Image Preprocessing In Multimodal Sparse Representation Based Classification for the Lung Needle Biopsy Images

Ms. S. R. Papinwar, Prof. P. H. Pawar

Abstract —**Multimodal Biometric System using multiple source of information for establishing the identity has been widely recognized. But the computational models for multimodal biometrics recognition have only recently received attention. In the proposed system multimodal biometric images such as fingerprint, face, lung needle cancer images are extracted individually and are fused together using a sparse fusion mechanism. A multimodal sparse representation method is proposed, which interprets the test data sparse linear combination of training data, while constraining the observations from different modalities of the test subject to share their sparse representations. The images are preprocessed for feature extraction Based on the results obtained, label edge detection was used for feature extraction. Extracted features were subjected to sparse representation for the fusion of different modalities.**

The fused template can be used for separate the chromosome level for lung needle biopsy images. Lung needle biopsy image classification is a critical task for computer-aided lung cancer diagnosis. In this study, a Novel method, multimodal sparse representation-based classification (MSRC), is proposed for classifying lung needle biopsy images.

In the data acquisition procedure of our method, the cell nuclei are automatically segmented from the images captured by needle Biopsy specimens. Then, features of three modalities (shape, color, and texture) are extracted from the segmented cell nuclei. After this procedure, MSRC goes through a training phase and a testing phase. These cell nuclei regions can be divided into five classes: four cancerous classes (corresponding to four types of lung cancer) plus one normal class (no cancer). The results demonstrate that the multimodal information is important for lung needle biopsy image classification.

Index Terms—**Feature Extraction, Dictionary learning, Lung needle cancer image classification, Multimodal biometrics, Sparse representation based classification (SRC).**

I. INTRODUCTION

Unimodal Biometrics are systems that are capable of using only one physiological or behavioral characteristic for enrollment, verification or in reality, but the matching score is higher than the threshold, then he is treated as genuine. The proposed the seminal sparse representation based classification (SRC) algorithm for genetic algorithm [3]. It shows that by exploiting the inherent of data, one can obtain improved performance over traditional methods [1]. Lung cancer studied through by doctors but its grading gives different decisions which may differ from one doctor to another. The classification and accurate determination of lung cancer grade is very vital because it influences and specifies patient's treatment scheduling and finally their life. A new technique multimodal sparse representation-based classification (MSRC), suggested for classifying lung needle biopsy images [1]. In this technique data acquisition is done through the new method, the cell nuclei are mechanically segmented by itself from the input images caught by needle biopsy specimens which are obtainable in this research work, which is samples of the human thinking methods and the classification results are compared with some other computer-aided lung cancers analysis methods showing the efficiency of the proposed methodology.

The three features modalities such as texture, color and shape are extracted from the segmented cell nuclei from input images. The training level, three discriminative sub dictionaries corresponding to three features information are together knowledgeable by a genetic algorithm directed multimodal dictionary learning approach.[8] The dictionary learning is used to select highest discriminative samples and encourage large disagreement amongst dissimilar sub dictionaries. In testing phase, when a novel image comes, a hierarchical fusion scheme is applied, which originally prediction of labels of all cell nuclei by fusing modalities such as color, texture and shape are predicts the label of the image by maximum popular voting. The above cell nuclei are as can be separated into five classes which consist of four cancerous classes and one regular class (non-cancer). Usually, lung cancer can be categorized into four types: squamous carcinoma (SC), adenocarcinoma (AC), small cell cancer (SCC), and nuclearatypia (NA). Fig. 1 shows several sample images of each of the four cancerous types. The results prove that the multimodal information is vital for lung needle biopsy image classification; this technique is particularly for classifying various cancerous types. The outputs of the proposed novel MSRC model presents reasonably higher accuracy, and are more similar with other existing algorithms [1].

Figure.1

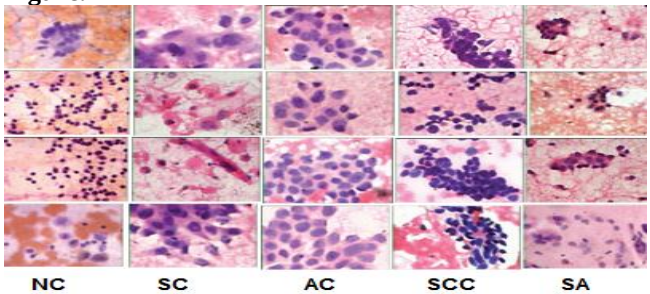

Fig.1: Typical examples of the normal (NC) images and four types of cancerous ones: SC, AC, SCC, and NA. The images are captured from needle biopsies Specimens by electronic microscopy and digital camera.

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Traditionally, the diagnosis of lung cancer is made by the pathologist. However, the pathologist's in experience in clinical practice can cause misdiagnosis. What is worse, the diagnosing process is time consuming and sometimes tedious when a pathologist is asked to analyze a huge volume of sample images from patients. Thus, the misdiagnosis can also be caused by the factors such as fatigue, even for an experienced pathologist. Therefore, the accuracy of the diagnosis is related to not only the pathologist's educational background and clinical experience but also his/her physical and psychological conditions. In recent years, several computer-aided methods for lung cancer diagnosis have been developed, such as magnetic resonance imaging [2], computerized tomography [3]–[5], and X-ray chest films [6], etc. In clinical practice, analyzing the images captured from needle biopsy specimens, which routinely follows the X-ray chest films checking, is one of the most popular and reliable ways to aid lung cancer diagnosis. However, classifying different types (SC, AC, SCC, NA) of lung needle biopsy images is still a significant and challenging problem because the images of different cancerous types sometimes might be very similar to each other [2] and, hence, are difficult to classify. To tame the aforementioned challenges, we propose a novel method, named multimodal sparse representation-based classification (MSRC), for lung needle biopsy image classification. There are two Phase in Multimodal sparse representation. In the training phase, I will show the classification of lung needle cancer biopsy images and that converted into data acquisition methods and it gives the output to three feature extraction method [4]. it will perform the new sub –dictionary[4].

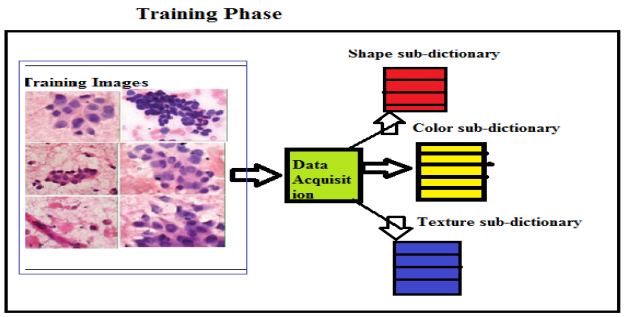

Fig.2: Framework of the proposed MSRC, including a training phase, the training phase outputs the discriminative sub dictionaries via genetic algorithm-based multimodal dictionary learning

It aims to improve the classification performance, especially in the case that the images of different lung cancer types are difficult to distinguish. Our method exploits the observation that the lung cell nuclei have different appearances in different classes. Particularly, we investigate the information of three cell modalities (shape, color, and texture). For example, the SC cell nuclei are usually round (shape modality), and the NA cell nuclei always largely deviate from others in color (color modality). Upon the multimodal information, our method builds a Sparse representation-based classifier for lung needle biopsy image classification with improved performance. Next phase is testing phase, in this phase there are two level fusion describe [3]

1) Cell level fusion
2) Image level fusion

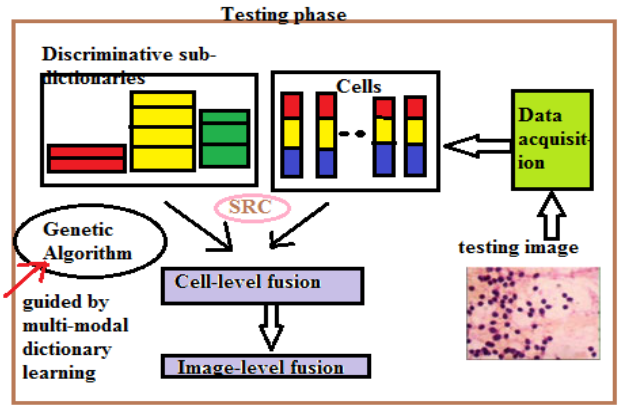

Fig.3: Framework of the proposed MSRC, including a testing phase. the testing phase outputs the predicted label for each testing image.

The rest of the paper is organized as follows. We first present the framework of our method and data acquisition procedure. Then, we introduce the feature extraction, training and testing phase, respectively. Finally, we present our experimental results and conclude the paper.

II. LITERATURE REVIEW

For lung needle biopsy image analysis, many efforts have been contributed in recent years. Zhou *et al.* [9] developed a lung cancer cell classification system based on a two-level neural network ensemble. In the system, the first-level ensemble determines whether a testing cell is normal or cancerous, and the second-level ensemble classifies the types of lung cancer for the suspected cancerous cells determined in the first level. Zhu *et.al* [10] proposed an image-level approach: multiclass multiinstance AdaBoost (MCMI-AdaBoost), which predicts the label of an image by incorporating the multi-instance distance measurement (Hausdorff distance) under the AdaBoost [11] framework. However, the similarity measurement ignores local information of cells. Shi *et al.* [8] recently introduced a transductive cost sensitive learning method for lung needle biopsy image classification, of which the goal is to achieve the best possible results with only a small number of labeled images. Unfortunately, the result of classification for different types of lung cancer is still unreliable, and there is still space for us to improve the classification performance. In addition, previous methods for lung needle biopsy image classification [9], [8] are single-modal based learning methods, which fail to make full use of the disagreement information among different modalities [8], [9]. It is noteworthy that, except for the needle biopsy specimens-based lung cancer diagnosis, many works that focus on cell/nodule/image classification in medical image analysis are highly related to our work. Works [2] belong to this category. For learning with multimodal data, also referred to multiview learning and ensemble learning in machine learning community, many algorithms [1] have been developed recently. Also, multimodal-based methods are promising in the field of medical image analysis since multimodal information is naturally available in the data acquisition procedures of various clinical tasks, such as Alzheimer's disease diagnosis [2], [3],
Prostate cancer prediction [6],and survival prediction for lung cancer [5].

The lungs are a complex tissue which contains numerous structures, such as vessels, splits, bronchi or

pleura that can be situated near to lung nodules. Very Simple threshold approaches are regularly enough for the separation of solid well-circumscribed nodules, while lung nodules close to vessels or pleura need additional complex schemes exploiting geometrical and gray level features mined from nearby structures of the lungs. Various methods have been suggested to summary of the lung nodules close to vessels or pleura. Human associated parasites create a problematic in maximum humid countries, producing death or physical and psychological illnesses. Their conclusion regularly trusts on the visual examination of microscopy images, with error rates that may collection from moderate to higher. [3] The problem has been addressed through computational image analysis, but only for a rare species and images free of fecal layers. In routine, fecal layers are a actual trial for programmed image analysis. First method exploits ellipse matching and image foresting transform for image subdivision, multiple item descriptors and their optimal grouping by genetic software design for object symbol, and the optimum path forest classifier for object acknowledgment. The output demonstrations that this method is a favorable method near the completely automation of the entree parasitizes diagnosis.

The effectiveness of sparse representations gained by learning a set of over complete basis or dictionary in the context of action recognition in videos. While the work focuses on distinguishing the movement of human, [6] physical appointments as well as the appearance of face and the suggested method is fairly general and can be used to address some other classification methods. The suggested approach is computationally effective, highly accurate, and is strong against partial sealing, spatiotemporal scale variants, and to some range to view changes. This robustness is attained by manipulating the discriminative nature of the sparse representations joined with spatio-temporal motion descriptors. The fact that the descriptors are mined over multiple temporal and spatial determinations makes them indifferent to scale variations. The descriptors being calculated locally make them robust beside blocking or other distortions. Features such as compressed sample can also develop the recognition accurateness but are highly costly computationally [8].

The presentation of the collective system is calculated in fact and the output correctness, rapidity, robustness, and an active retinal vessel segmentation method based on supervised classification using a collective classifier of boosted and bagged decision trees.

III. PROPOSED METHOD

Usually, the suggested method contains three phases (Fig.2). The first phase is the data acquisition procedure, which purpose is to extract the features for cell nuclei in lung needle biopsy images. Later this process and the technique under goes over the rest of the two training and testing phases. In the training phase, the new idea of dictionary in the pattern. Recognition/computer vision, where dictionary resources a collection of elements or words or feature vectors.

A. FRAMEWORK METHOD FOR IMAGE PREPROCESSING

The features extracted from the three modalities such as color, texture and shape of every single cell nucleus in the data acquisition procedure, which build three original sub dictionaries on color, texture and shape by collecting the corresponding feature vectors of individual cell nuclei. A feature extraction step goal to extract features for distinct cell nuclei from three modalities color, texture and shape respectively. Exactly, as shown in Table 2,shape based(9), color-based (11), and texture-based(16) features are mined.

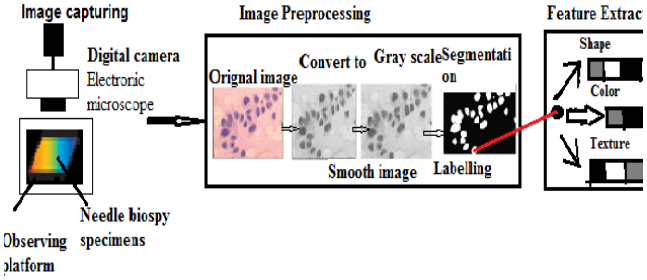

Fig.4: Flowchart of the data acquisition -procedure in our method, including three sequential steps: image capture, image preprocessing, and feature extraction.

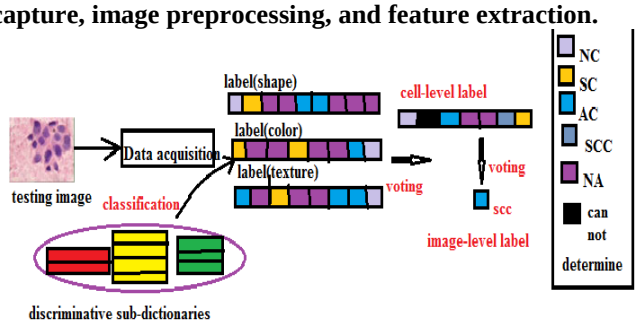

Fig.5: Extraction of features and the label of each testing image are determined by voting on the cell-level label.

Generally, our proposed method contains three phases (see Fig. 2). The first phase is the data acquisition procedure, which aims to extract the features for cell nuclei in lung needle biopsy images. After this phase, our method goes through the rest two ones: training and testing phases. In the training phase, we introduce the concept of *dictionary* [9] in pattern recognition/computer vision, where a dictionary means a collection of words/elements/feature vectors.

Traditional SRC belongs to single-modal learning approach, which only uses one dictionary. Since the information of three with the features extracted from the three modalities (shape, color, and texture) of each cell nucleus in the data acquisition procedure, we build three original sub dictionaries on shape, color, and texture by collecting the corresponding feature vectors of individual cell nuclei. Note that all the sub dictionaries mentioned in the following sections only contain the features coming from different individual cell nuclei instead of images. Moreover for each nucleus, its label is initialized as the same label of the image it belongs to. The sub dictionaries obtained in this way usually contain several similar samples coming from different classes, which might be harmful for classification. To learn discriminative sub dictionaries, we propose a genetic algorithm-based multimodal dictionary learning algorithm, which selects the topmost discriminative training cell nuclei, and encourages large disagreement among different sub dictionaries. In the testing phase, for a

new coming image, a hierarchical fusion strategy is adopted, including cell-level fusion and image level fusion, respectively. In the following sections, we will discuss the technical details of each phase in our method.

B. DATA ACQUISITION PROCEDURE

With the goal of capturing and preprocessing the lung needle biopsy images, the data acquisition procedure, whose main pipeline can be referred to Fig. 3, takes the following sequential
Steps:

1) An image capturing step aims to capture the images from the needle biopsy specimens by using an electronic microscopy and a digital camera.

2) An image preprocessing step aims to obtain the individual cell nuclei from the captured images by segmenting the cell nuclei from the background (i.e., cell sap). The image preprocessing step is with the following sub steps: smoothing the images with Gaussian kernel, segmenting the images using Otsu's algorithm, and labeling the connected cell nuclei regions. The reason of adopting Otsu's algorithm is that the contrast between the cell nuclei region and background is large enough to be easily separated (see sample images in Fig. 1). Basically, the segmentation results can meet clinical requirements according to the pathologist's suggestions.

3) A feature extraction step aims to extract features for individual cell nuclei from three modalities (shape, color, and texture), respectively. Specifically, as shown in Table I [1], nine table extracted features for each cell nucleus region from three modalities: shape, color, and texture shape (9) color (11) texture (16) height R, G, B energy (4) width H, S, I entropy (4) [2]circumference gray mean contrast (4)[2] area gray variance divergence (4) circularity feature gray elongation IOD Fourier descriptor (3)[2] central moment shape-based, 11 color-based, and 16 texture-based features are extracted. For the Fourier descriptor, the number "3" in the bracket means that we only use the second, third, and fourth coefficients. The first coefficient is the mean value of boundary coordinates, which is usually considered as useless in feature representation. In the texture-based features, the number "4" in a bracket means that we calculate the four directions,(0◦, 45◦, 90◦ , 135◦) for the four features (energy, entropy, contrast, and divergence)[2], so totally 16 texture-based features are extracted[2]. These features have demonstrated their robustness and effectiveness in several medical image analysis applications.

IV. CONCLUSION

The novel technique is suggested MSRC for categorizing the lung needle biopsy images. MSRC goal is to raise the classification performance, which exactly for the images of various cancerous types. The genetic technique goal is to select the topmost discriminative samples for every single distinct modality as well as to assurance the huge diversity among different features. From the perception of experimental practice, Misclassifying a cancerous image as a standard or normal one will be considerably more serious than misclassifying a standard or normal image as a cancerous one, Forthcoming work will examine how to implement the technique on the image set through various class relations, i.e., considering the ratio of malignant nuclei in every image. Similarly the multimodal data is broadly obtainable in medical image exploration due to the numerous data acquisition methods.

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