Skill Assessment AI Technology for Expert Skill Succession

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Abstract

We have developed an AI technology for assessing skill in mold-surface polishing work in order to transfer the superior skills of experts to non-experts. We developed an AI model which compares fingertip movements extracted from video taken by a camera during polishing work, and learns so that experts have higher assessment values than non-experts. As a result, the model was able to distinguish the movements of experts and non-experts with an accuracy of 96.3%. Furthermore, the assessment values found by the AI model tend to be higher when an area is polished broadly and uniformly, and this result was found to pertain to a polishing technique called “blending” that experts practice in order to minimize distortion. In the future, we plan to verify whether non-experts can master polishing methods that minimize distortion by assessing their ability to perform blending polishing.

1. Introduction

Over 75% of companies in the manufacturing industry need to secure human resources, and securing skilled human resources in particular is essential for continuing their business activities(1). The percentage of companies re-hiring expert skilled workers after retirement age and assigning them as instructors in order to develop skilled human resources has risen as high as 60%(2). Going forward, expert skilled workers will age further, and accelerating transfer of skills is an urgent issue. However, the skills cultivated by experts have been unconsciously optimized based on their own experience, and it is difficult to discover those skills and transmit them to non-experts. To address this, Mitsubishi Electric has been conducting R&D together with Kyoto University and the National Institute of Advanced Industrial Science and Technology (AIST) through the NEDO Project “AI for Extracting and Transferring Experts’ Tacit Knowledge.” The aim is to achieve early transfer of expert skills.

For this project, Mitsubishi Electric has adopted the theme of mold-surface polishing (mirror polishing) for finishing metal surfaces cut with NC machining into a distortion-free mirror surface, and we have developed AI technology for assessing that skill based on videos taken by a camera during polishing work by experts and non-experts (Fig. 1).

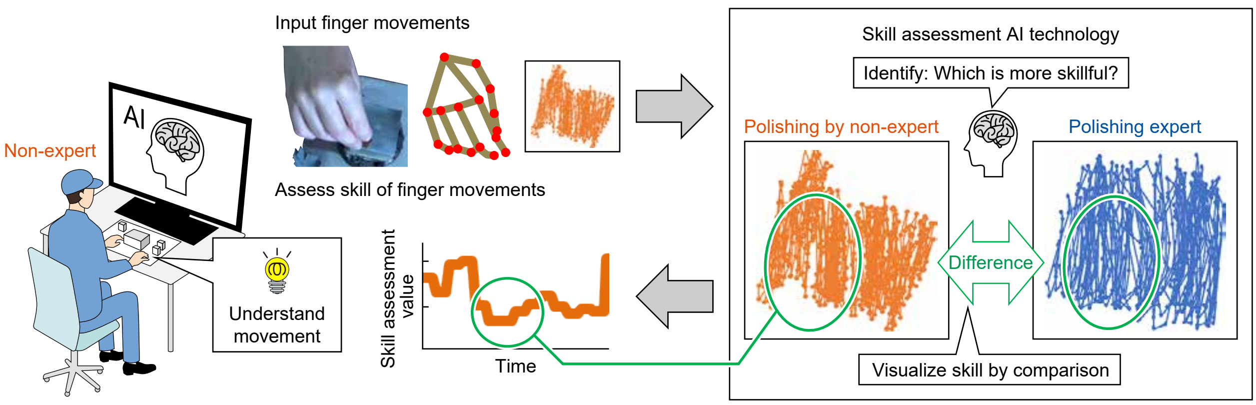


Fig. 1 Reducing the training period of technicians using skill assessment AI technologies

This paper explains the method of the developed skill assessment AI technology. It also evaluates the method and discusses its future outlook.

2. Skill Assessment AI Technology

To discuss the AI technology for assessing skills, we first explain the technical task of mirror polishing which is the theme in this paper. We also discuss the data extraction method and assessment method for assessing skills.

2.1 Technical task of mirror polishing

Mirror polishing is a type of work where the entire surface is smoothed to a mirror finish by applying a grinding stone or sandpaper to the surface of a mold part and polishing it. If mirror polishing skills are inadequate, the surface becomes distorted, and distortions occur in parts formed by the mold. This sort of distortion problem is determined by the motion with which polishing is done, and at what position polishing is done relative to the metal surface, and thus it was decided to assess differences in polishing trajectory between experts and non-experts. To secure input data in sufficient volume for an AI model, we had experts and non-experts perform repeated mirror polishing of mold parts, and took a total of 26 hours of video of this polishing process.

2.2 Extraction of polishing trajectories

To extract polishing trajectories, a video of the skilled worker's hands was taken by a camera during polishing, from a position above the worker. Polishing scenes were excerpted from the video. Hand skeleton information was extracted using MediaPipe(3), and the coordinates of the index finger of the polishing hand were extracted from that.

From the resulting work videos, 497 trajectory data sets were obtained for experts and 173 trajectory data sets were obtained from non-experts. There is more trajectory data for experts because they interrupted polishing at shorter time intervals, and we divided the trajectory in such cases. The reason why we divided the trajectory each time polishing was interrupted is that the position where polishing is resumed after the interruption is not always the same, and there is a high probability that the data will contain noise if the trajectories before and after the interruption are taken to be a series.

2.3 Skill assessment method

The skill assessment AI model developed in this case is based on a method of assessing which one of skill levels in to input videos are superior(4), and it was decided to do the assessment with 128 frames (4.3 seconds) of fixed-length data using a Temporal Convolutional Network (TCN). A TCN or Recurrent Neural Network (RNN) must be used to handle the polishing trajectories, which are time series data. However, experts take less time to polish than non-experts, and to prevent the model from capturing this tendency, we adopted fixed-length data using TCN rather than variable-length data using RNN. This AI model performs metric learning so that experts are assessed higher. This is achieved by taking pairs of trajectories from both experts and non-experts as input, and when the assessments of experts and non-experts are reversed, that difference is provided to the model as a loss. At inference time, if the polishing trajectory of a worker whose skill improvement is to be supported is input, the model can assess the skill level by comparing the input with previously learned trajectory data (Fig. 2).

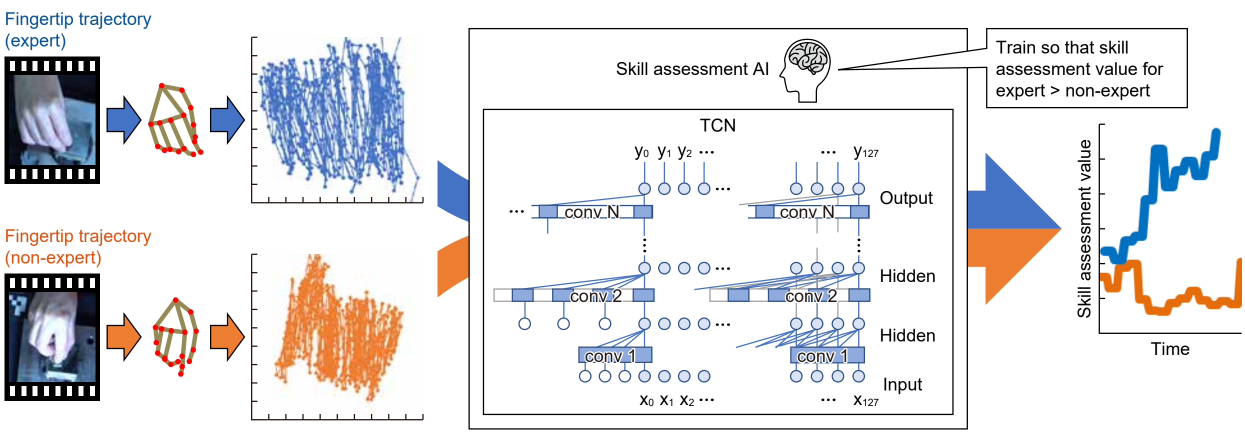


Fig. 2 Skill assessment AI model

3. Assessment

Measurements of surface distortion and other factors revealed that experts were able to perform work with good quality. Therefore, 39,873 trajectory pairs were created as training data from the obtained polishing trajectories, and training was carried out so that the assessment values of experts would always be higher than those of non-experts. As a result, the assessment accuracy marked 96.3%. In measuring the judgment accuracy, we recorded a right judgment when the model gave a higher scored for the expert than that of the non-expert and a wrong judgment in the reverse case, for each of all pairs of an expert and non-expert.

Next, to confirm whether the model has captured movement skills, a frequency graph was created showing how many frames of trajectory are used to assess skills (Fig. 3). Figure 3 shows in (a) and (b) that there is no difference in skill assessment values between experts and non-experts, but differences appear with 128 frames in (c). Therefore, the AI model does not capture the skill by reacting only to a specific position; it captures the skill through movement.

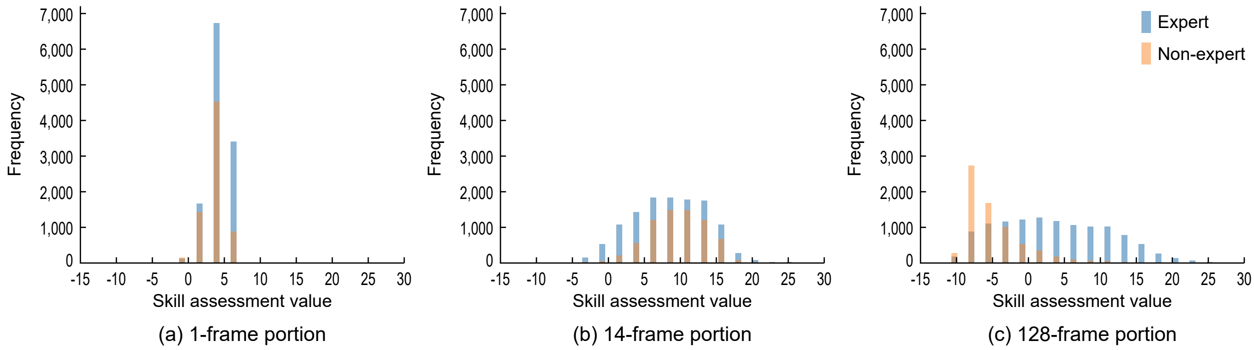


Fig. 3 Distribution of skill assessment values with respect to the number of frames in the trajectory

To further investigate which types of trajectories the AI model reacts to, we examined the correlation between the skill assessment values found by the AI model and the values of the features listed in Table 1, which we created in advance by observing movements of experts. Figure 4 plots the distribution of all polishing trajectories of experts and non-experts, with features from Table 1 on the horizontal axis and skill assessment values found by the AI model on the vertical axis, and shows the correlation coefficients between each feature and the skill assessment values. In Fig. 4, data indicating expert polishing is given in blue, and data indicating non-expert polishing is given in orange. The figure only shows distributions for the three features in Table 1 that are highly correlated with skill assessment values. From Fig. 4, it is evident that the assessment value tends to be higher if the polishing area is higher, and if polishing is highly imbalanced and locally focused, then the assessment value tends to be low. There is also cross-correlation between average stroke length and broadness of area, and thus average stroke length was found not to be an effective feature that could serve as a substitute for area.

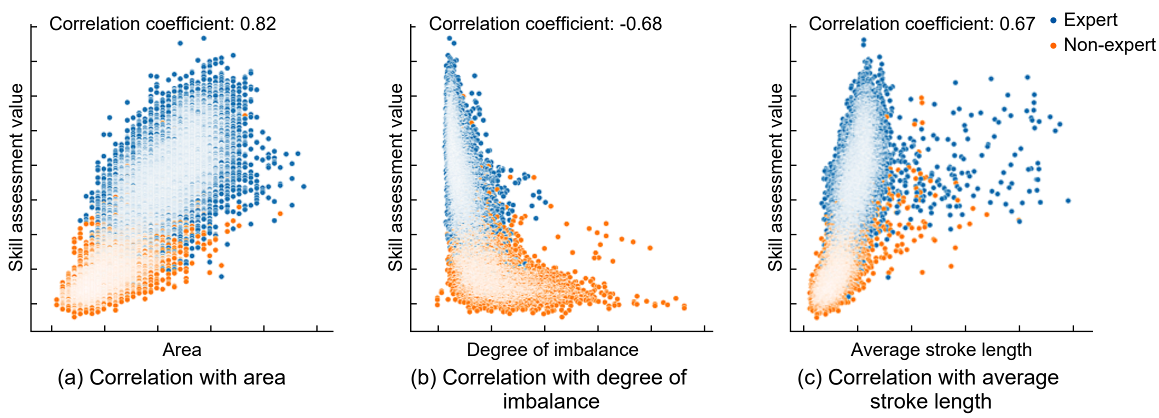
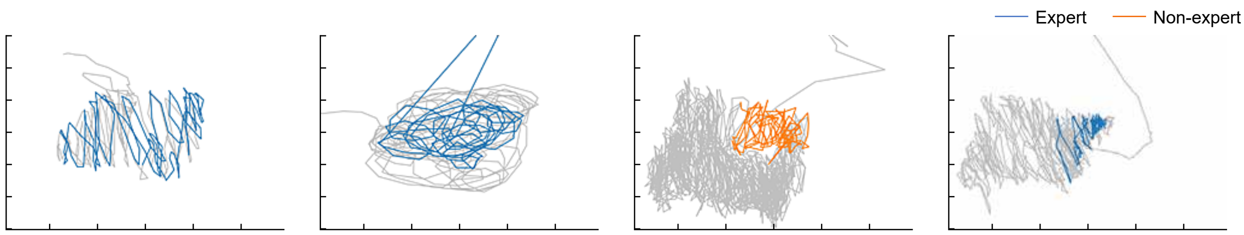


Fig. 4 Relationship between feature values and skill assessment values

Table 1 Description and name of hand-made features

Feature name	Explanation
Average X coordinate	Analysis of whether there is a polishing tendency imbalanced to the right or left side
Average Y coordinate	Analysis of whether there is a polishing tendency imbalanced to the near or far side
Total movement distance	Analysis of whether total movement distance of polishing trajectory is long or short
Average angle	Analysis of whether movement direction of polishing trajectory is always the same
Average variance	Analysis of whether movement direction of polishing trajectory has variation
Average stroke length	Analysis of whether round-trip stroke length of polishing trajectory is long or short
Stroke length variance	Analysis of whether round-trip stroke length of polishing trajectory has variation
Area	Analysis of whether area of polishing trajectory is broad
Average speed	Analysis of whether speed of polishing trajectory is high
Average acceleration	Analysis of whether acceleration of polishing trajectory is high
Degree of imbalance	Analysis of whether polishing trajectory is locally imbalanced compared to other points

Figure 5 visualizes trajectories that were ranked at the top and bottom as a result of sorting by assessment values calculated by the AI model. In Fig. 5, the overall trajectory is shown in gray, and 128-frame portions of the overall trajectory are shown in color. The expert's polishing trajectories are shown in blue and the non-expert's polishing trajectory is shown in orange. A trend was confirmed in which trajectories of polishing by an expert over a broader area, as in Fig. 5(a) and (b), were assessed with a high ranking, while trajectories of local polishing by a non-expert, as in Fig. 5(c), were assessed with a low ranking. It was also confirmed that the ranking was low for trajectories polished locally, even if done by an expert, as in Fig. 5(d).



(a) Top rank example 1, Expert

(b) Top rank example 2, Expert

(c) Bottom rank example 1, Non-expert

(d) Bottom rank example 2, Expert

Fig. 5 Polishing trajectory of top and bottom ranking assessed by skill assessment AI model

An expert interviewed beforehand commented, "To avoid distorting the surface, it's good to polish with a 'blending' technique. 'Blending' means that when you polish intensively in one area, you should also polish the surrounding areas and overall surface to maintain uniformity." This comment indicates that one should not intensively polish one area too much, but rather broaden the area by also polishing the surrounding areas and the overall surface. This matches the behavior of the AI model developed here.

4. Conclusion

We were able to capture the features of the "blending" polishing method, which is important for preventing surface distortion, through an AI model that was trained by comparing polishing trajectories of experts and non-experts and determining which had higher assessment values. With the previous method(4), videos containing multiple features distinguishing experts and non-experts were compared, and thus there was the problem that features unrelated to the skill were also extracted. With the developed method, in contrast, comparison is done by focusing on features for capturing the skill of finger movements, so it was possible to extract features relating to the above polishing method. By utilizing this kind of AI model, we can assess the polishing methods of non-experts, and support skill transfer by providing non-experts with examples of highly-assessed experts as models to follow so that non-experts can refer to them as necessary.

In response to the worsening shortage of skilled human resources in the manufacturing industry, we believe that incorporating the developed AI technology for skill assessment will help capture technical skills, promote their transfer, and accelerate the development of skilled personnel. In the future, we plan to develop a Skill Succession Support System using the developed AI technology for skill assessment, and we will verify its effectiveness, with the aim of accelerating the development of skilled personnel.

These results were obtained as result of a project (JPNP20006) commissioned by NEDO.

References

(1) Ministry of Economy, Trade and Industry, Ministry of Health, Labour and Welfare, and Ministry of Education, Culture, Sports, Science and Technology: White Paper on Manufacturing Industries 2019 (2019)

(2) Ministry of Economy, Trade and Industry, Ministry of Health, Labour and Welfare, and Ministry of Education, Culture, Sports, Science and Technology: White Paper on Manufacturing Industries 2022 (2022)

(3) Lugaresi, C., et. al.: MediaPipe: A Framework for Perceiving and Processing Reality, Third Workshop on Computer Vision for AR/VR at IEEE Computer Vision and Pattern Recognition (2019)

(4) Doughty, H., et. al.: Who’s better? who’s best? Pairwise deep ranking for skill determination, IEEE Conference on Computer Vision and Pattern Recognition (2018)