

ADVANCES AND APPLICATIONS OF TEMPLATE MATCHING IN IMAGE ANALYSIS

MAYTHAM KAREEM N. ALHASOONI

Faculty of Computer Science & Mathematics, Kufa University, Najaf, Iraq.
Email: maythamk.alhasooni@uokufa.edu.

MOHAMMED JASIM A. ALKHAFAJI

Computer Technology Engineering, Al_Taff University College, Karbala, Iraq.
Al-Zahraa University for women, Karbala, Iraq. Email: mohammedjasim3232@gmail.com

Abstract

Template matching corresponds to an old topic in the field of pattern recognition and image analysis with several important applications in many different fields. Many different algorithms and methodologies have been proposed to solve the problem, and several optimization techniques have been developed to speed up the search. In this short chapter, we will briefly revisit the basic concepts associated with the template matching problem. We will also provide some indicative applications and discuss some different constraints existing in the statement and solution of the problem. There is an abundant literature concerning template matching and its applications in the field, so in order to restrict ourselves to a specific number of pages, we will restrict the analysis to methodologies that we have been working with during the last years inside our research group. Another easy way to restrain the number of references is to include those corresponding to the assembled list of problems stated at the end of this chapter. The chapter is organized as follows. In the next section, we will briefly visit the problem of template matching in images. In Section 3, we will take a brief look at the three different methodologies under consideration: compressive, features, and advanced modeling. Some options concerning the choice of features will be discussed in Section 4. In Section 5, we will consider three different constraints associated with the problem. Then, we will revisit some applications in Section 6 and frame some conclusions in Section 7. Finally, in Section 8, we will state a list of open problems.

Keywords: Template Matching, Object Detection, Traditional Methods.

1. INTRODUCTION

The most basic stage of image analysis is the process of matching patterns within images. This is typically carried out by using a technique known as template matching [1]. This technique involves moving a target object along an image and comparing an object projected within a defined window against this object stored in a template [2]. If the objects are the same, a match results. Template matching is used in various fields such as town and city planning, geology and agriculture, subdivision and exploitation of natural resources, medical diagnosis, remote sensing, cartography, and commercial, industrial, and military image analysis [3][4]. Template matching has seen significant improvements in recent years as a result of the rapid development of computing and image processing, which has led to both improvements of the old concepts and the emergence of some new concepts to further enhance the capabilities of these techniques [5]. Template matching has existed ever since the field of pattern recognition began. Researchers in the past have come up with some techniques that have shown to be good at identifying patterns with varying degrees of similarity.

In the past, some problems had persisted with these techniques. Over time, some methods used in developing these techniques have been improved while some completely new concepts have emerged. With the increasing sophistication of technology and the emergence of so many new concepts, it becomes necessary that a comprehensive review of these concepts be carried out as a guide to researchers who may use these methods to achieve better results in their respective fields [6][7].

1.1. Definition and Concept

Template matching is a method for searching and locating referenced image patterns in target images. A template is a small-sized image to be matched with a sub-image of a target image having the same size as the template. The target can also be the whole image itself, but this reduces the searching scope. This method compares intensities of pixels in a template and a target image using a similarity measure to find the best or several correspondences [8][3]. The most similar sub-images are identified with the strongest match. Normalized Cross Correlation and Sum of Absolute Differences are similarity measures to find the best match.

To understand template matching, it is useful to know the following definitions. Template: a pattern, which is a part of a digital image, describing a typically repetitive structure. The term "template" is also known as a reference image or a query image. Target image: a target, also known as a source image, is an image field to be searched for finding the location of the template. This image will often be larger in size. The minimum size is equal to the size of the template only. Similarity measure: a similarity measure is a function that measures how much a portion of an image looks like another image.

The measure works over one or two images and returns a single scalar. When comparing a template and target images, a similarity measure between two regions is used at every translation position inside the target image. The result of each region comparison will form a signal for an image of correlations, which may be called the matching score.

Matching score: a matching score is a value derived from the comparison of template and target images. Ostensibly, the score indicates how well the template matches with a portion of the given target image, i.e., this is how much the template succeeds in explaining the power of the given region [9]. These locations are specified by the displacement variables. The amplitude of the matching score indicates the similarity between both images.

A higher value of the signal represents a higher agreement between the two images, i.e., a possible position in which the similarity between the query and the source image is much better. The inherent assumption here is that a high correlation value indicates dense correspondence between them. The information needed in the matching operation is mainly stored in this score and represents the degree of consistency between both images when they are compared with a portion or sub-region in the source image in terms of the Euclidean distance [10].

2. TRADITIONAL TEMPLATE MATCHING TECHNIQUES

Despite the increasing diversity of template matching methods, simplified methods are time-tested basic approaches to template matching. The first method to popularize template matching techniques was the function-based cross-correlation that evolved over the last four decades. The most common template matching approach is to use rectangular features identified in local textures in images. Template matching using features has become popular. Basic approaches to template matching originated from the simplified method of using non-overlapping rectangular features. This feature-based template matching method gradually evolved to use overlapping rectangular features and non-rectangular features. Normalized cross-correlation is a popular function-based approach to template matching and provides a good starting point in the analysis of computational time and accuracy. It is one of the most popular tools in medical image analysis and microscopy. The first category includes techniques based on direct search, hand-crafted Fourier domain methods, and blurred features. These methods have been developed for specific applications. Advanced methods focus on the problem of matching mechanically alike objects. Template matching techniques share some similarities with advanced approaches, since they can be used to find the positions of objects by comparing the objects with other objects. However, template matching works under different assumptions and may be used in other situations as well. Template matching techniques are generally evaluated in terms of accuracy, computational efficiency, and ease of implementation. We have discussed traditional methods of template matching and found that they work well under some conditions, but may not be robust and accurate enough for specific applications. In recent years, there has been a great deal of research conducted to address the limitations of these techniques. The analysis of traditional methods should be beneficial to those trying to address these issues. Many traditional methods work well under specific conditions, suggesting that new techniques should be flexible enough to intrinsically adjust to overcome limitations [11][12].

2.1. Cross-Correlation

2.1.1. Mathematics

In general, template matching matches a template image with a part of a source image. For two input images $I_1(l)$ and $I_2(l)$ with l (l rather than x and y is used to emphasize that images are 1D signals when flattened), the cross-correlation can be defined as. The value of r may change from -1 to 1 and may serve as an indication of image similarity. In the formula, $E(l_i)$ is the expectation of l_i , while the one between the samples of $I_1(l)$ and $I_2(l)$ is defined as $l_i(l) - E(l_i)$, and $\sigma(l_i)$ is the standard deviation between these two.

2.1.2. An Edge Case

There may be more natural images in which two identical images $I_1(l)$ and $I_2(l)$ produce $r = 1$ rather than -1 , given that most overlapping is among two copies of images in the former case.

2.1.3. Applications

The strategy of cross-correlation is compatible with some typical types of appearances in real-world patterns. For example, the satellite image and the proposed gray image of a fighter jet has a strong potential for exploitation in the early flight analysis, as the strong correlation nearby the airplane alongside the landing track value decreases quickly as the distance away from the airplane increases [13]. This is rather more informative in places, proving that the neighborhood of the parts of a fighter jet is far more informative, as the figure 1. Cross-correlation is the simplest method of matching templates, having several common functionalities [14]. In many approaches such as template matching, graphics, robotics, and pattern recognition, it is frequently used but not relevant in our implementation, incorporating window-based tracking.



Fig 1: Sample images after identifying the planes in green

3. ADVANCED TEMPLATE MATCHING TECHNIQUES

As described earlier, the basic template matching methods for image analysis aim to explore the intensity-based information contained in the original raw image. With the rapid increase in image data and the growing use of images by computer vision processes, a new approach should be used [15]. For time-consuming applications and non-precise results or conditions, the proposed feature-based template matching is a great solution as it elevates the image pattern, feature extraction, and matching route. There is a

demand to have the capability to adapt to different surroundings and be robust to noise and different locations. Several of the many recent methods capable of template matching are the scale-invariant feature transform, speeded-up robust feature, histograms of oriented gradients, binary robust independent elementary features, and position-based code keypoint detectors and descriptors [16]. In particular, the machine learning and AI branch has made significant strides in the area of separation and pattern recognition. One approach to evolving template matching is to integrate deep learning methods. The template matching based on the deep learning model is classified according to the amount of data. An end-to-end training method is used to train the matching deep learning model using an adequate number of matching images and non-matching images for better matching outcomes. It has an edge in the area of adaptability and non-exact matching similarity. The photos are never identical and are invariably subjected to deformation of some kind. To adapt to the changes in the input data, deep-learning-based matching approaches work robustly in a variety of scenarios [17]. In addition, the matching performance of this method was superior to that of traditional machine learning methods.

3.1. Feature-Based Template Matching

Matching feature points that contain informative and stable feature descriptors for an effective comparison is the base idea of feature-based template matching, which is usually performed through local image and template feature extraction. The essential step of feature-based methods lies in the extraction of useful and distinctive features in the image that can match the relevant template features of the object accurately. Moreover, feature-based approaches theoretically extract features with less impact from detrimental factors such as brightness, scale, orientation, and noise. However, unlike raw pixel comparison methods, feature-based template matching techniques are not restricted to normalized patches and can extract valid matches in the presence of in-plane rotational differences [8][18]. Several methods have been proposed for feature extraction purposes with elaborate techniques, such as corner detectors, SIFT-based image comparison, and feature extraction through convolutional neural networks. For feature extraction, a corresponding feature descriptor of each point in the image (or object template) is also extracted. These feature descriptors are used to generate a high-dimensional vector that represents detailed information around every interest point [19]. In brief, feature-based methods are beneficial in matching challenging patterns where significant variations or clutter are present in the image scene, a subset of which includes localized texture and surface-based features. In spite of these advantages, these methods necessitate an extensive amount of data during their training, making them computationally costly and impractical for scenarios like real-time response systems. Feature-based template matching methods are often complementary with machine learning-based techniques, where the feature-based step is utilized for informative feature extraction. In real-world scenarios, these methods have been proven to be quite robust and are used in various fields of image analysis, including dynamic object matching, augmented reality, and robot localization [20].

3.1.1. Feature Descriptor Calculation

Given an image $I(x,y)$, we aim to extract the descriptor of an interest point $P(x,y)$. The descriptor is often represented as:

$$F(P)=\phi(I(x,y)) \quad (1)$$

where ϕ is a transformation function for descriptor extraction.

For example, ϕ can be:

- ϕ *SIFT* for feature detection using SIFT.
- ϕ *CNN* to leverage a convolutional neural network for feature extraction.

3.1.2. Representing Points in a High-Dimensional Matrix

The extracted points are represented as a high-dimensional matrix:

$$D = \begin{bmatrix} d_{1,1} & d_{1,2} & \dots & d_{1,n} \\ d_{2,1} & d_{2,2} & \dots & d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m,1} & d_{m,2} & \dots & d_{m,n} \end{bmatrix},$$

where D contains the descriptors extracted from m points in the image.

3.1.3. Similarity Computation

To compare two points P_1, P_2 , a similarity function is often used:

$$S(P_1, P_2) = \exp\left(\frac{\|F(P_1) - F(P_2)\|^2}{2\sigma^2}\right) \quad (2)$$

where $F(P)$ represents the point descriptor, and σ controls the sensitivity.

Table 1: Comparison of Feature Extraction Methods

Method	Characteristics	Applications	Challenges
Corner Detectors	Detect interest points at edges or corners	Basic image processing	Sensitive to noise
SIFT (Scale-Invariant)	Rotation and scale-invariant features	Complex, multi-layered images	Computationally intensive
CNN-based Features	Learned features via deep learning	Large-scale pattern recognition	High data requirements

3.1.4. Important Note on Real-World Applications

When using CNN-based features in real-time scenarios, optimization techniques are essential:

- Acceleration algorithms like Quantization.
- Dimensionality reduction techniques like PCA:

$$X_{\text{reduced}}=U^T X \quad (3)$$

where X is the original feature matrix, and U is the principal components matrix.

4. CHALLENGES AND LIMITATIONS IN TEMPLATE MATCHING

Template matching still faces various challenges and limitations in practical applications. In particular, it is sensitive to several factors that may significantly degrade the alignment accuracy, including occlusion, scaling, and rotation changes. Other common factors that affect the brightness or appearance of the templates reduce the matching accuracy of the matching function. The matching quality is also significantly affected by the presence of environmental factors, such as illumination variations and noise in the images. It should be noted that, though some accurate matching functions have been proposed, the corresponding strategies may be too computationally expensive to be used in real-time applications. Thus, when developing a template matcher, it is important to consider the trade-offs between accuracy and efficiency. In some cases, such as when finding all possible template locations, the complete search for the best match may take an excessive amount of time [1][21]. Failures to perform the correct matching operations may, in some cases, have dramatic consequences on the results and significantly affect the final application. For example, if a pose detector fails to correctly recognize a template in a given image, the tracker, optimizer, or any other module directly depending on the pose could produce incorrect results. Using a voting-based algorithm in which the highest number of successful matches votes for the answer may partly hide the incorrect answers. However, such failure cases can still affect the issue, as well as its looks and smoothness. In most cases, therefore, the aim of a template matching system is to maximize the number of correct answers. In the computer vision literature, this is referred to as the recall if the retrieved matches belong to the correct template. Efforts to design template matching algorithms without considering the required efficiencies lead to the implication that the algorithm has to be capable of dealing with all possible situations. As the visual environment is composed of streams encountering a vast array of phenomena, this approach is too open-ended to lead to optimally efficient results [7][2][22].

5. APPLICATIONS OF TEMPLATE MATCHING IN IMAGE ANALYSIS

Template matching is a key task in the context of image analysis and finds its broad applications in various fields. It is particularly applied to biomedical imaging, for example, for invasive or non-invasive surgery in odontological and endodontic applications, in the surgery of the costal region to avoid the heart with minimally invasive surgery for readaptive tissue implants, in tumor surgery, with the need for auto-recognition to avoid the neuron layer during the first surgical step, in clinical anesthesiology, for multi-image tools of 3D heart, in retinal diagnosis, and in ultrasonography. It also has applications in robotics and in the industrial field, such as in the assembly of electronic packages, with the robot arm equipped with a camera that scans the workspace and recognizes objects to be manipulated, in the quality control of mechanical products, where template matching approaches are widely used for object recognition, in electronic packaging, and in luggage handling. The objects are usually recognized, and they are decomposed into a set of features with specialized algorithms for applications in which regions are deformed rigid objects [23]. Template matching is also needed for tasks that must detect and track objects from a video, such as augmented reality, security systems, video surveillance,

video-encoded traffic control systems, human behavior analysis, and in the visualization of medical images in the hyperthermia therapy process [24]. Matcher methods are also integrated with image retrieval approaches using dynamic templates to automatically detect and recognize common events or happenings in a set of images, and in games for recognizing shapes. The temporal redundancy of the TV sequence is exploited to perform improved noise reduction and image reconstruction. In the field of robotics, advanced techniques in template matching are also dedicated to the development of human-like machines, for the study of sensor organization and the perception of multiple visual sensor data. The matcher has been developed and integrated into a surface and volume rendering workstation for CT scans, and it is currently under development for applications in virtual hysteroscopy. Frameworks for heart motion estimation are also under development using a shape-based multimodality matcher and a heart mask. Techniques of matching are also applied in a cognitive science approach to restore consensus among different human decisions of a similar kind. Moreover, template matching is exploited for automatic recognition of soil sections, drilling images, to estimate depth in a fish image, in a system for bone mineral mass measurements in our research group, and for detecting in a slot machine the possible returns and visual audio effects [25][26][27]. Finally, recent techniques on approaching the template matching process also involve the use of AI algorithms, such as deep learning, which is going to open a huge area of research in the near future.

5.1. Object Detection and Recognition

Object detection and recognition are two components of image analysis that have been improved by the use of template matching. Object detection is the process of locating an object with its precise spatial location specified. It is also a critical research domain since failures in object detection can lead to significant faults in the object recognition process. Bounding boxes are usually created around detected objects to locate the region of objects, which can be represented as hit or miss based upon the existence and position of the detected bounding box. Recognizing what objects have been detected by an object detection algorithm is known as object recognition. Because an object of interest is often different from its context in the detected region, the bounding box of a detected object may not precisely locate the object, and it might include several parts of the background. It can be represented as true positive (TP if the entire detected object is the object of interest), false positive (FP if the detected region is not an object of attention), and so on.

The relevance and suitability of object detection and recognition have not been overlooked in recent works conducted on template matching. At the same time, template matching and several traditional object detection methods are chiefly focused on detecting objects or optimizing the position of objects. Therefore, it is possible to improve the recognition rate by incorporating additional methods such as spectral clustering, Hough transformation, and so on. Nevertheless, such traditional techniques have their intrinsic limitations, such as hard setting of parameters, dedication to specific objects, slow speed, low accuracy, and so on, whereas template matching considers all objects uniformly and can detect and identify multiple objects simultaneously. Moreover,

traditional methods take a significant amount of time to train and test because of the activities that occur, such as handcrafted feature extraction, learning, and customization of classifier rules according to the different object's configuration and constraints. Hence, a wrong setting parameter or rule can lead to high-level errors in operations. As one of the best examples of template-based detection, this paper will compare the localization and efficiency of our results with other traditional methods [24]. It is clear from the literature that one of the principal fields for which object detection is important is to prevent poor performance of surveillance video. It could be used in a wide range of applications, such as monitoring, safety, automatic vehicle management, and so on. It is notable that this process incorporates detection methods to ensure that useful information is derived from the incoming data [23][28]. Finally, these techniques give the time and location of the object, which is known as land prey. The current work is already producing good results and attracts the attention of more embracing researchers among computer vision and machine learning practitioners. Accordingly, current research seeks to contribute to improved object detection and localization methods according to the extent to which researchers and companies report the importance of surveillance video across a range of industries.

5.2. Object Detection Using Template Matching

The primary task is to match a given template $T(x,y)$ with a region in the target image $I(x,y)$. The template matching score S is computed over a region of interest (ROI) using a similarity measure:

5.2.1. Cross-Correlation for Matching

$$S(u, v) = \sum_{x=1}^m \sum_{y=1}^n T(x, y) \cdot I(x + u, y + v) \quad (4)$$

where:

- $T(x,y)$: Template image.
- $I(x+u,y+v)$: Image patch at location (u, v) in the target image.
- m,n : Dimensions of the template.

5.2.2. Normalized Cross-Correlation (NCC)

To handle variations in illumination, the similarity score is normalized:

$$S(u, v) = \frac{\sum_{x=1}^m \sum_{y=1}^n (T(x,y) - \bar{T}) \cdot (I(x+u,y+v) - \bar{I})}{\sqrt{\sum_{x=1}^m \sum_{y=1}^n (T(x,y) - \bar{T})^2 \cdot \sum_{x=1}^m \sum_{y=1}^n (I(x+u,y+v) - \bar{I})^2}} \quad (5)$$

where:

- \bar{T} : Mean of the template.
- \bar{I} : Mean of the image patch.

5.3. Object Localization and Bounding Box Representation

5.3.1. Bounding Box Parameters

The bounding box for a detected object can be represented by:

$$B=\{(X_{\min},Y_{\min}),(X_{\max},Y_{\max})\} \quad (6)$$

where:

- (X_{\min},Y_{\min}) : Top-left corner.
- (X_{\max},Y_{\max}) : Bottom-right corner.

The size of the bounding box:

$$AB=(X_{\max}-X_{\min})\cdot(Y_{\max}-Y_{\min}) \quad (7)$$

5.3.2. IoU (Intersection over Union)

To evaluate the accuracy of the detected bounding box B_d against the ground truth B_g :

$$IoU=|B_d \cap B_g|/|B_d \cup B_g| \quad (8)$$

where:

- $|B_d \cap B_g|$: Area of intersection between the detected and ground truth bounding boxes.
- $|B_d \cup B_g|$: Total area covered by both boxes.

5.4. Object Recognition Metrics

5.4.1. Precision and Recall

- **Precision (P):**

$$P=TP/TP+FP \quad (9)$$

where:

- TP: True Positives.
- FP: False Positives.

- **Recall (R):**

$$R=TP/TP+FN \quad (10)$$

where:

- FN: False Negatives.

- **F1-Score**

The harmonic mean of precision and recall:

$$F1=2\cdot P\cdot R/P+R \quad (11)$$

5.5. Improved Matching Using Hough Transformation

To detect shapes or optimize localization:

$$H(\theta, \rho) = \sum_{i=1}^N \delta(\rho - x_i \cos \theta - y_i \sin \theta) \quad (12)$$

where:

- $H(\theta, \rho)$: Accumulator array.
- (x_i, y_i) : Points in the detected region.
- (θ, ρ) : Parameters defining the shape (e.g., lines or curves).

5.6. Dynamic Templates in Video Analysis

For template matching in videos, temporal redundancy can be modeled using:

$$I_t(x, y) = I_{t-1}(x, y) + \Delta_t(x, y) \quad (13)$$

where:

- $I_t(x, y)$: Current frame.
- $I_{t-1}(x, y)$: Previous frame.
- $\Delta_t(x, y)$: Temporal change.

5.7. Heart Motion Estimation Using Shape Matching

A multimodal shape matcher estimates the heart motion:

$$E_{shape} = \int_{\Omega} ||T(x, y) - R(x, y)||^2 dx dy \quad (14)$$

where:

- $T(x, y)$: Template shape.
- $R(x, y)$: Reference shape from multimodal data.
- Ω : Region of interest.

6. FUTURE DIRECTIONS AND EMERGING TRENDS IN TEMPLATE MATCHING

Given its potential for robotics, medical image analysis, 3D model tracking, human behavior analysis, etc., template matching should transcend traditional research boundaries and be the subject of more interdisciplinary studies. Given the advances in artificial intelligence and machine learning, some potential research directions and emerging trends in the next few years are [25]: First, integrating artificial intelligence and machine learning with template matching to make greater advancements is necessary. Second, there should be new algorithmic solutions developed based on big data, which combine maximum average correlation height filters for transforming the data from big dimensions and the template images into an effective form, allowing them to handle searches wherein the target data are not readily available. Such solutions are expected

to accelerate the speed of the technique and achieve better accuracy than traditional techniques. Further, hybrid solutions of deep learning architectures will be developed to match the template matching methods for achieving robustness while ensuring accuracy in pattern recognition. The future template matching methods should consider real-time, in-time, and edge computing to develop solutions that meet the present hardware trends in super-resolution cameras and sensors. Further, new directions for emerging applications such as Industry 4.0, agriculture, autonomous vehicles, security and defense, and social computing using template matching are expected to emerge in the next few years [23][28][26]. Apart from the future directions and trends, some ethical considerations need to be taken into account due to the use of historical and contemporary human data and automation in various domains such as security, education, and healthcare, such as informed consent. However, automation can address the accuracy and less subjective-based systems. Overall, template matching in the emerging trends could be transformed from vision-based processing systems to actionable analytics.

7. CONCLUSION AND SUMMARY

Template matching is a method of image analysis that, given a reference object or template, identifies instances of it within a larger target scene. While researchers have been developing such techniques for decades, recent advances in both feature-based and machine learning-based matchers have succeeded in making these algorithms faster, more accurate, or both. However, template matching remains subject to two longstanding problems: (a) computational cost, particularly when classifying large numbers of similarly shaped templates, and (b) sensitivity to changes in pose, size, or appearance. The former issue largely affects feature-based methods, while the latter one is common to machine learning approaches. Future work in this area should focus on reducing the computational cost of creating and matching templates, while also enhancing robustness to changes of appearance, particularly in cases where only small numbers of training samples are available. Template matching has applications in a wide variety of image analysis tasks and can take on many forms. Some popular uses include the detection of objects in medical images and in aerial or satellite imagery, as well as quality control in industrial machine vision settings. Though much research in the field has recently focused on machine learning methods, feature-based methods continue to hold an important place, particularly as we continue to increase computational efficiency. As computer vision and image processing continue to evolve, it is worthwhile to stay apprised of ongoing work in this area, as some of these template matching strategies will continue to play an important role or serve as the foundation for future refinement.

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