an increased sensitivity to unpredictable fluctuations in material properties or boundary conditions during the production process. Digital sensor systems and quality control schemes are considered as key to solving this problem, however, digital technologies from other industries have not yet fully established themselves in concrete construction sector, especially in the quality control. Despite the fact that the concrete industry has extremely high repetition factors, big data based quality control is missing, as we currently lack both sensor systems providing data and concrete specific data treatment algorithms.

This paper presents an overview on digital methods based on computer vision and artificial intelligence to quantify the properties of concrete raw materials and the fresh concrete along the entire process chain. The methods differentiate between systems that are incorporated into the production process, i.e. in the concrete plant, and systems that are applied after production, i.e. at the construction site. While the first kind enables an online reaction and control of the concrete properties in real-time, namely already during the batch-production, the latter approach allows an offline and, therefore, post-production quality control. All proposed methods eventually contribute to a facilitation of a digital control loop for ready-mixed concrete production. The developed techniques can be easily applied to pre-cast elements production or concrete products.

Keywords: digital concrete production, automated process monitoring, digital quality control, digital concrete loop, computer vision, artificial intelligence.

1. INTRODUCTION

With the Paris and Glasgow agreements, the international community has set binding action targets and implementation instruments for global climate protection [1]. The construction industry, and in particular the building materials industry, plays a decisive role in achieving these climate and environmental protection targets. In order to reduce the worldwide CO_2-emissions, the use of composite cements containing three or more main constituents (including industrial wastes) and/or recycled aggregates is gaining significant importance, however leading to significantly more complex mixtures. This increasing complexity strongly stems from a strongly increased sensitivity to variations of the raw material properties and dosages as well as from the production-related side-conditions (deviations from the target composition, temperature and moisture conditions). As a result, concretes with recycled aggregate and composite cements are less robust than conventional concrete, especially due to variations in water content and water demand [2]. An increase of the robustness of such concrete mixtures can be achieved in different ways:

i. Compensating the negative effects of fluctuations in material properties by increased safety margins, such as a significant increase in cement or powder content [3-5]. However, this is neither economically nor ecologically justifiable [6, 7].
ii. Using new types of quality control methods, which are able to react to and compensate for fluctuations in the mix.

The focus of the paper at hand is on the second approach (ii). Herefore, we propose to continuously monitor the raw material properties and to quantify the concrete quality in real-time using newly developed sensor systems. In this way, for example, the influence of variations in recycled aggregate - but also other concrete raw materials - on the end product can be compensated for without negatively affecting the economic efficiency and environmental balance. The development of such methods and processes is currently the subject of various research projects at Leibniz University Hannover. The objective of the joint project *ReCyCONtrol*[1] is to significantly increase the sustainability and resource efficiency of concrete construction by introducing automated process monitoring and control methods in concrete production based on computer vision (CV) and artificial intelligence (AI). The project is carried out in a consortium with numerous industrial partners. The research network consists of the companies HeidelbergerBeton GmbH, MasterBuilders Construction Chemicals GmbH, Pemat GmbH, Bikotronic GmbH, alcemy GmbH, Moß GmbH and the Bundesanstalt für Wasserbau (BAW) - coordinated by the Leibniz University Hannover. In other related research projects, image-based methods for the digital evaluation of (fresh) concrete properties as part of the discharge process or the quality control on the construction site were developed.

In this paper, a concept and associated methods for digitization of the concrete process chain using computer vision and artificial intelligence is presented. The paper begins by giving a review on the current state of the digitization in context of automatic monitoring and control of the concrete production chain followed by an overview on our conceptual design towards the digitization of the concrete production chain. Building up on that, the developed methods for a real-time monitoring of the production process are described, including the sensor-based characterisation of raw aggregate material and the AI based determination of rheological properties already during the mixing process. Finally we provide an overview on image-based approaches for the characterisation of fresh concrete from both, video sequences of a discharge process of a mixing truck and from images of the flow table test.

2. RELATED WORK AND BACKGROUND

In many manufacturing industries, automation and digitization have enabled a strong increase in productivity in recent decades. However, productivity in the construction industry stagnated during this period [8]. The construction industry – and here especially the concrete sector – is still one of the least digitized industries of the global economy. This is despite the fact, that concrete dominates building industry worldwide with more than 380 Mio. m³ of ready-mix concrete produced in Europe annually (data status 2018; [9]). Due to the batch production of the fresh concrete, there are high repetition rates thus offering great potential for the use of digital methods (in particular of methods based on machine learning), often referred to as Industry 4.0.

The process chain of producing concrete structures includes the planning phase, the production phase, the manufacturing phase and the maintenance. Digital processes are already integrated in all phases, but the degree of digitization varies greatly. Methods for digital design and planning of structures (CAD, BIM etc.) are an integral part of the planning phase [10, 11] and BIM-based augmented reality systems are slowly gaining ground [12, 13]. Further, in recent years, various approaches for the additive manufacturing of concrete structures have been developed and some large-scale demonstration projects have been successfully completed [14-16]. The advantage of additive

[1] https://www.recycontrol.uni-hannover.de/

manufacturing or 3D printing of concrete is the high degree of automation and individualization. In addition, 3D printing technologies only uses material where it is structurally or functionally necessary [17]. However, one of the key challenges in additive manufacturing is the control over material properties.

With the technologies described above, the planning phase and the production phase can be directly linked digitally. However, a clear lack in the application of digital methods can be seen in concrete production. Especially the characterization of the properties of raw materials and the quality control of the concrete production process are still based on conventional non-digital methods. For this reason, an increasing interest has emerged in developing and providing methods for digitization in the concrete production industry. Regarding the prediction of concrete properties from its mix design, artificial neural networks have been successfully employed [18, 19], but mainly focus on properties like compressive strength instead of fresh concrete properties and are only based on the nominal composition design of the concrete so far. The use of actual or sensorial information on the raw material properties is not considered yet for the prediction and control of (fresh) concrete properties. Looking at the monitoring of raw material, in [20] a method for the classification of individual recycled aggregates based on convolutional neural networks (CNN) was proposed. However, the data requires the particles to be separated from each other, which is an unrealistic setting in practice and completely disregards properties like the particle size distribution, which has an essential impact on the concrete properties. In this paper, we present a computer vision based analysis of the grain size distribution of the raw aggregate material in order to enable a proper mix adaptation considering the actual grain size distribution of the aggregates.

A digital and holistic quality monitoring and quality control during the concrete production phase is quasi non-existent so far. A research approach for fresh concrete quality monitoring has been proposed in [21], where the concrete mix proportion is determined from images of fresh concrete using a convolutional neural network (CNN). In [22], an approach for determining the workability from image sequences acquired during the mixing process using a LSTM deep learning network has been postulated. While promising results were obtained, processing was done on rather low resolution grey scale images only and the approach relied on 2D transformations, ignoring the clearly visible effects perspective distortions. In contrast, the paper at hand proposes to introduce 3D data of the concrete's surface during the mixing process, as valuable additional information of the flow behaviour to a LSTM network, which is trained to determine the rheological properties of the concrete directly during the mixing procedure.

3. CONCEPT FOR A DIGITIZED CONCRETE PRODUCTION CHAIN

In the transition process towards a more sustainable high-quality concrete construction industry, essential process steps in the concrete process chain must be digitally mapped:
In the opinion of the authors, this comprises (i) a **continuous monitoring using automated sensor technologies** of the relevant parameters influencing the concrete properties such as raw material properties, environmental and production influences as well (ii) a **sensor monitoring of the result of the involved processes**, such as the fresh concrete properties after mixing or delivery at the construction site. Monitoring both input (e.g. raw material properties) and output (e.g. fresh concrete properties) will enable to establish a control-loop. For establishing this loop (iii) **deep learning based control schemes** are needed, with which the concrete properties can be predicted based on the concrete raw material properties and the mix composition and appropriate countermeasures can be defined in real-time in case of deviations between the prediction and the measured properties. With this 3-fold approach, the authors believe that the usage of recycled raw materials, composite cements and environmentally optimized concretes can be greatly increased without increasing the risks going along with that. At the same time, using such technologies will allow for a reduction of the large safety margins in the mix development of concrete, which are typically applied in order to counteract fluctuations in the raw material properties and in the processing conditions.

The proposed concept significantly extends the current state of the art in the concrete mixture development and concrete production process, which has so far been purely empirical. A key role in achieving this goal is played by a combination of contact and non-contact sensor systems, providing the data necessary for such a data-driven control loop.

An overview of the different AI based online monitoring methods addressed in this paper and their association to the individual process steps within the concrete production chain are shown Fig. 1. In this context, we differentiate between systems to be incorporated into the production process, i.e. in the concrete plant, and systems to be applied after production, i.e. at the construction site. While the first kind enables an online reaction and control of the concrete properties in real-time, namely already during the batch-based mixing of the concrete, the latter approaches allow for a post-production quality control (cf. Fig. 1). All methods can be combined into a digital control loop for ready-mixed concrete.

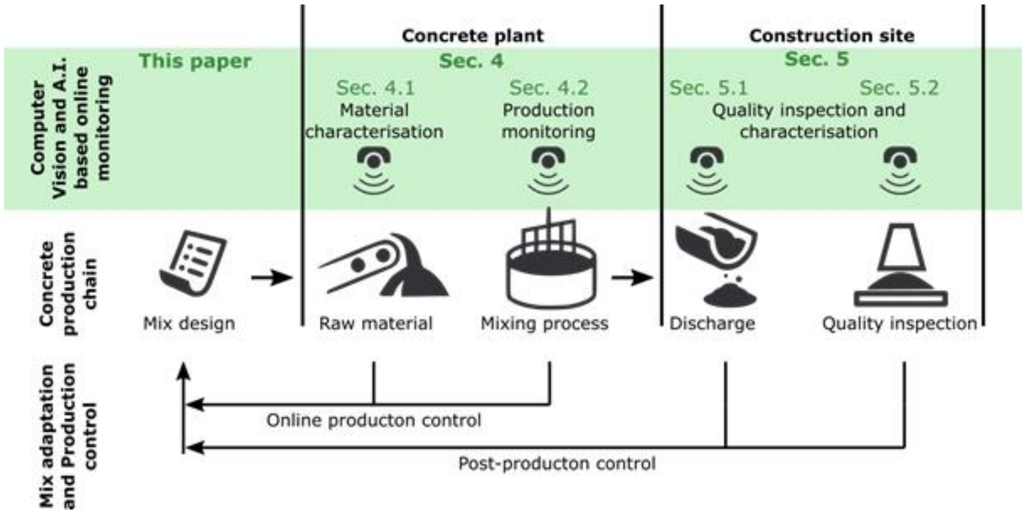

Figure 1 – Concrete production chain and AI based monitoring in the different process steps of the concrete production chain.

As shown in Fig. 1, the proposed sensor-based monitoring methods related to the **concrete production process** include the characterisation of the raw materials – here with a focus on the aggregates (e. g. grain shape, grading curve, composition of recycled aggregate fractions) – and the continuous quantification of the fresh concrete properties (rheological parameters, mix homogeneity) during the mixing process. Corresponding control algorithms make it possible to adjust the concrete composition before mixing begins as to react to fluctuations in the raw material properties or to add suitable additives during the mixing process in case deviations from the desired properties are detected. The characteristic values determined by means of optical non-contact measurement methods are thus fed directly back into the process and allow direct intervention in the production process (online production control). The proposed methods for **construction site concrete quality control** cover the concrete transport, the discharge, and the quality inspection at the construction site. The focus here is particularly on fresh concrete properties (in-situ composition, consistency, segregation tendency, pumping properties). The gained sensor information can be used as decision support for the further concrete processing on the construction site or can be fed back into the production process for a self-learning mix adaptation (post-production control).

4. DIGITAL PRODUCTION CONTROL IN THE CONCRETE PLANT

In this section, the proposed monitoring approaches that are dedicated to be applied during the concrete production process which enable an online control of the concrete properties are outlined.

4.1. Sensor based characterisation of concrete aggregates

With up to 80 % of volume, a large component of concrete consists of fine and coarse aggregate particles (normally with mean diameters between 0.125 and 32 mm) which are dispersed in the cement paste matrix. As an essential constituent of concrete, the aggregate's characteristics such as type, density, particle shape and particle size distribution have a substantial effect on the properties of the fresh and hardened concrete [23, 24]. In practice, the grading curve of the aggregates is usually determined from small random batch-samples using mechanical sieving (cf. (a) of Fig. 2), thus extrapolating from a sample of a few kilograms to many tons of aggregates. As a consequence, the unknown variations of the aggregate's grading curve (especially pronounced in the case of recycled materials), is not properly taken into account in the mix design. Further, variations in the particle shape and composition of the aggregates (e.g. fractions of brick rubble in recycled aggregates) remain undetected. In order to still adhere to the concrete's quality requirements, these variations are usually compensated for by a distinct increase of the cement conotext, which, however, is neither economically nor ecologically justifiable.

In contrast, we developed an approach for an image based sensor detection of the size distribution, particle shape and composition of concrete aggregates (cf. (b) of Fig. 2) which forms the basis for an automated concrete mix control. Herefore, an online measurement process has been established, in which cameras are installed over the aggregate feeding belt, thus, observing the total amount of aggregates actually used for the particular concrete mix. Modern techniques of artificial intelligence in form of convolutional neural networks (CNN) have been developed and trained in order to derive characteristics from the image data of the visible aggregate. Fig. 2 shows a schematic overview of the sensor-based prediction of the aggregate grading curve in comparison to the classical monitoring by mechanical sieving.

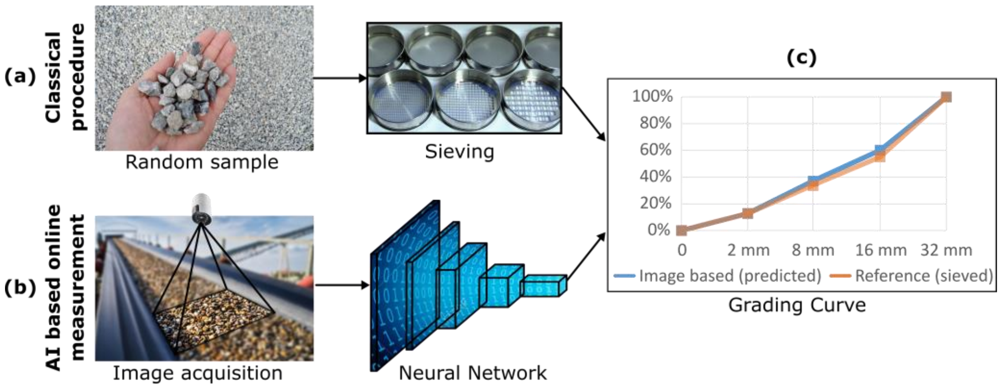

Figure 2 – Prediction of the grading curve by sieving (a) and automated AI based methods (b) and resulting grading curves (c).

For concrete production, usually aggregate fractions ranging from 0.125 mm up to 32 mm in mean diameter are employed, resulting in very large-scale differences of the object sizes to be considered. In order to account for these differences, a multi-scale mechanism has been implemented within the framework of the CNN, which enables the simultaneous consideration of aggregate particles of different sizes. More specifically, the CNN produces intermediate multi-scale feature maps that are able to deliver latent representations suitable for both, smaller and larger sized particles at the same time, which are used by a classification head in order to predict the final particle size distribution. Details on the described method can be found in [25]. Experiments demonstrate that the described method is able to predict the correct grading curve of the observed aggregates with an accuracy of more than 95 %. For the training and evaluation of the presented method, a large data set of images showing concrete aggregates with different grain size distributions was created [25] and made publicly available[2]. As can be seen from the exemplary results depicted in Fig. 2 (c), the computer vision based

[2] The Hannover Visual Granulometry Data above: https://doi.org/10.25835/etbkk0pb

methods in general tends to give higher fractions for larger particles in the grain size distribution. This result was expected, as classical sieve testing is an approximation in itself, as it only measures the smaller axis of non-spherical particles. The proposed optical methods in contrast allow to also measure the sphericity of the particles. The combined data then serves as an input for maximum packing density calculations using the CIPM model [26].
In ongoing research, we expand the approach to also quantify the material composition of recycled aggregates, i.e. the different fractions of crushed concrete, crushed masonry, natural aggregate, etc. contained in the recycled materials. Combined with the knowledge on the grain size distribution additional valuable knowledge, e.g. regarding the specific water absorption of the aggregates can be derived. Further, sensor information on the moisture content of the aggregates is implemented in the model using classical moisture sensors. The combination of the above mentioned sensor inputs is used as a basis for the development of an AI based concrete control scheme, with the goal to adapt the mix composition in real time to correspond to the detected fluctuations in the raw materials.

4.2. Image based monitoring of the mixing process

In current practice, the quality inspection of fresh concrete is mainly conducted offline, i.e. after the mixing and production process, using empirical test methods based on small batch samples of the concrete. However, at this stage of the production process, only very limited control of the concrete properties remains possible. For this reason, an online quality assessment during the mixing process is desirable, since it would enable real-time control of the concrete properties and an online reaction (i. e. during the mixing process) on potential deviations from the target properties. However, currently, the online quality assessment during the concrete mixing process is restricted to coarse consistency estimations based on the electrical energy consumption of the mixer. In the opinion of the authors, this method in itself is not sufficient for a precise derivation of the complex rheological properties of fresh concrete as it only allows to determine one parameter, i.e. the dynamic viscosity $\eta=\tau/\dot{\gamma}$ at one given shear rate $\dot{\gamma}$. However, the fresh concrete properties are characterized by a great number of parameters, such as the Bingham yield stress τ_0 and plastic viscosity μ (see e.g. [27]), the thixotropy A_{thix} (see [28]), the sedimentation and bleeding behaviour or setting behaviour. In the literature therefore mechanical probes to be installed in the mixer have been proposed, which however, are technically complex and nearly always result in prolonged mixing durations [29, 30].

In contrast, in this paper we propose to augment the electrical power measurements during mixing (which is a standard technology in concrete plants worldwide) with a video-optical monitoring of the mixing process as basis for a computer vision-based online derivation of the rheological properties of the fresh concrete. Starting from the hypothesis, that concretes with different rheological properties lead to different flow patterns during the mixing process, we investigate methods in order to solve the inverse problem, namely to infer the concretes fresh properties from camera observations of the mixing process. More specifically, we make use of a stereoscopic camera setup, allowing the reconstruction of the 3D concrete surface, carrying valuable additional information related to the fresh concrete properties. Based on the gathered video-data a recurrent neural network (RNN) is being developed and trained in order to infer characteristics from the three-dimensional image data of the flowing concrete in the mixer. In its current implementation, the 3D surface of the fresh concrete is calculated as a function of time from the acquired stereo-image sequences using classical image mapping methods [31]. Then, both, the acquired image sequences and the calculated 3D information are used as input data for the RNN. A Convolutional Neural Network (CNN) – as a component of the RNN – learns the extraction of a features embedding of the recorded image and depth frames. To consider the temporal aspect, namely the flow behaviour over time, a Long Short-Term Memory (LSTM) cell is applied on top of the architecture, as a realisation of the recurrent component of the network. The regression performed in the RNN finally produces values for viscosity and yield stress of the fresh concrete. For methodological and mathematical details on the described approach, we refer the reader to [32].

Building upon the proposed method for online concrete production monitoring, strategies can be applied that specifically control and adjust the concrete towards its target rheological properties, e.g. by developing a suitable concept of chemical additives that are added to the mixing process. The technical opportunity to determine the rheology of fresh concrete in real-time makes it possible to iteratively develop self-learning algorithms for controlling the concrete properties and, thus, to enable digital control and monitoring of the whole production process.

5. DIGITAL QUALITY ASSESSMENT ON THE CONSTRUCTION SITE

In order to gain precise control over the concrete properties, it does not suffice to digitally map the concrete production process. In addition to the previously described methodology to be implemented in the ready mix plant, digital quality control tests on the construction site are necessary. The digital test methods – here defined as automated contact-less digital determination of the concretes properties – must provide a much deeper insight into the concretes properties, i. e. must ideally detect all relevant fresh concrete properties. Herefore the authors developed various image-based quality acceptance test methods, which can be seamlessly integrated into the quality acceptance test scheme.

5.1. Image-based methods for evaluating concrete properties

Enabling a fast determination of the fresh concrete properties on the construction site has gained increasing interest in recent years. Approaches for determining the rheology, e.g. by correlating the energy consumption for rotating the mixing drum of a truck mixer to values obtained by rheometer tests or using a concrete mixing truck itself as a rheometer, have been proposed and represent a key step forward in digitizing the concrete industry [33, 34]. Nevertheless, all of the mentioned methods have in common, that they require substantial technical modifications on the mixing truck, thus limiting these techniques to the truck owner. Besides such truck mixer based systems, rheometer test methods have gained attraction in testing of fresh concrete [35]. However, these test methods today are exclusively batch-based, laborious and the data interpretation is highly challenging [36].
Fresh concrete testing today therefore remains primarily empirical and is dominated by batch-based methods such as the slump or slump flow test, where concrete exhibits a spread flow behaviour. With the introduction of self-compacting concretes, horizontal channels and flow boxes have become a common tool in concrete science for gaining information about rheological properties by observing the flow behaviour under non-stationary conditions, i.e. considering the gradual filling of a container going along with a horizontal, gravity driven levelling of the material [37-39]. Such a channel flow like behaviour can also be observed when observing the discharge behaviour of a mixing truck, where concrete flows down a chute. Even though the experienced technologist can gather an abundance of information in watching the flow behaviour of the concrete in the aforementioned tests, the possibilities for quantifying the individual properties are extremely limited. Currently, only the diameter of the flow cake of fresh concrete is measured. However, the surface topography and other surface features of the spread out fresh concrete yield an abundance of additional information, which until now was not accessible of a quantified assessment.

The goal of the presented work was to employ image-based analysis methods, which consist in monitoring the flow behaviour of the concrete or the resulting spread flow cake by cameras. A similar approach has been previously presented in [40] in order to determine the Bingham properties of fresh concrete. In our work, we however extend this approach by implementing photogrammetric computer vision and CNN based algorithms, to correlate optical patterns in the visual data with concrete technological properties determined using standard empirical tests. In a first step, a 3D-surface model of the spread out fresh concrete can be calculated using Multi-View Stereo (MVS) reconstruction. Furthermore, a semantic segmentation of the classes *table*, *suspension* and *aggregate* is performed using the approach of [41]. In this way, a large number of concrete properties (e.g. the paste content, the grain size distribution (> 4 mm) or the maximum grain size) can be digitally evaluated as part of the slump flow or flow table test on the construction site [42]. In addition, systematic investigations show that it is possible to quantify the homogeneity of the fresh concrete in analogy to the Visual Stability Index [43] based on images of the fresh concrete [44]. Fig. 3 exemplarily shows the application of algorithms for semantic segmentation the classes and individual areas of the concrete spread flow. As can be seen in this example, essential information on the concretes actual composition can be derived from a single image of the slump cake. For details, please see [44].

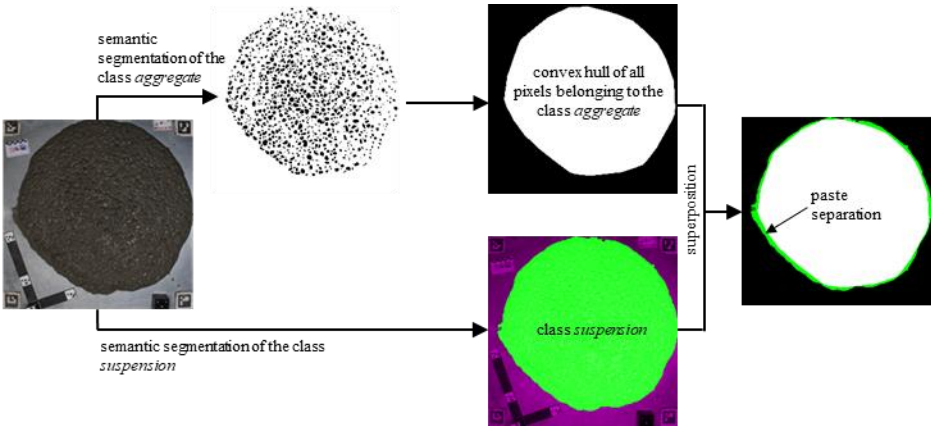

Figure 3 – Application of algorithms for semantic segmentation the classes and individual areas of the concrete spread flow (based on [44])

5.2. Image-based methods for evaluating the rheology properties at concrete discharge

The above mentioned computer vision techniques can also be applied to observations of fresh concrete flowing down the discharge-chute of a mixing truck. The corresponding measurement setup consists of an inclined open channel equipped with a camera system to investigate the flow behaviour under stationary flow conditions. As could be shown in [45] based on systematic laboratory tests, a digital evaluation of rheological properties (yield stress and plastic viscosity) can be performed accurately by observing the flow behaviour and deriving characteristic values (flow velocity, flow around obstacles, etc.) from optical flow computations of the recorded video data [46]. Furthermore, initial tests show a very good applicability of these image-based methods under practical conditions. Thus, the optical monitoring of the unloading process enables a holistic and automatic approach of quality control for the entire fresh concrete quantity, conducted directly at the truck mixer.

6. CONCLUSION

This paper give an overview on the potentials of digital methods in concrete production and quality control, spanning from concrete raw materials up to the final concrete product. The methods presented in this paper are based on photogrammetric computer vision and deep-learning algorithms. During concrete production, the information obtained by these methods (e.g. grading curve, rheological properties of fresh concrete) can be used to make specific modifications to the concrete composition or to optimize the concrete properties by applying an additive concept during the mixing process. Concrete discharge and the quality control on the construction site can additionally be assessed by means of image-based methods. In this way, information can be provided for a digital control loop and a self-learning concrete composition development.

In the opinion of the authors, these technical solutions will significantly reduce the possibility of human errors and will make it possible to ensure sustainable and high-quality concrete construction in the future. In addition, materials can be integrated into the concrete production process that were previously classified as unsuitable due to excessive material fluctuations (e.g. recycled aggregate). The methods presented in this paper provide tools that address this complex problem and provide a solution approach, so that complex eco-friendly concrete mixtures can be produced accurately, using recycled materials and meeting the highest quality standards.

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REFERENCES

1. United Nations: Paris Agreement - United Nations Framework Convention on Climate Change (UNFCCC). "UN Treaty Collection, Vol. II Sec. 27". 7d Paris Agreement, France, 2015.
2. Gonzàlez-Tabada I., Gonzàlez-Fonteboa B., Martínez-Abell F., Roussel N. "Robustness of self-compacting recycled concrete: analysis of sensitivity parameters". Materials and Structures 51(8), 2018
3. Kwan A.K.H., Ng I.Y.T. "Improving performance and robustness of SCC by adding supplementary cementitious materials". Construction and Building Materials 24, 2260-2266, 2010
4. García L., Valcuende M., Balasch S., Fernández-LLerbez J. " Study of Robustness of Self-Compacting Concretes made with Low Fines Conctent". J. Mater. Civ. Eng. 25(4), 497-503, 2013
5. Shen L., Jovein H.B., Shen S., Li M.: Effects of aggregate properties and concrete rheology on stability robustness of self-consolidating concrete. J. Mater. Civ. Eng. 27(5), 04014159-1- 04014159-10, 2015
6. Hoffmann C.; Jacobs F. „Recyclingbeton aus Beton- und Mischabbruchgranulat – Sachstandsbericht". EMPA, Eidgenössische Materialprüfungs- und Forschungsanstalt, Dübendorf, Switzerland, 2007.
7. Müller C. „Beton als kreislaufgerechter Baustoff". Deutscher Ausschuss für Stahlbeton, Heft 513, Berlin, Germany, 2001.
8. Green B. "Productivity in Construction: Creating a framework for the industry to thrive". Chartered Institut of Building (CIOB), Bracknell UK, 2016
9. ERMCO - European Ready Mixed Concrete Organization "Ready-Mixed Concrete Industry Statistics - Year 2018". 2019
10. Shou W., Wang J., Wang X., Chong H.Y. "A Comparative Review of Building Information Modelling Implementation in Building and Infrastructure Industries". Arch Computat Methods Eng 22, 291-308, 2015
11. Alwisy A., Al-Hussein M., Al-Jibouri S. "BIM approach for automated drafting and design for modular construction manufacturing". Computing in civil engineering, 221-228, 2012
12. Kropp, Ch., Koch Ch., König M. "Integrating visual state recognition with 4D BIM based indoor progress monitoring". Eindhoven, Netherlands, 2015
13. Park C.-S., Lee D.-Y., Kwon O.-S., Wang X. "A framework for proactive construction defect management using BIM, augmented reality and ontology-based data collection template". Automation in Construction 33, 61–71, 2013
14. Wangler T., Lloret E., Reiter L., Hack N., Gramazio F., Kohler M., Bernhard M., Dillenburger B., Buchli J., Roussel N., Flatt R. "Digital Concrete: Opportunities and Challenges". RILEM Technical Letters, 67-75, 2016
15. Mechtcherine V., Nerella V.N., Will F., Näther M., Otto J., Krause M. "large-scale digital concrete construction - CONPrint3D concept for on-site monolithic 3D-printing". Automation in Construction 107, 102933, 2019
16. Lowke D., Talke D., Dreßler I., Weger D., Gehlen C., Ostertag C., Rael R. "Particle bed 3D printing by selective cement activation – Applications, material and process technology". Cement and Concrete Research 134, 106077, 2020
17. Kloft H., Gehlen C., Dörfler K., Hack N., Henke K., Lowke D., Mainka J., Raatz A. "TRR 277: Additive manufacturing in construction". Civil Engineering Design 3, 113-122, 2021
18. Ziolkowski P., Niedostatkiewicz M. "Machine Learning Techniques in Concrete Mix Design". In: Materials Vol. 12(8), 2019.
19. Young B. A., Hall A., Pilon L., Gupta P., Sant G. "Can the compressive strength of concrete be estimated from knowledge of the mixture proportions? New insights from statistical analysis and machine learning methods". In: Cement and Concrete Research Vol. 115, 2019.

20. Lau Hiu Hoong J. D., Lux J., Mahieux P.-Y., Turcry P., Aït-Mokhtar A. “Determination of the composition of recycled aggregates using a deep learning-based image analysis”. In: Automation in Construction Vol. 116, 2020.
21. Yang H., Jiao, S.-J., Yin F.-D. “Multilabel Image Classification Based Fresh Concrete Mix Proportion Monitoring Using Improved Convolutional Neural Network”. In: Sensors Vol. 20(16), 2020.
22. Ding Z., An X. “Deep Learning Approach for Estimating Workability of Self-Compacting Concrete from Mixing Image Sequences”. In: Advances in Materials Science and Engineering Vol. 2018, 2018.
23. Fuller, W. B., Thompson, S. E. “The Laws of Proportioning Concrete.” T. Am. Soc. Civ. Eng. 59 (2), 67–143. 1907
24. de Larrard F. “Concrete Mixture Proportioning: A Scientific Approach.” Boca Raton: CRC Press. 1999
25. Coenen, M., Beyer, D., Heipke, C., Haist, M. “Learning to sieve: Prediction of grading curves from images of concrete aggregate”. ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences, 2022.
26. Fennis S. A. A. M. “Design of ecological concrete by particle packing optimization.” PhD-Thesis, Technische Universität Delft. 2011
27. Tattersall G. H. “Workability and Quality Control of Concrete” CRC Press. 1991
28. Roussel N. “A thixotropy model for fresh fluid concretes: Theory, validation and applications.” Cement and Concrete Research 36, 1797-1806. 2006
29. Baumert C., Garrecht, H. “Mischen von Hochleistungsbetonen“. In: Beton- und Stahlbetonbau 105 (2010), Nr. 6, S. 371-378.
30. Mazanec O., Schießl P., Gehlen C. “Fibre Dispersion, Rheology and Mixing Time of Fibre Reinforced UHPC”. The Third International fib Congress incorporating the PCI Annual Convention and Bridge Conference. Washington D.C., United States, 2010.
31. Förstner W., Wrobel B. “Photogrammetric Computer Vision”. Springer Nature, Cham, 2016.
32. Ponick A., Langer A., Beyer D., Coenen M., Haist M., Heipke C. “Image-Based Determination of Rheological Properties of Ultrasonic Gel as Reference Substance of Cement Paste”. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2022.
33. Amziane S., Ferraris C. F., et al. “Measurement of Workability of Fresh Concrete Using a Mixing Truck”. Journal of Research of the National Institute of Standards and Technology 110:55–66, 2005.
34. Wallevik J. E., Wallevik O. H. “Concrete mixing truck as a rheometer”. Cement and Concrete Research 127:105930, 2020.
35. EFFC/DFI Concrete Task Group “Guide to Tremie Concrete for Deep Foundations.” 2018
36. Ferraris C. F., Brower L. E., Banfill P., Beaupré D., Chapdelaine F., de Larrard F., et al. “Comparison of concrete rheometers.” National Institute of Standards and Technology. 2001
37. Roussel N. “Rheology of fresh concrete: from measurements to predictions of casting processes”. Materials Structures 40, 1001–1012, 2007
38. Thiedeitz M., Habib N., et al. “L-Box Form Filling of Thixotropic Cementitious Paste and Mortar”. Materials, 13 (7):1760, 2020.
39. Roussel N. “The LCPC BOX: a cheap and simple technique for yield stress measurements of SCC”. Materials and Structures 40:889–896, 2007.
40. Thrane L. N. “Form Filling with Self-Compacting Concrete.” PhD Thesis, Technical University of Denmark. 2007
41. Coenen, M., Schack, T., Beyer, D., Heipke, C., Haist, M. “Semi-supervised segmentation of concrete aggregate using consensus regularization and prior guidance”. ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences 5(2), 83-91, Nice, France, 2021.
42. Schack T. “Bildbasierte Eigenschaftsermittlung am Frischbeton zur digitalen Qualitätsregelung”. Submitted PhD-Thesis, Leibniz University Hannover, Germany, 2022.
43. ASTM C 1611: Standard test method for slump-flow of self-consolidating concrete. ASTM International, West Conshohocken, 2014.
44. Schack T., Coenen M., Vogel C., Beyer D., Haist M.: “Digital Slump Flow Test: Computer Vision for a digital Assessment of the Homogeneity of fresh Concrete”. Submitted to the Digital Concrete - Third RILEM International Conference on Digital Fabrication with Concrete. Loughborough, 2022.
45. Vogel C., Coenen M., Schack T., Heipke C., Haist M. “Image-based analysis of fresh concrete flow - determination of the correlation between flow behavior and rheological properties”. Submitted to the Digital Concrete - Third RILEM International Conference on Digital Fabrication with Concrete. Loughborough, 2022.
46. Farneback G. “Very high accuracy viscosity estimation using orientation tensors, parametric motion, and simultaneous segmentation of the motion field”. Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001:171–177, Vancouver, Canada 2001.