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OPERATION SKILL ANALYSIS USING PRIMITIVE STATIC STATES IN HUMAN-OPEATED WORK MACHINE

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ABSTRACT: Double-front construction machinery, which was designed for complicated tasks, requires intelligent systems that can provide the quantitative work analysis needed to determine effective work procedures and that can provide operational and cognitive support for operators. Construction work environments are extremely complicated, however, and this makes state identification difficult. We therefore defined primitive static states (PSS) that are determined using on-off data for the lever inputs and manipulator loads for each part of the grapple and front and that are completely independent of the various environmental conditions and operator skill levels. To confirm the usefulness of PSS, we performed experiments with a demolition task by using our virtual reality simulator. We confirmed that PSS could robustly and accurately identify the work states and that untrained skills could be easily inferred from the PSS-based work analysis. We also confirmed in skill-training experiments that advice information using PSS-based skill analysis greatly improved work performance. We thus confirmed that PSS can adequately identify work states and are useful for work analysis and skill improvement.

Keywords: Construction machinery; Operation skill; Work analysis; Skill analysis; State identification

1. INTRODUCTION

The double-front construction machinery (DFCM) [1] shown in the right side of Fig. 1 was developed in response to recent needs for construction machinery that can be used not only for conventional simple earthwork such as ground leveling, transportation, excavation, and loading but also highly skilled, complicated work such as sorted dismantling work needed for recycling and reusing resources, rescue and recovery work at disaster sites, and building construction work.

While double-front operations might be expected to be similar to skillful human actions, the fronts (as manipulators are called in the construction machinery field) on the double-front construction machinery have more than twice the number of degrees of freedom that those on single-front machinery do. This requires the equipment operators to have extremely high-level operating skills and this could lead to reduce the quality and efficiency of their work by making machine operation confusing. Operators concentrating on more difficult machine operations are also less likely to notice nearby workers or hear warnings from coworkers.

One way to address these skill and safety problems is by developing advanced human-operated work machines with an intelligent system that provides the operational and cognitive support that operators need to work efficiency and safety or provides a quantitative work analysis that needs to determine effective and safe work procedures. For providing more effective support, the system must adequately indentify the current work state (e.g., removing) or operator state (e.g., attentiveness). In other words, a state identification method is extremely important to construct an intelligent system. Surgeons and automobile drivers are supported by intelligent system using robot and information technology and these have been put to practical use, but their work states are more easily identified than those in which construction machinery used. This is because 1) the work environment is complicated, and this is especially true in demolition work where the use of DFCM is necessary. 2) The shape and position of the objects manipulated in construction work continually change, and 3) skill levels and operational methods differ from one operator to another.

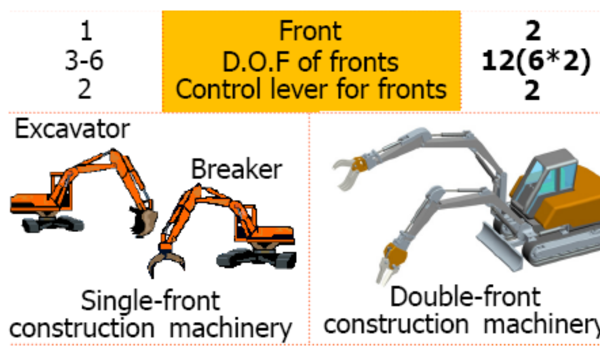

Figure 1. Greater difficulty in controlling advanced construction machineries

We can see that it is much more difficult to identify the work or operator states in the above three characteristics about construction machinery.

Technology for the intelligent control of construction machinery has conventionally been developed in an application-specific way, and research efforts have been devoted to areas such as oscillation-stopping control for cranes [2], remote operation of excavators [3], intelligent oil-hydraulic control [4], and the analysis of power shovel operational [5]. We know of no systematic examination of state identification technology for human-operated work machines like construction machinery.

2. RELATED AND REQUIRED WORK IN STATE IDENTIFICATION

2.1 Conventional State Identification Methods

Many researchers have already reported on different types of state identification techniques, and the hidden Markov models (HMM) [6], [7], dynamic Bayesian networks (DBN) [8], and support vector machines (SVM) [9] have been proposed. These methods have the advantages can handle identification systematically by optimization, but for getting a desired output result they must still require an enormous amount of input data for learning, a suitable pre-processing, parameter adjustments, and so on. A systematized theory for a method of adjusting these parameters has yet to be designed, and at present we have only a trial-and-error method [10].

2.2 Required State Identification Method for Construction Machinery

As mentioned Chapter 1, a state identification method needs to consider the characteristics of construction work environment and construction machinery. An important point for developing a state identification method is how to avoid misrecognition of work states. In other words, a state identification method for construction machinery strongly requires high reliability and robustness that mean not misidentification in any kind of situation. From this standpoint, we understand that it is difficult to use the above mentioned methods (e.g., HMM) that cannot sufficiently and stably respond to the variety of the applied field.

We therefore define a basic work state unit that is completely independent of the various environmental conditions and operator skill levels for certain and robust identification, and that are applicable to all types of construction machinery, including DFCM.

3. PRIMITIVE STATIC STATES

In developing a state identification method, we must address three factors: choice of input data, method of data processing, and extraction parts of input data.

3.1 Input Data

1) Relationship: Focused on I/O for the structure of human-operated machines, we can describe their system as follows: an operator operates manipulators by moving control levers (intention input) and then the machine recognizes the operation order and performs actions in the environment (movement output). Thus, to define the machine's most basic state unit, we must determine the operator's operational intention and the machine's movement output.

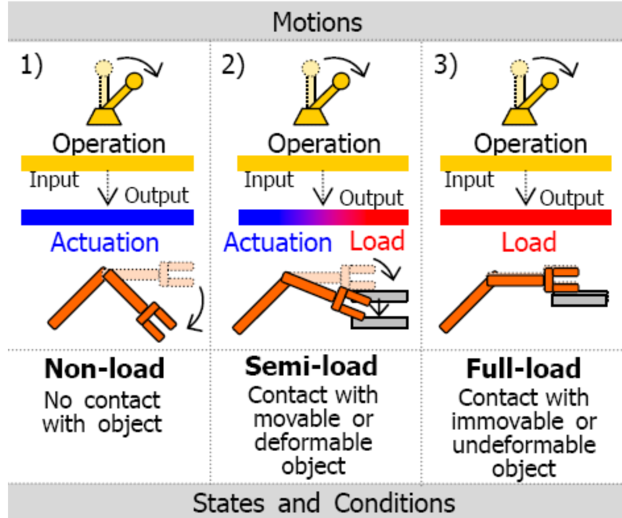

Figure 2. Basic three motions classified by relations among lever operation, joint actuation, and joint load

Analyzing the machine's movement outputs, we found that they can be classified into the following three patterns.
1) Non-load motion: when there is no contact with the environment (e.g., as in reaching), the machine outputs all the operation input as actuation. 2) Semi-load motion: when the machine makes contact with a movable or deformable part of the environment (e.g., when bending of a wooden beam), it divides the operation input into actuation of the manipulator and application of force to the environment. 3) Full-load motion: when the machine makes contact with an immovable or undeformable part of the environment (e.g., when pressing against a large wall), it applies all the operation input to the load. Furthermore, we understand that these three parameters (operation input, actuation output, and load output) are important. The relations among them are shown in Fig. 2.

2) Refinement: The eight work states identifiable by combinations of the on-off levels of the three parameters are listed in the rightmost column of Table 1. Analyzing this table, we found that state 5), external force motion, and

Ope.	Act.	Load	Work state
ON	**ON**	**ON**	**1) Semi-load motion: Bending**
ON	**ON**	**OFF**	**2) No-load motion: Reaching**
ON	OFF	ON	3) Full-load motion: Pressing
ON	OFF	OFF	4) Out of order: Abnormal state
OFF	ON	ON	5) Ex-force motion: Hit a falling object
OFF	ON	OFF	6) Inertia force motion: Sudden stop
OFF	**OFF**	**ON**	**7) Keeping load: Holding**
OFF	**OFF**	**OFF**	**8) Idling: Safety confirmation**

state 6), inertia force motion, are not appropriate for work state definition because they are passive motions. Furthermore, state 4) is also inappropriate because it appears to be a fault condition. We thus found that a basic work state is more highly selected by omitting actuation parameters. Although state 3), full-load motion, can be specified by using the actuation, it is also important to avoid redundant classification.

Therefore, the high-quality input data including relative parameters of operation intention and machine actuation is provided. We assumed that the operator's intention is conveyed by the angle of the control levers and that the machine's actions are the loads imposed on each manipulator's joints. Finally, four states can be identified: 1), 2), 7), and 8).

3.2 Data Processing

We think that work states would be defined better by using sensor date analogously or vectorially, but that information greatly depends on various elements (such as the position and the size of the work object, the machine's specifications, and the operator's skill levels), and it is difficult to define work states by using the trajectory of the end-effector or the magnitude of the joint load. This problem can be solved by optimizing the threshold using statistics processing or using machine learning, but that method cannot be used in all situations. When defining work states using uncertain data, the stability and certainty of the work states would be reduced and the utility value as a basic work states might fail.

We therefore decided to use only binary information: the on and off states of the above input data.

3.3 Extraction Parts of Input Data

Standard construction machinery has many kinds of actuation parts, such as crawler tracks, wheels, rotating pivots, fronts, attachments, and blades. We think that information on manipulators, which actually perform the work, can adequately describe working states, so we decided to treat only manipulator information. With the manipulator with multi joints it is desirable to treat all the DOFs of the manipulator when defining a basic work state that focuses the on and off states of the interaction with the environment. However, a manipulator having a DOF in the end-effector (EE) does different work depending on the attachment types such as a grapple, cutter, or clamshell.

We therefore divide this kind of manipulator into two components: a non-EE (hereinafter called the ARM) and an EE (hereinafter called the HAND). Furthermore, in a situation without a load, the manipulator applies direct action (e.g., grasping or cutting) to the environment via the HAND whereas the ARM performs indirect action (e.g., reaching), that means the ARM is only used to control the position and posture of HAND. Thus their usage purposes are clearly different.

We therefore decided to extract the input data (lever input and joint load) from the two components: the ARM and HAND for the more detailed work state identification.

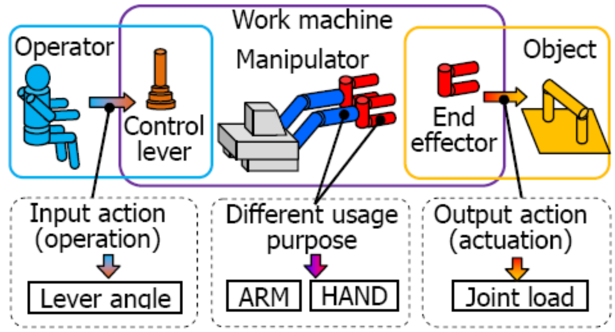

Figure 3. Design parameters derived by relations among operator, work machine, and object.

In addition, in DFCM with twin manipulators, we decide to treat the left and right ones individually.

3.4 Primitive Static States

Based on previous sections, we defined basic work states using on-off information for the lever operations and joint load, which represents the interaction between the operator and environment, for the HAND and ARM, which represent differences in interaction with the environment either directly or indirectly. These states are the most basic states determined static information, so we call them primitive static states (PSS). The model that we used to define them is shown in Fig. 3. When we focus on a single arm, there are 16 separate states (2^4), and when we focus on for a double arm, there are 256 (16^2). The work states assigned to each of the 16 combinations of input data values states (PSS: A-P) are listed in Table 2. For example, when HAND load = 0, Hand operation = 0, ARM load = 0, and ARM operation = 1, the PSS(B) is reaching work, and when HAND load = 0, Hand operation = 0, ARM load = 1, and ARM operation = 1, the PSS(D) is compressing work.

Table 2. Primitive Static States (PSS)

PSS no.	Input data*				Work state (example) (HAND: Grapple)
	HL	HO	AL	AO	
A (00)	0	0	0	0	Non-operation and Load
B (01)	0	0	0	1	Reaching
C (02)	0	0	1	0	Holding / Grasping
D (03)	0	0	1	1	Compressing
E (04)	0	1	0	0	Hand Open / Close
F (05)	0	1	0	1	Reaching + Hand Open / Close
G (06)	0	1	1	0	External force during handling
H (07)	0	1	1	1	Object operation in hand outside
I (08)	1	0	0	0	Holding of object on ground
J (09)	1	0	0	1	Abnormal state
K (10)	1	0	1	0	Holding of aerial object
L (11)	1	0	1	1	Transporting/ Bending/ Removing
M (12)	1	1	0	0	Cutting/ Setting
N (13)	1	1	0	1	Abnormal state
O (14)	1	1	1	0	Cutting/ Setting
P (15)	1	1	1	1	Throwing out

*HL: HAND load, HO: HAND operation, AL: ARM load, AO: ARM operation

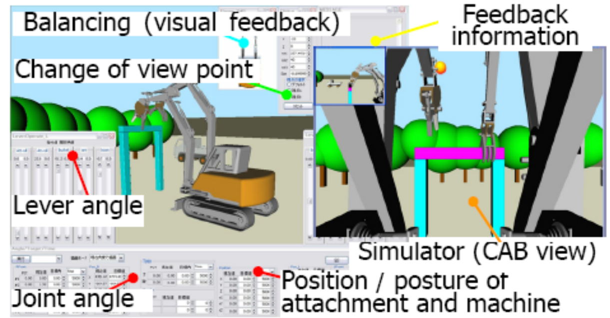

Figure 4. Graphical display of the developed simulator. We reproduced operational gain, sounds, and oil delay, and physical behavior in the environment.

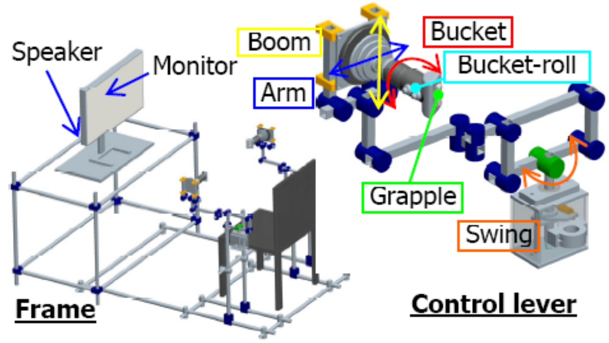

Figure 5. Experimental setup of the developed simulator. An operator controls CG models by grasping the control lever and inclining it.

4. WORK STATE IDENTIFICATION USING PSS

To evaluate the effectiveness of using primitive static states, we performed a state identification experiment in which the work environment conditions and operators were changed, using our VR simulator as shown in Figs. 4 and 5 (detailed specification given in [11]).

4.1 Experimental Conditions

Each experimental task (A or B) was to remove, using a single front, a beam fixed on two columns. For task A the beam was 5.0 m above the ground and 3.5 m from the front of the machine, and for task B the beam was 3.0 m above the ground and 5.0 m from the front of the machine. In task B the bond between the beam and column was twice as strong as it was in task A. Two operators who had used to VR simulator enough to be considered experts were used as subjects.

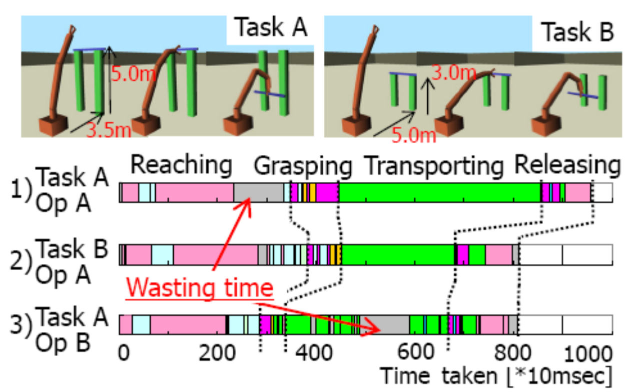

Figure 6. Work state identification using PSS

4.2 Results

The experimental results are shown in Fig. 6, where the horizontal axis is the time taken and the colors of the bars represent PSS (relations between state and color are given in Table 2). From the results with each different task condition and operator, we found that same work procedure (reaching, grasping, transporting, and then releasing) was identified under all experimental conditions. In other words, even when we changed the destination position, dynamic restriction, and operator, the PSS could distinguish the work states. Furthermore, we analyzed the results. Comparing the results shown in lines 1) and 2) in Fig. 6 for which the environmental conditions were the same, we found that for 1) the operation time to complete a task was longer than that for 2). And analyzing the PSSbased operation time, we also found that excessive transportation time was one specific cause of delay for 1). In addition, comparing the results shown in lines 2) and 3) for which operation time to complete a task was the same, we found that for 2) the reaching time was longer than that for 3) and that for 2) the transporting time was shorter than that for 3), and that for 3) there was a particularly useless stoppage during transportation.

When getting the two data that the total time taken is the same, we cannot help but judge the same operation

skill, but the unskilled work or cause of delay can be estimated
comparatively easily by analyzing those based on PSS.

5. WORK AND SKILL ANAKYSIS USING PSS

We applied the analysis results of PSS-based state identification to work and skills analysis.

5.1 Skill Analysis in a Demolition Task

Ten healthy adult males (20-25 years old) having no experience of any kind with the operation of construction machinery were used as subjects. The task, which modeled work done in the demolition of wooden house, was to remove roof boards by using DFCM. Five long boards were attached to a framework consisting of columns and

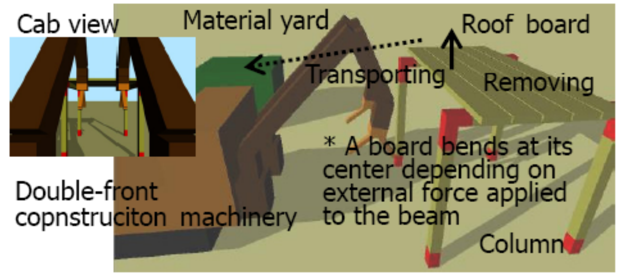

Figure 7. Experimental condition in Skill-training

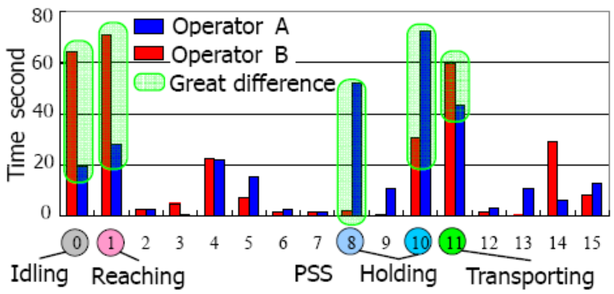

Figure 8. Comparison with two operators about left manipulator

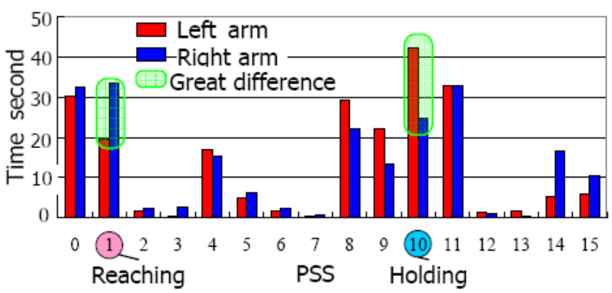

Figure 9. Comparison with left and right manipulator about one operator

beams. The subject's task (Fig. 7), using the two fronts, was to remove the board closest to him, and transport it to the target position without bending it, release it there, and then go back to remove the next beams until all five had been moved from the framework to the target position. We present skill analysis example concerning the time taken.Fig. 8 shows the PSS-separated time taken for the two subjects whose total time was the same and Fig. 9 showsthe PSS-separated time taken for right and left arm on one subject. The number of the horizontal axis represents each PSS (see Table 2).

1) Analysis of work: One can see in Fig. 8 that the idling time (PSS (00)) and reaching time (PSS (01)) of operator A were long. For operator B, on the other hand, the idling, reaching, and transportation time (PSS (11)) were short, but the holding time (PSS (08 and 10)) was long. From these analysis results, we can guess that operator A was not used to machine operation and therefore spent much time on reaching and transportation and that operator B spent much time con-firming that the two end-effectors stably held the beam.

2) Analysis for arms: From Fig. 9 we can see that the holding time for the left arm was so long that this subject might have operated the machinery by first reaching with the left hand and then performing the same action with the right hand. We can also see that the reaching time for the right arm was longer than that for the left one, suggesting that the left arm operation was more skillful than the right one. Further-more, a single-arm approach resulted in useless waiting time.

We can surely extract operator characteristics by work analysis using PSS. PSS-based analysis can provide useful information concerning not only time taken but also other data (e.g., position, speed, or load related to each joint).

5.2 Application to Operation Skill-Training

From the results of previous section, we think that providing advice information based on PSS-based skill analysis would improve the operator's work performance. We therefore performed an operation skill-training experiment. To validate the utility of support information with PSS (PSS support) we compared two other experimental conditions, one providing no advice (nonsupport) and the providing obtained data without PSS analysis (normal support).

We divided the subjects into three groups according to their simulator experience: group 1 (four novices), group 2 (three novices), and group 3 (three experts). After pretraining for 20 minutes, all subjects performed the task shown in Fig. 7 with four sets per day for three successive days. The support con-tent was changed for different groups and on different days. On the first day, all groups were given non-support to en-able us to measure standard skill improvement degree. On the second day, group 1 was given PSS support, group 2 was given normal support (total data through the whole work), and group 3 was given non-support to enable us to measure the effectiveness of PSS support in skills improvement. On the third day, we gave PSS support to all groups and inspected the improvement of work performance for group 3. Support information was the time taken, the relative position of the two EEs, and the number of lever operations used to get there and back. Furthermore, we compared the concerned trial data with the average of all the subjects and the latest trial data for the operator's own and then quantified their difference and clarified good or weak skills and tasks. We presented the analyzed data table and describe the great different data as the concrete improvement points. These are provided at pre-training and during the break time (5 min) between training sets. The relationship between the trial number of times (in total 12 times for three days) and time taken to complete a task for three groups is shown in Fig. 10.

1) Decrease in time taken: For groups 1 and 2, there was hardly any difference at the end of the first day, but we found that group 1, which was given PSS support, had largely improved operational skills by the end of the second day. Two-tailed t-testing revealed that at the end of the second day the difference between groups 1 and 2 was statistically significant ($t = 2.62$, $p < 0.05$). Furthermore, when we examined the first and second days for group 3, we found a tendency for the time taken to decrease as operations became used to the task. When the training extended over more than one day, however, we found that their operational skill level was reset to the level at the beginning of first day. Two-tailed t-testing showed no significant between trials at the end of the first day and the beginning of the second day ($t = 0.77$, n.s.). We can also see that at the end of the second day the time taken was

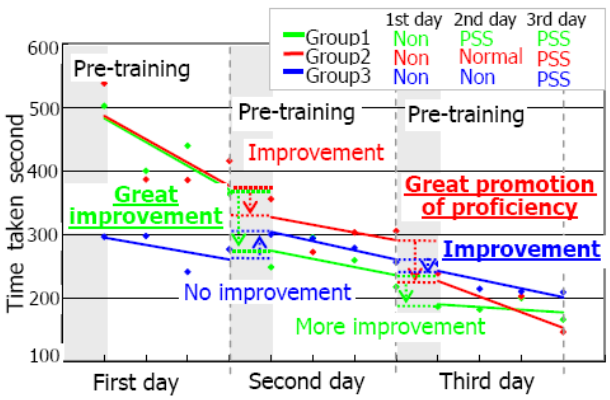

Figure 10. Training effect with information support

shorter for group 1 than it was for group 3 even though group 1 was less experience than group 3. From these results, we confirmed that information support based on PSS easily reveals the shortage operation skills and are very effective for improving operation skills.

2) Promoting skills improvement: For groups 2 and 3, which were provided PSS support on the third day, it would be expected that at the end of the second day the time taken is shorter for the group 3 as same as that for group 1. From Fig. 10, we found that the time taken for group 3 on the end of the third day was shorter than that taken for group 1 on the end of the second day. In addition, although the operators in group 3 trained for two days, no improvement in their work performance was seen. However, they could shorten the time taken by providing PSS-based advice. Two-tailed t-testing reveals that about group 3 the difference between at the beginning and end of the third day was statistically significant ($t = 2.59$, $p < 0.05$).

We found that not only time taken but also other data, which include failure rata or internal force applied to transported object, also decreased through this experiment. We thus confirmed that operators could easily understand specific improvement points and this makes great improvement in operational skill.

6. CONCLUSION AND FUTURE WORK

In this report we proposed basic work states that are independent of various work environment conditions and an operator's skill level. These states are determined using four sets of on-off information for the lever operations and joint loads for the HAND and ARM of manipulator (primitive static states: PSS). We confirmed their usefulness experimentally in a demolition task using a DFCM simulator. We first confirmed that primitive static states could robustly identify the working states accurately and then confirmed that work analysis using primitive static states easily enabled us to estimate the causes of the lack of skills. Finally, in skill training experiment, we showed that advice information based on the skill analysis with PSS greatly improved operator's work performance.

We thus confirmed that PSS can adequately identify work states and are useful for work analysis and skill improvement. PSS are extremely formal states. Thus many work states that have semantically same property are included in one PSS (PSS (11) include the transporting, bending, and removing work). To classify these, we think that advanced solutions based on PSS identification are demanded.

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