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Classification of Histopathological Images Through Bag-of-Visual-Words and Gravitational Search Algorithm

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Abstract The automated quantification of different cell structures available in histopathological images is a challenging task due to the presence of complex background structures. Moreover, the tissues of different categories, namely epithelium tissue, connective tissue, muscular tissue, and nervous tissue have heterogeneous structure which limits the applicability of an algorithm to only a single class of tissue for the quantification analysis of histopathological images. Therefore, this paper introduces a novel method for categorization of histopathological images into the respective tissue category before quantification analysis. The proposed method uses SIFT method for feature extraction which are further processed by gravitational search algorithm to obtain optimal bag-of-visual-words. Moreover, support vector machine is trained on these bag-of-visual-words to classify the images into respective categories. The experimental results show that the proposed method outperforms the traditional K-means-based method for histopathological image classification.

Keywords Histopathological image classification · Bag-of-visual-words
Gravitational search algorithm · SIFT method

1 Introduction

Histopathological image analysis plays an important role in the drug development and disease identification. Generally, this analysis is performed manually by pathologists and has inherent some flaws such as highly time-consuming, biased in nature as the analysis depends on the knowledge and experience of a pathologist, and low qualitative report [1]. Therefore, automated histopathological image analysis has become an important area of research in medical imaging [2]. Histopathological images may

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be categorized into four different types of tissue images [3], namely 1. epithelium tissue—lines and covers surfaces, 2. connective tissue—protect, support, and bind together 3. muscular tissue—produces movement, and 4. nervous tissue—receives stimuli and conducts impulses. Recently, a good number of automated methods have been proposed in the field of histopathological quantification [1, 2]. These methods include the process of quantification of different types of cells and differentiate diseased image from normal image. However, no method has been proposed for the classification of histopathological images into their respective tissue class (epithelium, connective, muscular, nervous). This will help to make a generalize method for all the tissue images for their quantification. Therefore, this paper introduces a novel method for histopathological image classification into different tissue categories.

The accuracy of a classification problem is generally associated with the extraction of relevant features [4]. A number of methods have been proposed for extraction of features from histopathological images which can generally be classified into two main classes [5], namely statistics-based and learning-based methods. The statistics-based feature methods use shape, size, and distribution of the nuclei to represent the histopathological images. However, it has been observed that key nuclei are sometimes not considered while feature measurement due to their limited quantity, which may degrade the performance of a classifier. Some researchers have also used graph-based features or mixed features to represent the histopathological images. Furthermore, learning-based methods use different machine learning methods to extract the features such as auto-encoders [6, 7], restricted Boltzmann machines [8, 9], convolutional neural network (CNN) [10, 11], and many more [12–16]. In general, the learning-based features extraction methods are computational expensive methods.

Moreover, some researchers also used classical feature descriptors for representing the histopathological images such as scale-invariant feature transform (SIFT) [17], histogram of oriented gradient (HOG) [18] and local binary pattern (LBP) [19]. Kandemir et al. [20] used color histogram, SIFT, LBP, and a set of well-designed nuclear features to represent the histopathological images. Classical features have given considerable accuracy in histopathological image analysis. Recently, bag-of-visual-words (BoVW), which is generally used for document classification, has widely been used in many computer vision applications [21, 22]. This approach considers an image as a histogram of code words. The BoVW approach aims at identifying the visual patterns that are relevant to the whole image collection. This approach has shown robustness in terms of occlusion and affine transformations. Further, it is computational efficient too. However, the generation of BoVW is generally done using K-means clustering method which is sensitive toward the initial clusters [23]. In such cases, meta-heuristic methods have exhibited better performance [24–34]. Therefore, this paper uses gravitational search algorithm (GSA) to find the optimal BoVW.

GSA is introduced by Rashedi et al. [35] and has been widely used in the solving computationally intensive real-world problems [36–38]. This paper focuses on using GSA for generating codebook by performing clustering on the collection of extracted features with intra-class distance as the objective function. Selection of GSA has been made on the basis of its performance as compared to other meta-heuristic methods such as particle swarm optimization (PSO) [39] and differential evolution (DE) [40], especially in the clustering task [25, 41–43]. The accuracy of proposed method has been tested on the histopathological image dataset.

Rest of the paper is organized as follows: Section 2 describes the gravitational search algorithm (GSA). The proposed method is explained in Sect. 3. In Sect. 4, experimental results are compared and discussed. Finally, Sect. 5 concludes the paper.

2 Gravitational Search Algorithm

Gravitational search algorithm (GSA) [35] is a meta-heuristic method based on physical phenomenon of mass interactions. The GSA is based on Newtonś law of gravity and law of motion. The algorithm considers each agent as an object and evaluates the performance in terms of masses. Each object applies force in the system according to law of gravity and changes its position according to law of motion. The number of objects exerting force at an iteration is represented by *Kbest* which controls the trade-off between exploration and exploitation [44]. The slower movement of heavier object corresponds to the exploitation and represents better solution. The fittest object is the heaviest mass and corresponding position represents the optimal solution of the problem at the end of the stopping criteria.

Consider a system of U objects in u-dimensional search space of GSA where the position of each object is depicted by Eq. 1.

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^u), i = 1, 2, \ldots, U \tag{1}$$

Here, ${x_i}^d$ denotes the dth dimension of the ith object.

The total force $F_i^d(t)$ in dth dimension of ith object at tth iteration is defined as randomly weighted sum of dth components of the forces from other *Kbest* objects and is shown in Eq. (2).

$$F_i^d(t) = \sum_{j=1, j\neq i}^{Kbest} rand_j {F_{ij}}^d(t), \tag{2}$$

Here, $rand_j$ is a random number in the interval [0, 1] and *Kbest* for the tth iteration is defined by Eq. (3).

$$Kbest(t) = final\_per + \left(\frac{1-t}{max\_it}\right) \times (100 - final\_per), \tag{3}$$

where max_it is the maximum number of iterations and $final\_per$ is the percent of objects which apply force to others. Equation (3) shows that the value of *Kbest* decreases linearly over iterations.

In Eq. (2), F_{ij} is the force of jth object on ith object and is computed by Eq. (4).

$$F_{ij}{}^{d}(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}(x_j^d(t) - x_i^d(t)) \tag{4}$$

Here, $G(t)$ is a gravitational constant computed as Eq. (5) at iteration t, ε is a small constant, and $R_{ij}(t)$ is an Euclidean distance between two objects i and j.

$$G(t) = G(t_0) * exp\left(-\beta * \frac{t}{max\_it}\right) \tag{5}$$

where $G(t_0)$ is the initial gravitational constant value and β corresponds to a constant.

In Eq. (4), M_i and M_j correspond to masses of objects i and j, respectively. For ith object with fitness value ($fit_i(t)$), M_i is calculated in every iteration t by Eq. (8).

$$M_i = M_{ii} = M_{gi}, i = 1, 2, \ldots, U \tag{6}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}, \tag{7}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}, \tag{8}$$

where M_{gi} is gravitational mass and M_{ii} is inertia mass of an object i. $best(t)$ and $worst(t)$ are measured by Eq. (9) and Eq. (10), respectively, for minimization problem.

$$best(t) = \min_{j \in \{1,\ldots,U\}} fit_j(t) \tag{9}$$

$$worst(t) = \max_{j \in \{1,\ldots,U\}} fit_j(t) \tag{10}$$

The calculated force $F_i^d(t)$ and mass $M_i(t)$ are used to find the acceleration of ith object in the dth dimension according to law of motion as shown in Eq. (11).

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)}, \tag{11}$$

Now, the updated velocity and position of an object are calculated as Eq. (12) and Eq. (13), respectively.

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t), \tag{12}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1). \tag{13}$$

Algorithm 1 Gravitational Search Algorithm (GSA)

Input: U objects having u dimensions. Assume the value of G_0, $final\_per$, and β.
Output: Best solution having heaviest mass.
Randomly initialize the initial population of U objects;
Evaluate the fitness (fit) of each object;
Compute the mass M of each object by Eq. (8) and G by Eq. (5) ;
Set $Kbest = U$;
while stopping criteria is not satisfied **do**
  Compute the acceleration a of each object by Eq. (11);
  Compute the velocity v of each object by Eq. (12);
  Update the position of each object by Eq. (13);
  Evaluate the fitness fit for each object;
  Compute the mass M of each object by Eq. (8);
  Update G;
  Update $Kbest$ as: $Kbest = final\_per + \left(\frac{1-t}{max\_it}\right) \times (100 - final\_per)$,
end while

As object's position corresponds to solution, heaviest object in the system will be the fittest agent and its position will represent the optimal solution of the problem at the end of stopping criteria. The pseudocode of the GSA is presented in Algorithm 1 [35].

3 Proposed Method

The proposed method uses bag-of-visual-words (BoVW) and gravitational search algorithm to classify the histopathological images into the respective classes, i.e., epithelium tissue, connective tissue, muscular tissue, and nervous tissue. The flow graph of the proposed method is depicted in Fig. 1. In the first step of the proposed method, scale-invariant feature transform (SIFT) is used to convert each image as a collection of feature vectors of 128 dimensions. The different vectors can be used in any order. These feature vectors are used to generate BOVW using GSA.

Like document classification, the bag-of-visual-words treat the image features as words termed as codewords. In other words, a codeword is a representative of several similar patches of images. The proposed method represents the image as a vector of occurrence counts of codewords. Generally, these code words are found by performing K-means clustering over all the feature vectors [45]. However, K-means clustering sometimes shows biased behavior due to initial clusters [23]. Therefore, this proposed method replaces the K-means clustering method by GSA which is a robust meta-heuristic method. GSA uses intra-class variance as a fitness function to

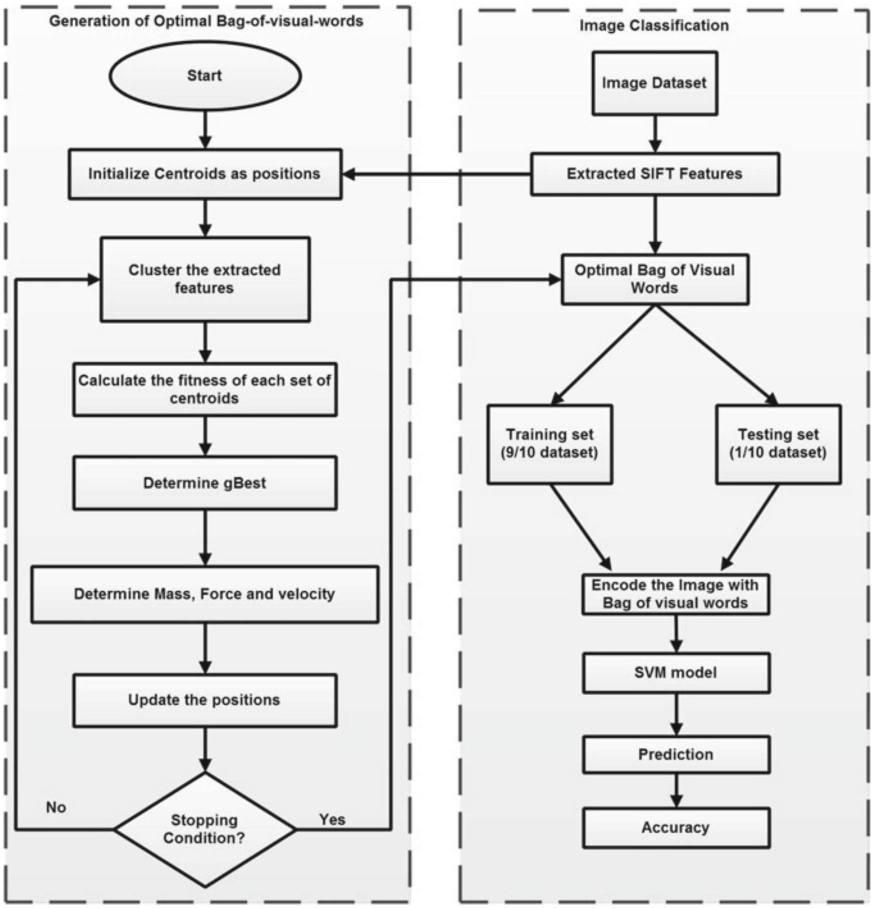

Fig. 1 The flow graph of the proposed method

find the optimal set of code words which serve as centers of the learned clusters. The number of clusters is known as codebook size. The proposed method then maps the learned code words with images and represents each image as a histogram of code words.

The final step of the proposed method includes the training of the support vector machine (SVM) with the generated BoVW. The trained SVM is further used to classify the test image into its respective class. The description of the proposed method is also depicted in Algorithm 2.

4 Experimental Results

The image dataset consists of four different histopathological categories, namely epithelium tissue, connective tissue, muscular tissue, and nervous tissue. Each image category contains 101 images. The images are taken from various publicly available sources [46, 47]. Each category contains images taken after various staining methods. The detailed information about the dataset is mentioned in Table 1. Moreover, Fig. 2 shows representative images from each category of histopathological image dataset. Furthermore, the dataset is divided into training and testing sets using stratified random sampling. For classification, multi-class SVM has been employed.

Algorithm 2 Proposed Approach

Extract features of each image.
Combine the features of all the images as a single matrix.
Identify N cluster centroids by performing GSA with intra-cluster variance as objective function.
The N cluster centroids define the visual dictionary.
Generate bag-of-visual-words for each image.
Train the classifier.
Extract the features of test image.
Generate the normalized term frequency of the test image.
Identify the label using trained classifier.

The performance of the proposed method has been compared with K-means-based method in terms of accuracy, precision, recall, and F-measure. Table 2 shows the performance values of accuracy, precision, recall, and F-measure. The best value is represented in bold. From the table, it is observed that the proposed method shows better performance for almost all performance parameters whereas K-means gives better results in only recall and precision values for connective tissues and muscle tissues, respectively. However, the proposed method outperforms the K-means-based method in terms of F-measure for all the histopathological categories. Moreover, the accuracy of proposed method is 51.6% which is better than K-means-based method.

Table 1 The different categories of image dataset and their staining methods

S. No.	Category	Staining	No. of images
1	Connective tissue	H&E, TRI, EL, TB, RET, CCY	101
2	Epithelial tissue	H&E, VG, MB, PAS/H&E	101
3	Muscle tissue	H&E, WHP, IH, HAFTEG	101
4	Nervous tissue	H&E, BC, ICC, VG, LFC, H&E/MB	101

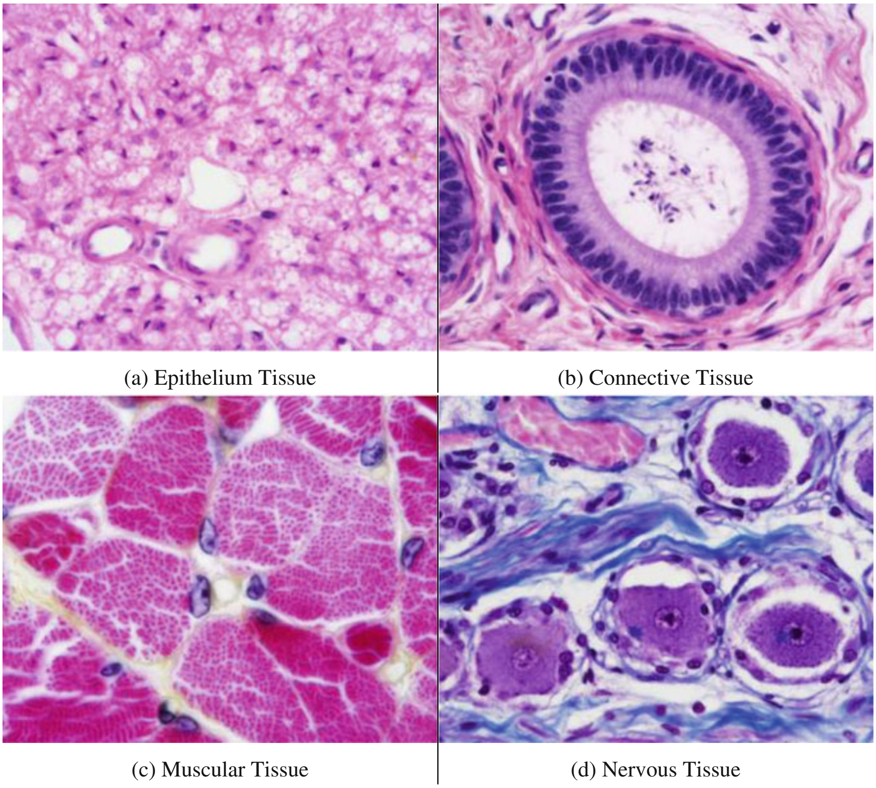
(a) Epithelium Tissue (b) Connective Tissue
(c) Muscular Tissue (d) Nervous Tissue

Fig. 2 Representative images of different categories from histopathological image dataset

Table 2 Comparative analysis of K-means-based method and proposed method

S. No.	Algorithm	Accuracy	Classes	Recall	Precision	F-measure
1	K-means	43.5	Muscle tissue	48.3	**68.1**	56.6
			Connective tissue	**61.2**	39.5	48.1
			Epithelial tissue	51.6	43.2	47.05
			Nervous tissue	12.9	23.5	16.6
2	GSA	**51.6**	Muscle tissue	**74.1**	57.5	**64.7**
			Connective tissue	45.1	**66.6**	**80.6**
			Epithelial tissue	**70.9**	**47.8**	**73.3**
			Nervous tissue	**16.1**	**29.4**	**20.8**

5 Conclusion

The proposed method introduces a novel method to classify the histopathological images into epithelium, connective tissue, muscular tissue, and nervous tissue classes. The method uses gravitational search algorithm for generating the optimal bag-of-visual-words (BoVW). For feature extraction, SIFT method has been used and these feature vectors are used by GSA for generating BoVW. Further, SVM is used to classify the images into respective categories. The performance has been compared with K-means-based method in terms of accuracy, recall, precision, and F-measure. The results depicted that the proposed method outperforms the considered method.

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