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Analysis of Differences between Skilled and Novice Subjects for Visual Inspection by Using Eye Trackers

Koichi Ashida, Department of Imaging Science, Chiba University, Chiba, Japan
Atsuyuki Kaneda, Gazo Co., Ltd, Niigata, Japan
Toshihiro Ishizuki, Gazo Co., Ltd, Niigata, Japan
Shuichi Sato, Niigata Artificial Intelligence Laboratory Co., Ltd, Niigata, Japan
Norimichi Tsumura, Graduate School of Engineering, Chiba University, Chiba, Japan
Akira Tose, Faculty of Engineering, Niigata University, Niigata, Japan

Abstract

The current state of visual inspection in the manufacturing industry is that there is a limit to human concentration in the work, and since concentration does not last for a long time, there is a problem of variation in accuracy depending on fatigue and physical condition. Therefore, there is such a thing as peripheral visual inspection, where visual inspection can be maintained stably over a long period of time by working with rhythmic movements. In this study, we propose an algorithm that can discriminate between skilled and novice subjects in visual inspection. In this algorithm, we used a gaze analysis system to detect differences in gaze direction (peripheral features for skilled and central features for novices) between skilled and novices. As a procedure, we built a database, extracted the necessary data, and then performed preprocessing. After that, the basic statistics of the features were calculated and SVM training was performed to build the model. As a result, we were able to classify novices and skilled with an accuracy of 93.3%

1. Introduction

In recent years, attempts have been made to automate the visual inspection of foreign matter and defects, but it is known that these attempts had to be abandoned due to the problems of inspection accuracy, image processing and image input unit. In the future, it will be necessary to overcome these problems in order to automate defect and foreign material inspection. We also surveyed the dissatisfaction with commercially available image processing equipment and found that dissatisfaction with detection accuracy and inspection speed were the main problems [1]. Therefore, human visual inspection is very important in the inspection process, and it cannot be fully automated at this stage. Therefore, the current status of visual inspection in the manufacturing industry is that there is a limit to the amount of concentration that a human being can put into the work, and since concentration does not last for a long time, there is a problem of variation in accuracy due to fatigue and physical condition.

However, in visual inspection, there is a method called the peripheral vision test method. The peripheral visual inspection method is a method that has been revised to make effective use of peripheral vision, instantaneous vision, and impulsive eye movements among the visual functions that people originally possess. By changing the inspection method from "searching for defects" to "checking for good products" in accordance with the change in the use of vision, and by working with more rhythmic movements, visual inspection can be maintained stably for a long time. Figure 1 shows the direction of the novice's line of sight in visual inspection. One of the characteristics is that the field of vision is narrow, so the viewpoint moves in a tracing manner. As a result, there is a tendency to center gaze and stare, and they are constantly repeating matching, recall, recognition, and judgment. This is thought to lead to high fatigue. Figure 2 also shows the direction of gaze of skilled workers in visual inspection. As a characteristic, they move as if they are flying to the next viewpoint due to their wide field of view. As a result, they tend to have peripheral vision and repeat rhythmic movements. This is thought to lead to relaxation and low fatigue [2].

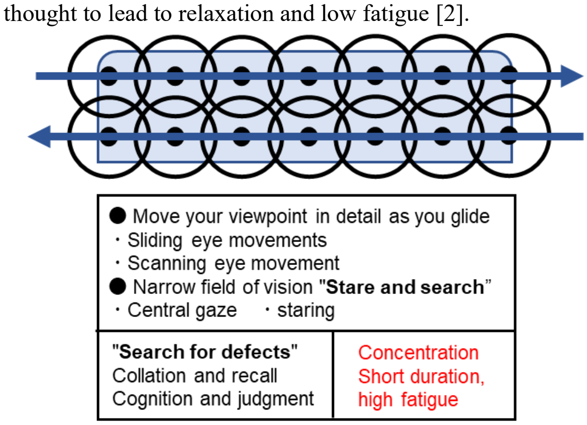

Figure 1. Conventional visual inspection method

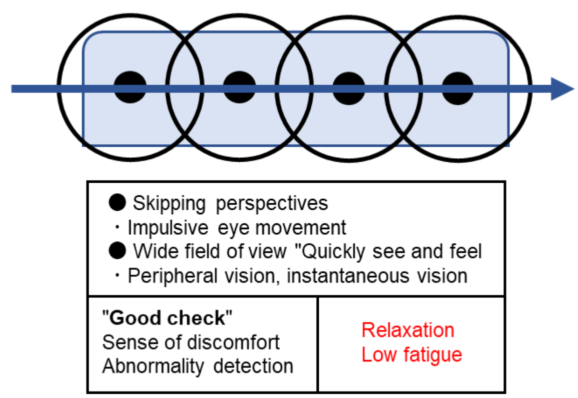

Figure 2. Peripheral visual inspection method

In this study, we proposed a highly accurate algorithm that can discriminate between skilled and novice subjects by visualizing peripheral vision and central vision and learning the visualized features in a learning model. This makes it possible to discriminate between skilled and novice subjects, and to provide a support service for visual inspection training. This will improve inspection efficiency and accuracy and enable efficient training. As a result, productivity will increase, and people will be able to learn visual inspection methods that reduce fatigue, making it possible to realize health management.

2. *Outline of the experiment*

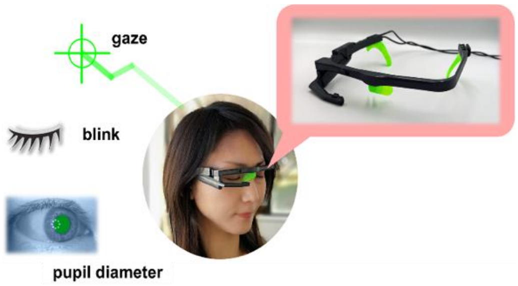

Figure 3. Overview of Gaze Analysis System

Figure 3 shows the gaze analysis system used in this study, which uses a near-infrared camera to capture images of the eyes and analyze gaze based on eye movements. It also detects blinking and analyzes it together with eye movements. The system is also equipped with near-infrared LEDs as standard, which provide sufficient light without causing glare. Analysis results are displayed on the screen in real time and can also be output to video or CSV files.

As an experimental method, we divided the participants into five groups and had them perform a visual inspection. Each of them was an expert, three beginners, and an intermediate. This time, we conducted a visual inspection of the presence or absence of scratches on the aluminum plate and analyzed if there was any difference. Using the eye analysis system described above, data in the direction of the line of sight was obtained. The number of workpieces performed by each group was 171 for the expert, 225 for beginner A, 45 for beginner B, 26 for beginner C, and 27 for intermediate.

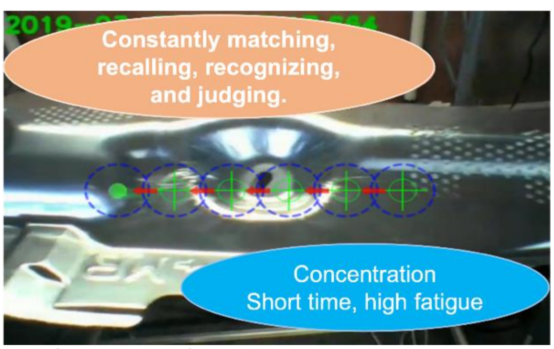

Figure 4. Gaze direction of novices in visual inspection

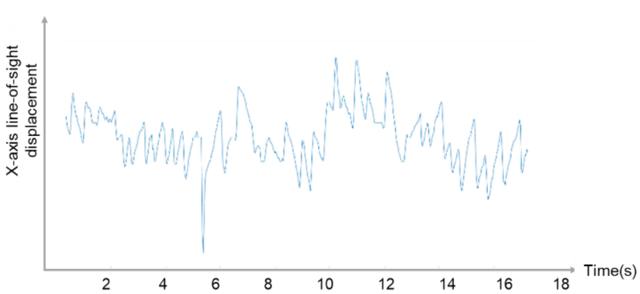

Figure 5. Time series data of gaze direction of novices

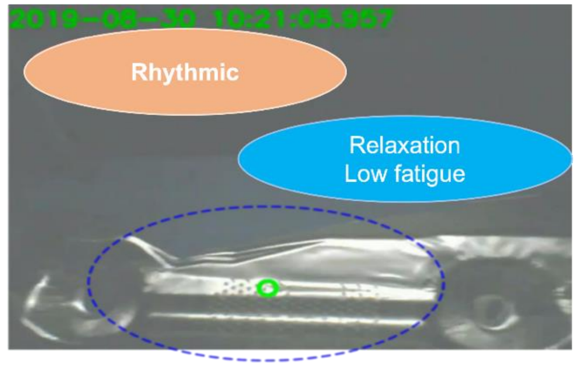

Figure 6. Direction of gaze of skilled subjects in visual inspection

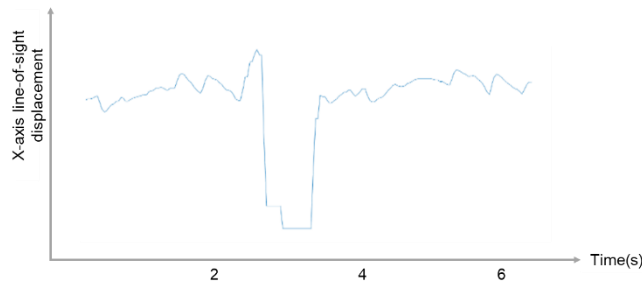

Figure 7. Time series data of gaze direction of skilled subjects

The figure 4, 5, 6, 7 shows the direction of the novice's gaze during visual inspection, and the figure shows the direction of the expert's gaze. The figure shows the direction of gaze of the novice and that of the expert. In this study, our task was to determine the difference between skilled and novice eye examiners, and at the same time, to quantify central vision and peripheral vision.

3. *Workflow in Machine Learning*

The workflow in machine learning is based on 3 steps as follows.

1) Data set creation and access

In analyzing a large amount of data, it is difficult to manage them individually. Therefore, it is necessary to manage the data information accurately and extract the desired information at any time. In order to manage the experimental data of visual inspection, we constructed a database using MySQL.

2) Preprocessing and conversion

In order to develop a prediction model, it is necessary to process the data, which is called "preprocessing". In this study, we developed an algorithm for detecting feature values using MATLAB, because the feature values of skilled and novice subjects are different. Then, we created functions to calculate "number", "area", "center of gravity", "side length", and "angle" from the feature values. Then, we calculated basic statistics (mean, maximum, median, minimum, standard deviation, and variance) and organized the data needed to develop a prediction model.

3) Development of the prediction model

We developed a prediction model by performing machine learning (supervised learning) to discriminate between skilled and novice users. SVM (Support Vector Machine) was used for supervised learning.

3.1 Creating and Accessing Data Sets

In order to make it easier to analyze the necessary data from the experimental data that is big data, it is necessary to build a database, and now we have set up a database environment using MySQL, connected it to MATLAB, imported the necessary amount of data, and made it possible to analyze the data. Figure 8 shows the database construction and access. This time, by using the Database Toolbox of MATLAB, the conversion between the database and MATLAB data type is automatically executed when exchanging data, and the data can be retrieved from phpMyAdmin on the browser via WampServer.

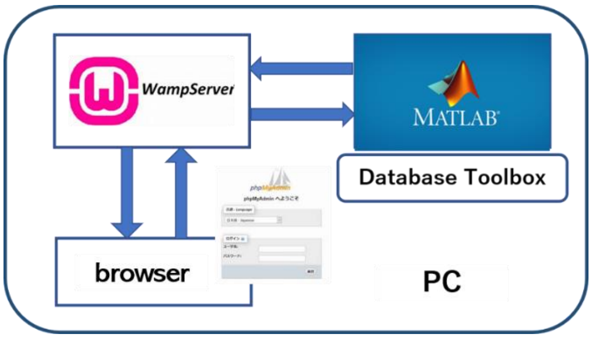

Figure 8. Database construction and access

3.2 Preprocessing and Conversion

1) Pre-processing of waveform data

Initially, the lines were approximated by Douglas Peucker to eliminate minor irregularities in order to detect accurate features. In addition, extreme outliers were removed in order to eliminate unnecessary features as shown in Figure 9. After these processes, the coordinates of each feature were detected by finding the local maximum and minimum values to detect the features. The shape of the features was then obtained using Delaunay triangulation as shown in Figure 10.

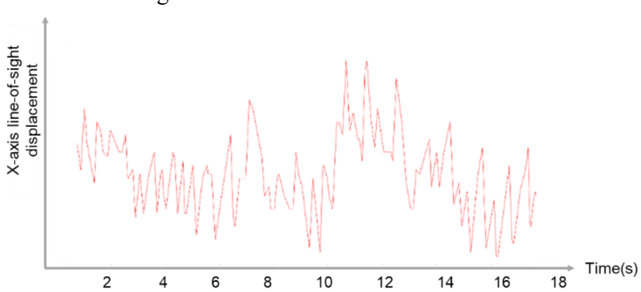

Figure 9. Line Approximation and Outlier Removal by DouglasPeucker

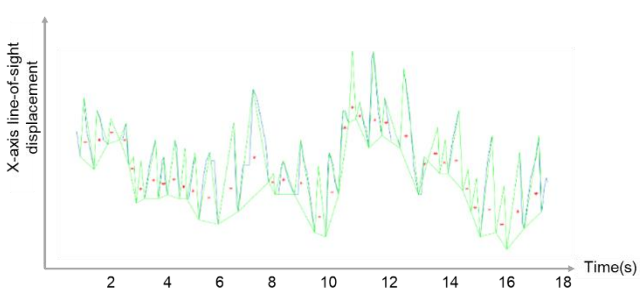

Figure 10. Obtaining the shape of the features

2) Programmed calculation of basic statistics

The number, area, center of gravity, edge length, and angle of the acquired rectangular waves were calculated programmatically. First, the distance (length of the side) was calculated using the coordinates obtained from the shape of the feature. Then, the angle was calculated using the cosine theorem, and the area was calculated. Next, the basic statistics (mean, maximum, median, minimum, standard deviation, and variance) were calculated. We created tables for each of the mean, maximum, median, minimum, standard deviation, and variance of the feature shapes, and processed them for automatic calculation and input. After that, we organized the data into a single table and exported it to a CSV file. Finally, in the selection of training data for the prediction model, the center of gravity and the number of data were omitted. The reason for this is that the center of gravity is unique because the position of the experimenter's eyes differs from person to person, and the number of pieces is unique because the number of novices inevitably increases in a time series. Therefore, the prediction model was constructed using 42 {(side length A, B, C, angle A, B, C, area) x basic statistics (mean, maximum, median, minimum, standard deviation, variance)} x 494 (number of experiments) as shown in Figure 11.

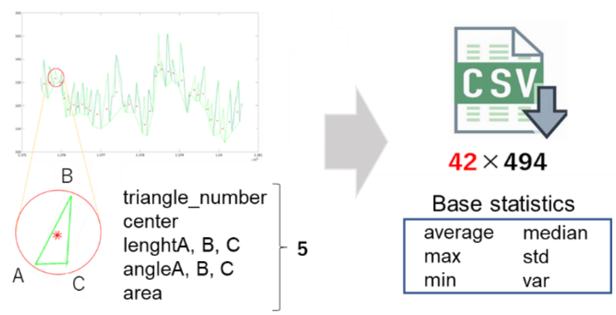

Figure 11. Flow of batch processing of basic statistics

3.3 Development of a prediction model

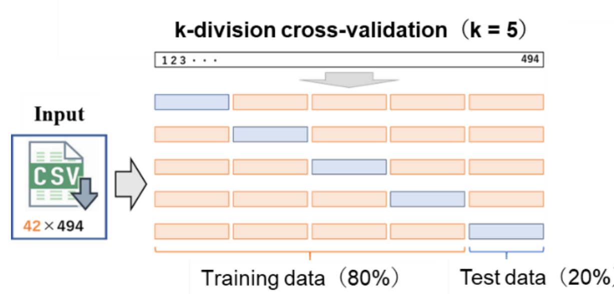

Figure 12. k-split cross-validation

SVM (Support Vector Machine) is a method for performing regression, classification, and outlier detection in supervised learning. The support vector is the point of data closest to the boundary, and it is important to keep the data as far away from the boundary as possible, even if it is close to the boundary, in order to prevent misjudgments when new data is input. In addition, we decided to use the k-split cross-validation method as the verification method. For all data to be used as verification data, the training and test data are interchanged and divided, and multiple combinations are prepared. Then, from the results of each validation, we finally take the average of multiple models to evaluate the performance. Depending on the number of patterns, it may require 3 to 10 times more computing resources, but it is currently the most widely used verification method. In this study, we divided the data into five parts as shown in the figure below and conducted 5-split cross-validation with 80% training data and 20% test data as shown in Figure 12.

4. Results

The figure 13 shows the average values of the feature shapes (angle A and angle B) obtained in the previous section, which can be classified as skilled and novice. The figure below shows the mixing matrix in supervised learning (SVM). The mixing matrix is the basic matrix when considering the evaluation of a classification model, and it represents the relationship between the predicted and observed values of the model. In the mixture matrix of supervised learning (SVM), classes 1, 2, and 4 can be identified with a high probability of over 94%. Class 3 is 86.7%, which is a high level. However, the accuracy of class 5 is not so good, at 63.0%. As shown in Figure 14, the overall accuracy was 93.3%..

※Class 1 is for novice A, Class 2 is for skilled, Class 3 is for novice B, Class 4 is for novice C, and Class 5 is for intermediates).

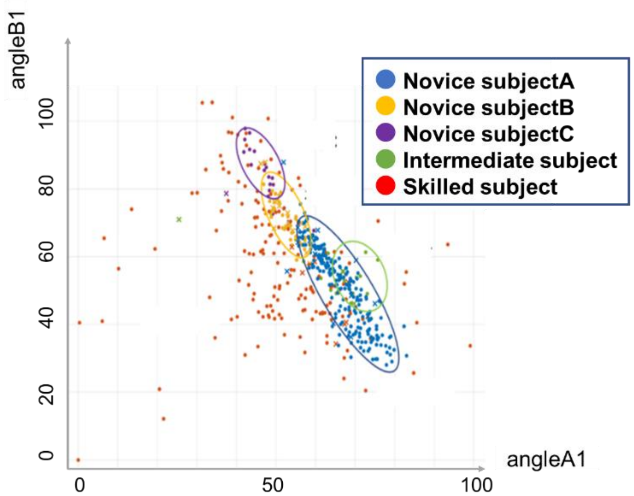

Figure 13. Scatter plot (angleA1, angleB1)

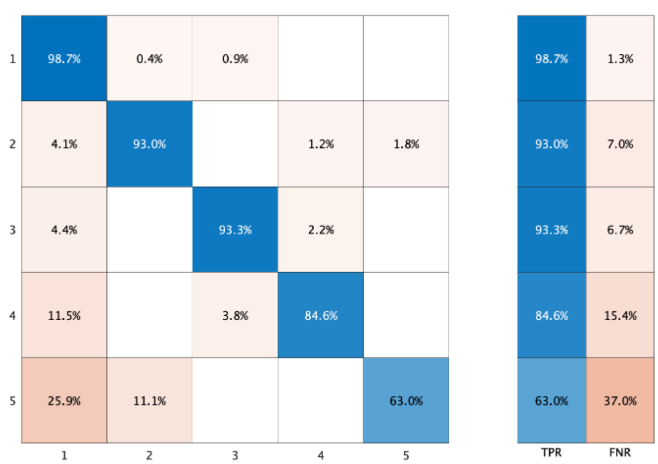

Figure 14. Mixture matrix (SVM)

5. Examination and Summary

In this study, we constructed a database, imported the necessary data, preprocessed the data, and developed an algorithm to detect shape of the feature. After preprocessing the data, we developed an algorithm to detect shape of the feature. We took the basic statistics of the detected shape of the feature and trained SVM to build the model. As a result, we were able to classify novices A, B, C, intermediates, and skilled with an accuracy of 93.3%. Therefore, we were able to develop an algorithm that can discriminate the difference between skilled and novice users.

As a future task, we would like to realize an application of the learning model developed in this study to realize a support service for eye examination training. If this is realized, it will be possible to provide a work training support service for the peripheral visual inspection method, which will improve inspection efficiency and accuracy and enable efficient training. As a result, productivity will increase and people will be able to learn visual inspection methods that reduce fatigue, making it possible to realize health management.

References

[1] K. Shigemori, M. sonoda , “Research Study on User's Requests for Visual Inspection”, p.5.

[2] “Tips for Understanding and Implementing the Peripheral Visual Inspection Method”, Chugoku Industrial Creation Center, 2017, p.1~2 (https://cirirc.jp/jigyonaiyou/research/jitsugen/pdf/hint.pdf)

Author Biography

Koichi Ashida received a bachelor’s degree from Niigata University. Currently, He belongs to the Graduate School of Integrated Science and Engineering at Chiba University. The current research field is studying non-contact emotion estimation by performing image processing and signal processing on moving images using the strong connection between biological information and human emotions.

Atsuyuki Kanada, graduated from the Department of Biology, Faculty of Science, University of Toyama. afterwards. After working as president of Microvision Co., Ltd., became independent. January 17, 2017, Established Gazo Co., Ltd. The company develops and sells equipment that uses image processing technology and provides high-quality products through specialization in image processing technology and integrated development of software and hardware.

Toshiro Ishizuki, He works for a company called Gazo Co., Ltd in Niigata, Japan. I have been engaged in non-academic research and development in the fields of econometrics and systems development engineering in small and medium-sized enterprises since 1986.

Norimichi Tsumura is an associate professor in department of information and image science at Chiba University. He received a PhD from Osaka University and was also visiting associate professor at Dept. of electrical and computer Eng. in University of Rochester. His current research field is mainly color and appearance engineering, affective computing and deep learning.

Akira TOSE is an Associate Professor of the Faculty of Engineering, Niigata University. He was appointed to Niigata University in 2016, he serves current role from 2019. His research focus is systems engineering

and safety engineering. He has an MA in System Engineering (2010) and Ph.D. in System Design and Management (2016) from Keio University, Japan.