



A Simplified Classification of Electronic Integrated Circuits Packages Based on Shape Descriptors

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Abstract. Automatic classification of electronic elements based on image analysis may be useful for verification of a proper selection of electronic integrated circuits previously assembled in the Printed Circuit Boards (PCBs), as well as for an automated sorting of such elements in robotic systems supporting their production. Although modern high speed pick and place machines dedicated for small surface-mount devices (SMD), utilising very small packages, largely replaced the through-hole assembling technology in many industrial application, there are still some types of applications where such technology is less suitable, e.g. due to thermal, mechanical or power constraints. Hence, a proper classification of electronic elements in dual in-line packages (DIP) using shape analysis may be an important element for the combination with further steps based on the recognition of alphanumerical markings. Some experimental results obtained for selected shape descriptions are presented in this paper, which are promising also for natural images.

Keywords: Classification · DIP · Shape analysis · Electronic packages

1 Introduction

Automatic classification of electronic components according to their package shape, such as popular dual in-line packages (DIP) containing various elements, such as transistors, switches, LEDs, resistors, etc., may be useful in semi-automatic assembling systems or prototyping of electronic circuits, in which the application of surface-mount devices (SMD) is not possible. Assuming unknown location of unsorted individual packages, similar methods may be useful in robotic applications, as well as for diagnostic purposes. Possible applications of such image based recognition might be related to checking the connections as well as the type of electronic components mounted on the printed circuit board (PCB).

Although an automatic classification of electronic components is not very popular topic of scientific research, its practical usefulness may be confirmed e.g. by the artificial intelligence system introduced in 2017 by Fujitsu company¹, utilizing template pattern matching during inspecting parts for misalignment. Some other attempts to recognition of electronic elements are typically based on the analysis of hand-drawn circuit diagrams [2, 9] or analysis of transfer function [1] without computer vision methods.

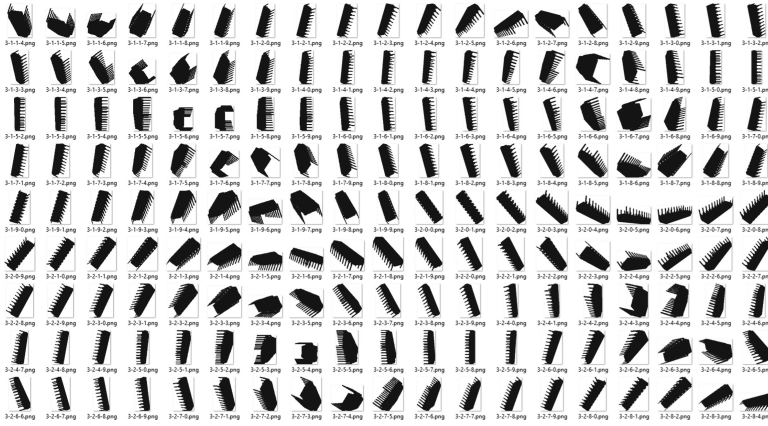


Fig. 1. A fragment of the set of binary images obtained assuming various views of an exemplary DIP.

Assuming the potentially limited visibility of alphanumeric markings, an important element of such systems, useful also for initial limiting the number of checked types of elements, is the recognition of the integrated circuit (IC) package type. This task may be conducted applying some of the shape analysis methods, assuming previous binarization of the image captured by the camera. Nevertheless, for unknown relative position (and rotation) of the individual IC packages, their proper recognition may be troublesome due to similarity of shapes obtained for various DIPs for different angles of observations. Therefore, an appropriate combination of shape descriptors would be necessary to ensure the proper classification regardless of the relative position of the analysed DIP.

The main purpose of research presented in the paper is the analysis of possible application of various simple shape descriptors and parameters during the initial stage of classification of IC packages without the use of text recognition. The first part of the conducted experiments consists of the classification of binary DIP images obtained from the intentionally prepared database containing the synthetic images of the STL 3D models captured assuming different views. After extensive experiments some of the most relevant shape descriptors were selected

¹ AI-Enabled Image Recognition System to Revolutionize the Manufacturing Line, Available online: <https://journal.jp.fujitsu.com/en/2017/04/19/01/>.

applying the Principal Component Analysis (PCA) method. Finally, some additional experiments were made using natural images as described in the respective sections of the paper.

2 Database Preparation

Preparation of the image database used in experiments was made using Javascript and PHP scripts. Initially, the STL 3D model was loaded and its screenshot was captured for a specified location of a virtual camera, after manual positioning on the canvas. Next, the captured image was cropped to ensure it contains only a single object and binarized for a faster further shape analysis. After calculation of shape parameters all data was saved in MySQL database. Each model was rotated by 18° around the X axis. After the rotation by 180° it was rotated around the Y axis, and after 180° around the Z axis. It was assumed that the 180° angle should be enough due to the symmetry of the shapes. After capturing such images, partially illustrated in Fig. 1 for an exemplary IC package, the process was repeated starting from taking a first screenshot of the next DIP. Finally, the database was created, which contains 1000 images for each package, and the set of all measured values.

3 Proposed Method and Experimental Verification

3.1 Shape Descriptors

Considering the exemplary binary images illustrated in Fig. 1, it can be easily noticed that some of the simplest shape parameters, such as e.g. Feret's coefficient defined as the ratio of two Feret diameters, or just the area or the perimeter of an object, would not be sufficient for a reliable classification of IC package images. Therefore, after the application of PCA algorithm, the following shape descriptors were selected as the most representative ones, combining good separation of classes with their simplicity. Hence, in further experiments the following shape descriptors were considered:

- aspect ratio (width/height of the bounding rectangle),
- relative area (number of object's pixels/area of the bounding rectangle),
- circularity (area of the bounding rectangle/(longRadius² · π),
- roundness (perimeter/(2 · π · longRadius),
- center of mass (average coordinates of the pixels in the object),
- shape signature.

The shape signature was calculated in the following way:

- for each pixel of the perimeter the distance from the centre of mass and the angle were determined,
- all values were normalized dividing each value by the largest distance,
- the results were sorted according to the angle (clockwise),

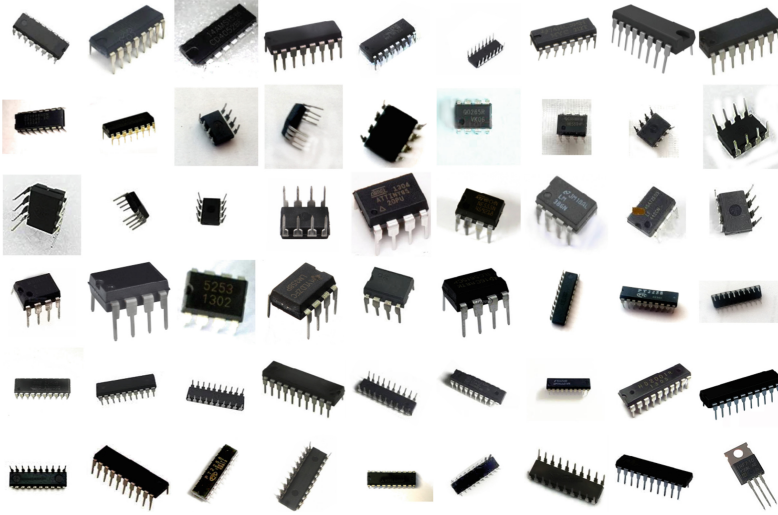


Fig. 2. Images of various IC packages used in experiments.

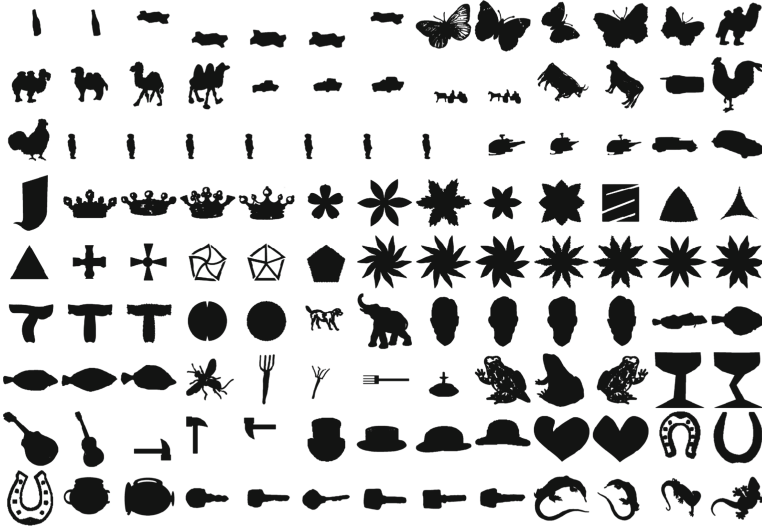


Fig. 3. Images of various random shapes used in experiments.

- the results were divided into 72 bins (5° each) and the average of the distances in each bin was calculated.

The images of various IC packages used in experiments are presented in Fig. 2, whereas Fig. 3 illustrates some other random shapes used for the initial verification of DIP shapes recognition, similarly as in typical General Shape Analysis approaches [3, 4].

3.2 Shape Similarity Calculation

The analysis of test images loaded by the user can be made using a dedicated testing website. The uploaded photo is converted into the binary image using the classical Otsu method [7] and the shape parameters described above are calculated. Next, the shape descriptors are compared with those stored in the database trying to find the best k matches for aspect ratio, area, circularity, roundness and centre of mass. For these parameters each similarity factor is calculated by dividing the smaller of the two compared values by the larger one and then multiplying by 100 to express the similarity as the percentage. The first-check score is the average of these percentages.

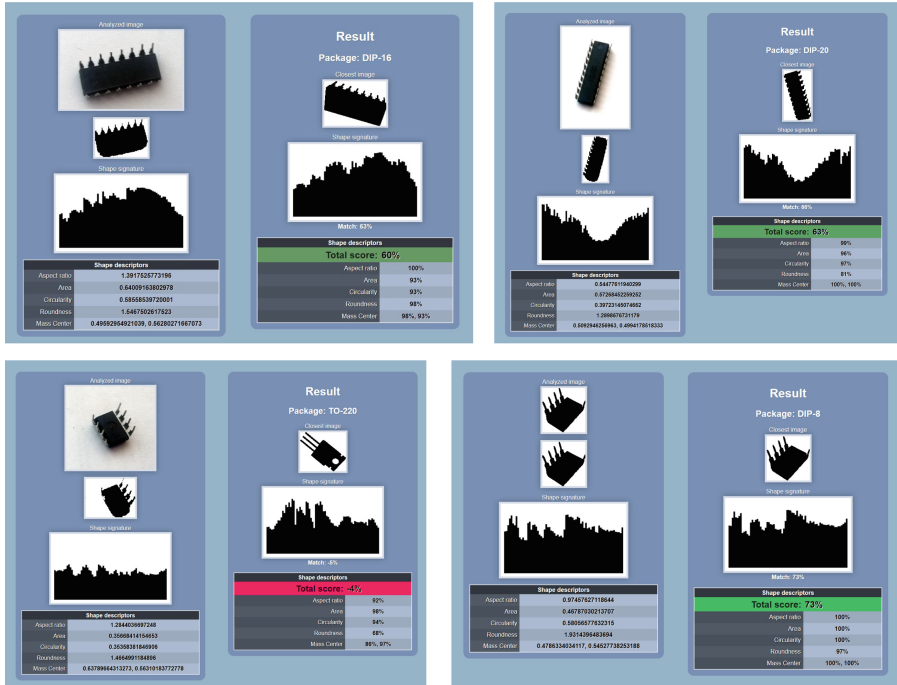


Fig. 4. Illustration of some exemplary results of classification.

In the second stage, the similarity factors between the shape descriptors for each result are determined - each element in the shape signature of the analysed image is compared with each element of the signature from the database. Since the value tends to stay below 10, the match percentage is calculated using the following formula:

$$\text{Match percentage} = 10 \cdot (10 - AD), \quad (1)$$

where AD is the aggregated distance of the shape signature elements. The procedure is then repeated with the shape signatures shifted from -3 to 3 . Each

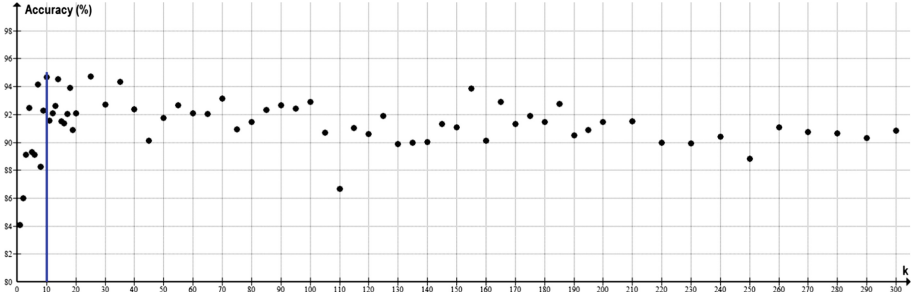


Fig. 5. Illustration of dependency of classification accuracy on the number of selected images using basic shape descriptors.

entry in the database differs from the next by 18° , and the shape signature has the 5° resolution, so by shifting the signature by 15° each side the best possible match can be found undoubtedly. Finally, the match percentage is multiplied by the average of all the others to calculate the highest score and choose it as the result. Some exemplary results of classification are shown in Fig. 4, where some problems caused by the presence of shadows can be noticed.

3.3 Experimental Verification

One of the disadvantages of the initial version of the proposed method was relatively high computational cost, hence the appropriate choice of the number of images chosen using basic shape descriptors (denoted as k) is crucial. To find the appropriate number of images k , some experiments were made using the synthetic reference “perfect” images. As illustrated in Fig. 5, the most reasonable choice seems to be $k = 10$ as too many selected images cause the necessity of calculation of their shape signatures.

Assuming $k = 10$ images selected using basic shape parameters, the verification of the system for real photos (containing only a single IC package after assumed segmentation) was conducted. For each image in the database, the algorithm checks, whether the recognized package is correct and then the accuracy can be determined, as shown in Table 1.

Another investigated problem was related to the choice of the best threshold for the detection of the integrated circuits among the other shapes, shown in Fig. 3. The goal of this experiment was to find the threshold of certainty, that allows to determine, whether or not, the image actually contains an IC package. Since the chosen images were going to be further analysed, the aim was to minimize false negatives, because false positives can be dealt with during the later stages of processing. The overall accuracy of 77% can be achieved for the threshold equal to 52, as shown in Fig. 6, whereas the number of false negatives is less than 10%. The detailed results are shown in Table 2, where TP, TN, FP and FN denote the numbers of true positives, true negatives, false positives and false negatives respectively (considering IC package images as “positives”).

Table 1. Experimental recognition results obtained for real photos of IC packages.

Package type	Number of images	Correct	Incorrect	Accuracy
DIP-8	45	40	5	88.89%
DIP-16	45	34	11	75.56%
DIP-20	45	36	9	80.00%
TO-220	32	31	1	96.88%
All	167	141	26	84.43%

Table 2. Experimental results of detection of the IC packages among the other shapes.

	Total	IC packages	others	TP+TN	FP+FN	FP	FN
Number	365	167	198	282	83	51	32
Percentage	100	45.75	54.25	77.26	22.74	13.92	8.77

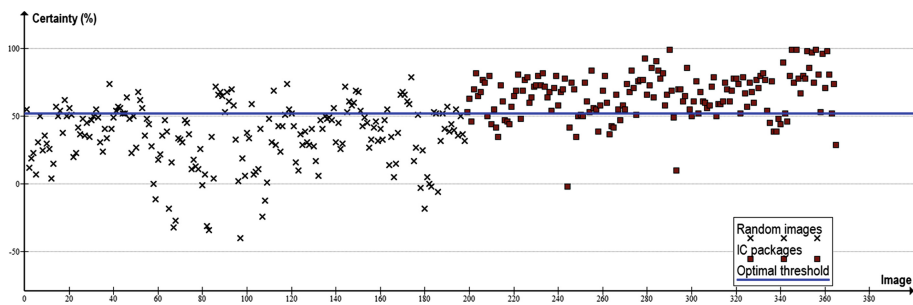


Fig. 6. Illustration of the experimentally selected threshold for the detection of IC packages.

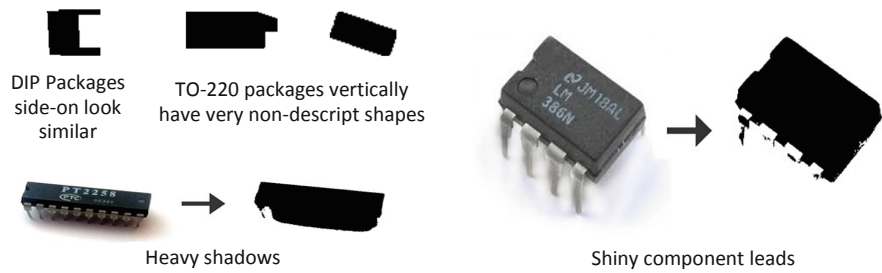


Fig. 7. Illustration of the exemplary problems occurring during the recognition.

Analysing the obtained results, some of the most troublesome images can be found in the database, where the main sources of problems can be noticed for some specific angles as well as in the presence of heavy shadows or shiny component leads, being troublesome for global binarization. The illustration of such exemplary issues is shown in Fig. 7.

4 Conclusions and Future Work

Presented system allows for the detection of IC package images as well as its reliable recognition utilizing relatively simple shape descriptors. Its potential applications and extensions may be considered not only in electronics and robotics but also - in a modified version - in some other areas of industry, where the recognition of similar object shapes plays an important role. In contrast to General Shape Analysis, the presented approach is based on the two-stage combination of some simple shape parameters, therefore a natural direction of its further development might be the use of neural networks or some other machine learning methods to improve the classification stage.

One of its limitations, which should also be considered in further research, is the influence of lighting conditions, since the results of global binarization in the presence of heavy shadows have a significant impact on the results of further shape analysis. One of the promising directions of experiments towards the solution of this challenge may be the application of adaptive binarization, e.g. Niblack [6] or Sauvola [8] algorithms. Nevertheless, their computational complexity is much higher in comparison to global thresholding, hence a reasonable compromise might be the application of region based approach [5].

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