ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 8, Issue 3, March 2020

Classification of Bacteria Contamination Using Support Vector Machine

Nishanth S.B[1], Prasanth M[2], Rithish S[3], Mahalakshmi B[4]

B.E Student, Department of Computer Science and Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India[1]

B.E Student, Department of Computer Science and Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India[2]

B.E Student, Department of Computer Science and Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India[3]

Professor, Department of Computer Science and Engineering, K.S. Rangasamy College of Technology, Tiruchengode, Tamilnadu, India[4]

ABSTRACT: Bacterial contamination of food products is a serious public health problem that creates high costs for the food processing industry. detection of bacterial pathogens is the key to avoiding disease outbreaks and costly product recalls associated with food-borne pathogens. Automated identification of pathogens using scatter patterns of bacterial colonies is a promising technique that uses image processing and machine learning approaches to extract features from forward-scatter patterns produced by irradiating bacterial colonies with red laser light. The feature vector used for this approach can consist of hundreds of features, and a sufficiently large number of training images is required for accurate classification. As most feature extraction algorithms have high computational costs, the feature extraction step becomes the bottleneck in the processing pipeline. This work reports the implementation of the laser-scatter-analysis technique on a computational grid. A set of more images was used for the training of classifiers. The invariant form of Zernike moments up to order 20, radial Chebyshev moments, and Hardwick features were extracted. Linear discriminate analysis and support vector machine classifiers were used for classification.

KEYWORDS: bacteria**,** contamination, vector machine.

I. INTRODUCTION

Food products contaminated by bacteria are a serious risk for the public and are responsible for various disease outbreaks and health hazards. Contaminated products also generate serious costs for the food-processing industry because of product recalls. Fast and accurate identification of pathogens present in the contaminated products is extremely important in order to avoid the harmful effects of such contamination. Numerous analysis techniques have been proposed for this purpose. Most current methods utilize expensive biochemical or molecular biology-based technologies and require complex sample preparation for accurate pathogen detection and recognition. Analysis and classification of microorganisms using forward-scatter patterns is a newly proposed, inexpensive, label-free technique. This approach requires a laser to illuminate bacterial colonies grown on agar plates, and a digital camera connected to a computer to collect information about forward-scattered light patterns. A number of different features, including Zernike moments, Chebyshev moments, and Haralick texture features, are extracted from the resultant patterns, providing the means for automated, rapid classification. This new technique provides reproducible results and does not require any special chemical treatments or sample preparation. However, accurate classification requires that the

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ISSN (Print): 2320-9798

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classifiers be trained and optimized using large training sets, even if just a few bacterial classes are detected. Extracting higher-order shape moments and texture features from large sets of patterns is extremely time-consuming and becomes the bottleneck for classifier optimization. Hence, the speed of the feature extraction step determines the speed of training. For industrial application, where thousands of samples may need to be processed rapidly, feature extraction slows down the testing phase as well. Computational grid technologies provide a cost-effective solution to this problem. Every year foodborne disease outbreaks due to contaminated food products significantly affect the food processing industry, food retail, and consumers. Rapid and automated identification and classification of microbiological samples is the first line of defense against such incidents. Most techniques designed for this purpose are based on biochemical or molecular biology technologies. Although these approaches are well established, they are also expensive and require complex sample preparation. A new and innovative technique employing classification of laser-induced scatter patterns for recognition of bacterial colonies has recently been proposed. This approach is non-destructive, inexpensive, and label-free. In this procedure, bacterial colonies grown on standard agar plates are illuminated with laser light, and the scatter patterns produced are recorded as bitmaps by a monochromatic digital camera. After further processing and application of pattern analysis techniques, the acquired data can be used to uniquely identify various bacterial species. The protocol involves extracting from the patterns a number of features such as Zernike moments, Chebyshev moments, and Haralick texture descriptors. These features provide a unique representation of different scatter patterns and—indirectly—of different bacterial colonies, and can be utilized to identify microbial species quickly and with high reproducibility. However, one significant challenge to overcome is the high computational cost of the feature extraction and feature selection steps.

1.2 PRE-PROCESSING

The main goal of the pre-processing is to improve the image first-rate to make it prepared to similarly processing by using disposing of or reducing the unrelated and surplus parts within the historical past of the mammogram photographs Mammograms are medical photos that complicated to interpret. Hence, pre-processing is vital to improve the fine. It will put together the mammogram for the following two-procedure segmentation and feature extraction. The noise and excessive frequency additives eliminated with the aid of filters. Image pre-processing is the call for operations on pix at the lowest degree of abstraction whose goal is a development of the photo information that suppress undesired distortions or enhances some picture features vital for further processing. It does not growth picture records content. Its techniques use the sizable redundancy in pictures. Neighboring pixels similar to one object in real pix have the equal or comparable brightness value and if a distorted pixel can be picked out from the image, it may be restored as an average cost of neighboring pixels. Image pre-processing tool, created in MATLAB, realizes many brightness variations and nearby pre-processing strategies.

1.3 OPERATION

Image pre-processing is the term for operations on pics at the lowest stage of abstraction. These operations do not growth image statistics content, but they lower it if entropy is a statistics measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image functions applicable for further processing and evaluation task. Image pre-processing use the redundancy in snap shots. Neighboring pixels corresponding to one actual item have the equal or similar brightness value. If a distorted pixel can be ninety-eight picked out from the image, it is able to be restored as an average fee of neighboring pixels. Image pre-processing methods can be categorized into categories in step with the dimensions of the pixel neighborhood that is used for the calculation of a new pixel brightness. In this paper, it is going to be presented a few pixel brightness adjustments and local pre-processing methods found out in Mat Lab.

1.4 IMAGE CROPPING AND FILTERING

The first step in image pre-processing is image cropping. Some irrelevant parts of the photograph can be removed and the photograph region of interest is focused. This device offers a user with the size information of the cropped image. Mat Lab characteristic for photograph cropping realizes this operation interactively anticipating a person to specify the crop rectangle with the mouse and operates on the current axes. The output picture is of the identical magnificence as the input photograph. The two-dimensional convolution operation is fundamental to the

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Vol. 8, Issue 3, March 2020

analysis of images. A new fee is ascribed to a given pixel based totally on the assessment of a weighted average of pixel values in a k × ok neighborhood of the important pixel. Convolution kernel or the filter out masks is represented with weights provided in a square matrix. It is applied to each pixel in an image. Discrete shape of the 2D convolution operator is defined by means of the following relationship among the factors (x, y) of the input photograph, the factors h (α, β) of the convolution kernel, and the factors g (x, y) of the output picture by means of the following grasp formula.

$$g(x,y)=\sum_{\alpha=-(k-1)/2}^{(k-1)/2}\ \sum_{\beta=-(k-1)/2}^{(k-1)/2} f_i(\alpha,\beta)h(x-\alpha,y-\beta),$$

Equation:1

x, y, α and β are integers. Coefficients of the kernel H constitute a discrete approximation of the analytical shape of the response function characterizing the desired filter. In sensible cases, the kernel is a rectangular array and kx = ky = k, where okay is odd and lots smaller than the linear photo dimension. There are the following steps, realized for each pixel P represented by (x, y):
• placement of H on P
• multiplication of every pixel inside the k × ok community by means of the appropriate filter out masks
• summation of all products
• placement of the normalized sum into role P of the output image
This tool for pre-processing we could a person explores 2-D Finite Impulse Response filters. By converting the cut-off frequency and filter out order, the user can layout filter and might see the designed clear out's coefficients and frequency response. Median filtering is a non-linear smoothing approach that reduces the blurring of edges and considerably removes impulse noise. It suppresses image noise without decreasing the image sharpness and can be carried out iteratively. The brightness fee of the contemporary pixel in the picture is replaced by way of the median brightness of either three-by-three or 4-through-four neighborhood.

1.5 INTENSITY ADJUSTEMENT AND HISTOGRAM EQUALIZATION

A gray-scale transformation T of the authentic brightness p from scale [p0, pk] into brightness q from a brand-new scale [q0, qk] is given by way of q = T(p). It does not rely on the position of the pixel within the photograph. Values below p0 and above pk are clipped. Values underneath p0 map to q0, and people above pk map to qk. Alpha argument specifies the shape of the curve describing the relationship among the values inside the input picture and output photograph. If alpha is much less than 1, the mapping is weighted in the direction of brighter output values. If alpha is more than 1, the mapping is weighted closer to decrease darker output values. If the argument is disregarded its default price is 1. Graphical controls enable a user to increase and decrease the brightness, assessment and alpha correction.
Another offered possibility to enhance the comparison of photo, via reworking the values in an intensity image so that the histogram of the output image fits a distinctive histogram, is histogram equalization method. Region description is based totally on its statistical grey-stage properties. Histogram gives the frequency of the brightness price in the picture. A photograph with n grey ranges is represented with one-dimensional array with n elements. The n-the detail of array includes the number of pixels whose gray level is assume that the pixel values are normalized and lie in the range [0, 1]. Let s = T(r), for any r ∈ [0, 1], is transformation function which satisfies the following conditions:
• T(r) is single valued and monotonically increasing in the interval [0, 1];
• $0 \leq T(r) \leq 1$ for any r ∈ [0, 1].
The original and converted grey ranges may be characterized by using their possibility density functions. Contrast is the local change in brightness and is defined because the ratio between common brightness of an object and the history brightness. Histogram equalization method is based on modifying the arrival of a photo by means of controlling the possibility density function of its gray levels by means of the transformation function T(r). This technique enhances the contrast in the photo.

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1.6 BRIGHTNESS THRESHOLDING

Brightness threshold is an imperative step in extracting pertinent information. A grayscale picture often contains the simplest level of great information: the foreground level constituting objects of hobby and the historical past level in opposition to which the foreground is discriminated. A whole segmentation of an image R is a finite set of areas R1, R2..., Rm,

$$R = \bigcup_{i=1}^{m} R_i, \quad R_i \cap R_j = \emptyset \quad i \neq j.$$

Equation:2

If Rb is a historical past within the image, then Sm i=1, i6=b Ri is considered the item and RC b = Sm i=1, i6=b Ri, wherein RC b is the set complement. While there are two principal a hundred and one peaks of the foreground and the background intensities in the photo histogram, there are numerous other gray intensities present. Binarization may be accomplished by the choice of a depth, between the 2 histogram peaks, that is the threshold between all history intensities under and all foreground intensities above. The input picture I1 is being transformed to an output binary segmented image I2, within the following way.

$$I_2(i,j) = \begin{cases} 1; & I_1(i,j) \geq T \\ 0; & I_1(i,j) < T \end{cases}$$

Equation:3

Where T is the edge. I2(i, j) = 1 for the object factors and I2(i, j) = zero for the history elements. There are different approaches for picture binarization depending on the type of image. Successful threshold segmentation relies upon on the edge selection. A variety of situations like poor photo assessment or spatial non uniformizes in historical past intensity can make difficult to clear up foreground from heritage. These cases require consumer interplay for specifying the desired item and its distinguishing depth features.

1.7 CLEARING AREAS OF A BINARY IMAGE

If there's a deformation of the expected form and length of the border and the whole area for the duration of the separation of picture object from its background, it is able to be in part overcome. Usually small polygon mask, positioned next to the place and out of it, is introduced to clear picture vicinity with comparable brightness of the region. This mask can reshape image objects and gives a separation image objects from every different and from their photo background.
This operation is realized interactively, adding vertices to the polygon. Selecting a final vertex of the polygon over a white colored photo place, the fill is begun and recolor to black. Created fill is a logical mask and the input photograph is logical matrix. Using logical operator AND below logical arguments, the output photo is also acquired as a logical array. If the white areas represent image foreground on the black background, while gadgets or their parts can be deleted. Special user requirements about the dimensions and shape of the observed item, can be found out by using the identical way.

1.8 DETECTING EDGES

Edges are pixels where the intensity image function changes abruptly. Edge detectors are collection of local image pre-processing methods used to locate changes in the brightness function. An image function depends on two variables, co-ordinates in the image plane. Operators describing edges are expressed by partial derivatives. A change of the image function can be described by a gradient that points in the direction of the largest growth of the image function.An edge is a vector variable with two components, magnitude and direction. The edge magnitude is the magnitude of the gradient. The edge direction is rotated with respect to the gradient direction by $-\pi/2$. The gradient direction gives the direction of maximum growth of the function, e.g., from black to white. The boundary and its parts are perpendicular to the direction of the gradient. The gradient magnitude and gradient direction

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$$|grad\, g(x,y)| = \sqrt{\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2}$$

$$\varphi = arg\left(\frac{\partial g}{\partial x}, \frac{\partial g}{\partial y}\right)$$

Equation:4

Are continuous image functions where arg(x, y) is the angle from x-axis to the point (x, y). A digital image is discrete in nature and these equations must be approximated by differences of the image g, in the vertical direction for fixed i and in the horizontal direction for fixed j, by following equations.

$$\Delta_i\, g(i,j) = g(i,j) - g(i-n,j)$$
$$\Delta_j\, g(i,j) = g(i,j) - g(i,j-n),$$

Equation:5

Where n is a small integer selected so to provide an awesome approximation to the by-product and to neglect unimportant changes in the picture function. Gradient operators approximating derivatives of the photo feature the use of differences use one or numerous convolution masks. Beside them, this tool makes use of operators primarily based on the zero-crossings of the image characteristic second derivative. Sobel, Prewitt, and Roberts techniques locate edges through threshold the gradient and by them horizontal edges, vertical edges or both may be detected. The Laplacian of Gaussian technique thresholds the slope of the zero crossings after filtering the image with a Log filter. Canny method thresholds the gradient the usage of the by-product of a Gaussian filter. One option in the primary menu offers processing of the image region of interest or the whole picture. It has to transport the pointer over the photo on the left and whilst the cursor changes to a crosshair, it has to click on points in the image to choose vertices of the place of interest. Offered operations to perform are unsharping, histogram equalization technique, low bypass filtering, median filtering, and brightening, darkening, increasing contrast, lowering comparison and boundary interpolation. The tool for photo pre-processing is found out in Mat Lab. The following illustration indicates the effects of many pre-processing actions. The input photograph is Doppler photograph of blood vessel. First, it can be cropped and its beside the point parts may be removed Image region of interest is focused.

II. EXISTING SYSTEM

In order to achieve satisfactory classification results, the classifier has to be trained on a large number of scatter patterns. The best combination of features has to be established as well. This is an extremely time-consuming process. In certain situations, such as fully automated industrial applications where thousands of samples may need to be tested, the computational complexity may be the limiting factor of the method.
Feature Selection computing provides a reasonable solution to this problem. The process of selecting the appropriate set of features for a particular problem is guided by the classification accuracy achieved on a sufficiently large training set. This set may consist of many hundreds to a few thousand scatter patterns. Owing to the inherently parallel nature of the problem, computer clusters or grids can be efficiently used for these types of applications.

III. PROPOSED SYSTEM

In my procedure an implementation of the laser light scatter technique within a distributed computing environment. In our earlier report, we demonstrated the preliminary implementation of bacterial scatter-pattern classification on a computational grid-using Condor as the grid toolkit. In this paper, we describe the implementation of the forward scatter–based feature extraction, and search for the best feature combinations on a grid computing system. We report results from a procedure to identify the most appropriate set of features for this application. The scatter patterns produced by scattering of laser light from a bacterial colony are first standardized. This involves image centering and

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histogram equalization. Subsequently, the features are extracted. The output of the feature-extraction step is a feature vector that contains up to several thousand features. The most discriminative features are selected and the classifier is trained. Finally, the fully trained classifier is used for recognizing unknown patterns and predicting the originating species or strains. The feature extraction is the most computationally expensive step of the procedure. In a high-throughput setting (such as analysis of large numbers of samples in the food-processing industry, or screening in research applications) in which possibly thousands of instances have to be analyzed in a minimal amount of time, a grid implementation can significantly increase the feasibility of a successful deployment. The increased data-processing speed also makes it possible to train the classifiers on much larger data sets. Finally, it allows training of multiple classifiers with different initial settings in order to select the best classifier for specific conditions. In this paper, we explore the computational cost of computing higher-order Zernike and Chebyshev moments, which may potentially improve classifier performance. In the context of the specific application for classification of pathogens, grid computing is the enabling technology that paves the way for developing large databases of bacterial scatter patterns that are used to identify microorganisms.

PREPROCESSING

Image acquisition is the process of capturing image with the help of a digital camera attached with an electron microscope. After this process, the capturing image will have some noises for instance the image may contain some unwanted artefact which are imperceptible by human eyes.
These kinds of noise will be removed by applying a particular noise to the original image and this noisy image will be filtered using filtering techniques. Later then, a restored image will be obtained. From the restored image, a particular portion of a cell structure should be chosen. For this purpose, a segmentation technique should be used.
The scatter images (640 × 480 pixels) were cropped to 300 × 300 pixels by keeping the center of the circularly shaped scatter patterns in the geometric center of the image and selecting a 300 × 300 rectangle around it. This is achieved in a semiautomatic manner in which the user selects the center of the colony and the rest of the process is carried out automatically.

PIECE MINING

Piece mining is the identification of particular characteristics of an object of interest in an image. The suitable mixture of these physiognomies is the key to the success of many recognition and analysis tasks. The skins I castoff for our scrutiny embrace Zernike and Chebyshev moments and Haralick texture. Subsequently their overview by Hu, moments have been utilized in numerous bids ranging from ophthalmic atmosphere appreciation and aspect recognition to twin cataloguing.
Chin variety also aids in unindustrialized restored understanding of the underlying data-generation process. In this study, I used Fisher's criterion, which selects skins based on the ratio of interclass variance to infraclass variance. Classification was performed using an SVM algorithm. The SVM progressions endeavor to maximize the margin between different modules by plotting the effort to a higher dimensional planetary and constructing the separating hyper smooth.
Segmentation is the process of partitioning an image into multiple regions/parts. Through this the image will be easily analyzed. Here, Region of Interest (ROI) technique is used for segmenting the image. After the segmentation process, the input image is converted into binary image which consists of 0's and 1's (0 represents black and white represents white), by a threshold method. To remove small blobs in the image, morphological techniques will be used. various features are extracted from the segmented region.
In this work, the size of the segmented cell structure will be identified, which is known as feature extraction. After that, the result (size) will be compared with the database and the bacterium which satisfies the criteria (size) will be displayed.

CLASSIFICATION TECHNIQUE

Support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one

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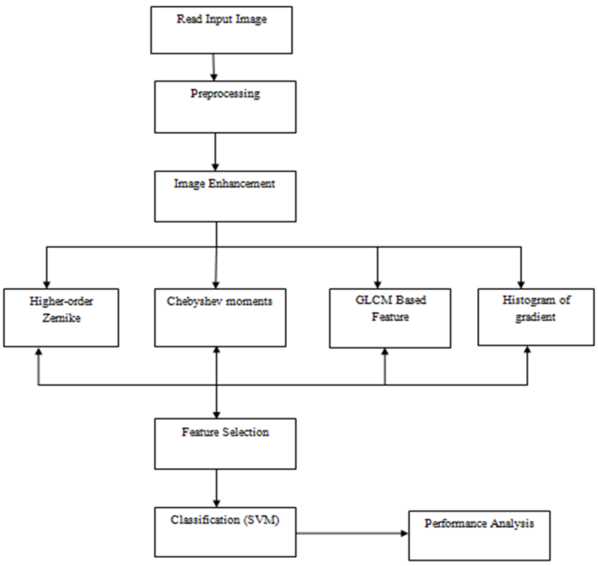
category or the other, making it a non-probabilistic_binary_linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

Properties:

SVMs belong to a family of generalized linear classifiers and can be interpreted as an extension of the perceptron. They can also be considered a special case of Tikhonov regularization. A special property is that they simultaneously minimize the empirical classification error and maximize the geometric margin; hence they are also known as maximum margin classifiers.

Block Diagram:



SNAP SHOT

Fig. 1. Sample Input Image1

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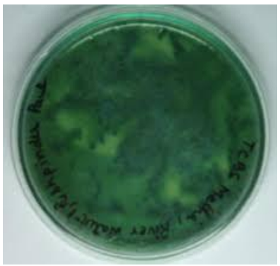

Fig. 2. Sample Input Image 2

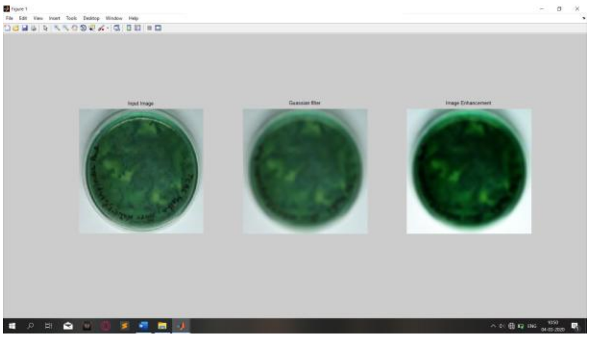

Fig. 3. Processing Image Enhance

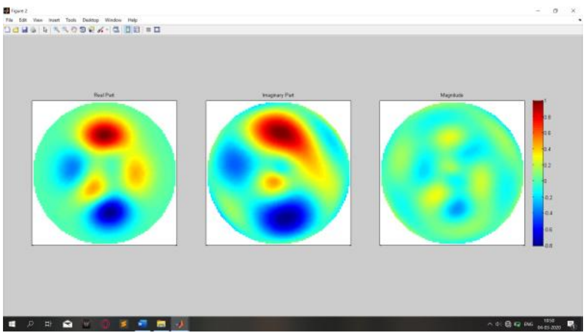

Fig. 4. Enhancement with RGB patten

IV. CONCLUSION

We have presented an application of image analysis for classification of scatter patterns formed by various bacteria. The light-scatter analysis is a simple-to-implement yet powerful technique for noninvasive identification of bacterial colonies. The feature-extraction part of this approach is the most computationally intensive, but the use of feature Selection provides an inexpensive and efficient solution to this problem. We also used the high computational power to analyze the contribution of different feature-extraction approaches to the overall classification accuracy. Our objective was to identify a small set of features with the highest discriminative power to further improve the speed of this approach. We conclude that Haralick texture features are the most useful for this application, and they outperform both Zernike and Chebyshev moments in terms of classification accuracy.

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