Optimization of Grading Path Planning
for an Autonomous Construction Machine

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The construction industry, which faces an aging workforce and shortages of skilled labor, presents attractive opportunities for autonomous heavy construction machinery. To achieve this goal, many difficulties must be overcome. Most of the problems are nonlinear and cannot be solved through convex optimization. Bulldozer operation presents especially difficult challenges, as it is a skilled trade and obtaining an operational method for bulldozers analytically is difficult. In this study, we optimized the route planning of a simulated bulldozer by using a genetic algorithm. To properly evaluate the solution candidates, we developed a simulator that emulates the dynamics of a sand mound. This paper describes the developed simulator and discusses the optimization of bulldozer paths on construction sites.

Keywords: heavy construction equipment, genetic algorithm, optimal route search, simulation

1. Introduction

Owing to labor shortages, automation is highly desired in the construction industry. Construction tasks require skill and experience, but the number of skilled workers is decreasing because of declining birthrates and the aging of the population. For these reasons, automation in the construction industry is desired. However, automation is not widespread yet, and labor productivity in construction remains low, compared with other industries.

Bulldozer operation is one of the most important tasks required for major construction projects. The task is more complex than that of a backhoe or a road roller, requiring a highly skilled operator. For an autonomous bulldozer to operate efficiently, the earth moving path used by the bulldozer must be optimized. However, the mathematical formulation of the interaction between a bulldozer and the dynamic motion of soil is difficult, making the interaction difficult to optimize.

One option for path optimization is to apply a genetic algorithm (GA). The automatic parking technology of the car by GA is proposed [1]. The proposed method does not use nonlinear formulation of car motion but it optimized the trajectory by applying GA method. The research motivated us to apply GA to optimize path planning for bulldozers moving soil. Because solution searches using GA require the evaluation of numerous solution candidates, a simulator emulating the dynamics of earth and sand (hereinafter referred to sand) is needed for efficiency and cost control. Figure 1 shows an overview of the simulator developed in this research.

In the simulator, it is necessary to reproduce the movement and dynamics of a sand mound deformed by the blade of a bulldozer. As discussed in Section 2, the simulator calculates the behavior of the mound from the mechanical interaction between individual sand grains by using a discrete element method [2,3]. In principle, the accuracy might be improved if the number of soil particles was increased, bringing it closer to the actual number of particles, but the calculation overheads involved would be enormous. This makes simulation of each individual sand grain unrealistic for practical use, particularly for GA, which requires many executions of simulations to evaluate solution candidates.

However, a method has been proposed to reduce the computational load by applying a cellular automaton to simulate the behavior of sand [4,5]. We improved the cellular automaton-based method and implemented it on the developed simulator. This simulator was then used for optimization of the grading path in this study. This paper describes the developed simulator, and shows the results of optimization based on GA.

2. Development of a Dynamic Simulator for Sand Movement

2.1 Simulation of Sand Movement

The earthmoving task being simulated is an example of grading. This requires the bulldozer to move a pile of sand into a designated...
2.2 Modeling of Sand Dynamics

In this study, we developed a simulator using an improved cellular automaton method with low computational load. As shown in (1), the surface of the simulation area, which is parallel to the ground, is divided into equal-sized meshes. The height of the sand in each mesh is expressed by a real number contained in the matrix $M$. In other words, each mesh is represented as a prism with a certain height, as illustrated in Fig. 3.

$$M(i, j) = h_{i,j} \quad \text{(1)}$$

where $h_{i,j} \in \mathbb{R}$ is the height of the sand pile at the mesh position $(i, j)$. An appropriate mesh size is chosen to balance the tradeoff between accuracy and the computational load.

2.3 Reproduction of Sand Behavior

The simulator is intended to simulate two behaviors of sand: movement due to gravity and deformation due to the external force from the bulldozer’s blade. The model of sand movement used here is based on ESPM (Enhanced Sand Pile Model), a method of sand movement calculation developed by Pal-Castells et al. Calculations of the deformation of the sand from external forces are conducted based on the principles of soil mechanics, such that the sand above the sliding surface given by the angle of repose is moved by the external force.

2.4 Sand Movement Model

The movement of sand is reproduced in the simulation by shifting sand from higher elevations to lower ones, until the angle of repose is reached. In ESPM, the movement calculation is conducted between an arbitrary cell and whichever of its nearest eight neighbors has the maximum height difference compared to the chosen cell. The movement amount $m$ at this time is calculated by (2) and (3), based on the difference amount $\Delta M$ of the adjacent cells and the threshold value $\bar{h}$, where $z$ is a constant amount. The procedure above is then repeated to cover the entire area until there are no height differences large enough to cause movement.

$$M(i, j) = \begin{cases} M(i, j) + z & (\Delta M < \bar{h}) \\ M(i, j) - z & (\Delta M > \bar{h}) \\ M(i, j) & (otherwise) \end{cases} \quad \text{(2)}$$

$$M(i + k, j + l) = \begin{cases} M(i + k, j + l) - z & (\Delta M < \bar{h}) \\ M(i + k, j + l) + z & (\Delta M > \bar{h}) \\ M(i + k, j + l) & (otherwise) \end{cases} \quad \text{(3)}$$

$$\Delta M = M(i, j) - M(i + k, j + l), \quad -1 \leq k, l \leq 1$$

In the developed simulator, the threshold value is calculated from the perspective of soil mechanics based on the angle of repose, and the movement calculation is conducted using all eight cells adjacent to a given cell. The amount of movement $z$ in the developed simulator is not constant but the value calculated by (4). Where $K_r$ is a coefficient, $L_d$ is the relative distance between cells ($1$ for vertical and horizontal cells, $\sqrt{2}$ for diagonal cells), and $H_r$ is the height of the non-movement limit calculated from the angle of repose. As shown in (4), amount of the movement $z$ depends on the inclination of the slope. When the slope is steeper, the sand moves more resulting faster collapse. By repeating this calculation, the collapse by gravity of the sand is reproduced.

$$z = K_r \left( \frac{\Delta M}{L_d} - H_r \right) \quad \text{(4)}$$

The collapse calculation is terminated when the largest differences between adjacent cells fall below the threshold value. This condition is defined as the stable state, and it is assumed that the sand does not collapse any further once a stable state is attained. However, not only does the spreading of sand by a bulldozer create an unstable state in which the sand shape changes as sand collapses, but also the bulldozer continues spreading while the sand is still moving, before it reaches a stable state. Therefore, while the bulldozer is moving sand, the collapse calculation is repeated a fixed number of times during each step of the bulldozer’s forward motion, which corresponds to the bulldozer moving forward one mesh unit. This procedure therefore simulates the evolving unstable state of the sand pile before finally reaching a stable state while the bulldozer pushes sand.

2.5 Deformation of Sand Shape by External Forces

Figure 4 shows a model of the forces between the blade
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Fig. 4. Diagram of forces applied to the sand

Fig. 5. Deformation of sand pile under external forces

Fig. 6. Image of real operator’s bulldozer paths

and the soil. Sand pushed by the blade slides along a surface defined by the sliding angle $\omega$, according to the laws of soil mechanics. Sand in front of the blade experiences its own weight force $W$, the force $P$ from the blade, and the resultant force $R$ from normal drag and the shear resistance force generated inside the sand. Under the effects of these forces, the sand above the sliding surface moves forward. Figure 5 shows the deformation of the sand shape caused by external forces.

2.6 Characterization of Bulldozer Paths

The construction paths followed by a representative sample bulldozer driven by a skilled operator were acquired at the actual construction site using RTK-GNSS. Analysis shows that typical paths consist of several back-and-forth movements. While pushing sand around the site, including during grading operations of the type being simulated here, the bulldozer typically followed a linear path. The height of the blade from the ground is maintained from the start to the end of any given path, and it is changed only when moving to the next path. Therefore, straight trajectories with constant blade height are assumed in the simulation. Figure 6 shows an example of eight paths followed by real operators during grading work. In all paths, the bulldozer moved from the bottom toward the top.

2.7 Cubic Interpolated Propagation (CIP) Method for Oblique Paths

In the simulated grading operation, the bulldozer moves at various angles relative to the grid, as shown in Fig. 6. However, the grid of the field is divided horizontally and vertically, and the bulldozer is assumed to push the sand along the mesh. Therefore, when the bulldozer turns and the moving direction is set to the angle $\theta$, the traveling direction of the bulldozer is relatively reproduced by rotating the sand, represented in (1). Because the rotation of sand can be regarded as advection phenomenon, the CIP (Cubic Interpolated Propagation) method, a high-precision approximation technique used for numerical analysis of waveforms, is used to redistribute the sand to the newly meshed grid. This makes it possible to cope with the bulldozer traveling at any angle, rather than strictly along the rectilinear grid of the simulation. Figure 7 shows the sand before and after rotation. As shown in the figure the bulldozer path (blue line) in the right figure is parallel to the j-axis (vertical line) while the it is not parallel in the left figure.

3. Optimization of Path Planning with Just Generation Gap (JGG) Based GA

In the context of the simulated grading operation, the problem setting can be rephrased in terms of maximization of the filling ratio of sand within the designated area. The purpose is then to maximize the output of the objective function whose input is the construction path, and whose output is the filling ratio. Because this objective function is calculated by invoking the simulator, it is difficult to find the optimal path by analytical means. However, in the evolutionary computation represented by GA, the differentiability of the objective function is not required, and so long as feasibility of the solution is judged, a semi-optimal solution can be obtained. In this study, a JGG (Just Generation Gap) based GA, which enables to solve a semi-optimal solution with fewer evaluations than ordinal genetic algorithms, was selected as a generation change model. As can be seen from Fig. 6, in the case of the bulldozer spreading sand, it is necessary to move back and forth several times, and the final state is considerably influenced by the initial path, along with the subsequent path. Therefore, the Real-Coded Ensemble Crossover, otherwise known as REX, which is robust with respect to inter-variable dependence, is applied for the crossover operation. Table 1 shows the parameters used in the JGG.

3.1 Genetic Representation of Construction Path

To apply a JGG based GA to path planning, it is necessary to express the path in terms of genes. To perform the simulation, it is necessary to provide three inputs: the start point, the end point, and the blade height. A path taken by a skilled operator during preliminary observations of a real construction site was given as the initial path. Modifications are applied to the parameters listed above, which are represented by genes.
Changing the position of the start point and end point of each path corresponds to the modification of the construction path planning. Because the position of the starting point of the first path is the position where the bulldozer is waiting for the dumped sand mound, its position is fixed (not modified).

30 genes are required to generate a candidate route; these contain 15 pairs of x and y coordinates. In Fig. 8, one of the initial paths is modified by four genes to create another solution candidate. By applying this operation to all eight of the observed paths taken by a skilled operator, a solution candidate for the whole construction path was generated.

3.2 Evaluation of Each Gene

The purpose of the bulldozer grading operation is to move sand into the target area, marked by a rectangle in Fig. 2. Therefore, genes can be evaluated by how much sand is placed within the target area in the final state. The score of each gene was calculated from the final state of the simulation. The score $r_a$ is calculated in (5),

$$r_a = \frac{V_i}{V_d}$$

where $V_i$ is the volume of sand contained in the target area in the final state, and $V_d$ is the volume of the target area. The volume of sand to be unloaded by the truck and the volume of the target shape is simulated as $25 \text{ m}^3$. A higher evaluation score indicates that less sand has been spread outside the target area.

4. Problem Setting

4.1 Simulation Conditions

The parameters used in the simulation were set as in Table 2. The sand dumped by the truck is assumed to accumulate in a conical shape. Because this cone is assumed to be stable, the angle between the sides of the cone and the ground is the angle of repose.

4.2 Deviation of the Initial States

In the construction process, the truck enters the field by moving backward to unload sand as shown in Fig. 9. In practice, dump trucks do not always unload sand at the exact target position. Deviation may arise from the desired unloading position. Therefore, the initial position of the unloaded sand was assumed to deviate from the expected position by as much as $-0.6 \text{ m}$ to $+0.6 \text{ m}$ along the horizontal axis, with different initial positions at $0.2 \text{ m}$ intervals. Then, the optimum construction path was searched for the seven initial positions of unloaded sand. Figure 10 shows the deviated initial state.

4.3 Interpolated Adjustment of Optimal Construction Path

In the seven different initial patterns, the initial path (skilled operator’s path) and the target shape are the same, and only the dumped position of the sand mountain changes. Therefore, the difference in the calculated paths is influenced by the location of the sand. We expected a correlation between the unloaded position of sand and the optimized path. Therefore, we used a least squares method, treating the displacement of sand as an independent variable and the values of the x and y coordinates in each path as dependent variables. Thirty approximate expressions can thus be obtained, one for each coordinate in the path. This approximation formula is used to adjust the optimum construction path when the initial unloaded position of the sand is shifted by 0.01 m steps from $-1.0 \text{ m}$ to $+1.0 \text{ m}$. The filling ratio in the predicted path is then evaluated by simulation.

5. Results of Optimization

5.1 Operator’s Route

Figure 11 is the final state
when the soil and sand were spread along the operator’s route. As shown in the figure, when the work is carried out by the route of the skilled operator, the sand is sufficiently spread within the target range. The filling rate of sand in the target shape was 93.36%.

5.2 Search Results for the Optimal Route Figure 12 shows the results using a JGG based GA in seven initial states. In each initial state, the evaluation score rises as the number of calculations increases, and almost all cases converge at the $1.0 \times 10^5$ calculations. Table 3 shows the filling ratio obtained with the optimized path in each of the seven initial states. In each case, the filling ratio exceeds that of the operator’s route. This result verifies that the optimization by the proposed method is superior to that by the skilled human operator. The calculation time in each case is also shown in Table 3.

5.3 Formulation of Optimum Construction Path for Initial Deviation Figure 13 shows the routes calculated under the initial conditions of seven different patterns. On examination, it is observed that the entire route changes in response to changes in Δdump, which is horizontal deviation of the initial position. Figure 14 summarizes the coordinate value on the vertical axis of the start point in the fourth route, which changes the most in accordance with Δdump. In the figure, the linear approximate line is obtained using the least squares method.

The graph shows that there is a linear relationship between Δdump and the coordinate values. This relationship can be seen in other coordinates. Therefore, by using the linear correlation, the optimum route can be predicted for the deviation of initial unloaded sand location. The path was predicted for 201 values of Δdump, chosen at 0.01 m intervals from the offset of $-1.0 \text{ m}$ to $+1.0 \text{ m}$. The evaluation scores of the predicted paths were calculated by simulation. Figure 15 shows the results. The interpolated routes show consistently superior scores, compared to the operator’s original path, which achieves 93.36% filling rate. These results indicate that the optimal route planning against initial deviation of sand performs well. While the maximum Δdump used to provide data

### Table 3. Score for each initial state

| Δdump [m] | Score [%] | Time [sec] |
|-----------|-----------|------------|
| -0.6      | 98.29     | 78,878     |
| -0.4      | 98.41     | 79,389     |
| -0.2      | 98.35     | 79,196     |
| ±0.0      | 98.24     | 80,025     |
| +0.2      | 98.34     | 79,429     |
| +0.4      | 98.28     | 79,961     |
| +0.6      | 98.21     | 78,377     |

Fig. 13. Routes calculated under different initial conditions
for the prediction was 0.6m as shown in Fig. 14, a \( \Delta \text{dump} \) of 1.0m nonetheless allowed the bulldozer to achieve superior work paths to the skilled operator by the optimization of the route.

6. Evaluation using Bulldozer-emulated Experimental Device with Real Sand

In order to evaluate performance on the dynamics of real sand, we newly developed an bulldozer-emulated experimental apparatus which can push sand along the designated route. The filling rate (score) for the route of the proposed method was evaluated by 3D measurement method. The size of this sand pushing area corresponds the scale of 1/100 of the actual construction site.

6.1 Experimental Setup  The experimental setup is shown in Fig. 16. The blade, which emulates the motion of the bulldozer, is actuated by PC-controlled motors with 4 degrees of freedom, which enables linear motions of x, y, z axis and yaw axis (rotation around z axis). The funnel in Fig. 16 is used to emulate the dumping the sand on the mound. Sand granules dropped through the funnel pile up the sand mountain on the base mound. During the experiments, the funnel was removed from the experimental apparatus and the blade was driven along the route calculated by the method in Section 5.2. Figure 17 shows the blade pushing sand.

After the completion of the designated motion of the blade,
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Fig. 20. Results of tasks on deviation of dumped sand

| Δdump [mm] | Score [%] |
|------------|-----------|
| 0.0        | 97.68     |

Table 4. Filling rate by the operator’s route

Table 5. Filling rate variations on deviation of dumped sand

| Δdump [mm] | Score [%] |
|------------|-----------|
| −6.0       | 95.45     |
| −4.0       | 94.53     |
| −4.0       | 95.88     |
| ±0.0       | 94.57     |
| +2.0       | 94.96     |
| +6.0       | 93.68     |

Table 6. Filling rate by the generated route from formula based on optimized routes

| Δdump [mm] | Score [%] |
|------------|-----------|
| −10.0      | 91.35     |

the shape of spread sand was measured by a method based on photo matching and converted into a three-dimensional point cloud for rating the filling score.

6.2 Experimental Results

Figure 18 shows an experimental result of spread sand using the operator’s route and Fig. 19 shows the one using optimized route. Figure 20 shows the results of 7 routes whose dumped sand position were deviated from the original position. These routes were optimized using GA at 5.2. The filling rate of each experimental result is shown in Table 4 and Table 5. The filling rate of all optimized paths exceeded that of the operator paths. In the experimental result by the execution route of the operator, the sand is not filled in the upper right of the target shape. On the other hand, the experimental results of the optimized route show that the whole target shape is filled with sand evenly in both cases. Therefore, the route optimized by the simulator achieved higher filling rate than the route of the operator even in experiments using actual sand.

Figure 21 shows the final state using the route generated by the formula calculated by the method described in Section 5.3. The score is shown in Table 6. Even though the dumped sand position shifted significantly to the left (−1.0 m), which exceeds the range by GA calculation (±0.6 m), the filling rate of the optimized path predicted by the formula was also better than that of the operator’s route.

7. Conclusion

This paper describes a newly developed earth and sand moving simulator, its use to reproduce the behavior of soil being moved by a bulldozer, and the optimization of the work path of the bulldozer. The route of the bulldozer was optimized by applying an REX+JGG based GA method. The optimized routes were evaluated by a comparison with a skilled human operator’s route, and it was found to perform better than the human operator. This paper also describes a method for adapting the optimized routes to the deviation of the initial unloaded sand position; routes adapted in this manner also showed a better performance than that seen from the human operator.

Additionally, in order to evaluate on the dynamics of real sand, a bulldozer-emulated device was newly developed and experiments were conducted by implementing both operator’s route and optimized routes calculated by GA. The experimental results confirmed that optimized route achieved higher filling rates than the operator’s routes.

References

(1) K. Okawa and A. Mogaki: “Path Planning and Consecutive Operation Based on Discrete Acquired Motion Data for Auto Parking System”, Journal of the Robotics Society of Japan, Vol.29, No.4, pp.376–383 (2011) (in Japanese)

(2) T. Tsuji, Y. Nakagawa, N. Matsutomo, Y. Kadono, T. Takayama, and T. Tanaka: “3-D DEM simulation of cohesive soil-pushing behavior by bulldozer blade”, Journal of Terramechanics, Vol.49, No.1, pp.37–47 (2012)

(3) M. Uçgül, J. Fiekle, and C. Saunders: “Three-dimensional discrete element
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