Optik 127 (2016) 5430–5438

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Original research article

An evolutionary approach for image retrieval based on lateral inhibition

Bai Li*

College of Control Science and Engineering, Zhejiang University, Hangzhou 310027, PR China

ARTICLE INFO

Article history:
Received 18 January 2016
Accepted 19 February 2016

Keywords:
Image retrieval
Lateral inhibition
Numerical optimization
Evolutionary algorithm
Artificial bee colony algorithm

ABSTRACT

Image retrieval refers to searching for specific pattern when browsing digital images in large databases. It is a fundamental topic in visual pattern recognition. The original image retrieval scheme is converted into a 2-dimensional optimization problem, during which image enhancement, a preprocessing step, is implemented to ease the template matching procedure. Image enhancement is achieved via lateral inhibition. Fundamental issues in this topic are investigated in this paper: (1) whether it is sensible to adopt an evolutionary algorithm to search for the best-match result, given that the concerned optimization problem has merely two dimensions; (2) how lateral inhibition takes effect to facilitate image retrieval. According to our comparative experimental results, there is no evidence that indicates lateral inhibition makes any subtle effort to ease the best-match optimization process. This paper also provides theoretical analyses regarding the evolutionary algorithm adopted.

1. Introduction

Image retrieval refers to the action of browsing and searching for digital images in large databases [1]. The incessant developments in image capturing devices and social media have led to an increase in the size of digital image collection, further aggravating the challenges to manual image retrieval in a variety of fields, including remote sensing [2–5], disease diagnosis [6–9], archive management [10,11], crime prevention [12,13], social networking service [14–16], etc. Numerous image retrieval methodologies have been developed and investigated, most of which have been broadly classified into two groups, namely, text-based and content-based methods: text-based methods are featured by the utilization of text descriptors to annotate images [17]; content-based methods aim to index images by their visual content (e.g., color, texture, shapes) [18]. This study focuses on content-based image retrieval.

How to search for a perfect match between a pre-define template and a candidate test image in the database is a critical issue in image retrieval. Given some specific similarity measurement criterion, evolutionary optimizers have been prevailing proposed to search for best-match solutions, e.g., chaotic quantum-behaved particle swarm optimization algorithm [19], Cauchy biogeography-based optimization algorithm [20], chaotic differential search algorithm [21], particle chemical reaction optimization algorithm [22], electimize approach [23] and imperialist competitive algorithm [24]. However, research studies in this community have been focusing overly on the computational efficiency of the optimizers, disregarding evaluating the entire approach in real-world problems [25,26]. As a remedy for the limitations in previous studies, this work provides in-depth analyses on the efficiency of evolutionary algorithms and the performance of lateral inhibition process to facilitate image retrieval.

The remainder of this paper is organized as follows. In Section 2, lateral inhibition based image retrieval model and our adopted optimizer are introduced. Simulations results are reported in Section 3, followed by detailed discussions in Section 4. Conclusions are drawn in Section 5.

2. Image retrieval scheme formulation

Image retrieval concerns about locating a given template image in a test image such that they best match each other. In this section, the image retrieval scheme is converted to a numerical optimization problem, during which an image enhancement process is implemented to ease the subsequent matching procedure.

2.1. Image matching principle and similarity measurement

Assuming that both the template image and the test image are described in gray-scale pixels, we describe the template image in a

* Tel.: +86 15700080810.
E-mail addresses: libaioutstanding@163.com, libai@zju.edu.cn

http://dx.doi.org/10.1016/j.ijleo.2016.02.056

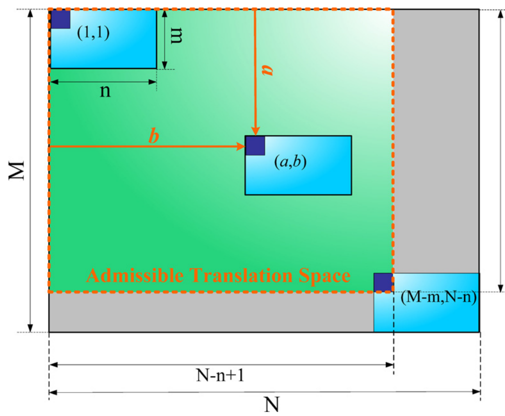

Fig. 1. Schematics on template translation. In this particular case, integer $a \in [1, \mathrm{M}-\mathrm{m}+1]$, and integer $b \in [1, \mathrm{N}-\mathrm{n}+1]$.

matrix form $\mathbf{temp}_{m\times n}$, wherein each element $\mathbf{temp}(\cdot,\cdot)$ records the gray level of the corresponding pixel location [5]. This induces that $\mathbf{temp} \in \mathbb{Z}^{m\times n} \cap [0, 255]^{m\times n}$. Similarly, the test image is described by matrix $\mathbf{test}_{M\times N} \in \mathbb{Z}^{M\times N} \cap [0, 255]^{M\times N}$. Now the original image retrieval problem becomes seeking for specific translations of $\mathbf{temp}_{m\times n}$ that maximize the similarity between $\mathbf{temp}$ and matrix

$$\begin{bmatrix} \mathbf{test}(a,b) & \cdots & \mathbf{test}(a, b+n-1) \\ \vdots & \ddots & \vdots \\ \mathbf{test}(a+m-1, b) & \cdots & \mathbf{test}(a+m-1,\ b+n-1) \end{bmatrix},$$

in which a denotes horizontal translation, and b denotes vertical translation of $\mathbf{temp}_{m\times n}$ (Fig. 1). The well-known normalized cross correlation (NCC) criterion [5] is adopted to measure the similarity according to the translation pair (a, b):

$$NCC(a,b) = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n}[\mathbf{temp}(a+x-1, b+y-1)\cdot \mathbf{test}(x,y)]}{\sqrt{\sum_{x=1}^{m}\sum_{y=1}^{n}[\mathbf{temp}^2(a+x-1, b+y-1)]}\cdot\sqrt{\sum_{x=1}^{m}\sum_{y=1}^{n}[\mathbf{test}^2(x,y)]}}. \quad (1)$$

It is easy to see that $NCC(\cdot,\cdot) \in [0, 1]$, and the optimal translation pair (a^*, b^*) would render $NCC(a^*, b^*)$=1.

2.2. Image enhancement via lateral inhibition

Image enhancement is implemented to facilitate the subsequent image matching process. This subsection involves image enhancement via lateral inhibition.

Lateral inhibition principle was discovered by Hartline and Graham in a limulus vision experiment, and this concept was introduced for digital image processing later [27]. Specifically, in our adopted lateral inhibition model [19], an original gray-scale image is denoted as $\mathbf{I}_0$ and the enhanced one is denoted as $\mathbf{R}$. Lateral inhibition is implemented according to

$$\mathbf{R}(x,y) = \mathbf{I}_0(x,y) + \sum_{i=-\mathrm{A}}^{\mathrm{A}}\sum_{j=-\mathrm{B}}^{\mathrm{B}} \alpha_{ij}\cdot \mathbf{I}_0(x+i, y+j), \quad (2)$$

where $\mathbf{I}_0(x, y)$ refers to the original pixel gray level at (x, y), $\mathbf{R}(x, y)$ denotes the enhanced pixel gray level, α_{ij} is an inhibition weight parameter, A and B determine the inhibition scale. There are various

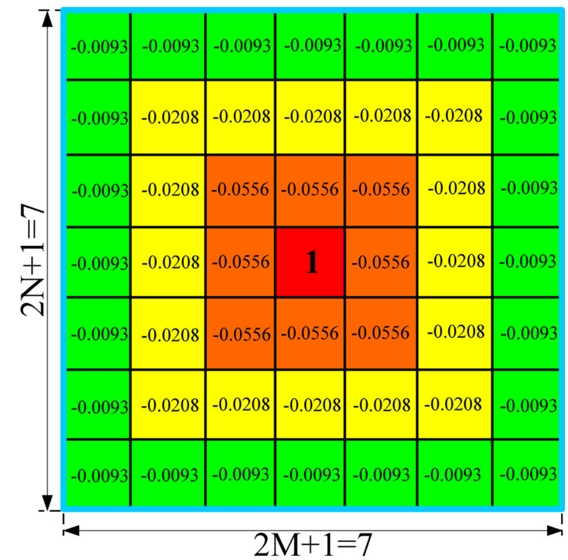

Fig. 2. Schematics on inhibition weight matrix based on the ring-like restrictions in Ref. [27] and M = N = ρ = 3.

ways to select α_{ij}, but the following requirement should be satisfied for balanced inhibition energy:

$$\sum_{i=-\mathrm{A}}^{\mathrm{A}}\sum_{j=-\mathrm{B}}^{\mathrm{B}} \alpha_{ij} = 0. \quad (3)$$

This present work adopts the definition of inhibition weight matrix in Ref. [27], wherein $[\alpha_{ij}]_{(2\mathrm{A}+1)\times(2\mathrm{B}+1)}$ is square and forms ρ rings (i.e., A = B = ρ). Specifically, each element α_r along the rth ring is defined as

$$\alpha_r = \begin{cases} 1 & \text{if } r = \rho \\ \dfrac{-1-r}{4(\rho+2)(\rho-1)(\rho-r)} & \text{if } r \le \rho - 1 \end{cases}. \quad (4)$$

Note that Eq. (3) holds true constantly according to the restrictions in Eq. (4). An instance under the condition that ρ = 3 is depicted in Fig. 2.

2.3. Best-match location search via an evolutionary algorithm

This subsection is about how to find the very translation pair (a^*, b^*) that maximizes $NCC(\cdot,\cdot)$. An evolutionary algorithm, namely, artificial bee colony (ABC) algorithm, is adopted to seek for (a^*, b^*).

In ABC algorithm, the bee swarm mainly consists of two groups, namely employed bees and onlooker bees [5]. Employed bees are responsible for global exploration and onlooker bees for local exploitation. Some well-known studies alleged that ABC algorithm is good at global exploration but poor at local exploitation [28–30], but they failed to fully understand the local exploitation stage in ABC. In more detail, prevailing research studies believe that the local search intensity in the conventional ABC algorithm is not so delicate as to meet high-accuracy search demands (e.g., the self-adaptive ABC variants [31–39]). But those studies may have disregarded roulette selection, which plays a critical role in sorting qualified candidates (i.e. employed bees) in preparation of local exploitation. Suppose there is one employed bee that is significantly superior to all the rest candidates (regarding solution quality), it is very likely that all the onlooker bees would crossover & mutate around that employed bee, because the probability to follow any other employed bee is significantly smaller. Although not being delicate in crossover & mutation, yet local exploitation is enhanced via more trials. Thus to criticize the local search capability of ABC