# MEASUREMENT STRATEGIES FOR OBJECT IDENTIFICATION

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## 0. Abstract

Advanced automation of industrial processes such as product handling, assembly and inspection requires further development of systems for the identification of objects involved in such processes. Various measurement methods for obtaining information about the identity of objects, based on the detection of features by which the objects can be characterised, are reviewed. Examples of such features are shape (or particular geometric properties) and material properties. The measurement of geometric features is performed by a colour camera, or the combination of a black-and-white camera and structured light. Material properties are detected by eddy current sensors. Most of these methods are illustrated with examples taken from a research project about the recognition of electronic components on PCB's, for recycling purposes. Finally, some comments on the combination of sensor data (sensor fusion) to enhance the reliability of the identification process are given.

**Keywords: object recognition; object identification; computer vision; machine vision; eddy current**

## 1. Introduction

Identification of an object implies two essential elements: a set of characteristic properties describing the actual object and a set of models or object classes to which the object is being assigned unambiguously. The identification process comprises the measurement of the properties that describe the object's identity, the matching of the acquired data with the model data and finally, the assignment of the object under observation to a particular class, according to a specified criteria. Looking to a cat (the measurement, data acquisition), we could identify this cat as an animal, or just a cat, or a Persian cat, or our left neighbour's cat, depending on the required level of classification and the availability of specific data. Obviously, going from a higher class down to a lower or subclass, the amount of information required for a proper classification increases, so does the complexity and processing time of the identification process. The more particular the class, the more specific should be the detection system.

Key problem in identification is the definition of the characteristic properties for a certain class. Each class should be described by a unique set of properties. Such properties need be detectable by a proper set of sensors (detectors). So, the detector or measurement system should be tailored to those features of the object that enable adequate identification.
Features may appear in a variety of modalities. We can identify a person upon observing his face, appearance, voice, particular clothes, or even a characteristic gait or sound of footsteps.



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In the recognition of persons, many features are involved, which can hardly be described completely by a machine. They appear in a large number of combinations within a frame of almost infinite variability. In this paper we only discuss the identification of man-made objects. The number of particular characteristics is low compared to that of natural entities and phenomena.

An example of identification of man-made objects is the recognition of buildings from aerial photographs [1]. This is an example of object recognition by remote sensing: the available measurement data is restricted to images from a number of different optical bands, but all of limited resolution.

An important application of (man-made) object recognition is product inspection: failures in a product should be detected automatically, to alleviate human exertion, to obtain a more objective and reliable criterion for rejection of faulty products, and to safe money. Also in inspection systems faults should be accurately defined first, while the detection system should be designed such that it is able to detect and classify those particular faults.

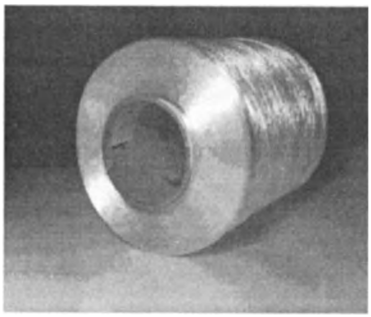

*Figure 1. Yarn package [AKZO-Nobel]; to be inspected on various faults: yarn failures (broken fibres, nooses, fluffs, pokes), shape faults, cone damage, transfer tail, contamination, all within specified tolerance bands. The inspection station consists of a number of detectors, each for a particular set of faults.*

This example illustrates the importance of a proper description of features to obtain an acceptable inspection result: neither correct packages might be rejected nor faulty ones accepted. Although faults can be considered as man-made objects, we will not take them into account further in this paper, and narrow down the discussion to complete objects only.
Further, we focus on a restricted set of features: geometric properties (shape) and material properties (electric, magnetic).

## 2. Retrieval of geometric properties from 2D grey-tone images.

The most common way to characterise an object is by observing its shape. Most automatic identification systems use one or more cameras to generate an image of the object. This image (or a set of two images or even a sequence when 3D information is required) is analysed by some image processing algorithm [2], using the intensity distribution in the image. The shape of the object is extracted from particular patterns in light intensity in the image.

Image processing alone is not enough for a proper recognition. First of all, specified conditions for getting a proper image must be fulfilled: an illumination that yields adequate contrast and no disturbing shadows; a camera set-up with a full view on the object in the scene and with a camera that has a sufficiently high resolution, not to loose relevant details. Obviously, a 2D image only shows a certain aspect of the object, never a complete view (self-occlusion). In case of more than one object, some of them could be (partially) hidden behind others (occlusion), a situation that makes the identification much more difficult.

Even in the most favourable situation, the image alone does not always reveal enough information for a correct identification result. At least we need a model of the imaging process itself: position and orientation of the camera(s), camera parameters like focal length, position of the light source(s) with respect to the object and camera, since all these aspects determine the properties in the image from which features are being extracted. Although the pose (position and orientation) of the object in the scene could be derived from the available information and a priori knowledge of the imaging system, we will disregard in this paper the possibility of pose determination, and restrict to identification only.

Many algorithms have been developed to extract particular features from an image, that is built up of thousands of samples (in space and time) having grey-tone values or just black and white (binary images). The image is searched for particular combinations of adjacent pixels such as edges, from which region boundaries are derived. Noise in the image may disturb this process, and special algorithms are developed to reduce noise effects. Finally, an image results that reflects in a way at least some geometrical aspects of the object.

We show two examples of object recognition from 2D images. The examples differ in available a priori information. In the first case, we just have two images (stereo) of a number of objects; from each object we have a complete and exact geometrical model. The goal is to identify all the objects in the scene (figure 2). Clearly, a single image only would lead to ambiguity: differently shaped objects can have identical projections. The use of stereo images can eliminate such an ambiguity.

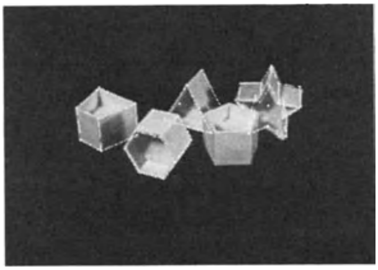

*Figure 2. Example of the identification of objects (toys). A geometric model (wire frames with corner points) is available; positions and orientations in the scene are unknown. Identification is performed by a matching algorithm, using geometric hashing. The white points indicate the result of the identification process.*

The original images are searched for corner points (on the crossings of edges). The result is a large number of points (some hundreds), many of them being false alarms, due to shadows, highlights or noise in the image. To identify the objects, all possible aspects of each model are compared (matched) with all the possible combinations of points in the scene. Using a special search algorithm (geometric hashing), we end up with a hypothesis about the most probable objects [3]. The result is shown in figure 2. Obviously, not all the objects have been identified; note also that some objects that are partly occluded are identified correctly.

In this identification process, both images from the stereo set-up have been used. This yields two sets of candidate corner points. Each point in one image corresponds with one single point in the other, however, it is not evident which one. This general problem in stereo vision, the corresponding problem [4], is solved here by using knowledge about the position of the cameras. As a matter of fact, many other methods have been studied to obtain the required information from a set of stereo images [5].

The second example illustrates a completely different strategy for obtaining 3D shape information from 2D images. The method is based on "structured light", a kind of optical coding. A set of lines with known spacing is projected onto the object of interest (figure 3). From the observed shift and rotation of the projected lines with respect to the lines on the reference plane (the background), height information can be achieved. To obtain a complete range image, a sequence of grids is projected, each with different (binary related) spacing.

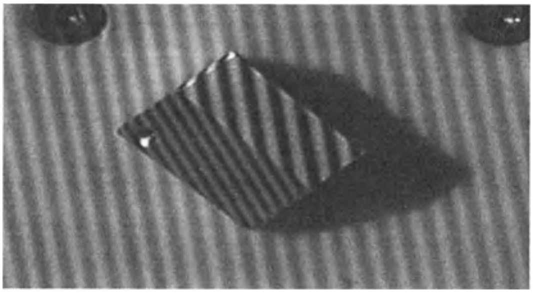

*Figure 3. Principle of the structured light method to obtain 3D information from a 2D image. Only one grid out of a set of 8 is shown here. Shadowed areas are eliminated by illumination from two different angles.*

The method yields a range image representing geometric properties of the object. In order to identify the object, this range image should be matched to a known model of the object. Again, the application dictates the amount and type of a priori information. In the application of the components on a PCB, the components of interest are modelled by a set of superquadrics, mathematical functions with five parameters that describe the size and shape of the bodies. The surface points of a superquadric satisfy the equation

$$\left\{\left(\frac{x}{a_1}\right)^{\frac{2}{\varepsilon_2}}+\left(\frac{y}{a_2}\right)^{\frac{2}{\varepsilon_2}}\right\}^{\frac{\varepsilon_2}{\varepsilon_1}}+\left(\frac{z}{a_3}\right)^{\frac{2}{\varepsilon_1}}=1$$

The parameters $a_i$ define the size and $\varepsilon_i$ the shape of the body. The range images as observed by a camera are fitted to the available models; the best fit results in a hypothesis about the identity of the component that is subjected to the test [6,7]. Some results will be discussed in section 5 of this paper, together with examples of colour images and high-resolution greytone images.

## 3. Object identification based on tactile imaging

A tactile imager provides shape information based on physical contact with the object under test. Basically, a tactile sensor consists of a matrix of pressure sensors, each responding to the local force that is exerted by the object. The output is a spatially sampled pressure image, with a resolution that is mainly determined by the pitch of the sensor grid. Many principles for the construction of tactile sensors have been proposed, during the last three decennia [8].

The most popular types are those based on elastomeric, piezoresistive materials, preferably those that are available in continuous sheets. Such materials allow the realisation of high-resolution tactile imagers. Disadvantages of this type of sensors are the strongly non-linear force-resistance relation, poor reproducibility and hysteresis. The resulting image data (figure 4) are not accurate and not stable. However, even with inaccurate pressure data, object identification can be performed, by using a priori knowledge about the characteristics of the objects.

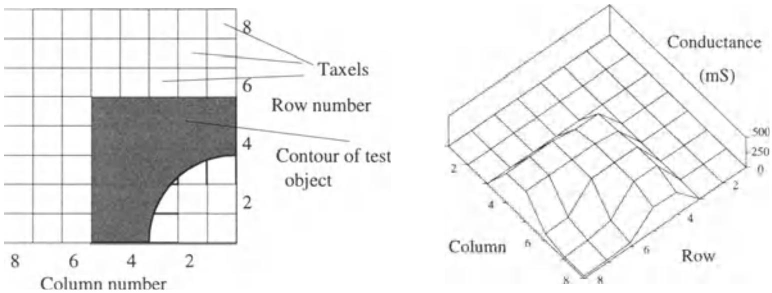


*Figure 4. left: positioning of an object on a 8 by 8 tactile sensor; right: sensor response.*

The quality of resistive tactile matrix sensors is also limited by mechanical and electrical cross-talk. The former is caused by the mechanical stiffness of the elastomeric layer, resulting in broadening of the point spread function describing the sensor's transfer characteristic. In order to minimise wiring, selection by rows and wires is preferred, although this strategy might cause electrical cross-talk as is illustrated by the equivalent electric circuit of figure 5.

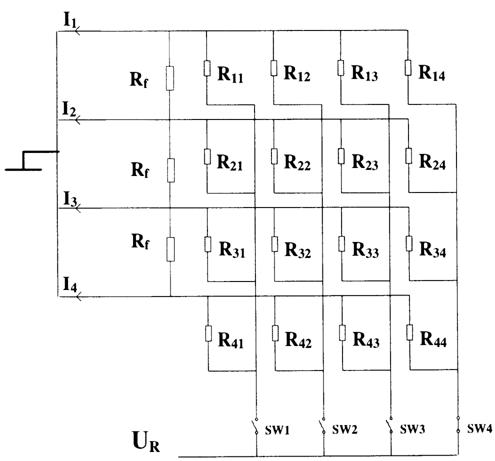


*Figure 5. Simplified electronic model of a 4x4 tactile matrix sensor based on a piezoresistive sheet; taxel selection is performed here by connecting a reference voltage through a multiplexer to only one column, and the individual measurement of all row currents.*

In this diagram, the taxel resistances are represented by the parameters $R_{ij}$. The resistances $R_f$ account for the resistance between adjacent rows. In fact, all these resistances are distributed over the sensitive sheet, but for simplicity they are modelled as lumped elements. Taxel $R_{11}$ is selected by closing switch SW1, and simultaneous measurement of current $I_1$. Obviously, there is a subnetwork of all other resistances in parallel to $R_{11}$, so the measurement of $R_{11}$ is disturbed by the resistance values of all non-selected taxels. Elimination of this effect is achieved either by (virtual) grounding or active guarding of the non-selected rows and columns. The method is rather effective, but requires complex additional electronics.

Despite poor performance of the individual sensor elements, it appears possible to use tactile matrix sensors for identification of objects. A 16x16 tactile sensor based on highly conductive rubber has been tested successfully in a three-finger robot for grip optimisation in autonomous control with dextrous grippers [11]. In this experimental set-up, a neural network has been trained to identify three classes of objects, based on the characteristic properties of the contact surface: spheres (point contact), cylinders (line contact) and flat objects. Moreover, the system is also able to localise the objects in the gripper, and for cylindrical and flat objects to determine their orientation.

**4. Identification based on material properties.**

Among the various features of an object, the kind of material of which it is composed is a property that can be employed for identification, when the acquisition of suitable optical images fails. In this section, specificity in bulk material is the feature that will be looked for. Again, various modalities can be candidate to extract the required information, such as thermal capacity, mass density, compliance or electric conductivity, of which in particular the latter can be implemented in a rather simple way. The method we discuss here is based on the occurrence of eddy currents, induced in the material by an alternating magnetic field brought in the vicinity of the object. It should be noted that eddy currents flow mainly in the outside layer of the object, so identification occurs on the basis of the material just in the outer shell of the object.

Basically, an eddy current sensor consists of a coil supplied with an alternating current, resulting in a magnetic field protruding outside the sensor body. When a conductor is present in the region of the external field, free charge carriers (electrons) experience Lorentz forces and will move around in a rather disordered manner by non-homogeneities of the material. These eddy currents counteract the field of origin, resulting in a reduction of the magnetic flux in the coil, which in turn lowers the self-inductance L. The strength of the eddy currents increases with the conductivity of the object, which makes the sensor material specific. Obviously, the output of this sensor also varies with the distance between object and sensor, which is the basis of the well-known contactless proximity sensor.

Ferromagnetic objects that are subjected to the eddy-current sensor will raise the coil's self-inductance, due to a lower magnetic resistance (reluctance) of the magnetic circuit. Hence, the eddy current sensor can distinguish between objects with different conductivity and different magnetic permeability.

The eddy current sensor together with the object can be modelled by a simple transformer circuit, in which the object acts as the secondary coil of the transformer with a material-dependent resistive load. With this model, the equivalent impedance at the primary terminals of the transformer can be derived:

$$R = R_1 + \frac{k^2 L_1 \omega^2 L_2/R_2}{1+\omega^2 (L_2/R_2)^2}$$

$$L = L_1 - \frac{k^2 L_1 \omega^2 (L_2/R_2)^2}{1+\omega^2 (L_2/R_2)^2}$$

Here, k is the coupling factor, accounting for the distance to the object, whereas $L_2$ and $R_2$ reflect the object's ferromagnetic and resistive properties, respectively. $R_1$ and $L_1$ are the resistance and self-inductance of the sensor coil. From the simultaneous measurement of the real and imaginary parts of the sensor impedance, and using this model, material specific information can be obtained (parametrized by the ratio $L_2/R_2$), and independent of the gap width between object and sensor head.

In its most simple form, the eddy current sensor can be used in a single-point measurement of the material feature: after a training (calibration sequence) with the complete set of objects it is possible to distinguish between, for instance, steel, aluminium and copper objects, and between ferro- and non-ferro materials [10]. When combined with a scanning mechanism, the eddy current sensor can be used to obtain a conductivity image of objects. Figure 6 shows a picture of a piece of PCB with different components on it; the goal is to identify these components on the basis of differences in the materials, as shown in the impedance images in the same figure.

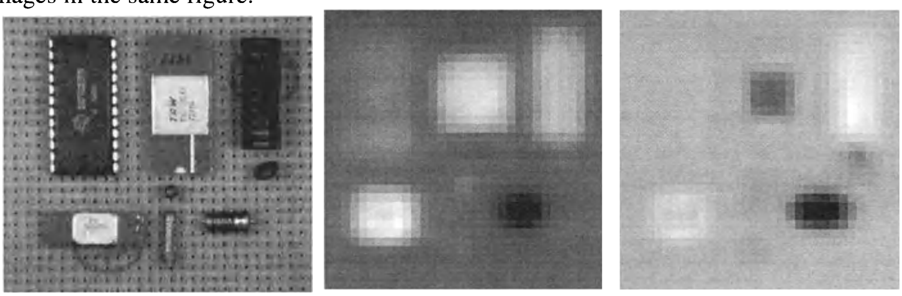

*Figure 6. Left: grey-tone reproduction of a colour image of a test PCB with various components. Middle and left: impedance images taken by a scanning eddy-current sensor, showing the real and imaginary parts of the impedance, respectively.*

## 5. Identification of electronic components on PCB's: a case study

Recycling of waste materials contributes to reduction of environmental problems. A prerequisite for recycling is the separation of the primary waste streams into more homogeneous material flows. In this example we discuss the recycling of printed circuit boards (PCB's) from outdated electronic equipment (TV sets, computers). A PCB might contain components that could be reused (memory chips) or that are harmful for the environment (batteries). We describe here a project in which a system is being developed for the identification of components on waste PCB's.

The system consists of four identification units: a range imager based on structured light, a high-resolution grey-tone camera, a colour camera and an eddy current sensor. The PCB under test passes subsequently these stations. Each station comes up with a hypothesis about certain components on the PCB, restricted in the prototype system to IC's (of various types), electrolytic capacitors and batteries. The range imager identifies the components on the basis of 3D shape. Characteristic details in a high-resolution image are checked in the second station, for instance the presence of an array of small bright points, indicating an IC. The colour camera system uses the spectral characteristics in the image of the PCB, to obtain a proper segmentation of the regions representing the objects of interest [12]. The segmentation process is further improved by using a priori knowledge about the component's shape, whereas the object recognition is performed using the technique of inexact attributed graph matching [13]. Finally, the eddy-current sensor is used here as an additional test for suspicious components that are identified with insufficient certainty [14].

Figure 7 shows a picture of a complete PCB, taken with a standard black-and-white camera, and using diffuse illumination. Figure 8 is a height map of the same PCB, as obtained from the range imaging system (using structured light).

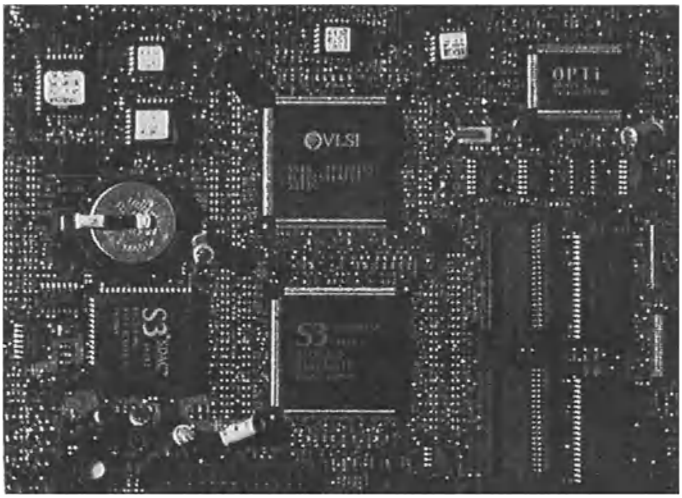


*Figure 7. Example of a PCB. A variety of electronic components (IC's, capacitors), some empty sockets, and left-middle a battery.*

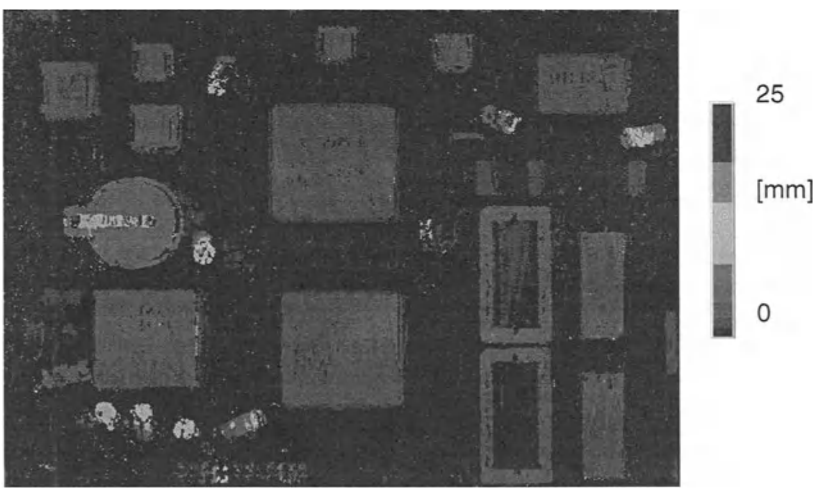


*Figure 8. Range image (height map) of a PCB; the tilted, upstanding capacitors are clearly visible.*

Figure 9 illustrates the difference in the images obtained from a standard area-scan camera (right) and a high-resolution line-scan camera (left). A complete high-resolution image is obtained by moving the PCB in front of the line-scan camera. The image is used for component identification based on specific details, for instance the pins of the IC's (by template matching) and the characters printed on the components (OCR).

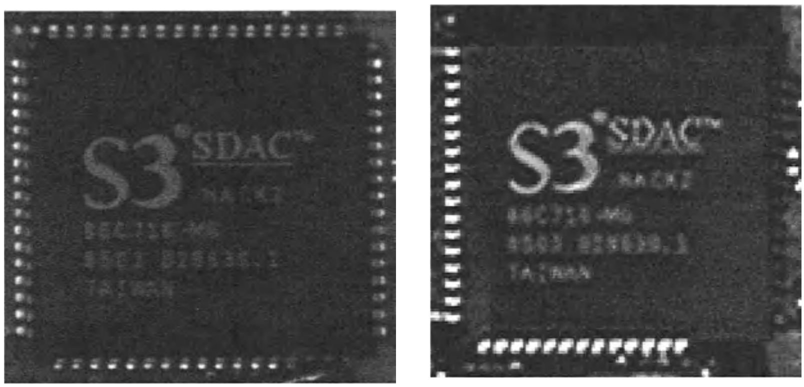


*Figure 9. Detail from (left) a high-resolution line-scan camera (1728 pixels per line) and (right) a standard black-white camera image.*

Each of the first three stations generates a set of hypotheses about the possible identity of the components on the PCB, and to each of these hypotheses an uncertainty level has been connected. The uncertainty about the identity of an object could be reduced by combining the outputs of the individual systems in such a way that the total uncertainty is lower than that of the individual systems. This is not a trivial process, because the uncertainty is different for the various identification systems, and not all objects are identified by all systems. For instance, the range imager can hardly distinguish between empty and occupied IC-sockets, and the colour camera has some difficulties in detecting electrolytic capacitors. In this application the hypotheses from the first three stations are combined using Dempster-Shafer theory of data fusion [15]. This method takes into account the differences in levels and classes of uncertainty.

## 6. Conclusions

In this paper we reviewed a number of methods for the identification of (man-made) objects. Evidently, the quality of the identification (the certainty of the generated hypothesis about the object's identity) increases when more a priori information about the object is available and actually used in the recognition process. All systems discussed here and probably most others as well suffer from the fact that they can only detect a limited number of features (if they are able at all to detect them). It is shown that identification upon a single feature or a single modality will not result in a sufficiently high certainty. The key solution to this problem is the use of a multi-sensor system, that is designed to detect various features of different nature. A proper combination of the individual results (sensor or data fusion) should enhance the overall quality of the identification.

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