A Survey on Evolutionary Computation for Computer Vision and Image Analysis: Past, Present, and Future Trends

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Abstract—Computer vision (CV) is a big and important field in artificial intelligence covering a wide range of applications. Image analysis is a major task in CV aiming to extract, analyze and understand the visual content of images. However, image-related tasks are very challenging due to many factors, e.g., high variations across images, high dimensionality, domain expertise requirement, and image distortions. Evolutionary computation (EC) approaches have been widely used for image analysis with significant achievement. However, there is no comprehensive survey of existing EC approaches to image analysis. To fill this gap, this article provides a comprehensive survey covering all essential EC approaches to important image analysis tasks, including edge detection, image segmentation, image feature analysis, image classification, object detection, and others. This survey aims to provide a better understanding of evolutionary CV (ECV) by discussing the contributions of different approaches and exploring how and why EC is used for CV and image analysis. The applications, challenges, issues, and trends associated to this research field are also discussed and summarized to provide further guidelines and opportunities for future research.

Index Terms—Artificial intelligence (AI), computer vision (CV), evolutionary computation (EC), image analysis, image processing, pattern recognition.

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I. Introduction

COMPUTER vision (CV) is an important and well-established research field that studies the use of machines and/or computers to mimic human vision systems and acquire, extract, understand, and analyze information from images and videos [1]. CV has many fundamental applications in various fields, such as security, remote sensing, engineering, biology, and medicine [2]. Image analysis is a major task in CV that aims to extract and analyze meaningful information from images. A wide range of CV and image analysis tasks, such as image segmentation, image feature extraction, image classification, face recognition, object detection, and object tracking, have been studied for decades [3]. However, these tasks are still very challenging due to a number of reasons, such as data complexity, computational cost, low interpretability, lack of sufficient labeled data, high data dimensionality, and high variation across images. Therefore, CV is still a very rapidly developing area, where many new research and techniques are being proposed to effectively solve different tasks.

Artificial intelligence (AI) covers a variety of techniques that simulate human intelligence to solve different tasks [4]. Evolutionary computation (EC) includes a family of population-based techniques under the big umbrella of AI [5]. Typical EC techniques are evolutionary algorithms, swarm intelligence and others [6]. EC techniques have successfully solved many tasks related to engineering, finance, medicine, biology, management, business, manufacturing, and remote sensing [7].

Their population-based characteristics make EC techniques applicable and effective for many CV and image analysis tasks without requiring extensive domain knowledge while providing optimal or at least human-competitive solutions [8], [9]. EC techniques use one or more populations to search for optimal solutions through a number of generations guided by one or more fitness/objective functions. The population-based search provides EC techniques with powerful search ability and the problem-dependent fitness functions guides the evolutionary process toward promising solutions. Many image analysis tasks, such as image feature selection and extraction, typically have a large search space within which manually designed solutions and exact methods may not be effective. EC techniques can provide high-quality and sometimes human-interpretable solutions to these tasks. Furthermore,
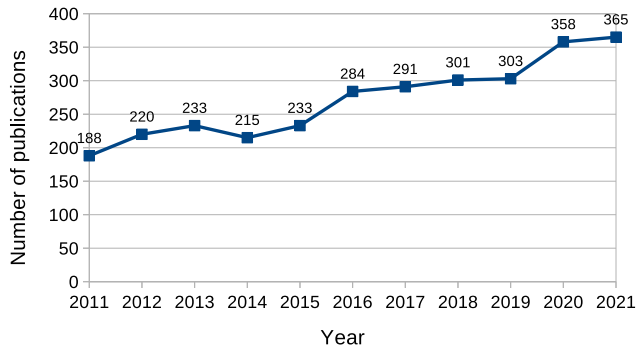
Fig. 1. Number of publications related to ECV from 2011 to 2021. The data is collected from Scopus with the keywords of "evolutionary" AND "CV" OR "image analysis." The total number of publications from 2011 to 2021 is 4955.

EC techniques can well handle problems that have multiple conflicting objectives by producing a set of nondominated solutions. These problems, which cannot be easily solved using exact methods, are known as multiobjective optimization problems.

Since the 1970s, EC techniques have been successfully applied to CV and image analysis [8]. This field has also been termed evolutionary CV (ECV) [9]. It is worth mentioning that Gustavo Olague published the first authored book on ECV in 2016 [9]. Recent research on ECV has been published in fully refereed journals and annually held conferences related to EC, CV, image processing, and pattern recognition. This is a fast-developing research field in which the number of publications has been gradually increasing in the recent decade, as shown in Fig. 1. There have been several "specialized" surveys related to this topic, but they focus on particular tasks/aspects. Nakane et al. [10] reviewed typical works on genetic algorithms (GAs), differential evolution (DE), particle swarm optimization (PSO), and ant colony optimization (ACO) for CV tasks, including image matching, visual tracking, face recognition. However, that survey mainly focuses on applications and ignores other important EC methods including genetic programming (GP) and evolutionary multiobjective optimization (EMO). Cagnoni and Zhang [8] discussed questions, issues, challenges and future directions of EC for CV and image processing. However, there has been no comprehensive survey covering all recent ECV techniques. Therefore, this article fills this gap by providing a comprehensive survey on this topic.

This survey reviews the main trends and algorithms based on EC techniques for CV and image analysis, dealing with edge detection, image segmentation, image feature analysis, image classification, object detection, and other tasks, according to a task-based taxonomy. This field is developing very fast and many works on this topic have been published recently. Fig. 1 summarizes the number of total publications from 2011 to 2021 on EC for CV and image analysis extracted from Scopus.[1] This survey paper reviews over 150 publications from databases, such as IEEE Xplore, ACM Digital Library, Scopus, Springer, and Google Scholar. The selected publications meet at least one of the following criteria: 1) they are
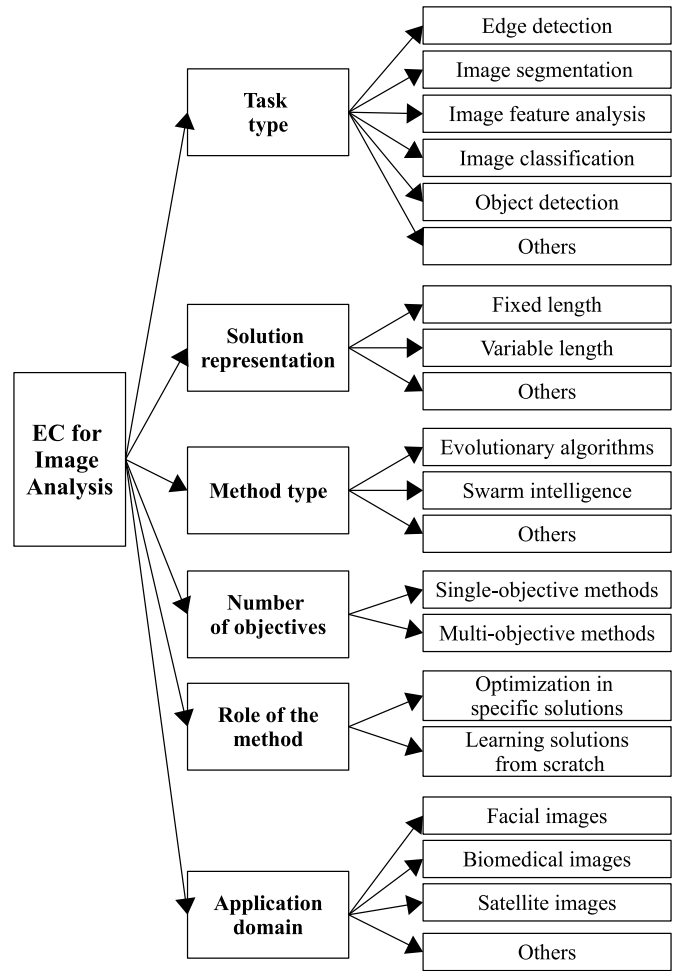
Fig. 2. Categories of existing EC methods for image analysis.

published in international journals and major conferences with high reputation and relevance in the last ten years (from 2012 to 2022); 2) they have been frequently cited; and 3) they are from well-recognized researchers or research groups in this field. Specifically, the survey paper includes over 140 publications from 2012 to 2022 and about 100 publications from 2017 to 2022. The survey provides a comprehensive overview of these works, summarizes the application areas, challenges and issues, and highlights future research directions.

II. TAXONOMY AND SCOPE

Existing EC approaches to CV and image analysis, as shown in Fig. 2, can be categorized into the following groups based on different criteria, i.e.,
1) edge detection, image segmentation, image classification, object detection, etc., according to *the task type*;
2) flexible variable-length representation and fixed-length string or vector-based numeric representation, according to *the solution representation*;
3) GAs, GP, PSO, ACO, DE, EMO, etc., according to *the method*;
4) single-objective methods and multiobjective methods, according to *the number of objectives*;

TABLE I
SUMMARY OF EC APPROACHES TO IMAGE ANALYSIS

Task	EC-based approach	References
Edge detection	Optimise existing methods	[11–15]
	Construct solutions from scratch	[16–23]
Image segmentation	Threshold-based methods	[24–38]
	Region-based methods	[39–43]
	Clustering-based methods	[44–50]
	Classification-based methods	[51–62]
	Others	[63–65]
Image feature analysis	Feature selection	[66–83]
	Feature extraction and learning	[5, 84–106]
Image classification	Evolving NN-based Methods	[107–126]
	Evolving non-NN-based Methods	[127–149]
Object detection	Optimising object detection systems	[150–158]
	Automatically evolving detectors	[159–166]
Others	Interest point detection	[167–170]
	Image registration	[171–174]
	Remote sensing image classification	[175–178]
	Object tracking	[179–181]

5) optimization of specific solutions/models and learning/constructing models from scratch, according to *the role of the EC method*;

6) facial image analysis, biomedical image analysis, remote sensing/satellite image analysis, etc., according to *the application domain*.

This article follows a task-based taxonomy for a better understanding of how EC is used to solve different tasks, including edge detection, image segmentation, image feature analysis, image classification, and object detection, which are representative CV and image analysis tasks. A summary of the reviewed works on EC for these tasks is listed in Table I.

EC techniques have also been applied to other CV tasks, e.g., video games [182], image retrieval [183], change detection [184], or image reconstruction [185]. Due to the page limit, those works cannot be covered in this survey. Also notice that this article focuses on CV and image analysis, while image processing tasks, such as image enhancement, image restoration, and image compression are beyond the scope of this article. As well, this review does not include all the CV tasks, since the applications of EC methods to some of them are very limited.

III. EDGE DETECTION

Edge detection is the task of finding or detecting discontinuities of pixels in the image. A simple example solution is to compare the value of the current pixel with the values of its neighboring pixels from different directions to approximate the pixel value gradient. If it changes significantly, the current pixel will possibly be an edge pixel. Edge detection is an important task in CV to obtain low-level image features for many image analysis tasks, such as object detection and image segmentation. However, due to the complex background and noise in images, edge detection is challenging. EC techniques applied for edge detection are shown in Fig. 3.

ACO is the most commonly used method for edge detection using a graph-based representation. An image can be represented by a graph where a node represents a pixel. Ants can move from one node to another node and mark the node by increasing the corresponding cell in a "pheromone" matrix.
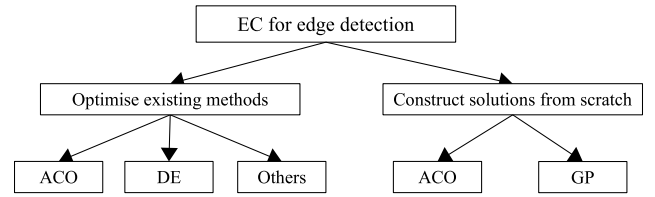

Fig. 3.   EC techniques used for edge detection.

Edges can be detected by setting a threshold on the pheromone deposited by ants. In the ACO methods for edge detection, the movement of ants and the pheromone matrix updating are the main operations. Early works on ACO for edge detection can be found in [19] and [20], that present different strategies of moving ants. Kumar and Raheja [21] applied an advanced version of a bilateral filter to suppress image artifacts and used ACO to detect edges. The results show that guided image filtering can improve the ACO-based edge detection results by detecting some nonprominent edges. Pajouhi and Roy [22] applied ACO to edge detection and implement the ACO algorithm using memristive networks. The edge detection process includes three steps, i.e., filtering, image enhancement, and edge detection. In ACO, each ant can move to four neighboring directions during the search process.

Instead of searching from scratch, ACO has also been used to improve the results obtained by traditional edge detection methods. Lu and Chen [12] applied ACO to repair broken edges in the results obtained by two traditional edge detectors, i.e., Sobel and Canny. This method places ants where the edges break to extend edges based on four moving policies to reduce search redundancy. This method is effective and efficient in improving edge detection performance. Sengupta et al. [11] proposed an ACO method for skin lesion edge detection by searching for edge contours in the results generated by Canny, Sobel or Prewitt. Combining ACO with Canny achieves the best results on three skin lesion images.

Besides ACO, GP can automatically construct models that classify pixels into the edge or nonedge groups or identify edge pixels from images. Fu et al. [16] developed a GP method with a new function set and a new program structure to evolve tree-based edge detectors on natural images. The evolved edge detectors mark a pixel as edge or nonedge based on a predefined threshold. The results show that the automatically constructed edge detectors are very effective. Fu et al. [17] developed an unsupervised GP method that do not require ground truth (training) images to automatically evolve edge detectors. This method uses a special tree structure, new function and terminal sets to evolve programs to classify pixels. It uses an energy function based on the average of the image gradients and the sum of image gradients as the fitness function. This method achieves significantly better results than a baseline GP method and the Canny edge detector. Fu et al. [23] applied GP to evolve the combinations of different Gaussian filters and their parameters for edge detection. This method uses a new fitness function based on the localization accuracy. Fu et al. [18] developed a GP method to evolve Bayesian programs that construct a high-level feature for edge detection.
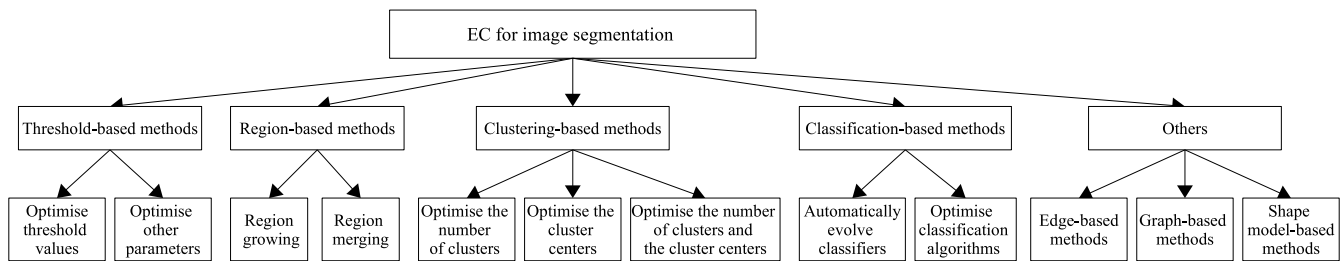
Fig. 4. Categories of existing EC-based approaches to image segmentation.

Other EC methods have been used for edge detection. Setayesh et al. [13] proposed two PSO methods with different constraint-handling strategies to detect edges in images. Specifically, a particle is encoded by a number of consecutive pixels representing the detected edges. This method achieves better performance than Canny and the robust rank order-based algorithm. In [14], DE is shown to be an effective method to find optimal coefficients of the cloning template in a cellular neural network (NN) for edge detection. Zheng et al. [15] proposed an improved DE method to generate better images as inputs of the generator of generative adversarial network (GAN) for edge detection. The fitness function of DE is the loss function calculated from the discriminator of the GAN. This method achieves good performance on two benchmark datasets. However, it requires a number of ground-truth images to train the models and is time consuming.

To sum up, EC techniques can automatically evolve edge detectors, construct graphs for edge detection, optimize the results produced by traditional detectors, and optimize the parameters of existing algorithms. ACO with a graph-based representation and GP with a tree-based representation are more popular than other EC methods for edge detection. The ACO-based methods are typically applicable to a single image. In most GP-based methods and the methods optimizing existing learning methods, training images are typically needed for learning the models/detectors. The learned models can be generalized to different images. However, the potential of EC-based edge detection methods has not been fully investigated on complex real-world images. The combinations of EC with existing powerful learning methods and the use of EC to automatically construct edge detectors from scratch will be potential future directions for the complex edge detection tasks.

IV. Image Segmentation

Image segmentation aims to divide an image into multiple nonoverlapping regions each of which is homogeneous [186]. It is an important step in image analysis, often necessary to solve higher-level tasks, such as image classification and object detection. Image segmentation is a difficult task that may involve complex or large search spaces, have high computational cost, and require rich domain knowledge. Typical image segmentation methods include region based, clustering based, threshold based, graph based, edge based, and classification based [53], [187], [188]. Existing methods can also be categorized according to the type of images, e.g., biomedical images, satellite images, and thermal images.

EC has been widely applied to image segmentation because of the powerful global search ability and low requirement of domain knowledge. Early works can be dated back to the 1990s [189], [190]. Liang et al. [53] reviewed typical works on EC for image segmentation before 2014. Mesejo et al. [191] provided a survey on metaheuristics-based methods for image segmentation with a special focus on the deformable model-based methods. However, at least in the last five years, there is no systematic review on EC methods for image segmentation. This section will fill this gap by discussing recent works, categorized into five major classes, i.e., threshold based, region based, clustering based, classification based, and others. The last group includes edge-detection-based methods [63], graph-based methods [64], and model-based methods [65]. The taxonomy is shown in Fig. 4.

A. Threshold-Based Image Segmentation Methods

One of the simplest and popular approaches to image segmentation are threshold-based methods. The main idea is to calculate the histogram or other statistics of images and subdivide the images by comparing predefined threshold values with the histogram/statistical values and then grouping similar pixels. For example, a region (segment) may be formed by pixels with histogram values larger than the threshold. For complex images, multiple threshold values are often needed to achieve good performance. However, it is difficult to manually set appropriate threshold values due to the large (search) space and the unknown optimal number of threshold values. EC methods have been widely used to find optimal threshold values by optimizing different objective functions.

DE has been the most popular method in this category in the last decade. Sarkar and Das [32] proposed a DE method to find multiple optimal threshold values based on the 2-D histogram of image pixels by maximizing the 2-D Tsallis entropy. This method achieves better convergence and performance than PSO and GA. Ali et al. [33] developed a synergetic DE method with opposition-based learning, a new mutation operator using the best base individual, and dynamic population updating. DE is used in two different threshold-based methods, i.e., to find optimal parameters for the Gaussian functions approximating the distributions of the pixel values by minimizing the probability error, and to find optimal threshold values by maximizing Kapur's entropy, respectively. Ayala et al. [34] developed a beta-DE method using a beta probability distribution to tune the control parameters during the evolutionary process. The DE method is used to optimize histogram threshold values in the Otsu-based image segmentation method [192] by maximizing the interclass variance. In [35], the beta DE method is applied to color image segmentation by maximizing Kapur's entropy

and the Tsallis entropy, respectively. Muangkote et al. [36] proposed a DE method with a new mutation operator for Otsu on pseudo images, real images and satellite images by optimizing the number of threshold values. Tarkhaneh and Shen [37] proposed a new DE method with an adaptive scheme and new mutation strategies based on different distributions to search for multiple threshold values in Otsu for medical image segmentation.

PSO is also popular for finding the optimal threshold values for image segmentation. Li et al. [25] proposed a quantum-behaved PSO method based on dynamic context cooperation for Otsu for medical image segmentation. This method achieves better results than several quantum-behaved PSO variants and traditional methods. Zhao et al. [26] proposed a modified PSO-based method with a fitness function based on the sum of the 2-D K-L divergences of different regions. PSO's performance is improved by using an adaptive factor in updating the position of particles to prevent premature convergence. This method achieves better performance than existing methods and PSO variants on color images. Suresh and Lal [27] proposed a PSO-based method adopting chaotic sequence mitigation and a cross-entropy or Tsallis entropy for satellite image segmentation. The performance of this method is investigated by evolving different numbers of threshold values. Li et al. [28] proposed a cooperative method and search space partitioning in quantum-behaved PSO to find optimal threshold values in Otsu for medical image segmentation. Mirghasemi et al. [29] proposed a PSO method to find optimal threshold values for images transformed by the 2-D discrete wavelet method. This method is effective for severely noisy image segmentation.

Other EC methods have been developed to find optimal threshold values. Zhao et al. [30] modified the continuous ACO by using a random spare strategy and chaotic intensification strategy to improve its search ability for image segmentation. Zhao et al. [31] further improved the ACO-based method by proposing a horizontal and vertical crossover search mechanism to reduce randomness. Extensive experiments confirm the effectiveness of the new components in ACO.

The problem of optimizing parameters or threshold values can be formulated as a many-objective optimization (MaOP) problem based on different objective functions. Elaziz and Lu [38] proposed a MaOP method based on the Knee-point-driven evolutionary algorithm (KnEA) to search for threshold values by simultaneously optimizing seven objective functions, e.g., Otsu measure, Kapur's entropy, fuzzy entropy, cross-entropy, etc. This method outperforms four MaOP methods on six images.

To sum up, most EC-based methods aim to find optimal threshold values based on Otsu. The most popular methods are based on DE and PSO due to the real-value representation that matches the problem well. The results show that the EC-based methods typically outperform the basic threshold-based image segmentation methods. In addition, different population initialisation and updating strategies and entropy-based fitness functions are often used in these EC methods to improve their performance. EMO algorithms have also shown

a promise in handling multiple objectives in threshold-based image segmentation systems.

B. Region-Based Image Segmentation Methods

Region-based image segmentation methods typically find regions with similar pixel values that satisfy predefined rules by preserving the spatial relationships between pixels. There are two types of region-based methods, i.e., region-growing methods and region-merging methods. A region-growing method is a bottom-up approach that uses some pixels as the seed pixels and grows the region by checking neighboring pixels. If the neighboring pixels meet predefined rules, they will be grouped into the same region as the seed pixel. The region merging method, instead, is a top-down method that splits an image into small regions and then merges these regions according to predefined rules. EC techniques have been used to optimize both region-growing and region-merging methods.

In the region growing-based image segmentation methods, EC techniques have been used to find optimal initial seed pixels. Xie and Bovik [39] applied GA to select seed pixels by optimizing between-class variance and use the self-generating neural forest to generate rules for growing regions. A new strategy is used to adaptively determine the number of seed pixels. This method achieves better performance than other clustering-based image segmentation methods. Gong and Zhou [40] proposed a DE method with a fitness function integrating within-superpixel error, boundary gradient, and a regularization term. This method uses DE to find the optimal differential lengths along the vertical and horizontal directions to obtain optimal seeds. Nearest-neighbor is employed to group pixels into small regions. This method shows the powerful global search ability of DE.

In region merging-based segmentation, EC techniques have been used to evolve rules or select regions for merging. Lee et al. [41] proposed a PSO-based method for color image segmentation based on saliency maps. This method consists of four steps, i.e., color quantization, feature extraction, small-region elimination, and region merging. PSO is used to optimize two threshold values for determining the difference between two regions based on the features extracted for region merging. This method provides better color image segmentation results than four other algorithms. Rogai et al. [42] applied GA with a real-value encoding to optimize the parameters for a fuzzy logic information fusion method that can score regions produced by a segmentation step and merge those regions to form the final segmentation results. In addition, an ACO-based method is proposed to search for the fuzzy rules for region selection. Both methods provide satisfactory results, ACO being more efficient than GA. Liu et al. [43] proposed an EMO method to merge a set of regions by simultaneously optimizing color similarity and texture similarity.

To sum up, in both region-growing and region-merging-based methods, EC techniques have been developed and employed in multiple ways, i.e., selecting the seed pixels, optimizing parameters, and evolving region-growing or region-merging rules. These methods use different representations and problem-dependent fitness functions. The promising results

demonstrate that EC methods are very flexible and easy to adapt to the problem. However, region-based image segmentation methods have not yet thoroughly explored both the potential of EC methods to improve the search mechanisms and possible hybridizations with other existing methods.

C. Clustering-Based Image Segmentation Methods

Clustering-based methods aim to group pixels into different clusters that have low intercluster and high intracluster similarity to achieve image segmentation. Clustering-based methods are a kind of region-based image segmentation methods using techniques, such as K-means clustering, meanshift, and fuzzy C-means. In these methods, prior knowledge is often needed to set the number of clusters. In addition, the initial cluster centroids are often selected randomly, which affects the performance and the stability of the method. To address these limitations, EC techniques have been proposed to improve the image segmentation performance by finding the optimal number of clusters and/or the optimal initial cluster centers.

Khan et al. [46] proposed a DE method to search for the optimal number of clusters in a spatial fuzzy C-mean clustering method for image segmentation. The DE method is improved by introducing a mutation operator based on an archive and an opposition-based population initialisation strategy. The fitness function is based on the average ratio between fuzzy overlap and fuzzy separation. This method outperforms several image segmentation methods.

EC methods have been used to find good initial cluster centroids for image segmentation. Khan and Jaffar [44] apply a self-organizing map to generate the initial set of clusters and propose a GA method with an opposition-based population initialisation strategy to evolve clusters in the fuzzy C-means method for color image segmentation. In GA, a chromosome is encoded by a string of $3 \times k$ real values, representing k cluster centers, each represented by three color channels. The fuzzy C-means clustering method groups all pixels into the corresponding clusters, and the cluster compactness and separation are optimized by the GA. This method achieves better performance than eight other methods in terms of qualitative and quantitative results. Singh [45] applied PSO to evolve cluster centers for image segmentation in a sunflower leaf disease detection system. Zhao et al. [49] proposed an EMO method for multiobjective clustering-based image segmentation. To fully handle noise in images, a noise-robust intuitionistic fuzzy set is defined and the EMO method is used to find the optimal intuitionistic fuzzy representation of the cluster centers while simultaneously optimizing the compactness and separation functions. Zhao et al. [50] proposed a method that builds a Kriging model to predict the fitness values in an EMO for finding cluster centers by simultaneously optimizing fuzzy compactness and separation. The results show that this method achieves competitive performance and short computation time.

EC methods have been used to evolve both the number of clusters and the initial cluster centroids. Das and Konar [47] applied a DE method to automatically find the optimal number of clusters and the cluster centers in the fuzzy c-means method for image segmentation. A DE individual is encoded by a vector of c_{max} and $d \times c_{max}$ real values, denoting the selection of clusters from a predefined maximal number c_{max} of clusters and their centers, represented by d-dimensional vectors. The fitness function is based on three different cluster validity indices. This method achieves better performance than the GA-based method and the fuzzy c-means method. Das and Sil [48] further improve the performance of the DE method in [47] by developing a kernel-based cluster validity index, i.e., the kernelised Xie-Beni index, as the fitness function and a new neighborhood topology. This method achieves better results than the GA-based and DE-based methods.

To sum up, EC methods, including GAs, PSO, DE, and EMO, are popular for optimizing clustering-based image segmentation methods. These methods optimize the number of clusters, initial cluster centers, or both. In these methods, a real-value vector-based representation is typically used to represent the solutions. In the segmentation system, fuzzy C-mean clustering is often used. The EC-based methods typically achieve better performance than traditional clustering methods, and avoid human intervention in setting the number of clusters and the cluster centers.

D. Classification-Based Image Segmentation Methods

Classification-based methods typically build models or classifiers that are able to associate each pixel in an image with different classes to achieve image segmentation. Unlike the majority of the aforementioned image segmentation methods, classification-based methods are supervised methods that need a set of training samples to learn the classifier models. In recent years, classification-based methods including NNs and GP have been very popular for image segmentation because of their powerful learning ability and excellent performance on complex images. EC-based image segmentation methods can be broadly classified into two types, i.e., using EC (mainly GP) to automatically evolve/construct classifiers/models and using EC to optimize existing classification algorithms.

GP is the main method that automatically evolves models/classifiers for image segmentation without relying on other segmentation or learning methods. Early works on GP for image segmentation can be found in [51], [52], and [53]. Liang et al. [54] proposed several GP methods to evolve classifiers from a set of features and assign each pixel to the foreground or the background. In [54], a GP method using raw pixel values and pixel statistics as inputs is developed to evolve classifiers for segmentation. This method achieves better results than four traditional methods including thresholding, region growing, clustering, and active contour models. Liang et al. [55] proposed a GP method using seven types of features including pixel values, histogram statistics, texture features, Fourier power spectrum, and Gabor features as the terminal set. The GP method using pixel values achieves the best results on texture images while using the Gabor features achieves the best results on two other datasets. Liang et al. [56] proposed multiobjective GP methods to evolve solutions with a good balance between the program/solution complexity and the classification accuracy for figure-ground image segmentation. Liang et al. [57] also propose the StronglyGP method featuring an image processing layer, an image segmentation layer and a post-processing layer to automatically evolve image segmentation solutions consisting of image operators. The

StronglyGP method achieves better performance than three GP variants that use a co-evolution mechanism and a two-stage learning strategy to evolve combinations of operators in each layer.

EC techniques have been applied to optimizing NN-based image segmentation methods. The NN-based methods, particularly convolutional NNs (CNNs), have become popular for image segmentation in recent years. However, these methods have limitations, such as having a large number of parameters and requiring rich domain knowledge to design the architectures of NNs. EC techniques can address these limitations by automatically searching for the best NN models for a specific task. Zhou et al. [58] proposed the ECDNN method to find less important filters and prune these filters for compression of deep NNs (DNNs) for biomedical image segmentation. This method optimizes the loss of DNNs and the number of parameters simultaneously. ECDNN can improve the segmentation performance by using more efficient DNNs. Hassanzadeh et al. [59] proposed an evolutionary DenseRes model using GA to automatically search for U-Net architectures based on Dense and Residual blocks. This method outperforms several manually or automatically designed U-Nets on six datasets for medical image segmentation. Hassanzadeh et al. [60] proposed the EvoU-Net method using GA to evolve small networks based on U-Net for medical image segmentation. EvoU-Net outperforms U-Net and AdaResU-Net using significantly smaller models. Wei et al. [61] proposed the Genetic U-Net method using GA to automatically design U-Net based on several building blocks, such as ResNet and DenseNet blocks for retinal vessel segmentation. Lima et al. [62] designed a grammar to define the building blocks of U-Net and propose the dynamic structured grammatical evolution to automatically evolve U-Nets for edge detection and image segmentation.

To sum up, the classification-based methods typically use GP to automatically evolve models/classifiers and use EC-based methods to optimize CNN-based models. The GP-based methods typically find easily interpretable tree-based models consisting of functions and terminals to group pixels into different classes. The EC-based CNN methods aim to find promising CNNs to achieve an effective image segmentation by addressing limitations of existing CNNs. Unlike other image segmentation methods, classification-based methods are supervised learning methods that use a set of training images to learn models. Classification-based methods are often more effective for complex images including natural images and medical images compared to other types of methods [36], [50]. EC methods have shown potential in deriving classification-based methods for image segmentation, but there is still room for research, including exploring new solution representations, new applications, computationally efficient fitness evaluations, and multiobjective search mechanisms.

V. IMAGE FEATURE ANALYSIS

Image feature analysis is an important process in many image-related tasks. Images are typically represented by rasters of raw pixels that may contain both meaningful and useless
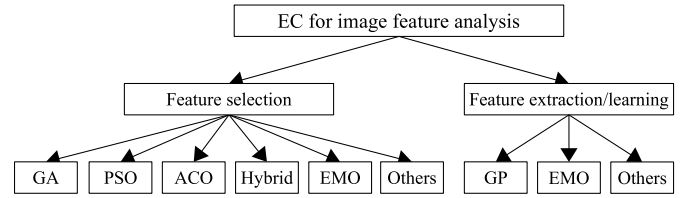

Fig. 5. Brief summary of existing EC methods for image feature analysis.

information. Image features are often used to achieve a compact image representation containing as much useful information as possible. Image feature analysis focuses mainly on analyzing the meaningful information/features of images. It typically includes feature selection, feature extraction, feature construction or a more general step, i.e., feature learning. The goal of image feature analysis is to improve the performance of a CV task, such as classification and recognition. This section reviews and discusses works related to image feature analysis. The taxonomy is summarized in Fig. 5.

A. Feature Selection

Typically, different types of features, such as color, histogram, shape, and texture features, can be extracted from images using different image descriptors. To represent images with sufficient information, a large number of features are usually desirable. However, some of those features can be redundant or irrelevant for the task at hand. Feature selection that selects the most relevant features from a set of pre-extracted ones [6] is a necessary step in image analysis. Feature selection becomes challenging when the number of features is large and there exist complex interactions between features. With a population-based search mechanism, EC methods have been widely used to select features for image-related tasks including image annotation, image classification, and image retrieval.

1) GA-Based Methods: With a binary string-based encoding/representation, GAs are naturally suitable for feature selection. Specifically, a 1 in a chromosome represents selecting the feature while 0 represents not selecting it. Lin et al. [66] proposed a GA method to select color and texture features for texture and object image classification. This method achieves better performance than traditional feature selection methods and other existing methods on four datasets. Alirezazadeh et al. [67] improved a GA-based method by introducing new crossover and mutation operators and using different types of hand-crafted features, including linear binary patterns (LBP) and histogram of oriented gradients (HOGs) features, for kinship verification. This method achieves better performance than several metric learning-based methods and feature learning-based methods on two datasets. Hemanth and Anitha [69] proposed three GA variants with different offspring generation strategies in the crossover and mutation operators to select texture features for classifying tumor images. Kirar and Agrawal [68] proposed a two-stage feature selection method where the Quantum GA method is employed to further reduce the number of features selected by a graph-theoretic filter method for motor imagery classification.

2) PSO-Based Methods: In recent years, PSO has become a popular image feature selection method. Naeini et al. [71] developed a binary PSO-based method to select features from pre-extracted spectral, textural, and structural features for object-based classification in satellite imagery. This method achieves better performance than using all features and the feature selection methods based on GA and ABC. Tan et al. [72] proposed a PSO method with two subswarms and corresponding search strategies to select features for skin cancer detection. This method outperforms a large number of EC-based and non-EC-based feature selection methods. Tan et al. [73] investigated different strategies, such as adaptive and random acceleration coefficients, subdimension search, and reinitialization in PSO and proposed two enhanced PSO methods for feature selection. An ensemble of classifiers is built to achieve effective skin cancer diagnosis. Kavuran [74] has developed a PSO method to select features extracted from pretrained deep CNN models (i.e., AlexNet and ResNet-50) for the classification of scanning electron microscope images. This method achieves good performance by finding a small number of features. However, this task is computationally expensive, so a small population size and a small number of iterations are used for PSO, which may lead to finding local optima.

3) ACO-Based Methods: ACO has also been widely used for image feature selection. Rashno et al. [75] presented two feature selection methods based on ACO and extreme learning machine using wavelet and color features for pixel classification of Mars images. The first method selects a feature subset for all the pixel classes, while the second method selects feature subsets for each pixel class. The results show that both methods are effective for reducing the running time, while the second method achieves higher accuracy. Sweetlin et al. [76] used ACO to select features for detecting lung disorders from computed tomography images. This method detects regions of interest (ROI) from images and extracts texture and geometric features from each ROI. The ACO method with a tandem run recruitment strategy is used to search for promising paths toward important features. This method achieves better performance than using all the original features. Devarajan et al. [77] proposed an ACO method to select features for a NN classifier for medical image segmentation. This method achieves better performance than Bayesian net and NN.

4) EMO-Based Methods: Feature selection often involves two objectives: minimizing the number of selected features and maximizing the performance measure, e.g., classification accuracy. EMO-based methods have been adopted for multiobject feature selection in image analysis. Mlakar et al. [79] presented a multiobjective DE method to select features for facial expression classification by minimizing the number of features and maximizing the classification accuracy. This method extracts HOG features from small facial regions of different sizes. The authors investigate two selection strategies, i.e., selecting emotion-specific features and the most discriminative features for all emotions. The effectiveness of these methods is verified on three face image datasets and compared with using all features and other existing methods. Liang et al. [80] proposed a single-objective GP method and two multiobjective GP methods to automatically select features from a set of

edge, color, and statistical features for image segmentation. The results show that the multiobjective GP methods achieve better performance using a smaller number of features.

5) Hybrid Methods: The hybridisation of EC methods has been proposed for image feature selection. Ghamisi and Benediktsson [82] proposed a hybrid method based on PSO and GA for feature selection in hyperspectral image analysis. This method achieves better performance than individual GA and PSO methods on two datasets. Thangavel and Manavalan [81] presented hybrid methods based on rough sets, GA and ACO to classify cancer images. The hybridisation of ACO and rough sets achieves better classification accuracy than the other hybrid methods. However, the total number of original features they consider is 22, which is quite small. Mistry et al. [83] embedded PSO with the concepts of micro-GA to select features for facial emotion recognition. This method outperforms PSO variants, classic GA and PSO, and other methods.

6) Other Methods: Other EC methods, such as DE and GP have also been studied for image feature selection. Ghosh et al. [78] developed a self-adaptive DE (SADE) method to select features for hyperspectral image classification. This method uses ReliefF to reduce the redundant features and a fuzzy KNN to evaluate the effectiveness of features. SADE achieves better performance than four other EC methods, i.e., GA, ACO, DE, and a combination of ACO and DE, in terms of accuracy and kappa coefficient. GP has implicit feature selection properties since the leaf nodes of the GP trees/programs represent the selected features. Ain et al. [70] proposed a GP-based feature selection method for skin cancer classification. This method achieves better performance than traditional methods.

To sum up, many EC-based methods including GA, ACO, PSO, EMO, DE, and GP have been developed to select image features for dealing with image-related tasks, such as image classification and image segmentation. In those tasks, the image features are typically manually extracted and the number of features is often not too large. Therefore, most existing methods deal with a small number of features, e.g., less than 300, thus a moderately sized set. Complex feature interactions can be handled by using different solution representations, search mechanisms and feature subset evaluation measures in different EC methods. This leads to using different types of EC methods to select features for different tasks. In addition, feature selection is a multiobjective optimization problem. EMO methods have shown a big potential in dealing with this problem. However, not so many works exist on EMO for feature selection in image analysis. Future research directions can focus on using EC to solve large-scale feature selection problems and multiobjective feature selection problems.

B. Feature Extraction and Learning

Feature extraction consists in extracting informative features from raw images to solve a task. Feature construction consists in building high-level features as compositions of the original ones. Unlike feature selection, feature extraction and construction can therefore generate new features to solve a task [5]. When a learning algorithm is used to learn features by

performing feature selection, extraction or construction from the original data, the task is also termed *representation learning* or *feature learning*. EC methods have been used for feature extraction and construction in image analysis. Existing methods focus mainly on optimising existing feature extraction methods, constructing features from pre-extracted features, or automatically learning models/solutions from scratch.

1) Optimization of Existing Feature Extraction Methods: Several EC methods have been developed to optimize the parameters or components of existing image feature extraction methods. Albukhanajer et al. [84] proposed a method based on NSGA-II to optimize three functionals in the trace transform and extract effective and robust features that simultaneously optimize two objectives: minimizing the within-class distance and maximising the between-class distance. The results show that this method can extract effective and noise-invariant features for image classification. Gong et al. [85] introduced an EMO method to optimize auto-encoder biases for sparse feature learning from images. This method simultaneously optimizes two objectives, i.e., the reconstruction error and the hidden units' sparsity, to learn useful sparse features from images. Albukhanajer et al. [86] proposed an EMO method to find multiple Pareto image features based on the trace transform with a good tradeoff between two different objectives (the within-class variance and between-class variance) and build an ensemble for object classification.

2) Automatic Evolution of Models/Descriptors for Feature Extraction: GP-based methods have been widely used for feature extraction and learning from raw images by automatically evolving solutions from scratch. In other words, the input of a GP system is an image, while the output is a single feature or a set of image features. Early works on using GP for evolving descriptors can be found in [87], [88], [89], and [90].

Texture is an important image property considered in EC-based applications. Al-Sahaf et al. [91] proposed a GP-based method to automatically evolve texture descriptors to extract rotation-invariant texture features from images. This method uses a tree-based representation, where the leaf nodes are pixel statistics computed from a small region of the image and internal nodes are arithmetic operators. The root node of the tree is a special one having a predefined number of child nodes to output a binary vector. The way of using the evolved GP trees for texture description is similar to LBP, i.e., transforming the pixel values by applying a rule and generating a histogram as features. The GP-evolved descriptor improves the classification performance over the traditional texture descriptors, such as LBP and its variants, on several texture classification tasks. However, the descriptors can only generate a fixed number of texture features. Therefore, in [92], an improved GP method is developed to extract a flexible number of features. Specifically, the method uses a root node accepting a flexible number of child nodes. This method shows its superiority in classifying several datasets in comparison to other texture descriptors. Al-Sahaf et al. [93] used a multitree GP method instead of a special root node to automatically evolve texture descriptors for classification, where only two instances per class are used in the learning process.

Rodriguez-Coayahuitl et al. [94] proposed a structured layered GP method for representation learning. This method uses two GP forests, i.e., an encoding forest and a decoding forest. The representation of the image data is learned from the encoding forest. Rodriguez-Coayahuitl et al. [95] investigated different population dynamics and genetic operators in GP-based autoencoders for representation learning. Rodriguez-Coayahuitl et al. [96] proposed a cooperative co-evolutionary GP method to automatically construct features from raw pixels. This method considers co-evolution at genotype, feature, and output levels. The results show that the co-evolution at the output level is the most effective.

In recent years, many GP methods with image-related operators have been developed to automatically learn/extract different types of image features. Liu et al. [97] proposed a multiobjective GP method with a multilayer representation to learn spatio-temporal features for action recognition. The features learned by GP are more effective than manually extracted ones and other machine-learned features for action recognition. Liu and Shao [98] presented a GP method to learn models that generate a low-dimensional representation for image hashing. This method evolves multiple GP trees to transform features into binary codes by optimising the empirical risk with a boosting strategy on the training set. This method achieves promising results on two large datasets. Bi et al. [99] investigated the use of Gaussian filters in GP for image feature learning for classification. In [100] and [101], two GP methods with well-developed image descriptors as functions are proposed to automatically learn global and/or local features for image classification. The methods are very effective in different image classification tasks. Bi et al. [102] proposed a GP method with a flexible program structure and many image-related operators to learn various types and numbers of features from raw images for classification. Similar to feature selection, feature extraction can also be formulated as a multiobjective optimization problem. In [103] and [104], multiobjective GP methods are proposed to automatically learn features for face recognition. These methods simultaneously maximize the classification accuracy and minimize the number of features.

A potential issue with using EC methods for automatic feature extraction is the high computational cost due to a large number of fitness evaluations. Bi et al. [105] propose a divide-and-conquer GP method using multiple small populations to learn features from small subsets of the original large training set. In [106], an instance selection-based surrogate method is developed to use multiple well-selected subsets of the large training set to perform fitness evaluation in GP for image feature learning. These methods can significantly reduce the training time without affecting, or even improving, their performance.

To sum up, in recent years, many EC-based methods, particularly GP-based methods, have been developed for image feature extraction and learning for different tasks including texture classification, image classification and action recognition. Compared with traditional methods, the EC-based methods require less domain knowledge and are easier to adapt to different tasks. These methods can find optimal parameter
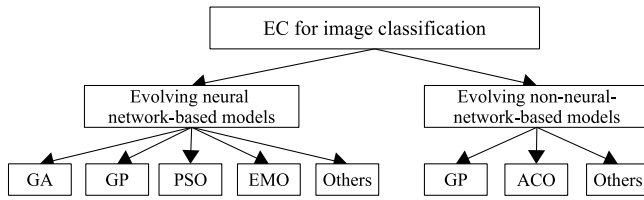
Fig. 6. Summary of EC approaches to image classification.

values of existing solutions or automatically evolve effective image descriptors for feature extraction from scratch. Therefore, EC-based feature extraction methods typically improve the performances of the tasks being solved. Image feature extraction can often be treated as the multiobjective problem of maximising the performance of the task and minimizing the number of features. However, very few EMO methods have been developed to address this problem. In addition, the high computational cost of using EC for image feature extraction needs further attention in the future.

VI. IMAGE CLASSIFICATION

Image classification is a fundamental and essential task in CV and machine learning. Image classification aims to assign an image to one out of a set of predefined classes based on its content. It has a wide range of applications to many important fields, such as medicine, remote sensing, biology, engineering, and business [5]. However, it is a difficult task due to a high image variability, caused by scale variations, deformations, occlusions, view-point changes, and rotations. The task becomes even more challenging when the image data are noisy, blurred and/or affected by other kinds of distortion. EC techniques have been widely applied to image classification. Existing EC-based methods can be broadly classified into four types, i.e., EC-based feature analysis for image classification, EC-based NNs for image classification, EC for automatically evolving image classification models from scratch, and others. EC-based feature analysis methods are reviewed and discussed in Section V. Therefore, this section focuses on the remaining categories, as summarized in Fig. 6.

A. EC for Evolving NNs for Image Classification

Using EC to evolve NNs has been proposed for many years [193]. This topic is becoming increasingly popular in the deep learning era when deeper NN architectures have popularized many important NN variants and components for image-related tasks, like CNNs. Recently, EC techniques have been successfully used to evolve deep CNNs for image classification. Recent related works can be found in survey papers [194], [195]. In this section, we review and discuss representative works focused on image classification.

1) Evolving NN Weights and/or Architectures: EAs are the most common methods for evolving DNN weights and architectures. Sun et al. [107] proposed the EvoCNN method that uses a variable-length encoding to evolve CNN architectures and connection weights. This method has shown its superiority in comparison with 22 existing methods on nine image classification datasets. Anaraki et al. [197] presented the CNN-GA method that uses GA with a variable-length representation to automatically evolve CNN architectures based on the idea of skip connections. CNN-GA achieves promising performance in terms of classification accuracy, number of parameters, and computation time. Chen et al. [108] proposed a GA method with a variable-length encoding scheme for evolving the architectures of deep convolutional variational autoencoders consisting of four different blocks. The evolved NNs are then trained and applied to image classification achieving performance competitive with nine autoencoder variants. O'Neill et al. [109] developed a GA method to automatically search all components, including feed-forward and DenseNet networks, employing a low-fidelity performance predictor for efficient search. This method can evolve different types of skip-connection structures in CNNs to improve the performance of DenseNet.

Real et al. [110] proposed the AmoebaNet-A method using a specific mutation operator for neural architecture search (NAS). This method discards the oldest models/individuals in the population and selects the newer models for evolution. This method obtains better results and runs faster than reinforcement learning methods. Zhang et al. [111] proposed an evolutionary one-shot NAS method with partial weight sharing to generate submodels from the one-shot model. New crossover and mutation operators are developed to facilitate weight sharing. This method achieves competitive performance with 26 state-of-the-art algorithms on ten datasets. Zhang et al. [112] proposed the reinforced I-Ching divination EA with a variable-length encoding for NAS. A reinforced operator is employed to improve the search efficiency. Li et al. [113] considered resource constraints in EC-based NAS methods by developing an adaptive penalty method for fitness evaluation and a selective individual repair operation. The model complexity is set as a constraint in order to find small models with high classification performance.

Besides GA, other EC methods including GP and PSO have been developed to find optimal architectures and/or parameters for CNNs. Suganuma et al. [114] proposed the CGP-CNN method with a tree-based representation for NAS based on standard convolutional operators or ResNet blocks. This method achieves high classification performance and low model complexity. Li et al. [115] applied quantum-behaved PSO to evolve deep CNNs by introducing a binary encoding. Gong et al. [116] proposed a co-evolutionary method along with backpropagation to search the parameters of DNN models for image classification. In co-evolution, the parameter learning task is decomposed into many small tasks for effective search. This method is better than the traditional parameter learning techniques in DNNs.

2) EMO for Evolving NNs: Evolving NNs can be formulated as a multiobjective optimization problem that simultaneously optimizes multiple potentially conflicting objectives, such as accuracy, model size, and complexity. EMO methods have been developed to optimize CNNs for image classification. Lu et al. [121] proposed the NSGANetV1 method for NAS by simultaneously optimising two objectives, i.e., the classification accuracy and the number of floating-point operations. This method achieves better performance than many manually designed or automatically evolved CNNs on several datasets.

Lu et al. [122] proposed the NAT method to automatically search subnets of CNNs based on NSGA-III. A surrogate model is built to predict model performance during the evolutionary search. NAT can find multiple subnets with a good tradeoff between different objectives that can be easily transferred to solve other problems. This method achieves outstanding performance on 11 datasets. Wen et al. [123] developed a two-stage EC-based NAS method that transfers the searched subnetworks from a source task to a target task. The knee-guided EMO is used as the search mechanism. The method demonstrates the power of evolutionary NAS in transfer learning. Zhu and Jin [124] proposed an EMO-based method to optimize the NN structures in federated learning. This method optimizes multilayer perceptron and CNN models with reduced communication costs. Zhu and Jin [125] developed an EMO-based NAS method under the real-time federated learning framework with the goals of maximising model performance and minimizing local payload. This method can effectively reduce computational and communication costs by using a double-sampling technique. Wang et al. [126] presented a multiobjective PSO-based NAS method, which simultaneously optimizes two objectives, i.e., classification accuracy and the number of floating-point operations.

3) Computation Efficiency in EC for Evolving NN: Using EC to optimize NNs is computationally expensive because it requires a large number of fitness evaluations. Therefore, recent research focuses on developing computationally cheap evaluation strategies. Zhang et al. [117] proposed an evolutionary NAS method that uses small sampled training data and a node inheritance strategy to reduce the computation cost of fitness evaluation. Lu et al. [118] proposed NSGANetV2, employing surrogates to predict the performance of CNN models during the evolutionary process. A selection method dubbed adaptive switching is proposed to automatically select one of four surrogate models for fitness prediction. Sun et al. [119] proposed a surrogate-assisted EC-based method for NAS by building an offline performance predictor based on random forest. This method achieves comparable performance with less computational cost than 18 methods. Wang et al. [120] proposed a new surrogate model based on SVM using a new training-data sampling method to assist PSO in searching for variable-length CNN blocks. This method achieves competitive performance by reducing training of CNN blocks by 80% during the search process.

To sum up, EC-based methods including GA, GP, and PSO have shown great potential in optimising CNN-based models for image classification. EC methods have powerful global search ability and a very flexible representation, suitable and effective for optimising complex CNN models. In recent years, this topic has become very popular and the CNNs evolved by EC methods have outperformed many well-known manually designed CNNs on several image classification datasets, including CIFAR10, CIFAR100, and ImageNet. Furthermore, EMO-based methods have been widely used to evolve CNNs by simultaneously optimising multiple objective functions. However, EC-based methods for evolving CNNs have some limitations. One issue is the high computation cost. Therefore, some attempts to improve computational efficiency have been based on methods like surrogates and training-data sampling

strategies. However, the potential of EC for evolving NNs has not been fully explored yet on many other types of image classification tasks and NN components or variants.

B. EC for Evolving Non-NN-Based Methods

1) Evolving Classifiers From Image Features: EC methods have been developed to automatically generate classifiers based on pre-extracted image features. The most commonly used methods are based upon GP. Choi and Choi [127] applied GP to classify nodules and non-nodules in computed tomography images using pre-extracted 2-D and 3-D features. This method achieves very high sensitivity. Ryan et al. [128] employed GP to evolve classifiers for detecting breast cancer in digital mammograms obtaining 100% sensitivity. Ghazouani [129] extracted geometric and texture features and proposed a GP method to perform classification of facial expression images.

GP is naturally suited for evolving binary classifiers but needs special designs/strategies to perform multiclass image classification. Smart and Zhang [130] proposed three GP-based classification strategies for multiclass object classification, namely, static range selection, centered dynamic range selection, and slotted dynamic range selection, which use different threshold values to determine the class labels according to the outputs of GP trees. Zhang and Smart [131] proposed a GP method with a fitness function that computes the overlap of the distributions of all possible pairs of classes for multiclass object classification using domain-independent features. The classification decision is based on multiple GP classifiers and normal probability density function. This method performs well on three datasets.

2) Evolving Classifiers From Raw Pixels: In the most common methods, GP evolves tree-like models from raw pixels to achieve image classification. Multitier or multilayer tree structures have been used in GP to evolve binary classifiers based on raw pixels. Al-Sahaf et al. [132] presented a two-tier GP method featuring an aggregation tier and a classification tier: the former focuses on detecting small image regions and extracting features while the latter is the image classifier. This method achieves high accuracy on four datasets while the learned classifiers/models show high interpretability. Lensen et al. [133] proposed the HOG-GP method for simultaneous region detection, feature extraction, feature construction, and image classification. Unlike the above methods, HOG-GP extracts features from the detected regions using the HOG descriptor. The method shows how GP can be used to extract high-level features using well-developed descriptors. Burks and Punch [134] combined a two-tier GP architecture with the genetic maker diversity algorithm and apply this method to automatically detecting active tuberculosis sites in X-ray images. Bi et al. [135] proposed a multilayer GP method that adds an image filtering layer in order to extract high-level features for image classification. Fan et al. [136] proposed a GP method to extract features using edge detectors, LBP, and fractal dimension functions for image classification. This method achieves performance competitive with a number of other GP methods on four image datasets.

GP has also been used to evolve end-to-end models for binary and multiclass image classification. Fan et al. [137] proposed a GP method that can automatically extract features using image filtering functions and image descriptors and select functions suitable for building image classifiers. This method also uses a new mutation operator that dynamically adjusts the sizes of trees, achieving promising performance on eight datasets. Bi et al. [138] proposed the IEGP method that, besides extracting features from raw images, also evolves ensembles of image classifiers built using those features in a single tree. This method achieves better performance than a large number of methods on 13 image datasets. Bi et al. [139] proposed the EvoDF method in which GP evolves tree-like models based on image feature-extraction operators and random forest ensembles. This method can evolve shallow or complex models by combining these operators effectively. The EvoDF method achieves better performance than several traditional and existing methods on reference datasets using only a small number of training images.

Other EC methods have been used to optimize classification from raw pixels. Plichoski et al. [140] developed a DE method to automatically select a subset of predefined image-processing and feature-extraction operators and the parameters of a face-recognition algorithm. This method uses a fixed-length binary-vector encoding in which 1 denotes selecting the corresponding operation and 0 denotes not selecting it.

3) Feature Learning and Emerging Topics: Most works on feature analysis using EC for image classification have been reviewed in Section V. This section will review more works that are not covered in Section V and emerging topics. Shao et al. [141] proposed a GP-based method to automatically learn image features that simultaneously minimizes the tree size and the classification error. This method uses image filters as functions to construct descriptors and achieves better performance than manually designed features and other two feature-learning methods on four datasets. Agapitos et al. [142] proposed a GP method with a filter bank layer, a transformation layer, an average pooling layer, and a classification layer, similar to deep CNNs, to automatically extract features from raw pixels for classifying digits. Olague et al. [144] proposed a brain programming (BP) method that uses a multitree representation to automatically evolve a set of descriptors to generate features within a hierarchical structure for classification. The BP method is further investigated in [143] under the scenario of adversarial attacks. The results show that BP is more robust against adversarial examples than deep CNNs on art media categorization tasks.

GP-based methods have shown great potential in image classification with a small number of training images. Al-Sahaf et al. [145] proposed one-shot GP to evolve classifiers directly from images and a compound GP for region detection, which facilitates feature extraction for binary image classification. This method only needs a few training images and achieves better performance than traditional methods. Bi et al. [146] proposed a GP-based method with a dual-tree representation and design an efficient and effective fitness function to improve the generalization performance of GP for few-shot image classification. This method achieves better

performance than popular few-shot learning methods under the 3-shot and 5-shot scenarios on nine image datasets. In [147], the poor generalization caused by using small training data is further addressed by developing a new multiobjective GP method to simultaneously optimize two objectives, i.e., the classification accuracy and a distance measure between instances (i.e., distances between instances from the same class and from different classes). The results show that GP simultaneously optimising these two objective functions achieves better results than GP optimizes only one objective function.

Transfer learning has also been investigated in EC to evolve non-NN-based models. Iqbal et al. [148] transferred the code fragments of GP trees evolved from one source dataset/task to improve the learning performance of GP on a target data/task. This method is focused on texture and object classification. Bi et al. [149] proposed a GP method with a multitree representation and a co-evolution learning strategy to learn features for simultaneously solving two image classification tasks. The knowledge of the two tasks is encoded as GP trees and explicitly shared during the learning process; this improves the performance of GP when the training set is small.

To sum up, evolving non-NN-based models using EC methods is also promising in many image classification tasks. The majority of these methods are based on GP, which typically evolves tree-based models with different types of operators. Compared with the CNNs, the models evolved by GP are typically less complex and more interpretable. In addition, GP has shown a promise in learning effective models for image classification using a small number of training images, while CNNs typically need a large training set. In recent years, some new ideas, such as surrogate functions, transfer learning, and few-shot learning, have been investigated in the GP-based methods for image classification. Future research can further explore the above aspects and focus on some less explored directions such as developing GP with deep structures, and investigating more computationally efficient GP methods.

VII. OBJECT DETECTION

Object detection is a fundamental task in CV and image analysis. It regards not only detecting objects but also locating their position in the images. Thus, object classification and localization can be considered subtasks of object detection, which is therefore more complex than either subtask. Object detection has many important real-world applications such as detecting humans in self-driving vehicles. EC techniques have been successfully applied to object detection. Existing methods can be broadly classified into two categories, i.e., using EC methods to optimize an object detection system and using EC methods to automatically evolve detectors from scratch. Fig. 7 shows a simple taxonomy of these methods.

A. Optimizing Object Detection Systems

In an object detection system, EC methods can be used to optimize features, parameters, positions of objects, etc. Ganesh et al. [150] proposed an entropic binary PSO method to optimize an entropy map in an ear detection system. A threshold is used to perform classification
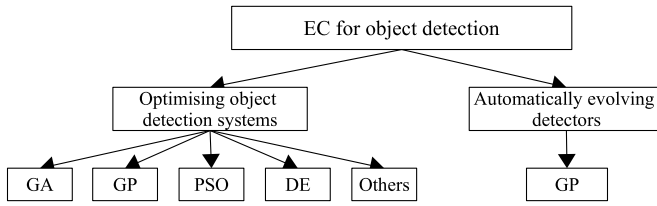
Fig. 7.   Taxonomy of EC approaches to object detection.

based on the optimized entropy map. This method achieves promising performance on four face image datasets. Abdel-Kader et al. [151] proposed a PSO-based method for eye detection and tracking. In this method, PSO is used to optimize parameters, such as the center point and the scaling factor of the deformable multiple template matching algorithm. Ugolotti et al. [152] optimized the model parameters in two model-based object detection systems, in one case using PSO and DE in the other. The two models solve two distinct tasks, i.e., human body pose estimation and hippocampus localization in histological images. Mussi et al. [153], [154] developed a real-time PSO-based method in CUDA that finds the locations of road signs based on the search of the parameters of the perspective transform of a set of key contour points and their shape and color information.

Salient object detection is a special case of object detection that only detects the most important object in an image and ignores other irrelevant ones. Singh et al. [155] proposed a PSO method to find the optimal weights associated to three features and obtain a saliency map for object detection. A fitness function evaluating the attention pixels and the background pixels is used to guide the PSO search. This method outperforms existing methods according to different performance measures. Iqbal et al. [156] proposed a learning classifier system-based method to evolve weights to linearly combine nine different feature maps for salient object detection. Afzali et al. [157] proposed a PSO method to find the optimal weights for combining nine feature maps with the goal of minimizing the error rate. This method achieves better performance than five other methods on various images. Moghaddam et al. [158] proposed a GP-based method to construct high-level features from low-level saliency features for salient object detection. The feature sets are divided into four subsets and a GP method is used to construct features from each of them, which are combined to obtain the final saliency map. Unlike the PSO-based methods, GP-based methods perform nonlinear combinations of the feature maps.

B. Automatically Evolving Detectors

EC methods have also been applied to automatically evolving detectors of objects in images. The main methods to evolve detectors are based on GP. Early works can be found in [159], [160], [161], and [162]. [163], and Zhang [163] proposed a new GP-based object detection method by investigating three feature sets, developing a new fitness function and a two-phase learning method. In the first phase, GP-based detectors are evolved and evaluated using a small subset of the training samples with the objective of maximising classification accuracy. In the second phase, the evolved detectors are further refined

by using all training samples with the objective of maximising detection accuracy. The results show that the two-stage GP method is more stable and effective than a single-stage GP method for object detection. Liddle et al. [164] proposed a multiobjective GP method simultaneously maximising true positive rate and true negative rate based on a two-stage learning scheme that detects shapes or coins in images. This method can evolve an effective diverse set of object detectors. Li and Shang [165] proposed a GP method to evolve a similarity measure for person reidentification. This method achieves better performance than a method based on the Euclidean distance. Olague et al. [166] applied the BP method [144] to automatically evolve a set of operators to generate the saliency map and combine them to achieve salient object detection. This method achieves a better performance than other EC-based methods and commonly used methods on two datasets.

To sum up, compared with image segmentation, image feature analysis, and image classification, there are fewer works on EC for object detection. Compared with these tasks, object detection is typically more difficult since it requires conducting both object localization and object classification. However, EC methods have shown great potential in both optimising existing object detection systems and automatically evolving object detectors. But the potential of EC-based methods for object detection has not been comprehensively investigated. Future possible research directions may be investigating EC-based methods for evolving NNs, new EC methods with powerful representations to evolve detectors, and fast EC methods for object detection. Furthermore, the applications of EC-based methods to well-known object detection tasks, such as COCO or real-world problems are desirable.

VIII. OTHER TASKS

EC methods have shown great potential in other image-related tasks, including interest point detection, image registration, remote-sensing image classification, and object tracking. In this section, we will provide a brief review of works that have used EC for such applications.

A. Interest Point Detection

Interest points detection implies detecting interesting points, such as corners, blobs, and edges that convey interesting or salient visual information. GP has been applied to automatically evolve interest point detectors in images. Most works are from Gustavo Olague's group. Trujillo and Olague [167] developed a GP method containing arithmetic functions and image operators, such as histogram normalization and Gaussian derivatives, to construct detectors from images. A new fitness function that measures detectors' repeatability, global separability, and information content is developed to guide the GP search. This method evolves two detectors, which are simpler but achieve better results than one hand-crafted solution. Trujillo and Olague [168] further investigated the GP-based interest point detection method by analyzing the effectiveness and robustness of 15 constructed detectors. The task of interest point detection often involves multiple potentially conflicting objectives, i.e., stability, point dispersion and

information content. In [169], a multiobjective GP method optimising the objectives of stability and point dispersion is investigated for interest point detection. Two new detectors are evolved and analyzed to show their effectiveness. Trujillo and Olague [170] developed a multiobjective GP method to simultaneously optimize three objectives, which measure stability, point dispersion and information content. The results show that the nondominated solutions found by GP outperform manually designed detectors.

B. Image Registration

Image registration is an important preprocessing task in many applications such as medical imaging. The task aims to align two or more images by finding an optimal transformation of the images in the geometric space. EC methods have been developed for image registration, in particular finding the optimal transformation, where most of the works are from Cordón, Damas, and their collaborators and can be found in the survey papers [171], [172]. In [173], a self-adaptive evolutionary optimization (SaEvO) algorithm is introduced to simultaneously search for the image registration solutions and the control parameters. Gómez et al. [174] presented several methods including a DE method to search for optimal parameters in a 3D-2-D silhouette-based image registration system. In the above methods, EC techniques have been used to find the optimal parameters of transformation models in image registration, achieving promising results. However, since EC techniques have flexible representations and powerful search ability and the EC-based applications to image registration have not been extensively investigated in recent years, there is still research potential in this direction.

C. Remote Sensing Image Classification

Remote sensing or hyperspectral image classification typically aims to classify each pixel in the images into different groups, not the entire image. Many EC-based methods have also been developed within this context, performing tasks like finding optimal cluster centers for the clustering-based methods, feature subset or band selection, and parameter optimization. Mai et al. [175] proposed a PSO-based method to optimize the cluster centers and parameters in the interval type-2 semi-supervised possibilistic fuzzy C-means clustering method for satellite image classification. This method is tested on the tasks of landcover classification and landcover change detection. The results show that this method achieves better accuracy than most of the methods to which it is compared. Wang et al. [176] proposed an ACO method with a binary encoding to simultaneously find optimal SVM parameters and select a subset of the 76 original features including Gabor wavelet, grey-level co-occurrence matrix (GLCM), histogram statistics. This method achieves better performance than other EC-based methods. Liu et al. [177] proposed four different EMO-based remote sensing image classification methods to prune ResNet by removing filters, simultaneously minimizing classifier complexity and maximising classification accuracy. Wen et al. [178] applied GP to evolve classifiers based on spectral, shape and texture features for cropland field classification

on very high resolution images. This method achieves better performance than five traditional classifiers on two datasets.

D. Object Tracking

Object tracking aims to track objects in a series of images/frames by locating the objects' positions. Typically, a target object is given and the task is to find its position in multiple consecutive frames. Kang et al. [179] proposed a hybrid gravitational search algorithm (HGSA) to search for the locations of objects by maximising a cosine-similarity function that evaluates the similarity between the target objects and potential objects in the image using features extracted by CNNs. This method improves the accuracy of a state-of-art SI-based object tracker. Song et al. [180] proposed a GP method to evolve detectors for tracking moving targets on a stationary background. This GP method uses pixels in a sliding window as terminals and a number of operators/functions to evolve the detectors/classifiers. The proposed method shows promise under different scenarios such as noise conditions. Yan et al. [181] proposed an EC-based one-shot object tracking NAS method to search for optimal trackers based on a pretrained supernet. This method is more effective and efficient than the original methods without NAS search.

IX. Applications, Challenges, and Trends

This section summarizes the application areas, the challenges and future trends of ECV methods. Due to the page limit, information regarding the software/tools/packages and datasets related with EC for CV and image analysis have been included in the supplementary materials.

A. Applications

Existing EC-based image analysis methods have been applied to a variety of areas, including
1) Facial image analysis, e.g., face recognition [104], facial expression classification [129], ear detection [150], and eye detection [151].
2) Biomedical image analysis, e.g., skin cancer classification [70], breast cancer classification [128], prostate cancer classification [81], brain tumor classification [69], lung nodule classification [198], leukocyte segmentation [199], retinal vessel segmentation [61], cell image segmentation [200], and ultrasound image segmentation [42].
3) Remote sensing image analysis, e.g., land cover classification [175], scene classification [177], cropland field classification [178], hyperspectral image classification [82], satellite image segmentation [27], and seasonal change detection of riparian zones [201].
4) Image analysis related to humans, e.g., action recognition [97], body pose estimation [152], and motion and human detection [180].
5) Agricultural image analysis, e.g., flower classification [202] and leaf disease detection [45].
6) Others, e.g., motor imagery classification [68], art classification [101], digit recognition [105], kinship verification [67], fish classification [203], and vehicle detection [160].

B. Challenges

Despite many successful EC applications to image analysis, there are still significant issues and challenges as follows.

1) Scalability: Scalability is a common issue in most EC-based methods for image analysis. In recent years, big data have become a trend in image analysis, where the number of images in the datasets is very large (see the datasets summarized in the supplementary materials). Some well-known image/object classification datasets include the CIFAR10, CIFAR100, and ImageNet datasets. For instance, CIFAR10/CIFAR100 comprises 60 000 32×32 color images and ImageNet more than 14 million images. There are also well-known large-scale image datasets for segmentation and object detection, such as the Berkeley Segmentation Dataset and Microsoft COCO. Dealing with such large datasets using EC-based methods is often time consuming and resource intensive. Powerful computing devices such as GPUs may shorten execution time, but the computational cost is still very high if a large number of fitness evaluations are conducted, as happens when the search space is very large and characterized by many local optima.

2) Representation: A careful design of representations is essential to the success of EC-based image analysis. Several different representations are used in EC methods, including string based, vector based, tree based, and graph based, allowing EC methods to solve a variety of image-analysis tasks. Even within the same specific task, EC methods may use multiple representations. For example, strings, vectors and graphs can be used as a representation for image feature selection [6]. Since representations are typically task-dependent, their design is challenging. In addition, they are highly related to the search space and the search mechanism, which are also key factors to a successful search. Due to their flexibility, however, there is still great potential for developing powerful EC representations for specific CV and image analysis tasks.

3) Search Mechanisms: The underlying search mechanisms are at the heart of EC methods. Search mechanism means evolutionary operators, heuristics, and/or strategies that can make the search toward good directions and alternately (close to) optimal/good solutions in a (more) effective and efficient way. A good search mechanism can better balance exploration and exploitation and find globally optimal solutions. Image analysis tasks are typically very difficult, requiring powerful search mechanisms. Some works improve the search mechanisms of EC-based image analysis methods [37], [69], [111]. EC methods are very flexible to be cooperated with other strategies, heuristics and operators to further improve their search. In addition, multiobjective search mechanisms are much less explored than single-objective ones in EC-based image analysis methods. Future work can consider these two directions to further explore the potential of EC methods in CV and image analysis.

4) Interpretability: Interpretability is very important in many image analysis tasks, such as biomedical image analysis. The most popular CV and image analysis methods in the last decade have been based on DNNs [195], including DNNs optimized or designed by EC methods. A well-recognized drawback of DNN-based methods is their "black-box" input/output mapping, often resulting in poor interpretability of their results. It is hard to explain how DNNs solve an image analysis task, e.g., why certain image features are selected/extracted and why the models are effective. Compared with DNNs, traditional methods relying on domain knowledge are typically more transparent and interpretable. However, traditional methods are affected by poorer performance, domain knowledge requirements, and poor flexibility. A tradeoff can be found by making the use of domain knowledge more flexible and automatic by using EC methods. A typical example is to use GP to automatically evolve models with image filters and operators [5], [141], which reduces the reliance on domain experts and improves the performance. More importantly, the models using image operators are more interpretable than DNNs. However, explainable AI using EC [204] is a topic on which research is just starting blossoming.

5) Computational Cost: Computational cost is an essential factor for EC-based image-analysis applications. Compared with random or exhaustive search methods, EC methods are by far less computationally expensive. In some cases, their powerful search ability makes them even faster than traditional CV methods. For example, in thresholding-based and clustering-based image segmentation methods, EC methods have shown their advantages in reducing computational cost while achieving results that are competitive with traditional methods [38], [50]. However, in many supervised learning tasks, such as image classification, EC methods may be computationally expensive. Some attempts to improve the computational efficiency of EC-based image analysis have used surrogates to predict fitness values [119] or a small subset of a larger training set [106] for fitness evaluation. However, this topic has seldom been explored and therefore requires further work on improving computational efficiency of EC methods without sacrificing performance.

6) Recognition by the Main CV Community and Publishing Papers in Major CV and AI Conferences: Despite the above technical challenges, other important challenges include the awareness of the contributions of EC-based methods by the CV community and publishing EC-based works in major CV and AI conferences, such as CVPR, ECCV, ICCV, IJCAI, and AAAI. For the EC-based contributions to be fully recognized by the major CV community, it is necessary to publish at these major conferences. However, this is very challenging due to the low acceptance rates. It is worth mentioning that some EC-based methods have been published in these conferences, such as [118], [181], and [205]. But the total number of EC-related publications is very small, e.g., only about 0.24% of CVPR publications out of 12 724 publications include some EC-based mechanism (from Scopus). To popularize ECV, it is urgent to address this challenge. One chance might be offered by finding a relevant application/problem that EC can effectively solve but other AI techniques cannot, e.g., evolutionary NAS and EMO for image analysis.

C. Trends

In this section, several popular research trends of EC for CV and image analysis are summarized.

1) Evolutionary Deep Learning: The field of evolutionary deep learning (EDL) studies the combinations of EC and deep learning [206], which is typically accomplished in two forms, i.e., using EC methods to optimize deep learning models and using EC methods to automatically evolve deep models from scratch. Most of the existing EDL methods belong to the first group, e.g., evolving deep CNN architectures for image segmentation and image classification [195]. A few GP-based methods belong to the second group, comprising studies in which GP has been used to automatically evolve deep models for image classification [202], [207]. The topic is of great interest and open to significant future developments due to the limitations of EC methods, the limitations of deep learning methods, and the wide variety of image analysis tasks that have been explored only very partially up to now.

2) Computationally Efficient ECV Methods: Improving the computational efficiency becomes important and popular in EC-based image analysis methods because image data are often large, high dimensional, and complex. Computationally efficient EC methods have been studied from different perspectives, e.g., building surrogate models for fitness approximation [106], [119] and implementing EC methods on GPUs [152]. Most of the existing computationally efficient EC methods are not originally designed for image analysis and they have a difficulty being transferred directly to image analysis because of differences in representations, search mechanisms, and tasks. Future work can be aimed at making EC-based image analysis methods, and particularly large-scale image analysis, more efficient and practical.

3) EMO for CV and Image Analysis: Many CV and image analysis tasks typically have multiple (partially) conflicting objectives, for example, the model performance and the model complexity, or the number of features and the classification accuracy. EMO is very suitable for solving these tasks by providing nondominated solutions with good tradeoffs between different objectives. Existing works show the potential of EMO in CV and image analysis [43], [50], [177], but the potential can be further explored by designing different objective functions, developing powerful and task-dependent EMO search mechanisms, etc.

4) EC With Transfer Learning for CV and Image Analysis: Transfer learning aims to extract knowledge from some (source) tasks and reuse it to improve the learning of other (target) tasks. CV and image analysis problems are often related or share similar characteristics. Transfer learning can be explored in EC-based image analysis methods to improve performance. Transfer learning can occur in a multitask learning manner [149] or a sequential transfer learning manner [148]. The knowledge can be transferred between the same type of tasks or different types of tasks [208]. It is worth investigating how to effectively use the knowledge learned from one task in EC to improve its performance on another task.

5) ECV Using Small-Scale Training Data: Few-shot learning or data-efficient learning has recently been a hot topic [209], which aims to learn from small training data. Current popular DNNs often rely on large-scale training data to achieve satisfactory performance in image-related tasks. However, dealing with small training data is also necessary, since labeling huge data can be extremely expensive and learning from them is very time consuming. In this scenario, ECV methods may have a potential to achieve DNN-competitive results and overcome the limitations of DNNs [146].

6) EC Methods for Interpretable CV and Image Analysis: Improving interpretability of the models/solutions is important for model reuse and acceptance, and poor interpretability is a drawback of DNN-based methods. EC methods can be used to provide more interpretable solutions by evolving high-quality but small-size models. However, this direction has not been fully explored in EC-based CV and image analysis methods. Future work can further explore how to reduce solution complexity, how to effectively evolve small-size solutions without affecting performance, etc.

X. CONCLUSION

This article provided a comprehensive survey on recent works of EC techniques for CV and image analysis problems covering all essential EC techniques (e.g., GAs, GP, PSO, ACO, DE, and EMO) and major CV and image analysis tasks, including edge detection, image segmentation, image feature analysis, image classification, object detection, interest point detection, image registration, remote sensing image classification, and object tracking. This survey showed how these EC methods are applied to different image-related tasks by using/developing different encoding, search strategies, and objective functions. More importantly, the limitations, challenges and issues of the reviewed works were discussed to provide more insights into this field.

Since the 1970s, the field of ECV and image analysis has made great progress. By reviewing the related works in recent years, it is evident that EC-based methods have been applied to many different types of image-related tasks and showed great potential. Considering the recent history of the field, one can see that deep learning methods, especially CNNs, are dominant approaches in CV and image analysis, whose performance is hardly approached by the corresponding EC-based CV and image analysis methods. However, even those popular CNN-based methods have limitations, such as having poor interpretability, requiring rich expertise in the NN domain, and requiring expensive GPU computing resources. To address these limitations, it is necessary to develop effective, efficient and interpretable AI approaches to CV and image analysis. EC-based methods can be a good choice to address those limitations. For instance, EC-based NAS approaches reduce the requirement of expertise in the NN domain. In spite of the good performances frequently exhibited by EC-based methods, they still have to face several challenges and limitations in terms of scalability, representations, search mechanisms, computational cost, and interpretability. In parallel, the outbreak of new AI methods have fostered the emergence of new trends in EC-based image analysis, i.e., EDL, computationally efficient ECV methods, multiobjective approaches, EC with transfer learning, ECV using small-scale training data, and EC for interpretable CV and image analysis. It is desirable to develop new and powerful EC-based methods that provide effective but interpretable solutions to CV and image analysis

tasks without expensive computing resources. This wide picture shows how EC-based CV and image analysis still has big potential for new research and offers great opportunities for new groundbreaking discoveries.

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