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Application of Multi-Descriptor Binary Shape Analysis for Classification of Electronic Parts

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Abstract: Rapid growth of availability of modern electronic and robotic solutions, also for home and amateur use, related to the progress in home automation and popularity of the IoT systems, makes it possible to develop some unique hardware solutions, also by independent researchers and engineers, often with the help of the 3D printing technology. Although in many industrial applications high speed pick and place machines are used for assembling small surface-mount devices (SMD), especially in mass production of electronic parts, there are still some applications, where the traditional through-hole technology used in Printed Circuit Boards (PCB) is utilised, particularly considering some mechanical, thermal or power conditions, preventing the use of the SMD technology.

One of the possibilities of supporting such types of production and prototyping, in some cases supported by relatively less sophisticated robotic solutions, may be the application of vision systems, making it possible to classify and recognize some electronics parts with the use of shape analysis of their packages as well as further optical recognition of markings. Another application of such methods may be related to the automatic vision based verification of the assembling quality and correctness of the placement of electronic parts after completing the production.

In the paper some experimental results, obtained using various shape descriptors for the classification of electronic packages, are presented. The initial experiments, obtained for a prepared dedicated database of synthetic images, have been verified and confirmed also for some natural images, leading to promising results.

Key Words: shape analysis, electronic packages, image features, classification
Category: I.4.6, I.4.7, I.4.8, I.4.9, I.5.4

1 Introduction

Increasing availability and lowering prices of cameras cause growing popularity of machine vision applications in various areas in industry. More and more advanced vision systems can be found e.g. in automotive industry, automatic inspection of products, navigation of mobile robots, non-destructive evaluation of materials, remote sensing and many other areas of science and technology. Due to increasing capabilities of deep learning solutions, even more computer vision tasks can be executed using deep Convolutional Neural Networks (CNNs), although in many applications their use is limited by the unavailability of big enough training data sets as well as the necessity of full ”explainability” of these methods, especially in robotic and industrial applications. Hence, the necessity of development of some more classical machine vision solutions, based on handcrafted features, is still up-to-date in many areas of technology. Such examples of applications, considered in this paper, can be the semi-automatic assembling systems as well as the prototyping of electronic circuits, where the big number of training data cannot be expected.

Considering these applications, where the usage of surface-mount devices (SMD) may not be possible, an interesting solution is the automatic classification of electronic components according to their package shape. Such housings, e.g. popular dual in-line packages (DIP), contain various elements, such as transistors, switches, LEDs, resistors, etc., which might be recognized assuming unknown location of unsorted individual packages. A similar approach may also be useful for diagnostic purposes, such as checking the connections, as well as the type of electronic components mounted on the printed circuit board (PCB). From practical point of view, the usefulness of automatic classification of electronic elements can be confirmed e.g. analysing the solution introduced in 2017 by Fujitsu company[1], where template pattern matching was used in the artificial intelligence system, applied for the inspection of parts for misalignment.

2 Related Works

The application of image processing techniques for automatic shape recognition in electronics is not a very popular area of research. Nevertheless, some attempts have been made during recent several years, e.g. recognition of hand-drawn circuit diagrams [Edwards and Chandran, 2000], where diagrams consisting nodes, connections and components are segmented using variable thresholds and the classification of components is made by invariant moments combined with scalar pixel-distribution features and vector relationships between straight lines. The overall recognition accuracy of components reaches 82% for 449 components used for verification. Another method, utilising the structural and topological relations matching mechanism, was proposed in the paper [Valois et al., 2001], where the scale, translation and rotation invariance was preserved. The method was validated for 200 samples of 4 hand-drawn symbols using the digital tablet, although the accuracy of the final results was strongly limited by the initial segmentation of the stroke.

In the paper [Zhang et al., 2008] the use of Hidden Markov Models (HMM) was analysed on a dataset of 100 hand-drawn sketches, where the proposed

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

method allows to classify correctly more than 83% of the points. The segmentation was carried out by the Viterbi algorithm and 9 possible components were assumed, namely resistor, capacitor, inductor, AC voltage, DC voltage, current, Earth ground, chassis ground and transistor. Nevertheless, even 17% of connector points were wrongly recognized as components. On the other hand, 16% of the points representing components were recognized as connector points.

Some other researchers have also tried to analyse the transfer function of electronic components [Barrah et al., 2015] without the use of computer vision methods. Although such approaches can be potentially combined with results of image based recognition in future solutions to provide better classification accuracy, they belong to active methods, whereas passive machine vision may be a more desired approach in some applications, similarly as non-destructive testing (NDT) of materials.

In this paper the focus is on the analysis of possible application of various shape descriptors and parameters during the initial stage of classification of IC packages. Hence, it is assumed that the visibility of alphanumerical markings may be limited and therefore the text recognition is not used. Due to such assumption, an initial limitation of the number of checked types of electronic elements may be conducted using previously binarized images followed by the shape analysis. Since some elements, especially DIPs, may look similar to some others, assuming unknown relative position of the camera and angle of observation, finding an appropriate combination of shape descriptors for possibly highly accurate classification is not trivial and should be considered as scientifically challenging task.

Considering the above issues, two types of experiments have been made, using the binary DIP images obtained from the intentionally prepared database in the first part. It contains some synthetic images of the STL 3D models, which have been captured assuming different views and used for the preliminary analysis of the relevance of the simple shape descriptors. The second part of the experiments has been made using some additional descriptors, such as Fourier descriptor, Zernike moments [Khotanzad and Hong, 1990; Hwang and Kim, 2006; Tahmasbi et al., 2011] and Bessel-Fourier moments [Xiao et al., 2010], briefly described in the further parts of the paper. Finally, some experiments have been conducted, using natural images captured by cameras in various lighting conditions, for the additional verification of the proposed approach.

3 Proposed Method

3.1 Database Preparation and Shape Parameters

The proposed method of the classification of the integrated circuit (IC) packages is based on the application of several shape parameters, which can be determined

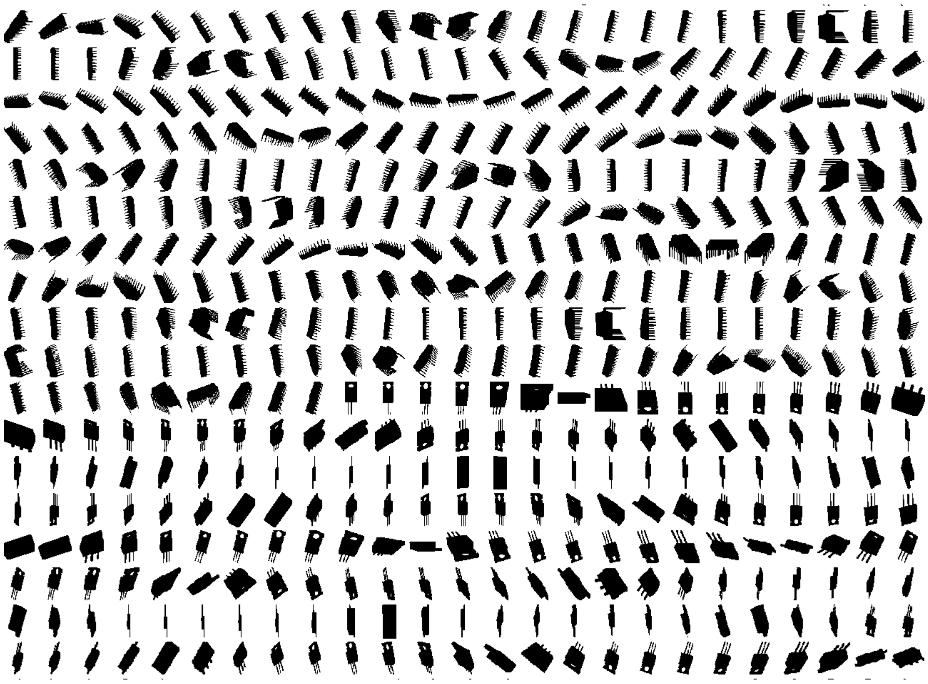

Figure 1: Sample binary images captured for various views of exemplary IC packages

for binary images. Considering the necessity of relatively fast computation and the possibility of using some embedded solutions and low computational power devices, some simple shape descriptors were examined during the first stage of experiments.

The first set of 100 binary images illustrating the IC packages was obtained using the STL 3D models subjected to rotations and translations according to a specified location of a virtual camera followed by taking a screenshot and cropping. Considering the symmetry of the analysed shapes, the rotation by 180 degrees was assumed to be enough for experiments. Each model was rotated by 18 degrees around each axis 10 times, delivering the total number of 1000 images for the analysis. The prepared database contains the captured images together with the values of the calculated shape descriptors. Some sample obtained images are shown in Fig. 1, whereas some randomly selected shapes, other than IC packages, similar as used in typical General Shape Analysis approaches [Forczmański and Frejlichowski, 2010; Frejlichowski, 2010], are illustrated in Fig. 2.

The shape parameters, used in the first stage of experiments, selected after the application of the Principal Component Analysis (PCA) algorithm, are:

- **aspect ratio** $= \frac{width\ of\ the\ bounding\ rectangle}{height\ of\ the\ bounding\ rectangle}$,
- **relative area** $= \frac{number\ of\ pixels\ inside\ the\ object}{area\ of\ the\ bounding\ rectangle}$,
- **circularity** $= \frac{area\ of\ the\ bounding\ rectangle}{longRadius^2 \cdot \pi}$,
- **roundness** $= \frac{perimeter}{2 \cdot \pi \cdot longRadius}$,
- **centre of mass** (average coordinates of the pixels in the object),
- **shape signature**.

The shape signature, being the last mentioned feature, is calculated as follows:

- for each pixel of the perimeter the distance from the centre of mass and the angle is determined,
- all values are normalized dividing each value by the largest distance,
- the results are sorted according to the angle (clockwise),
- the results are divided into 72 bins (5 degrees each) and the average of the distances in each bin is calculated.

As results from the conducted experiments, the above shape descriptors combine good separation of individual classes with their simplicity and therefore they were considered as the most representative ones in further experiments.

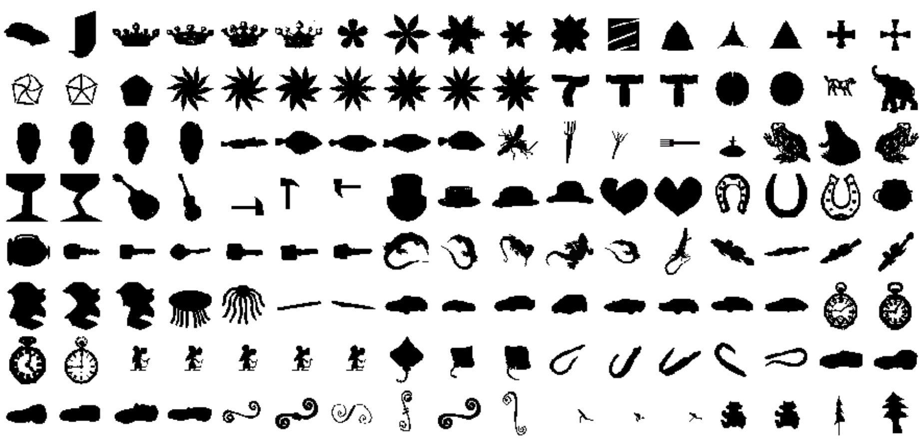

Figure 2: Images of sample random shapes used in IC detection experiments

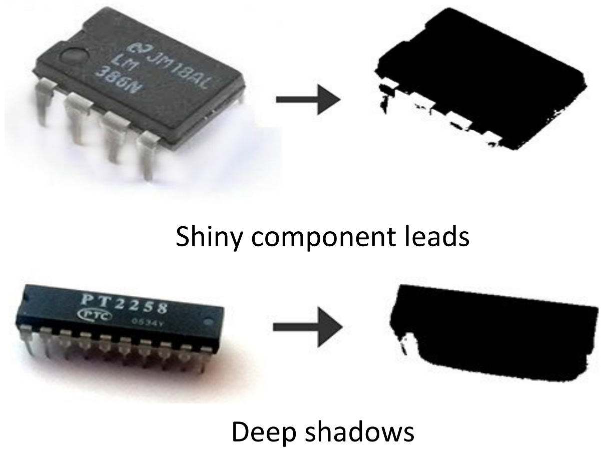

Figure 3: Illustration of some problems caused by illumination influencing the binarization results

3.2 Detection of IC packages

The first goal of our research was the examination whether the analysed image contains an integrated circuit (IC) package. For this purpose the database of 200 synthetic binary images containing various IC packages, as well as different shapes, was prepared, which was used during the development of the method. Nevertheless, its further verification was made using a bigger database containing 488 natural images subjected to further binarization (240 ICs and 248 non-ICs).

The first attempt to detection of the IC packages was based on the choice of the optimal certainty threshold minimizing the number of false negatives, assuming the possibility of further elimination of false positives during the next processing steps. Nevertheless, due to some problems occurring in natural images, illustrated in Fig. 3, caused by e.g. deep shadows or shiny component leads, the overall accuracy was relatively low. More detailed results are presented in Table 1.

Table 1: Experimental results of detection of the IC packages among the other shapes using the optimal certainty threshold

	Total	IC packages	others	TP+TN	FP+FN	FP	FN
Number	488	240	248	403	85	69	16
%	100	49.18	50.82	**82.58**	17.42	14.14	3.28

To improve the detection accuracy, a simple range check is performed according to the following steps:

- for all the entries in the database the minimum (MIN) and maximum (MAX) values of each parameter (aspect ratio, relative area, circularity, roundness, centre of mass, Zernike moments) are calculated,
- the range width for a given parameter is determined as the absolute difference between minimum and maximum values ($R = |MAX - MIN|$),
- for each new image all the parameters are calculated to check if their values are in the range between the determined minimum and maximum values,
- for each parameter with its values (P) outside the range its normalized distance from the range is calculated as $D = \frac{|MIN-P|}{MAX-MIN} = \frac{|MIN-P|}{R}$ if $P < MIN$ or $D = \frac{|P-MAX|}{MAX-MIN} = \frac{|P-MAX|}{R}$ if $P > MAX$, otherwise the distance is set to 0,
- the final classification score is calculated as the sum of all distances of all parameters.

Algorithm 1 Algorithm for calculating the ranges of paramaters

```
procedure determineRanges
    i ← 0
    for all parameters do
        MIN[i] ← database[0].parameter[i]
        MAX[i] ← database[0].parameter[i]
        j ← 0
        for all images do
            if database[j].parameter[i] < MIN[i] then
                MIN[i] ← database[j].parameter[i]
            end if
            if database[j].parameter[i] > MAX[i] then
                MAX[i] ← database[j].parameter[i]
            end if
            j ← j + 1
        end for
        R[i] ← |MAX[i] − MIN[i]
        i ← i + 1
    end for
end procedure
```

Algorithm 2 Range check algorithm

procedure CALCULATEDISTANCE(imageParameters)
  $i \leftarrow 0$
  $score \leftarrow 0$
  for all parameters **do**
    if $imageParameters[i] < MIN[i]$ **then**
      $D[i] \leftarrow \frac{MIN[i]-imageParameters[i]}{R[i]}$
    else if $imageParameters[i] > MAX[i]$ **then**
      $D[i] \leftarrow \frac{imageParameters[i]-MAX[i]}{R[i]}$
    else
      $D[i] \leftarrow 0$
    end if
    $score \leftarrow score + D[i]$
    $i \leftarrow i + 1$
  end for
  $score \leftarrow \frac{score}{i}$
  return $score$
end procedure

Table 2: Experimental results of detection of the IC packages among the other shapes using the range check method

	Total	IC packages	others	TP+TN	FP+FN	FP	FN
Number	488	240	248	431	57	42	15
%	100	49.18	50.82	**88.32**	11.68	8.61	3.07

The optimal threshold for the classification score is determined by the calculation of distances for the known set of images (the obtained result is 1.43 as shown in Fig. 4). The illustration of the determined threshold for 200 training binary samples is presented in Fig. 4, whereas more detailed results of classification for 488 test images are presented in Table 2. A comparison of some classification metrics calculated for both approaches is presented in Table 3.

4 Classification of the IC Packages for Natural Images

The classification of the IC packages is based on the calculation of the similarity of the shape parameters for binary images, obtained using the classical Otsu's thresholding method based on the minimization of intra-class intensity variance [Otsu, 1979]. Determined shape descriptors are: aspect ratio, area, circularity, roundness and centre of mass. Additionally some more advanced features are calculated, namely invariant moments, Fourier descriptor, Zernike moments [Hwang and Kim, 2006; Khotanzad and Hong, 1990; Saki et al., 2013; Tahmasbi et al., 2011] and Bessel-Fourier moments [Xiao et al., 2010]. Then, the range based shape classification, described in Section 3.2, is conducted.

The illustration of the values of Bessel-Fourier and Zernike moments, obtained for various sample IC packages, is shown in Figures 5 and 6 respectively, whereas Fig. 7 illustrates the result of conversion of a sample image of the IC package into polar coordinates, used for the calculation of Bessel-Fourier moments.

For the objects classified as potentially representing the IC packages, the next step of the algorithm is the comparison of the shape descriptors and moments with the database to find the best n matches for aspect ratio, area, circularity, roundness, centre of mass, Zernike moments and Bessel-Fourier moments. Each similarity value is normalized by dividing the smaller of two values by the larger

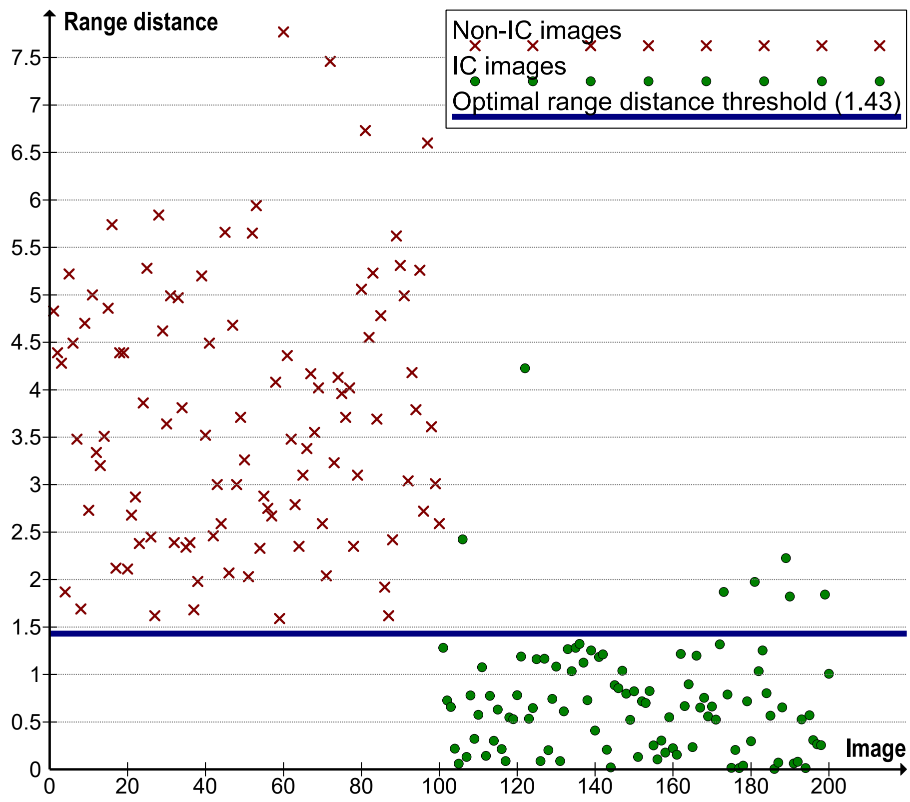

Figure 4: Illustration of the determined threshold for the detection of IC packages

Table 3: Comparison of the results obtained using the basic method with the results of the improved method

Metric	Method	
	Basic (Table 1)	Improved (Table 2)
Precision	76.69	84.50
Recall (Sensitivity)	76.69	84.50
Specificity	91.67	93.09
Negative Predictive Value	91.67	93.09
False Negative Rate	6.58	6.15
False Positive Rate	35.94	19.35
False Discovery Rate	23.31	15.50
False Omission Rate	8.33	6.91
Critical Success Index	72.76	80.07
F-Measure	76.69	84.50
Accuracy	**82.58**	**88.32**

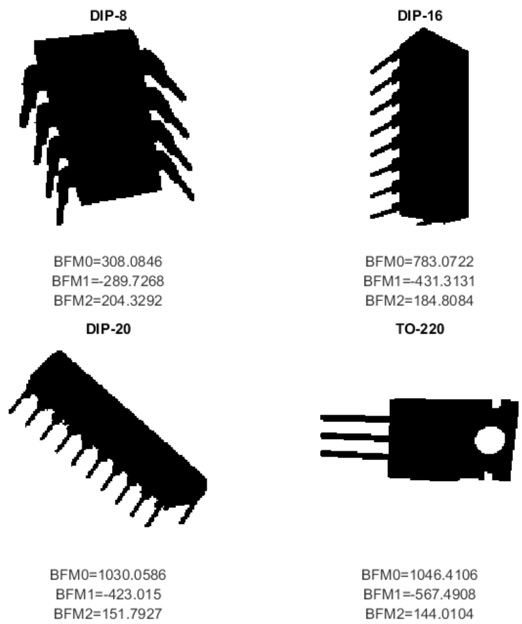

Figure 5: Illustration of Bessel-Fourier moments obtained for various sample IC packages

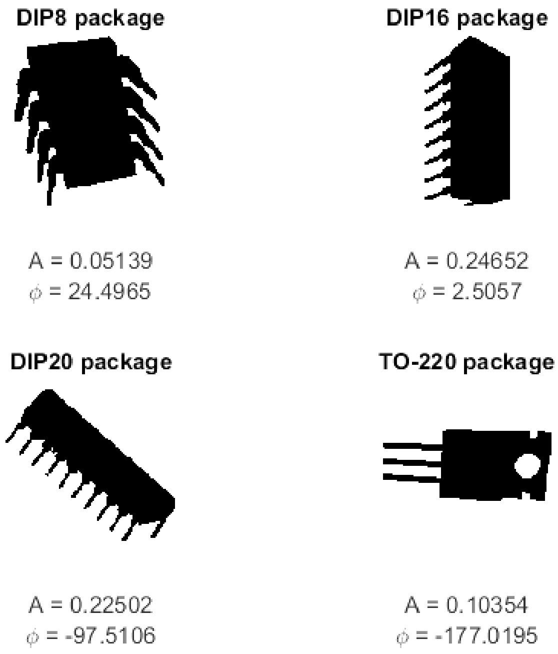

Figure 6: Illustration of Zernike moments obtained for various sample IC packages

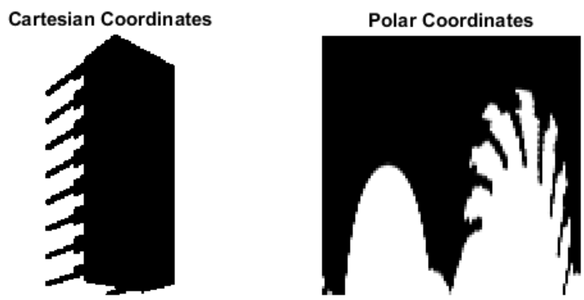

Figure 7: Illustration of the conversion into polar coordinates for the calculation of Bessel-Fourier moments

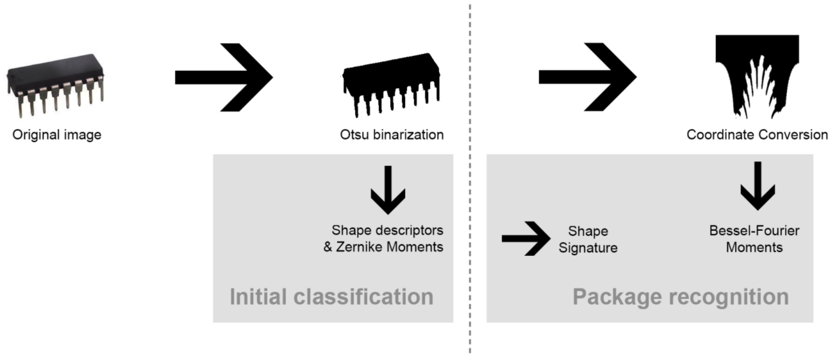

Figure 8: The simplified flowchart of the proposed method

one and then multiplying by 100, leading to the similarity percentage, and finally the first-check score calculated as the average similarity. According to previously conducted experiments, the best results are obtained for $n = 10$ best matches.

After choosing the n best matches, using the above method, the similarities between the shape descriptors for each result are checked. Hence, 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

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

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 entry in the database differs from the next by 18 degrees and the shape signature has the resolution of 5 degrees, therefore the best possible match can be undoubtedly found, assuming shifting the signature by 15 degrees for each side. Finally, the match percentage is compared with all the others to find the best match and choose it as the result. The average of the scores based on the basic parameters, Bessel-Fourier moments and the shape signature is considered as the final score. The proposed method can be described as presented in Algorithm 3, and its simplified flowchart is illustrated in Fig. 8.

5 Analysis of Experimental Results

The experiments have been made for the dataset of 240 natural images consisting of 60 images captured for each of four types of IC packages (DIP-8, DIP-16, DIP-20 and TO-220). Some sample natural images used for experimental evaluation of the proposed approach are shown in Fig. 9.

Algorithm 3 Algorithm for finding the best match in the database

```
procedure calculateScore(image)
    if calculateDistance(image) < 1.43 then
        j ← 0
        for database do
            i ← 0
            paramScore[i] ← 0
            for all parameters do
                if image.parameters[i] < database[j].parameters[i] then
                    similarityParam[i] ← image.parameters[i] / database[j].parameters[i]
                else
                    similarityParam[i] ← database[j].parameters[i] / image.parameters[i]
                end if
                paramScore[j] ← paramScore[j] * similarityParam[i]
                i ← i + 1
            end for
            paramScore[j] ← paramScore[j] * 100
            j ← j + 1
        end for
        sorted ← sort(database) using paramScore
        for j ←< 0; 9 > do
            BFMScore[j] ← 0                                   ▷ Bessel-Fourier Moments
            for all BFM do
                if image.BFM[i] < sorted[j].BFM[i] then
                    similarityBFM[i] ← image.BFM[i] / sorted[j].BFM[i]
                else
                    similarityBFM[i] ← sorted[j].BFM[i / image.BFM[i]
                end if
                BFMScore[j] ← BFMScore * similarityBFM[i]
                i ← i + 1
            end for
            BFMScore[j] ← BFMScore[j] * 100
            for k ←< −3; 3 > do
                SSScore[j] ← 0                                ▷ ShapeSignature
                i ← 0
                for all SS do
                    tempScore ← 0
                    tempScore+ = |database.SS[i + k] − image.SS[i]|
                    i ← i + 1
                end for
                tempScore ← 10 * (10 − tempScore)
                if tempScore > SSScore[j] then
                    SSScore[j] ← tempScore
                end if
            end for
            finalScore[j] ← (paramScore[j]+BFMScore[j]+SSScore[j]) / 300
        end for
        final ← sort(sorted) using finalScore
        return final[0]
    else
        return 0
    end if
end procedure
```

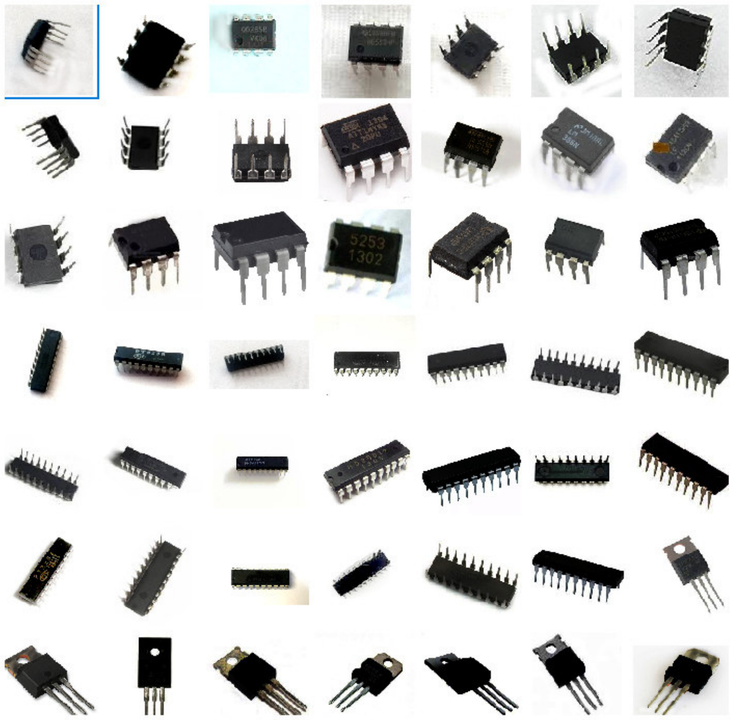

Figure 9: Sample natural images of IC packages used in experiments

The initial version of the classification method, based on shape descriptors without moments, leads to encouraging results, although the incorporation of Fourier descriptor does not increase the overall recognition accuracy. Despite it finds some samples rejected by simpler shape features, some additional false results appear. Therefore, in the final version the shape signature has been used instead of Fourier descriptor. More detailed results are shown in Table 4, where it can be noticed that even the combination of both methods leads to worse results than the use of the shape signature.

Nevertheless, the use of Fourier-Bessel and Zernike moments improves the classification results noticeably. The detailed final results of classification for individual types of IC packages are presented in Table 5. It is worth noting that the recognition accuracy of the most characteristic TO-220 package slightly decreases when the additional moments are applied, whereas the other DIP type packages are classified much better. To reduce the feature space, the choice of the most relevant shape features has been made using two approaches, namely Principal Component Analysis (PCA) and Independent Component Analysis (ICA), leading to the same results.

Table 4: Experimental classification results of the IC packages in natural images with and without Fourier descriptor

Package type	Classification accuracy for simple shape features with		
	shape signature	Fourier descriptor	both combined
DIP-8	88.9%	87.1%	85.4%
DIP-16	75.6%	76.3%	77.8%
DIP-20	80.0%	73.7%	76.1%
TO-220	96.9%	93.5%	94.2%
Average	**85.3%**	82.6%	83.4%

Table 5: Experimental final classification results of the IC packages in natural images with and without moments

Package type	Classification accuracy for simple features and shape signature	
	without moments	with Bessel-Fourier and Zernike moments
DIP-8	88.9%	93.3%
DIP-16	75.6%	81.7%
DIP-20	80.0%	83.3%
TO-220	96.9%	95.0%
Average	85.3%	**88.3%**

Some additional experiments have also been made, using the Convolutional Neural Networks (CNN), although due to relatively small number of training samples, the obtained results are much worse, confirming the necessity of developing novel solutions based on the combination of some classical methods, as proposed in this paper.

6 Summary and Future Work

The new method of classification of integrated circuits packages, based on shape analysis, presented in the paper, provides promising classification accuracy obtained for natural images. The initial classification based on parameter ranges is a quick and effective way of discarding irrelevant images before calculating the more computationally expensive parameters. In some applications, the second phase of the process might even be unnecessary, or may be handled by an entirely different system. In those cases, the range distance is a simple and effective metric for finding potential images of IC packages. The additional use of Bessel-Fourier and Zernike moments makes it possible to improve the classification, particularly for the most troublesome DIP elements.

Considering the fact that in many industrial systems and other applications of machine vision in automation and robotics, some dedicated illuminators are typically used to ensure the uniform lighting conditions, the influence of some shadows may be eliminated. Alternatively, some more advanced adaptive binarization methods, including well-known ones, e.g. Niblack's method [Niblack, 1986] or Sauvola's thresholding [Sauvola and Pietikäinen, 2000], as well as some other region based methods, proposed recently [Michalak and Okarma, 2019], may be applied, however additionally increasing the overall computational cost.

Further improvements of the proposed two-stage approach may be related to the use of machine learning and neural networks to improve the final classification step. Another direction of future investigations is the analysis of the potential advantages of using adaptive binarization, which may be speeded up in some cases, e.g. by the use of the Monte Carlo method limiting the number of analysed pixels.

References

[Barrah et al., 2015] Barrah, E. M., Ahdid, R., Safi, S., and Malaoui, A. (2015). New technique to determination of electronic circuits for semiconductor components by recognizing Nyquist curve. Journal of Computer Sciences and Applications, 3(4):100–104.

[Edwards and Chandran, 2000] Edwards, B. and Chandran, V. (2000). Machine recognition of hand-drawn circuit diagrams. In Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), vol. 6, pp. 3618–3621.

[Forczmański and Frejlichowski, 2010] Forczmański, P. and Frejlichowski, D. (2010). Robust stamps detection and classification by means of general shape analysis. In Bolc, L., Tadeusiewicz, R., Chmielewski, L. J., and Wojciechowski, K. (editors), Computer Vision and Graphics, LNCS vol. 6374, pp. 360–367. Springer Berlin Heidelberg.

[Frejlichowski, 2010] Frejlichowski, D. (2010). An experimental comparison of seven shape descriptors in the general shape analysis problem. In Campilho, A. and Kamel, M. (editors), Image Analysis and Recognition, LNCS vol. 6111, pp. 294–305. Springer Berlin Heidelberg.

[Hwang and Kim, 2006] Hwang, S.-K. and Kim, W.-Y. (2006). A novel approach to the fast computation of Zernike moments. Pattern Recognition, 39(11):2065–2076.

[Khotanzad and Hong, 1990] Khotanzad, A. and Hong, Y. (1990). Invariant image recognition by Zernike moments. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(5):489–497.

[Michalak and Okarma, 2019] Michalak, H. and Okarma, K. (2019). Fast adaptive image binarization using the region based approach. In Silhavy, R., (editor), Artificial Intelligence and Algorithms in Intelligent Systems, AISC vol. 764, pp. 79–90. Springer International Publishing.

[Niblack, 1986] Niblack, W. (1986). An introduction to digital image processing. Prentice Hall, Englewood Cliffs.

[Otsu, 1979] Otsu, N. (1979). A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man, and Cybernetics, 9(1):62–66.

[Saki et al., 2013] Saki, F., Tahmasbi, A., Soltanian-Zadeh, H., and Shokouhi, S. B. (2013). Fast opposite weight learning rules with application in breast cancer diagnosis. Computers in Biology and Medicine, 43(1):32–41.

[Sauvola and Pietikäinen, 2000] Sauvola, J. and Pietikäinen, M. (2000). Adaptive document image binarization. Pattern Recognition, 33(2):225–236.

[Tahmasbi et al., 2011] Tahmasbi, A., Saki, F., and Shokouhi, S. B. (2011). Classification of benign and malignant masses based on Zernike moments. Computers in Biology and Medicine, 41(8):726–735.

[Valois et al., 2001] Valois, J.-P., Cote, M., and Cheriet, M. (2001). Online recognition of sketched electrical diagrams. In Proceedings of Sixth International Conference on Document Analysis and Recognition (ICDAR), pp. 460–464.

[Xiao et al., 2010] Xiao, B., Ma, J.-F., and Wang, X. (2010). Image analysis by Bessel-Fourier moments. Pattern Recognition, 43(8):2620–2629.

[Zhang et al., 2008] Zhang, Y., Viard-Gaudin, C., and Wu, L. (2008). An online hand-drawn electric circuit diagram recognition system using Hidden Markov Models. In Proceedings of 2008 International Symposium on Information Science and Engineering, vol. 2, pp. 143–148.