

PARAMETER SETTING THROUGH DESIGN OF EXPERIMENTS FOR THE AUTOMATED DELINEATION OF REGIONS OF INTEREST

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ABSTRACT

In the field of image processing, the complete implementation of segmentation procedures, in order for example to delineate automatically regions of interest in images, requires usually adjusting various parameters, which interfere each with the others. Analysis of all the possible combinations is cumbersome and time consuming. Moreover, settings obtained should remain valid for families of images of the same type. In this paper, in view of the accurate delineation of an object out of gray level images, we describe a method for efficient parameter setting of a level set based segmentation procedure. The experimental approach proposed makes use of a Design of Experiments methodology in order to identify the most influential parameters and optimize their values. This allows the optimal determination of a mask delineating the object of interest in gray level images and necessary for the following application dependant processing steps.

1. INTRODUCTION

For industrial applications of computer vision, such as quality control and quantitative inspection of machined parts, it is necessary to make available automated tools for the computation of 3D descriptions out of the image contents. Within the framework of European Projects, a system aiming at the reliable, flexible and contact-free inspection of 100% of a production of (quasi polyhedral) workpieces, which may be partially composed of free-form surfaces, has been realized [1-3].

Basically, 3D information is obtained by imaging an object (or a whole scene) with a CCD sensor and deriving the 3D coordinates of selected image points using a triangulation method based on the projection of a structured light pattern. For applications requiring fields of view of large extent, covering areas much larger than that of the used sensor, spatial sequences of images of the scene to evaluate are acquired and registered, in order to provide the desired 3D information in the form of a unique description. Lastly, geometric inspection of the object is performed comparing the observed data with reference data, *i. e.* through the determination of a set of correspondences between the two data sets. Our developed hardware and software have been applied, amongst others, to non-standard surface inspection tasks requiring extremely high processing rates and to

robotics. The observed accuracy is typically and routinely around 20 μm for a field of view of 5 cm * 5 cm.

A prerequisite is a labeling scheme aiming at the automated extraction out of gray level images of the areas belonging to the object, specifically in order to separate the object areas from the irrelevant background. With that objective, two segmentation methods, based respectively on a mean shift approach [3] and on a level set technique, to be analyzed here, have been implemented and evaluated. The labeling process requires approximate *a priori* information on the observed scene, in order to generate the desired object mask. This information can conveniently be provided by a planning system covering the whole application. More specifically, this knowledge describes the number, rough localization and general shape of the regions corresponding to the background. Thus, no post-processing step after segmentation is required, as the *a priori* information allows validating implicitly results. Further, the procedure can also be applied to selected areas of the image, leading to strong reduction of computation times. However, the segmentation parameters implied by the level set method have to be carefully adjusted, on a case by case basis, using a Design of Experiments approach taking into account estimates of the acquisition conditions (e. g. acquisition parameters).

Section 2 presents the level set segmentation approach used and the parameters to be considered, whereas the fundamentals of Design of Experiments are briefly described in section 3. The experimental methodology proposed for the setting of parameters is outlined and analyzed in section 4, together with a representative experimental result. Lastly, a conclusion and outlook are given in Section 5.

2. LEVEL SET SEGMENTATION

The general principle, when applying active contour based methods, consists in locating an initial contour C in the image and defining a strength F enabling the contour C to evolve so as to cancel this strength when it reaches the boundary between two regions (in other words, a discontinuity). As a result, this principle can be generalized easily to the use of more than one initial contour. The segmentation result of such a process is in all cases one or more closed contours, defining implicitly the desired regions.

2.1 Theoretical background

An effective implicit representation for evolving curves describing active contours is provided by the level set approach [4-6]. In this approach, which leads to efficient implementations, the curve C is embedded in the representation as the zero level set of a surface Ψ of higher dimensions. The main advantage of this kind of representation is that it allows coping with topology changes. In other words, the approach, as a consequence, enables to detect simultaneously several contours belonging, as an example, to one or more objects (merging or splitting of contours) and this regardless of the initialization (one or several initial curves).

It can be proven that Ψ , which represents implicitly the curve C , evolves according to the following partial differential equation, expressed using a finite differences scheme:

$$\Psi^{n+1} = \Psi^n + \Delta t (g(\nabla I) (\lambda_k \kappa(\Psi^n) + a) |\nabla \Psi^n| + \lambda_{CAG} \langle \nabla g, \nabla \Psi^n \rangle)$$

Definition and signification of the parameters is as follows:

- Δt : temporal step,
- a : propagation constant (also called balloon force) enabling the contour C to evolve inwardly (a negative) or outwardly (a positive),
- λ_k : weighting factor depending on the curvature of the contour,
- $\kappa(\Psi)$: curvature of C computed as the divergent of the normal and acting as a regularity constraint for the contour,
- $g(\nabla I)$: data driven function (sometimes called edge function) expressed as a function of the image gradient. This function is chosen positive, monotonous, strictly decreasing, and such that $g(0)=1$ and $\lim_{|\nabla I| \rightarrow \infty} g(\nabla I)=0$. As a result, low values of the gradient (*i. e.* homogeneous regions of the image) correspond to a high value of $g(\nabla I)$ and high values of the gradient (*i. e.* boundaries of the object) correspond to a low value of $g(\nabla I)$. Rather than using the standard function for the data driven function $g(\nabla I)$ [4], we have chosen to use as gradient dependant function the sigmoid function:

$$g(\nabla I) = 1 - \frac{1}{1 + e^{-\frac{|\nabla I| - \alpha}{\beta}}} \quad (1)$$

- λ_{CAG} : weighting factor enabling to take into account a geodesic factor in the active contour model,
- $\langle \nabla g(\nabla I), \nabla \Psi \rangle$: geodesic corrective term attracting the curve C towards the discontinuities in the image (as can be noticed, $-\nabla g(I)$ points towards the middle of the boundary zone) and allowing to detect contours characterized by high variations of the gradient (and leading thus to local minima for $g(\nabla I)$).

In order to decrease the number of operations required for computing an evolution step of contour C , it is more effective to evaluate Ψ only in a narrow band centered on C , rather than for the whole image [5]. Once this band of half-

width δ is defined, one makes this band evolve, taking into account the fact that the zero level of Ψ corresponds to the contour one looks for. However, for each iteration, it is systematically necessary to verify that the curve C remains inside the band. One solution to this constraint consists in making use of the current band as long as possible and to reinitialize the narrow band when a part of the curve C comes too close to the boundaries of the band. Re-initialization of function Ψ is obtained through the following discrete partial differential equation:

$$\Psi^{n+1} = \Psi^n + \Delta t (1 - |\nabla \Psi^n|) \text{sign}(\Psi^n)$$

where $\text{sign}(\Psi)$ is set to -1 if Ψ is strictly negative, to 0 if Ψ is zero and to $+1$ if Ψ is strictly positive.

2.2 Assigning values to significant parameters

The most significant parameters to be tuned are the curvature factor λ_k , the balloon force a , the geodesic factor λ_{CAG} , the temporal step Δt , and the inflexion point and slope of the function $g(\nabla I)$ (namely the parameters α and β ; see equ.(1)). Various conventional manufactured parts including sculptured surfaces have been used in order to carry out experiments enabling both to fix adequate values for these parameters and to determine their broad ranges of variation. This is to be described in the next section.

Among the remaining parameters, the choice of the value of the narrow band half-width δ has direct influence on the progress of the algorithm, and thus execution time, but has no impact on the localization accuracy. δ has been experimentally set to 4. This is also the case for N_{iter} , the fixed maximal number of iteration steps of the equation of evolution for function Ψ between two re-initialization stages. N_{iter} is directly related to the parameters λ_k , a , λ_{CAG} , δ and Δt , and has to satisfy equation (2) below:

$$\lambda_k \max(\kappa(\Psi)) + a + 2 \lambda_{CAG} < \frac{\delta}{N_{iter} \Delta t} \quad (2)$$

In equation (2), the largest value of the curvature κ of function Ψ is fixed with respect to the initial contour (and thus acts as some kind of threshold).

3. FUNDAMENTALS OF DESIGN OF EXPERIMENTS

A Design of Experiment (DOE) is a structured, organized method for determining the relationship between factors affecting a process, or procedure, and the output of that process. DOE refers to experimental methods used to quantify the effects of factors, each characterized by a number of levels (a level being associated with a given parameter value). Also, they characterize the interactions between these parameters statistically. This quantification is carried out through observation of forced changes made methodically as specified by mathematically established systematic tables [7-9].

Fractional factorial DOEs are good alternatives to a full factorial DOE, especially when the number of parameters (and their interactions) $N_{factors}$ or the number of levels N_{levels} are high. One has then to choose a standard DOE table of N_{exp} experiments superior to the number of degree of freedom N_{dof} given by the following equation :

$$N_{dof} = 1 + N_{factors} \times (N_{levels} - 1)$$

Instead of a direct comparison of results against a control or a standard, a DOE evaluates first all effects of factors and interactions and then determines if there are statistically significant differences among them. The sub-optimal level of each factor thus corresponds to the level maximizing the measured effect.

DOEs also allow to estimate statistical confidence levels for each measurement. For evaluation of the relevance of a factor in the procedure, the differences of the responses from one level of the factor to another are taken into account. Given the parameters $V_1 = N_{levels} - 1$ and $V_2 = N_{exp} - N_{dof}$, and a threshold of 5%, the Snedecor-Fisher table gives a theoretical statistical number F_{theo} which has to be compared to the experimental number F_{exp} defined as the factor variance divided by the residual variance. The number of relevant effects (*i. e.* factors characterized by F_{exp} greater than F_{theo}) in a so-called factorial experiment is usually small. Empirically, it has been shown that lower order effects are more likely to be important than higher order effects (*i. e.* interactions). Further, effects of the same order are equally likely to be important. In order for an interaction to be significant, at least one of its parent factors should be significant.

4. PARAMETER SETTINGS PROCEDURE AND EXPERIMENTAL RESULTS

We made use of the NEMRODW software [10] in order to analyze both the effect of the parameters defined section 2.2 on the segmentation results and the associated variance.

4.1 DOE model

The DOE model used comprises the 6 parameters defined section 2.2 and is expressed according to following equation, where Y is the so-called objective:

$$Y = m + \lambda_k + a + \lambda_{CAG} + \Delta t + \alpha + \beta$$

m is the mean of all experiments considered, and Y the theoretical response. Remember that, given the value of the six parameters considered, the parameter N_{iter} has to be fixed according to equation (2).

4.2 Notation system used

For each experiment, the objective Y gets a mark between 0 and 10 determined automatically and related to the accuracy of localization of the contour. This mark is computed as the ratio of the number of points belonging to the extracted contours to that on reference contours. The one pixel wide

reference contours are determined manually and further dilated by one pixel in order to allow for some errors when processing actual images.

4.3 Parameter settings using a DOE approach

The approach involves three steps carried out sequentially:

- Identification of possible interactions between parameters.
- Determination of a sub-optimal parameter set.
- Optimization of the set previously obtained.

Results are given for a representative application (*i. e.*, the turbine blade depicted fig. 1), exemplifying the use and behavior of the DOE parameter settings procedure.

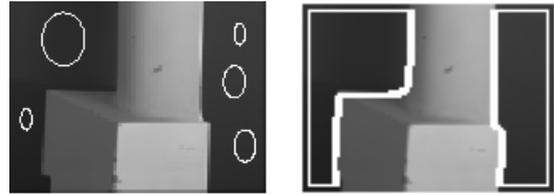


Figure 1: Initial contours (left) and reference contours (right) used for the turbine blade experiment.

The levels used, the measured effect at each level and the experimental number F_{exp} for each parameter are summarized for the three steps in Table 1.

	<i>Factor</i>	λ_k	a	λ_{CAG}	Δt	α	β
Table 1.A	<i>Lvl. 1</i>	0.3	-3.2	0	0.3	1	1.10
	<i>Lvl. 2</i>	0.9	-0.2	0.42	0.6	2.5	1.55
	<i>Effect_{Lvl1}</i>	-0.15	2.55	0.63	0.26	-0.29	0.007
	<i>Effect_{Lvl2}</i>	0.17	-2.53	-0.62	-0.24	0.21	0.006
	F_{exp}	0.17	44.02	2.66	0.42	0.43	0.01
Table 1.B	<i>Lvl. 1</i>	0.3	-3.2	0	0.3	1	1.10
	<i>Lvl. 2</i>	0.5	-2.2	0.14	0.4	1.5	1.25
	<i>Lvl. 3</i>	0.7	-1.2	0.28	0.5	2	1.4
	<i>Lvl. 4</i>	0.9	-0.2	0.42	0.6	2.5	1.55
	<i>Effect_{Lvl1}</i>	-0.3	1.65	0.16	0.65	-0.67	-0.57
	<i>Effect_{Lvl2}</i>	0.17	1.25	0.48	-0.00	0.39	0.46
	<i>Effect_{Lvl3}</i>	0.57	-0.04	0.19	-0.80	0.08	0.10
	<i>Effect_{Lvl4}</i>	-0.12	-4.49	-0.96	-0.45	0.89	0.60
F_{exp}	0.61	32.85	1.62	1.69	1.87	1.21	
Table 1.C	<i>Lvl. 1</i>	0.7	-3.2	0	0.3	1.5	1.25
	<i>Lvl. 2</i>	0.8	-3.0	0.14	0.4	2.0	1.40
	<i>Lvl. 3</i>	0.9	-2.8	0.28	0.5	2.5	1.55
	<i>Effect_{Lvl1}</i>	-0.1	-0.19	0.1	0.7	0.03	-0.44
	<i>Effect_{Lvl2}</i>	0.41	0.17	-0.69	0.88	0.54	0.53
	<i>Effect_{Lvl3}</i>	-0.7	-0.13	1.3	-2.43	-1.09	-0.58
F_{exp}	1.8	0.2	5.74	18.92	3.9	2.13	

Table 1: DOEs used for the study of interactions between parameters (1.A), the determination of a sub-optimal parameter set (1.B) and the determination of an optimal parameter set (1.C). The tables present the levels associated with each factor, the effects at each level for each factor (in bold: the maximum values corresponding to the selected level) and the comparison with F_{theo} (variance analysis). The effect of a given factor u at a level v is determined as the average of the objective Y when the factor u is at level v minus the general average of the objective Y .

Analysis of the interaction between parameters

We first considered the 6 parameters and the 15 corresponding first order interactions between parameters ($N_{factors} = 21$). With 2 levels per factor ($N_{levels} = 2$) and the extreme values found experimentally in section 2.2, corresponding to $N_{dof} = 22$ and $F_{theo} = 4.96$, a factorial design of 32 experiments has been devised instead of the full set of 2^{21} .

The effect of the interactions and the corresponding F_{exp} values having been found negligible, they are not presented in Table 1.A. With $F_{exp} = 44.02$, it appears that only parameter a (balloon force) can be considered of influence. The only interaction, with value close to F_{theo} is $\langle \lambda_k, \lambda_{CAG} \rangle$, with $F_{exp} = 4.16$. But since neither λ_k or λ_{CAG} are significant, the probability of this interaction to be significant is ruled out. This step allowed establishing that the interactions between parameters have no influence on the quality of the segmentation result and thus can be eliminated from the DOE to be used for determining the parameter optimal values.

Determination of a sub-optimal parameter set

Here also, we considered all the 6 parameters, but with no interactions ($N_{factors} = 6$), with 4 levels per factor chosen between the extreme values found experimentally in section 2.2 ($N_{levels} = 4$). This corresponds to $N_{dof} = 19$ and $F_{theo} = 4.76$, and leads to a factorial design of 25 experiments, instead of the full set of 4^6 experiments. As presented in table 1.B, it appears again that parameter a , with $F_{exp} = 32.85$, has still the largest influence. In order to optimize its value, a new DOE needs to be run, with parameter values close to the levels maximizing the factor effects.

Optimization of the sub-optimal parameter set

According to the results of the preceding section, we finally devised a DOE with the 6 parameters with no interactions ($N_{factors} = 6$), with 3 levels per factor ($N_{levels} = 3$). This corresponds to $N_{dof} = 13$ and F_{theo} of 9.55, and results in a factorial design of 16 experiments. Table 1.C shows in bold the levels maximizing the effect of each factor, leading to the optimized value for each parameter : $\lambda_k = 0.8$, $a = -3.0$, $\lambda_{CAG} = 0.28$, $\Delta t = 0.4$, $\alpha = 2.0$ and $\beta = 1.40$.

4.4 Segmentation results with the optimal parameter values

The optimal parameter set determined by the three step procedure of section 4.3 has been applied to different images acquired under quite similar illumination conditions. Typical results are shown in figure 2. The accurate segmentations observed enable to validate the approach used for this parameter setting procedure.

5. CONCLUSION

In this contribution, we have introduced an approach for the efficient setting of the parameters of a segmentation procedure, delivering, as a result, masks delineating automatically regions of interest of objects. The large number of parameters to be set is a natural drawback of such segmentation

methods, but the use of orthogonal factorial DOE techniques is an effective way to lower the computational cost. Extensive experimental work has shown that setting the parameters is highly critical but can this way be automated.

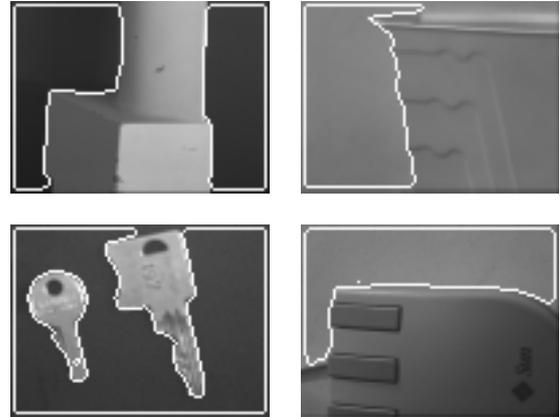


Figure 2: Typical segmentation results obtained using the optimized level set parameters determined in section 4.3. Regions characterized by narrow and elongated shapes (like the top background region in the plastic cup and keys pictures) are tricky to extract since, in these cases, only few points of the active contour evolve at each iteration step.

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