Image Texture Feature Extraction Using GLCM Approach

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Abstract- Feature Extraction is a method of capturing visual content of images for indexing & 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.

Index Terms- Texture, Pattern recognition, Features, Frames.

I. INTRODUCTION

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Texture tactile or visual characteristic of a surface. Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects. Though texture plays a significant role in image analysis and pattern recognition, only a few architectures implement on-board textural feature extraction. In this paper, Gray level co-occurrence matrix is formulated to obtain statistical texture features. A number of texture features may be extracted from the GLCM. Only four second order features namely angular second moment, correlation, inverse difference moment, and entropy are computed. These four measures provide high discrimination accuracy required for motion picture estimation. These features are calculated and implemented using Xilinx ISE 13.4.

II. EXTRACTION OF GLCM

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 Coocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features.
The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

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). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel).

neighbour pixel value ---> ref pixel value:	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

Fig 2.1. GLCM calculation

The MATLAB code used for the GLCM is

```
q1 = imread ('Jerry.jpg');
w1 = rgb2gray (q1);
e1 = imresize (w1, [128 128]);
r1 = graycomatrix (e1);
disp (r1);
t1 = imhist (e1);
figure, imshow (e1), title ('transformed gray Jerry .jpg in gray');
```

The output will be an 8*8matrix which is a GLCM of input image.

III. EXTRACTION OF TEXTURE FEATURES OF IMAGE

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, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. In this paper four important features, Angular Second Moment (energy), (inertia moment), Correlation, Entropy, and the Inverse Difference Moment are selected for implementation using Xilinx ISE 13.4.

3.1. Angular Second Moment

Angular Second Moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCMAngular Second Moment measures the image homogeneity. Angular Second Moment is high when image has very good homogeneity or when pixels are very similar

$$ASM = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P_{ij}^2 \qquad \dots 1$$

Where i, j are the spatial coordinates of the function p (i, j), Ng is gray tone.

3.2 Inverse Difference Moment

Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high.

$$IDM = \frac{\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P_{ij}}{1 + (i - j)^2} \qquad \dots 2$$

IDM weight value is the inverse of the Contrast weight.

3.3. Entropy

Entropy shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

$$ENTROPY = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} -P_{ij} * logP_{ij} \qquad \dots 3$$

3.4. Correlation

Correlation measures the linear dependency of grey levels of neighboring pixels.Digital Image Correlation is an optical method that employs tracking & image registration techniques for accurate 2D and 3D measurements of changes in images. This is often used to measure deformation, displacement, strain and optical flow, but it is widely applied in many areas of science and engineering. One very common application is for measuring the motion of an optical mouse.

$$Correlation = \frac{\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (i, j) p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \qquad \dots 4$$

The formulation and extraction of the four given image features are extracted using matlab for calculating GLCM as image cannot be directly given as input to implement using FPGA.Image feature extraction method used in this paper is given in fig 3.1.All the texture features are real numbers. Real numbers cannot be displayed using waveforms which show only bits as outputs.
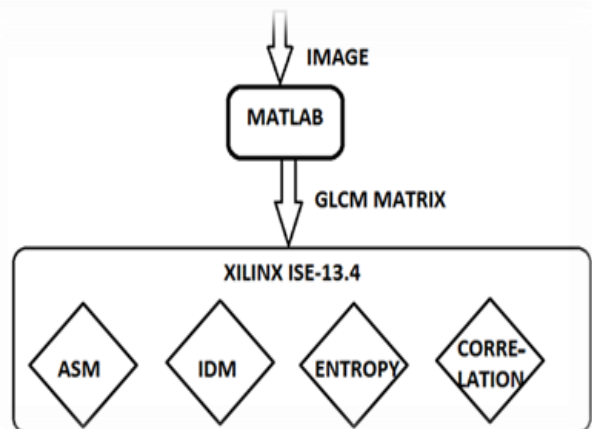

Fig 3.1.Extraction of image features.

So bits are converted to real numbers using "$bitstoreal" command. Hence the real number output will be displayed in the console window. As the delay given is 10ns, till 10ns the 64 inputs are –nan and after 10ns the inputs will be assigned. The last one is the output which is the texture feature.
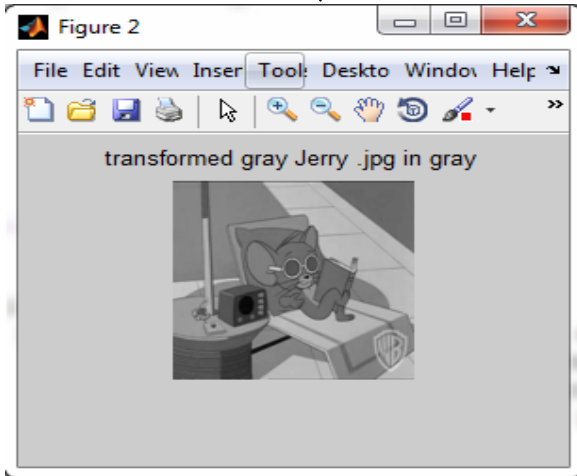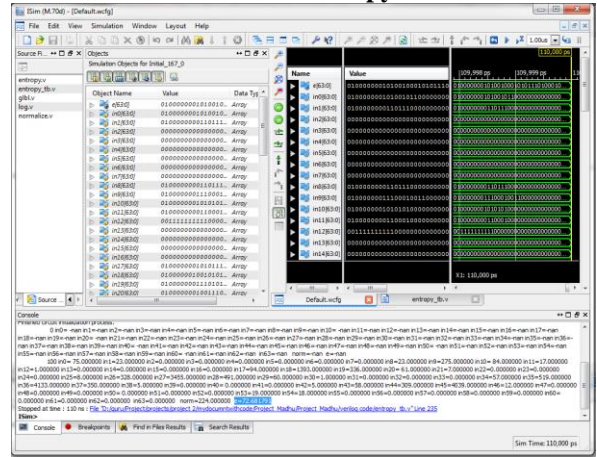
IV. RESULTS

RGB to Grey Converted

Fig 4.1. Input image & Converted output sample Image of a video
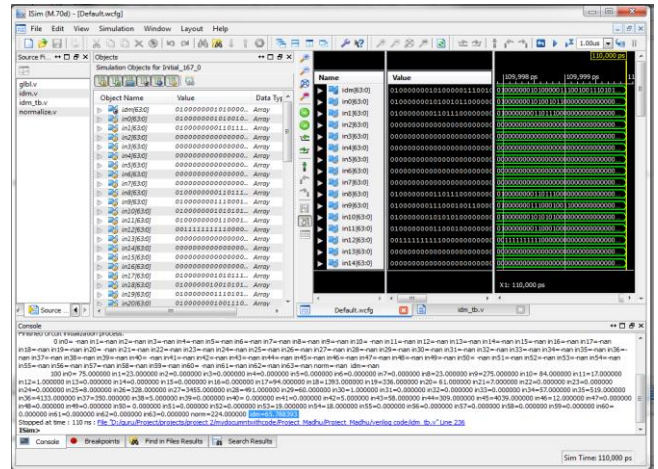
4.2. Grey Level Co-occurrence Matrix

$$\begin{pmatrix} 75 & 23 & 0 & 0 & 0 & 0 & 0 & 0 \\ 23 & 275 & 84 & 17 & 1 & 0 & 0 & 0 \\ 0 & 94 & 1393 & 336 & 61 & 7 & 0 & 0 \\ 0 & 8 & 328 & 3455 & 491 & 60 & 1 & 0 \\ 0 & 0 & 57 & 519 & 4133 & 350 & 5 & 0 \\ 0 & 0 & 5 & 58 & 309 & 4039 & 12 & 0 \\ 0 & 0 & 0 & 0 & 0 & 19 & 18 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$
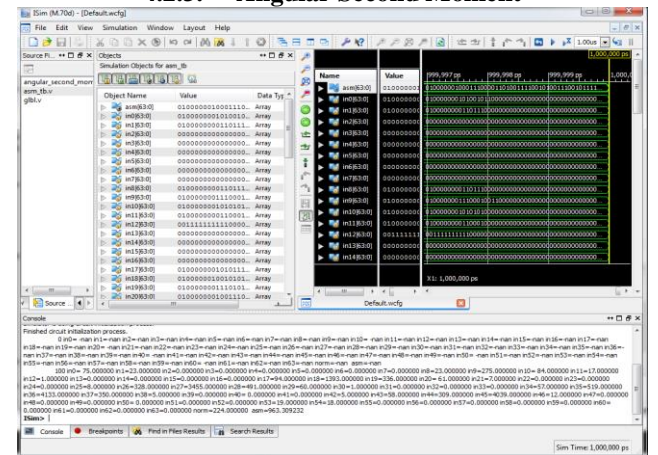
4.2.1. Entropy

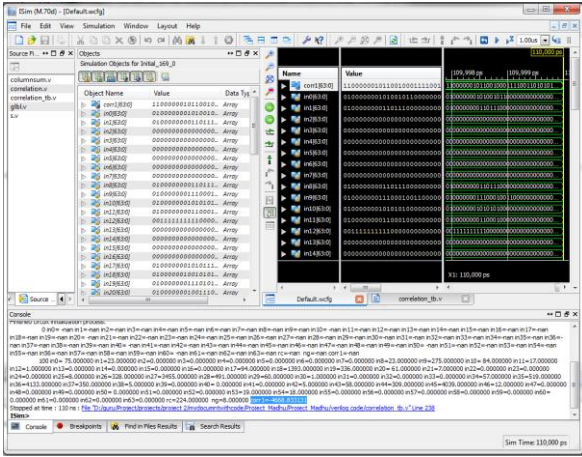**Entropy =72.68175**

4.2.2. Inverse Difference Moment

IDM=65.738

4.2.3. Angular Second Moment

Asm=963.309

4.2.3.   Correlation

Correlation=-4668.833

Texture Features Extraction for Cartoon Image

	Image Size		
Features	**64 x 64**	**128 x 128**	**256 x 256**
ASM	54.8659	963.309232	17059.1454
Entropy	5.0947	64.164512	436.382
Correlation	-108951.191	-4668.83318	-161.7655
IDM	15.8964	65.788393	271.589

As the size of the image for which Texture features are extracted increases the values of all the features are also increased proportionally. So the optimum size to be used for extraction is 128x128 for better resolution and minimum loss of information.

V.   CONCLUSION

The Gray Level Co-ocurrence Matrix (GLCM) method is used for extracting four Statistical Texture Parameters i.e., Entropy, Inverse Difference Moment, Angular Second Moment and Correlation. By extracting the features of an image by GLCM approach, the image compression time can be greatly reduced in the process of converting RGB to Gray level image when compared to other DWT Techniques, but however DWT is versatile method of compressing video as a whole. These features are useful in motion estimation of videos and in real time pattern recognition applications like Military & Medical Applications.

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