Used Dry-cell Battery Classification Using Convolutional Neural Networks for Battery Recycling

T. Aoki and T. Takeuchi

*Abstract***—To construct used dry-cell battery recycling systems, classification of batteries (manganese / alkaline / rechargeable batteries) is the most important task. In this paper, we present a novel classification method for used batteries based on Convolutional Neural Network (CNN). To achieve high-accuracy classification, we turn our attention to cross-section images of a battery instead of shapes, weights and labels etc. We convert raw cross-section images of used batteries into the weighted polar-representation images. The weight of these images is given by sigmoid function. By using these images as input, the system drastically improve the classification performances. Experimental results show the proposed method achieves accuracy of 97.10% within 0.2 second per one battery.**

*Keywords***— convolutional neural network, deep learning, polar representation, used dry-cell battery classification**

I. Introduction

Although a battery contains a lot of precious materials, it is not recycled until now. The biggest reason of this situation is that used battery recycle systems do not exist at all in the world. For example in Japan, approximately 80 percent of batteries are landfilled by local governments. According to the experts on Environment Engineering, the key technology to construct used battery recycle systems is the high-accuracy classification of batteries. All types of batteries (manganese battery, alkaline battery and rechargeable battery) are almost the same shape. Also, the weights of them are a little different, but they become almost the same weight when a battery gets rusted or liquid spill occurs. Therefore these types of information cannot be utilized to discriminate the types of batteries. Another approach is to recognize battery labels by CV (Computer Vision) technologies. However, the labels of used batteries are often dirty or come unstick. That is why it is very difficult to achieve high-accuracy classification (more than 95%) by this approach.

In this paper, we present a novel method to classify 3 types of used batteries using CNN[14]. As described above, general information such as shape, weight, and labels of batteries cannot be utilized for distinctive feature for battery classification. Therefore, we turn our attention to cross-section images of batteries because both sides of batteries are inevitably cut out at the beginning stage of the recycling process.

Fig.1: Cross-section images of used batteries. They often look similar in appearance even if they are different types of batteries. On the contrary, they often look totally dissimilar in appearance even if they are the same type of batteries. So we have a lot of challenges to be tried.

As shown in Fig. 1 cross-section images of used batteries often look similar in appearance even if they are different types of batteries. On the contrary, they often look totally dissimilar in appearance even if they are the same type of batteries. So we have a lot of challenges to be tried.

At present, Convolutional Neural Network (CNN) is one of the best tools for a variety of Computer Vision (CV) tasks such as image classification, object detection, and image segmentation etc. [1][2]. Although CNN often shows much better performances than traditional methods such as BoF (Bag of Features)[3]-[9], only a few researches focus on texture recognition (texture-based classification) [10]-[13]. Also, CNN is not suited for non-rectangular (arbitrarily shaped) images because input of CNN has to be rectangular images.

The cross-section images of used batteries are circle-shaped, and the most distinctive features in them are texture of cross section surfaces. Under this situation, we convert raw cross-section images of used batteries into the weighted polar-

Manuscript received Feb.19.2018.

T. aoki is with Tohoku University, 6-6-10, Aza Aoba, Aramaki, Aoba-ku, Sendai, Miyagi 9808579 JAPAN.

T. Takeuchi is with Tohoku University, 6-6-10, Aza Aoba, Aramaki, Aoba-ku, Sendai, Miyagi 9808579 JAPAN.

https://doi.org/10.17758/URUAE.AE03181010

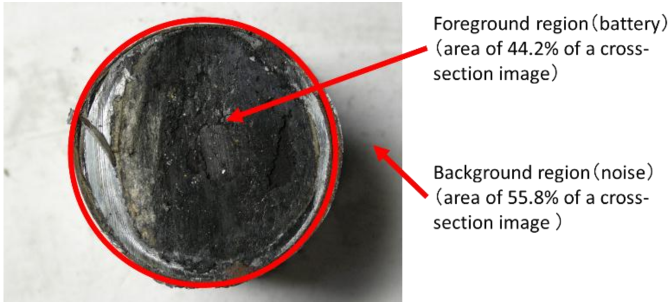


Fig.2: Example of the cross-section image of a used battery.

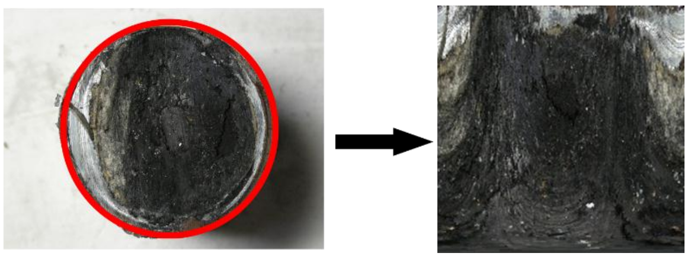


Fig.3: Removal of noisy background. We convert a raw cross-section image into a polar representation image.

representation images. The weight of these images is given by sigmoid function. By using these images as input into CNN, the system drastically improve the classification performances because the proposed method is optimized for texture recognition of non-rectangular objects.

The rest of the paper is organized as follows: In section 2, we present the proposed method in detail, which is composed of 3 steps. Experimental results of our method are reported in Section 3. Finally, conclusions and future work are described in section 4.

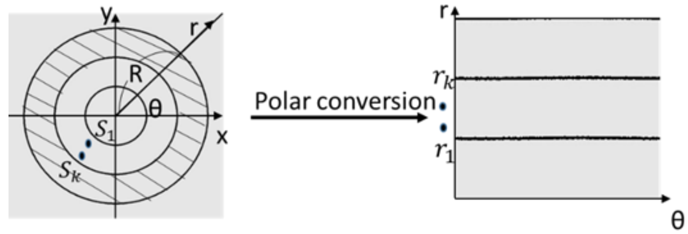
II. Proposed Approach

In this section, we present the proposed method in detail, which is composed of 3 methods: Removal of noisy background (in A), weighted polar representation of cross-section images (in B), and fusion of the results of both sides of each battery (in C).

A. Removal of Noisy Background

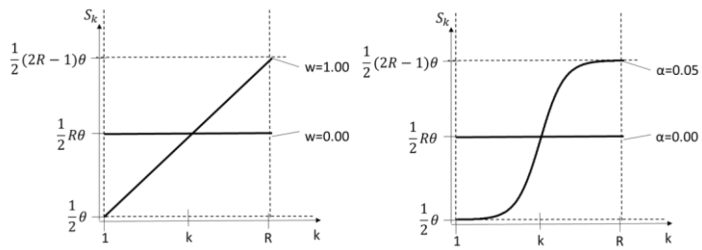
Fig.2 shows the example of cross-section images of used batteries. As is clear in this figure, the background region is usually much larger than the foreground (= battery) region in spite of the fact that the background region is not informative at all for battery classification. In other words, more than half of pixels in training data and test data are noise.

To solve this problem, we introduce polar coordinates. When we convert raw cross-section images into polar representation images, we can remove most pixels in the background region (Fig.3). This process must be useful for improvement of classification accuracy. The algorithm of our method is as follows:



(a)orthogonal coordinate system (b) polar coordinate system

Fig.4: Orthogonal coordinate system and polar coordinate system.



(a)linear function (b)non-linear function

Fig.5: Two weighting functions: linear function(a) and non-linear function(sigmoid function)(b).

1. Obtain the center position of a circle (=battery) and its radius by Hough Circle [15].
2. Generate a polar representation image by using the center position of a circle and the radius.

By this algorithm, the background pixels of a raw image are almost completely removed and only foreground pixels are mapped into a polar representation image.

B. Weighted Polar Representation Based on Sigmoid Function

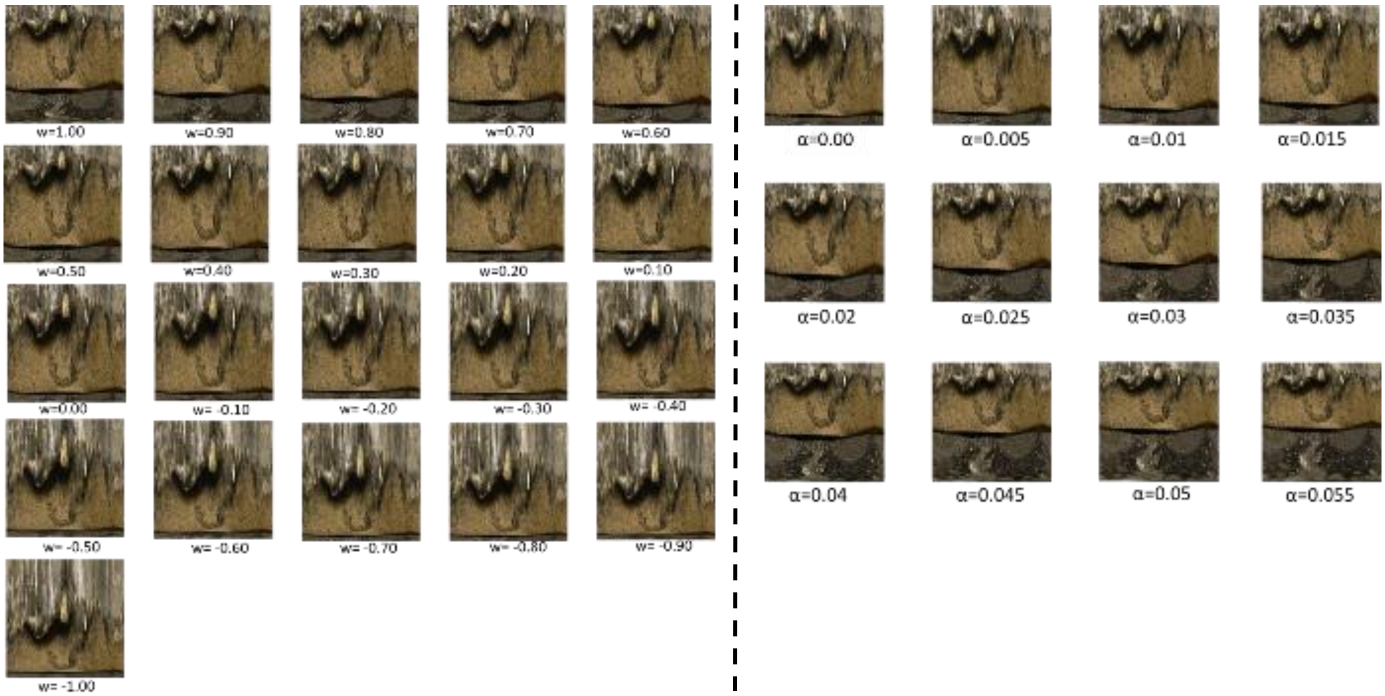
Polar representation is an easy and effective method to remove the pixels in the background region, but it has a serious defect that the weight of each pixel varies. That is, when each pixel in a raw image is mapped into the polar representation image, a pixel near the center of a battery increases its weight, and on the contrary, a pixel away from the center decreases its weight. To overcome this defect, we present a novel method for weighted polar representation.

Fig.4, (a) shows orthogonal coordinate system and (b) shows polar coordinate system. When we convert a raw image into polar representation image, the value of r_k in polar coordinate system is defined as:

$$r_k = \sqrt{\frac{2}{\theta}\sum_{i=1}^{k} S_i} \tag{1}$$

where S_i is the region of i-th circular ring (for example, the region of the shaded part in Fig.4 (a)). To control the value of

https://doi.org/10.17758/URUAE.AE03181010



(a) Images where linear function is used as a weighting function. (b)Images where Sigmoid function is used.

Fig.6: Examples of weighted polar representation images.

S_i based on any function, we can change the weight of S_i. In this paper, we select two weighting functions: linear function (Fig.5(a)) and non-linear function. Also, Sigmoid function is used for a non-linear weighting function (Fig.5(b)).

When we apply a linear function as a weighting function, the equation of S_i is defined as:

$$S_k = w\theta\left(k - \frac{R+1}{2}\right) + \frac{1}{2}R\theta \tag{2}$$

where R is the radius of a battery, and w is the weight.

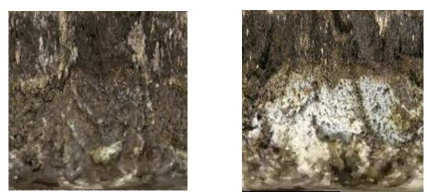
On the other hand, when we apply Sigmoid function, the equation of S_i is defined as:

$$S_k = \frac{(1+R)\theta}{2}\left(\frac{2}{1+e^{-\alpha\left(k-\frac{1+R}{2}\right)}} - 1\right) + \frac{1}{2}R\theta \tag{3}$$

where α is the weight. Examples of weighed polar representation images are shown in Fig.6. Fig.6, (a) shows the images where linear function is used as a weighting function. In contrast, Fig.6, (b) shows the images where Sigmoid function is used.

C. *Integration of the classification results of two images on both sides of the same battery*

Two cross-section images are obtained from one battery (One image from the cathode, and the other image from the anode of a battery). To improve the classification accuracy, we integrate two classification results of these two images. We first obtain the classification result for each image. The classification result for the image i is represented by 3 dimensional vector $V_i = (v_{i1}, v_{i2}, v_{i3})$, where v_{i1}, v_{i2}, and v_{i3} are the possibility of Manganese battery, the possibility of Alkaline battery and the possibility of rechargeable battery respectively. Next, we generate average vector V_{ave} which takes the average value of each element of three-dimensional vectors V_i, V_j obtained from images i and j (both sides of the same battery). Finally we classify the battery by following V_{ave}. This process can enhance the performances of the proposed method. Now, we assume that V_i = (0.501, 0.499, 0.00) and V_j = (0.001, 0.999, 0.000). In this case, if we do not introduce this algorithm, image i is classified incorrectly. However, we can classify this battery correctly by using this algorithm as shown in Fig.7.



$\rightarrow V_{ave} = (0.251, 0.749, 0.000)$

V_i= (0.501, 0.499, 0.00) V_j = (0.001, 0.999, 0.000)

Fig.7: Classification results of two images obtained from one battery and the final result.

III. Experimental Results

As far as the authors know, there are no dataset of cross-

TABLE I: SIZES AND TYPES OF THE BATTERIES

Classes	Size D battery	Size C battery	Size AA battery	Size AAA battery	Total number of batteries
Manganese	57	6	10	27	100
Alkaline	20	7	45	0	72
Secondary	0	0	37	32	69

TABLE Ⅱ: THE DATASET WE USE

Classes	Size D battery	Size C battery	Size AA battery	Size AAA battery	Total number of batteries
Manganese	114	12	20	54	200
Alkaline	40	14	90	0	144
Secondary	0	0	74	64	138

section images of used batteries. So, we generate a new dataset for the experiments. All of the batteries (= 241 batteries) are given by a recycling manufacture. Sizes and Types of the batteries in these batteries are shown in Table. I. Since we can obtain 2 cross-section images from one battery, the dataset contains 482 images as shown in Table. II. Furthermore, to increase the data in the dataset, we generate 4 images from one original image by generating the inverted images in the vertical direction, the horizontal direction and the both direction. Examples of the dataset have already been shown in Fig.1. As is clear in Fig.1, the dataset is very challenging because batteries often look very similar (dissimilar) in appearance even if they are different (the same) type of batteries.

By using this dataset, we generate the following three types of images as input in CNN.

D1: raw cross-section images of batteries.

D2: polar representation images without weighting (images generated by section II.A)

D3: polar representation images with weighting (images generated by section II.B)

Also, the integration method described in section II.C for input data D3 is called "D3 with integration".

A. Comparison with D1 and D2

The comparison result of D1 and D2 are shown in Table. III. As shown in Table. III, we can see that polar representation images (D2) shows better performances than raw images (D1) even if the weights of pixels are not properly assigned. The reason for this result is that polar representation can easily remove the background pixels.

B. Comparison with D2 and D3

We presented two weighting functions (linear function in Fig.5(a) and sigmoid function in Fig.5(b)) in section II.B. We first did some preliminary experiments for parameter optimization for these two weighting functions. From the results of the preliminary experiments, we found that w= 1.00 (in linear function) and α=0.05 (in sigmoid function) are the best for battery classification. We also found that sigmoid function shows better performances than linear function for this application. So, we generated D3 for sigmoid function (the parameter α of which is 0.05). As shown in Table. III, the performance of D3 is better than the performance of D2. This result indicates that traditional polar representation images (D2) are not the best solution because the weights of pixels are not properly assigned.

TABLE Ⅲ: EXPERIMENTAL RESULTS

Images as input in CNN	Accuracy (%)
D1	90.03
D2	91.50
D3	94.40
D3 with integration	**97.10**

C. Evaluation of D3 with integration

The evaluation result of D3 with integration is described in Table. III. Table. III shows that the performance of D3 with integration has achieved 97.1% of classification accuracy. Since the target value of the classification performance is said to 95 % (or more) in general, this result proves the proposed method can be put into practice for battery classification. We think this result is better than we expected when taking into account the fact that our dataset is challenging and even humans cannot classify them by 100% accuracy. Also, the average time of the classification per one battery (2 images) is approximately 0.18 [sec]. This result satisfies the target time of battery classification (=1.0 sec).

IV. Conclusion And Future Work

This paper presented a deep learning approach for used battery classification. We turned our attention to cross-sections of batteries instead of shapes, weights, and the labels of batteries. To improve the performance, we introduced 3 techniques. First, we converted raw images into polar representation images to remove noisy background efficiently. Second, we introduced the concept of "adjusting weight" into polar representation to obtain the best input images for battery classification. Thirdly, we present the integration method for two classification results obtained from both sides of one battery. We demonstrated that our methods outperformed the conventional CNN method and our proposed method achieves the accuracy of 97.1%. This result indicates the proposed method can be put into practice soon.

As described in section I, researches on texture recognition using CNN are very few. Also, CNN is not suited for non-rectangular (arbitrarily shaped) images because input of CNN has to be rectangular images. So, we would like to develop a classification method for general-purpose arbitrary-shaped texture by extending our method.

REFERENCES

[1] Alex Krizhevsky, Ilya Sulskever, Geoffrey E Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

[2] Large Scale Visual Recognition Challenge 2012 (ILSVRC2012)(http://image-net.org/challenges/LSVRC/2012/results.html)

[3] G.E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R.R. Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprint arXiv:1207.0580, 2012.

[4] L. Wan M. Aeiler S. Zhang Y. LeCun R. Ferguns, “Regularization of Neural Networks using DropConnect” ProceedingICML'13 Proceedings of the 30th International Conference on International Conference on Machine Learning - Volume 28 Pages III-1058-III-1066 2013.

[5] L. J. Ba B. Frey, “Adaptive dropout for training deep neural networks ”Proceeding NIPS'13 Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2 Pages 3084-3092 ,2013.

[6] Takayoshi Yamashita, Masayuki Tanaka, Yuji Yamauchi, Hironobu Fujiyoshi ”SWAP-NODE :A REGULARIZATION APPROACHI FOR DEEP CONVOLUTIONAL NEURAL NETWORKS” Data Mining (ICDM), 2016 IEEE 16th International Conference

[7] J. Duchi E. Hazan Y. Singer, “Adaptive subgradient methods for online learning and stochastic optimization”, Journal The Journal of Machine Learning Research archive Volume 12, 2/1/2011 Pages 2121-2159

[8] M.D.Zeiler, “ADADELTA: AN ADAPTIVE LEARNING RATE MATHOD”, arXiv:1212.5701 , 2012.

[9] D.Kingma J.Ba, “Adam: a method for stochastic optimization”, arXiv:1412.6980 2015.

[10]] Sue Han Lee, Chee Seng Chan, Paul Wilkin, Paolo Remagino "DEEP=PLANT IDENTIFICATION WITH CONVOLUTIONAL NEURAL NETWORKS" (2015 IEEE International Conference on Image Processing(ICIP)) https://doi.org/10.1109/ICIP.2015.7350839

[11] A.Shahriari, "Learning Deep Filter Banks in Parallel for Texture Recognition", IEEE International Conference on Image Processing 2016 (ICIP2016), Sept., 2016. https://doi.org/10.1109/ICIP.2016.7532635

[12] M. Cimpoi and S. Maji and A. Vedaldi, “Deep filter banks for texture recognition and segmentation”, Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 2015 https://doi.org/10.1109/CVPR.2015.7299007

[13] Hussein Adly, Mohamed Moustafa”A Hybrid Deep Learning Approach for Texture Analysis” arXiv:1703.08366

[14] C. Szegedy, W. Lin, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, Going deeper with convolutions ,arXiv preprint arXiv: 1409.4842, 2014 http://arxiv.org/abs/1409.4842

[15] OpenCV HP(https://docs.opencv.org/2.4/doc/tutorials/imgproc/imgtrans/hough_circle/hough_circle.html#theory)

(We request color printing except the final page.)

Terumasa AOKI is an associate professor at NICHe (New Industry Creation Hatchery Center), Tohoku University, Japan. He received his B.E, M.E and Ph.D degree from the University of Tokyo, in 1993, 1995 and 1998 respectively. He has received various academic excellent awards such as Young Scientist Award from MEXT (the Ministry of Education, Culture, Sports, Science and Technology in Japan) in 2007, Yamashita Award and the Best Education Award from IPSJ (Information Processing Society of Japan) in 2001 and 2007 respectively, two Best Paper Awards from IIEEJ (the Institute of Image Electronics Engineers of Japan) in 2004 and 2009 etc. He is well known as the developer of DMD (Digital Movie Director) and NeoPoster etc. His current research topics are digital content technology, especially image processing, computer vision and computer graphics.

Takahiro TAKEUCHI received his B.E. degree from Yamagata University in 2016. He is currently a M.S. student in Tohoku University. His research interests is machine learning.