

SCALE INVARIANT TEMPLATE MATCHING

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Abstract –

Template matching is a technique in image processing to find small parts of an image (template) in a reference image. Finding a template patch in a reference image is the main component in a variety of computer vision applications such as object detection, tracking image. The naive Template matching method is insufficient for real-life applications, the technique that is proposed, performs a scale invariant template matching handling arbitrary changes in size effectively. The extensive experiment demonstrates this techniques pairs the best match without missing, using sum of absolute differences.

Key words: Template matching, sum of absolute differences, Scale invariant.

1. INTRODUCTION

Template matching is a technique in image processing to find small parts ^[1] of an image in a reference image. Locating the best matching patch ^[3] in a reference image is a challenging problem. The naïve template matching method is insufficient for real life applications. This performs actual search by positioning the template given over the reference image at every possible location^[5] and we will compute measure of similarity

between the template^[2] and the image that overlaps with. Then we finally identify the

position that has highest similarity measure as the occurrence of template. The template and the reference image should be robust against the changes in brightness ^[5]. To perform template matching we actually look for specific patterns or features that is unique ^[6] and can be compared. Basically corners are considered to be the good feature

in an image and in some cases blobs (binary large object) are considered as good feature^[6]. The best approach is to convert the images into gray scale for matching (if it is a area based matching)^[2] and another approach is feature based matching (if it is non area based matching).

To handle the distortions in the image such as change in orientation or size of image, an exhaustive search of all combinations of sizes are done, which comparatively efficient and robust for matching images with deformations and distortions. The basic idea is to extract some statistical features from the template image and identify whether these features occur in reference image. Since the features that match may not appear at the exact position^[5] or may not be of same scale. Thus this requires a computationally intensive process that generates feature for multiple scales. Based on the similarity measure between the reference image and template the matching process is carried on.

2. RELATED WORK

a. Randomness Normalized Cross Correlation:

In order to decrease the computational complexity of template matching, the adaptive Randomness Normalized Cross

Correlation (RNCC) is proposed. The new approach we proposed depends on random pixels' computation, instead of going through every pixel in I to analyze. Randomness Normalized Cross Correlation (RNCC) uses a group of sub-images $I(i, j)$, corresponding to random selected pixels (i, j) , noted as Random Pixel (RP), to compute the NCC value between T and itself.

b. Best-Buddies Similarity:

BBS is based on counting the number of Best-Buddies Pairs (i.e.) pairs of points in source and target sets, where each point is the nearest neighbor of the other. Best-Buddies Similarity (BBS), analyze its key features, and perform extensive evaluation of its performance. To apply BBS to template matching, one needs to convert each image patch to a point set in R_d , which requires computing the distance between each pair of points.

c. Buried Object Discrimination In Gpr Data:

A template matching approach to buried object discrimination problem is proposed over ground penetrating radar (GPR) B-scan images. The technique is scale invariant, which compensates for the change in the swinging speed of the detector. GPR signals

can be represented in several ways. Here template matching is done on binarized images to speed up the algorithm. After binarizing the images, an efficient similarity measure approximating correlation for binary images is exploited. To provide scale invariance, a modified version of Gaussian pyramid is used.

3. METHODOLOGY

Our goal is to match the template and reference image irrespective of its scale^[8] of the image efficiently with accuracy. Here we follow a traditional approach to match the template with the reference image. The technique used will move the template over the reference image for comparing^[2], and stores the overlapped patches. There are several comparison methods such as by taking square difference of the given images, by taking the correlation coefficient^[7] values and by using sum of absolute differences.

Among the methods mentioned above sum of absolute differences yields a high result on comparing two images^[1]. Hence the template matching is implemented by using sum of absolute differences, which is a measure of similarity of two objects related

to one another^[2]. To yield a better result, template and reference image is subjected to sum of absolute differences.

To search for multiple occurrence^[5] of the template we use threshold. By using a threshold value we could retrieve all possible locations, where the template matches in the reference image. Now, the next step is to perform scale invariant template matching. When we resize an image, the quality of the image should be retained to compare patches. This could be achieved by using interpolation techniques. Interpolation is the process of determining the values of a function at positions lying between its samples. The image quality^[6] highly depends on the used interpolation technique. A statistical interpolation method is computationally inefficient we precede using deterministic interpolation.

4. EXPERIMENTAL RESULTS

In this section, the output of existing system and the expected results of applying the proposed technique to a dataset collected are given. The dimension of the template image used is 168x89 and of size 20KB. The dimension of the reference image used is

385x451 and of size 44.2 KB. The images are downloaded from Google images.

Existing System Results:

Template:

 template



Fig 1

Detected image:

 Detected



Fig 2

Expected Result for proposed system:

Template:

 Template



Fig 3

Expected output:



Fig 4



Fig 5



Fig 6

5. CONCLUSION:

There are various naïve algorithms and methods to perform template matching, but these algorithms depend on the size and geometric position of the template in the reference image. To overcome this difficulties in handling distortions of the templates, the proposed system has introduced scale invariant template matching technique, where the patch of the template can be identified in the reference image with great accuracy and efficiently irrespective to its scale factor. The similarity measure between the two images is obtained using

SAD. Before obtaining the similarity measure between the two images convert them to gray scale. Fine matching is performed on the largest value is selected as the final matching result. The final correlation value is scaled to $[-1, 1]$ range, so that SAD of two identical images equals 1.0, while SAD of an image and its negation equals -1.0.

6. REFERENCES:

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