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RESEARCH ARTICLE

Aggregate-Forming Planner for Autonomous Earth-Moving

TOM SHAKED[1], KAREN LEE BAR-SINAI[1,2], ARI MELES-BRAVERMAN[3], OREN ELMAKIS[4], AND AMIR DEGANI[1,4], (Member, IEEE)

[1]Faculty of Civil and Environmental Engineering, Technion—Israel Institute of Technology, Haifa 3200003, Israel
[2]Associate Professorship of Urban Design, Technical University of Munich, 80333 Munich, Germany
[3]Faculty of Mechanical Engineering, Technion, Haifa 3200003, Israel
[4]Technion Autonomous Systems Program—TASP, Haifa 3200003, Israel

Corresponding author: Tom Shaked (shakedtom@campus.technion.ac.il)

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ABSTRACT Research in advanced construction and autonomous earthworks begins to explore the shaping of aggregates for construction, military, and environmental purposes. However, while current work in autonomous earthworks focuses on grading and pushing aggregates, there is limited research on moving aggregates to form specific shapes on a surface. This action can aid in gathering aggregates for on-site construction of re-configurable formations, performing architectural tasks, or piling material reservoirs for concrete production. To support aggregate-forming, an autonomous agent is required to move non-labeled aggregates from multiple locations to numerous proximate target points in a predefined desired shape. In this process, the agent needs to push the aggregates, handle material spills, and update both the material location and the outcome formation. The paper presents a planner for autonomous aggregate shaping to support this task. The path generation is first demonstrated in a simulation environment and validated in an in-lab experimental setup, showing over 90% success rate. The results show that employing the planner can assist in advancing autonomous earthworks toward on-site aggregate-forming.

INDEX TERMS Advanced construction, autonomous earthworks, path planning, robotics and automation.

I. INTRODUCTION

There is a growing body of work on the use of robotic autonomous systems (RASs) for forming aggregate-based materials. This research is pursued in the context of autonomous earthworks [1], environmental purposes [2], military applications [3], landscape architecture [4], and construction [5]. Existing research includes the development of dedicated tools for automating earthworks [6], methods, and protocols supporting such processes [7], [8], [9].

In this context, there is a need for planners for various earthworks and aggregate moving tasks that rely on pushing material as their primary action. While research on path planning for unmanned earth-moving vehicles exists [10], there are currently no methods for moving scattered, unlabelled aggregates for the purpose of forming specific shapes on a ground surface. The term aggregates is commonly used in construction to refer to granular materials such as sand, gravel, or crushed stone. In this context, the term unlabeled aggregates refers to the inability of identifying specific particles for visual tracking purposes.

A. DEFINITION OF CHALLENGE

This work addresses the lack of planning methods that enable an agent to move multiple unlabeled scattered objects to a predefined target in an iterative process. During this process, the agent is required to operate under changing, uncertain conditions, and perform (1) ongoing mapping of the material, (2) positioning the tool, and (3) update the agent's path accordingly.

B. INNOVATION AND CONTRIBUTION

The novelty of the presented approach is expressed by allowing the forming of aggregates into desired shapes using

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pushing actions while handling spills, updating the material location, and tracking the process progression. In this context, the presented approach and planner meet the current gaps in research and advance the field of autonomous earthworks by making the following contributions:

- Enabling an autonomous agent to manipulate unlabeled aggregates to form specific shapes on a surface using pushing actions.
- Facilitating the forming of aggregates for the creation of re-configurable formations on-site, carrying out architectural tasks, or piling material reservoirs for concrete production.
- Mitigating material spills by updating the material location and resulting formation between iterations.
- Supporting the forming process with a simulation-based validation of the planned path before execution.

C. STRUCTURE

The paper presents the related work and state-of-the-art regarding autonomous shaping of aggregates and robotic object transport. It then presents a path planner for moving and shaping aggregates. The planner is demonstrated in a custom simulation environment and then validated experimentally using an industrial using an industrial robotic arm, a desktop experimental setup mimicking an autonomous earth-moving tool. The results of the simulations and experiments are then compared and analyzed. The paper concludes with a summary of the contribution to the field and outlines future work.

II. RELATED WORK

This section will review the state-of-the-art in two aspects at the core of the research - autonomous shaping of aggregates and robotic object transport.

A. AUTONOMOUS SHAPING OF AGGREGATES

Work in the field of automated earthworks and robotic construction begins to address the challenge of forming aggregates in various sizes, from sand and soil to large stones, using robotic tools. In this context, researchers demonstrate a method for gathering large stones into a desired shape and autonomously forming dry stone walls by defining the placement position for each stone using a custom planner [11], [12]. While algorithms which pick and place single objects from a single point to a single target well-support construction with either small constructs or with large, boulder scale stones, this approach is less suitable for forming numerous unlabeled objects as aggregates. Alternative approaches, exploring the vertical gathering of smaller, variable-sized rocks, provide a solution for jamming aggregates by combining pouring and fiber-based reinforcement in a single robotic process [13]. The algorithm locates the center points of the jammed aggregate clusters, and these, in turn, define the robotic trajectory for the vertical laying of the tensile reinforcement.

In the context of earthworks, autonomous surface grading of uneven sites with multiple sand piles is explored through a decision process geared at reducing uncertainties [14]. However, the resulting form of the pushed sand piles at the edge of the graded surface is irrelevant to autonomous grading processes and presents the core of this study. While vertical aggregate-forming remains largely reliant on additional reinforcement systems, and horizontal forming is centered on grading and not on the resulting formation, there is need for methods supporting autonomous horizontal forming of multiple aggregates for the shaping of a specific form using an iterative path planning method.

Recent research provides a task planner for earth shaping using an autonomous excavator, relying on a separately controlled bucket capable of digging, lifting, and dumping soil [8]. However, there is a need for planners for earth-moving vehicles that rely on simpler, pushing actions such as bulldozers. This need is discussed in [15], where heuristics and learning strategies guide an agent to solve an earth grading task. In contrast, the presented paper focuses on a classical approach to solving the path planning problem. The advantages of this approach are (1) faster runtime, (2) reduced computational intensity, and (3) more interpretability and transparency in decision-making.

B. ROBOTIC OBJECT TRANSPORT AND MANIPULATION

Rearranging scattered objects into desired forms is a long-standing challenge in robotics. While existing approaches towards optimizing pick-and-place advance [16], they are more satiable to manufacturing tasks. A non-manufacturing related example for desktop manipulation employs a linear model for pushing small objects into a desired target region. This research demonstrates the advantage of classical path planning in relation to machine learning approaches [17]. In the context of search and rescue missions (SAR) in hazardous or inaccessible sites, research advances the possibilities for robotic disassembling of piled objects [18].

When handling aggregates, there is a need to extend existing capacities to support the transport of multiple objects using pushing to multiple target locations. To address this, research begins to apply vision-based machine-learning algorithms for robotic object transport, rearrangement, or reconfiguration of numerous items [19]. To support the challenge posed by numerous items, research explores reinforcement learning which allow autonomous tools to utilize repertoires of behavioral skills for improved task and path planning [20]. This approach was applied for autonomous earthworks on the macro scale, the management and sequencing of earth-moving tasks using two Markov decision process (MDP) in scenario simulations. An alternative approach for handling onsite materials and masonry debris using earth-moving tools in construction contexts proposes a nonlinear model for predictive control [21]. However, the focus, as in much of the research on autonomous earthowrks, is placed on the action of pushing and gathering the material, not on rearranging the material or debris in a desired formation. The transport of multiple aggregates to multiple targets which compose together a desired form remains a challenge.

III. METHOD

The paper addresses the lack of planners for transporting and rearranging scattered aggregates in multiple form-driven locations. To this end, it presents a custom path planner for autonomous forming of aggregates. The path is first demonstrated in a simulation environment and then validated in an experimental setup using a UR5e industrial robotic arm.

A. PLANNER FORMULATION

This stage aims to devise a combined task and path-planning strategy for moving unlabeled aggregates from multiple depots to a single destination (as seen in Fig. 1). The system employs a custom earth-moving path planner for construction site preparation tasks. The planner is developed in IronPython (a Python implementation for.NET Framework) and includes Emgu CV (a.Net wrapper for OpenCV image processing library).

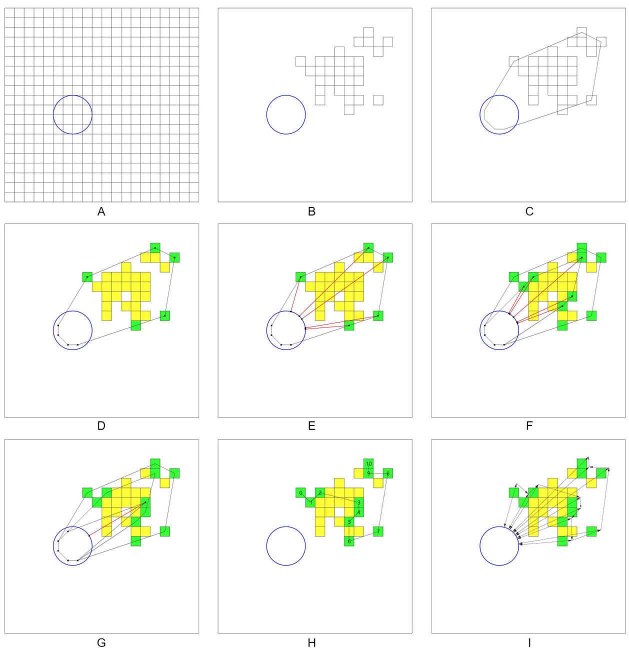

FIGURE 1. An example illustrating the path planning process, from left-to-right and top-to-bottom: (A) generating an initial grid and (B) identifying the locations of the material aggregates, (C) generating a convex hull to enclose both the material and the target shape, (D) marking material cells on the convex hull as pushing-cells, and (E) drawing lines between these cells and the closest points on the target shape. (F-G) The algorithm ignores any intersecting cells and generates additional convex hulls until all cells are either marked as pushing-cells or intersecting cells. (H) The shortest path between the pushing-cells is calculated using the traveling salesman algorithm, and (I) a path is added from each pushing cell to the closest point on the target shape to facilitate the pushing action.

As the future goal of this research is supporting autonomous earth-moving vehicles such as converted earth-moving machinery or custom Unmanned Ground Vehicles (UGVs), the planner was implemented so the robot is constrained to mimic the behaviour of a ground vehicle. This means that the robot was not allowed to leave the table or move in the Z-axis, similar to the way a differential drive vehicle would move.

The planner receives two inputs: (1) the material map as an image from the RGB camera and (2) the desired material location as a shape curve from the user. The material map image is then converted to an occupancy grid of 70-by-50 pixels. The grid size is derived from the width of the shoveling tool and can be altered to fit different shovel sizes, which in turn affects the resulting path. Based on these inputs, the planner generates an optimal path for moving the aggregates into the predefined shape. The path is then converted into a set of waypoints for the UR5e robotic arm motion, determining the material-pushing actions.

The main challenge in the path planning process is finding the points from which the UR5e should start pushing the aggregates out of all existing material locations. The advantage of earth-moving challenges, as opposed to other coverage problems (such as inspection or pollution detection), is that the robotic arm pushes all material on its way to the target as long as it is within its loading capacity and considering there is no spill. Therefore, once all of the pushing points are determined, the next step is organizing them in the shortest possible way to minimize idle motion between the points.

B. IMPLEMENTATION

The algorithm, shown here in Algorithm 1, works in a 2D Cartesian grid, denoted by $\mathcal{M}$, representing an aggregates occupancy map. The map $\mathcal{M} = \{(i, j) \mid X_{ij} = 1\}$ consists of binary cells X_{ij} indicating that cell i, j is occupied.

The algorithm uses two maps: $\mathcal{M}_i$ for the iterative aggregate mapping and $\mathcal{M}_T$ for the algorithm target map. Then to transform $\mathcal{M}_i$ to $\mathcal{M}_T$, the algorithm starts an iterative process in which it estimates the convex hull $\mathcal{C}_m$ that encloses all the aggregates in $\mathcal{M}_i$. Followingly, the algorithm takes the external aggregates found on the boundary of the convex hull $\mathcal{M}_i \cap \partial\mathcal{C}_m$ and defines a primitive pushing action between

Algorithm 1 Minimal Pushing

Input: $\mathcal{M}_T, \mathcal{M}_i$
while $\mathcal{M}_i \backslash \mathcal{M}_T \neq \emptyset$ **do**
  $\mathcal{C}_m \leftarrow$ a sequence of edges that define the convex hull.
  for $X_{i,j} \in \mathcal{M}_i \cap \partial\mathcal{C}_m$ **do**
    $\mathcal{P}_i \leftarrow X_{i,j}, \partial\mathcal{M}_T$ compute the primitive pushing action between $X_{i,j}$ to $\partial\mathcal{M}_T$
  $\mathcal{M}_i \leftarrow X_{i,j} if X_{i,j} = 1$
  $\mathcal{P}$ minimal travel distance $\forall\mathcal{P}_i$
  execute($\mathcal{P}$)

these aggregates to the edge of the target map, X_{ij} to ∂M_T. The primitive pushing action is performed with a consistent forward-backward motion in a fixed direction, moving the aggregates from X_{ij} to ∂M_T and then returning the shovel to its original position. Lastly, the algorithm optimizes the path planning and connects all the primitive pushing actions by minimizing the traveling path length and executing the set of actions $\mathcal{P}$.

C. SETUP AND TOOLS

The forming of the aggregates was tested in an in-lab setup comprised of a UR5e 6DoF Universal Robots industrial arm with a 5 kg payload and a reach of 850 mm, a 90-by-120 cm X-Y positioning table, an RGB camera mounted on a 1.8M tall tripod, and a selection of aggregates sized approximately 1.5- 2 cm. (see Fig. 2)

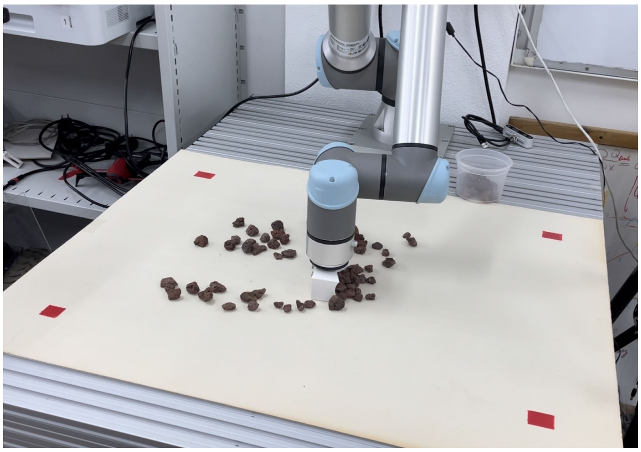

FIGURE 2. The experimental setup, including the UR5e robot, table, and aggregates.

The tools used for the simulation and experiments include (1) Rhinoceros 3D modelling environment for visualization of the path, simulations, and generating the target shapes; (2) Grasshopper visual programming plugin for controlling the robot motion in simulation and sending motion commands to the robot in the experiments; and (3) the Flexhopper Grasshopper plugin to simulate the aggregate motion based on the Nvidia FleX GPU-based physics engine.

D. SIMULATION

The task of the planner was to transport aggregates from multiple locations into a predefined region, represented by the desired shape. To test the path planning, a 3D model of the table and robot was created in Rhinoceros 3D (see Fig. 3). An array of between 60-70 aggregates was generated and randomly spread on the table. The moving of the aggregates was then simulated using Flexhopper. The simulation tested three types of curves as targets: (1) a circle, (2) a square, and (3) an amorphous shape containing convex and concave segments (similar in shape to a kidney bean). Each shape sized approximately 78 cm^2 in area. The simulations are

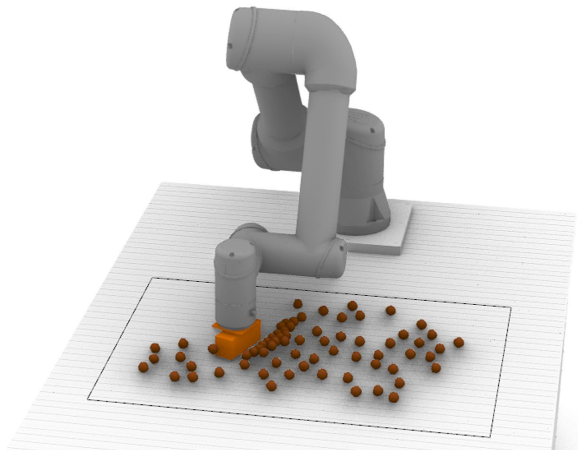

FIGURE 3. The simulation setup in Rhinoceros 3D, including the UR5e robot, positioning table model, and simulated aggregates.

performed five times for each shape. These shapes allow to examine the use of the planner for supporting the formation of various shapes in the context of earthworks and construction.

A grid of 50-by-70 was generated on the table and the location of the aggregates was determined by performing an inclusion test with the each of the grid cells. The simulated aggregates locations were input into the planner which generated a path. Following a simulation of the robot motion, the location of each aggregate was recorded and examined their inclusion in the target shape. This process was repeated until all aggregates were inside the target shape. (see Fig. 4)

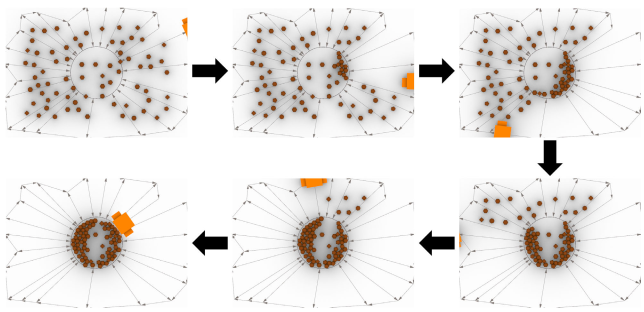

FIGURE 4. Visualization of the behavior of the aggregate shaping simulation. The UR5e robotic arm is hidden to enable a view of the table, and the shovel is marked in orange.

E. EXPERIMENT

The experiment aimed to validate the planner by reproducing the simulation results using the same shapes with aggregates. Here, the location of the material was obtained using an RGB camera and image processing (see Fig. 5). In each experiment, an initial image of the table was captured and the location of the material was derived. The experiments are performed three times for each shape. Each experiment is performed in two iterations, and the performance is measured by various parameters such as the total amount of material, the percent of material inside the target shape, and the length of the path used.

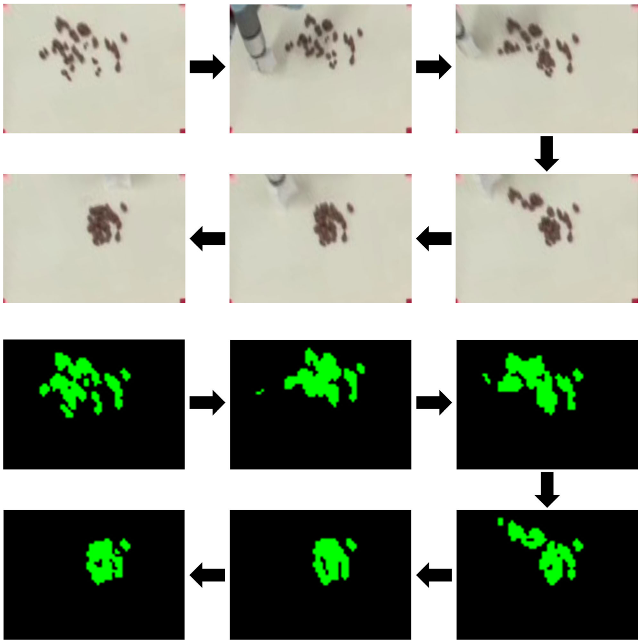

FIGURE 5. Visualization of the progression of the aggregate shaping experiment. Raw image (top) and processed image (bottom).

IV. RESULTS AND ANALYSIS

A. SIMULATION RESULTS

The results of the simulation show a possibility to achieve successful shaping of the three tested shapes (defined here as over 90% of the material inside the target shapes) after a single iteration in most cases, aside for a single case which required a second iteration (square shape, 84% success after first iteration and 94.4% following the second iteration).

The simulation initial conditions include 60-72 randomly placed aggregates, with the initial percentage of material already inside the target shape varying slightly between the different shapes (10-20%). The results of the simulations are provided in Table 1.

TABLE 1. Simulation results.

Target Shape	Initial Conditions	Final Conditions
Circle	11.3 – 16.9%	98.5 – 100.0%
Square	11.6 – 19.4%	94.4 – 97.1%
Amorphous	9.9 – 14.9%	97.3 – 100.0%

B. EXPERIMENT RESULTS

The results of the experiment show a possibility to achieve successful shaping of the three tested shapes with increasing success after two iterations, in contrast to the simulations, which required a second iteration only in one instance. This difference might be due to the material behaviour which is not easily possible to simulate - namely material stacking and spill. After two iterations, over 90% of the material was moved into the target shapes, regardless of the shape's form. The initial percentage of material already inside the target shape varies slightly between the different shapes, but the end results are similar.

The experiments results are presented and classified by the target shape in Table 2. The success rate increased over the two iterations, with the highest success rate being around 97%. The path length also decreased over iterations, indicating an improvement in performance.

TABLE 2. Experiment results.

Target Shape	Initial Conditions	1 Iteration	2 Iterations
Circle	16.8 – 22.6%	82.1 – 84.8%	93.8 – 94.8%
Square	11.2 – 15.8%	75.2 – 78.9%	92.0 – 93.5%
Amorphous	9.7 – 14.3%	75.6 – 79.8%	89.1 – 91.0%

In Fig. 6, it is possible to see the evolution of the material from randomly scattered to positioned within the target shape by observing the material occupancy images used by the algorithm to determine the position of the aggregates.

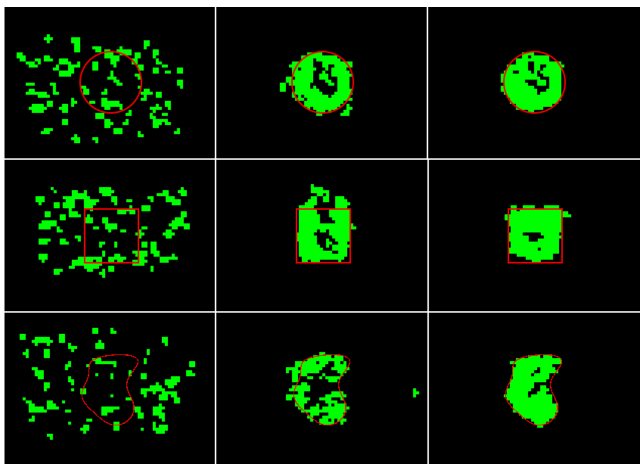

FIGURE 6. Material occupancy images for the initial position (left), after first iteration (middle), and after second iteration (right), with a circular (top), square (middle), and amorphous (bottom) target.

C. ANALYSIS

In general, after two iterations, most of the material was moved inside the target shape for all three experiments, with the circle experiment having the highest percentage of material inside the target shape. A comparison between the experimental and simulated results presented in Fig. 7 show a close match between the two, with the simulated results generally displaying slightly more material inside the target shape than the experimental results. The differences can be attributed to real-world random effects that simulations do not fully capture. There are also material properties like aggregates stacking and spilling that are difficult to simulate. Additionally, there may be minor variations in

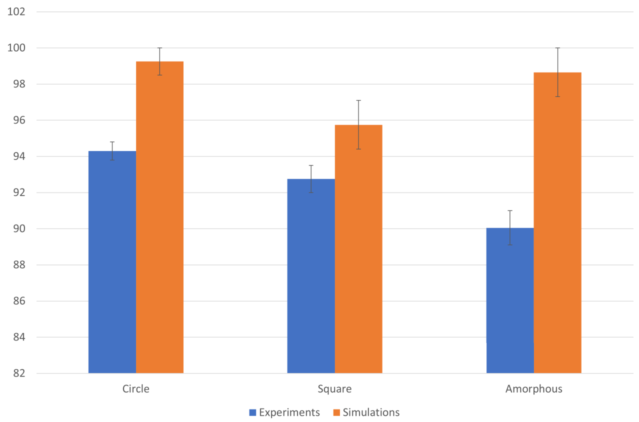

FIGURE 7. A comparison of the simulations (orange) and experiments (blue).

the experimental conditions between runs that introduce randomness.

The results of the experiments show that the effectiveness of the planner is influenced by the target shape. The circle seem to be the most successful shape for this method, with 93.8-94.8% of the material being moved inside the target after two iterations. The amorphous shape is the least successfully, with 89.1-91.0% of the material being moved inside after two iterations. While the circular shape may be expected to yield optimal results, variations in tool design or initial material position can impact the outcome. As such, configuration changes require additional experiments.

The performance varied between the different shapes, and further analysis may be necessary to understand the causes of this variation and how it affects the results. For instance, the success rate of forming a circle were better than forming a square, and the success of forming the amorphous shape were lower than the square shape. The higher effectiveness of circles can be attributed to the lack of corners or their symmetrical attributes. On the other hand, the square and amorphous shapes have irregular edges and contours that make it more difficult for the planner to move the material inside the target shape. The amorphous shape presents an increase complexity, due to its convex and concave segments.

The improved effectiveness of the method after two iterations can be attributed to the opportunity for material to be redistributed more evenly. The increased success after two iterations suggests that multiple iterations of the method can lead to higher levels of aggregation inside the target shape - as long as the shape is not 'saturated', meaning that the material pile is to large for the shape to contain.

D. LIMITATIONS

While the forming task is defined here as transporting aggregates from multiple locations into a predefined region, the current system may not cover all areas within a specific shape with material. To increase the success of the method, future work will investigate ways to optimize the material's movement into the target shape. For example, adjusting the velocity and direction of the material flow or exploring different methods of distributing the material inside the target shape. Additionally, incorporating techniques such as using magnetic fields or varying the density of the material may also lead to increased success.

V. CONCLUSION AND FUTURE WORK

The paper presented a planner for autonomous forming of aggregates into a desired form on a surface. The results of the simulations and the experiments validating them demonstrate over 90% success rate in aggregate-forming by effectively handling material spillage and real-world uncertainties. While the experiments were preformed using a desktop manipulation setup, the ultimate goal is to support autonomous shaping of aggregates on-site (Fig. 8- 9).

The planner is aimed at assisting the production of motion instructions for a ROS-controlled vehicle by complementing two previous publications on controlling a UGV and localizing it using an unmanned aerial vehicle (UAV) [6], [7].

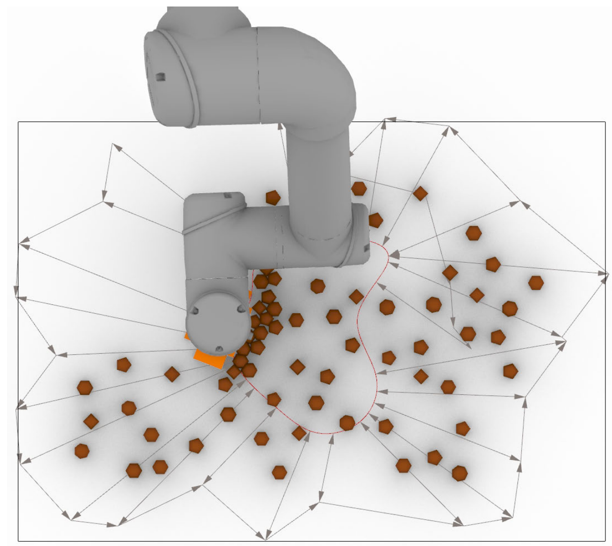

FIGURE 8. Path planning for a desktop manipulation setup.

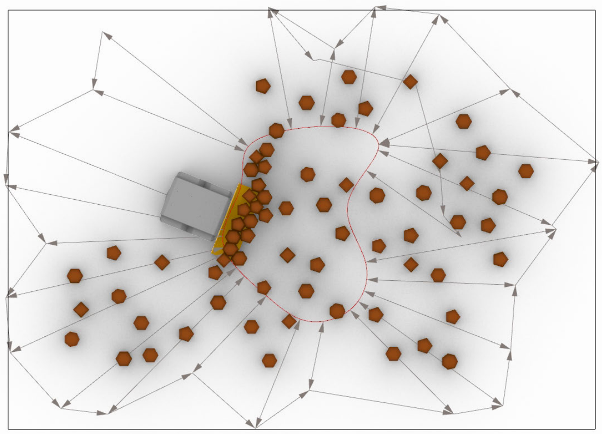

FIGURE 9. Transfer of the desktop path planning to a Clearpath Jackal UGV setup with a front shovel for on-site aggregate shaping.

As the planner generates a path for the aggregate-forming task, future work will focus on integrating this capability for large-scale experiments involving outdoor construction site preparation tasks.

Future work will perform these experiments using UGVs to replace the robotic arm and a UAV to replace the static camera. In this scenario, an added complexity will be the localization of the UGVs throughout the task in relation to the changing material formation. These capabilities can further expand the possibilities of robotic handling of aggregates toward autonomous earthworks, military and mining applications, as well as for a range of landscape architecture and construction tasks.

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REFERENCES

[1] H. A. D. Nguyen and Q. P. Ha, "Robotic autonomous systems for earthmoving equipment operating in volatile conditions and teaming capacity: A survey," *Robotica*, vol. 41, no. 2, pp. 486–510, Feb. 2023.
[2] C. Wong, E. Yang, X.-T. Yan, and D. Gu, "Autonomous robots for harsh environments: A holistic overview of current solutions and ongoing challenges," *Syst. Sci. Control Eng.*, vol. 6, no. 1, pp. 213–219, Jan. 2018.
[3] Q. P. Ha, L. Yen, and C. Balaguer, "Robotic autonomous systems for earthmoving in military applications," *Autom. Construct.*, vol. 107, Nov. 2019, Art. no. 102934.
[4] I. Hurkxkens, A. Mirjan, F. Gramazio, M. Kohler, and C. Girot, "Robotic landscapes: Designing formation processes for large scale autonomous earth moving," in *Impact: Design With All Senses*, C. Gengnagel, O. Baverel, J. Burry, M. R. Thomsen, and S. Weinzierl, Eds. Cham, Switzerland: Springer, 2020, pp. 69–81.
[5] N. Melenbrink, J. Werfel, and A. Menges, "On-site autonomous construction robots: Towards unsupervised building," *Autom. Construct.*, vol. 119, Nov. 2020, Art. no. 103312.
[6] T. Shaked and A. Degani, "Shepherd: A fabrication-oriented tool for simulation and control of mobile robotic platforms for collaborative earthworks," in *Proc. 41th Annu. Conf. Assoc. Comput. Aided Design Archit., Realignments, Toward Crit. Comput. (ACADIA)*, 2021, pp. 480–489, doi: 10.52842/conf.acadia.2021.480.
[7] O. Elmakis, T. Shaked, and A. Degani, "Vision-based UAV-UGV collaboration for autonomous construction site preparation," *IEEE Access*, vol. 10, pp. 51209–51220, 2022.
[8] D. Jud, I. Hurkxkens, C. Girot, and M. Hutter, "Robotic embankment: Free-form autonomous formation in terrain with HEAP," *Construct. Robot.*, vol. 5, no. 2, pp. 101–113, Jun. 2021.
[9] K. L. Bar-Sinai, T. Shaked, and A. Sprecher, "A pedagogical protocol for iterative robotic fabrication on remote grounds," *Archnet, Int. J. Architectural Res.*, vol. 14, no. 3, pp. 453–468, Apr. 2020.
[10] M. Hirayama, J. Guivant, J. Katupitiya, and M. Whitty, "Path planning for autonomous bulldozers," *Mechatronics*, vol. 58, pp. 20–38, Apr. 2019.
[11] D. Jud, G. Hottiger, P. Leemann, and M. Hutter, "Planning and control for autonomous excavation," *IEEE Robot. Autom. Lett.*, vol. 2, no. 4, pp. 2151–2158, Oct. 2017.
[12] F. Furrer, M. Wermelinger, H. Yoshida, F. Gramazio, M. Kohler, R. Siegwart, and M. Hutter, "Autonomous robotic stone stacking with online next best object target pose planning," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2017, pp. 2350–2356.
[13] P. Aejmelaeus-Lindström, A. Mirjan, F. Gramazio, M. Kohler, S. Kernizan, B. Sparrman, J. Laucks, and S. Tibbits, "Granular jamming of loadbearing and reversible structures: Rock print and rock wall," *Architectural Design*, vol. 87, no. 4, pp. 82–87, Jul. 2017.
[14] Y. Miron, Y. Goldfracht, C. Ross, D. D. Castro, and I. Klein, "Autonomous dozer sand grading under localization uncertainties," *IEEE Robot. Autom. Lett.*, vol. 8, no. 1, pp. 65–72, Jan. 2023.
[15] Y. Miron, C. Ross, Y. Goldfracht, C. Tessler, and D. Di Castro, "Towards autonomous grading in the real world," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2022, pp. 11940–11946.
[16] F. Nagata, K. Miki, A. Otsuka, K. Yoshida, K. Watanabe, and M. K. Habib, "Pick and place robot using visual feedback control and transfer learning-based CNN," in *Proc. IEEE Int. Conf. Mechatronics Autom. (ICMA)*, Oct. 2020, pp. 850–855.
[17] H. J. T. Suh and R. Tedrake, "The surprising effectiveness of linear models for visual foresight in object pile manipulation," in *Algorithmic Foundations of Robotics XIV, Proceedings of the Fourteenth Workshop on the Algorithmic Foundations of Robotics, WAFR 2021, Oulu, Finland, June 21–23, 2021* (Springer Proceedings in Advanced Robotics), vol. 17, S. M. LaValle, M. Lin, T. Ojala, D. A. Shell, and J. Yu, Eds. Springer, 2021, pp. 347–363, doi: 10.1007/978-3-030-66723-8_21.
[18] S. Temtsin and A. Degani, "Decision-making algorithms for safe robotic disassembling of randomly piled objects," *Adv. Robot.*, vol. 31, nos. 23–24, pp. 1281–1295, Dec. 2017.
[19] A. Zeng et al., "Transporter networks: Rearranging the visual world for robotic manipulation," in *Proc. Conf. Robot Learn.* PMLR, 2021, pp. 726–747. [Online]. Available: https://proceedings.mlr.press/v155/
[20] S. Gu, E. Holly, T. Lillicrap, and S. Levine, "Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2017, pp. 3389–3396.
[21] S. Khan and J. Guivant, "Nonlinear model predictive path-following controller for a small-scale autonomous bulldozer for accurate placement of materials and debris of masonry in construction contexts," *IEEE Access*, vol. 9, pp. 102069–102080, 2021.

TOM SHAKED received the B.Arch. and M.A. degrees from Tel-Aviv University, in 2012 and 2014, respectively, and the Ph.D. degree from the Technion—Israel Institute of Technology, in 2021, focusing on developing robotic tools for adaptive fabrication in construction.

He was a lecturer and the digital fabrication lab manager. He was a two-time recipient of the Azrieli Research Fellowship (2012–2014) and (2018–2020). He co-founded CTwiz real estate analytics start-up and was the Head of Education with Infolio, an Apple Mobility Partner Company (2014–2016). He was a Lead Researcher with The David & Barbara Blumenthal Israel Center for Innovation and Research in Textiles (CIRTex), Shenkar College of Engineering (2016–2017). He is currently a registered architect. He is also a Visiting Lecturer with the School of Engineering and Design, Technical University of Munich (TUM), and a Postdoctoral Researcher with the Civil, Environmental, and Agricultural Robotics Laboratory (CEAR), Faculty of Civil and Environmental Engineering, Technion—IIT. His research interests include collective robotic construction and autonomous systems in unstructured environments.

KAREN LEE BAR-SINAI received the B.Arch. degree from the Technion—Israel Institute of Technology, in 2004, the M.Sc. degree in cities from the London School of Economics, U.K., as a Chevening Scholar, in 2007, and the Ph.D. degree in architecture from Technion, in 2021.

She is currently a Marie Curie/Eurotech Post-doctoral Fellow and a Visiting Lecturer with the School of Engineering and Design, Technical University of Munich (TUM), Germany (2021–2023), and a Postdoctoral Researcher with the Civil, Environmental, and Agricultural Robotics Laboratory (CEAR), Faculty of Civil and Environmental Engineering, Technion (2022–2023). She is also a licensed architect. Previously, she was a founding Partner with SAYA/Design for Change (2005–2017), practicing architecture, landscape architecture, and urban design. Her Ph.D. thesis developed cross-scalar methods for reconstituting found matter into landscape architecture and architectural structures using robotic tools. Her postdoctoral research, supported also by the Rothschild Fellowship (2021–2022) and the Israeli Council for Higher Education (2021), explores the possibilities of modulating grounds for environmental performance using collective robotic construction. She is an Azrieli Research Fellow during the Ph.D. degree. She received the Loeb Fellowship from the Harvard Graduate School of Design, in 2013.

ARI MELES-BRAVERMAN was born in Philadelphia, PA, USA. He received the B.S. degree in mechanical engineering from the Technion—Israel Institute of Technology, Haifa, in 2021, where he is currently pursuing the M.Sc. degree in mechanical engineering with the Civil, Environmental, and Agricultural Robotics Laboratory (CEAR).

OREN ELMAKIS received the B.Sc. degree in mechanical engineering from the Technion – Israel Institute of Technology, Haifa, Israel, in 2016 and 2019, respectively. He is currently a direct track Ph.D. student at the Civil, Environmental, and Agricultural Robotics Lab (CEAR) as part of the Technion Autonomous Systems Program – TASP. His research focus is on robotic multi-agents decision making, motion control, and collaborative state estimation in civil and environmental applications.

AMIR DEGANI (Member, IEEE) received the B.Sc. degree (summa cum laude) in mechanical engineering from the Technion Israel Institute of Technology, Haifa, Israel, in 2002, and the M.S. and Ph.D. degrees in robotics from Carnegie Mellon University, Pittsburgh, PA, USA, in 2006 and 2010, respectively.

From 2011 to 2019, he was an Assistant Professor in civil and environmental engineering with Technion and the Director of the Civil, Environmental and Agricultural Robotics (CEAR) Laboratory, researching robotic legged locomotion and autonomous systems in civil and agriculture applications. In 2019, he was promoted to a tenured associate professor. He is currently an Associate Professor with the Technion—Israel Institute of Technology. His research interests include mechanism analysis, synthesis, control, and motion planning and design, with an emphasis on minimalistic concepts and the study of nonlinear dynamic hybrid systems.

Prof. Degani has six patents in the robotics field and has received the Best Paper Award at the IEEE BioRob Conference, in 2006, the Best Video Award at the IEEE ICRA Conference, in 2010, and the JTCF Novel Technology Paper Award in IEEE IROS 2015. Until recently, he has been an Associate Editor of IEEE Transactions on Robotics and the IEEE ICRA and IROS Conferences.