Classifying cervix tissue patterns with texture analysis
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Abstract

This paper presents a generalized statistical texture analysis technique for characterizing and recognizing typical, diagnostically most important, vascular patterns relating to cervical lesions from colposcopic images. The major contributions of this research include the development of a novel generalized statistical texture analysis approach for accurately characterizing cervical textures and the introduction of a set of textural features that capture the specific characteristics of cervical textures as perceived by human. Experimental study demonstrated the feasibility and promising of the proposed approach in discriminating between cervical texture patterns indicative of different stages of cervical lesions. © 2000 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved.

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1. Introduction

The incidence of cervical cancer mortality has been dramatically reduced since the introduction of the Papanicolaou (Pap) test. However, the Pap test is unable to accurately and consistently identify premalignant and malignant disease of the cervix. The incidence of false-negative Pap tests has become shockingly high. In fact, certain studies [1] show that the false-negative Pap tests account for up to 40\% of the actual positives in the sample. The high false-negative rate from Pap tests has motivated the use of colposcopy as a standard screening procedure for precancer examination [1].

Another serious problem with Pap-smears is that they produce an enormous number of positive findings which need to be followed up. Most of these findings turn out to be false positives based on insignificant cellular changes. A computer-supported colposcopy can help reduce the false positives of Pap-smears, therefore substantially reducing costs and patient suffering associated with the unnecessary biopsies. Finally, colposcopy can significantly improve the ability of physicians to perform accurate punch biopsies for histological analysis. Today, regular cytological screening of the cervix via the Pap test, supplemented by colposcopy and colposcopically directed cervical biopsies, has become an established part of modern gynecological practice.

One of the major factors hindering the full utilization of colposcopy is the difficulty in training physicians in the recognition of pathology. Colposcopic images contain complex and confusing lesion patterns. Correctly analyzing and classifying different types of tissues require substantial training. The average physicians in private practice do not get to examine enough patients to maintain such expertise and may need to rely on consultation with colposcopy experts. Furthermore, there is also the rapidly increasing trend for people other than highly trained colposcopists, such as primary care physicians, to be involved in the screening procedure. Therefore, it is necessary to simplify the use of colposcopy and to enhance its capability so that average physicians can correctly recognize various tissue patterns in a consistent and uniform fashion. For this reason, we developed an image analysis system to help physicians better interpret various patterns on colposcopic images and to simplify the operation of colposcopy.
A careful examination of various cervical images reveals regular and repeatable vascular patterns, indicating different stages of dysplasia. In fact, vascular pattern is the most important diagnostic criteria used by colposcopists for recognizing pathology [2]. For example, two basic types of vascular patterns observable in normal or benign lesions are hairpin and network capillaries. On the other hand, different versions of punctation and mosaic vascular patterns may be observed in areas of dysplasia and carcinoma in situ. Fig. 1 shows typical vascular patterns encountered in cervical lesions.

Various texture analysis methods have been developed to analyze and classify patterns like these. Classification based on texture analysis is a well-established technique. Many techniques have been developed [3–7] over the years. They have been successfully applied in many fields including remote sensing, medical diagnosis, and product inspection.

The applications of texture analysis techniques in biomedicine focus on cell and tissue classification. For example, Wu and Chen [8] proposed a multi-threshold texture vector for liver tissue classification. Houston et al. [9] investigated different texture measures of ultrasound images for diagnosing prostate cancer and for identifying cancerous lesions. Lachmann et al. [10] proposed to use texture analysis for brain tissue classification from MRI images. Finally, Fortin et al. [11] advocated the use of texture analysis for segmentation of cardiac images.

These examples demonstrate the importance and utility of texture analysis for tissue classification. However, the use of texture analysis techniques (or other image processing approaches) for recognizing and classifying cervix lesions has not been reported in the literature to the best of our knowledge. For this project, we introduce a texture analysis technique for recognizing and classifying cervical tissues. Texture analysis results in a set of feature metrics that describe the characteristics of different vascular patterns. For example, a texture analysis of mosaicism will result in a set of feature measurements which characterize the class of tissues exhibiting mosaicism.

Texture analysis is a three-layer process. The first layer identifies the texture primitives, of which texture patterns are composed. The texture primitives are usually geometric entities like pixels or line segments. The second layer extracts certain properties of the identified texture primitives. Depending on the types of primitives, the properties can be tonal properties like intensities for pixels or geometric attributes like length and direction for line segments. The last layer describes the spatial and/or statistical distribution of the primitives in terms of their attributes. The description can be symbolic or statistical.

Parallel to the above categorizations, there are two basic approaches to the analysis of textures: structural and statistical. In the structural approach, textures are characterized by the texture primitives and the placement rules. The placement rules relate the centroids of various
primitives in terms of their relative positions like adjacency or nearness. Structural approach emphasizes the shape aspects of the primitives. All structural methods assume that textures are made up of primitives which appear in a near regular, repetitive or periodic spatial arrangement.

In statistical methods, the granulation, linearization and randomness that constitute a texture pattern are characterized by taking statistics on the pixels. Traditional statistical methods assume that spatial intensity distribution is related to texture patterns. For example, fine textures have a spectrum rich in high frequencies while coarse textures are rich in low spatial frequencies. Different techniques [4,6,12] have been developed to describe the intensity distribution. For example, texture may be described as the auto-correlation function, which measures the linear dependence between pixels; or as the gray tone run length, which characterizes textures by the statistics of the gray tone of the run. One of the most popular statistical methods is the spatial gray tone co-occurrence matrix (GTCM) [12]. The entries of the co-occurrence matrix are the second-order joint conditional probabilities of two gray tones occurring at certain distance apart in a given direction. First- and second-order statistics derived from this matrix are used as measures for texture analysis. Statistical methods are good for analyzing disordered textures.

A careful examination of the textural patterns relating to cervical lesions revealed the followings. First, texture patterns for cervical lesions are primarily due to the vascular patterns. The non-vascular structures in the cervical images contribute very little to the formation of texture patterns in cervical lesions. Furthermore, the vascular structures are mainly characterized by the geometric shape and spatial distribution of capillaries. The gray levels and thickness of capillaries are irrelevant to vascular patterns. Thus, cervix texture patterns cannot be characterized by the spatial intensity distribution of capillaries. Second, texture patterns for cervical lesions do not exhibit regular repetitive or periodic structures.

Based on the above observations, we may conclude that the conventional structural and statistical texture analysis approaches are not directly applicable to characterizing cervical texture patterns. The structural approach is not applicable in that it looks for regular repetitive or periodic spatial arrangements, which are not present in cervical texture patterns. On the other hand, the statistical approach characterizes textures by their intensity distribution. It depends more on the intensity transitions within texture elements than on the structural organization of the texture.

To best characterize the texture patterns relating to cervical lesions, we proposed a novel generalized statistical method. Recognizing the fact that cervical textures are primarily represented by the vascular structures, we assume that a significant proportion of the texture information in cervix lesion is contained in the vascular structures and that the vascular structures can be extracted and approximated by a set of connecting line segments of different lengths and orientations. We therefore chose line segments as the textural primitives. Other researchers proposed the use of edgels as primitives [13]. We believed that capillaries can be better characterized by the high level line segments rather than the low level edgels. Given line segments selected as primitives, the length and orientation of line segments are the natural choices for the primitive properties.

In summary, our approach first extracts the vascular structures from the original cervical lesion images, followed by vectorizing the extracted vascular structure using line segments. Statistical distributions of the line segments are then constructed. First- and second-order statistics derived from the joint and/or marginal distributions are used as textural measures for cervical lesions classification. The beauty of such a texture characterization is that while it takes full advantage of the statistical approach, it also inherents the power of the structural approach by emphasizing the shape aspects of textures.

2. Algorithm development

In this section, we detail our texture analysis technique for analyzing the textural patterns relating to cervical lesions. Following the 3-layer texture characterization process described in the previous section, this section further divides into three subsections. The first subsection focuses on texture primitives (line segments) extraction, the second subsection discusses properties of the extracted texture primitives, and the third subsection deals with the texture feature formulation and extraction.

2.1. Texture primitive extraction

In the preceding section, we introduced our generalized statistical approach for characterizing the texture patterns relating to cervical lesions. The approach captures the cervical textural information contained in the vascular structures using a set of connecting line segments. This section describes our approach for extracting the line segments that approximate the vascular structures. The approach consists of three steps: image preprocessing, skeletonization, and vectorization as detailed below.

2.1.1. Image preprocessing

Image preprocessing is important for classification since it directly affects the classification accuracy. This is particularly relevant to this project since vascular structures often coexist with other irrelevant artifacts on the surface of a cervix. Furthermore, the presence of fluids and/or other discharges on cervix surface causes
As a result, the primary purpose of preprocessing is to digitally remove artifacts present on the surface of a cervix and to compensate the uneven luminance. To this end, a gray-level morphological operation was performed to remove the artifacts, followed by an image normalization operation to adjust for non-uniform luminance and contrast of the original image so that vascular structures differ only in luminance and contrast would not be distinguished.

Artifacts on the surface of a cervix image are identified and separated from the underlying vascular structures based on the morphological differences between artifacts and capillaries. The capillaries usually are much more tortuous than artifacts. Artifacts, on the other hand, are usually short and straight segments or small dots. The differences in morphology were exploited in separating them based on the theory of mathematical morphology. The technique of morphological opening with a rotating structure creates an image containing only artifacts, which are then subtracted from the original images, yielding images containing predominantly vascular structures. The rotating structure elements are necessary due to random orientations of the artifacts. Detailed description of this algorithm may be found in Ref. [14].

Image normalization is achieved through background subtraction. The morphological rolling ball algorithm [15] creates a mask image that contains the background. The mask image is subtracted from the original to obtain a normalized image, with enhanced vascular structures. Fig. 3(b) shows an example of a morphologically enhanced image. The radius of the ball varies depending on the vascular patterns being studied and image scales. For the examples shown in Fig. 3, a radius of 3 pixels was chosen.

2.1.2. Vascular structure extraction

Given the images after preprocessing, the next step is to extract the vascular structures. This is accomplished with a thresholding operation, resulting in a binary image containing primarily vascular structures. Adaptive thresholding is chosen due to variations in local contrasts as shown in Fig. 3(b). Such variations make the vascular

Fig. 2. A colposcopic image of a cervix displaying mosaic vascular pattern. Note the presence of artifacts and uneven luminance and contrast in the underlying mosaic vascular pattern.

Fig. 3. (a) original image containing mosaic patterns; (b) morphologically enhanced image; (c) binary image of (a) after adaptive thresholding of (b).
structures difficult to separate from its surroundings with a global threshold. We therefore implemented an automatic adaptive thresholding technique introduced in Ref. [16]. Fig. 3(c) shows the binary image after adaptive thresholding.

2.1.3. Skeletonization and vectorization

Following preprocessing, the binary images of vascular structures are skeletonized since we observed that vascular structures can be fully captured by their skeletons. Skeletonization can be regarded as a shape normalization process so that the shape of capillaries are independent from digitization, lighting, scale, and other factors. Furthermore, skeletonization can preserve the critical shape information while removing redundant pixels, greatly facilitating the feature extraction and improving the pattern recognition efficiency. For the skeletonization process, we employed the thinning algorithm provided by Zhang [17]. The algorithm is simple, fast, and easy to implement. With this algorithm, each capillary is thinned to a skeleton of unitary thickness. Fig. 4(a) shows the skeletonized image of the image in Fig. 3.

Primitive extraction is subsequently accomplished through vectorization. Vectorization approximates the thinned vascular structures with connecting line segments. The Hough Transform (HT) is used for line segment detection. A drawback with the conventional HT is that it does not provide any information regarding the line segments. It merely clusters collinear points. Points on a line may represent different line segments. A heuristic method was therefore developed through this research to extend the conventional HT for detecting line segments.

Specifically, the line segment detection method developed through this research consists of two steps subsequent to the conventional HT: the first step involves grouping collinear points into line segments based on their proximity. To do so, the collinear points are first ordered by their column coordinates if their orientations are greater than 90° and by their raw coordinates otherwise. Two sequential pixels belong to the same line segment if the distance between their end points is less than a pre-specified distance. For each line segment, this continues until the distance to the next ordered pixel exceeds the threshold. This ends the previous line segment and starts a new line segment.

In many cases, the first step results in many short line segments lying along straight lines, some of which are broken because of erroneous edge directions. These shorter line segments must therefore be replaced by the corresponding longer line segments through line merging. This is accomplished in the second step. A metric is needed for line segment merging. It measures how likely two or more shorter line segments are part of the same longer line segment in the image. The metric we chose consists of the following three criterion: first, the line segments to be merged must be collinear. Collinearity is measured by the two HT parameters \( \theta \) and \( \rho \). Two merging line segments should have the same (or close) \( \theta \) and \( \rho \). The second criteria is proximity, i.e., they must be adjacent to each other. Proximity (nearness) is measured by the ratio of distance between the end points of the two line segments to the length of the line segments. After merging, line segments shorter than a pre-specified threshold are discarded as noises. Fig. 4(b) shows the vectorized image of the image shown in Fig. 3(c).

![Fig. 4. (a) the skeletonized image of the image in Fig. 3 (c); (b) the vectorized image of the image in (a). In (b), (a) is approximated by connecting line segments.](image-url)
2.2. Primitive properties extraction and distribution construction

With texture primitives extracted, we have available a list of primitives (line segments) that model the vascular structures of the original image data. We need to proceed to the next phase of texture characterization—texture primitive attributes computation and their distributions construction.

2.2.1. Primitive properties

What we need to do here is to define and extract properties that can best characterize the selected primitives. Since a line segment can be fully described by its length and orientation, line segment length and orientation are the natural choice of their properties. Given two end points of a line segment, its length and orientation can be easily derived. To be consistent, the orientation of a line segment, a real number, takes counterclockwise with respect to the positive X-axis and is limited to 0–179° inclusive. Similarly, the length, also a real number, can be computed using the two end points.

2.2.2. Distribution construction

The properties of line segments can be treated as random variables. To study these properties, we need to estimate their probability density functions, based on sample observations. Since line segment length and orientation are real values, discretization becomes necessary to study the statistical distributions of line segments. Discretization groups line segments into bins, based on their original values. Specifically, the orientations of line segments are uniformly discretized into 180 bins ranging from 0 to 179°. The line segment length is discretized in a similar fashion into \( L \) bins, where \( L \) was empirically selected as 50. After discretization, the length of each line segment is referred to by the number of the bin it belongs to rather than by its actual length.

With the attributes of line segments discretized, we can proceed to construct the density functions (histograms) of the line segments in terms of length and orientation. A total of three distributions were constructed: one joint distribution and two marginal distributions. The joint distribution characterizes the line segment distribution by its length and orientation. Each point in the joint distribution represents the probability of a line segment with a particular length and orientation. The marginal distributions represent the line segment distribution with respect to length/orientation. Each point in a marginal distribution represents the probability of the line segment of a particular length (or orientation). Since line segments are of different lengths, the orientation distribution of line segments is therefore weighted by their lengths. This results in a more realistic orientation distribution. Fig. 5 shows the two marginal distributions of line segment length and orientation for the vectorized mosaic pattern shown in Fig. 4(b).

2.2.3. Distribution normalization

Since texture features are subsequently extracted from the above distributions, we need to ensure the invariance of the above distributions to affine transformations, i.e., rotation, translation, and scale invariant. These will, in turn, ensure the extracted texture features invariant to affine transformations, which is an important practical concern for classification. To do so, the above distributions should be normalized. The normalization approaches we followed need to achieve only rotation invariance for orientation distribution since it is invariant to translation and scale. Similarly, for length distribution, only scale normalization is needed since it is invariant to translation and rotation.

The length distribution is normalized via discretization as discussed before. Since fixed discretization level (50) is used to discretize line segment length, scale only affects the discretization intervals. Given the fact that the lengths of the discretized line segments are referred to by

![Fig. 5. (a) Marginal probability density functions for orientation (a) and length (b) of the line segments in the vectorized mosaic pattern shown in Fig. 4(b).](image-url)
their bin numbers rather than by their actual lengths, the discretization makes the distribution independent of scale. Fig. 6 shows the normalized length distributions for the image with mosaic pattern at two different scales. It is clear that their shapes are very much similar after normalization.

For orientation distribution, a rotation (which is equivalent to adding or subtracting an angle to each line) may not only cause a linear shift for the interior bins (which may not affect the shape of the distribution) but also cause a circular shift for the boundary bins (bins close to 0 or 179) as shown in Fig. 7(a), where the local peak at 0° results from a circular shift of the corresponding local peak at about 140° in Fig. 5(a). This will alter the shape of the original distribution, rendering incorrect feature values. Therefore, it must be normalized. The normalization is carried out as follows. Identify the peak of each distribution and shift the peak to the 90° bin and perform the same amount of shift for other angles. The choice of the peak for normalization rather than other distribution marks like valley is because the peak is less sensitive to noises. Fig. 7 shows the orientation distributions image with mosaics at two different orientations before and after normalization.

2.3. Texture features extraction

Feature extraction is a dimension reduction process. It consists of deriving characteristic measurements from the input image or its transformations. The characteristic measurements characterizing the cervical lesion patterns are derived from the vectorized images and from the statistical distributions of the extracted line segments. Most textual features we suggest are extracted from...
distributions of line segments. They characterize the shapes of line segments distributions. Additional features are derived directly from the vectorized images to describe the spatial complexity and density (vascular concentration) of the texture patterns.

Efforts were made during feature extraction to select features that can relate to the specific textural characteristics of the cervical texture patterns. For example, some features relate to such textural characteristics as randomness, contrast, correlation, etc., while others characterize the spatial complexity of the texture patterns. We suggest a set of nine features which can be extracted from each of the two marginal distributions, four features from the joint distribution, and two features directly from the vectorized images, yielding a total of 24 features ($2 \times 9 + 4 + 2$). For illustrative purpose, we will define 4 of the 24 features in this section and explain their significance in relating to the specific characteristics of the cervical textures as perceived by human. For detailed definitions of all 24 features, refer to Appendix A.

Peak density ($f_1$): measures the strength of the local dominant peak in a marginal distribution, i.e., length or orientation distribution.

$$ f_1 = \max(p(i)) \text{ for } i = 1, 2, \ldots, N, $$

where $p(i)$ is the probability of the $i$th bin and $N$ is the discretization level.

Entropy ($f_2$): measures the randomness or homogeneity of a distribution with respect to length or orientation.

Ratio of the number of intersection points to the number of endpoints ($f_{14}$): measures the spatial complexity of the textures.

Density ($f_{15}$): measures the coarseness (or fineness) of a texture in terms of the amount of edgels per unit area. The average number of edgels per unit area for all pixels is used as a measure of the density.

During feature design process, every effort was made to devise features that represent the specific characteristics of the cervical textures as perceived by human. In this section, we will analyze some of the textural features we proposed and try to relate them to certain textural characteristics.

Peak density ($f_1$) measures the strength of the dominant length (or orientation) of line segment distribution with respect to a particular attribute. Take the orientation for example, hairpin texture pattern, with most line segments oriented in one direction as shown in Fig. 1, should have the highest $f_1$ values among all cervical textural patterns while mosaics, with line segment directions scattering in all directions as shown in Fig. 1, should have the lowest. Similarly, for length distribution, hairpin texture pattern also has the highest peak density. Therefore, this feature can discriminate the mosaic and hairpin patterns.

Entropy ($f_2$) measures the randomness or homogeneity of a distribution with respect to length or orientation. Entropy takes a higher value for more random distribution. Take the orientation for example, Mosaics takes the highest value while hairpin takes the lowest value for the same reason as explained before. Therefore, this feature can discriminate the hairpin pattern from other patterns.

$f_{14}$, the ratio of number of intersection points to the number of endpoints ($f_{14}$) measures the spatial complexity of a texture. It takes a large value if capillaries interweave each other. For example, mosaics has the highest $f_{14}$ value while punctation takes the lowest. Furthermore, network pattern also has much higher value than those of hairpin and punctation. Therefore, this feature can discriminate mosaic and network patterns from others.

Density ($f_{15}$) measures the coarseness (or fineness) of texture in terms of amount of edgels per unit area. Coarse textures have a small number of edgels per unit area while fine texture have a high number of edgels per unit area. It measures the capillary concentration. For example, network pattern has the highest density while punctation has the lowest density. Therefore, this feature can discriminate the network from punctation patterns.

While these features reflect our subjective perception, much more experimentation and analysis should be done on this subject to analyze the correlation of other proposed features with specific characteristics of cervix texture patterns.

2.4. Feature analysis and selection

Before proceeding to carry out classification, an analysis of the extracted 24 features was conducted to study the effectiveness of each feature. Such an analysis is useful in determining which feature may be eliminated due to redundancy and which may be eliminated due to weak discriminatory power. Motivations for such an analysis include cost savings associated with data acquisition and processing. Feature analysis started with the removal of the correlated features, followed by ranking the remaining features.

Redundant features are features whose presence does not contribute very much to the improvement of the classification accuracy. One type of redundant features is features that are linearly correlated with each other. The linearly correlated features can be identified by computing the linear correlation coefficients between any two features. The identified correlated features are subsequently removed via feature pruning. Criterion used for feature pruning include consistency, invariance, and discriminatory power. Consistency is measured by the within group variance, invariance measures features invariance to transformation, and discriminatory power determines a feature’s discriminatory capability as discussed below. For example, angle peak density negatively correlates well with angle contrast, angle contrast feature can be removed since it has lower discriminatory power as shown in Appendix B.
Feature ranking rates the discriminatory power of each feature based on its capability in discriminating all classes. The ratio of between-class variance to the within group variance was used as a criteria. Appendix B shows the result of feature ranking. Analysis of the inter-class and intra-class variance revealed some of the features to be ineffective, yielding a feature vector of reduced dimensionality. For example, angle kurtosis and skewness are ineffective measures since they are the measures for unimodal distribution while angle distributions contain multiple modes. On the other hand, length kurtosis and skewness are effective measures since length distributions are close to unimode.

Subsequent to correlation computation and feature ranking, a subset of features can be selected to form a new feature set that will be used for classification. This requires retaining those features having the highest discriminating power and deleting those that are redundant or provide minimum information for class separation. Redundant features can be deleted through removing correlated features. Features providing minimum information for classification can be removed through ranking. We will demonstrate this in the experimental section.

2.5. Classifier design

With features extracted, algorithms are needed to take the extracted features as input and output the required class labels. Of many different classifiers, we chose the minimum distance classifier. To design the minimum distance classifier, we compute the mean feature values for each pattern class. The distance to the mean of each class from a given input vector is computed and the vector is assigned to the class for which the distance from the vector to the class mean is the shortest since that class has feature measurements most similar to those of the unknown sample. Euclidean distance is used as a measure of the “nearness” of a cluster, although other measures of similarity are also possible.

To prevent features with large numerical values from dominating the distance calculations, both the feature values and the distances are normalized. This normalization procedure takes into account the spread of the values within a cluster. For example, in the one-dimensional case, for a cluster with a mean \( \mu_i \) and a standard deviation \( \sigma_i \), if \( f - \mu_1 = (f - \mu_2) \) but \( \sigma_1 > \sigma_2 \), the sample would be classified as belonging to class 1 since it has a larger variability, where \( f \) a query vector.

For each of the six classes, the distance from the unknown sample to the class mean is computed. The class to which the distance is minimum is the class to which the unknown sample is assigned. The results of this classification are recorded in a confusion matrix.

3. Experimental evaluation

In this section, we present the preliminary results of our studies on the usefulness of the proposed texture features for categorizing a series of typical vascular patterns as shown in Fig. 1. This evaluation starts with a discussion of image data acquisition, followed by textural feature extraction and analysis, classifier design, and finally a presentation and analysis of the classification results.

3.1. Image acquisition and feature extraction

The experiment started with cervical image acquisition and preparation. The images to be prepared should contain the typical vascular pattern classes characterizing different stages of dysphasia. Typical vascular patterns to be recognized in this project include six vascular pattern classes. They are network capillaries, hairpin capillaries in normal and benign cervical lesions; and two different versions of punctation and mosaic patterns in preinvasive and invasive lesions as shown in Fig. 1. Sources of images include our existing library of colposcopic images, published photographs, and commercial slides. All images came with diagnosis and biopsy results.

To characterize each vascular pattern class accurately, 50 images were collected for each vascular pattern class, resulting in a total of 300 images. These images represent six classes. For each acquired image, we identified and marked a rectangular region corresponding to a known vascular pattern. The identified regions of interest were preprocessed. The preprocessed images were subsequently skeletonized and vectorized. The line segments distributions were then constructed, followed by the extraction of the 24 texture features. To perform feature selection, 5 images were randomly selected for each pattern class from the 300 images. Feature selection and analysis on the selected images yields 13 optimal features as shown in Table 1. Detailed results for feature analysis may be found in Appendix B.

| Table 1 |
| A subset of 13 optimal features |
| Joint entropy |
| Angle entropy |
| Angle peak ratio |
| Length peak density |
| Angle peak density |
| Length entropy |
| # Intersections/# Ends |
| Info entropy |
| Energy |
| Length median |
| Angle contrast |
| Length median/range |
3.2. Classification and results

To study the classification performance of the proposed technique, we divided the remaining images (270) into two sets: one for testing and one for training. Due to the large feature vector dimension (24) and relatively smaller number of images (45 for each class pattern), the conventional classification technique, which requires dividing the original data set into separate training and testing data sets, cannot generate accurate results since we do not have sufficient data for training. Instead, cross-validation method was used for classification design and evaluation. This method is widely used by investigators in the pattern recognition field when the data set does not contain sufficient samples to have separate training and testing data.

The decision boundaries (training) are obtained by leaving out some samples in the original data set, the samples which are left out are then classified (tested). The procedure is repeated for all samples in the data set, with new samples left out each time, to obtain the overall accuracy of the classification scheme. The final classification error is the average for each left-out.

Specifically, for each training and testing session, 240 (40 for each class) sample images were used as the training data and the 30 (5 for each class) left-out were used as the testing data. This process iterated 9 times so that every sample image had the chance to be the left out and to be in the training set. The total number of correct classification over the 9 iterations was used to evaluate the classification performance. For each testing, the minimum distance decision rule was used to classify the left-out image into one of six vascular pattern classes.

Two experiments were conducted. First, classification was performed using 24 features. Second, the 13 optimal features defined in Table 1 were computed and used for classification. The performance of the classifier was recorded in the confusion matrix as shown in Tables 2 and 3.

The left most column of the confusion matrix is labeled with the actual classes, the top row shows the classified classes. Table 2 shows the results using all 24 features while the confusion matrix in Table 3 shows the resultant output, using the optimal 13 features. In summary, we obtained the best discrimination performance (87.03%) by using all 24 features as shown in Table 2. However, by using only the 13 optimal features resulting from feature ranking, our technique experiences a loss in classification accuracy (80.36%). The loss in accuracy seems to be minimal compared to the computational saving (almost 40%). Further experiments are needed to validate this.

4. Conclusion

This paper describes a texture image analysis technique for characterizing and recognizing typical, diagnostically most important, vascular patterns relating to
cervical lesions. Preliminary experimental study demonstrated the feasibility of the proposed technique in discriminating between cervical texture patterns indicative of different stages of cervical lesions. Study is underway currently to further characterize the performance of the proposed approach with a larger data set.

The major contributions of this research include the development of a novel generalized statistical texture analysis technique for accurately characterizing cervical textures and the introduction of a set of textural features that capture specific characteristics of the cervical textures as perceived by human. These contributions could potentially lead to a system that can accurately recognize typical vascular patterns indicative of different stages of cervix lesions.

Appendix A. Textural features

The following equations define textural features.

Notations:

\( p(r, c) \) is the \((r, c)\)th entry in a normalized joint line segment distribution with respect to both length and orientation.

\( p(i) \) is the \(i\)th entry in a marginal line segment distribution with respect to either length or orientation.

\( N \) is the number of distinct discretization levels with respect to either length or orientation.

\( \mu \) and \( \sigma \) are the mean and standard deviation of a marginal line segment distribution.

A.1. Textural features for marginal density distributions:

1. Peak density \( (f_1) \) measures the strength of the local dominant orientation (or length) of a line segment distribution.

\[
\begin{align*}
\text{for } i = 1, 2, \ldots, N,
\end{align*}
\]

2. Peak ratio \( (f_2) \) measures the relative strength of the second dominant orientation (or lengths of a line segment distribution).

\[
\begin{align*}
& f_2 = \frac{p_2}{f_1}, \\
& p_2 = \text{max}(p(i)) \quad \text{and} \quad p_2 < f_1 \quad \text{for } i = 1, 2, \ldots, N.
\end{align*}
\]

3. Median \( (f_3) \) measures the homogeneity of a line segment distribution with respect to length or orientation.

\[
\begin{align*}
\sum_{i=1}^{N} p(i) = 0.5.
\end{align*}
\]

4. Mean \( (f_4) \) measures the global (average) trend of a line segment distribution with respect to length or orientation.

\[
\begin{align*}
& f_4 = \frac{1}{N} \sum_{i=1}^{N} p(i) \cdot i.
\end{align*}
\]

5. Median to range ratio \( (f_5) \) measures the homogeneity of a line segment distribution with respect to length or orientation.

\[
\begin{align*}
& f_5 = \frac{f_3}{N}.
\end{align*}
\]

6. Contrast \( (f_6) \) measures the local variation or contrast in a distribution around its mean with respect to length or orientation.

\[
\begin{align*}
& f_6 = \sum_{i=1}^{N} \frac{|i - \mu|}{\sigma} p(i).
\end{align*}
\]

7. Entropy \( (f_7) \) measures the randomness or homogeneity of a distribution with respect to length or orientation.

\[
\begin{align*}
& f_7 = -\sum_{i=1}^{N} p(i) \log(p(i)).
\end{align*}
\]

8. Skewness \( (f_8) \) characterizes the degree of asymmetry of a univariate distribution around its mean.

\[
\begin{align*}
& f_8 = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{i - \mu}{\sigma} \right)^3.
\end{align*}
\]

9. Kurtosis \( (f_9) \) measures the relative peakness or fatness of a univariate distribution.

\[
\begin{align*}
& f_9 = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{i - \mu}{\sigma} \right)^{-3}.
\end{align*}
\]

A.2. Textural features for the joint distribution:

10. Joint entropy \( (f_{10}) \) measures the randomness or homogeneity of a joint distribution.

\[
\begin{align*}
& f_{10} = -\sum_{i=1}^{N} \sum_{c=1}^{M} p(r, c) \log(p(r, c))
\end{align*}
\]

11. Informational entropy \( (f_{11}) \) measures the correlation between two random variables (orientation and length) that are not brought about by the linear correlation coefficient.

\[
\begin{align*}
& f_{11} = (1 - e^{-2.0(H_{xy} - f_{10})^{1/2}}),
\end{align*}
\]

where \( H_{xy} = -\sum p(i) \sum p(j) \log[p(i) \cdot p(j)] \).

12. Correlation \( (f_{12}) \) measures the linear dependence between the orientation and length of line segments.

\[
\begin{align*}
& f_{12} = \frac{\sigma_{lr}}{\sqrt{\sigma_l \sigma_r}},
\end{align*}
\]

where \( \sigma_{lr}, \sigma_l, \) and \( \sigma_r \) represent the covariance of length and orientation, marginal variance of length and orientation, respectively.

13. Energy \( (f_{13}) \) measures the uniformity of the entries in the joint distribution. It is the lowest when all entries are equal.

\[
\begin{align*}
& f_{13} = \sum_{i} \sum_{j} p^2(i, j).
\end{align*}
\]
14. Ratio of the number of intersection points to the number of endpoints \((f_{14})\) measures the spatial complexity of the textures.

\[
f_{14} = \frac{\text{number of intersection points}}{\text{number of end points}}.\]

15. Density \((f_{15})\) measures the coarseness (or fineness) of a texture in terms of amount of edgels per unit area.

### Appendix B. Feature ranking

<table>
<thead>
<tr>
<th>Features</th>
<th>Between (G) variance/</th>
<th>Within (G) variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joint entropy</td>
<td>125.87</td>
<td></td>
</tr>
<tr>
<td>Angle entropy</td>
<td>29.22</td>
<td></td>
</tr>
<tr>
<td>Angle peak ratio</td>
<td>25.92</td>
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<tr>
<td>Length peak density</td>
<td>16.98</td>
<td></td>
</tr>
<tr>
<td>Angle peak density</td>
<td>15.06</td>
<td></td>
</tr>
<tr>
<td>Length entropy</td>
<td>12.42</td>
<td></td>
</tr>
<tr>
<td># Intersections/# Ends</td>
<td>10.87</td>
<td></td>
</tr>
<tr>
<td>Info-entropy</td>
<td>10.78</td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>10.57</td>
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</tr>
<tr>
<td>Length median</td>
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<td></td>
</tr>
<tr>
<td>Angle contrast</td>
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</tr>
<tr>
<td>Length median/range</td>
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<td></td>
</tr>
<tr>
<td>Length skewness</td>
<td>5.42</td>
<td></td>
</tr>
<tr>
<td>Length peak ratio</td>
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</tr>
<tr>
<td>Length mean</td>
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</tr>
<tr>
<td>Density</td>
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<td></td>
</tr>
<tr>
<td>Length kurtosis</td>
<td>2.84</td>
<td></td>
</tr>
<tr>
<td>Correlation</td>
<td>2.15</td>
<td></td>
</tr>
<tr>
<td>Length contrast</td>
<td>1.62</td>
<td></td>
</tr>
<tr>
<td>Angle median/range</td>
<td>1.07</td>
<td></td>
</tr>
<tr>
<td>Angle kurtosis</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>Angle mean</td>
<td>0.85</td>
<td></td>
</tr>
<tr>
<td>Angle median</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>Angle skewness</td>
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<td></td>
</tr>
</tbody>
</table>

### References


### About the Author

Qiang Ji received a MS degree in electrical engineering from the University of Arizona in 1993 and his Ph.D. degree in electrical engineering from the University of Washington in 1998. His areas of research include computer vision, image processing, pattern recognition, and robotics.

Dr. Ji is currently an assistant Professor at the department of computer science at University of Nevada at Reno. Between May, 1993 and May 1995, he was a research engineer with Western Research Company, Tucson, Arizona, where he served as a principle investigator on several NIH funded research projects to develop computer vision and pattern recognition algorithms for biomedical applications. In summer 1995, he was a visiting technical staff with the Robotics Institute, Carnegie Mellon University, where he developed computer vision algorithms for industrial inspection. From 1995 to 1998, he worked as a research associate at the Intelligent Systems Laboratory (ISL) at the University of Washington, involving in a Boeing-funded research project consisting of developing computer vision techniques for 3D geometric tolerancing of manufactured parts from their images.
He has published numerous papers in referred journals and conferences in these areas. His research has been funded by local and federal government agencies and by private companies including Boeing and HONDA. He currently serves as PI for a project funded by HONDA involving developing a computer vision system for monitoring driver’s vigilance level.

About the Author—Dr. JOHN ENGEL obtained his Ph.D. in physics from the University of California, Los Angeles. He is now a senior engineer with Etec Systems, Inc. He has, since 1980, been involved with software engineering, scientific programming, algorithm development and image processing on micro-, mini-, and mainframe computer systems. He is a member of the Pattern Recognition Society, SPIE, IEEE, and the American Physical Society and the American Geophysical Union.

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