Work State Identification using Primitive Static States –Implementation to Demolition Work in Double-Front Work Machines-

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Abstract

Double-front construction machinery, which has been designed for adaptation to complicated work, demands higher operational skills to control two manipulators with more multiple joints. To handle more complicated machinery skillfully, intelligent systems that can autonomously identify the current work states and also provide cognitive and operational supports to their operators are inevitably required. Particularly, work state identification methods strongly require high reliability and robustness due to the variety of the construction work environment and operator's skill level. However, most current construction machinery has unique functions that only reproduce the movements originating from the operator. We therefore addressed the need for a new conceptual design of operator support system and evaluated it using our newly developed simulator. Our experimental results showed that the support system improves the work performance, including decreasing the operational time for completing a task, the number of error operations, and the mental workload on the operators.

Keywords: Construction machinery, Intelligent system, State identification, Operator support.

Introduction

The adaptation of construction machinery to highly skilled, complicated work has been expected. Such tasks, which include sorted dismantling for recycling and reusing resources, rescue and recovery work at a disaster site and building construction, are different from the conventional simple earthwork tasks such as ground levelling, transportation, excavation, and loading. In response to such changes in recent social needs, double-front construction machinery (DFCM), which has two manipulators, was developed, as shown in the right side of Figure 1 (detailed specifications are given in (Ishii, A. 2006)).

In conventional single-front construction machinery (SFCM) such as excavators, breakers, or cranes, one manipulator is operated using two control levers. On the other hand, DFCM has two manipulators operated using two control levers (Figure 1). When comparing them with SFCM, although the adaptability to a wider range of construction works is surely improved, the manipulators have more than twice the number of degrees of freedom, and therefore, operators need extremely high level of operating skills. This is a major drawback that can lead to lower efficiency and work quality by making machine operations more confusing. Additionally, it could lead to dangers being overlooked, such as operators not noticing the existence of outside workers or warnings from co-workers, because operators are concentrating more on the difficult machine operations.

As one means of addressing of these skill and safety problems, we suggest an intelligent system that makes it easier for an operator to operate a machine and to accomplish complicated tasks. This type of intelligent system framework is composed of the functions to autonomously distinguish between several states such as a working or a dangerous state, and to provide information and operational support corresponding to the identification results. For example, in minute work in which an operator endures a lot of stress, such as moving breakable things using double-front, the machine provides an automatic switching support of the operation gain, or in a dangerous state, such as those overlooked because of an operator's devotion to a machine operation, the machine informs the operator of the danger.



Figure 1. Greater difficulty in controlling advanced construction machineries.

However, most of the current construction machinery has unique functions that only reproduce the movements originating from the operator. Even an angle sensor to detect the posture of a manipulator is rarely used. 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 (Takemoto, A. 2004), (Yoneda, M. 1997), remote operation of excavators (Sakai, R. 2004), intelligent oil-hydraulic control (Sakurai, Y. 2004), and analysis of power shovel operation (Rodriguez, J. 2004). However, comparing the fields of advanced automobile (Inoue, G. 2008) and surgical robot (Sun, L. W. 2007), which have human-operated machine systems like DFCM, there has been less movement toward incorporating an intelligent system.

We thus aimed at constructing a new framework for an intelligent system for construction machinery. To make it easier to adapt this system to fit all construction machinery, we targeted DFCM, which uses the most complicated hardware constitution at present. On the basis of above, we have designed an operator support system for DFCM.

Analysis of Intelligent Support Scene

It is important to adequately consider the characteristics and problems associated with construction machinery and construction sites. In this chapter, we derive the overt or covert needs, and embody a highly effective intelligent support scene.

Fundamental Problems

We analyzed the actual condition and problems with construction machinery and construction sites. We wrote them up in the following elements after reviewing construction documentations and talking to construction company workers.

1) Construction machinery: a) The size and weight are big, so the risk of a collision with a worker is extremely big, b) there is a delay in the oil pressure system and the inertia force is big, so instantaneous or quick movements are difficult and dangerous, c) there are many blind spots for an operator, so it is difficult for them to check the danger spots, and d) the vibration and noise created by the machine's movement decreases the cognitive ability of an operator and promotes fatigue.

2) Construction sites: a) The construction machinery and outside workers must cooperate, so there is always danger of contact with workers, b) an operator must take excessive care to recognize other equipment (e.g., wheel loaders, dump trucks, or outside workers), so the operator's awareness of the whole situation may weaken, making it hard to concentrate on work.

From these analyses, we are better able to understand that an operator must have the operation skills and cognitive ability to ensure a safe work environment by always grasping the situation while also paying attention to the machine characteristics.

Advanced problems

A standard intelligent support system consists of three modules, an inside or outside information detection module, a state discrimination module for recognizing the working or danger states based on the information detection module, and an operator support module based on the state identification module. Based on the analyses mentioned in the previous section, we collected information on the problems associated with applying this type of intelligent system framework.

1) Information detection: a) Usage environment is inferior, so an indestructible structure and high noise immunity are required for sensors. b) Sensors are not easily mounted on current construction machinery, so a mechanical design taking into account their installation is necessary.

2) State identification: a) The work environment is complicated, and this is especially true for demolition work where the use of DFCM is necessary. b) The shape and position of the objects manipulated in construction work continually change. c) Skill levels and operational methods differ from one operator to another. Therefore, from these three characteristics we have determined that it is much more difficult to adequately identify working states.

3) Operator support: a) The level of demanded support differs depending on the situation and operator. b) Machine characteristic (e.g., inertia or hydraulic system) support is necessary.

We found from these analyses that there are many unknown parameters involved in using construction machinery, so state identification is very difficult. Therefore, we think that it is indispensable to create state identification technology taking into account each characteristics of construction machinery.

Embodiment of Intelligent Support Scene

Based on the analysis results given in previous sections, we extracted the assumed needs, and considered demanded technical standards. We created a specific situation where the support could be useful to the operators and workers, and construction machinery. We used the following procedure to gather feedback for designing the system. Firstly, we asked operators and workers what types of situations they thought some support would be useful, secondly the states that are necessary for concerned support should be provided, thirdly, the required information for state identification and the method involved, and finally the sensors necessary for detection of concerned information. We took into account the input information, working state, support, including the situation, the sensor and its installation position, and then arranged more than 60 situations in which support is necessary. Table 1 shows some examples in which it is thought that the effectiveness is high.

System Design

We now understand that a state identification is a key module of operator support system, which influence the usefulness of the system. We therefore designed an operator support system, particularly focusing a state identification method.

Semi-autonomous Support Method

In a manually human-operated work machine, a fully autonomous system would be the ultimate support method because of having merits, such as not only freeing a machine operator from dangerous work, but also reducing personnel expenses. However, autonomous systems are adapted for use in a limited number of simple tasks where many of the conditions are approximately determined, such as ground levelling or digging a broad mine without on-site workers. When we take into account examples of practical situation use such as the advanced surgical operation support, we can better understand how important it is that the

SCENE	INPUT	STATE	OPERATOR SUPPORT
Sorted dismantling work	Angle of operation lever	Minute work	Depending on lever operation, machine automatically changes operation gain. In minute work, machine lowers gain. -Parameter Optimization Support
Cooperative transporting work with double-front	End- effector position / load	Cooperative transporting work with double-front	Depending on gap of position of end-effectors and load, machine revise relative position of end- effectors -Operation Support
Demolition work / Rescue work	End- effector position / object position	High place work /Work at blind side	To feed back image from virtual camera installed in end-effector, machine offers to effectively expand field of vision. -Information Support

Table 1. Intelligent support scenes (extract).

operator makes the final decisions. Even if a machine autonomously determines that it can directly support the operator in situation recognition or operation, it is important that system only visually and acoustically assist them, and which is especially true for addressing the problems mentioned in Section 2. Therefore, we decided to create a semi-autonomous support method.

State Identification

1) Concept of new method: Many researchers have already reported on different types of state recognition techniques, and the hidden Markov model (HMM (Rabiner, L. R. 1989)), dynamic Bayesian network (DBN (Murphy, K. 2002), (Laet, T. D. 2008)), and support vector machine (SVM (Cristianini, N. 2000)) have been proposed as promising techniques. 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.

A state identification method needs to take into account the characteristics of construction machinery and the construction work environment as mentioned in Chapter 2. From the problems mentioned in Section 2.1 1), for points c) and d), an interface provides cognitive support such as reminding the workers what the current situation is that they are working in would be effective. On the other hand, for points a) and b), if construction machinery moves in a direction that an operator did not intend due to a false state identification, the construction machinery can become extremely dangerous to neighbouring workers and environment. On this account, an important point for developing a state identification method is how to avoid misrecognition of work states. Therefore, a work state identification method 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.



Figure 2. Relations among operator, work machine, and object.

2) Design of new method: As is well known, construction machinery has a human-operated system and applies force to an environment, and therefore, we focused on three corresponding elements: an operator, a work machine and an environment (Figure 2). An operator and a work machine interact through control levers and their interaction represents the existence of the machine operation due to the operator's operation. A work machine and an environment interact through end-effectors and their interaction represents the existence of applied force due to physical contact by machine's actuation. These interactions are defined without using vectorial or time-series information concerning the work object (e.g., position or weight) or the manipulator (e.g., velocity or trajectory), which greatly depends on the work environment condition or operator's skill level, or the machine's specifications, and therefore, the combination of these interaction information can describe the basic work states. From these analyses, we decided to use on-off information for the lever operations and joint load. In addition, focused on the mechanical structure of construction machinery, the attachment part directly interacts with the environment (e.g., grasping or cutting), but the front part is used for positioning the attachment by not interacting with the environment (e.g., reaching). From these different usages, we decided to extract the above information from two parts, the attachment (hereinafter called the HAND), and the front (hereinafter called the ARM).

3) Primitive Static States (PSS): Based on previous sections, we designed a base work state unit using on-off information for the lever operations and joint load, which represents the condition of relations among the operator, work machine and environment, for the HAND and ARM, which represent differences in interaction with the environment either directly or indirectly. These states express the most basic states using static information, so we call these state units primitive static states (PSS). When we focus on a single arm, there are 16 separate states (2⁴), and when we focus on for double arm, there are 256 (16²). In addition, we can apply a specific working state to each of the 16 states (A-P) as shown 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.

Operator Support System

We developed a prototype of an operator support system (OSS) based on the primitive static states. As mentioned in Section 2, the OSS consists of three modules. We concretely explain the contents of these modules. A developed system flow is shown in Figure 3.

1) Information detection: The angle of the control lever and the joint load for HAND and ARM are used as the input information. The former data is obtained from a potentiometer mounted the control lever. As mentioned later, we performed experiments using VR simulator. Therefore, the latter can be easily obtained using the function of the dynamics engine.

2) State identification: From detected information, the PSS identifies the reaching states (B, E and F), grasping state (M and P), and transporting state (L) of each manipulator. We redefined the reaching and grasping states which are demanded to recognize the depth feeling as the long-range-work state and also redefined the grasping states which are demanded precision operations as the minute work states. Additionally, when both manipulators are transporting states, the system identifies this situation as a

PSS no.	Input data* HHAA LOLO	Working State (example) (HAND: Grapple)	PSS no.	Input data* HHAA LOLO	Working State (example) (HAND: Grapple)
A-00	0000	Non-operation and load	I-08	1000	Holding of object on ground
B-01	0001	Reaching	J-09	1001	Abnormal state
C-02	0010	Holding/ Grasping	K-10	1010	Holding of aerial object
D-03	0011	Compressing	L-11	1011	Transporting/ Bending/ Detaching
E-04	0100	Hand operation	M-12	1100	Cutting/ Setting
F-05	0101	Hand operation in reaching	N-13	1101	Abnormal state
G-06	0110	External force during grasping	O-14	1110	Cutting/ Setting
H-07	0111	Hand operation in compressing	P-15	1111	Throwing out

Table 2. Primitive static states (PSS).

cooperative transporting state.

3) Support: In both the minute work and double-front transporting states, the system reduced the operational gain to half in order to make precise work easier. In the long-range-work state, the system presents an enlarged image of the end-effector from a different viewpoint in order to provide positioning in formation assistance as shown in Figure 4 (a small window circled by a broken line at the upper left side of the cab view display).



Figure 3. Developed operator support system using primitive static states.

Experiment

We newly developed a double-front construction machinery simulator and performed experiments to inspect the utility of our operator support system using the simulator.

DFCM-VR simulator

To lower the estrangement in the real world, and to simplify the model as much as possible, we implemented only the element that was the most dominant for the construction machinery simulator. The operation lever arranged two joysticks the same as in actual machine. In addition, we reproduced operational gain, sounds, and oil delay, and moreover physical behavior, such as contact judgment functions, inertia, adhesive strength, and frictional force in the environment, which is indispensable in above mentioned work assuming interaction with the environment. We implemented these functions with a physics engine (Open Dynamics Engine (Russell, M)), also with OpenGL and Microsoft MFC. The screen of the graphical user interface and an image from the cab, and the hardware system are shown in Figure 4 (detailed specification given in (Kamezaki, M. 2008)).



Figure 4. Graphical display and experimental setup of the developed simulator.

Experimental Task

We performed an experiment on minute work and cooperative transporting work states, as shown in Table 1 and Figure 3. We set the removal of a wooden beam as a task. The beam was put on top of two columns in a position to be able to be grasped without the construction machinery being moved. The initial posture of the manipulators was one where both manipulators could be lifted to a high position. An operator reaches just enough to not let the end-effector collide with the beam and grasps it with the two end-effectors. Then the operator places the beam just in front of the two columns. In other words, this task can be divided three states: reaching, grasping, and transportation state. In every state, operation supports are provided as shown in Figure 3. Figure 5 shows the operation supports and work state identification demanded in a work sequence.

Eight healthy adult males (20-25 years old) without any experience at any kind of construction machinery operations were used as subjects. We let them train on the operation for about 20 minutes so that they could get used to the simulator and then perform experiments on three types of patterns in the same task, which were: off-support, support with a gain switch, and support using a view from a virtual camera. All the subjects were randomly tested on all the patterns. We measured the working time (time before grasping from the start and time before placing after grasping). We judged that there was an overload when the relative distance between each end-effector was more than 200 mm. In addition, we quantitatively measure the operator's mental workload by using the NASA-TLX (Hart, S. G. 1988).

Result

The operational time to complete a task is shown in Figure 6, the number of overload in Figure 7, and the mental workload in Figure 8.

We found that the time taken to complete a task decreased with the on-support and also that the virtual camera view support is the most effective. The time taken to complete a task decreased by an average of about 30% when using the virtual camera view, and the maximum-recorded decrease was 70%. We performed two-tailed t-testing about off-support and virtual camera view support, and identified a significant difference t = 1.85 (p < 0.1). The number of overloads decreased when providing the gain switch and virtual camera view supports. On average there was a 72% decrease (from 6 to 0 times in the best-case scenario). The operator's mental workload decreased when providing supports. We performed two-tailed t-testing about off-support and virtual camera view support, and identified a significant difference t = 2.79 (p < 0.05).

We found that work performance in more than half of the subjects was improved by our operator support system, and we also found that virtual camera support was the most effective means of support in all evaluations.



Figure 5. Operation supports demanded in a work sequence.

Discussion

For the inspection of the support effect in the each subject, we calculated the ratio that divided offsupport by on-support about above evaluation index about every subject, and Figure 9 shows the results. This figure shows that if the positive value is bigger, the effect of the support was stronger and if the negative value is bigger, the support had an adverse effect.

1) Virtual camera view support: The mental workload when using virtual camera view support is less than two-thirds that of off-support for over half of subjects. We also confirmed that virtual camera view support is effective at both shortening the accomplish time and decreasing the mental workload despite a simply



information support. We think that assistance with depth perception, which is sometimes hard for operators, was effective. Although a positive effect was not found for subjects A and B, it is thought that this support would be more useful if we could control the camera direction and zooming function based on more detailed state identification.

2) Gain Switching Support: The gain switching support provided a decrease in number of overloads for an



Figure 9. Difference of support effect by subjects.



Figure 10. Mental workload - difference of support effect by examinees -.

object. It is essential not to give overload an object during material transportation. We also found that the effectiveness is greatly different for each subject about the accomplish time. Questionnaire results showed that some subjects felt that gain switch support was troublesome when changing the movement properties. For example, mental workload for subjects C, D, and F decrease when using gain switch support (Figure 10), and the EFFORT (an evaluation item of NASA-TLX) particularly shows a remarkable decrease. On the other hand, in subjects A and B, the mental workload increases when using gain switch support. Correspondingly, EFFORT increases by more than 1.5 times. Subject A answered that the movement of a manipulator slowed, so he felt operational effort is increased. From these results, we understood that it was necessary for the gain adjustment method to adequately set the parameter for both an operator's skill level

and a task condition.

To provide more useful operator supports, we think that it is important to mutually improve not only the support methodology but also the state identification method. In other words, the state identification level (e.g., number of identifiable states, probability, or static or dynamic) and the operator support type (e.g., cognitive, operational, or parameter optimization) have a close relationship, and there is a suitable identification level for each support. We found that PSS is useful for cognitive support (virtual camera view). For a parameter optimization support (gain switching), we think that the state identification technique using a fixed parameter for support of all situations or variable parameters for9 individual support and combing them is useful.

Conclusion and Future Works

Taking into account peculiar problems for construction work, we proposed the primitive static states which is independent the various environmental conditions and operator skill levels for certain and robust identification. Based on the primitive static states identification, we developed the operator support system, which provides a virtual camera view and gain switch supports for the minute and cooperative transportation works. As a result of having experimented by evaluating novices, we confirmed that the use of on-support decreases the mental workload of operators, the operational time to complete a task, and the number of false operations. Thus, we were able to confirm the effectiveness of the developed operator support system.

For future work, we will present a probabilistic state identification technique, and examine a fusion method with the primitive static states identification. In addition, we will perform an experiment with an actual machine for confirming the practicality of the proposed method.

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References

- [1] Cristianini, N., and Shawe-Taylor, J. (2000) "An Introduction to Support Vector Machines. Cambridge." UK: Cambridge University Press
- [2] Hart, S. G., and Staveland, L. E. (1988) "Development of NASA-TLX(task load index) : results of empirical and theoretical research." in P. A. Hancock & N. Meshkati (eds.), Human Mental Workload, North-Holland, 139-183
- [3] Hitachi Construction Machinery, http://www.hitachi-c-m.com (Dec. 2008)
- [4] Inoue, G., and Yasunobu, S. (2008) "An intelligent MIMO control and its application to two-wheeled vehicle for driving support." Proc., the World Congress on Intelligent Control and automation, 2804-2809
- [5] Ishii, A., and Tomita, K. (2006) "Total Design of a Double Fronts Work Machine." Proc., the 2006 JSME Conf. on Robotics and Mechatronics, 2A1-B07 (in Japanese)
- [6] Ishii, A. (2006) "Operation System of a Double-Front Work Machine for Simultaneous Operation." Proc., 23rd Int. Symp. on Automation and Robotics in Construction, 539-542
- [7] Kamezaki, M., Iwata, H., and Sugano, S. (2008) "Development of an operation skill-training simulator for double-front work machine." Proc., IEEE / ASME Int. Conf. on Advanced Intelligent Mechatronics, 170-175
- [8] Laet, T. D., Schutter, J. D., and Bruyninckx, H. (2008) "Rigorously Bayesian Range Finder Sensor Model for Dynamic Environments." Proc., IEEE Int. Conf. on Robotics and Automation, 2994-3001
- [9] Murphy, K. (2002) "Dynamic Bayesian networks: representation, inference and learning," PhD thesis, University of California, Berkeley
- [10] Open Dynamics Engine, Russell, S. http://www.ode.org/
- [11] Rabiner, L. R. (1989) "A tutorial on hidden Markov models and selected applications in speech recognition." Proc., the IEEE, vol. 77, no. 2, 257-286
- [12] Rodriguez, J., et al. (2004) "Operating experience of shovel drives for mining applications." IEEE Trans. on Industrial Applications, 664-671

- [13] Sakurai, Y., Nakada, T., and Tanaka, K. (2004) "Design method of intelligent oil-hydraulic system (load sensing oil-hydraulic system." Proc., IEEE / RSJ Int. Conf. on Intelligent Robot and System, 626-630
- [14] Sasaki, R., Miyata, T., and Kawashima, K. (2004) "Development of remote control system of construction machinery using pneumatic robot arm." Proc., IEEE / RSJ Int. Conf. on Intelligent Robot and System, 748-753
- [15] Sun, L. W., Meer, F. V., Bailly, Y., and Yeung, C. K. (2007) "Design and Development of a Da Vinci Surgical System simulator," Proc., the 2007 IEEE Int. Conf. on Mechatronics and Automation, 1050-1055
- [16] Takemoto, A., Yano, K., Miyoshi, T., and Terashima, K. (2004) "Operation assist control system of rotary crane using proposed haptic joystick as man-machine interface." Proc., the IEEE Int. Workshop on Robot and Human Interactive Communication, 533-538
- [17] Yoneda, M., Arai, F., Fukuda, T., Miyata, K., and Naito, T. (1997) "Operational assistance system for crane using interactive adaptation interface -design of 3D virtual crane simulator for operation training -." Proc., IEEE Int. Workshop on Robot and Human Communication, 224-229