A Synopsis on
Textural Classification using Transform
Domain based Features

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INTRODUCTION

Texture

An **image texture** is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image. An example of texture is given in Fig 1 and Fig 2.

Image textures can be artificially created or found in natural scenes captured in an image. Image textures are one way that can be used to help in segmentation or classification of images. For more accurate segmentation the most useful features are spatial frequency and an average grey level. To analyse an image texture in computer graphics, there are two ways to approach the issue: Structured Approach and Statistical Approach.
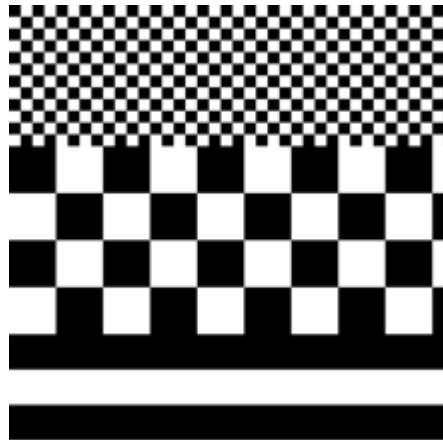

Fig 1. Artificial texture example.

Fig 2. Natural texture example

The analysis of texture in images provides an important cue to the recognition of objects. It has been recently observed that different image objects are best characterized by different texture methods. Successful applications of texture analysis methods have been widely found in industrial, biomedical, remote sensing areas and target recognition. In addition, the recent emerging of multimedia and the availability of large image and video archives has made content-based information retrieval become a very popular research topic. Texture is also deemed as one of the most important features when performing content-based information retrieval. Various textural features have been adopted to fulfill these applications. Since there are a lot of variations among natural textures, to achieve the best performance for texture analysis or retrieval, different features should be chosen according to the characteristics of texture images. A number of texture analysis methods have been proposed over the years and it is well-recognized that they capture different texture properties of the image.

Texture analysis methods used can be categorized as statistical, geometrical, model-based and signal processing. Early works were based on the analysis of statistical properties of the texture which deals with the spatial distribution of gray values. Some statistical methods used are co-occurrence matrix features and auto-correlation function. In geometrical methods textures are considered to be composed of texture primitives and are extracted and analyzed. Several stochastic models have been proposed for texture modeling and classification such as Gaussian Markov random fields and spatial auto-correlation function model.
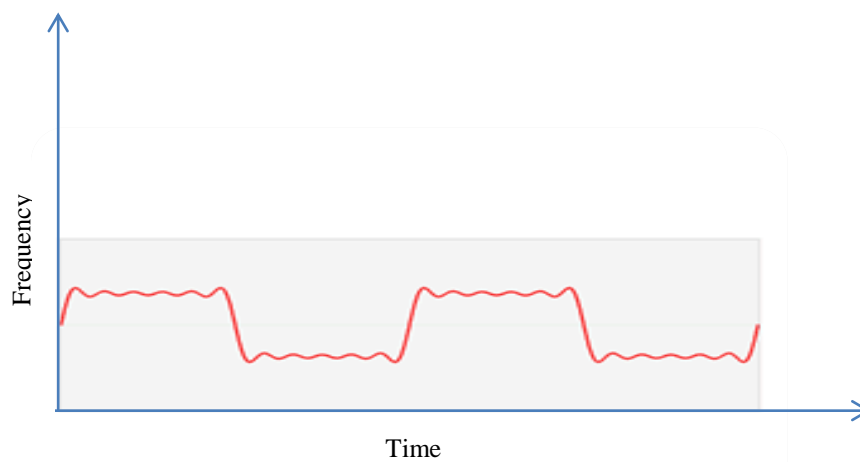
TRANSFORM DOMAIN

Fig : 3

The Fourier transform converts the function's time-domain representation, shown in red (Fig 3), to the function's frequency-domain representation, shown in blue. The component frequencies, spread across the frequency spectrum, are represented as peaks in the frequency domain.

In electronics, control systems engineering, and statistics, the **Transform** refers to the analysis of mathematical functions or signals with respect to frequency, rather than time. Put simply, a time-domain graph shows how a signal changes over time, whereas a frequency-domain graph shows how much of the signal lies within each given frequency band over a range of frequencies. A frequency-domain representation can also include information on the phase shift that must be applied to each sinusoid in order to be able to recombine the frequency components to recover the original time signal.

DISCRETE WAVELET TRANSFORM

In numerical analysis and functional analysis, a **discrete wavelet transform** (**DWT**) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency *and* location information

FAST FOURIER TRANSFORM

A **fast Fourier transform** (**FFT**) is an algorithm that samples a signal over a period of time (or space) and divides it into its frequency components. These components are single sinusoidal oscillations at distinct frequencies each with their own amplitude and phase. This transformation over the time period measured in the diagram, the signal contains 3 distinct dominant frequencies.

DISCRETE FOURIER TRANSFORM

The DFT is the most important discrete transform, used to perform Fourier analysis in many practical applications. In digital signal processing, the function is any quantity or signal that varies over time, such as the pressure of a sound wave, a radio signal, or

daily temperature readings, sampled over a finite time interval (often defined by a window function). In image processing, the samples can be the values of pixels along a row or column of a raster image.

LITERATURE SURVEY

Rusmir Bajric at el., 2016, developed Feature Extraction Using Discrete Wavelet Transform for Gear Fault Diagnosis of Wind Turbine Gearbox. That paper investigates a new approach for wind turbine high speed shaft gear fault diagnosis using discrete wavelet transform and time synchronous averaging. First, the vibration signals are decomposed into a series of sub-bands signals with the use of a multi-resolution analytical property of the discrete wavelet transform. Then, 22 condition indicators are extracted from the TSA signal, residual signal, and difference signal. Through the case study analysis, a new approach reveals the most relevant condition indicators based on vibrations that can be used for high speed shaft gear spalling fault diagnosis and their tracking abilities for fault degradation progression. It is also shown that the proposed approach enhances the gearbox

fault diagnosis ability in wind turbines. The approach presented in this paper was programmed in Matlab environment using data acquired on a 2 MW wind turbine.

Jaison Bennet at el., 2014, developed A Discrete Wavelet Based Feature Extraction and Hybrid Classification Technique for Microarray Data Analysis. That paper investigates the recent arrival of DNA microarray technology has led to the concurrent monitoring of thousands of gene expressions in a single chip which stimulates the progress in cancer classification. In this paper, we have proposed a hybrid approach for microarray data classification based on nearest neighbor (KNN), naive Bayes, and support vector machine (SVM). Feature selection prior to classification plays a vital role and a feature selection technique which combines discretewavelet transform(DWT) and moving window technique (MWT) is used. The performance of the proposed method is compared with the conventional classifiers like support vector machine, nearest neighbor, and naive Bayes. Experiments have been conducted on both real and benchmark datasets and the results indicate that the ensemble approach produces higher classification accuracy than conventional classifiers. This paper serves as an automated system for the classification of cancer and can be applied by doctors in real cases which serve as a boon

to the medical community. This work further reduces the misclassification of cancers which is highly not allowed in cancer detection.

S. Sumathi at el., 2014, developed Wavelet Transform Based Feature Extraction and Classification of Cardiac Disorder. This paper approaches an intellectual diagnosis system using hybrid approach of Adaptive Neuro-Fuzzy Inference System (ANFIS) model for classification of Electrocardiogram (ECG) signals. This method is based on using Symlet Wavelet Transform for analyzing the ECG signals and extracting the parameters related to dangerous cardiac arrhythmias. In these particular parameters were used as input of ANFIS classifier, five most important types of ECG signals they are Normal Sinus Rhythm (NSR), Atrial Fibrillation (AF), Pre-Ventricular Contraction (PVC), Ventricular Fibrillation (VF), and Ventricular Flutter (VFLU) Myocardial Ischemia. The inclusion of ANFIS in the complex investigating algorithms yields very interesting recognition and classification capabilities across a broad spectrum of biomedical engineering. The performance of the ANFIS model was evaluated in terms of training performance and classification accuracies. The results give importance to that the proposed ANFIS model illustrates potential advantage in classifying the ECG signals. The classification accuracy of 98.24 % is achieved.

PROBLEM STATEMENT

In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes. Texture classification is one of the four problem domains in the field of texture analysis. The other three are texture segmentation (partitioning of an image into regions which have homogeneous properties with respect to texture; supervised texture segmentation with a priori knowledge of textures to be separated simplifies to texture classification), texture synthesis (the goal is to build a model of image texture, which can then be used for generating the texture) and shape from texture (a 2D image is considered to be a projection of a 3D scene and apparent texture distortions in the 2D image are used to estimate surface orientations in the 3D scene).

Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. A successful classification or segmentation requires an efficient description of image texture. Important applications include industrial and biomedical surface inspection, for example for defects and

disease, ground classification and segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases. However, despite many potential areas of application for texture analysis in industry there is only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high.

Texture classification process involves two phases: the learning phase and the recognition phase. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image. These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images, such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match. Optionally, if the best match is not sufficiently good according to some predefined criteria, the unknown sample can be rejected instead.

OBJECTIVES

Most of the textural classification techniques use spatial transformation domain, which is more costly ,slower than transform domain classification.

Basically frequency domain represents the rate of change of spatial pixels and hence gives an advantage when the problem you are dealing with relates to the rate of change of pixels which is very important in image processing. For example :high frequency in the frequency domain represents rapidly or sharply changing pixels such as boundaries or edges in an image. A high pass filter can be extremely helpful in identifying or removing these edges easily but the same problem is much more difficult in spatial domain (x-y domain). Similarly a simple low pass filter

can be used to get a smoother image. As you can guess images can be easily made sharper or smoother by manipulating different parts of frequency domain.

Some points on why it is so powerful :

1. Frequency domain gives you control over the whole images, where you can enhance(eg edges) and suppress (eg smooth shadow) different characteristics of the image very easily.

2. Frequency domain has a established suit of processes and tools that be borrowed directly from signal processing in other domains.

3. Some tools used for even image recognition such as correlation , convolution etc are much simpler and computationally cheaper in frequency domain.

4. Frequency domain allows for techniques which could be used to determine the stability of the system. Also, these techniques can be used in conjuction with the S-domin which gives more insight to stability of the system, transient response, and steady state response.

5. The Fourier Transform is used to convert images from the spatial domain into the frequency. A related term used in this context is spatial frequency, which refers to the (inverse of the) periodicity with which the image intensity values change.

METHODOLOGY

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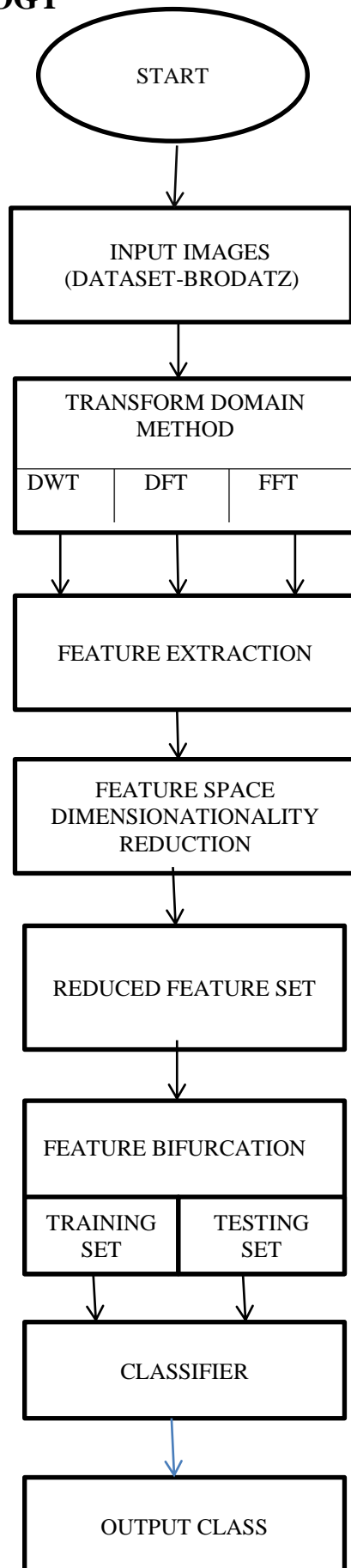
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