Human Skill Quantification for Excavator Operation using Random Forest

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Abstract
In the construction field, the improvement of the work efficiency is one of important problems. However, the work efficiency using construction equipment is depend on their operation skills. Thus, in order to increase the work efficiency, the operation skill is required to be quantitatively evaluated. In this study, the Random Forest (RF), one of machine learning method, is adopted as the quantitatively evaluation for the operation skill of construction equipment. Evaluated target is the operation on an excavation to load onto a truck for a hydraulic excavator. The RF learns to classify some states by the pilot of skilled worker’s operation. States are defined as ‘dig’, ‘lift’, ‘dump’, ‘reposition’, and ‘idle’. The RF with the learning result of skilled worker is applied to other operator’s operation. It is revealed that the ratio of ‘idle’ is related to their skill.

Keywords: human skill, machine learning, random forest, hydraulic excavator

1. Introduction
In the field of construction industry, the application of Information and Communication Technology (ICT) for construction equipment has been proceeded to improve the productivity, which is called ‘i-Construction’ in Japan. However, work efficiencies of some construction equipment depend on operation skills for each operators. Therefore, it is necessary to establish a method to evaluate the operation skills so that it is possible to improve the productivity in the field of construction industry.

In previous studies, the human skill evaluation based on the engineering approach has been proposed and the evaluation of operation skills based on interviews has been investigated. However, these methods focus on the qualitative evaluation only and it is difficult to utilize them to improve the productivity.

In this paper, a quantification method of operation skills for construction machines based on classifications of operation state using the Random Forest (RF) is

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proposed. The proposed method is applied to the excavator operation.
RF is a kind of machine learning methods proposed by Leo Breiman in 2001.\(^4\) RF is constructed by some decision tree. Since the decision tree is an aggregate of branching rules, it is widely used to perform data mining for the certain classification problems because the learning result is more readable than other machine learning methods.\(^5,6\) Moreover, RF has the lower computational cost for the classification.

2. Proposed method

2.1. Classification of decision tree

The learning data for the decision tree is comprised of a set \(X\) and a set \(Y\). The set \(X\) consists of feature vectors, \(x_t\), which are one-dimensional vectors included the feature of data. The set \(Y\) consists of natural number, \(y_t\), which are labels for the classification. Those formula are shown by:

\[
X = \{x_t | t = 1, 2, ..., n\}, \quad y_t = \{x_{ti} | j = 1, 2, ..., m\} \tag{1}
\]

\[
Y = \{y_t | t = 1, 2, 3, ..., n\} \ (y_t = 1, 2, 3, ..., K) \tag{2}
\]

where \(n\) is defined as the number of training data, \(m\) is defined as the dimensions of the feature vector and \(K\) is defined as the number of labels. A set of training data, \(T\) is defined as follows:

\[
T = \{t_t | t = 1, 2, 3, ..., n\}, \quad t_t = \{x_{ti}, y_t\} \tag{3}
\]

2.1.1. Training procedure

The set of initial training data is shown as \(T_0\). The branch part is expressed as a node \(N_t\), and the initial node is \(N_0\). The learning procedure is shown for each step below.

[Step 1-1] Sampling feature vector
The sampled feature vector given as follow:

\[
\tilde{x}_t = \{x_{ti} | j \in J\} \tag{4}
\]

where \(J\) is a set of \(m\), whose components are natural numbers selected randomly without overlap among \(1, 2, 3, ..., m\).

[Step 1-2] Determination of branching condition
\(j\) is defined as the selected index of feature vector element, \(c\) is defined as the threshold that threshold that divide the training data into two. The selected index, \(j\), and the threshold, \(c\), have the following conditions:

\[
j \in J \quad \min(x_{ij}) < c \leq \max(x_{ij}) \tag{5}
\]

\[
T \text{ is divided into a set } T_1 \text{ with } x_{ij} \leq c \text{ and a set } T_2 \text{ with } x_{ij} > c. \text{ Then, } j \text{ and } c \text{ which minimize the following } \Phi(T, T_1) \text{ are obtained.}
\]

\[
\Phi(T, T_i) = I(T) - \sum_{k=1}^{2} P(T_k|T) I(T_k) \tag{6}
\]

\[
I(T) = 1 - \sum_{k=1}^{2} P^2(C_k|T) \tag{7}
\]

\[
\text{here } P(A|B) \text{ is the ratio of elements } A \text{ in } B. C_k \text{ is a set of } t_t \text{ with label } k; j, \text{ and } c \text{ are obtained with the state of minimized } \Phi(T, T_i). \text{ Further, nodes } N_{t_1} \text{ and } N_{t_2} \text{ are generated for } T_1 \text{ and } T_2.
\]

[Step 1-3] Save training data
\(j, c, t_1, t_2, \text{ and } T\) are saved as training data of \(N_t\).

[Step 1-4] End judgment
When \(T_1\) or \(T_2\) do not satisfy the following termination condition shown below, Step 1-1 is repeated with \(T_{t_1} \rightarrow T, t_{1,2} \rightarrow t\).

Termination condition:
(i) \(T_1\) or \(T_2\) has a only single label.
(ii) The number of data in the data set is less than or equal to a certain value.
(iii) The certain depth is achieved at a branch.

2.1.2. Classification procedure

\(N_{t_1}\) or \(N_{t_2}\) is called the child node. The feature vector of validation is \(x = \{x_j | j = 1, 2, ..., m\}\). \(l\) is initialized with 0.

[Step 2-1] Confirm existence of child nodes
If there is a child node in \(N_{t_1}\), step 2-2 is performed. Otherwise step 2-3 is performed.

[Step 2-2] Go to the child node
If \(x_j \leq c\), step 2-1 is performed with \(N_{t_1}\) again, otherwise step 1 is performed with \(N_{t_2}\) again.

[Step 2-3] Output of results
The label \(y\) with the largest number of data is the output at \(T\) of \(N_t\).

2.2. Random Forest

The scheme of random forest is shown in Fig. 1.
2.2.1. Training of Random Forest

RF is composed of a plurality of decision trees. Therefore, RF needs to generate training data of decision trees. It is assumed that training data is given to RF as Eq. (1) and (2). Thus, a training data of the decision tree in RF is given as follows:

\[ \hat{X} = \{x_i | i \in I \}, \hat{Y} = \{y_i | i \in I \}, \]

where \( I \) is a set of \( n \), whose components are natural numbers selected randomly without overlap among 1, 2, 3, ..., \( n \). The data sets expressed by (9) is generated for the number of decision trees and used for training each decision tree. The overlapping between data of decision trees is allowed.

2.2.2. Quantification

\( N \) is defined as the total number of decision trees. \( L \) is defined as the number of decision trees outputting the specific label. The ratio of \( L \) in \( N \) is shown as \( Q \) below:

\[ Q = \frac{L}{N} \]

The result of ratio can express the quantification.

3. Experiment Evaluation

3.1. Experimental device

The experiment focused on the quantification of the operation skill by the hydraulic excavator. As shown in Fig. 2, it is known that the general work of loading dump of earth and sand with a hydraulic shovel is classified into four states of "dig", "lift", "dump" and "reposition". This study classify the state of work into 5 state, which are above states with "idle". The "idle" state shows no operation. The operation of the hydraulic excavator is composed of four operations of "bucket", "arm", "boom", and "swing". These input signals of operations were acquired as pilot pressures. The pilot pressure is the input pressure to the valve corresponding to the lever operation amount. A simple configuration diagram of the hydraulic system is shown in Fig. 3. In this paper, eight types of pilot pressures is adopted as the elements of the feature vector to be used for RF, bucket dig / dump, boom up / down, arm pull / push and right turn / left turn.

3.2. Experimental procedure

The experimental procedure in this paper is shown below. [Step 1] RF learn labels of 5 states by pilot pressures of a skilled worker. [Step 2] Using the Result of Step 1, operation data of unskilled worker, general worker, and skilled worker is classified. At this time, the ratio of the predicted label is evaluated.

Ta ratio of the "idle" state is related to the skill level.
3.3. Evaluation results

Table 1 shows parameters of the proposed method. Table 2 shows the result of quantification, that is the ratio of decision trees with the "idle" state. Table 3 shows the result of training with 50 times using the same input / output data. This result shows the validity of RF. The ratio of decision trees with "idle" is getting bigger from the skilled worker to the unskilled worker in Table 1. The operation that have the larger difference, dump motion, is extracted in Fig. 4-6. The general worker has the single operation with the “idle” state around 1900 step in Fig. 5. The unskilled worker has the shortage of the operation of dump and arm push. The pilot pressure does not reach to 80% or more. Thus, “idle” ratio represents the lack of operation in the work.

![Part of pilot pressure by skilled worker](image1)

![Part of pilot pressure by general worker](image2)

![Part of pilot pressure by unskilled worker](image3)

4. Conclusion

This paper has proposed a quantification method of operation skills in excavation work of a hydraulic excavator based on RF. The paper also clarified the lack of operation by observing the proportion of decision trees in the RF that determined the operation state to be in the "idle" state. As the future work, other state are classified by using internal state and output. Moreover, the proposed method can be utilized to improve the work efficiency.

References


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