Rapid crack fillability benchmarking using position-based physics simulation for robotic pavement crack repair

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***Abstract*— For robotic crack filling tasks in highway pavement maintenance, the crack fillability (achievable filling fullness) can vary along its length depending on the flowability of the repair material subject to the crack geometry, which directly impacts the mechanical performance of the resulting repair. Currently, the crack fillability is evaluated using trial-and-error-based human experience before field repairs, with no efficient ways of transferring this knowledge to a field crack repair robot. In this work, we present a computational approach to aid in rapid fillability benchmarking of random cracks. A customised simulator is developed based on the position-based dynamics, capable of automatically evaluating the filling performance of a repair material along a crack. Our experimental results show that the simulator achieves an average crack fillability prediction accuracy of 86.0%, especially accurate (> 94%) for more flowable repair materials. We believe such computational tool can not only be useful for material development, but also contribute to a holistic robotic crack repair simulation framework for solving the fundamental optimisation problem of pavement maintenance tasks.**

I. Introduction

Deploying robotic systems to conduct precise crack repair by material filling operations is a promising preventative maintenance measure to tackle the increasing pavement deterioration challenge [1,2]. In our previous work, we introduced the particle-based, fast yet approximate fluid physics simulation technique, position-based fluid (PBF) to guide robotic crack filling operations [3]. With PBF simulations, one can predict the sub-surface material flow to achieve desired repair surface quality. Other work involving PBF-based robotic fluid handling can be seen in [4,5].

Given the nature of cracks in dimensional and geometric variance, a repair material can generate varying filling fullness if applied at different locations along a crack. Understanding the fillability of a target crack for a given repair material is vital for ensuring material applicability and informing necessary material modifications to achieve desired repair surface quality, and optimal mechanical performance and durability after repair.

Currently, crack fillability is assessed using human experience, created from a time-consuming trial-and-error process in the lab by a material scientist; traditional computational fluid dynamics methods [6] can be available for this purpose but these normally are computationally heavy and fall short of a desired speed, making it hard to transfer the knowledge to a crack repair robot in the field. In this work, we propose an efficient crack fillability benchmarking simulator based on the PBF model to aid in rapid fillability understanding of random cracks. We elaborate on the details of the simulator and its validation through experiments.

II. SIMULATION ESTABLISHMENT

A. Simulation framework for task optimisation

The proposed crack fillability benchmarking simulator is part of a holistic robotic crack repair simulation framework (Figure 1) developed in the Digital Roads of the Future initiative. This initiative (drf.eng.cam.ac.uk) aims to integrate road digital twins, smart materials and robotics to enable autonomous highway pavement maintenance.

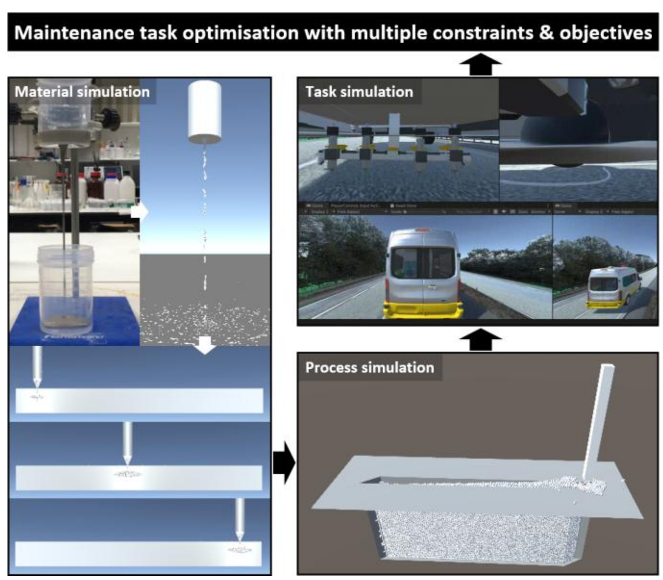

Figure 1. The Digital Roads robotic crack repair simulation framework

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The framework involves three interlinked steps:

- Step 1: *Material simulation* maps the physical flow behaviour of a repair material into its PBF simulation through real-to-sim flow cup test calibration (upper part in Figure 1). The flow cup test captures the flowability of the material by its continuously recorded discharge volumes from the bottom hole of a cup under gravity over constant time intervals, as reported in [7]. The calibrated virtual material is then applied to benchmark the fillability of given virtual cracks (lower part in Figure 1).
- Step 2: *Process simulation* offers a data-driven manner via feedback control for accurate and fast robotic crack filling processes using the calibrated material from Step 1, which then informs real-world repair operations [8].
- Step 3: *Task simulation* integrates the process simulation into a simulated robotic pavement maintenance vehicle [9] which completes the repair task at the full scale of road pavement.

The autonomous pavement maintenance task can be modelled as a high-dimension optimisation problem with multiple constraints (e.g., variable lane width and number, uncertain human driving behaviour, environmental condition, etc.) and objectives (e.g., repair accuracy, repair speed, repair cost, etc.). The simulation framework underpins the solution to this fundamental and challenging optimisation problem.

B. *Crack fillability benchmarking simulator*

A random crack with variable dimensions along its length can be treated as an aggregation of finite unit-length segments regardless of its geometric complexity (a schematic is provided in Figure 2a). The fillability concept applies to each of these segments and the length of the segment is determined according to the required inspection resolution. The fillability (F_i) is quantitatively defined as the ratio between the fillable space volume (V_{if}) of the associated segment and its entire volume (V_i):

$$F_i = V_{if} / V_i \quad (1)$$

We establish the crack fillability benchmarking simulator using the NVIDIA *Flex* simulation environment in Unity. Figure 2b shows the fillability test setup for an example crack in simulation. Provided that advanced sensing technologies such as high-resolution LiDAR or photogrammetry [10,11] are available for capturing the crack geometry, a digital mesh model of the crack can always be created and input in the simulator for the fillability test. For the *Flex* simulation environment, key parameters (*fixed timestep*, *substep count*, *iteration count*, *fluid rest*, *gravity*, etc.) should be tuned to allow effective particle movement computation.

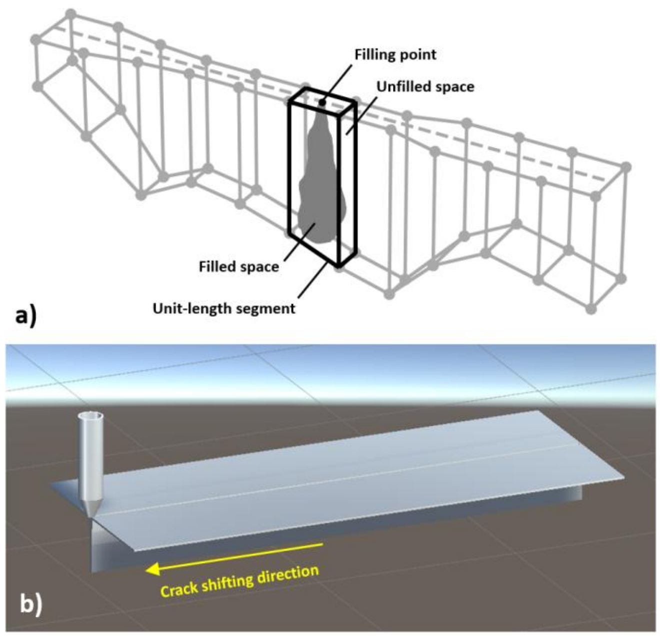

Figure 2. a) The schematic showing a crack with variable widths and depths, divided into multiple unit-length segments with one example segment under the fillability test; b) the developed crack fillability benchmarking simulator with a stationary material filling nozzle and a moving example crack

During each simulation run, one unit-length segment is extracted from the crack and blocked at both ends. A small amount of repair material particles (e.g., 5-10 ml), dynamically created by the *Flex* source actor, is deposited (driven by gravity) into the crack segment while the filling nozzle stays stationary above it. The filling flow rate (e.g., 0.2-0.8 ml/s) is determined dependent on the material flowability. Each run lasts for a designated period given the captured segment volume (V_i) and the filling flow rate. Right before the end of each run, the final positions of particles are checked to determine the fillable fluid volume (V_{if}) and then the fillability of this crack segment can be obtained.

The entire crack shifts from one end to the other as segment inspection continues. When all the crack segments are inspected, their fillability values will be automatically plotted against their locations in the crack using Unity's Python Scripting package, showing the fillability of the entire crack.

III. EXPERIMENT

For validation, we designed a controlled variable experiment to investigate the closeness between simulated and physical crack fillability test results. Considering the real-world challenge of filling thin cracks (i.e., < 5 mm wide) in the field, we selected 4 mm as the target. As mentioned above, we used a flow cup test to calibrate the simulated repair material intended for use in the fillability test.

A. Physical flow cup and crack fillability tests

A concrete prism was split into ~equally sized pieces perpendicular to the long axis of the prism and then two adjacent pieces were separated by 4 mm to generate crack specimens of 4 mm (wide) × 40 mm (long) × 40 mm (deep), enclosed by a aluminium tape on three sides. Four cement mortar repair materials were prepared using Rapid Set Cement All (RS; KORODUR International GmbH) with different volume percentages of polyvinyl acetate fibres (PVAF): 0, 0.2, 0.25 and 0.3% (v/v).

For each crack fillability test, the crack specimen was placed onto a digital scale and a repair material contained in a cup was manually poured into the crack from a height of 2 cm above the crack surface with a visually- modulated constant filling flow rate recorded by the scale (as shown in Figure 3a). The filling was stopped when the repair material was level with the crack top surface. For each repair material, the fillability test was repeated three times. The physical crack fillability test configuration parameters are shown in TABLE I.

TABLE I. PHYSICAL CRACK FILLABILITY TEST CONFIGURATION

Repair materials for different specimens	Filled weight [g]	Filled weight ratio [%]	Filling flow rate [g/s]
RS_1	16.1	100	1.61
RS_2	16.2	100	1.40
RS_3	14.5	100	1.34
RS_Avg	***15.6***	***100***	***1.45***
RS+0.2%PVAF_1	13.4	86	-
RS+0.2%PVAF_2	15.1	97	0.74
RS+0.2%PVAF_3	12.8	82	0.51
RS+0.2%PVAF_Avg	***13.8***	***88***	***0.62***
RS+0.25%PVAF_1	15.1	97	1.02
RS+0.25%PVAF_2	10.3	66	0.48
RS+0.25%PVAF_3	7.6	49	0.70
RS+0.25%PVAF_Avg	***11.0***	***71***	***0.59***
RS+0.3%PVAF_1	2.5	16	0.69
RS+0.3%PVAF_2	4.2	27	0.46
RS+0.3%PVAF_3	12.2	78	0.61
RS+0.3%PVAF_Avg	***6.3***	***40***	***0.59***

After the crack fillability test, 10 ml of each repair material was prepared to undergo the physical flow cup test, although a smaller diameter flow cup with a 10 mm discharge hole was used in this work. The captured flow cup test data were then used to calibrate the material flow in simulation.

B. Simulated flow cup and crack fillability tests

For the material calibration in simulation, we constructed a virtual flow cup as per the physical test. For each repair material, the calibration process was repeated 10 times, and each calibration process contained 30 iterative virtual flow cup tests driven by a Python Bayesian optimizer, resulting in one simulated material. This material calibration process was the same as that reported in [7]. The resulting 10 simulations of each repair material were then used in the crack fillability test.

For the simulated crack fillability test, the virtual crack model was prepared according to the physical specimen. Instead of using a cup to pour the repair material into the cracks in the above physical test, a material application cylinder with a nozzle was prepared and positioned at the same height as the physical test setting to guide material application, as shown in Figure 3b. This is a simplified alternative to simulating the cup pouring action.

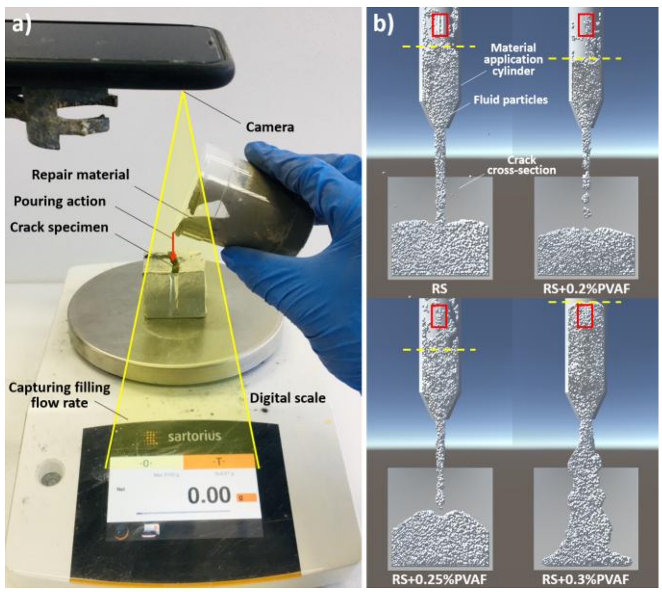

Figure 3. Comparing a) the physical crack fillability test and b) the virtual crack fillability tests of four example simulated repair materials (red box: particle generation source; yellow dashed line: constant fluid level observed)

The key to a successful crack fillability test simulation is adaptively modulating the cylinder nozzle size and the fluid level in the cylinder to match the corresponding filling flow rates measured in the physical test. This flow rate control in simulation is done by: 1) at the upper part of the material application cylinder, generating the fluid particles as per the average filling flow rates for each physical repair material in TABLE I; 2) blocking the cylinder nozzle for a few seconds to allow the particles to accumulate to a certain level; and 3) releasing the particles and visually checking the particles maintaining a constant level in the cylinder during the application process. The material application lasted for a calculated time based on the filling flow rate and the given crack volume, before the final filled material (particle) volume was calculated and recorded.

IV. RESULTS

Figure 4 presents the comparison between the physical and simulated crack fillability tests results. The physical results refer to the average physical crack fillability data (bold and italic) TABLE I; while the simulated result of each repair material is plotted using the average virtual crack fillability data for the 10 simulated materials (from the virtual flow cup test). On average, we achieved an 86.0% crack fillability prediction accuracy given by the 'sim-to-real' closeness (red dashed line).

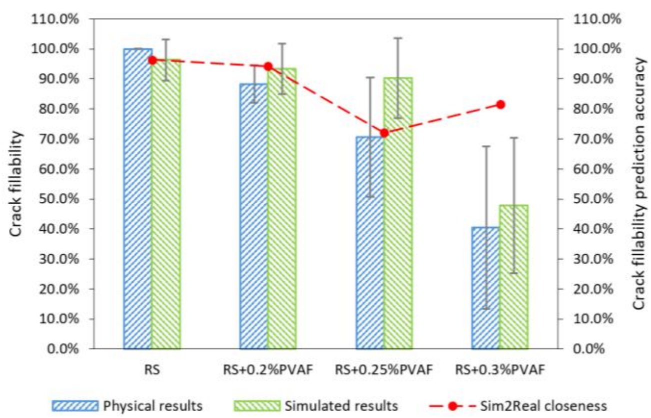

Figure 4. Results of physical and simulated crack fillability tests

It is observed that the simulation demonstrates particularly high prediction accuracies (i.e., > 94%) for more flowable repair materials (RS and RS+0.2%PVAF). When the material becomes less flowable, the simulation prediction accuracy drops to around 80% or less; and the larger error bars show higher uncertainties in both physical (related to mixing and spatial distribution of fibres) and simulated results; the simulation also shows a trend that the prediction accuracy may gradually decrease with the decreasing material flowability until a certain flowability is reached where the prediction accuracy rebounds. This implies the limitation of the current virtual flow cup test in identifying the flow behaviour of less flowable materials (due to several factors including viscosity, adhesion, etc.) as reported in [7]. The prediction accuracy may converge with the increase of material calibration.

V. CONCLUSION

Targeting robotic pavement crack repair, this paper presents a computational simulator for automatically identifying the crack fillability for a given repair material. The proposed simulated crack fillability test is performed on finite crack segments, which is experimentally validated by comparing with the physical fillability test on a 4 mm × 40 mm × 40 mm crack for four different repair materials. The results show that the simulator achieves an average crack fillability prediction accuracy of 86.0%. Such simulation shows potential to aid material development, and more importantly, forms an essential part of a holistic robotic crack repair simulation framework for solving the autonomous pavement maintenance optimisation problem.

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REFERENCES

[1] Orr, D.P., 2006. Pavement maintenance.

[2] Awuah, F.K., Garcia-Hernández, A., 2022. Machine-filling of cracks in asphalt concrete. Automation in Construction 141, 104463.935.

[3] Schaefer, S.D., Xu, J., Palin, D., Al-Tabbaa, A., Iida, F., 2024. Position-based fluid simulation for robotic injection sealing of pavement cracks. Journal of Field Robotics.

[4] Guevara, T.L., Taylor, N.K., Gutmann, M., Ramamoorthy, S., Subr, K., 2017. Adaptable pouring: Teaching robots not to spill using fast but approximate fluid simulation, in: 1st Conference on Robot Learning 2017, pp. 77–86.

[5] T. Lopez-Guevara, R. Pucci, N. K. Taylor, M. U. Gutmann, S. Ramamoorthy, and K. Suhr, "Stir to pour: Efficient calibration of liquid properties for pouring actions," in 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2020, pp.5351–5357.

[6] Ansys Fluids, https://www.ansys.com/products/fluids, last access: 8-5-2025.

[7] Xu, J., Palin, D., Schaefer, S.D., Al-Tabbaa, A., Iida, F., 2025. Real-to-sim-to-real: rapid flow cup-enabled liquid perception using a position-based physics simulator for accurate robotic liquid manipulation. In preparation.

[8] Schaefer, S. D., Xu, J., Al-Tabbaa, A., & Iida, F. A Data-Driven Approach for Optimal Robotic Crack Filling in Pavement Maintenance. *Available at SSRN 5218258*.

[9] Xu, J., N'Zebo, R.A., Taha-Abdalgadir, H., d'Avigneau, A.M., Palin, D., Wei, R., Hadjidemetriou, G., Schaefer, S., De Silva, L., Al-Tabbaa, A. and Iida, F., 2024. Highway digital twin-enabled Autonomous Maintenance Plant: a perspective. Data-Centric Engineering, 5, p.e24.

[10] Phung, M. D., Hoang, V. T., Dinh, T. H., & Ha, Q., 2017. Automatic crack detection in built infrastructure using unmanned aerial vehicles. arXiv preprint arXiv:1707.09715.

[11] Guan, J., Yang, X., Ding, L., Cheng, X., Lee, V.C., Jin, C., 2021. Automated pixel-level pavement distress detection based on stereo vision and deep learning. Automation in Construction 129, 103788.