Neural Networks Applied to Recognition of CCD Camera Images where a 3-Digit Number is Stamped on the Surface of Chip Resistors

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ABSTRACT

We describe Back-Propagation neural networks (BP model) [1] implemented into a visual verification system of numbers stamped on the surface of chip resistors. A 3-digit number is stamped whitely on the rectangular black area, that is on the surface of each chip resistor, bordered by a white frame. The number and a fragment of the frame are imaged from a CCD camera. Firstly, the number is circumscribed by a rectangular frame for segmentation in each CCD camera image (this is a segmentation module). Secondly, while a narrow slit window is scanning across the partial image inside the segmented rectangular area, each digit is classified one after another concurrently with separation from its neighbors (this is a recognition module). Both modules are developed by training BP models, Position Network and Recognition Network. Experimental results show that the proposed method could correctly recognize the number even if digits were stamped poorly and imaged with extraneous substances.

1. Introduction

We are calling for a novel method which can be implemented into a visual verification system of numbers stamped on the surface of chip resistors assembled on the circuit board. A 3-digit number is stamped whitely on the rectangular black area, that is on the surface of each chip resistor, bordered by a white frame. The number and a fragment of the frame are imaged through a CCD camera. Two major matters described below make it difficult to construct algorithm of the verification system.

Firstly, since numbers are stamped on irregular surface of very small (3.0mm x 1.2mm) chip resistors, pinpoint and clear stamping is a very difficult work. And chip resistors should be supplied at low cost. Therefore, it is inevitable that almost all of these numbers are stamped poorly and shifted accidentally from the center.

Secondly, extraneous substances are occasionally imaged with the number, when the method is put into the verification system used in the process of factory automation. Because, dirt and/or dust adhere to the surface of the chip resistor.

So, the verification system must satisfy following capabilities as described below. Firstly, segmentation of the number in the image where extraneous substances are also imaged. Secondly, separation of each digit from its neighbors and extraneous substances. Thirdly, recognition of digits that have its own lacked parts, blurred parts, and/or shaded parts. Furthermore, recognition works must be carried out very quickly, and illegible digits must be rejected.

Recently, neural networks are gathering great interest from engineers in hopes of that neural networks have great capabilities to approximate non-linear systems in engineering needs by training. Applied researches of neural networks are ranging widely in the area of image processing, as well as speech recognition, motion control, etc. We experimented to apply neural networks to visual verification system of numbers stamped on the surface of chip resistors. In this application it is necessary

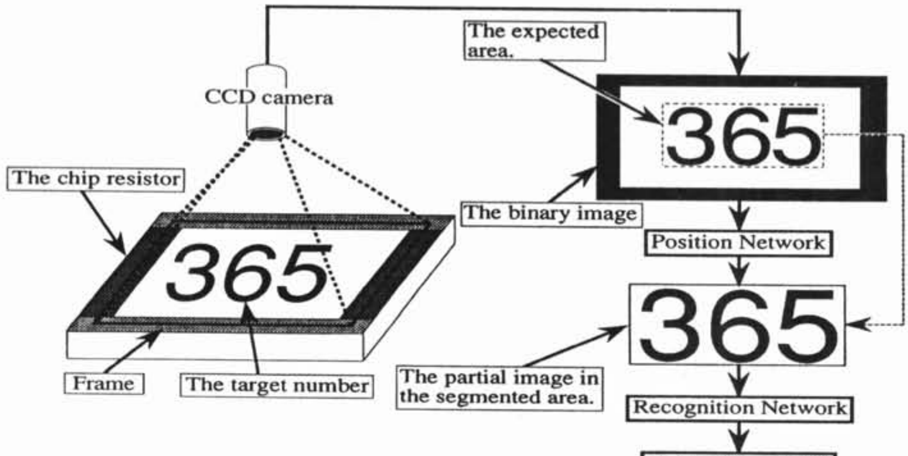


Fig.1 The recognition procedure by the proposed method.

to segment the number in each CCD camera image (*i. e.* to detect the position of the number), as well as to recognize the number (*i. e.* to classify each digit appearing in the number). We presents two neural networks, Position Network (PN) for segmentation module and Recognition Network (RN) for recognition module, and methods to train them.

2. Schematic of the Proposed Visual Verification System

Fig.1 shows schematic of the proposed visual verification system of numbers (*e. g.* "365") stamped on the surface of chip resistors. The system consists of two major independent modules [3] − *i. e.* circumscription of the number by the rectangular frame for segmentation in each CCD camera image (segmentation module), and recognition of the number appearing in the segmented rectangular area (recognition module). Both modules are developed by training neural networks.

2. 1. Segmentation Module

The surface of each chip resistor is imaged from a CCD camera (the 224 x 128 pixel gray level image). After the CCD camera image is set into the same resolution binary image, the binary image is sent to PN.

2. 1. 1. PN for Segmenting the Number

In our previous papers, we have shown that PN, which consists of the 3-layered BP model, can acquire the function to map an image into orthogonal coordinates at the center of an object appearing in the image as analog output values of a pair of output units. PN is available for segmentation of an object in the image, even if extraneous substances are also imaged as well as the object [2], [3], [4].

PN detects orthogonal coordinates at the center of the number in the CCD camera image. Fig.2 shows the architecture of PN. The binary image is projected onto the input layer. A pair of output units sends the orthogonal coordinates (x_c, y_c) at the center of the number independently of what remains in the image with the number − *i. e.* a fragment of the frame, extraneous substances (caused by dust and/or dirt), or other clutter

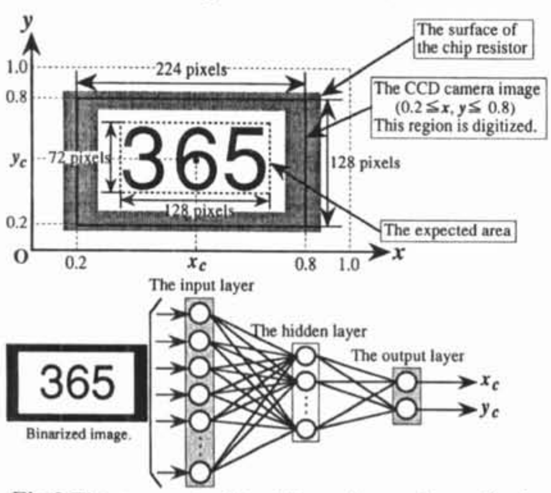


Fig.2 The process to detect the orthogonal coordinate of the center of the target number, and the structure of Position Network.

(*e. g.* caused by halation of the CCD camera), and so on. To avoid the range where the curve of the sigmoid function (the activation function of every unit)

$$f(net) = 1 / (1 + e^{-net})$$

is gentle, x_c and y_c are limited in the range of

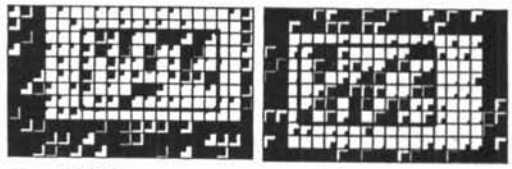
$$0.2 \leqq x_c, y_c \leqq 0.8.$$

Since the approximate size of the number in the whole image is known (the width of the area is fixed as 128 x 72 pixel), the frame for segmentation is calculated from the values of x_c and y_c.

2. 1. 2. Training PN

Fig.3 shows three examples of the training sets, pairs of an input image (A) and target output values (B). A new training set was generated at each cycle to adjust connection weights using random numbers [4]. In the figure, edge length of each solid square denotes the density of the corresponding pixel.

(A)



(B) $x_c = 0.590$ $\quad$ $x_c = 0.590$

$y_c = 0.500$ $\quad$ $y_c = 0.400$

Fig.3 Two examples of the training sets for Position Network.

2. 2. Recognition Module

The partial image inside the segmented area is sent to the RN.

2. 2. 1. RN for Classifying Each Digit Concurrently with Separation from Its Neighbors

Each digit appearing in numbers has its own lacked parts, blurred parts, and/or shaded parts, and extraneous substances and other clutter are sometimes also imaged with the number. Also, there is a little gap between real frame to circumscribe the number and the frame for segmentation generated in the segmentation module. Furthermore, illegible digits caused by incorrect stamping may be accidentally included. RN can recognize the number settling problems described above. Namely, RN should recognize poorly stamped number with a narrow gap between the the frame for segmentation and the real frame.

Again in our previous paper, we proposed a method to recognize character strings using the 3-layered BP network with feedback connections [5], [6]. Each character is classified one after another concurrently with separation from its neighbors, independent of the order they appear in.

Fig.4 shows the architecture of recurrent neural network to recognize the number. RN consists of the 3-layered BP network with feedback connections. A slit window scans across the partial image in the frame for segmentation. Every slit image is projected onto the input layer at every interval of slit movement. The output units send three signals, the Scanning Step Signal (**SSS**), the Category Assignment Signals (**CASs**), and the Security Signals (**SECs**). **SSS** and **CASs** are sent to the context layer, and sent to the hidden layer with the next slit image. Thus, these three signals gradually change as the slit window moves.

Classification is carried out by matching the wave forms of **CASs**. It is very easy to classify the digit appearing in the slit image by finding a **CAS** having a value near by 1. However, wave forms of **CASs** are greatly disturbed when unlearning image pattern is appearing. **SSS** is introduced so that its wave form can assist in finding a single letter even if the wave forms of **CASs** rise and fall intensely. The wave forms of **SECs** assist in rejecting incorrect classification.

2. 2. 2. Training RN

The wave form of every target wave form, which was a time-series output, was given as algebraic sums of sigmoid functions. The target function of every signal is given so as to hold the initial value of 0 in every blank area and in every joint area where two digits are connected. Fig.5 shows two examples of the training sets, pairs of a source image (A) and target functions (B) of **SSS** (a), **CASs** (b), and **SECs** (c). A new training set was generated using random numbers at each adjustment of weights. Peculiar matters in generating the target function of each kind of signals will be described below.

(a) SSS

While the slit image includes no digit, **SSS** holds the value of 0. When a certain letter appears in the slit image, **SSS** rises. A steep wave form of **SSS** is chosen where the correlation between the former and the present slit image is small, and a gentle wave form is chosen where the correlation is great.

(b) CASs

While the slit image includes no digit, all **CASs** hold the value of 0. When a certain letter appears in the slit image, possible candidates of **CASs** hold the value of 1.

(c) SECs

The wave forms of **SECs** are peculiar to the category of letters appearing in the slit window.

3. Experiments and Results

The unit numbers of neural networks are chosen as shown in Table 1. The input layer of PN consisted of 20 (horizontally) x 12 (vertically) pixels. The slit window used in RN consisted of 3 x 12 pixels. To recognize digit strings), single **SSS**, ten **CASs** (for ten categories), and four **SECs** were required.

	Input Layer	Context Layer	Hidden Layer	Output Layer
PN	240 (= 20 x 12)		100	2
RN	36 (= 3 x 12)	11 (= 1 + 10)	160	15 (= 1+ 10 + 4)

Table 1 Network Architectures.

We carried out an experiment to segment and recognize a 3-digit number, which has been stamped on the surface of the chip resistor, imaged from a CCD camera. Fig.6 shows six examples of results.

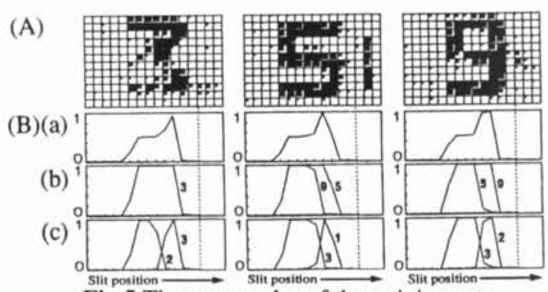


Fig.5 Three examples of the training sets for Recognition Network.

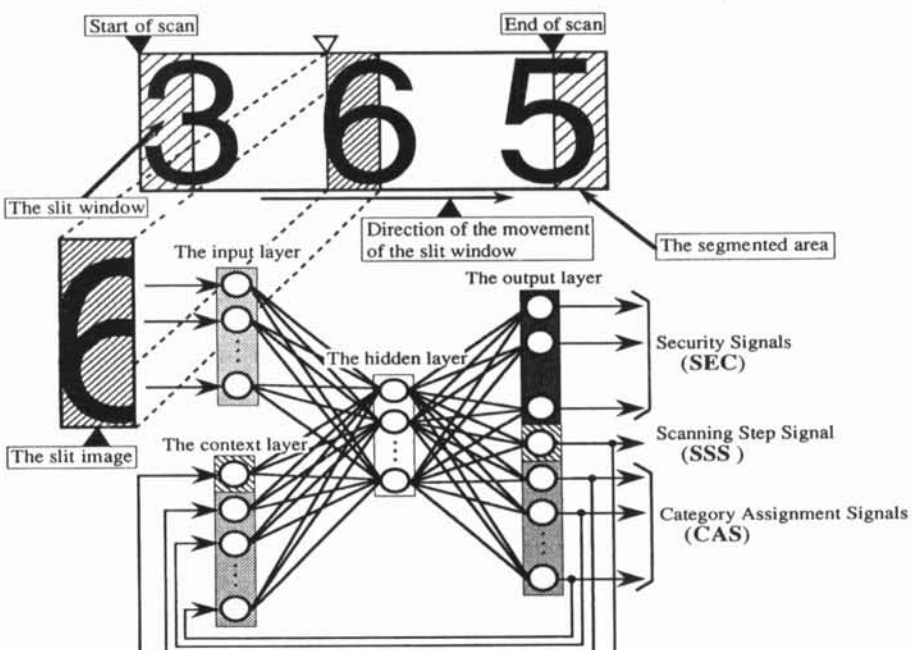


Fig.4 The process of recognition of the target number in the segmented area, and the structure of Recognition Network.

Fig.6(A) shows the 224 x 128 pixels digitized images, and the broken lines show the frame for segmentation generated in the segmentation module. Fig.6(B)(a), (b), and (c) respectively show the waveforms of all **SSS**, **CASs**, and **SECs** at position of the slit window. Every numeral assigned to the right side of each **CASs** wave and each **SEC** wave shows the corresponding unit number. **CASs** and **SECs** with the unseen unit numbers always hold the value of 0. Fig.6(C) shows recognition results, and the character 'x' indicates the rejected digit.

These results show that the proposed method can segment and recognize the 3-digit number even if the conventional method cannot do. In the case of Fig.6(1), the number is very clear. In these cases, the verification tasks were carried out correctly and very easily by both the conventional method and the proposed method. However, two digits are accidentally connected in the case of Fig.6(2), and the CCD camera image involves clutter, that were caused by extraneous substances or halation, in the cases of Fig.6(3) and (4). Again in these cases, the proposed method was able to recognize the numbers, whereas the conventional method was unable to. In the case of Fig.6(5), two legible digits were correctly recognized, and an illegible digit was rejected.

However, there exist a few incorrectly rejected digits. But, incorrectly classified digit was never existed.

4. Conclusions

This paper proposes a method implemented into a visual verification system of numbers stamped on the surface of the chip resistors. The method consists of two independent functions $-$ *i. e.* segmentation of the number in the CCD camera image, and recognition of the number. These two functions are developed by training neural networks (PN for segmentation and RN for recognition). Experimental results show that the method is applicable to the visual verification system for factory automation.

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References

[1] D.E.Rumelhart, J.L.McClelland, and PDP Research Group:"Parallel Distributed Processing", Vol.1, Chap.8, The MIT Press (1986).

[2] K.Gouhara, K.Imai, and Y.Uchikawa:"Position and Size Representations by Neural Networks", Int. J. Control and Computers, Vol.20, No.1, pp.1-5 (1992).

[3] K.Imai, K.Gouhara, and Y.Uchikawa:"Pattern Extraction and Recognition for Noisy Images Using the Three-Layered BP Models", Proc. of IJCNN'91-Singapore, Vol.1, pp.262-267 (1991).

[4] K.Imai, K.Gouhara, and Y.Uchikawa:"Handwritten Letter Segmentation and Classification on a Noisy Background Using Multiple Neural Networks", J. Artificial Neural Networks, To be appeared.

[5] M.I.Jordan:"Attractor dynamics and parallelism in a connectionist sequential machine", Proc. of the Eighth Annual Conference of the Cognitive Science Society, pp.531-546 (1989).

[6] K.Imai, K.Gouhara, and Y.Uchikawa:"Recognition of Printed Sequential Plural Patterns Using the 3-Layered BP Model with Feedback Connections", Proc. of IJCNN'92-Baltimore, Vol.3, pp.754-759 (1992).

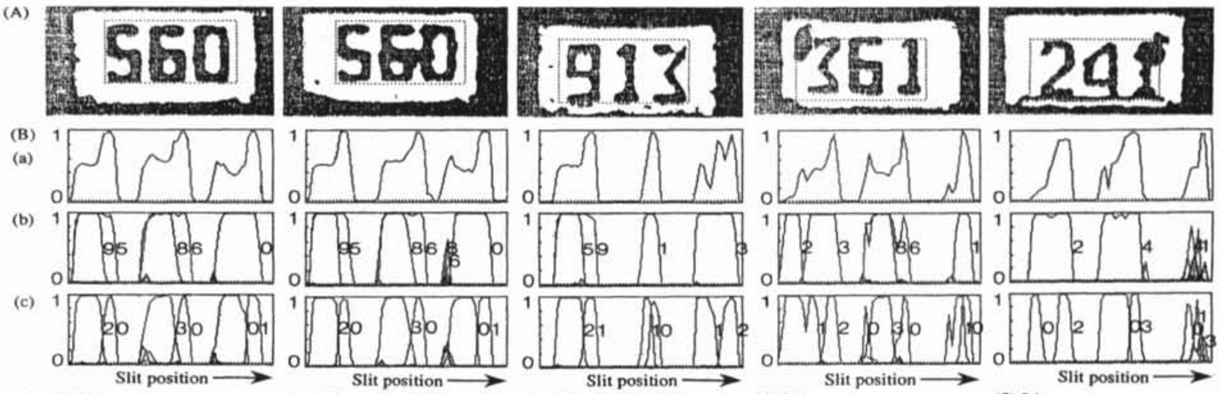

Fig.6 Examples of recognition results.