Research Journal of

Information Technology

ISSN 1815-7432

Academic
Journals Inc.

www.academicjournals.com

Research Journal of Information Technology 4 (4): 204-211, 2012
ISSN 1815-7432 / DOI: 10.3923/rjit.2012.204.211

Fast and Accurate Template Matching Algorithm Based on Image Pyramid and Sum of Absolute Difference Similarity Measure

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ABSTRACT

Template matching is an important topic in the field of Artificial Intelligence (AI) and has wide applications such as object recognition and industrial inspection. The main objective of this study was to investigate and propose a combined approach to enhance the performance of template matching system using image pyramid in conjunction with the Sum of Absolute Difference (SAD) similarity measure. Based on results, it was found that the capabilities provided by the proposed method can significantly improve the accuracy and execution time of template matching system. The experimental investigations were based on the use of color and gray scale images with different sizes and different illumination. The study presented a detailed description of the experiments and provided an analysis of the performance of the proposed method.

Key words: Template matching system, object recognition, images, accuracy, execution time

INTRODUCTION

A basic problem faced in image processing is to determine the position of a given pattern in an image i.e. so-called the region of interest. The template matching is considered as one of the basic approaches that can be used in determining the region of interest (Goshtasby *et al.*, 1984). In template matching technique, the position of a given pattern is located by a pixel-wise comparison of the source image with a given template which contains the desired pattern. In order to calculate this comparison, a lot of different well known algorithms were developed by many researchers. Such examples are Normalized Cross Correlation (NCC), Sum of Absolute Difference (SAD), the Sum of Squared Differences (SSD) (Zhu and Ma, 2000; Li *et al.*, 1994; Po and Ma, 1996; Li and Salari, 1995; Gao *et al.*, 2000; Lee and Chin, 1997).

More recently, Fu and Liao (2011) proposed a projection transform of wavelet coefficient based multi resolution data-structure algorithm for faster template matching. The proposed approach reduced the number of computation by around 70% over multi resolution data structure algorithm. It was also noticeable that the proposed fast algorithm provided not only the same retrieval results as the exhaustive search, but also a faster searching ability than existing fast algorithms. Hayashi and Kadosaki (2010) presented a fast and accurate object search algorithm based on template matching. The experimental results showed that the proposed search has higher accuracy than the simple active search and the brute force search because the silhouette masking works efficiently and the computational cost can be greatly reduced by the proposed search.

Zitova and Flusser (2003) demonstrated that NCC measure is more robust comparing to SAD and SSD under uniform illumination changes and is widely used in object recognition and industrial inspection. Lewis (1995) found that NCC is computationally slow and referred to compute the numerator and denominator of its algorithm. Recently, Wei and Lai (2008) proposed a fast pattern matching algorithm based on NCC which accomplished by combining adaptive multilevel partition with the winner update scheme to achieve very efficient search.

Barnea and Silverman (1972) showed that SAD and SSD are computationally fast especially when compared to NCC. Sebe *et al*. (2000) demonstrated that SSD is justified when the additive noise distribution is Gaussian. Also, the SAD measure is justified when the additive noise distribution was exponential and based on the maximum likelihood perspective. Hel-Or and Hel-Or (2005) proposed a fast template matching method based on accumulating the distortion on the Walsh-Hadamard domain in the order of the associated frequency using SSD. Previously, many investigators introduced the image pyramid technique, as speed enhancers, into the field of template matching (MacLean and Tsotsos, 2000; Takei, 2003). These studies concluded that using image pyramid in template matching helped to reduce the computation which in turn lead to speed up the corresponding system 100%.

A review of literature did not provide much information on the performance of fast and accurate template matching algorithm based on image pyramid and sum of absolute difference (SAD) similarity measure under local conditions. Therefore, the main objective of this study was to investigate and propose a combined approach to enhance the performance of template matching system using image pyramid in conjunction with the Sum of Absolute Difference (SAD) similarity measure.

MATERIALS AND METHODS

The template matching system involved two stages of operation. (1): This stage is the model registration which is concerned with the storage of an image in computer memory. (2): This stage is the process of searching for a given pattern in an image. This study mainly focused on the latter process of template matching system.

The simple definition of template matching is as follows. Given a source image S and a template image T (Fig. 1, 2), where the dimension of S are both larger than T, output whether S contains

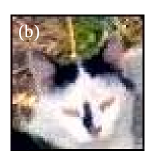

Fig. 1(a-b): Cat image; (a) Source image containing the template pattern and (b) Template image

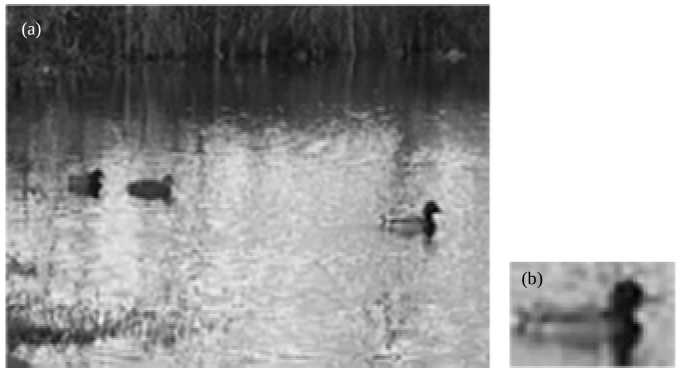

Fig. 2(a-b): (a) Duck source image and (b) Template image

a subset image I where I and T are suitably similar in pattern and if such I exists, output the location of I in S. The location of I in S, will be referred to as the location of the closest match and will be defined as the pixel index of the top-left corner of I in S.

In the present study, a combined approach was proposed to enhance both the accuracy and execution time of template matching system based on creating the image pyramid both for the source and template images Eq. 5. The search was then conducted using SAD similarity measure Eq. 4 with the most compressed template and source images. The resulting pixel location provided a coarse location of the template pattern in the next lower level of the source image. Therefore, instead of performing a complete search in the next level, one require to only search a close neighborhood of the area computed from the previous search. This sequence is iterated until the search in the source image (zero level of the image pyramid) is searched. Therefore, instead of performing a complete search in the next level, one require to only search a close neighborhood of the area computed from the previous search. This sequence is iterated until the search in the source image (zero level of the image pyramid) is searched. The proposed approach was named as Pyramid Sum of Absolute Difference (PSAD). The proposed approach is expected to enhance the overall performance of the template matching system due to the individual capabilities of each of the two techniques involved. For example, the use of pyramid technique helped to reduce the area to be searched in the source image by discarding areas classified as unimportant. On the other hand, use of SAD as template matching algorithm enabled the proposed algorithm to use less number of operations as compared to NCC according to Barnea and Silverman (1972) and MacLean and Tsotsos (2000).

NCC algorithm: The NCC algorithm computed the likeliness of a match by performing a discrete 2-D correlation of the template image matrix at every possible location in the source image matrix based on the methodologies described by Goshtasby *et al.* (1984), Zitova and Flusser (2003) and Wei and Lai (2008). For example: Let S(x, y) denote the intensity value of the source image of size P×Q at the point (x, y). The pattern was represented by a given template T of the size M×N. A common way to calculate the position (i_{pos}, j_{pos}) of the pattern in the image S was to evaluate the normalized cross correlation value $\lambda(i, j)$ at each point (i, j) for S and the template T, which was shifted by i steps in the x direction and by j steps in the y direction. Basic definition of the normalized cross correlation coefficient is presented in the following equation:

$$\lambda(i,j)=\frac{\sum_{X=O,y}^{(N-1),(M,1)}\Big((S(i+x+,j+y)-\bar{S}(i,j)\Big)(T(x,y)-T)}{\sqrt{\sum_{x=o,y=o}^{(n-1),(M-1)}\big(S(i+x,j+y)-S(i,j)\big)^2\sum_{x=o,y=o}^{(N-1)(M-1)}(T(x,y)-T)^2}} \tag{1}$$

where, $0 \le i < (P-M)$, $0 \le j < (Q-N)$:

$$\bar{S}(i,j) = \frac{1}{M \times N} \sum_{x=0,y=0}^{(N-1),(M-1)} S(i+x, j+y) \tag{2}$$

$$\bar{T} = \frac{1}{M \times N} \sum_{i=o,j=o}^{(N-1),(M-1)} T(i,j) \tag{3}$$

In other words, the highest value of correlation coefficient obtained, between the corresponding template and the subimages inside the source image, should determine the correct position for that template. Then, NCC returns (i_{pos}, j_{pos}) as the closest match in S. However, it was mentioned that the maximum possible value for $\lambda(i_{pos}, j_{pos})$ is 1.

SAD algorithm: The sum of absolute difference (SAD) is a simple algorithm for measuring the similarity between template image T and sub-images in source image S. It works by taking the absolute difference between each pixel in T and the corresponding pixel in the sub-images being used for comparison in S. These differences are summed to create a simple metric of similarity. For example, let us assume that a 2-D M×N template, T(x,y) is to be matched within a source image S(x,y) of size P×Q where (P>M and Q>N). For each pixel location (x,y) in the image, the SAD distance is calculated according to the procedures given by Barnea and Silverman (1972), Sebe *et al*. (2000), Essannouni *et al*. (2007) and Chen *et al*. (2001) as follows:

$$SAD(x,y) = \sum_{k=o}^{(M-1)(N-1)} \sum_{l=o}^{(N-1)} \left| S(x+k, y+l) - T(k,l) \right| \tag{4}$$

In this algorithm, the smaller the distance measure obtained by SAD function between the template image T and a sub-image in the source image S, the closer match between the searched template and that corresponding sub-image is. Therefore, if the measured distance by SAD function is zero, the local sub-image is identical to the template.

Image pyramid: MacLean and Tsotsos (2000) and Takei (2003) concluded that the idea of compressing and storing images as pyramid plays a significance role in the field of template matching algorithms. The image pyramid technique does not perform the process of template matching itself but it just functions as speed enhancers. Image pyramid consists of sequence of copies of an original image in which both sample density and resolution are decreased in regular steps. The reduced resolution levels of the pyramid are obtained through an efficient iterative algorithm. For example: Consider the following algorithm which reduces the dimensions of the image by a factor of f, a predefined positive integer, at each level. Assume a 2-D source image S(x,y) of dimension P×Q, and let $S^k(x,y)$ be the image at the kth level of the pyramid ($S^0 = S$). Each pixel in level k is the average value of f×f pixels at level (k-1), then for f = 2 the new image in the pyramid can be constructed by the following Equation:

$$S^k(x,y) = \frac{1}{4}\left(S^{k-1}(2x,2y) + S^{k-1}(2x+1,2y) + S^{k-1}(2x,2y+1) + S^{k-1}(2x+,2y+1)\right) \tag{5}$$

A pyramid with 3 levels of source image and template image are presented in Fig. 3 and 4, respectively.

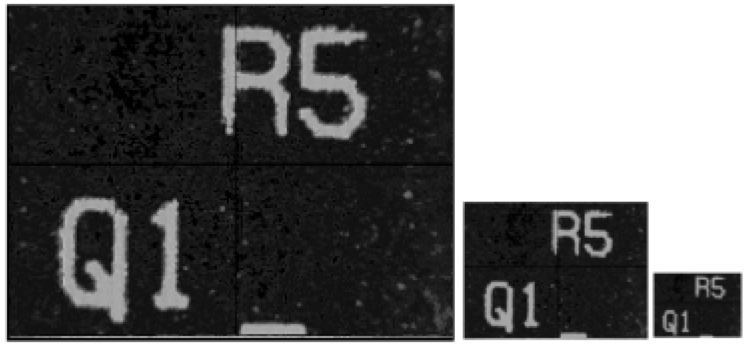

Fig. 3: Letter image: The pyramid representation for the source image, The pyramid has three levels, with level 0 being the original image (left) and level 2 being the smallest (right)

Fig. 4: The pyramid representation of a region of interest having the same number of levels as in Fig. 3

RESULTS AND DISCUSSION

The experimental studies were mainly concerned with enhancing the performance of template matching systems. The term performance, in this study, included both the execution time and the accuracy. The later term expressed the ability of a template matching system to determine the correct position for a template in a source image. The investigations were based on two samples of source images and their templates in clean and noisy data conditions. These samples contain one color image and one gray scale image. Such images were named as Cat and Duck as shown in Fig. 1 and 2, respectively. The sizes of Cat image and its corresponding template matching were 206×281 and 64×66, respectively. Whereas, the size of the Duck image and its corresponding template matching were 240×320 and 32×48, respectively. The experiments were performed using MATLAB 7.0 on a Laptop with an Intel (R) Core(TM)2 Duo CPU T7500 at 2.20 GHz and 1.99 GB RAM.

In this study, the process of template matching was based on the use of Normalized Cross Correlation (NCC), Pyramid Normalized Cross Correlation (PNCC), Sum of Absolute Difference (SAD) and the proposed approach of Pyramid Sum of Absolute Difference (PSAD). Basically, the

Table 1: Execution time (sec) of applying NCC, PNCC, SAD and PSAD to the clean source images and their corresponding templates

	Cat (color image)		Duck (gray scale image)	
	Execution time (sec)	%	Execution time (sec)	%
NCC	15.78	100.00	11.00	100.00
PNCC	8.86	56.15	3.98	36.18
SAD	8.26	52.34	5.20	47.27
PSAD	3.86	24.45	1.83	16.64

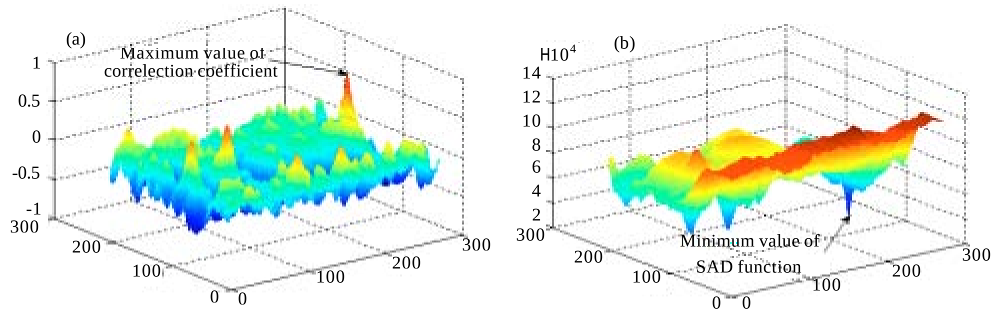

Fig. 5(a-b): (a) Surface plot of correlation coefficient between the sub-images in source image and its corresponding template and (b) Surface plot of SAD function between the sub-images in source image and its corresponding template

idea was to determine the level of effectiveness enhancement offered by the proposed method when compared to the most popular template matching approaches.

Template matching under clean data conditions: The study investigated the effectiveness of PSAD in enhancing the reliability of template matching system when the images and their templates are free from degradation. The results of experiments for the execution time were presented in Table 1.

The results indicated that the use of PSAD always lead to the lowest execution time both for the colour and grey scale images (Table 1). These outcomes confirmed the earlier suggestion that the use of PSAD can enhance the performance, in terms of execution time, of template matching system. This might be due to the two folds characteristic of PSAD. (1): The use of pyramid technique discarded the areas in the source image that were classified as unimportant and (2): the SAD algorithm enabled the proposed method to use less number of operations compared to NCC. On the other hand, the accuracy obtaining the correct position for the templates in their corresponding source images of all these algorithms was 100%. This was achieved by calculating the maximum value of correlation coefficient between the corresponding template and the sub-images inside the source image (in case of NCC as well as PNCC). However, the minimum value of SAD function was calculated (in case of the algorithms SAD and PSAD). These processes are illustrated in Fig. 5a and b. Similar findings were reported by Essannouni *et al*. (2007) who proposed a fast frequency algorithm to speed up the process of SAD matching by using an approach to approximate the SAD metric by cosine series which can be expressed in correlation terms. Also, Chen *et al*. (2001) proposed a fast block matching algorithm based on the winner-update strategy using SAD measure, which can significantly reduce the computation and guarantee to find the optimal solution.

Table 2: Execution time (sec) of applying NCC, PNCC, SAD and PSAD to the noisy source images and their corresponding templates

	Cat-color image		Duck-gray scale image	
	Execution time (sec)	%	Execution time (sec)	%
NCC	15.79	100.00	10.94	100.00
PNCC	8.39	53.13	3.92	35.83
SAD	8.13	51.49	5.23	47.81
PSAD	5.75	36.42	1.83	16.73

Template matching under noisy data conditions: The usefulness of PSAD was investigated in template matching systems when the qualities of the source images and their corresponding template images are considerably different. This was achieved by adding noise to the source images. The variance of added noise started from 1-6 in the case of color image and 0.1-0.6 in the case of gray scale. The reason of applying a variance with a small number in case of gray scale image was that this type of images are more sensitive to noise as stated by Ma *et al*. (2009). After adding the noise to the source images, the image matching tests were performed by applying all the above mentioned template matching algorithms on the noisy images. The execution time and accuracy of these algorithms were collected and compared.

The execution time required for NCC, PNCC, SAD and PSAD was presented in Table 2. The data in Table 2 demonstrated only the execution time when the noise with variance value of 6 and 0.6 was added to the color and gray scale images, respectively.

The results clearly showed that PSAD algorithm is still the fastest template matching technique compared to NCC, PNCC and SAD algorithms. Data in Table 2 also showed that applying PSAD algorithm on the noisy Cat image (color image) takes only 36.42% execution time as compared to NCC algorithm costs when applied on the same image. On the other hand, PSAD saved 83.27% execution time compared to NCC algorithm when applied on the Duck image (gray scale image) with variance value of 0.6. In conclusion, the study results showed that the template matching accuracy is still quite significant. The exceptions to this were the results obtained in the case of SAD algorithm where the accuracy dropped to 67%. The study results agree with those of Dawoud *et al*. (2011) who proposed a fast template matching technique based Optimized Sum of Absolute Difference (OSAD) instead of using NCC to reduce the effects of such variation problems.

CONCLUSION

This paper reported an investigation into the use of pyramid sum of absolute difference (PSAD) for template matching systems. Based on the experimental investigations, it was found that PSAD offered considerable improvements to the overall performance, execution time and accuracy of the template matching system both under the noisy and clean data conditions. The proposed algorithm consistently outperformed the execution time offered by the other three template matching algorithms. The reason for this seems to relate to the individual characteristics of the two techniques i.e. Pyramid technique can help discard areas in the source image that are classified as “unimportant”; whilst SAD algorithm can make use of less number of operations as compared to NCC. Additionally, the experimental results showed that PSAD algorithm can also obtain accurate matching location results even with noise presence.

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