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Incorporation of neural network analysis into a technique for automatically sorting lightweight metal scrap generated by ELV shredder facilities

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ABSTRACT

In an attempt to improve the technique of automatic sorting of lightweight metal scrap by sensing apparent density and three-dimensional shape, realized by the combination of a three-dimensional (3D) imaging camera and a meter to weigh a moving object on a conveyor belt, neural network analysis was integrated into the scrap identification algorithm, and its effect on the sorting accuracy of this technique was examined using approximately 1750 pieces of scrap sampled at three different end-of-life vehicle (ELV) shredder facilities. As a result, the newly developed algorithm, in which an unknown fragment is identified by passing through two discriminant analyses and one neural network analysis, was demonstrated to greatly decrease the time required for data analysis to prepare the identification algorithm without reducing the sorting accuracy. The average sorting accuracy for a mixture of three types of lightweight metal fragments was found to be 85%, based on the fact that the fist-sized fragments of cast aluminum, wrought aluminum, and magnesium sampled at the three ELV shredder facilities had similar apparent densities and 3D shapes. It was also suggested that still higher sorting performance is possible by repeating the procedure of modifying the database and re-learning of the neural network in the identification algorithm.

1. Introduction

In the automotive industry, in order to improve fuel efficiency by reducing weight, the substitution of lightweight metal parts for conventional steel parts is becoming increasingly common. Wrought aluminum parts are increasing used in body panels (e.g., hoods, roofs, and deck lids), and cast aluminum has been widely used for engine parts (Inaba, 2002; Sakurai, 2007). As a consequence, in the future, the demand for wrought aluminum parts will likely surpass that for cast aluminum (Okubo, 2005). Meanwhile, in the recycling of aluminum scraps recovered from end-of-life vehicles (ELV), only cast alloy, which allows for some contamination that negatively affect its mechanical and chemical properties, is currently produced as secondary aluminum, because recovered aluminum scrap, which is a mixture of cast and wrought aluminum, is not suitable for use in wrought aluminum production (Brown et al., 1986). This may lead to a supply-demand imbalance in secondary aluminum production in the future, and therefore a closed recycling system, in which wrought aluminum parts are recycled as wrought aluminum parts, is desired. In order to establish such a system, in addition to removing other contaminants, it is necessary to separate cast aluminum and wrought aluminum scrap during the recycling process.

Although wrought and cast aluminum scrap are not separated at most ELV shredder facilities at present (because the economical incentive remains small), several studies have considered future demand. From a technological point of view, conventional mechanical separation technologies (e.g., color sensing separation, dense media separation, eddy current separation, and air classification) can remove contaminants of steel, nonferrous metals, and nonmetals, but these technologies are not applicable to the precise separation of wrought and cast aluminum scrap because the differences in the physical properties of wrought and cast aluminum are relatively small. The hot-crush separation process, which is based on the difference in the mechanical properties of wrought and cast aluminum in the 520–580 °C temperature region (Ambrose et al., 1983) is a high-cost process and is not widely applied in waste processing. Therefore, several novel scrap sorting techniques using X-ray transmission analysis (Mesina et al., 2007), X-ray fluorescence analysis (TFS, 2008), or laser breakdown spectroscopy (Gesing et al., 2003), have been developed in recent years. In the X-ray transmission analysis method, however, the effects of shape irregularity of shredded metal fragments on sorting accuracy, i.e., differences in thickness in the direction of X-ray transmission, have not been clarified in detail. In the X-ray fluorescence analysis and laser breakdown spectroscopy method, high sensitivity to contam-

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ination on the surfaces of metal scrap becomes a serious problem in the recycling process. Furthermore, these techniques generally require high initial cost with respect to the instruments of the sorting system.

In a previous study (Koyanaka and Koyanashi, 2010), we demonstrated a new automatic sorting technique by which to realize high separation efficiency and low processing cost for the separation of fragments of lightweight metal scrap generated at ELV shredder facilities. The developed sorting system, which combines a three-dimensional (3D) imaging camera and a meter to weigh a moving object on a conveyor belt, was shown to be capable of separating several hundred wrought aluminum, cast aluminum, and magnesium fragments according to differences in apparent density and three-dimensional (3D) shape with an accuracy of 85–95%. The effectiveness of this sorting technique with respect to simplicity and generality, however, remains a subject of debate because this sorting technique is based on data accumulated in past measurements. In other words, the identification process used in this technique is a process in which a measured object is checked against previously recorded data in the database, and the material of the unknown fragment is identified by an algorithm based on a multitude of discriminant analyses. Thus, if the number of sample fragments becomes large, the structure of the algorithm inevitably becomes complex because of the low data capacity of one discriminant analysis. This means that lengthy and tiresome data analysis is necessary in advance in order to prepare the algorithm. Furthermore, in the previous study, the number of tested samples, which was several hundred fragments obtained from a single ELV shredder facility, was not sufficient to determine the usefulness of the technique for mass processing at various facilities.

The purpose of the present study is to improve the above described automatic sorting technique with respect to simplicity and generality. In the present paper, the incorporation of a neural network into the identification algorithm is examined to ensure its feasibility. First, an outline of the neural network used for this sorting technique is explained and its effects on the simplification of the procedure required to prepare the algorithm are confirmed. An investigation of the generality of this sorting technique is then carried out by adding sample fragments obtained from two other ELV shredder facilities. The similarity of the physical properties of the fragments obtained from the three ELV shredder facilities is clarified by repeated measurements of weight and 3D shape. Finally, the reduction in sorting accuracy that occurs when applying an algorithm prepared using fragments from one shredder facility to fragments from the other two facilities and the effect of re-learning of neural networks on the sorting accuracy are examined by comparing the fragment sorting results for the three shredder facilities.

2. Neural network

The neural network is a mathematical model for information processing that imitates the structure of the human brain, and it is possible to obtain an output similar to that obtained by discriminant analysis. In using a neural network, learning data, which consists of a combination of input variables and desired outputs, are prepared in advance, and the neural network is trained and optimized using these data. The data of an inspected fragment are then input to the neural network, and the material of the fragment is identified based on the output. The advantages of this neural network model are that it can infer an arbitrary relation between the explained and explanatory variables, can deal with a large amount of data, and can output two or more potential material types in one calculation. Moreover, the accuracy of identification can be improved by re-learning based on additional data.

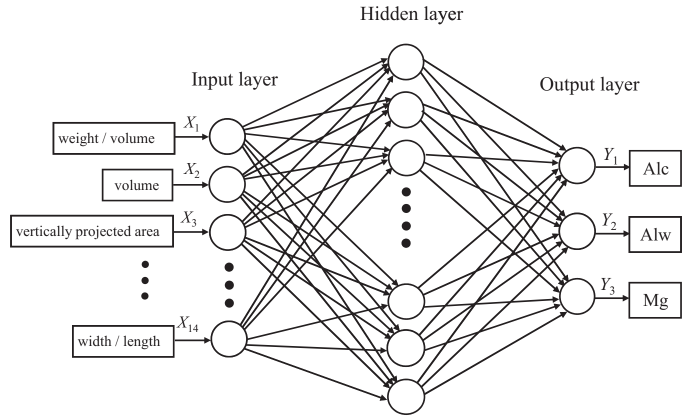

Fig. 1. Three-layer neural network model for the identification of the fragment material.

Although there are several types of neural network, we used the feedforward neural network, which consists of multiple layers of computational units. Fig. 1 shows the three-layer neural network model used in the present study for the identification of the material of cast aluminum (Alc), wrought aluminum (Alw), and magnesium (Mg) fragments. With regard to the network architecture, 14 units (neurons) corresponding to the fragment's weight and 3D shape were set at the input layer, and 3 units corresponding to the material of the fragment were set at the output layer. The number of units in the hidden layer was set to between 10 and 30 according to the degree of difficulty of the identification. Each unit in one layer was connected to the units of the subsequent layer with the weight of the input value. The calculation process of this neural network is as follows. First, the variables of X_1–X_{14}, normalized to a value between 0 and 1 by the following equation are input to the input layer:

$$x_i = \frac{X_i - X_{i\,\min}}{X_{i\,\max} - X_{i\,\min}} \tag{1}$$

where x_i is the variable after normalization, X_i is the variable before normalization, $X_{i\max}$ is the maximum value of X_i in the learning data, and $X_{i\min}$ is the minimum value of X_i in the learning data. In each unit in the hidden layer, the incoming value x_i is multiplied by the corresponding weight w_i and the difference between the sum of these products and a threshold value h is substituted for the sigmoid function. The calculated values of the function given by the following equation are transferred from unit j to each unit in the output layer:

$$y_j = \frac{1}{1 + \exp\left[-\sum_{i=1}^{14}(w_{ji}x_i - h_j)/T\right]} \tag{2}$$

where w_{ij} is the weight between input value x_i and unit j, T is the parameter of the sigmoid function, and y_i is the output value of unit j. A similar calculation was conducted for each unit in the output layer, and the output values of Y_1–Y_3 were finally obtained. The values of Y_1–Y_3 are normally 0 or 1, except for the case in which the calculation does not converge. In order to construct and optimize the neural network structure, we used the supervised learning method computed by conventional neural network simulation software (NEUROSIM/L V4, Fujitsu Co. Ltd.). The weights of the input values for each unit were corrected based on the backpropagataion algorithm. The operational settings of the simulation software, e.g., the number of learning steps, the admissible error, the number of supplementary learning steps, were decided according to the properties of each input data group. The material of the unknown sample was identified by comparing the Y_1–Y_3 values from the output layer of the optimized neural network as follows. If Y_1 is maximum, then