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Detect Symptoms of Human Errors from Worker Body Movement in Monotonous Work

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***Abstract*: Management of monotonous works where human workers are indispensable has paid a lot of efforts to prevent human errors. However, many human errors still occur. Workers repeating monotonous works have unique rhythm in their body movement when they are in good conditions. The paper propose a method to calculates how strong symptoms of human errors workers have as the danger degree, From body movement of workers continuously acquired with accelerometers, the proposed method calculates the danger degree, comparing the body movement just before they commit errors with that in their good conditions. The method improves the precision of error prediction, focusing on period where the danger degree is high. The method contributes to prevention of errors, because it predicts human errors from the danger degree indicating the significance of symptoms. In an experiment to confirm the effectiveness of the method, workers repeat monotonous works tracing a circle shown on a tablet PC display many times. Focusing on the danger degree, the method can detect periods just before workers make errors with the f-measure over 0.7.**

***Keywords:* Human Errors, Accelerometer, Body Movement , Deep Learning.**

I. INTRODUCTION

There is no manufacturing factory making no effort to decrease human errors. Since human errors lead to accide-nts injuring workers and product defects reducing profits, any manager aims at eradication of human errors from their factories.

Human errors are faults workers commit unintentionally . Human errors frequently occur in assembly lines. Workers have strong tendency to commit errors when they engage in monotonous tasks, which is dominant in assembly lines adopting the line production systems. The worker repeats a single and simple task there, which takes attention from workers away. Let us consider to repeat a task to cut a round plate out from an iron plate with a welding burner. It is a trivial task, itself. Workers engaging in such a monotonous task are likely to commit human errors, because they cannot keep their willingness to work. Human errors might injure the workers because of the high temperature of the burner, or might cause the workers to engage in the same task again because of irregular outcomes. The introduction of factory automation (FA) technologies might be one way to solve these problems. However, the cost to introduce FA technologies is so huge that many working processes are still operated by human power. Many other systems are proposed to prevent workers from errors [1] [2]. [1] imposes workers on comply with a specific protocol. The adequate confirmation can reduce human errors. [2] enhances the visibility of workers. It is possible to reduce human errors, because the fair visibility facilitates activities of workers. However, human errors still occur. These studies cannot prevent human errors completely, because they do not address the decline of the worker attention directly.

The paper proposes a method to detect the decline of worker attention. We assume workers have a certain rhythm in their body movement when they repeat their task precisely. On the contrary, the rhythm is assumed to get wrong, when their attention declines. The method continuously acquires the body movement of workers with accelerometers, to find symptoms implying the decline of worker attention. The method compares the body movement just before they commit errors with that during their stable working free from errors for a long time. Through the comparison, the method calculates the danger degree to indicate how strong symptoms of human errors workers have. Many warnings based on error prediction with small probability would make workers worn out or the production efficiency degrade. The method improves the precision of error prediction, focusing on period where the danger degree is high. Since the method founds on the danger degree indicating the significance of error symptoms, it contributes to providing workers with effective and efficient warnings to take breaks.

The remaining parts of the paper are organized in the following way. Section 2 explains concepts and tools necessary to detect symptoms of human errors. It also describes existing approaches to prevent human errors. Section 3 introduces the proposed method. After an experiment to validate the method is presented in section 4, the paper discusses the experiment results in Section 5. Section 6 shows conclusion and future works.

II. HUMAN ERROR IN MONOTONOUS WORKS

A. Symptoms of human errors

When tasks of workers proceed properly, they are in good tune with their tasks under their working environments. However, even senior workers might commit errors, if they keep working for a long time. It attributes to exhaustion of their concentration coming from long monotonous tasks, which makes their attention decline. The decline disturbs their tune in the working. This paper considers symptoms of human errors appear when something disturbs tune in which workers move their bodies. If we detect symptoms of human errors, we can take any safety measure such as a break before an accident, to prevent them from inhibiting working. [3] notifies a driver of his irregular movement to prevent him from making an accident. When workers engaging in monotonous tasks have symptoms of errors, they are likely to take larger body movement unnecessarily, such as they widely swing their heads [4]. This study assumes that symptoms of human errors are irregular body movement of workers.

B. Movement Acquisition with Accelerometer

Some studies discuss acquisition of body movement with accelerometers [4]. Accelerometers have advantages in capturing human movement [5]. As the first advantage, it is so inexpensive as to be equipped with a smartphone. It is feasible to attach accelerometers to each worker to detect symptoms of human errors. The wearability is another advantage [5]. Though methods to acquire body movement with accelerometers are independent from each worker, symptoms of human errors vary with persons. Reflecting personal characteristics, we can enhance the precision, using symptoms specific to every worker. Wearable sensors can take characteristics of every worker. It improves the precision to detect personal symptoms.

C. Related Works

There are several researches which study the movement of bodies of workers to prevent human errors [6] [7]. [6] [7] find wrong tasks with sensors tracing body movement of workers. However, cameras used in [6] give discomfort to workers. In addition to that, any camera cannot shoot outside the scope. Since sensors are attached to tools used for works, the method proposed in [7]. The purpose in these research is to detect product defects through the recognition of mistakes by worker. They detect mistakes regardless of symptoms of human errors. They detect only human errors that actually occur. It is too late. Once they happen, they might cause accidents injuring workers. Workers also have to test products and rework if necessary, which reduce the efficiency of the production. We need a technique that detects symptom of human errors in advance.

III. Detecting Error Symptoms from Body Movement

A. Danger Degree Indicating Error Symptoms

The purpose in this research is to detect symptoms of human errors from body movement of workers.Fig.1 shows an overview of the proposed system detecting symptoms of human errors. Each worker wears an accelerometer on the head and the wrist of the dominant arm. The accelerometers continuously acquire body movement of the worker, transmitting it to the computer. The body movement is represented with 6 dimensional digital data consisting of 3 dimensional acceleration a_x, a_y, a_z and 3 dimensional angular velocity v_x, v_y, v_z where x, y, z and represent the directions which are orthogonal with each other. When a worker stays in a stable working mode, his body movement is in a tune with his task and working environment. As we explained in section 2.1, the decline of worker attention disturbs the tune in the working. Before a worker commits an error, he would take movement different from that in his stable working. This paper considers symptoms of human errors appear as disturbance of his body movement. We define

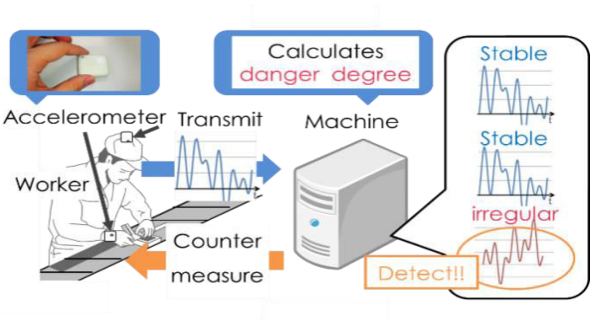

Fig. 1 Overview of proposed system

the danger degree as the probability that the worker causes a human error. The larger the disturbance of body movement is, the higher the danger degree is.

The calculation of danger degree provides flexible counter measures. For example, if danger degree is very high in a specific worker, the method suggests him to take rests immediately. Instead, if danger degree is not so high, the method warn his administrator to beware of the worker.

B. Working Rhythm to Predict Errors

Workers have their own rhythms when they move their body properly to engage in their monotonous work. If they work for a long time, however, it breaks the rhythm. In this paper, we define a working rhythm as characteristics of body movement of workers who engage in monotonous tasks. Body movement according to a specific rhythm means a worker engages in the task in a stable mode. On the contrary, disturbance of his rhythm implies he is working out of tune. The proposed method detects the disturbance as a symptom of a human error. Fig.2 shows a flow of data processing for the proposed method to detect symptoms of errors. To train the classifier, the method acquires the body movement as a time series of values measured by accelerometers attached to the worker. It collects the body movement just before the worker commits a human error, as well as that while he works satisfactorily. Each of them is considered to indicate a specific working rhythm. The

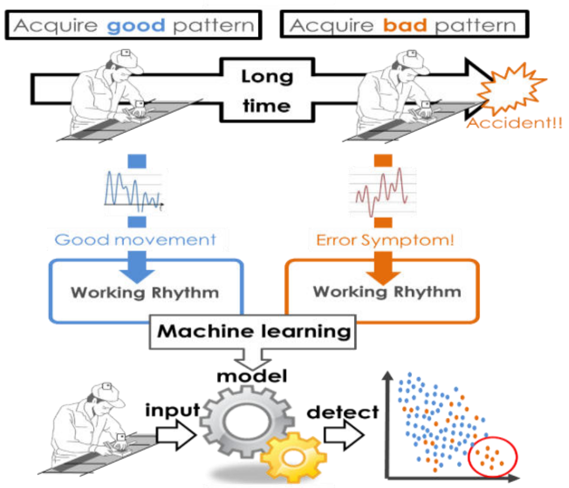

Fig. 2 Overview of proposed method

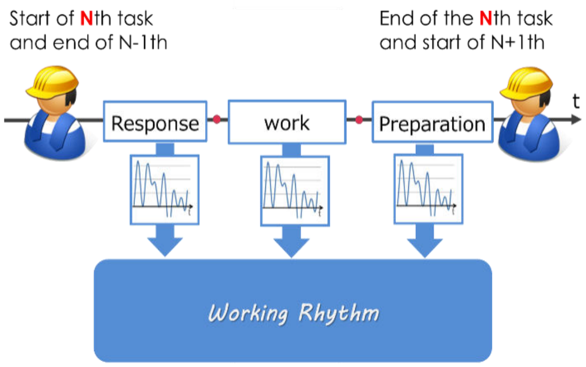

Fig. 3 Calculation of working rhythm

proposed method constructs a classifier to discriminate the working rhythm, based on a probability model.Given a series of values measured by the accelerometers, the classifier calculates the probability indicating the strength of the symptom of a human error from the working rhythm.

C. Calculation of Working Rhythms

A monotonous work is a process to repeat a short task. We focus on the transition of body movement in every task. Regarding the short work as one period, the proposed method acquires a series of data representing the body movement of the worker during one period with several accelerometers. The proposed method divides a task into three phases. The first one is a phase from the advent of a new task to the start of a task by the worker. In the task to cut out a round plate, for example, it is a time from the present of an iron plate in front of the worker until his start of cutting. This paper refers to the phase as a response time. [8]estimates a status of a worker by the response time. The second is the phase in which the worker is actually working. The paper refers to it as a work time. In the task to cut out a round plate, it corresponds to the time in which the worker is cutting a disc. The third is the phase from the completion of cutting out to the advent of the next task. This phase is referred to as a preparation time. The response time has characteristics of body movement indicating how workers start tasks. The working time represents how workers perform tasks. The preparation time shows a way of preparation for the next work. The proposed method calculates working rhythm for each phrase. Fig.3 shows the way to calculate the working rhythm in the N-th task. This method derives the working rhythm from the following values:

- the length of the phrases[9],
- the variance of the acceleration and the angular velocity in the 3 directions[10],
- the spectrum[11] figured out through the Fourier transform, and
- the sum of the incremental difference of DTW for each phase in the recent 5 tasks, where DTW is the Dynamic Time Warping distance[12].

The paper refers to the combination of these values as a working rhythm vector. We have chosen the elements of the working rhythm vector from the following reasons. The decline of worker condition is related to the length of the response time and the length of the working time. The variance shows blurring of the body movement of the worker when he is working. It increases if he has the irregular movement. The spectrum shows what periodic movement the worker takes during tasks. [11] shows the usefulness of the spectrum as a feature of the body movement. The length of the time series measured for one task varies with every task, even if the worker engages in the same task. The proposed method uses the DTW to calculate the similarity of waves different in the length. The DTW is robust for the variation of the time length of waves, because it is derived base on the Levenshtein Distance. If the DTW is large, the two time series data are quite different from each other. The paper adopts the sum of the incremental difference of DTW in five successive tasks to calculate the working rhythm. In monotonous work, the body movement of a worker in a stable mode gets refined so much that he repeats similar movements in successive tasks. In that case, the sum of the incremental difference of DTW in five successive tasks gets smaller. On the contrary, a worker showing its value gets large disturbs his rhythm of the work.

D. Calculation of Danger Degree

The danger degree is calculated from the working rhythm vectors. The proposed method collects a lot of working rhythm vectors when a worker has a symptom of a human error as well as when he has no symptom of a human error. The proposed method trains a classifier, assuming that the working rhythm vector just before a human error indicates a symptom of a human error. The explanatory variable is the working rhythm vectors calculated in 3.3. The objective variable indicates whether the time series has a symptom of a human error. Using the Deep Learning [13], the proposed method gets a classifier which calculates the probability the worker is about to commit an error. The method considers the probability as the danger degree. If the current working rhythm vector is similar to working rhythm vectors just before the worker commits an error, the classifier determines that the worker has a symptom of a human error with high probability. On the contrary, if it is similar to working rhythm vectors during long engagement in the tasks free from errors, the classifier regards the worker has no symptom to commit an error.

IV. Experiment

A. Environment and Setups

To demonstrate the usefulness of the working rhythm, we have conducted an experiment regarding on a simple task anyone can accomplish. As a simple task in experiments, we adopt a task to trace a circle pre-drawn on the tablet PC many times. We have chosen this task, assuming a frequent task in welding. Workers out of concentration cannot trace the pre-drawn circle precisely. Fig.4 shows the screen of the tablet PC. The tablet PC displays a pre-drawn circle subjects should trace. With a stylus, every subject traces a circle whose line width is w on the tablet PC. In the experiment, w is set to 8 pixels. There can be two kinds of failures in this experiment. One is the time over, while the other is to protrude from the line of a pre-drawn circle. In the experiment, subjects should finish the tracing within 7 second. Expression (1) indicates the condition of the protruding error.

$$\sqrt{(x_k - x)^2 + (y_k - y)^2} < w^2 \quad (1)$$

where r , (x, y) , and (xk, yk) are the radius of the pre-drown circle, the coordinate of the center of the pre-drawn circle, and the coordinate of the grounding point of the stylus, respectively. 15 subjects in their 20s have carried out the experiments. Each of the subjects performs a task to trace the circle 255 times, wearing accelerometers on the head and the wrist of his/her dominant arm in one set. All the subjects conduct 4 sets, taking breaks between them. One task in this experiment starts from the appearance of the circle on the tablet PC screen and ends up with the appearance of the next circle. The proposed method divides the period of one task into the response time, the working time, and the preparation time. The response time is from the appearance of a circle to the touch of the stylus on the screen. Starting from the touch, the working time continues until the subject releases the stylus from the screen. The preparation time is from the release to the appearance of the next circle. The proposed method extracts a working rhythm vector for each of the three kinds of time. In this experiment, we assume a symptom of a human error stays in 5 tasks just before a subject occurs error. The proposed method aims to detect symptoms of human errors of workers who have worked for a long time without any error, not to find workers who often commit errors for a shot time. In the experiment, we focus on subjects who have succeeded in more than 20 continuous tasks. The proposed method gives a label of 'error symptom' to the working rhythm vectors acquired from five tasks just before the subject actually commits an error. Conversely, it gives a label of 'stable' to the working rhythm vectors from the remaining.

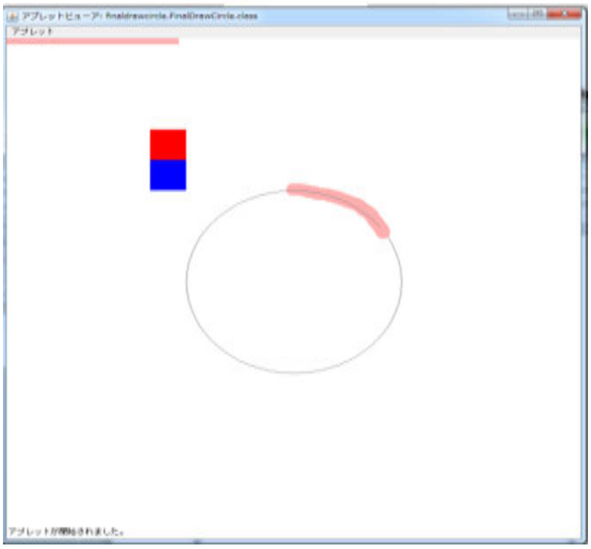

Fig. 4 Screen shot of tablet PC

B. *Evaluation Criteria*

This experiment aims to confirm:

- the ability of the classifier, and
- the usefulness of the danger degree.

1) Ability of the classifier

Only 5 working rhythm vectors have symptoms of human errors. It is far less than working rhythm vectors labeled as 'stable'. We have reduce the number of 'stable' working rhythm vectors up to the same number as working rhythm vectors labeled as 'error symptom'., with the down sampling. We compose a group to train and test the classifier of these 10 working rhythm vectors for every actual error. Out of each group, one is used for test, and the remaining are used for the training of the classifier, to perform the 10-fold cross validation. To evaluate what learning algorithm is superior to others, we have tried Deep Learning, Naive Bayes filtering, and Random Forest to train the classifier.

Repeating the 10-fold cross validation above 10 times, we figure out the recall rate r and the precision rate p for each of them. This research adopts the harmonic mean of r and p, the f-measure, to show how proper the classifier discriminates symptoms.

2) Usefulness of danger degree if we issued warnings based on small probability in actual production lines, workers would get tired of them. We should detect workers who are about to commit an error to provide workers with effective and efficient warnings to take breaks.

The danger degree in the method is the probability for a worker to commit an error. The probability model adopted in this method determines that a subject has a symptom of a human error, if the danger degree is high enough. The danger degree shows how significant the current working rhythm is. Namely, if subjects have high values in the danger degree, we can regard them to be about to commit an error.

To confirm it, we increase the threshold value to determine a subject has a symptom of an error from 0.5 in units of 0.05. The larger the threshold value is, the more working rhythm vectors that have error symptoms the classifier misses. We figure out the followings:

- the recall rate given d, denoted by R_d, which is the number of actual error cases predicted by the method over the number of actual error cases,
- the precision rate given d, denoted by P_d , which is the number of actual error cases predicted by the method over the number of predicted error cases, and
- the rate for the classifier to be unable to determine, denoted by U_d, which is the number of cases the classifier cannot determine over the number of all cases

We refer to U_d as the unknown rate.

If R_d and P_d get larger as the threshold value gets larger, we can conclude that a symptom of a human error gets more significant. It means the danger degree derived based on the working rhythm properly represents a symptom of a human error.

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Table. I Result table

	random forest		naive bayse		deep learning	
	non	error	non	error	non	error
A	0.686	0.562	0.667	0.468	0.631	0.623
B	0.541	0.540	0.670	0.369	0.577	0.592
C	0.580	0.645	0.457	0.708	0.652	0.670
D	0.534	0.560	0.660	0.289	0.587	0.609
E	0.641	0.522	0.692	0.556	0.658	0.663
F	0.725	0.586	0.542	0.557	0.649	0.661
G	0.613	0.533	0.773	0.722	0.588	0.577
H	0.673	0.641	0.733	0.733	0.674	0.655
I	0.647	0.537	0.637	0.537	0.666	0.659
J	0.530	0.640	0.194	0.638	0.618	0.640
K	0.591	0.534	0.413	0.684	0.603	0.620
L	0.660	0.534	0.686	0.560	0.658	0.652
M	0.729	0.789	0.706	0.783	0.639	0.630
N	0.657	0.688	0.750	0.729	0.711	0.736
O	0.593	0.560	0.174	0.623	0.689	0.699
avg	0.627	0.592	0.584	0.597	0.640	0.646
std	0.062	0.073	0.185	0.137	0.038	0.039

V. RESULT

A. Result of Each Machine Learning Algorithms

Table. I shows the average of the F measure in 10 times of the 10-fold cross validation for each machine learning algorithm. For every subject from A to O, the table shows the average value of the F-measure in cases the subject commits an error and no error. Fig.5 shows the average of all subject for each machine learning algorithm. The result indicates that Deep Learning produces the best classifier which detects symptoms of human errors from body movement.

B. Usefulness of Danger Degree

When danger degree d of workers is higher than a specific threshold, the proposed method regards them as those who have symptoms of errors, as it is explained in section4.2, we have examined how R_d and P_d transit when the threshold is increased by 5%.Fig.6 shows the transition of R_d and P_d. The horizontal axis shows d, while the vertical axis shows the average of R_d and P_d for all subjects. The graph shows R_d and P_d continues to increase as the threshold increases. It means we can detect

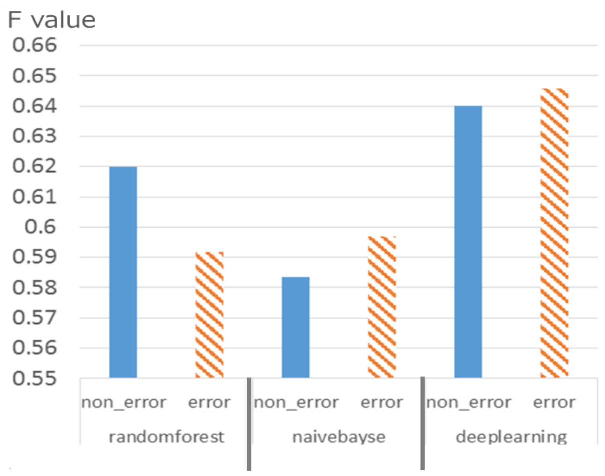

Fig. 5 Average of F value each machine algorithm

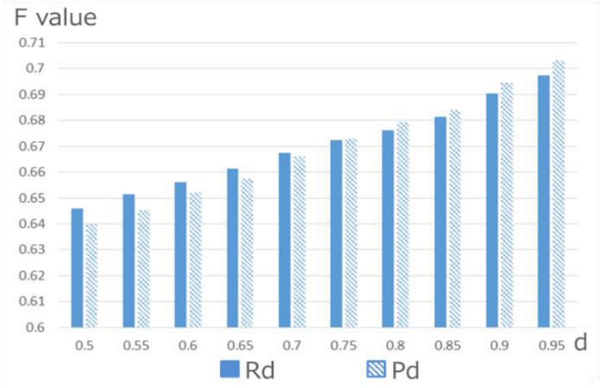

Fig. 6 Transition of $\boldsymbol{R_d}$ and $\boldsymbol{P_d}$.

workers who are about to commit errors, using high values of the danger degree. Suppose we recommend to take a break to only workers whose danger degree is high, we can avoid human errors, without the degrading the production efficiency.

C. Optimal Value for Threshold

If the proposed method used a quite high value for the threshold, it would fail to detect some workers who are about to commit errors. A high threshold increases cases the method cannot determine whether workers have symptoms of errors. In this case, the scope of the proposed method becomes narrow.

We should find an optimal value of the threshold that is as high as possible, and suppresses the unknown rate as low as possible. Fig.7 shows transition of unknown rate U_d if the threshold is increased by 5%. The graph indicates that the slope of$U_d$changes when d is around 80%. The optimal value for the threshold is 80%. With this threshold, the method is expected to detect many symptoms of human errors, covering many cases.

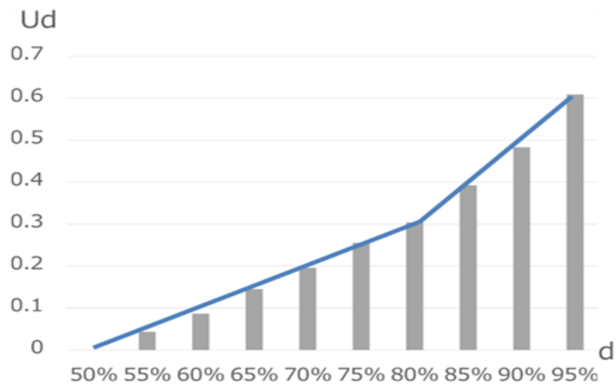

Fig. 7 Transition of $\boldsymbol{U_d}$

VI. CONCLUSION

This paper has proposed a method to detect symptoms of human errors in monotonous works found frequently in assembly lines. The proposed method acquires body movement of workers using accelerometers. It creates a classifier to determine whether a specific worker has a symptom of a human error. The classifier provides the probability the worker commit an error as the danger degree. As workers who are about to commit errors, the method picks up workers with the danger degree higher than a specific threshold value.

To demonstrate the usefulness of the proposed method, 15 subjects have conducted monotonous tasks in an experiment. From the result of the experiment, the optimal value for the threshold for the proposed method to detect symptoms of human errors is determined to be 80%. We plan to apply the method to other works in the future.

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