Harvey A. Cohen and Alan L. Harvey "*Stochastic Search Approach to Object Location* " Proc IEEE Int'l Conf Systems, Man and Cybernetics, San Antonio, October 2,3, 1994, Vol 3, pp 2237-2241. Preprint

Stochastic Search Approach to Object Location

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Abstract

Object location within an image involves establishing a location within an image for which a particular error function is minimised, and thus is essentially an optimization problem. Within the context of location via template matching, a random search approach, called a cluster search, based on an extension of mathematical methods due to Matyas has been studied to determine the most appropriate parameter β. For well chosen β the cluster search has been shown to be on average significantly faster than the fastest deterministic search schemes, notably coarse fine approaches.

1 INTRODUCTION

Object location within an image via template matching is a classic operation of Optical Character Recognition. In early machine vision template matching was used to determine information that might guide manipulators or alert to the presence of undesirable entities. In contemporary image coding the blocks mostly 8x8 in one image frame are matched against another frame to determine the motion vector for interframe coding.[8]

In the context of a study of speed-up methods for template matching, the shape of the surface of the template matching error, as a function of pixel location was determined for typical templates/images, and it was found that the position of match was the apex of a very deep notch - typically of 10 pixel diameter. [9] The width of the match notch was found to be a vital parameter in setting parameters for coarse-fine search strategies for template matching [3]. It is also clear from this perspective that object location amounts to the determination of the minima of a function with just such spiky minima, for which indications of the near presence of a minima is available in some local region, with rapid diminuation any further from the minima.

In sum, object location within an image involves establishing a location within an image for which a particular error function is minimised, and thus is essentially an optimization problem. In this paper we report on a study where random search has been applied to object location, for the first time to our knowledge. For any minimization/optimization's problems, random search techniques are a well established methodology [1] but we do not know of any previous efforts to directly apply established mathematical techniques of random search to object location. However, random search methods are well known in other computer systems, as in the development of tuned masks for texture recognition,[4][5] in the many applications of simulated annealing,[6] and in various approaches to speeding up neural net convergence.[8]
Conventional methods of object location involve the systematic scanning of an image - traditionally in a TV raster scan. - although other schemes such as "cross search" have been recently introduced [7] Speed-up approaches, whether multi-resolution,[2] or multi-grid "coarse-to-fine: approaches such as [3]. depend on their effectiveness on a knowledge of the scale of principle features of the object - which is expressed as the size of

the 'dip' in the error function - that is, depend on a presumed knowledge of the dip half-width.

The idea of random search is to search starting at a random location, noting the best-so-far location as the search proceeds. The location of the best-so-far is used to bias further searches, at both a random search point and at further locations determined by the best-so-far and the random position of that particular iteration. Convergence of the basic scheme is well established [1] In object location within images, we are dealing with functions that have very fine extrema areas, [3a], Hence our approach to random search has been to perform a small local search about each best-so-far - a methodology directly related to the established random search techniques [1]

The plan of this paper of this paper is to first provide a survey of Random Search, wherein a new variety of random search called Cluster search is introduced. In Section 3 a review of speed up methods in template matching is given, In Section 4 our experimental study of the comparative effectiveness of random search in comparison with the most effective coarse-fine approaches is presented. Conclusions are presented in Section 5.

2 RANDOM SEARCH

To elucidate just what is Random Search, we first detail what we term Simple Random Search as used to determine the minima of some function

$f: R_n - R$

and from this starting point introduce the Matyas Algorithm for Random Search, and the generalization of Matyas which we call Cluster Search.

2.1 Simple Random Search

Simple Random Search has the following algorithmic form:

Iteration 0: Using probability distribution μ_0 select an arbitrary point in R_n and call it x_b. Goto Iteration 1.

Iteration k: Using probability distribution μ_k select an arbitrary point in R_n and call it x_r.

If $f(x_r) < f(x_b)$ set $x_b = x_r$

if NOT finished goto Iteration k +1

In the numerical analysis literature the probability distribution chosen is normally gaussian. For image processing applications a uniform distribution over the image is most appropriate. In using this algorithm to determine the minima of functions there is some decided awkwardness in determining an appropriate terminating condition; however, applied to object detection some arbitrary threshold can be readily used as to provide a termination like so:

if $f(x_b)$ < Threshold

then Finished = True.

This simple variety of Random Search can be made more effective by use of probability distributions centred on the best-so-far co-ordinate that are adaptive in the sense that the σ of the gaussian reduces with iteration level k. Such a methodology is of course very prone to locking in at local minima.

2.2 Random Search-Matyas Algorithm

In Pure Random Search, at each iteration the value of the function at the best-sofar position is compared with the value at a random location. The basic idea of the Matyas and related Random Search Algorithms is that at each iteration, further locations are searched which are dependent on the best-so-far and random location, what we term a computed location. The algorithm then becomes.

Iteration 0: Using probability distribution μ_0 select an arbitrary point in R_n and call it x_b. Goto Iteration 1.

Iteration k:
Step 1:Using probability distribution μ_k select an arbitrary point in R_n and call it x_r.

If $f(x_r) < f(x_b)$ set $x_b = x_r$

Step 2: Compute

$x_c = M(x_r, x_b)(x_r - x_b)$

Step 3:

If $f(x_c) < f(x_b)$ set $x_b = x_c$

Step 4:

if NOT finished goto Iteration k +1

The convergence of these algorithms has been proved [1].

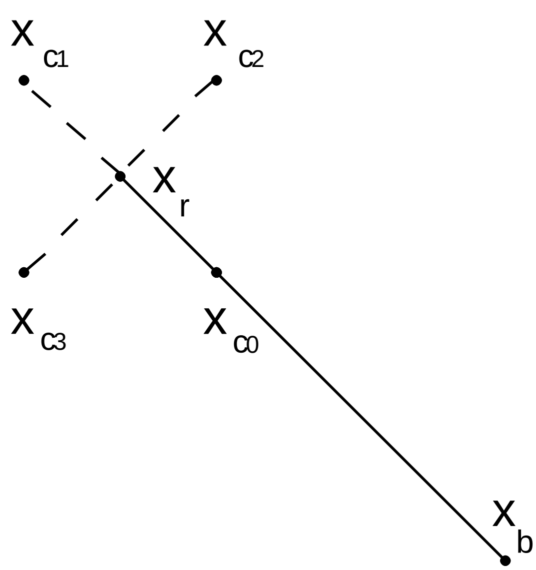

Fig (i) Random Search Scheme. At a particular iteration, the search 'best -so -far' location is x_b while x_r is a random position in the image. On the line joining these two locations a 'computed position' is x_{c0}. In this study up to three further computed locations are also searched which are equidistant from x_r.

2.3 Random Search Cluster-Algorithm

The Random Iteration so far described involves at each iteration a search at the best-so-far location x_b, the random location x_r and at a computed location $x_c = x_b + \xi$ where ξ lies along $x_r - x_b$. Matyas pointed out the practical merit of using a second computer location, a "reversal" :
$x_{c1} = x_b - \xi$

In this study we are concerned to make a further extension to random search methodology via a cluster search, where at each iteration, the new best-so-far location is determined by a search at

x_r, x_r and 1, 2, 3, or 4

of $\{ x_{c0}, x_{c1}, x_{c2}, x_{c3} \}$

where $x_{c0} = x_b + \xi$; $x_{c1} = x_b - \xi$

and $x_{c2} = x_b + \xi^*$; $x_{c3} = x_b - \xi^*$

where ξ^* is the same length as ξ but perpendicular to it: $\xi \bullet \xi^* = 0$;

This study is restricted to Cluster Search with

$$\xi = \beta (x_r - x_b)$$

so that one is dealing with a cluster bound about the best-so-far with a bond strength of β. To flag results detailed below, we find that a bond strength β.= 0.07 appears most satisfactory.

3 COARSE FINE APPROACHES

For a template of size m*n and an image M*N the computational cost of a template search through the entire image is mnMN units, the exact cost being dependent on the particular error function used.. However, due to the finite size of the mismatch region, coarse-fine approaches are practical whereby in a first coarse stage the location of the dip in the error function is found approximately, and in a second fine stage the centre of the dip region is determined with pixel accuracy. As far as the coarse stage goes, there are two complementary approaches that naturally emerge:

a) Subsampling image and template over a rectangular grid - a methodology we term sparse templates.

b) Stepping the image by large steps c pixels along each row, and with row spacing of r lines - a sparse image approach.

The data presented here involve a hybrid approach using sparse templates (on a 5*5 grid) and using a range of sparse image sampling (r,c) parameters.

Note that the coarse fine approach utilised here is in the same spirit but rather different in detail to the multi-resolution approach of Rosenfeld and Vanderberg, who do not use sub-sampling but instead use an averaging operation to produce coarse images and templates. [2]

4 EXPERIMENTAL RESULTS

We have compared the cluster algorithm with We present a scheme for estimating the number of searches required to locate an object by random search. We present data comparing random search variants including one that proves to be faster than a systematic coarse grid search on a range of images. (Typical result was object location after 400 searches in a 10,000 position search space.)

Data Set 1

Image : Brodatz Pebbles Template 12x12 (cut from image). Rendered Sparse using 5x5 gid Object location fixed at 'representative position' of 50,50 for exhaustive search and coarse-fine search schemes, and at 30,30 for random search.

EXHAUSTIVE SEARCH

Involves a cost of 5051

CLUSTER RANDOM SEARCH

β = 0.070

Size	Cluster Members	Cost Mean	SD of Cost	Search time secs
1	Co	3989	4129	1.78
2	Co C1	1288	1133	0.61
3	Co, C1, C2	1174	1088	0.64
4	Co, C1, C2, C3	1083	964	0.48

COARSE-FINE SEARCH
(No backtracking)

Coarse SearchSearch Params	Search Cost	Time
r=1 c=4	2056	0.44
r=1 c=5	1742	0.38
r=1 c=6	FAIL	

COARSE-FINE SEARCH
(with backtracking)

Coarse SearchSearch Params	Search Cost	Time
r=1 c=4	5655	1.51
r=1 c=5	4764	1.26

r=1 c=6	4122	1.12
r=1 c =7	FAIL	

Fig (ii) Brodatz Pebbles D54 Image used in this study

5 CONCLUSIONS

In this study we compared a new approach to object location via a new variety of random search we termed cluster search with other methods of location via template methods. This study was essentially preliminary, and did not include the range of image and template sizes desirable for a total appraisal of the methodology. Nevertheless, very striking indications were obtained as to the efficacy of the approach.

In the study using a particular prototype image 'pebbles D54' with gray-scale template, the direct search by raster scanning has an average cost of 5000 on the 100x100 image region. Best coarse fine searches of those compared required 1742. In contrast, the cluster search, using a 4-cluster, had mean computation cost of 1083 , but with a large standard deviation.

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