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Picture Component Technique based SVM Classification and GLCM for Diagnosis and Detection of Dermoscopic Images

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Abstract: Picture Component Technique (PCT) based Support Vector Machine (SVM) classifier is supervised learning model used for classification, regression analysis. This classifier associated with learning algorithms and this learning algorithms are used to analyze data and recognize patterns. Gray Level Co-Occurrence Matrix (GLCM) is used to extract second order statistical texture features and it has done motion estimation of images. In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified position relative to each other in the image.

Keywords: Picture Component Technique (PCT), Support Vector Machine (SVM) classification, Gray Level Co occurrence Matrix (GLCM), Expectation Maximization (EM), Optical Coherence Tomography (OCT).

I. INTRODUCTION

Over the past decade, the field of image analysis research has undergone a rapid evolution. Image processing Now-a-days have varied applications in the fields of medical imaging, whether meteorology, computer vision, digital photography, microscopy etc. Super-Resolution Imaging consolidates key recent research contributions from eminent scholars and practitioners in this area and serves as a starting point for exploration into the state of the art in the field.

Recent advances in camera sensor technology have led to an increasingly larger number of pixels being crammed into ever-smaller spaces. This has resulted in an overall decline in the visual quality of recorded content, necessitating improvement of images through the use of post-processing. This paper particularly features on developing suitable method for rapid and efficient way to perform hardware implementation for some of Basic crucial image processing algorithms that can be used in simple application specific devices.

II. LITERATURE REVIEW

In paper [1], An automatic method for segmenting skin lesions in conventional macroscopic images presented. Automatic segmentation of macroscopic images is a very challenging problem due to factors such as illumination variations, irregular structural and color variations, the presence of hair as well as the occurrence of multiple unhealthy skin regions. To address these factors, a novel iterative stochastic region-merging approach is employed to segment the regions corresponding to skin lesions from the macroscopic images, where stochastic region merging is initialized first on a pixel level and subsequently on a region level until convergence. In paper [7], Photo acoustic imaging also called opt acoustic or thermo acoustic imaging has the potential to image animal or human organs such as the breast and the brain with simultaneous high contrast and high spatial resolution. Imaging techniques, including depth profiling in layered media, scanning tomography with focused ultrasonic transducers, image forming with an acoustic lens and computed tomography with unfocused transducers are introduced. Promising biomedical applications are discussed throughout the text, including

1. Tomography imaging of the skin and other superficial organs by laser-induced photo acoustic microscopy, which offers the critical advantages, over current high-resolution optical imaging modalities of deeper imaging depth and higher absorption contrasts.
2. Breast cancer detection by near-infrared light or radio-frequency–wave-induced photo acoustic imaging, which has important potential for early detection and
3. Small animal imaging by laser-induced, this paper measures unique optical absorption contrasts related to important biochemical information and provides better resolution in deep tissues than optical imaging.

In paper [8], Feature Extraction is a method of capturing visual content of images for indexing and retrieval. Primitive or low level image features can be either general features such as extraction of color, texture and shape or domain specific features.

This paper presents an application of gray level co-occurrence matrix (GLCM) to extract second order statistical texture features for motion estimation of images. The Four features namely, Angular Second Moment, Correlation, Inverse Difference Moment, and Entropy are computed using Xilinx FPGA. The results show that these texture features have high discrimination accuracy, requires less computation time and hence efficiently used for real time Pattern recognition applications.

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III. IMAGE ENHANCEMENT ALGORITHM

Image quality can be enhanced by some of basic morphological and intensity image transforms such as controlling its illumination, contrast stretching, thresholding. Similarly some applications needs image segmentation via edge detection, boundary extraction, image negatives or extraction of positive from image negatives , image subtraction etc. This paper aims at

1. Developing algorithmic models in MATLAB.
2. Creating workspace in MATLAB to process image pixels in the form of multidimensional image signals for input and output images. Opt acoustic tomography has demonstrated optical contrast imaging through entire small animals or human tissues in high resolution. Implementations in the sub-10 MHz ultrasonic region can achieve penetration depths of several centimeters with resolutions ranging in the few hundreds of micrometers. This performance enables structural and functional optical imaging of tissues at several millimeters to centimeters depth.

IV. GRAY LEVEL CO-OCCURRENCE MATRIX

A Gray Level Co-Occurrence Matrix (GLCM) is to extract second order statistical texture features for motion estimation of images. The four features energy, correlation, contrast, homogeneity are to be calculated. Gray Level Co-occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Hara lick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images.

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element $P(i, j \mid \Delta x, \Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance $(\Delta x, \Delta y)$, occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element $P(i, j \mid d, \theta)$ contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a $G \times G$ matrix for each combination of $(\Delta x, \Delta y)$ or (d, θ).

GLCM matrix formulation can be explain with four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbor). The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. Within the image area, how many times, a pixel with grey level 0 (neighbor pixel) falls to the right of another pixel with grey level 0 (reference pixel).

V. SUPPORT VECTOR MACHINE

In machine learning, support vector machines (SVMs, also support vector networks) 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 category or the other, making it a non-probabilistic binary linear classifier. Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in Fig 1. In this figure, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).

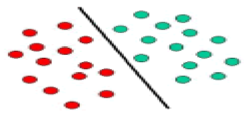
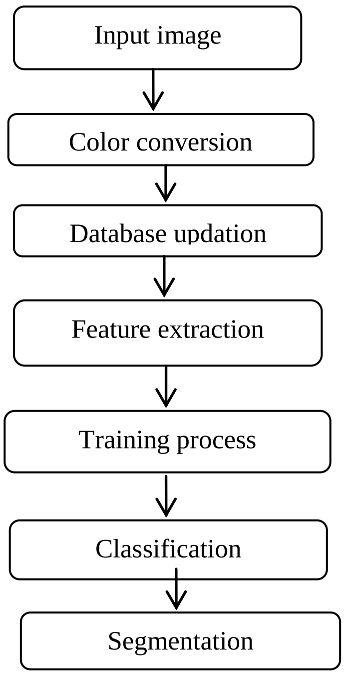


Fig1. Schematic diagram

The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line).



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Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyper plane classifiers. Support Vector Machines are particularly suited to handle such tasks.

A. Input Image
Here, the query input is given in the form of an affected image for the process of detection for getting segmented outputs.

B. Color Conversion
Here, the process of converting an RGB to Gray has to be done. The original given image is to be taken, the RGB components have to be converted to gray components.

C. Database Updation
It defines that the given image is to be compared with the database images. This operation is to be going to processed for an finding an affected areas in an given query image.

D. Feature Extraction
Feature that characterizes the shape of the skin burn representation. The affected parts should be done segmentation process and the features are extracted here.

E. Training Process
This is the process of training for a classification of an given query images. The given image has should be skin burned or skin normal, that has to be classified. Here for a classification, the SVM algorithm is to be used of done.

F. Classification
The classification is that the skin has to be classified by the SVM and it is used to find out whether the skin is normal or burned.

G. Segmentation
If the skin is affected by the diseases, it is spilded into various segments and the process of segmentation is to be done.

VI. RESULTS AND ANALYSIS

The semantic gap between low level features and high level concepts is more and the retrieved output consisted lot of errors. Hence the retrieval accuracy will be high and less interaction is needed. We propose two different algorithms: content and texture based ED between color histograms and ED between wavelet energies.
The below images shown RGB plane separation and its corresponding Histograms.

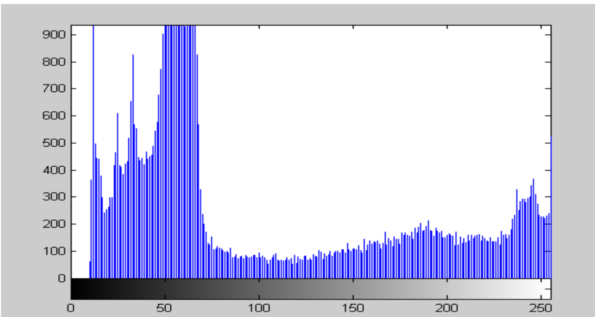

Fig2. Histogram for RED Plane

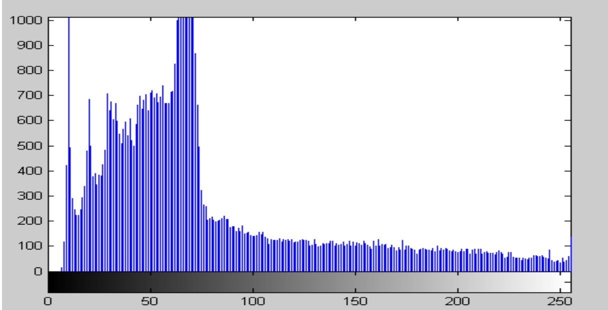

Fig 3. Histogram for GREEN Plane

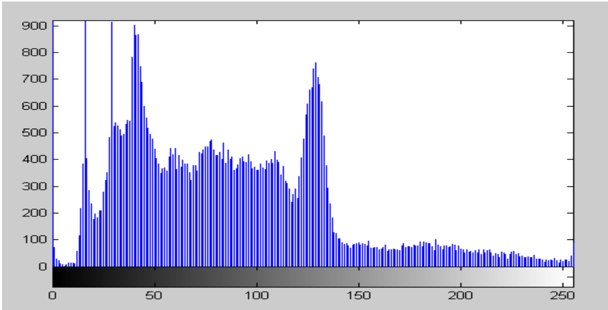

Fig 4. Histogram for GREEN Plane

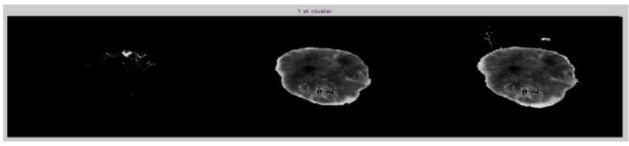

Fig 5. 1th Clustering of affected image

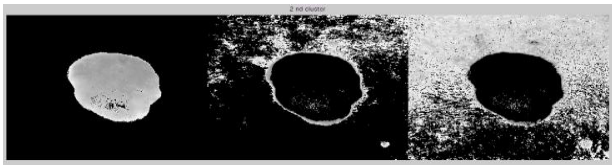

Fig 6. 2nd Clustering of affected image

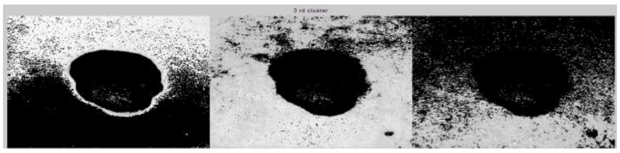

Fig 7. 3rd Clustering of affected image

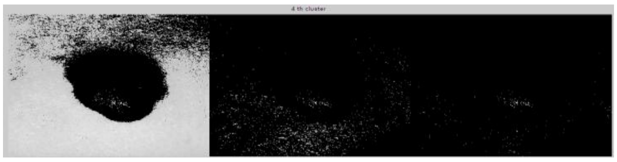

Fig 8.. 4th Clustering of affected image

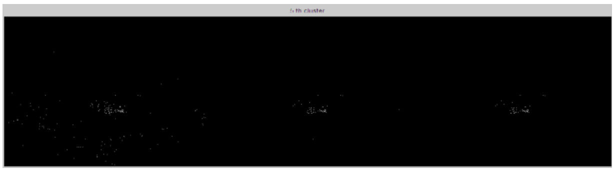

Fig9. Segmentation output of affected image

VII. CONCLUSION

As a concluding note we would like to observe that while dermatology is well served today by visual inspection and good quality photography, there may be a particular segment of applications that can be benefit not only by the ability to offer cross-sectional images and assess the depth of different lesions but also by combining the spectral and time characteristics of opt acoustic imaging to improve the detection specificity and better understanding of underlying physiology.
Further we determine if the resolution offered at 24 MHz, it would also be sufficient for visualizing malignant melanoma penetrating several millimeters deep into skin tissue or if adjustments in the frequency utilized may be required, at the expense of penetration depth, to better visualize melanoma invasion. These include co focal imaging, multi photon tomography and Optical Coherence Tomography (OCT) including OCT using Doppler shift. Superficial reticular dermis of healthy skin, the microvasculature of solid tumors, the retinal and choroid vasculature hair follicles, blood vessels, sweat ducts, as well as superficial skin conditions have been imaged.

REFERENCES

[1] Alexander Wong, Paul Fieguth, and Jacob Scharcanski,"Automatic Skin Lesion Segmentation via Iterative"Member, IEEE, Senior Member IEEE, and Member IEEE.
[2] Beard.P, "Biomedical photoacoustic imaging," Interface Focus, vol.1, no. 4, pp. 602–631, 2011.
[3] Brechtetal.H.P., "Whole-body three-dimensional optoacoustic tomography system for small animals," Journal of Biomedical Optics,vol. 14, no. 6, p. 064007, 2009.
[4] Dimaetal.A, "Optoacoustic imaging of blood perfusion: Techniques for intraoperative tissue viability assessment," Journal of Biophotonics, vol. 6, no. 6–7, pp. 485–492, 2013.
[5] Herzogetal.E, "Optical imaging of cancer heterogeneity with multispectral optoacoustic tomography," Radiology, vol. 263, no. 2, pp.461–468, 2012.
[6] Krugeretal.R.A., "Photoacoustic angiography of the breast," Medical Physics, vol. 37, no. 11, pp. 6096– 6100, 2010.
[7] Minghua Xua and Lihong V. Wangb" Photoacoustic imaging in biomedicine" Optical Imaging Laboratory, Department of Biomedical Engineering, Texas A&M University, 3120 TAMU, College Station, Texas 77843-3120 Received 15 January 2004; accepted 20 February 2006; published online 17 (April 2006).
[8] Mohanaiah.P, Sathyanarayana.P,GuruKumar.L " Image Texture Feature Extraction Using GLCM approach" Professor, Dept. of E.C.E, N.B.K.R.IST, Vidyanagar, Nellore, India.Professor, Dept. of E.C.E, S.V University Tirupati, India,Asst.Professor, Dept. of E.C.E, N.B.K.R.IST, Vidyanagar, Nellore, India.
[9] Ntziachristos.V, "Going deeper than microscopy: The optical imaging frontier in biology," Nature Methods, vol. 7, no. 8, pp. 603–614, 2010.
[10] Ntziachristos.V and Razansky.D, "Molecular imaging by means of multi spectral optoacoustic tomography (MSOT)," Chemical Reviews, vol. 110, no. 5, pp. 2783–2794, 2010.