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Intelligent Optical Classification System for Electronic Components

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Introduction

Since the revival of neural networks in the mid eighties, only fairly recently practical systems started to be developed using intelligent in favour of purely statistical methods together with image processing [4]. In this perspective, this paper presents the development of the machine vision part of a practical fully automatic system that sorts electronic components according to their type. This prototype system is specially designed to deal with a high volume of samples. Therefore, it may be used in electronics laboratories at educational institutions to assist the staff with laborious task of keeping the equipment in place and ready to use for teaching purposes.

The generic model of the modular machine vision system as suggested by Awcock and Thomas [2] was used as a general guide for the design process of this system. This model splits any machine/computer vision system in seven distinct modules. In order of data flow these are:

- *Scene constraints*. This includes lighting and the setting of the scene so that the properties of the objects of interest are profound.
- *Image acquisition*, which includes the configuration and the type of the imaging device to enable the acquisition of image of appropriate quality for the specific application.
- *Image pre-processing* ensures that the acquired images are free of noise, well-framed and ready for further processing.
- *Segmentation* is the module that splits the image into regions of interest. In other words, it separates the background from the samples.
- The next module is *feature extraction*, which calculates a list of properties out of the samples so that substantial reduction of the dimensionality is performed.
- *Classification* or *interpretation* is the intelligent module of the system that takes decisions based on the data gathered from the samples through feature extraction.
- *Actuation* includes actions of system as a consequence of the decisions made by the classification module. It may also interact with the scene by changing aspects of it, thus closing the loop of actions of the system.

This developed system presented here incorporates all of the above modules, but not necessarily in strictly the same order and not as well defined. This is because the design process was optimised for the specific needs of the application to produce an efficient system [7].

Image acquisition hardware

The acquisition of images took place at the laboratories of the Fisheries Research Institute at Nea Peramos, Kavala, Greece. The institute kindly provided all the necessary equipment and laboratory space for the needs of this study. Several image acquisition devices were considered. The device characteristics that were desired for this application were the adequate image resolution of the sensor, good quality optics, the space available between the objective lens and the sample, the adaptability to various lighting techniques and the speed of operation.

The devices available under review were:

- a high resolution flatbed scanner,
- a digital camera with macro lens,
- a stereoscopic microscope equipped with digital image sensor and
- a high precision desktop photographic system with a standalone control unit.

Modern flatbed scanners offer sensor resolutions from 300 to 4800 dpi. They are unable to provide optical magnification, because they have static lens systems. The resolution of the produced image depends on the size of the sample. For example, in 4800 dpi resolution an object sized 2.5 cm by 1 cm produces images of 4724x1890 pixels, while smaller objects of 3mm by 1mm will produce 567x189 pixel images. Consequently, they provide images of a certain size, which are essential for an automated system. They are also very slow in operation and they are not capable of dealing with a constant flow of samples that this application demands. However, they provide even illumination of the scene that will not cast shadows.

The commercial photographic cameras offer high resolution sensors of up to 16 MPixels at a reasonable price. These cameras can be fitted with a macro lens or switched to macro mode so that they can acquire a properly focused image from as close as 1 cm from the subject. Their optics are usually of very good quality so they produce image with high fidelity especially important on capturing the fine details of the outline of the samples. The training and evaluation of the classification module required a large number of images to be acquired. Therefore, a device that can function normally for long periods of time was necessary. Unfortunately, the cameras available overheated after long use on the mains power supply and did not fulfil the needs of this application.

The next candidate imaging tool considered was a Leica MZ6 stereoscopic microscope equipped with a Leica DFC320 image sensor with 3MPixel resolution. This instrument offers very good quality images and can be combined with several lighting techniques. Its image sensor uses a firewire connection to a computer so that enlarged live images can be produced for the precise adjustment of focus. The available objective lenses offered enough working space between the instrument and the samples. However, these lenses over-magnified the samples so that the larger ones could not fit within the field of view. A different set of objective and eyepiece lenses can rectify this.

A Nikon high precision desktop photographic system with a standalone control unit was able to handle the demands of this application without any serious disadvantages. This image acquisition system consists of a 5 MPixel cooled CCD Nikon DS-Fi1sensor accompanied by a DS-Fi1 standalone control unit with an 8.4 inch LCD screen, which assists with the precise focusing and image storage. This system also contains a stand for the precise yet quick control of the camera position so that the desired framing of the images can be achieved. The stand ensured that there was enough room for the proper installation of the lighting equipment needed. A picture of this system is shown in Fig. 1.

Fig. 1. The image acquisition system

Scene lighting

For the most detailed acquisition of the outline of the samples, several different lighting techniques were implemented and examined. The main problems encountered during the preparation of the scene were the presence of shadows and the reflections of metal surfaces. These phenomena impeded the precise description of the sample outline as they distorted its actual shape and size.

The lighting of the scene was provided by two Leica L2 variable fibre optic light sources. Initially, the samples were positioned on a black matte background with four opposing fibre optics so that even illumination was supplied. This background colour was selected to create a high contrast with the brighter coloured electronic components.

This method did not give acceptable results because of the intense shadows and the colour difference of the light sources. In order to rectify the problem, white carton diffused reflectors were installed around the sample area to provide more even illumination. Although this approach did offer a substantial improvement to the scene, image segmentation tests showed that the end result was not consistent for all the training images. Proper management of the lighting and scene constraints can prevent further more complex image processing in the following stages of the system. Therefore, it is good practice to set up the scene in such manner that the image processing only performs trivial operations.

The use of back illumination was considered to deal with the problems that arise from the previous lighting techniques. In this case the sample was situated in between the light source and the image sensor. In this manner, the sample appeared to be dark in a bright background. The advantages of this technique were that the foreground-to-background contrast was very high, there were no apparent shadows and no metallic reflections as the whole of the sample body was of dark colour. The fact that there was decreased colour information was not important for the specific application.

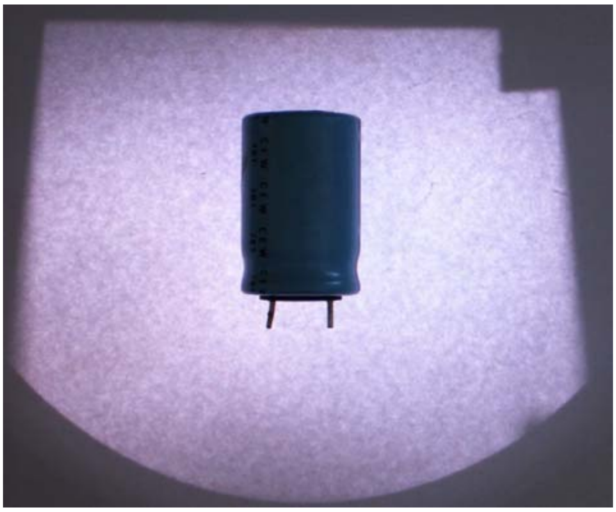

Fig. 2. Image of an electrolytic capacitor captured with back-illumination

As there was not any back illumination device available, a Leica stereoscopic microscope stage was used in conjunction with a Leica L2 fibre optic light source and a transparent sample holder. This stage achieves the capability of back illumination by directing the light using an adjustable mirror under the sample holder. A piece of A4 paper was placed between the sample and the sample holder to diffuse the light as needed in this technique. This technique gave excellent results and minimised the need for advanced image-processing algorithms to extract the sample outlines. An example of an image acquired with this illumination is presented in Fig. 2.

Image processing

According to the generic model of the modular machine vision system, the next stage is the pre-processing of the acquired images. Digital image processing is generally used to remove unwanted noise from the images, correct any misalignments and framing problems and make the region of interest along with its important features more profound. The overall goal is to make the extraction of the needed information as trivial as possible.

In this study, custom code was developed to perform the image processing and feature extraction to automate the procedures. The open-source and Java-based application ImageJ was used as a platform for this task [1]. It was chosen because it can be run in nearly all computer operating systems and it offers a user-friendly interface. Moreover, it provides a long list of image processing and analysis algorithms and it is extensible via Java plug-ins and recordable macro-code. ImageJ supports image *stacks*, a series of images presented as image slices of a single window, and it is multithreaded, so time-consuming operations such as image file reading can be performed in parallel with other operations. This was particularly beneficial for the feature extraction of the system as more than a hundred images need to be processed as one set.

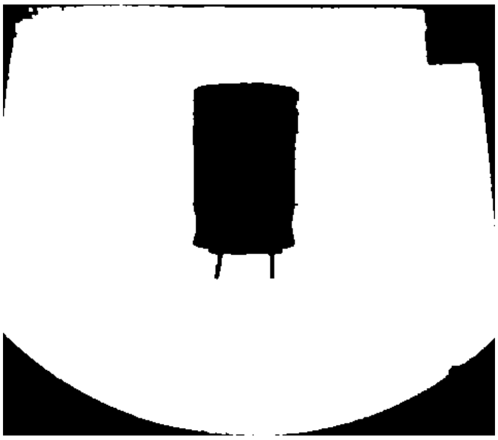

Fig. 3. The image of Fig. 2 after processing

The code developed was composed in the ImageJ macro language. This piece of code included the pre-processing of the images, their segmentation and the feature extraction without explicit segregation. Test segmentations showed that no image filtering would be needed as the noise levels were low enough not to cause problems. The images were scaled and cropped to 477x420 pixels and the colour information was discarded by converting the images from 24bit colour to 8bit greyscale. This was done to reduce the unnecessary volume of data and speed up the processing.

ImageJ offers a list of automatic thresholding algorithms for image segmentation. The best results were obtained with the use of the '*Minimum Auto Threshold*' algorithm [8]. This method works best on bimodal image histograms. The histogram is iteratively smoothed until there are only two local maxima. The threshold t is such that satisfies the following condition in equation (1):

$$yt - 1 > yt \leq yt + 1 \qquad (1)$$

After the image segmentation, the mathematical morphology algorithm '*closing*' was applied, which includes a '*dilation*' and then an '*erosion*' [10]. This was performed in order to fix any broken lines as a result of local miscalculation of the threshold limit. This ensured the reliable production of image measurements for the extraction of the features. A processed image can be seen in Fig. 3.

As a direct way of filtering the images, the image measurements did not include objects that lied on the image borders and did not apply for objects smaller than 250 pixels. Therefore, the less illuminated edges of the images and any noise particles did not take part in the calculations. This method eliminated all the cases of features extracted from non-electronic component objects.

Data extraction and manipulation

Feature extraction is performed as a way to reduce the dimensionality of the data produced by the image sensor. In the computer vision field, each pixel represents one data dimension. The images used in this study provided data of 200340 dimensions. It is impractical to feed data of such high dimensionality into a classifier. Among a long of candidate features, the six more powerful features were selected to form an input feature vector. This vector was then used to train and validate the classifier. The selected features were:

- **Solidity**

It is the ratio of the area of the sample (A) over the area of its convex hull ($A_{convexHull}$) [3]. The formula for solidity is

$$Solidity = \frac{A}{A_{ConvexHull}}. \qquad (2)$$

- **R factor**

The R factor measures the perimeter of the convex hull of the sample over its maximum Feret's diameter [3]. R factor is given by

$$Rfactor = \frac{P_{ConvexHull}}{(\pi Feret)}. \qquad (3)$$

- **MBR aspect ratio**

This is the ratio of the sides of the 'minimum bounding rectangle' (MBR) that includes the sample. The minimum bounding rectangle, also known as 'bounding box', is an expression of the maximum extents of a 2-dimensional object (e.g. point, line, polygon) within its 2-D (x,y) coordinate system, in other words min(x), max(x), min(y), max(y) [5]. It may be useful to give a measure of the elongation of the samples. The formula for aspect ratio is

$$Aspect\ ratio = \frac{x_{max} - x_{min}}{y_{max} - y_{min}}. \qquad (4)$$

- **Convexity**

It is the ratio of the perimeter of the convex hull of the sample ($P_{convexHull}$) over the actual perimeter of the sample (P). For *planar objects*, the convex hull may be easily visualized by imagining an elastic band stretched open to encompass the given object; when released, it will assume the shape of the required convex hull [6]. The formula for convexity is

$$Convexity = \frac{P_{ConvexHull}}{P}. \qquad (5)$$

- **Rectangularity**

This is the ratio of the area of the sample over the area of its MBR [9]. It approaches 0 for cross-like objects, 0.5 for squares, π/4 for circles and 1 for long rectangles [3]. The formula used for rectangularity is

$$Rectangularity = \frac{A}{A_{MBR}}. \quad (6)$$

- **Feret's aspect ratio**

This is the ratio of the maximum Feret's diameter over the maximum diameter of the object which is perpendicular to the one of Feret's, in other words the *breadth* of the object. It is given by

$$AR = \frac{Feret}{breadth}. \quad (7)$$

Classifier training and evaluation

The experimental work of the classifier training was carried out using the WEKA software, an open source package for data mining made by the University of Waikato, New Zealand [11]. The neural network of choice for this study was the multilayer perceptron or MLP with a single hidden layer. This network was trained with six neurons in the input layer to match the number of features, and six neurons in the output layer that represent the number of possible types of electronic components. Several configurations of its hidden layer were studied to determine the best performing number of hidden neurons. The best results were produced by 8 neurons. A schematic of the neural network is illustrated in Fig. 4.

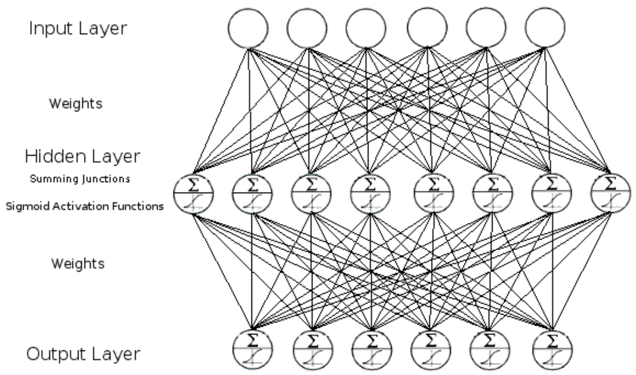

Fig. 4. The MLP classifier of the system

The neural network was trained by the back-propagation algorithm, which is by far the most common and trusted learning method for this type of classifiers. Common settings were used for all the nodes of the network. The most efficient learning rate was found to be 0.8 and the momentum factor was set to 0.3 in this application. The length of the training sessions were 1000 cycles as anything longer did not improve the performance of the system. The data consisted of 87 cases and was split in 70% for training and the rest 30% for evaluation purposes.

After the training sessions, the classifier evaluation yielded an overall performance of 92.3%. The various classes gave differing degrees of successful recognitions that can be described by two metrics. *True Positive* (TP) rate is the actual rate of successful recognitions and *False Positive* rate (FP) shows the percentage of mistakenly classified cases per class. Table 1 presents the detailed results.

The class *Elcap* refers to electrolytic capacitors, *Cercap* to square and round ceramic capacitors, *Res* to resistors, *Trans* to transistors and *PowTrans* to power transistors.

Table 1. Detailed classification performance per data class

Class	TP	FP
Elcap	0,857	0,053
Cercap sq	0,833	0
Cercap rd	1	0
Res	1	0
Trans	1	0
PowTrans	1	0,045

An alternative presentation method of these results is the *contingency table*, where it the misclassification are shown more clearly. The diagonal of the table depicts the true successful recognitions. The contingency given in Table 2. It suggests that the overall classification rate was very high. However, the electrolytic capacitors can be confused with power transistors and the square ceramic capacitors as round ones. Considering the nature of feature within the input vector, it can be realised that these classes have indeed very similar shape and outline properties.

Table 2. Contingency table of the classifier

Classes classified as...						
Elcap	Cercap sq	Cercap rd	Res	Trans	Pow Trans	**Classes**
6	0	0	0	0	1	Elcap
0	5	1	0	0	0	Cercap sq
0	0	1	0	0	0	Cercap rd
0	0	0	5	0	0	Res
0	0	0	0	3	0	Trans
0	0	0	0	0	4	PowTrans

Conclusions

A thorough account of the development of a computer vision system that is able to classify electronic components using multilayer perceptron neural networks through a morphological feature vector was presented.

The system was designed with the generic model of the modular machine vision system by Awcock and Thomas [2] as a guide. Several possible devices were considered for the acquisition of the images required for the training and evaluation of the classifier. The selected equipment was a Nikon high precision desktop photographic system with a standalone control unit. This system offered the best image quality, adaptability to various lighting techniques and speed of operation. The lighting technique the provided the desired results was back-illumination so that the creation of shadows and reflections of metallic surfaces can be avoided. This was achieved with the use of a stereoscopic microscope stage fitted with a mirror and a glass sample holder and a twin fibre optic light source.

The processing of the images and the feature extraction required were implemented as a custom ImageJ macro code. The images were cropped and the colour information was discarded to reduce the volume of the data. They were segmented with the minimum automatic thresholding algorithm so that the components could be separated from the background. A list of six morphological features based on the outline of the samples were calculated to reduce the dimensionality of the image data.

The feature data extracted from all the images formed the input vector of the classification module of the system. The data was split in two sets to train and evaluate the classifier. The classifier was chosen to be a multilayer perceptron trained with the backpropagation algorithm. After experimentation with several configurations the system was able to successfully recognise 92.3% of the cases.

The system presented in this paper is a prototype system not capable for routine operation. Several additional capabilities have to be developed to transform it into a fully operational product. Some suggestions are: 1) Transparent conveyor belt for the automatic positioning of samples in the scene that can accommodate back illumination; 2) Addition of recognisable component types. This will require the review of the feature vector for ensuring high recognition rates; 3) Robotic sorting system. The components need to be put to the appropriate tray according to their classification; 4) Communications system. A data connection should be implemented with a server that will record the system's actions and calculate statistical information.

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D. Lefkaditis, G. Tsirigotis. Intelligent Optical Classification System for Electronic Components // Electronics and Electrical Engineering. – Kaunas: Technologija, 2010. – No. 2(98). – P. 10–14.

The development of a prototype system for the automated identification and classification of six types of electronic components is presented. This system is meant to be used as a part of an autonomous sorting machine of electronic equipment for the educational electronics laboratories of the Kavala Institute of Technology. The design process followed was that of a modular machine vision system. The methodology exploits the inherent shape variability of the electronic components according to their type. This was based on the processing and analysis of images acquired using a precision desktop digital camera system equipped with a standalone control unit. A feature vector was constructed, which describes the outline morphology of the components. The recognition was carried out by an intelligent classifier made of multi-layer perceptron neural networks. After the training of the classifier, the system is able to offer 92.3% successful recognition rates. Ill. 4, bibl. 11 (in English; summaries in English, Russian and Lithuanian).

Д. Лефкадитис, Г. Тсириготис. Интеллектуальные оптические системы для классификации электронных компонентов // Электроника и электротехника. – Каунас: Технология, 2010. – № 2(98). – С. 10–14.

Представлена разработка прототипа системы автоматизированной идентификации и классификации шести типов электронных компонентов. Эта система предназначена для использования в составе автономной машины сортирования электронного оборудования для учебных лабораторий электроники Кавала технологического института. Процесс проектирования состоял в том, что был введен модуль машинного видения. Методология использует изменчивость формы электронных компонентов в зависимости от их типа. Это было основано на обработке и анализе изображений, полученных с использованием прецизионной системы цифровых камер, оснащенных автономным блоком управления. Был построен вектор функций, который описывает морфологию компонентов. Опознание было проведено интеллектуальным классификатором из многослойного персептрона нейронных сетей. После обучения классификатора, система обеспечивает 92,3 % успешных опознаний. Ил. 4, библ. 11 (на английском языке; рефераты на английском, русском и литовском яз.).

D. Lefkaditis, G. Tsirigotis. Intelektuali elektroninių komponentų optinio klasifikavimo sistema // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2010. – Nr. 2(98). – P. 10–14.

Aprašytas šešių tipų elektroninių komponentų automatinio identifikavimo sistemos prototipas. Sistema yra autonominės elektroninių komponentų rūšiavimo mašinos dalis. Mašina naudojama Kavalos technologijų instituto mokomosiose elektronikos laboratorijose. Pasirinktas modulinis vaizdų apdorojimo principas. Metodui pritaikytas elektroninių komponentų tipo ir jų formos ryšys. Vaizdams apdoroti panaudota tikslaus fotografavimo sistema su valdymo moduliu. Sudarytas savybių vektorius apibūdina komponentų kontūrų morfologiją. Atpažinimui panaudotas daugiasluoksnio perceptrono neuroninių tinklų pagrindu sudarytas klasifikatorius. Apmokius klasifikatorių, sistemos sėkmingų atpažinimų dalis sudarė 92,3 %. Il. 4, bibl. 11 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).