A Method of Automated Work Observation for Ship Production Using Deep Neural Networks

Shinoda, Takeshi
Department of Marine Engineering Systems, Faculty of Engineering, Kyushu University

Tanaka, Takashi
Department of Marine Engineering Systems, Faculty of Engineering, Kyushu University

Okamoto, Hayato
九州大学大学院工学府

Umemoto, Daisuke
九州大学大学院工学府

https://hdl.handle.net/2324/7181921

出版情報：2021-10-18. The Japan Society of Naval Architects and Ocean Engineers
バージョン：

SNAME Maritime Convention 2021
25-29 October, Providence RI

A Method of Automated Work Observation for Ship Production using Deep Neural Networks

Takeshi SHINODA[1] (M), **Takashi TANAKA**[1] (V), **Hayato OKAMOTO**[2] (V) and **Daisuke UMEMOTO**[2] (V)
1. Department of Marine Engineering Systems, Faculty of Engineering, Kyushu University, Japan
2. Department of Urban and Environmental Engineering, Graduate School of Engineering, Kyushu University, Japan

It is important to increase the productivity of every shipyard. Visualizing the actual work status during any industrial activity is essential. Work observation as one of the methods of industrial engineering has been applied in various fields in shipyards in Japan to increase productivity. However, current work observation requires both time and labor, and in some cases, shipyards hesitate to implement work observation. The aim of this study is to develop a methodology that uses deep neural networks to reduce the disadvantages of current work observation approaches while identifying work tasks and the accuracy of this observation.

KEY WORDS: Shipbuilding; Ship production; Industrial Engineering; Work Observation; Deep Neural Networks.

INTRODUCTION

Work observation is a method in industrial engineering (IE) that has been applied in various fields in shipyards in Japan to increase productivity. Work observation in IE serves as a solution to reduce the waisting of resources, e.g., personnel, materials, equipment, and energy, during ship production. It improves the productivity and reduces production time and costs. However, the disadvantage of work observation in IE is that it requires considerable time and effort to determine the current work productivity.

Recently, pattern recognition, which focuses on the recognition of patterns and regularities in image data, has made progress through the use of deep neural networks (DNN). DNN are artificial neural network methods that have multiple hidden layers between the input and output data for representing complex nonlinear relationships.

We attempted to employ a DNN to analyze work observation data that is recorded as movie data by attaching a miniature head-mounted camera to a worker in a shipyard. However, there are some problems associated with the application of a DNN for extracting the work status.

To employ a DNN, it is necessary to considerably increase the number of photos or the amount of various image data to identify the work items. Another issue is determining the influence of increasing the amount of image data on the image recognition accuracy. When using the DNN method, these issues increase the difficulty of identifying the work items.

We reported a thesis on a DNN work observation method for shipyards at the SMC 2018 conference(TANAKA, T., SHINODA, T., 2018), and this paper is a follow-up report. In this study, to resolve the problems associated with the application of a DNN for identifying work items, we have created an operational object recognition method to automatically classify many images into work items based on definition of image information about the work object.

WORK OBSERVATION METHOD IN IE

To visualize the actual work status in any industrial activity, work observation methods in IE is useful for improving production. It is possible to analyze the current work productivity in a shipyard and to generate a plan of improvements using this approach. Currently, work observation methods in IE can be performed in two ways: 1) using a continuous observation method or 2) instantaneous observation method (HIRANO, H., 2001).

The continuous observation method involves tracking and observing the behavior of workers at all times. This makes it possible to measure the work factors during the actual working time without omitting any factors. However, because one observer observes one worker at a time, it requires time and labor to analyze the process.

In contrast, the instantaneous observation method reduces this intense labor requirement. This method prepares observed work items in advance and records observed data of the worker at particular moments. The frequency of each work item is summarized, and the ratios of the work items are evaluated. This method allows observation of more than one person, and an estimation of the ratio of accuracy can be obtained quickly, depending on the work item. The disadvantage of the instantaneous observation method is that observers must prepare for the observed work items in advance; in addition, the observers must be familiar with the work that they are to observe. The accuracy of the ratios of the observed work items depends on recording a large amount of observation data. Large amounts of data are needed to increase the reliability in the case of short periods of work. Therefore, in general, it requires considerable effort to aggregate the observations.

The main disadvantages of current IE work observation methods are as follows: 1) the observers must be familiar with the work allocated to them, 2) the collected data may not be convincing because the results of the observation depend on stochastic means that observation data are summed during the analysis, and 3) this approach requires additional time and labor to analyze the current work productivity. It is necessary to improve the current work observation methods in IE.

THE DNN WORK OBSERVATION METHOD

We aim to create a DNN work observation method to solve the above disadvantages of the current work observation methods in IE. DNNs provide several pattern recognition methods. A DNN is an artificial neural network with multiple hidden layers between the input and output data. A DNN can be used to construct a useful model for representing complex nonlinear relationships and to analyze human image recognition using pattern recognition (OKATANI, T., 2015). We utilize the image recognition of the DNN and attempt to apply the DNN for work observation to extract the work status of a shipyard.

Use of a head-mounted camera in a shipyard

We employ the DNN to analyzing work observation data recorded as movie data by attaching a miniature head-mounted camera to a worker in a shipyard. Many kinds of head-mounted cameras, herein referred to as HCs, are provided. However, most kinds of HCs have restrictions on their usage, such as recording hours, capacity, image resolution, and whether they are dust-proof. A suitable HC should be selected for the intended work observation.

Fig. 1 shows outline of use of the head-mounted camera. For this investigation, after studying several kinds of HCs, we used two types of HCs: 1) a POV.HD produced by V.I.O., Inc., USA and 2) a MOHOC camera produced by MOHOC, Inc., as shown in Fig. 1(a). These have recording capacities of 4 hours when using two lithium battery packs of 1400 mAh. The camera image captures 1920 × 1080 picture elements.

Outline of the DNN Work Observation

To employ a DNN, it is necessary to considerably increase the number of photos or the amount of various image data to identify the work items. Another issue is determining the influence of increasing the amount of image data on the image recognition accuracy. When using the DNN method, these issues increase the difficulty of identifying work items (SHINODA, T., TANAKA, T., 2016).

For image data processing, the first interval time for extracting the work status is set; then, large amounts of static image data of the work status are extracted with 1920 × 1080 picture elements. Next, teaching data, including extracted image data that is used as input data, and items for the work status are used as output data; the teaching data are input to the DNN. The extracted static image data are allocated the name of the work item from continuous observations or from instantaneous observation data. After the DNN finish learning, it identify the work items from the image data. The DNN observation method is evaluated based on its ability to identify the work items.

Fig. 2 shows the image identification process of the DNN. There are main two processes: image processing and construction of the DNN. During the first step of image processing, still image data with 192 × 108 picture elements is extracted from the moving image and processed by a bicubic filter. The still image

(a) Head-mounted camera **(b) Recording working status by the head-mounted camera**

Fig. 1 Outline of use of the head-mounted camera

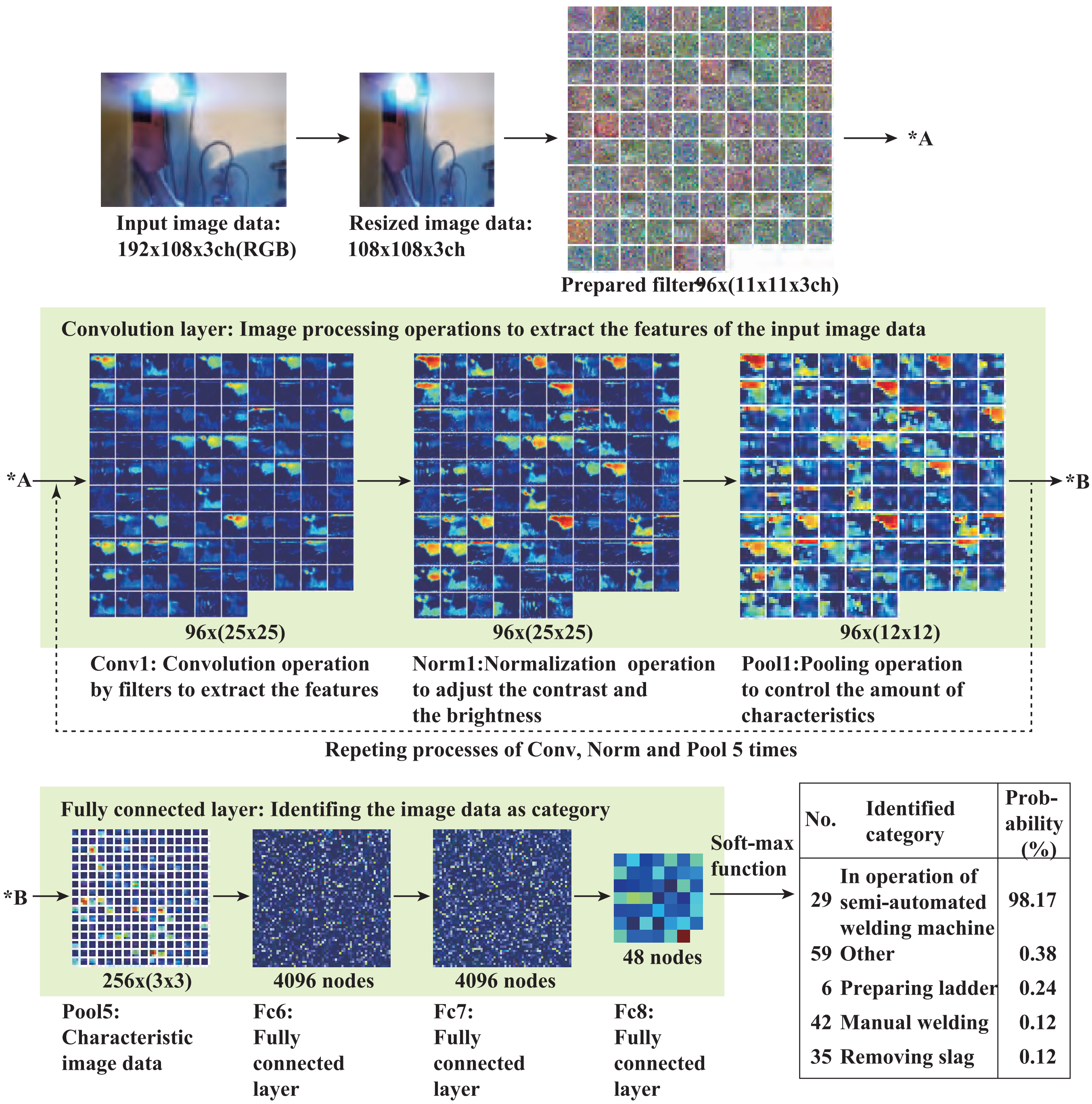


Fig. 2 Process of image identification by the DNN

is transferred to 108 × 108 picture elements.

During the next step, typical tree image processing operations are continuously executed as follows: 1) the features of the image data are extracted by a convolution operation with a prepared 96 unit of filtration pictures, 2) the image data contrast is tuned by a normalization operation, and 3) the amount of characteristics in the image data are extracted by a pooling operation. The above operations are repeated five times to create the input image data for the DNN (KRIZHEVSKY, A. etc., 2012).

During the process of constructing the DNN, image data and work items are input to teach DNN the ability to observe the work. The rectified linear function and the soft-max functions are used to make a fully connected layer to construct the DNN. After completing the formation of the DNN, the DNN observed and identified the work items in the input image data with an identification probability; the figure on the bottom-right corner in Fig. 2 shows an example of the calculation (TANAKA, T. ,SHINODA, T., 2017).

The DNN system structure used in this study is explained below. The hardware components are structured in a computer system with a workstation (key components: Intel Core i7 5820K, 3.30 GHz, 64 GB memory and GPU, NVIDIA Geforce GTX 970 4 GB). The installed software components include DIGITS (version: 2.0.0) for the deep learning training system, Caffe (version: 0.13.1) for the open framework to develop deep learning, and AlexNet for the convolutional neural network.

Benchmarks for the DNN work observation

After the calculation, the DNN extracts all the work statuses fully that involve well or weak identified work; therefore, it is necessary to have benchmarks for the DNN to improve its identification ability. The identification probability determined by the DNN is one of the evaluation methods. However, the calculated identification probability has ambiguous values in the range 0 to 1; the ambiguity of probability disturbs the evaluation of the identification ability of the DNN. To remove this ambiguity, a criteria of identification is defined; for example, the first order of the probability of identification is replaced by the value of 1. Then, the number of identified work items is calculated by taking into account the value of 1.

The work item, i, and the total number of work items, N, are denoted. The number of input image data for a work item i, Mi, are denoted. The identification probability of a work item, i ($1\leq i\leq N$), and image data number, k ($1\leq k\leq Mi$), is denoted as $Pid_{i,k}$, and the replaced probability is denoted as $Fid_{i,k}$; then, the above operation can be described as follow:

$$\begin{aligned} Fid_{i,k} &= 1: \text{ when } Pid_{i,k} \text{ is } Cr \\ Fid_{i,k} &= 0: \text{ when } Pid_{i,k} \text{ is not } Cr \end{aligned} \tag{1}$$

where Cr is a criteria of recognition, and it depends on the quality and reliability of identification. In this paper, Cr is taken the first order of identification probability after DNN calculation.

Additionally, the number of identified work items i, are denoted by Nid_i; this is then calculated by the following summation of $Fid_{i,k}$:

$$Nid_i = \sum_{k=1}^{M_i} Fid_{i,k} \tag{2}$$

Thus, the first benchmark for the identification ability of the DNN is defined as the following recognition ratio of the DNN $Rr_{i,j}$;

$$Rr_{i,j} = Nid_j \,/\, Ninp_i \tag{3}$$

where i is index of input image data on work item i, and j is index of output work item j. The total number of input image data on a work item i is $Ninp_i$.

$Rr_{i,i}$ is used to evaluate whether work item i is identified according to the acceptability criteria. The acceptability criteria are denoted by Ac, which is the basis of evaluating acceptable identification:

$$Rr_{i,j} > Ac \tag{4}$$

The Ac also depends on the quality and reliability of identification. In this research, Ac is $Rr_{i,j}$ ($i\neq j$). When $Rr_{i,i}$ satisfies the condition Eq.(4), the work item i is well identified. Contrary to this, the work item i is weak identified.

When the acceptability criteria of identification is a comparison between $Rr_{i,i}$ and $Rr_{i,j}$, the identification index on a work item i, Id_i, is defined as follows:

$$\begin{aligned} Id_i &= 1: \text{ when } Rr_{i,i} > Rr_{i,j} \\ Id_i &= 0: \text{ when } Rr_{i,i} \leq Rr_{i,j} \end{aligned} \tag{5}$$

Id_i takes the value of 1 when $Rr_{i,i}$ is dominant because it is greater than $Rr_{i,j}$, and in any other case, it takes the value of 0.

We introduced a second benchmark to evaluate the total coverage number of recognized work items by DNN observation, *Tc*, which is defined using Id_i as follows:

$$Tc = \sum_{i=1}^{N} Id_i \tag{6}$$

In addition, it is important to improve the degree of coverage of total work observed by the DNN. We introduced a third benchmark to evaluate the total coverage ratio of the identified work items observed by the DNN, which is *Tid* and can calculated using the following formula:

$$Tid = \sum_{i=1}^{N} Nid_i \,/\, \sum_{i=1}^{N} Ninp_i \tag{7}$$

IMPLEMENTATION OF THE DNN WORK OBSERVATION

Working site and its work assignment

To improve work efficiency, a shipyard aims to typically increase the use of spaces in the sub-assembly factory of the shipyard.

Fig. 3 shows the working site of the sub-assembly stage. Fig. 3 (a) shows an overview of the working site, and all workers manned their working sites. The even small empty space in the factory is always occupied with outspread plates and stiffeners. Proper worker arrangement and work assignments based on work standardization and standardized work time are important to reduce work inefficiencies. Therefore, the implementation of the DNN work observation is examined during the sub-assembly stage of the shipyard.

(a) Overview of the working site

(b) Table of worke assignment during the sub-assembly stage

Worke assignment	The number of workers	The number of workers wearing HC	Code of workers wearing HC (Name of wearing HC)
1) Distribution	1	1	YO (P-1)
2) Tack welding	1	1	MO (M-2)
3) Simplified auto-welding	1	1	YA (P-2)
4) Manual corner welding	5	3	SA*) (M-5), KO (M-3), MR (M-4)
5) Quality inspection	1	1	SH(M-1)
Total	9	7	

Remark: ( ): Name of wearing HC, Symbols: M(MOHOC Camera), P(POV. HD)
*): Analysis worker

(c) Table of date of work survey and image data set

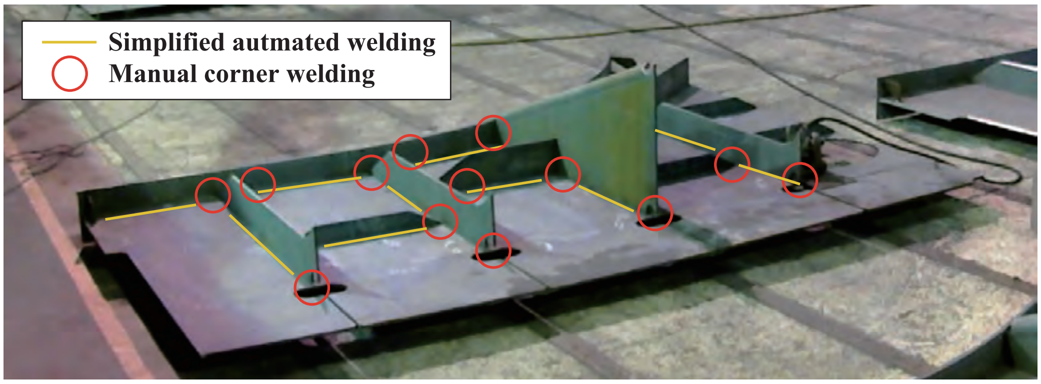
Name of image data set	The number of image data (pictures)	Date of recorging movie by HCs	Duration of hour (From/To)
Image set A	13,885	Oct. 23rd, 2018	1 pm - 5 pm
Image set B	14,794	Oct. 24th, 2018	8 am - 12am
Image set C	14,280	Oct. 24th, 2018	1 pm - 5 pm
Image set D	14,383	Oct. 25th, 2018	8 am - 12am

Fig. 3 Details of work survey during the sub-assembly stage

The worker arrangement and work assignment during the sub-assembly stage is shown in the table in Fig. 3 (b). There are five work assignments; 1) the distribution of assembly members, 2) tack welding for assembly members, 3) welding work with a simplified automatic welding machine, 4) manual corner welding with a semi-auto welding machine on the remains after welding work with simplified automatic welding machine, and 5) quality inspection work for checking right and wrong of welding beads. These work units are conducted in sequence. The table shows the number of workers and workers wearing HCs for these work assignments and the workers of the initial letters. Nine workers were assigned to this site in the shipyard.

The work survey of the shipyard were performed from October 23rd to 25th in 2018 as shown in Fig. 3(c) and the image data or specific tasks were recorded by HCs. The image data are divided into 4 data sets form A to D. In particular, the work of manual corner welding requires a long time. It requires five assigned workers as a consequence of bottleneck work in the sub-assembly stage. In this paper, we focus on specific work assignment of manual corner welding.

Fig. 4 shows the unit work of manual corner welding during the sub-assembly stage. Fig. 4(a) shows the welding places on the sub-assembly parts upon manual corner welding. After



(a) Welding places on sub-assembly parts by manual corner welding

(b) Table of details of work items of manual corner welding during the sub-assembly stage

Code Work items	Code Work items
Preparation and Clean up Work	**Main Work**
2: Moving at work site	42: Manual corner welding
3:Preparing tools (wire feeding machines, bucket of tools, etc.)	**Ancillary Work**
4: Replacing consumable stores for tools	24: Cleaning welding torch
5: Wearing protector (gloves, dust mask)	26: Wearing protector (face shield)
12: Preparing and arranging lines (gas hose, control cable and torch cable)	35: Removing slag with air chipper, etc.
13: Preparing and arranging air hose	46: Fixing bead with grinder
16: Preparing air chipper	71: Cleaning with air
19: Connecting gas hose, control cable and torch cable	74: Cleaning with broom
22: Supplying weld wire	75: Check welding bead
28: Adjusting semi-automated welding machine	**Margin work**
45: Preparing antirust paint	58: Meeting
51: Detaching and winding gas hose, control cable	59: Rest
52: Detaching air hose	60: Troubleshooting
56: Tidying up tools	62: Remove hard hat (Rest)
70: Preparing air	**Others**
73: Preparing broom	1: Installing head-mounted camera

Fig. 4 Work items of manual welding during the sub-assembly stage

welding work with a simplified automatic welding machine, manual corner welding began. The simplified automatic welding machine cannot reach the stiffener edges and corners, as shown in Fig. 4(a). The worker that performs manual corner welding has to weld many stiffener edges and corners. Additionally, the work includes removing slag with a chipper and grinding for treatment of welding beads. The work is one of bottle neck work in the the sub-assembly stage.

The details of the work items during manual corner welding in the sub-assembly stage are shown in the table in Fig. 4(b); these are defined via an interview with skilled workers and expert engineers in ship construction. From the viewpoint of valuable work for productivity, the manual corner welding work on the site can be classified into four work groups: main work, ancillary work accompanying to main work to give an value to products, auxiliary work such as preparation and clean up work, margin of work, and other work, which are divided into 28 work items. For work improvement, it is necessary to reduce ancillary work and auxiliary work to increase welding work during the manual corner work. Therefore, an understanding of the work productivity provides insights into how to make improvements to the work items.

Fig. 5 shows the method of extracting image data for teaching image data. We apply the continuous observation method to make teaching image data by following some steps. During the first step of the method, an expert engineer needs to take the role of observer. The observer observes the recorded image data of manual corner welding work by using the list of work items previously defined, as shown in Fig. 4(b). During the second step, the observer records the starting time of when he monitors the work item in the recorded image data. All starting times that are based on work items are reserved with the recordings.

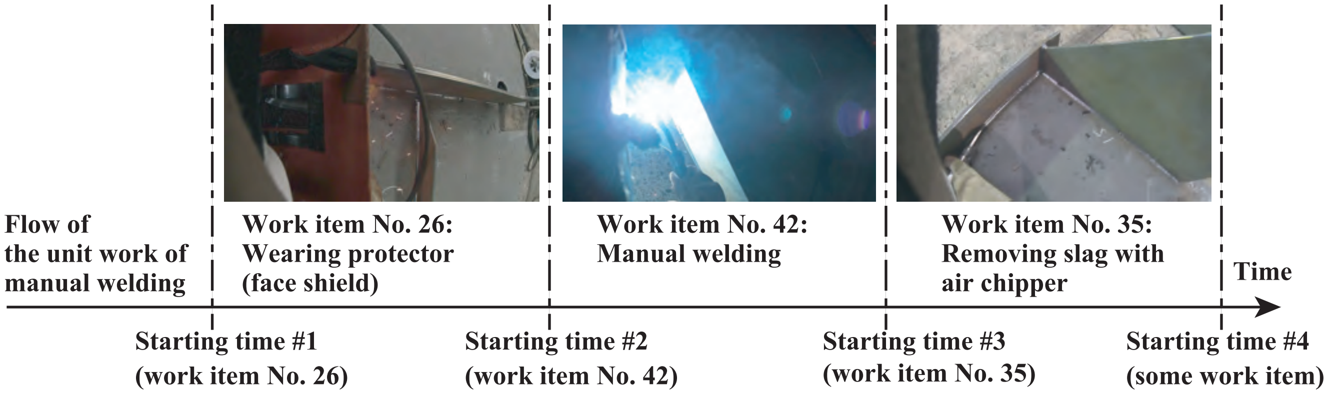


Fig. 5 Method of extracting image data by using continuous observation to create teaching images for the DNN work observation

(a) Work item No. 4: Replacing consumable stores for tools

(b) Work item No. 22: Supplying weld wire

(c) Work item No. 26: Wearing protector

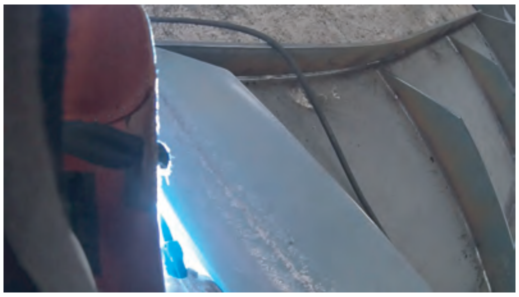
(d) Work item No. 35: Removing slag with air chipper

(e) Work item No. 42: Manual corner welding

(f) Work item No. 46: Fixing bead with grinder

Fig. 6 Examples of extracted image data from the recorded welding work for manual corner welding during the sub-assembly stage

Name of worker:	**Worker SA**
File name:	**20181023-PM-1**
No. of image data:	**00-16-26**
No. of work item:	**No. 42**
Work item:	**Manual welding**



(a) Input image data

(b) Table of identification probability on work item

Work item	Identification probability (%)
42: Manual corner welding	99.94
35: Removing slag with air chipper	0.03
46: Fixing bead with grinder	0.01
2: Moving	0.01
24: Preparing manual welding	0.01

Fig. 7 Example of identification probability of the DNN work observation

During the third step, image data are extracted every 1 second owing to the reserved starting time, and then the image data associated with that work item are extracted. The specific teaching image data for the DNN are carefully examined by the observer visually checking it one-by-one. The total teaching image data for 4 hours results in approximately 14,000 images. Thus, creating teaching data for the DNN are required a long time.

Fig. 6 shows examples of the extracted image data from the recorded manual corner welding work during the sub-assembly stage. They are used to input to the DNN as teaching image data. There are some features in the image data among the extracted image data; for example, the image data for work item No. 42: the manual corner welding shown in Fig. 6(e), shows strong light during the welding, and the image data for work item No. 35: removing slag with the air chipper shown in Fig. 6(d), shows the operation tool of the air chipper. Originally, because the movie data are captured from the viewpoint of the workers, the data have characteristic features, such as a strong light from the welding, welding protection masks, operation tools, and welding wire. In this study, the extracted image data are identified using the DNN work observation.

Trial implementation of the DNN work observation

DNN work observations are implemented as a trial for manual corner welding work during the sub-assembly stage, and the identification ability of the DNN work observation is evaluated.

Table 1 shows an example calculation of the recognition ratio of the DNN $Rr_{i,j}$ of manual corner welding work during the sub-assembly stage. The calculating conditions input into the DNN are shown in the table as a remark, and they are as follows:
1) Analysis of name of image data set: Image set A and B in Fig. 3(c)
2) The number of image data for teaching the DNN: 20,708 pictures
3) The number of work item data for teaching the DNN: 25 work items and 1 work item for the camera setting
4) The attribute image data of the worker: The worker's initials are SA
After the teaching process for the DNN, all the original image data are supplied to the input data of the DNN again to evaluate the identification ability of the learned DNN.

After the above process, the identification probability is calculated. Fig. 7 shows an example of the identification probability for the DNN work observation. The captured image data are filled with details of the contents, including the work items, which are shown in the figure. The identification probability for each work item is calculated, and the work items that have a high identification probability are indicated. In this case, as shown in Fig. 7(a), manual corner welding work, which is the most valuable work, is identified as work item No. 42: manual corner welding.

In Table 1, the recognition ratio of the DNN $Rr_{i,j}$ is calculated by Eq. (3). The rows in the table denote the input work items, and the columns denote the output work items after identification by the DNN. Particularly, the value of $Rr_{i,i}$, which is the diagonal part in the table of recognition ratio and is defied Eq. (4), shows verification of well identified or weak identified work item i. For example, work item No. 22: supplying weld wire involves 1.1% of work rate and only 55 pictures of image data. After data inputted into the DNN work observation, the work item No. 22 is recognized with 72.7% of the recognition ratio of $Rr_{22,22}$.

The shipyard aims to increase the main work of welding, which is valuable work for productivity, and to reduce the other work. Work item No. 42: manual corner welding involves 34.9% of work rate and 8,574 pictures of image data. After data input into the DNN, the work item No. 42 is well recognized with 98.4% of the recognition ratio of $Rr_{42,42}$. The ancillary work includes supporting operations of the main work. For example, work item No. 46: fixing beads with a grinder tool involves 2.4% of work

Table 1 Calculation example of the recognition ratio of the DNN $Rr_{i,j}$ of manual corner welding work during the sub-assembly stage

Input (i): Work item	Work rate (%)	Num. of data	Output (j): 2	3	5	12	13	16	19	22	24	26	28	35	42
2:Moving	13.5	2726	87.8	0.0	0.7	0.0	0.0	0.0	0.0	0.0	3.3	0.0	0.0	3.3	0.3
3:Preparing tools	0.4	30	46.7	0.0	6.7	0.0	0.0	0.0	0.0	3.3	6.7	0.0	0.0	33.3	0.0
5:Wearing protect.	3.2	261	16.9	0.0	47.5	0.0	0.0	0.0	0.0	0.8	11.1	0.0	0.4	16.1	0.0
12:Prep. gas hose	0.6	25	20.0	0.0	0.0	32.0	0.0	0.0	0.0	0.0	0.0	0.0	40.0	4.0	0.0
13:Prep. air hose	0.4	29	79.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.9	0.0	3.4	6.9	0.0
16:Detaching chip.	0.2	41	7.3	0.0	4.9	0.0	0.0	0.0	0.0	0.0	9.8	0.0	0.0	56.1	0.0
19:Connecting hose	0.3	34	2.9	0.0	2.9	0.0	0.0	0.0	20.6	38.2	0.0	0.0	0.0	23.5	0.0
22:Supplying wire	1.1	55	0.0	0.0	14.5	0.0	0.0	0.0	0.0	72.7	3.6	0.0	0.0	5.5	0.0
24:Cleaning machine	9.4	1711	8.2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	72.4	0.0	0.0	12.0	4.3
26:Wearing protector	0.7	61	16.4	0.0	34.4	0.0	0.0	0.0	0.0	3.3	23.0	3.3	0.0	11.5	3.3
28:Adjust weld machine	0.3	34	2.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.9	0.0	94.1	0.0	0.0
35:Remove slag	20.2	4469	2.1	0.0	0.2	0.0	0.0	0.0	0.0	0.0	5.1	0.0	0.0	91.5	0.2
42:Manual corner welding	34.9	8574	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.4	0.0	0.0	0.1	98.4
45:Prep paint	0.6	9	66.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	22.2	0.0	0.0	0.0	0.0
46:Fixing bead	2.4	636	0.9	0.0	3.0	0.0	0.0	0.0	0.0	1.6	0.6	0.0	0.2	9.4	0.6
51:Winding gas hose	0.2	10	40.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	0.0
52:Winding air cabel	0.4	6	16.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	33.3	0.0	0.0	0.0	16.7
56:Tidying up tools	0.2	34	5.9	0.0	32.4	0.0	0.0	0.0	0.0	8.8	0.0	0.0	0.0	38.2	0.0
58:Meeting	1.0	120	39.2	0.0	0.8	0.0	0.0	0.0	0.0	1.7	0.0	0.0	0.0	1.7	0.0
59:Rest	2.1	417	2.2	0.0	0.5	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
62: Remove hard hat	3.5	972	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
70:Prep. air	0.4	9	55.6	0.0	11.1	0.0	0.0	0.0	0.0	11.1	0.0	0.0	0.0	22.2	0.0
71:Air Cleaning	1.8	218	31.7	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.9	0.0	0.0	3.2	2.3
74:Broom	1.1	131	66.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	0.0	2.3	3.8
75:Check welding beads	0.8	89	14.6	0.0	13.5	0.0	0.0	0.0	0.0	1.1	16.9	0.0	0.0	31.5	0.0

Input (i): Work item	Output (j): 45	46	51	52	56	58	59	62	70	71	74	75
2	0.0	0.1	0.0	0.0	0.0	1.1	1.1	0.0	0.0	2.3	0.0	0.0
3	0.0	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	1.5	0.0	0.0	0.0	3.4	1.1	0.0	0.0	1.1	0.0	0.0
12	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13	0.0	0.0	0.0	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0
16	0.0	7.3	0.0	0.0	0.0	2.4	0.0	0.0	0.0	12.2	0.0	0.0
19	0.0	8.8	0.0	0.0	0.0	2.9	0.0	0.0	0.0	0.0	0.0	0.0
22	0.0	3.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24	0.0	0.3	0.0	0.0	0.0	0.0	0.8	0.0	0.0	1.0	0.0	0.0
26	0.0	1.6	0.0	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0
28	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
35	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.0	0.0
42	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
45	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.1	0.0	0.0
46	0.0	82.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.2	0.3
51	0.0	10.0	0.0	0.0	0.0	0.0	40.0	0.0	0.0	0.0	0.0	0.0
52	0.0	0.0	0.0	0.0	0.0	0.0	33.3	0.0	0.0	0.0	0.0	0.0
56	0.0	8.8	0.0	0.0	0.0	2.9	0.0	0.0	0.0	2.9	0.0	0.0
58	0.0	0.0	0.0	0.0	0.0	55.0	1.7	0.0	0.0	0.0	0.0	0.0
59	0.0	0.0	0.0	0.0	0.0	0.0	96.4	0.0	0.0	0.0	0.0	0.0
62	0.0	0.0	0.0	0.0	0.0	0.0	0.1	99.7	0.0	0.0	0.0	0.0
70	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
71	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	61.5	0.0	0.0
74	0.0	2.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	22.1	2.3	0.0
75	0.0	6.7	0.0	0.0	0.0	1.1	0.0	0.0	0.0	7.9	0.0	6.7

Remark 1: Calculating conditions input to the DNN

Teaching items for the DNN	Teaching contents
The image data set:	Image set A and B
The number of image data:	20,708 pictures
The number of work item data:	25 work items
The attribute image data of worker:	Worker SA

Remark 2: Meaning of colored frame

- **Well identified work item**
- **Weak identified work item**

rate and 636 pictures of image data. The result of calculation of No.46 is well recognized with 82.4% of the recognition ratio of $Rr_{46,46}$.

This means that main work and ancillary work can be recognized well by the DNN work observation. The manufacturing engineers can evaluate the main work and the ancillary work by using DNN work observations. The calculation result shows that the total coverage number of identified work items is 12 of the 25 total items by Eq. (6) and the coverage ratio for the work status is 89.2% by Eq. (7).

However, some work items are badly recognized, such as work item No. 12: preparing and arranging the gas hose, which is auxiliary work, and it is not clearly recognized with 32.0% of the recognition ratio of $Rr_{12,12}$. Instead of work item No. 12, the work is recognized as work item No. 28: adjusting the welding machine and it is recognized with 40.0% of $Rr_{12,28}$.

In another example, work item No. 13: preparing and arranging the air hose exhibits a 0% percent of $Rr_{13,13}$ when 29 pictures of image data are inputted. Instead of work item No. 13, the work is recognized as work item No. 2, which is moving to the work site, at 79.3% of $Rr_{13,2}$. This suggests that some work items of auxiliary work cannot be clearly recognized by the DNN because of a small number of data collections.

From these calculations, the results of the identification ability of the DNN work observation can be summarized as follows:
1) The total coverage number of identified work items is calculated by Eq. (6), and 13 of the 25 total items are accepted. Approximately half of the work items are recognized.
2) The coverage ratio for the work status is calculated using Eq. (7). The total coverage ratio of the identified work items is 89.2% and covers almost all the work of manual cutting welding. The main work and the ancillary work can be evaluated by using DNN work observations.
3) A new issue appears. The DNN have difficulties in recognizing work items that have a small work rate and belong to the auxiliary work, for example, work item No. 12: preparing and arranging the gas hose, No. 13: preparing and arranging the air hose, No. 51: detaching and winding the gas hose, No. 52: detaching and winding the air hose. These work items include similar line operational objects, such as a hose and cable.

As a result of the above trial implementation of a DNN work observation, we find that the method is useful to determine the actual work conditions in the shipyard, and the results can facilitate many suggestions for productivity improvements. However, it is still necessary to reveal how work items that have small work rate affect the recognition accuracy**.**

Formulating input image data for the DNN work observation

To determine the influence of work items that have a small work rate, effective ways of teaching the DNN are investigated. Because teaching data considerably influences the identification ability of the DNN, we investigated a method of formulating the teaching image data for the DNN work observation.

Some classified teaching image data involve many objects and multiple meanings, although the observer classifies the image data into the work items according to definition of continuous observation in Fig. 4.

This gap is expected to be compensated by DNN work observations; however, the DNN work observation cannot correct for it when the gap is too large difference. Therefore, we focus on this gap, and we define similar or common operational object in the image data to decrease this difference.

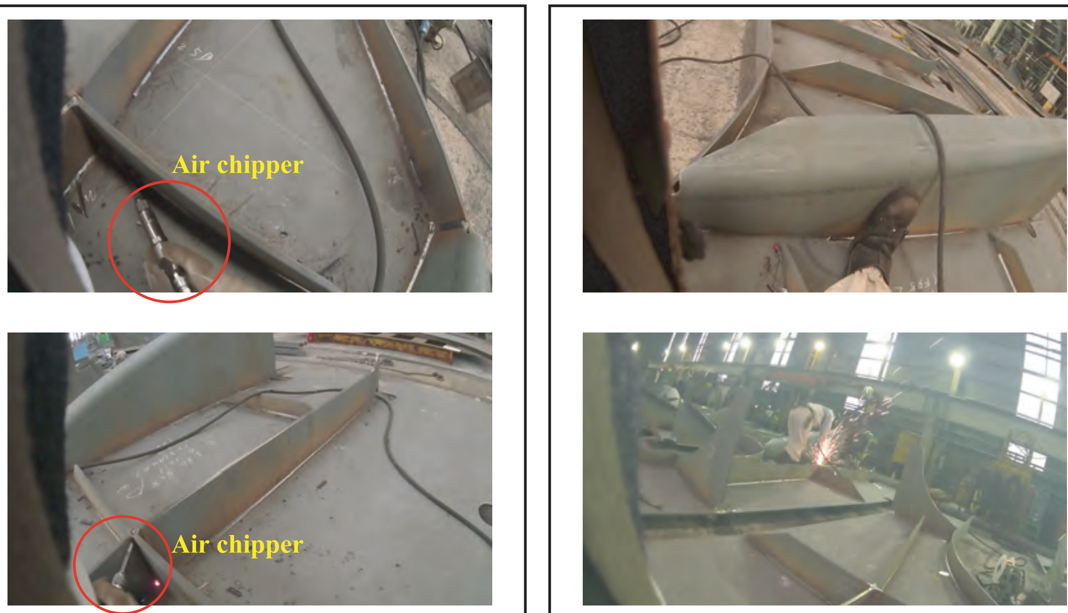
Formulating the teaching image data is performed as follows:
1) The worker operates tools and members of the ship structure at his work site. Thus, the image data includes information about the tools, machines, members of the ship structure, the work site, the parts of the worker's body, parts of fellow workers, information about the work site, etc. In this study, common tools and machines are selected as typical objects in a work item.

2) According to the former calculation results shown in Table 1, work items No. 12, No. 13, No. 51, and No. 52 involve similar operational objects, gas and air hoses, and an electric power cable. Therefore, we integrated these work items as No. 12. Work items No. 19, No. 22, and No. 28 also involve similar operational objects, such as a welding wire feeder machine. Therefore, we set the welding wire feeder machine as the common object and integrated these work items as No. 22. Also the number of image data is increased.

Fig. 8 shows example images of the orientation for selecting teaching data for the DNN work observation. The pictures show examples of the difference in work item No. 35: removing slag with an air chipper. Although every image should be identified as work item No. 35, some pictures are identified as another work item, such as work item No. 2: moving in the work site and No. 24: cleaning torch. Therefore, the air chipper is used to remove slag, and we set the air chipper as the common object. The image data are selected as teaching image data for the DNN when the air chipper is included and removed from the teaching image data.

When we carefully examine all teaching image data for the DNN, we remove 19,423 images from the total 57,342 images, and we set 37,919 images as the teaching image data for the DNN. Additional work items, which had a low number of image data, are eliminated from the DNN work observation.

Table 2 shows a calculation example of the recognition ratio of the DNN $Rr_{i,j}$ of manual welding work during the sub-assembly stage after applying this common objects method. The calculating conditions input into the DNN are shown in the table as a remark, and they are as follows:



Examples of collecting pictures from DNN teaching image data

Examples of removing pictures from DNN teaching image data

Fig. 8 Example images of the orientation for selecting teaching data for the DNN work observation (Work item No. 35: Removing slag with air chipper)

1) Analysis of name of image data set: Image set A, B, C and D in Fig. 3(c)
2) The number of image data for teaching the DNN: 37,919 images
3) The number of work item data for teaching the DNN: 17 items
4) The attribute image data of the worker: The worker's initials are SA.
After the teaching of the DNN, all the original image data are input into the DNN again to evaluate the identification ability of the learned DNN.
In Table 2 the recognition ratio of the DNN Rr, i,j is calculated by Eq. (3). The input work item is selected by considering the important manual corner welding work during the sub-assembly stage. The rows of the table denote the input work items, and the columns denote the output work items after identification by the DNN.

Almost all work items, 15 items of 17 items are improved. Particularly, 9 work items of 17 work items are improved with more than 80% of the recognition ratio of $Rr_{i,i}$ and the first dominant value, which is shown in the diagonal line on the table as a benchmark of the identification ability of the DNN. The coverage ratio for the work status reaches to 94.6%.

On the other hand, there are the work items concerning weak identified work item, for example; work items No. 58: meeting and No. 75: checking on the welding beads are only recognized at 34.1% and 13.8% of the recognition ratio of $Rr_{58,58}$ and $Rr_{75,75}$, and for the second or third dominant value, these are not clearly recognized.
For example, the image data from work item No. 75: checking on welding beads has the second dominant value of $Rr_{75,35}$. This means that work item No. 75 includes the similar image information to the work item No. 35. It is necessary that the work item No. 75 is carefully examined in work tools in related work image data. However, from the point of view of work rate, an impact of the work item No. 75 is considerably-low, only 0.7%. Additionally, the work items, which include greater than or equal to the second dominant value and relate to $Rr_{i,35}$ and $Rr_{i,2}$, also have low impacts of work rate.

Based on these calculations, the results of the identification ability of the DNN work observation are summarized as follows:
1) The total coverage number of identified work items is calculated using Eq. (6) and 15 items of the total 17 items are accepted. Almost all work items are recognized.
2) The value of the coverage ratio of the work status is calculated using Eq. (7). The value is 94.6% and covered almost all the work.
3) Impacts of weak identified items have considerably-low work rate.
4) New formulating the teaching image data has been performed successfully.

Fig. 9 shows the time series analysis for the work status of worker SA via the DNN work observation. The duration of analysis is on October 24th, 2018 from 1:00 pm to 1:30 pm that is in the part of image data set C, and the figure includes verification of calculation between the DNN work observation and continuous observation with the eye. The actual progress of work includes various work items, and the method traces it well. The validity of the DNN work observation method is confirmed through verification.

Table 2 Calculation example of the recognition ratio of the DNN $Rr_{i,j}$ of manual corner welding work during the sub-assembly stage after applying the common objects method

Input (i): Work item	Work rate (%)	Num. of data	Output (j): 2	4	5	12	22	24	26	35	42	46	56	58	59	62	71	74	75
2:Moving	16.2	4849	92.7	0.1	0.2	0.1	0.0	1.6	0.0	1.5	0.1	0.1	0.0	0.1	1.1	0.0	1.7	0.8	0.0
4:Replacing goods	0.4	123	3.3	81.3	0.0	2.4	0.0	0.0	0.0	8.9	0.0	1.6	0.8	0.8	0.8	0.0	0.0	0.0	0.0
5:Wearing protect.	2.6	125	17.6	0.0	53.6	0.0	2.4	2.4	4.8	0.8	0.0	3.2	0.0	3.2	0.0	0.0	4.0	0.8	7.2
12:Prep. gas hose	1.9	104	24.0	23.1	0.0	34.6	1.0	1.0	0.0	7.7	0.0	0.0	1.0	0.0	5.8	0.0	0.0	1.9	0.0
22:Supplying wire	3.6	520	2.3	0.2	0.0	0.6	81.2	1.7	0.0	8.3	0.0	0.8	2.3	0.0	0.0	0.0	0.2	2.3	0.2
24:Cleaning machine	10.2	4354	0.8	0.0	0.0	0.0	0.1	90.1	0.2	7.4	0.4	0.2	0.1	0.0	0.2	0.0	0.3	0.0	0.1
26:Wearing protector	0.5	97	4.1	0.0	11.3	0.0	4.1	20.6	52.6	1.0	4.1	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
35:Remove slag	18.6	7304	1.3	0.0	0.0	0.0	0.0	2.8	0.0	94.4	0.2	0.4	0.1	0.0	0.0	0.6	0.6	0.2	0.1
42:M. corner welding	34.9	17298	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	99.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
46:Fixing bead	2.2	1003	0.4	0.0	0.0	0.1	1.2	1.2	0.1	4.9	0.3	90.1	0.0	0.0	0.1	0.0	0.7	0.5	0.4
56:Tidying up tools	0.3	74	4.1	10.8	2.7	0.0	0.0	4.1	0.0	31.1	0.0	2.7	37.8	0.0	2.7	0.0	0.0	2.7	1.4
58:Meeting	1.1	85	60.0	2.4	2.4	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	34.1	0.0	0.0	0.0	0.0	0.0
59:Rest	3.6	725	0.6	0.1	0.0	0.0	0.1	1.0	0.0	0.1	0.0	0.0	0.1	0.0	97.9	0.0	0.0	0.0	0.0
62:Remove hard hat	0.8	656	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.8	0.0	0.0	0.0
71:Air Cleaning	1.5	308	17.5	0.0	0.0	0.0	0.0	2.9	0.0	3.2	1.3	0.6	0.0	0.0	0.0	0.0	69.5	4.9	0.0
74:Broom	1.0	185	19.5	0.0	0.0	0.5	0.0	2.7	0.0	7.0	0.5	1.1	0.0	0.0	0.0	0.0	26.5	42.2	0.0
75:Chk welding beads	0.7	109	7.3	0.0	0.9	0.0	0.0	12.8	0.0	23.9	0.0	20.2	0.0	0.0	0.0	0.0	14.7	6.4	13.8

Remark 1: Calculating conditions input to the DNN

Teaching items for the DNN	Teaching contents
The number of image data	37,919 pictures
The number of work item data	17 items
The attribute image data of worker	Worker SA

Remark 2: Meaning of colored frame

- Well identified work item
- Weak identified work item

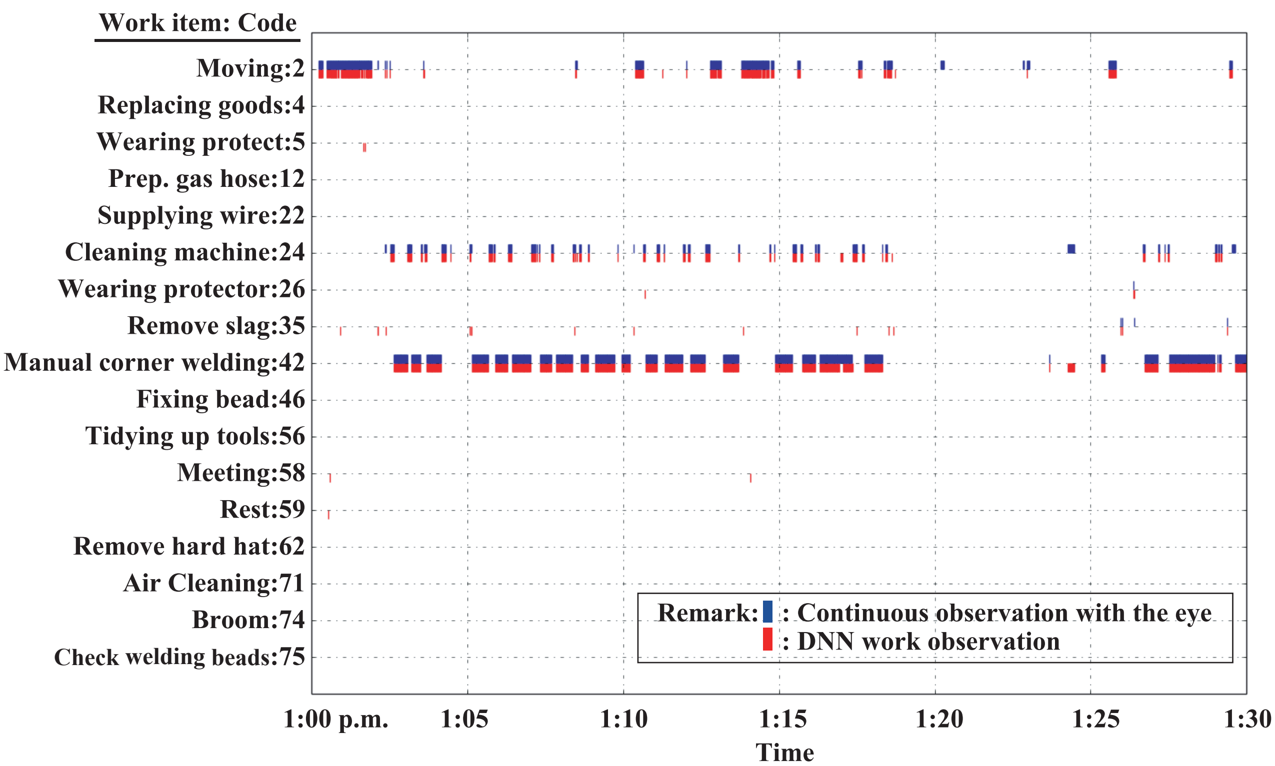


Fig. 9 Time series analysis for the work status of worker SA by the DNN work observation (October 24th, 2018, from 1:00 p.m. to 1:30 p.m.)

CONCLUSION

This paper has proposed that a DNN work observation method can be used instead of the current work observation methods in IE. We evaluate the identification ability of the DNN using the proposed benchmarks. The following results are obtained:

1) The method of extracting teaching image data for the DNN is determined. The concept of a continuous observation method in IE can be applied to the extracting method of teaching image data for the DNN, and it is possible to use the knowledge of an expert engineer to recognize work items.

2) The original method before the improvement worked well for identification when analyzing its own work data. According to the results of the total coverage identified work items using the proposed benchmarks, 12 of the 25 items are identified. The coverage ratio of the identified work items is 89.2%. However, its implementation needs to include an increase in recognizing work items that have a small work rate.

3) The important challenge is how to select common image data to improve the identification ability of the DNN work observation. A teaching method of defining common objects is proposed, so it is refinement for DNN recognition. According to the results of the benchmark, 15 of the 17 items are identified. The coverage ratio of the identified work items is 94.6%.

The effectiveness of the proposed methodology for DNN work observation is confirmed through implementation. The advantages of the method are as follows: 1) can easily set teaching image data for work items, 2) can fully use expert knowledge on the production techniques, 3) can quickly decrease misidentification of a work item by the common objects method, and 4) can visibly open a gate for an automated work observation for ship production.

However, it is still necessary to consider defining common image data when increasing the number of workers and work items. We will continue to apply this to other processes of ship construction and will further improve the DNN work observation method.

REFERENCES

TANAKA, T., SHINODA, T.: *A Method for Extracting the Work Status in Shipyard Using Deep Neural Networks,* SMC 2018, 2018.

HIRANO, H.: *New Work Study*, Nikkan Kogyo Shimbun-sya, p.121-124, 2001.

OKATANI, T.: *Deep learning*, Kodan-sya, p.79-110., 2015.

KRIZHEVSKY, A. SUTSKEVER, I. HINTON, G. E.: *ImageNet Classification with Deep Convolutional Neural Networks*, Neural Information Processing Systems Proceedings, Neural Information Processing Systems, Conference, 2012

TANAKA, T. SHINODA, T.: *Study on a Methodology of Extraction of Working Information by Deep Learning for Shipyard*, Conference Proceedings, The Japan Society of Naval Architects and Ocean Engineers, p.549-550, 2017.

SHINODA, T. TANAKA, T.: *Extraction Technique of Working Information by Deep Learning*, Conference Proceedings, The Japan Society of Naval Architects and Ocean Engineers, p.427-428, 2016.