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Product Identification Using Image Processing and Radial Basis Function Neural Networks

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Abstract. This paper presents a product identification using image processing and radial basis function neural networks. The system identified a specific product based on the shape of the product. An image processing had been applied to the acquired image and the product was recognized using the Radial Basis Function Neural Network (RBFNN). The RBF Neural Networks offer several advantages compared to other neural network architecture such as they can be trained using a fast two-stage training algorithm and the network possesses the property of best approximation. The output of the network can be optimized by setting suitable values of the center and the spread of RBF. In this paper, fixed spread value was used for every cluster. The system can detect all the four products with 100% successful rate using ±0.2 tolerance.

Introduction

Product identification using image processing and radial basis function neural networks is related to a system that can recognize a product in real-time using a webcam as an image acquisition and RBFNN as a classifier or recognizer. Image processing will be applied to the acquired image of an object or a model from a webcam (Fig. 1). For example, if we had 4 models of a product i.e. A, B, C and D, the system can differentiate and recognize the specific product.

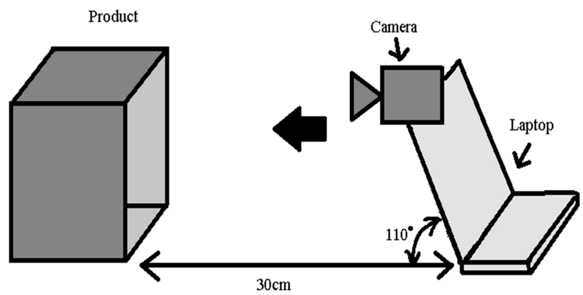

Fig. 1 Prototype of the system.

Image Processing

The acquired image will go through an image processing process before it is fed into the RBF network. Fig. 2 shows the image processing process.
The steps involved in the image processing are as follows:

a) Acquire image from webcam;
b) Undergo the threshold process (binary and filtering);
c) Detect the edge; and
d) Fill the holes.

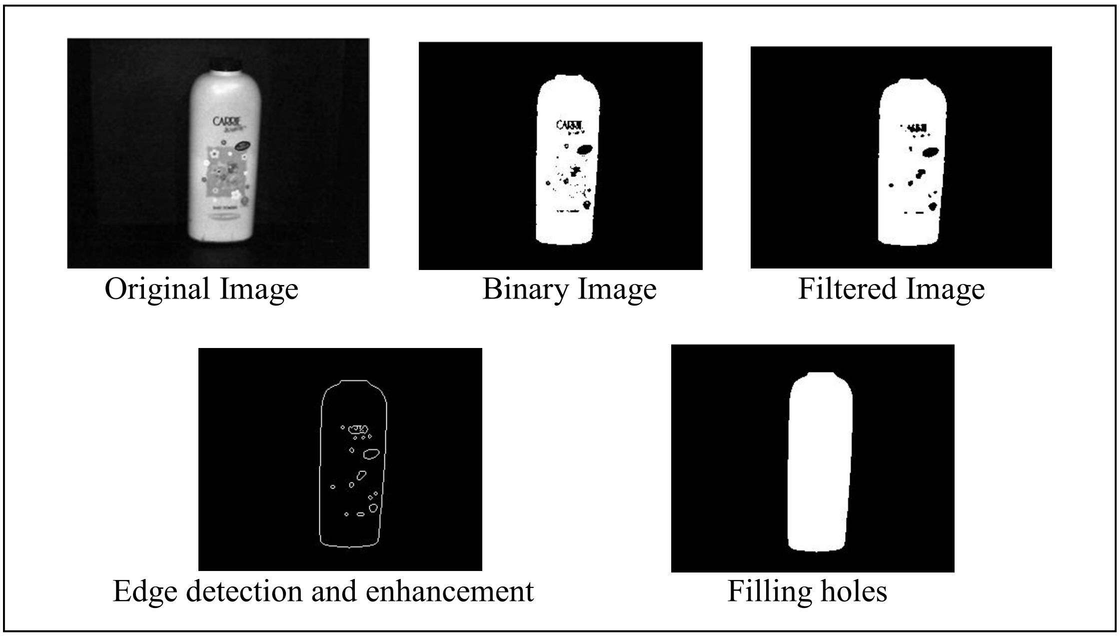

Fig. 2 Image processing.

The image to be fed into the RBF network will first be normalized using several image processing steps. In this project, the image was first converted into a double class in matrix form. The matrix was then converted into a column matrix 1 x n. This input would be fed into the RBF network for the next process. Fig. 3 and 4 shows the conversion of an image into a matrix form.

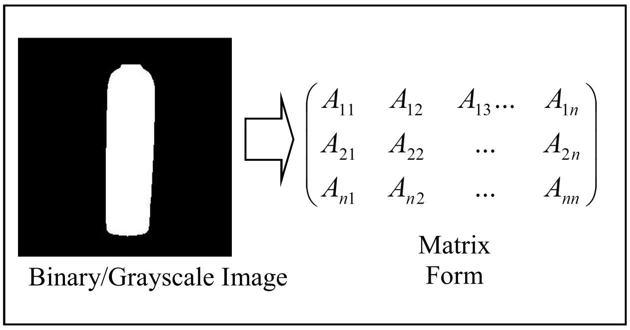

Fig. 3 Converting Image to matrix.

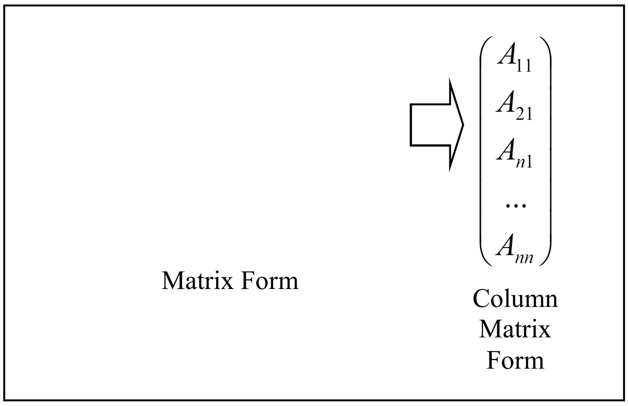

Fig. 4 Converting Matrix to Column Matrix.

RBFNN offers several advantages as compared to the Multilayer Perceptrons. Two of these advantages are:

1. They can be trained using a fast 2-stage training algorithm without the need for the time consuming non-linear optimization techniques.
2. ANN RBF possesses the property of 'best approximation' [9]. This means that if in the set A of approximating functions (for instance the set F(x, w) spanned by parameters w), then the RBFNN has the minimum distance from any given function of a larger set, *H*.

RBFNN had been successfully used in face detection such as in Mikami, et al. [7]. Fig. 5 illustrates the architecture of the RBFNN used in this work.

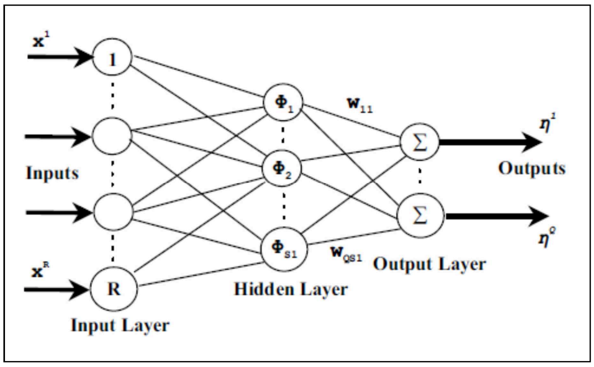

Fig. 5 RBF Neural Network.

The network consists of three layers: an input layer, a hidden layer and an output layer. Here, R denotes the number of inputs, while Q the number of outputs. For Q = 1, the output of the RBFNN in Fig. 8 is calculated according to:

$$\eta(x,w) = \sum_{k=1}^{S1} w_{1k}\phi(\| x - c_k \|)_2 \tag{1}$$

where is an input vector, is a basis function, ||.|| denotes the Euclidean norm, w_{1k} are the weights in the output layer, S_1 is the number of neurons (and centers) in the hidden layer and are the RBF centers in the input vector space. Equation (1) can also be written as the following

$$\eta(x,w) = \phi^T(x)w \tag{2}$$

where

$$\phi^T(x) = [\phi(\| x - c_1 \|) \ldots\ldots \phi_{S1}(\| x - c_{S1} \|)] \tag{3}$$

and

$$w^T = [w_{11} w_{12} \ldots w_{1S1}] \tag{4}$$

The output of the neuron in a hidden layer is a nonlinear function of the distance given by:

$$\phi(x) = e^{\frac{-x^2}{\beta^2}} \tag{5}$$

In this case, β is the spread parameter of the RBF. For training, the least squares formula was used to find the second layer weights while the centers are set using the available data samples. Supervised learning was used where training patterns are provided to the RBFNN together with a teaching signal or target. 50 images of the same product were taken for training. The distance from camera was the same, but for each images the product was moved to the left or right in the range of 1 mm to 10 mm. The target for each product gave the value of Product A = 1, Product B = 2, Product C = 3 and Product D = 4, while the value of spread was 25. Fig. 6 shows the products used for training and testing.

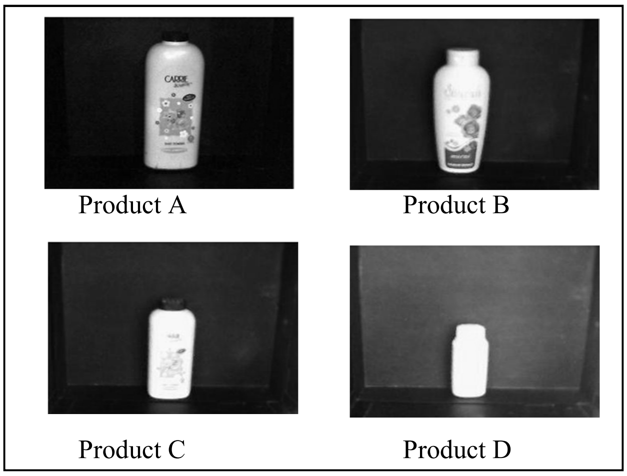

Fig. 6 Product for training and testing.

Results

Fig. 7 shows the image of each product after going through the image processing. Table 1 shows the results of the system. Several tests were done under the same distance and lighting condition as shown in Fig.1. Based on Table 1, it is shown that for each product, the tolerance is about ±0.2. The system could detect all the four products from A to D within this tolerance.

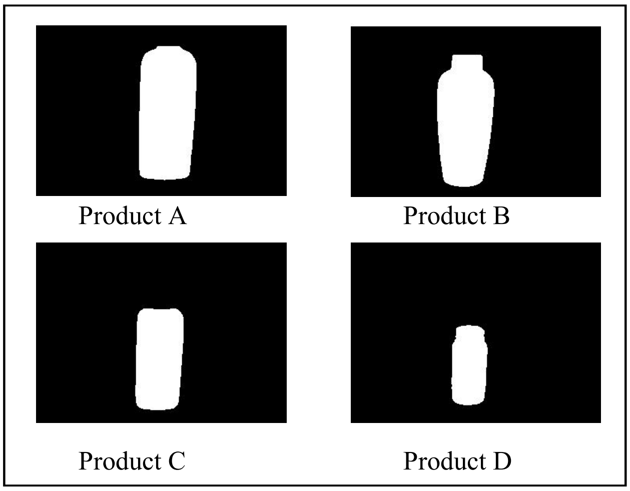

Fig. 7 Image after image processing.

Table 1 Result of Neural Network Classification.

Product	No. of testing	Recognition values	Range	Successful rate
Product A	45	1	0.8 - 1.2	100%
Product B	45	2	1.8 - 2.2	100%
Product C	45	3	2.8 - 3.2	100%
Product D	45	4	3.8 - 4.2	100%

Summary

The results shows that RBFNN can be used to identify products after the image went through the image processing. As for the network setting, a fixed spread for each cluster was used and the range of tolerance is ±0.2 so that the system can identify all of the products that had been trained.

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