MULTICLASS SKIN DISEASE CLASSIFICATION USING NEURAL NETWORK

Manish Pawar¹, Prof. Dipesh Kumar Sharma², Prof. R.N. Giri³

^{1,2,3}Department of Computer Science and Engg. Raipur Institute of Technology, Raipur, India

Abstract: Skin recognition is used in several applications ranging from algorithms for face recognition hand gesture analysis, medical image diagnosis and to offensive image filtering. In this effort a skin recognition system was developed for different classes of skin disease images and tested. As many skin segmentation algorithms relay on skin color, our work relies on texture features (features derives from the GLCM) to give a better and more efficient recognition accuracy of skin textures. We used feed forward back propagation neural networks to classify input textures images into three different classes. These classes represent three different skin disease conditions. The system gave very encouraging results during the neural network generalization face.

Keywords: skin recognition, texture analysis, neural networks.

1. INTRODUCTION

Skin is a multifaceted landscape that is difficult to model for several reasons. The skin texture features depends on numerous variables such as body location (knuckle vs. torso), subject parameters (age/gender/health) and imaging parameters (lighting and camera). Also as with several real world surfaces, skin look is strongly affected by the direction from which it is viewed and illuminated.

Recognition of human skin is an significant task for both computer vision and graphics. For computer vision, precise recognition of skin texture can greatly assist algorithms for human face recognition or facial feature tracking. In computer graphics, facial animatronics is an significant problem which necessitate consistent skin texture recognition. In accumulation to computer vision and graphics, skin recognition is helpful in dermatology and several industrial field in dermatology, the skin recognition can be used to enlarge methods for computer-assisted diagnosis of skin disorders, as in the pharmaceutical industry quantification is supportive when applied to measuring healing progress.

Several skin segmentation methods depend on skin color [5] [6] which have lots of difficulty .The skin color depends on human pursuit and on lighting circumstances, although this can be avoided in some ways. There still many problems with this method because there are many objects in the genuine world that have a chrominance in the range of the human skin which may be wrongly considered as skin. For the above reasons we use texture feature of the will raise the accuracy of skin recognition.

Texture refers to visual patterns in images that have properties for homogeneity, contrast, energy which do not result from the presence of any single color or intensity. These regions may contain unique visual pattern or spatial arrangements of pixels which may not be described by gray level or color values alone.

2. RELATED WORK

Most existing skin segmentation techniques involve the classification of individual image pixels into skin and non-skin categories on the basis of pixel color. Lots of relative studies of skin color pixel classification have been reported. In [1]

ISSN 2348-1196 (print) International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online) Vol. 2, Issue 4, pp: (189-193), Month: October - December 2014, Available at: www.researchpublish.com

Nidhal K. Al abbadi proposed a method for skin texture recognition using neural network. They proposed a skin recognition system. This system is using skin color feature and texture feature. In [2] authors proposed a texture recognition system based on Grey Level Co-occurrence Matrix (GLCM) for automatic recognizing the texture. Features extracted from GLCM are contrast, homogeneity, mean and variance. Based on the differences in texture appearance skin texture is categorized into 3 different disease classes. Brand and Mason [3] compared three different techniques on the Compaq database: thresholding the red-green ratio, color space mapping with 1D pointer and RGB skin probability map. In [4] authors implemented a classifier using MLP neural network for face detection. Face can be detected through different features similar to shape skin texture and skin color. They are interested by the design of ANN not by the features. In [7] authors proposed a technique for image segmentation using texture content. Texture features are extracted from spatial blocks using quad tree decomposition. All feature sets are computed from Quadrature Mirror Filter (QMF) wavelet representation. Texture feature extraction can be done based on block-based features, wavelet sub band features.

3. TEXTURE FEATURES EXTRACTION

Texture is a very interesting image feature that has been used for classification of images, a key characteristic of texture is the repetition of a pattern or patterns over a region in an image. The elements of patterns are occasionally known textons. The size, shape, color, and orientation of the textons can vary over the region.

Texture in image processing describe as a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Texture refers to visual patterns or spatial arrangement of pixels that regional intensity or color alone cannot sufficiently.

Texture analysis has been an active area of research in pattern identification. A variety of techniques have been used for measuring textural similarity. In 1973, Haralick et al. projected co-occurrence matrix (GLCM) representation of texture features to mathematically represent gray level spatial dependence of texture in an image [8]. In this method the co-occurrence matrix is constructed based on the orientation and distance between image pixels.

GLCM is a popular statistical method of texture analysis. GLCM is the matrix defines the

Probability of gray level *i* occurring at a distance *d* in direction θ from gray level *j* in the texture image. These probabilities generate the co-occurrence matrix

$$M(i,j \mid d,\theta) \tag{1}$$

GLCM texture considers the relation between two pixels at a time, called the reference and the neighbor pixel.

Here we are calculating the GLCM along the four directions. Directional GLCMs are computed along four directions: horizontal ($\theta = 0^{\circ}$), vertical ($\theta = 90^{\circ}$), right diagonal ($\theta = 45^{\circ}$) and left diagonal ($\theta = 135^{\circ}$), and a set of features Contrast, Homogeneity and Energy computed from each, are averaged to give an estimation of the texture class.

Contrast:
$$C = \sum_{i=1}^{N} \sum_{j=1}^{n} S_{i,j} (i-j)^2 \dots (2)$$

Homogeneity: $H = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{s_{i,j}}{1 + (i-j)^2}$...(3)

Energy:
$$E = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} S_{i,j}^{2}}$$
 ... (4)

A set of feature values are computed from GLCM and the average of features values over 4 directional GLCM are computed. Feature value F1 is expressed as:

F1 =
$$\frac{\sum (f0 \, f45 \, f90 \, f135)}{4}$$
 ... (5)

where f0, f45, f90 and f135 are the feature calculated from the GLCM at 0, 45, 90 and 135 respectively. In this present work contrast is illustrated as:

$$C = \frac{C0 + C45 + C90 + C135}{4} \qquad \dots (6)$$

Research Publish Journals

Page | 190

Vol. 2, Issue 4, pp: (189-193), Month: October - December 2014, Available at: www.researchpublish.com

4. THE PROPOSED SKIN RECOGNITION ALGORITHM

The system is designed to classify different skin conditions automatically by some texture features. The algorithm behind the system is defined below:

Algorithm of System:

- 1. Read the image files from the source.
- 2. Convert the RGB image to Gray Scale image.
- 3. Convert the Gray Level values to its double precision value.
- 4. Calculate GLCM along 4 directions.
- 5. Compute GLCM based features.
- 6. Train the network with these feature values for classification.
- 7. Test the system with test data set feature values.
- 8. Determine the class probability
- 9. Calculate accuracy of class determined.



Figure 1: Skin texture recognition algorithm.

4.1. Skin Texture Library

The total media-set consists of 225 images, divided into 75 images for each class corresponding to three disease conditions The classes are henceforth referred to as D (Atopic dermatitis), E (Eczima), U (Urticaria) respectively. The images are scaled to standard dimensions of 100×100 and stored in JPEG format. A sample of the images is shown in Fig.2.

ISSN 2348-1196 (print)

International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online) Vol. 2, Issue 4, pp: (189-193), Month: October - December 2014, Available at: www.researchpublish.com



Figure 2: Sample images of class D, E, U

4.2 THE STRUCTURE OF THE NEURAL NETWORK

Here a three layer feed forward neural network with back-propagation learning rule is used. Algorithm used in training is Gradient Descent Back propagation algorithm. The first layer is input layer contains the number of neurons equal to the number of texture features. Here 3 features are used for classification so the number of input neurons is 3. The hidden layer consists of 110 neurons and the output layer consists of 3 neurons for recognizing 3 different classes or three different skin conditions. Here the activation function used is log-sigmoid for both hidden and output neurons. Learning rate used in this case is 0.01 and the goal is set to .01 for desired output network.



Figure 3: The neural network structure.

5. RESULT

The NN training process is done using texture image from the image library. The output of the neural network is assumed to be [1 0 0] for the first class that is Atopic Dermatitis, [0 1 1] for second class that is Eczima, [0 0 1] for third disease classification that is Urticaria. The performance criterion used is MSE (mean square error) and the goal was 10^{-2} which is a very proved to be very acceptable goal. Maximum number of epochs is set to 500000. The performance goal is reached after 148579 training iteration. As shown in figure 4.





At our approach we have trained 225 images 75 of each class. Result for different classes has been tabulated in the given table.

Table. 1

Classes	Class D	Class E	Class U	Overall
Percentage efficiency	75%	50%	75%	66.66%

6. DISCUSSION AND FUTURE WORK

6.1 Conclusion

The proposed system is used to design an automated system for recognizing different skin conditions. This system is based on texture analysis. Here GLCM is taken as a method of texture analysis. For analyzing texture, symmetrical normalized GLCM is computed along four directions. From this matrix texture features are calculated and averaged over 4 directions. There are many texture features but in this work contrast, homogeneity and energy are used for better result. These features are very useful to recognize texture of skin in this present work. This work is applied in the field of health informatics as well as in the telemedicine for automatic diagnosis of different dermatitis conditions. It also helps dermatologists to give better treatment to the patients by proper diagnosis of the disease conditions. The system proposed in this paper can be used to provide a low cost and efficient solution for automated recognition of skin diseases. On one hand this would be helpful for dermatologists to reduce diagnostic errors, while on the other it can serve as the initial test bed for patients in rural areas where there is a dearth of good medical professionals.

6.2 Future Scope

The accuracy of the current system can be enhanced upon along the two directions:

(1) Color features can be used along with texture, by employing GLCMs on individual R, G and B color channels.

(2) Color images have features like brightness, contrasts etc. which are not considered in this work. Consider these conditions for more accurate result.

REFERENCES

- [1] Al abbadi, N.K. et. al., "Skin texture recognition using neural network," In Proc. of the International Arab Conference on Information Technology, Tunisia, 2008.
- [2] Parekh, R., Mukherjee, A., "Advances in Telemedicine: A Multimedia-Based Texture Recognition Diagnostic System", In Proc. of the Business and Health Administration Association (BHAA "09) International Conference, Chicago, Illinois, USA, pp. 88-97, March 18-20, 2009.
- [3] J. Brand and J. Mason, "A Comparative Assessment of Three Approaches to Pixel- Level Human Skin Detection," Proc. IEEE Int'l Conf. Pattern Recognition, vol. 1, pp. 1056-1059, Sept. 2000.
- [4] Smach, F. et. al., "Design of a neural networks classifier for face detection", Science Publication, Journal of Computer Science, Vol. 2, issue 3, pp. 257-260, 2006.
- [5] Hwei-Jen Lin, Shu-Yi Wang, Shwu-Huey, and Yang –Ta-Kao "Face Detection Based on Skin Color Segmentation and Neural Network" IEEE Transactions on, Volume: 2, pp1144- 1149, ISBN: 0-7803-9422-4, 2005.
- [6] Son Lam Phung, Abdesselam Bouzerdoum, and Douglas Chai "Skin Segmentation Using Color And Edge Information" IEEE ISSPA ISBN: 0-7803-7946-2 2003.
- [7] Smith, J.R. et.al., "Quad tree segmentation for texture based image query", In Proc. of the second ACM international conference on Multimedia, San Francisco, California, United States, pp. 279 286, 1994.
- [8] Haralick, R M., "Statistical and structural approaches to Texture", In Proc. Of IEEE, 67, 786 804, 1979.