MVA '96 IAPR Workshop on Machine Vision Applications, November. 12-14, 1996, Tokyo, Japan

Object recognition from range images using superquadric Representations

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Abstract

Segmentation of range images using superquadric entities has been pointed out by a number of researchers as a powerful approach towards object recognition. Problems exist in finding an unbiased decision function for the assignment of a superquadric representation with an object prototype. This paper discusses current distance measures between recovered models and prototypes and presents a novel method for classification of uncertain superquadric representations using a maximum likelihood criterium and incorporating the range image characteristics of an active optical triangulation sensor. The main advantage of this probabilistic method is its inherent minimisation of the classification error rate. The approach is applied to recognition of electronic components for printed circuit board waste management.

1 Introduction

Recently, superquadric models have received substantial interest from several researchers [1] as a solid primitive for range image segmentation. Besides, it proved to be a promising tool for object recognition because of the viewpoint invariant recovery of these entities (which ensures the tractibility of the model matching process) and the ability to represent a large range of objects with a limited amount of parameters. The global object parameters captured during superquadric segmentation provide a sound basis to index the modelbase into geometrically distinct classes [2], whereas local deviations between measured data and fitted model can be used to identify a prototype within an object class. However, the issue of assigning a fitted model to an object class was not solved satisfactory. This paper discusses current definitions of distance measures between superquadric representations and object prototypes and proposes a new one.

The approach is applied to an object recognition task which involves electronic components on printed circuit board (PCB) scrap. Detection and extraction of some of these components (for example electrolytic capacitors) helps to protect the environment from being burdened by toxic chemicals that are emitted during regular PCB waste processing. Furthermore, valuable components (like memory modules) make intelligent processing of PCB waste economically feasible.

This paper describes the segmentation of range images in superquadrics (section 2) and presents a novel approach towards the classification of the recovered models (section 3). Based on the range imaging characteristics (section 4), uncertainties in the superquadric parameters are determined and a decision function is computed (section 5).

2 Superquadric segmentation

A superquadric surface is defined by the equation:

$$1 = \left(\left(\frac{x}{a_1}\right)^{\frac{2}{\epsilon_2}} + \left(\frac{y}{a_2}\right)^{\frac{2}{\epsilon_2}}\right)^{\frac{\epsilon_2}{\epsilon_1}} + \left(\frac{z}{a_3}\right)^{\frac{2}{\epsilon_1}}$$

Parameters $a1$, $a2$ and $a3$ define the size and ϵ_1 and ϵ_2 define the shape of the superquadric. The shapes that can be modeled by these parameters include cylinders, spheres, blocks and shapes in between (figure 1). The representational power of superquadrics can be increased further by applying global deformations like tapering and bending on the basic model [3, 4].

For objects separated from the background through a threshold operation, a robust algorithm for the superquadric recovery is known [5]. In this algorithm the error of fit (EOF) for the model is minimized in a non-linear least-squares way (Levenberg-

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Acknowledgements: This work used software provided by the GRASP laboratory of the University of Pennsylvania

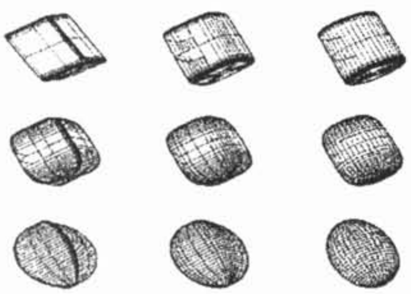

Figure 1: *Superquadric models*[6]. *From left to right* $\epsilon_2 = 0.1, 0.5, 1.0$, *from top to bottom* $\epsilon_1 = 0.1, 0.5, 1.0$.

Marquardt), with a distance function:

$$D = -\sqrt{a_1 a_2 a_3} * [1 - [((\frac{x}{a_1})^{\frac{2}{\epsilon_2}} + (\frac{y}{a_2})^{\frac{2}{\epsilon_2}})^{\frac{\epsilon_2}{\epsilon_1}} + (\frac{z}{a_3})^{\frac{2}{\epsilon_1}}]^{\epsilon_1}]$$

This function follows from the superquadric equation, after modifying it by adding the exponent ϵ_1 to cancel out the effect of low values of ϵ_1 during the recovery process [4]. Furthermore, the volume factor $\sqrt{a_1 a_2 a_3}$ is added to force the recovery of a superquadric with minimal size. The associated error of fit is:

$$EOF = min \sum_{i=1}^{N} D^2$$

The parameters to be estimated by the minimization procedure are related to the location (p_x, p_y, p_z), the orientation (ϕ, θ, ψ), the size (a_1, a_2, a_3) and the shape (ϵ_1, ϵ_2) of the modeled superquadric.

As an initial condition the center of gravity of the range data and the direction of the principal axes are chosen to define position and orientation of the initial coordinate system, with the Z-axis along the principal axis with least moment of inertia. Extremities along the estimated axes will be the starting point for the size estimates, while the shape estimates are initially set to 1 (an ellipsoid). Noise is added during minimization to prevent local minima to occur and ϵ_1 and ϵ_2 are restricted between 0.1 and 1 to avoid ambiguities in the recovered superquadrics.

An example of a range image of a cilinder, its true parameters and the modeled parameters show that the algorithm recovers the object parameters with 10 to 30 % accuracy (figure 2).

3 Classifying superquadric segments

Several attempts have been made towards superquadric classification based on size and shape parameters. Some of these use a decision function related to the (weighted) minimal Euclidian distance

	Real cylinder parameters	Modeled object parameters
length (pixels)	24.0	22.8
width (pixels)	10.5	11.0
height (pixels)	10.5	11.3
latitude 'squareness'	1.0	0.7
longitude 'squareness'	0.1	0.2

Figure 2: *range image of a cilinder. The superquadric parameters fitted to this data are displayed in the table and show that the global parameters are recovered with 10 to 30 % accuracy.*

in parameter space between superquadric primitives and prototype models [7, 8, 9]. Although these measures seem attractive from a cognition point of view, they result in biased classifiers because the conditional probability densities of the recovered parameters are neither independent nor Gaussian (even for range images corrupted with Gaussian noise).

Pentland [10] suggests a physics based measure indicating the amount of energy necessary to mold a superquadric such that it fits the prototype of an object. However, the relationship between elasticity coefficient of an object which represents the molding effort and uncertainties in its superquadric representation is unclear, so classifier optimalisation using this technique remains an open question.

Another decision function implemented by Whaite [11, 12] uses a maximum confidence criterium, where the covariance matrix computed during the model recovery determines an objects ellipsoid of confidence. This approach holds when parametrisation errors are small and the error metric of the recovery process is assumed to be Gaussian, but this is generally not the case.

To cope with these problems, we suggest a decision function $\hat{\omega}(\vec{x})$ based on the maximum likelihood criterium:

$$\hat{\omega}(\vec{x}) = argmax\{p_{\vec{x}|\omega}(\vec{x}|\omega)\}$$

Classification according to this criterium is equivalent with Bayes classification with a uniform cost function and unknown prior probabilities, inherently resulting in a minimal error rate. The required conditional probability of the superquadric parameter vector modeling an object can be estimated by noting its relation with the average global residue (or total error of fit after the superquadric recovery). Averaged over a large number of noise realisations, the probability that an object will be modeled with a certain parameter vector decreases as the average global residue for this parametrisation becomes larger. The superquadric whose parametrisation has minimal average global residue is most likely to model the object. Partitioning the five dimensional measurement space (i.e. representing superquadric size and shape parameters) into bins, followed by off-line computation of an average global residue map for all objects in the modelbase will thus be sufficient to determine a look-up-table of parameter vectors and their associated conditional probabilities. Since the probable parametrisations of an object occupy only a small volume of the five dimensional space, the look-up-tables remain limited in size.

4 Range image characteristics

Errors in a range image determine the uncertainties in the recovery of superquadric primitives. So, imaging characteristics should be determined in order to compute the average global residue for a parameter vector close to the true parameter vector of an object.

We discuss the case for range images acquired with an active optical triangulation method [13]. This means that the range of a point in the scene is calculated from the triangulation of the parameters of a structured light source and the parameters of a camera. The structured light source is a spatially coded light pattern generated by projecting a sequence of N different multiline binary images on the scene. These can be united to one uniquely spatially coded image with 2^N lines. By designing the binary patterns according to the Gray-code scheme, the robustness of the method is optimized.

Due to unsharpness in the black to white transitions of the projected pattern, the finite CCD pixel size and camera noise, a pixel misclassification can occur on such a transition. Assuming a linear change of grey-value when a pixel is shifted over a pattern transition, Gaussian camera noise will introduce a possibility of misclassification that increases as the distance to the transition decreases (figure 3). This effect can be modeled by corrupting the theoretical range data with spatially low frequency Gaussian noise and subsequent discretisation. Experiments show that this noise model is adequate in a sense that it describes the measured range data well. Synthetic range images constructed according to this noise model therefore enable us to analyse our volumetric segmentation method.

5 Experimental results

To establish a relationship between the average global residue and the conditional probability, a global residue map averaged over twenty noise realisations was computed for a modelbase consisting

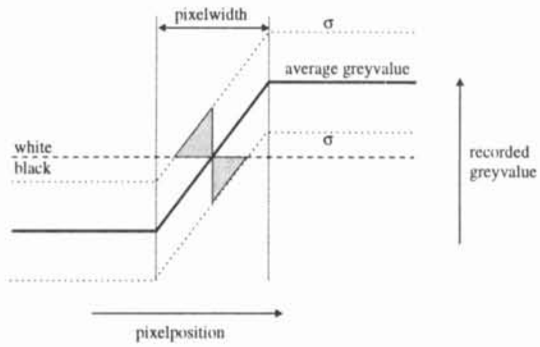

Figure 3: *An assumed linear grey-value change (solid line) when a pixel is shifted over a black to white transition. Gaussian camera noise (dotted lines are 1 σ uncertainty bounderies) introduces possibilities of pattern misclassification (shaded areas).*

of six simulated objects. These represent electronic components with block-like (16 lead dil-ic, 8 lead dil-ic, 15 turn potentiometer), cylinder-like (electrolytic capacitor, operational amplifier with metal casing) and sphere-like (tantalum capacitor) shapes whose range image is taken with a resolution of 0.25 mm. This means that every object is described by several hundreds of data points. Superquadric parametrisations recovered for a test set of noisy range images of these objects were binned and a histogram was made of their corresponding average global residues (figure 4). This reveals, that the conditional probability of a representation roughly shows a linear decrease with increasing average global residue. The conditional probability is zero when the average global residue is more than $\frac{4}{3}$ of the minimum average global residue.

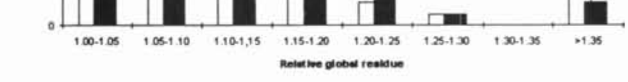

Figure 4: *Histogram of the relative average global residue with respect to the minimum average global residue for two objects in the modelbase (white: opamp, black: ic16). Roughly, a (negative) linear relationship exists between the average global residue of a parametrisation and the probability of its recovery.*

Based on this relation, look-up-tables (covering a small segment of the parameter space) were constructed associating a binned superquadric representation with the conditional probability of an object. When an evaluation set of noisy range images of the operational amplifier is classified accordingly (figure 5), 10% of the parametrisations are not detected as possible operational amplifiers. Executing this approach for all objects in the modelbase and counting misclassifications results in the confusion matrix of our object recognition system (figure 6).

Simulation number	Conditional probability
1	0.65
2	0.48
3	0.52
4	0.68
5	0.65
6	0.85
7	0.55
8	0.68
9	0.64
10	0.45

Simulation number	Conditional probability
11	0.33
12	0.91
13	0.51
14	0.86
15	0
16	0.79
17	0.68
18	0.30
19	0
20	0.81

Figure 5: *Superquadric segmentation of a range image of an operational amplifier was performed for a set of noise realisations. The conditional probability associated with the recovered parametrisation is shown in the right column.*

As can be seen, errors are exclusively due to not classified superquadric representations which means that our empiric rule is chosen a bit too strict. Misclassification does not occur, because the overlap of the possible parametrisations of the objects in 5D-space is limited, indicating the high discrimanitive power of the system.

The displayed results are only preliminary. Tuning of our empiric relation and extending the modelbase are some of the research activities necessary to analyse our approach thoroughly.

	ic16	ic8	elco	tant	pot10	opamp	no match
ic16	18	0	0	0	0	0	2
ic8	0	19	0	0	0	0	1
elco	0	0	20	0	0	0	0
tant	0	0	0	19	0	0	1
pot10	0	0	0	0	20	0	0
opamp	0	0	0	0	0	18	2

Figure 6: *Confusion matrix. Frequency table of assigned classes versus true classes.*

6 Conclusions

In this paper we analysed decision functions applied to superquadric shape recognition. To face the disadvantages of current methods we chose a maximum likelihood classification approach, since it minimizes the classification error rate and incorporates the range image characteristics of our active optical triangulation sensor. An empiric relation is established between the average global residue and the conditional probabilities of a modeled object in order to compute the decision function of the classifier. Preliminary results show that an object recognition system based on this method is able to distinguish different electronic components.

However, enlargement of the modelbase is necessary for a statistically more reliable analysis of the object recognition power of our strategy. Furthermore, we will address the constraints currently set to the pose of an object in the scene. Since the angle of the main axis of an object with respect to the imaging direction influences the distribution of the conditional probability density, only objects whose orientation is fixed with respect to the direction of the range data acquisition were considered thusfar.

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