Machine-learning-based quality-level-estimation system for inspecting steel microstructures

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Abstract
Quality control of special steel is accomplished through visual inspection of its microstructure based on microscopic images. This study proposes an ‘automatic-quality-level-estimation system’ based on machine learning. Visual inspection of this type is sensory-based, so training data may include variations in judgments and training errors due to individual differences between inspectors, which makes it easy for a drop in generalization performance to occur due to overfitting. To deal with this issue, we here propose the preprocessing of inspection images and a data augmentation technique. Preprocessing reduces variation in images by extracting features that are highly related to the level of quality from inspection images. Data augmentation, meanwhile, suppresses the problem of overfitting when training with a small number of images by taking into account information on variation in judgment values obtained from on-site experience. While the correct-answer rate for judging the quality level by an inspector was about 90%, the proposed method achieved a correct-answer rate of 92.5%, which indicates that the method shows promise for practical applications.

Key words: steel microstructures, visual inspection, machine learning, overfitting, data augmentation

Introduction
Special steel has excellent heat-resistant and corrosion-resistant properties making it useful in a wide range of fields including tool steel, electronic materials, industrial-equipment materials and aircraft-related materials. Special steel results from the addition of carbon and alloy elements to iron. Adding carbon and alloy elements in this way controls physical characteristics such as toughness, abrasion resistance and shock resistance. The manufacturing of special steel involves the processes of casting, rolling, forging and heat treatment, and inspecting its metallic structures is essential to guaranteeing high quality. One inspection method is a ‘microstructure test’ in which an inspector visually judges the quality of the steel’s metallic structure based on inspection images captured by a microscope [1]. Examples of such inspection images in tool steel are shown in Fig. 1. The white bands and grains in these images are carbides—compounds of carbon and alloy elements—that are deposited when steel solidifies. It is known that the shape and distribution of these carbides have a high correlation with the physical characteristics of tool steel and fracture toughness and abrasion resistance in particular [2]. Carbides are distributed with a chain-like shape in the rolling direction and cracks can easily progress alongside carbides. Smaller and fewer carbides make for higher toughness and better quality. Coarse carbides and locations where carbides join up can be points where cracks begin and can therefore heighten the risk of cracking. On the other hand, there is also the characteristic that fewer carbides lower abrasion resistance, so it is necessary to use steel materials with a level of quality appropriate to current needs.

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Fig. 1. Examples of inspection images for tool steel. The white bands and grains in these images correspond to carbides of carbon and alloy elements. The shapes and distributions of the carbides have a high correlation with the physical characteristics of tool steel and can therefore be used as a material for judging the level of quality. Sample 1 has a higher level of quality than Sample 2.

To the automation of inspections based on external appearance have been reported [5–7]. On the other hand, machine learning suffers from the problem of ‘overfitting’ in which over-optimization with respect to specific training data prevents correct inferences from being made for unknown data resulting in a drop in generalization performance [8]. As described above, there is much variation in inspection images, but the collection of images and the teaching of quality levels must be performed manually by the inspector, which makes it difficult to prepare a large volume of training data. In addition, the correct-answer values for quality levels taught may fluctuate or be incorrect due to individual differences between inspectors. Under these conditions, it is particularly easy for overfitting to occur. The preprocessing of inspection images and the use of data augmentation are known to be common methods for suppressing overfitting.

The preprocessing of images is a technique that reshapes and processes captured raw images to convert them to images suitable for judging by machine learning. Conversion methods include processing that removes patterns such as shading and noise deemed unnecessary for making judgments [9–11] and processing that extracts feature patterns [12–14]. In our proposed method, we consider the extraction of carbide regions as material for judging quality to be an effective approach. Inputting information on carbide regions can be expected to reduce the training load and obtain good judgment results from a small volume of training data. Conversely, this method excludes information other than that on carbide regions, so there is the possibility that judgment performance can drop. In this paper, however, we demonstrate the effectiveness of this extraction process in judging the level of quality through actual testing.

Data augmentation is a technique that inflates the number of data items by artificially generating images for use as training data. The main methods for generating images can be broadly divided into processing that performs geometric conversions (flip, crop and rotate) [15–17] and processing that performs regional deletion, blending, etc. (Cutout, CutMix and Mixup) [18–20]. These techniques can also be considered useful in our proposed method in compensating for a deficiency in training data, but they cannot be expected to be greatly effective with respect to variation in correct-answer values included in training data. In response to this issue, we propose data augmentation of correct-answer values based on on-site experience with respect to variation in correct-answer values. This technique generates training data that gives multiple and different correct-answer values for the same image. Generally, there is a one-to-one correspondence between the inspection image and the quality level, but multiple correct-answer values are assigned for one inspecting image by data augmentation of correct-answer values at the learning phase.

Quality-level-estimation system

The proposed automatic-quality-level-estimation system is shown in Fig. 2. This system consists of a learning phase and an inspection phase. The learning phase begins by obtaining multiple inspection images \(\{f_i\} (i = 1, \ldots, N_f)\) for learning using a microscope. Then, for each inspection image, an inspector assigns a correct-answer value for quality level \(g_i\) in the range from 1.0 to 5.0 in increments of 0.5 for a total of nine levels. Results are taken to be training data \(\{(f_i, g_i)\}\) (the smaller the value, the higher the quality). This training data are used to optimize estimator parameters treating the inspection images as input and the quality level as output. In the inspection phase, the trained estimator is used to estimate the quality level of actual inspection images and
create a ‘mill sheet’ as an inspection certificate for that steel material.

In the proposed method, two processes are performed against each training sample \( (f_i, g_i) \) as a mechanism for suppressing overfitting. The first process performs preprocessing on inspection image \( f_i \) to remove image information having little relevance to the quality level. This is expected to reduce the number of samples needed for learning. The other process extends training samples. Specifically, considering that correct-answer values assigned by inspectors for quality level \( g_i \) includes some variation, this process generates multiple extended correct-answer values for learning purposes. This suppresses over-optimization by the estimator with respect to correct-answer values that may include errors.

The above preprocessing and data augmentation processes are described in detail below as Step 1 and Step 2. In addition, the network model used by the estimator is described below as Step 3.

Methods

Step 1: carbide extraction from inspection images by preprocessing

In general, if a large volume of training data should exist even with all sorts of image variation, it is still possible to obtain through learning a network that extracts image features that are useful in making judgments from that data. On the other hand, it is difficult to configure a general-purpose network from a small number of training samples. The proposed method deals with this situation by extracting only those carbide shapes that are highly related to the quality level from the inspection images through image processing. This preprocessing step removes excessive shading and reduces image variation. Specifically, it replaces inspection image \( f_i \) with image \( f'_i \), preprocessed by Eq. (1) and inputs \( f'_i \) into the estimator.

\[
f'_i = \text{Opening}(\text{Binary}(f_i)), \quad (1)
\]

Here, \( \text{Binary}() \) and \( \text{Opening}() \) are functions for performing adaptive thresholding and opening processing, respectively.

As supplementary information on Eq. (1), the first step is to binarize the inspection image through adaptive thresholding [21]. Since gradation occurs in an inspection image due to a reduction in the intensity of peripheral light associated with the lens being used, a binarization threshold is established here by discriminant analysis for each local region. In addition, opening processing (a type of morphology processing) removes salt and pepper noise from the image [22].

The results of applying preprocessing to the inspection images of Fig. 1 are shown in Fig. 3. It is thought that combining this preprocessing with rule-based image processing should enable a reduction in learning load in a learning-type discriminator and a suppression of overfitting even for a small number of training samples.

Step 2: data augmentation based on variation distribution of correct-answer values

Variation exists in the correct-answer values for quality levels assigned by inspectors. Here, ‘variation’ includes fluctuations and errors in judgments in sensory-based inspections. The problem here is that improving the quality of training solely on the efforts of inspectors is difficult. For this reason, it is important to have a mechanism that can maintain judgment performance even if the quality of training data should drop.

To provide this mechanism, the proposed method performs data augmentation based on a statistical distribution of variation in correct-answer values. Specifically, as shown in Fig. 4, this is performed by taking correct-answer values for quality levels \( g_i \) assigned by inspectors and generating multiple extended correct-answer values \( [g^*_i, g_i] \) \((i = 1, \ldots, N_0)\) according to variation distribution \( d \). The process generates multiple items of training data that differ only in correct-answer values from a single inspection image \( f_i \). These data are treated as a group of extended training samples \( [(f_i, g^*_i)] \) for learning purposes. As shown by the example in Fig. 4, eight correct-answer values \((0–8)\) are given for inspection image \( f_1 \) based on variation distribution \( d(g^*_1; g_1) \) thereby generating extended training samples \( [(f_1, g^*_j)] \) \((i = 1, \ldots, 8)\). Dispersing correct-answer values in this way can be expected to suppress over-optimization of each training sample even if taught correct-answer values are somewhat inaccurate thereby improving generalization performance.

A problem that arises here is how to appropriately give the variation distribution, which is generally difficult to do so since this distribution reflects the tendency for inspectors to make mistakes. We therefore performed a preliminary experiment in which we had six inspectors judging the same group of 90 inspection images to examine trends in the fluctuation of judgments by people. Based on these actual trends, the variation distribution was approximately modeled in a histogram with a total frequency of eight. We then determined

Fig. 3. Results of preprocessing the inspection images of Fig. 1 and extracting carbides. The performance of judging the quality level can be improved by excluding shaded patterns having low correlation with physical characteristics.
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Fig. 4. Extension of training data. Multiple extended correct-answer values $g_{ij}^*$ are generated from correct-answer values $g_i$ of training samples according to variation distribution $d$.

Fig. 5. Variation distribution of correct-answer values for the quality level, which defines ease of making a mistake for each correct-answer value $g_i$. (a) $g_i = 1.0$, (b) $g_i = 1.5$, (c) $g_i = 2.0$, (d) $g_i = [2.4, 4.5]$ and (e) $g_i = 5.0$.

The variation distribution based on these actual trends. In the proposed method, we switched variation distribution $d$ according to correct-answer value $g_i$. Specifically, as shown in Fig. 5, the variation distribution is given as probability distribution $d(g_{ij}^*; g_i)$ for each correct-answer value where extended correct-answer value $g_{ij}^*$ and correct-answer value $g_i$ are taken to be a variable and parameter, respectively. As described above, this variation distribution reflects the ease at which mistakes can be made as obtained from on-site experience. For example, there is a discontinuous change in appearance between quality levels 1.5 (Fig. 5b) and 2.0 (Fig. 5c), which shows that erroneous judgments spanning this interval tended not to occur. Detailed information on data augmentation processing is given in Algorithm 1. This algorithm selects variation distribution $d$ according to correct-answer value $g_i$ assigned by an inspector for image $f_i$. It then decides on the number of extensions for each extended correct-answer value $g_{ij}^*$ and adds extended correct-answer value $g_{ij}^*$ to image $f_i$ for that number of extensions. This procedure is applied to all training data.

Extending training data based on an erroneous variation distribution can generate a large volume of false training data...
Algorithm 1. Data augmentation

Input: Training data \( S_n = \{(\text{Image } f_i, \text{Correct-answer value } g_i)\} \).

Output: Extended training data \( S_{\text{out}} \).

\[
S_{\text{out}} = \emptyset
\]

for \( i = 1 \) to \( N_f \) do

\[
S_i = \emptyset
\]

for each \( g_i \) do

\[
g_i' = g_i
\]

repeat \( d(g_i', g_i) \) times

\[
S_{\text{out}} = \text{add}(f_i, g_i')
\]

end repeat

end for

\[
S_{\text{out}} = \text{add}(S_i)
\]

end for

return \( S_{\text{out}} \)

Algorithm 1. Data augmentation.

and conversely degrade judgment performance. Appropriate data augmentation can be performed by explicitly reflecting on-site experience in the variation distribution.

Step 3: network model

The network model used by the estimator is shown in Fig. 6. This model is based on a network called ‘Visual Geometry Group (VGG)’ [23], which is typical of networks having a CNN structure. It is known as architecture having high expressive power and stability by convolving small filters multiple times. Network parameters are optimized through the iterative use of training data. Here, a subset formed by an extracting part of these training data is called a ‘mini-batch’ and all mini-batches, that is, the number of times that all training data are used for training is called an ‘epoch’.

The first stage of the network inputs an inspection image and extracts features by convolutional layers and pooling layers. Normalization processing follows a convolutional layer, which has the effect of preventing large fluctuations in the input distribution and suppressing overfitting. Commonly used batch normalization outputs a mean of 0 and a variance of 1 for each mini-batch, but instability has been reported in the case of small batch sizes. For the proposed method, we adopted group normalization, which is a derivation of batch normalization [24,25]. Here, the output of a convolutional layer is divided into multiple groups and normalization is performed against each group so as to alleviate the above problem of instability. In addition, we used the Leaky Rectified Linear Unit (ReLU) function for the activation function [26]. This function, which is a variant of the ReLU function known as a typical activation function, deals with the problem of vanishing gradients when learning cannot progress against negative input values. In addition, the second stage of the network fully connects the extracted features and outputs the quality level.

We also used the ε-insensitive loss method to optimize network parameters [27]. This technique is said to prevent excessive minimization of the loss function and to suppress overfitting. The loss function in the learning step of the \( k \)-th mini-batch is given by the following equation:

\[
\text{Loss}_k = \sum_{i \in \Phi_k} \sum_{j \in \Psi_k} \max (|\hat{g}_{ij} - g_{ij}| - \epsilon, 0),
\]

where \( \hat{g}_{ij} \) is the estimated quality level for extended training sample \((f_i, g_{ij}^*)\), \( \epsilon \) is the insensitive loss error, and \( \Phi_k \) and \( \Psi_k \) are the set of training sample IDs included in the \( k \)-th mini-batch and the set of extended training sample IDs, respectively. All extended training samples are trained within one epoch.

Results and discussion

Experimental conditions and system

We conducted an experiment to test an automatic-quality-level-estimation system based on the proposed method. In the experiment, we used SKD11 alloy tool steel (JIS G4404 [28]). SKD11 is a steel material excelling in hardness and abrasion resistance by adding chromium, molybdenum and vanadium to carbon tool steel (composed of iron, carbon, silicon and manganese). It is frequently used as a cold die for forging at normal temperatures. We collected test specimens based on the American Society for Testing and Materials (ASTM) E3
standard, and after grinding, etching (5% nital (5% nitric acid and 95% ethyl alcohol)) and washing, we observed the specimens using an optical microscope with a magnification of 100. The field of view of the image is 430 mm × 300 mm, inspectors judge the average quality level of the field of view. A carbide width is at most 1/10 or less of the image width. We used 362 inspection images collected by the technique described earlier. The correct-answer values for quality levels are determined by the consensus of six inspectors. The evaluation was conducted by 4-fold cross-validation with the number of training, validation and testing samples having a ratio of 6.0:1.5:2.5.

Here, to test the effectiveness of inspection-image preprocessing and data-augmentation processing described above in Step 1 and Step 2, respectively, we also evaluated a method that excludes these processes taken from the proposed method. This method, called the ‘comparison method’ below, performed existing types of data augmentation such as image rotation and flipping the same as conventional methods and the proposed method. The number of training images was extended to 16 times the number of original inspection images.

A screenshot of the Graphical User Interface (GUI) prepared for the automatic-quality-level-estimation system is shown in Fig. 7. At learning time, variation distribution $d$ of the quality-level correct-answer value can be given for each correct-answer value $g_i$. Then, at inspection time, inspection images automatically captured with a microscope are successively input to the estimator, which displays quality levels estimated at a rate of 0.3 s per image. If necessary, the inspector can check estimation results and perform additional learning if errors are found. If the performance of the estimator is stable, there is no need for an inspector to do any checking, which greatly improves work efficiency.

**Estimation accuracy and learning curves**

In Fig. 8, the results of estimating the quality level against testing data are shown in the form of a confusion matrix, where the horizontal axis and vertical axis represent the estimated quality level by the estimator and the correct quality level taught by an inspector, respectively. The greater number of samples lined up on the matrix diagonal, the estimated results are considered to be more favorable. Results for the comparison method are shown in Fig. 8a. These results show that the distribution of samples is also spread around the diagonal resulting in estimation accuracy of 84%. In contrast, the results for the proposed method in Fig. 8b show little spread in the distribution resulting in estimation accuracy of 92.5%. In short, estimation accuracy by the proposed method shows great improvement over that by the comparison method. In this regard, estimation accuracy for visual judgments of the quality level by inspectors is taken to be about 90%, and for this reason, an accuracy value of 90% has become the performance target required for practical applications. The proposed method was therefore able to achieve a level of accuracy equal to or better than that of inspectors.

Learning curves are plotted in Fig. 9. The horizontal axis and vertical axis represent epoch (number of learning cycles) and loss-function value, respectively. In the learning of network parameters, the aim is to solve a minimization problem for this loss value, so this value tends to decrease as the number of epochs increases. Incidentally, this learning process uses the dropout method that inactivates nodes at a fixed ratio, but the loss value with respect to training data plotted in the figure was calculated in a state in which all nodes are activated. For training data, it can be seen from the figure that the loss value by the comparison method decreases much faster than that of the proposed method. For validation data, however, the loss value by the proposed method shows a greater drop than
that of the comparison method. The proposed method suppresses overfitting with respect to training data as observed in the comparison method and obtains high generalization performance with respect to validation data.

Even in the case of no overfitting, the loss value of training data used for optimization in typical training tends to be smaller than the loss value of validation data. However, for the proposed method, it is deeply interesting that the loss value of validation data is, in contrast, smaller than the loss value of training data. The reason for this is that correct-answer values are dispersed by data augmentation, but since the loss values are somewhat reversed here, the possibility should be considered that the variation distribution in data augmentation is somewhat out of line with the actual distribution. Of course, giving an accurate variation distribution is difficult, but an approach that varies the variation distribution for each training sample based on loss value may have value in future studies.

Concluding remarks

In this study, we proposed an automatic-quality-level-estimation system based on machine learning. Although the automation of inspections based on external appearance is progressing at manufacturing sites, there are still many inspections that are conducted visually by inspectors. The proposed method introduced the preprocessing of inspection images and data augmentation taking on-site experience into account. In this way, the method suppressed the problem of overfitting when training with a small number of images and achieved a correct-answer rate of 92.5%, which is a level of performance on par with that of visual judgments by inspectors.

Going forward, we plan to introduce this system into actual manufacturing sites to test its applicability with the aim of eliminating individual differences between inspectors in the inspection process and reducing costs. We also plan to study application to metal materials other than alloy tool steel tested in this study so as to expand the range of automation by this system.

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