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Recognition of Dry and Blurred Fingerprint Using Local Entropy Thresholding Method

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ABSTRACT

Dry fingerprint has blurred image, because of overlapping of valleys, singular point to the fingertip and ridges. By using local entropy thresholding method, we extract the fingerprint images. This method is compared to canny filter images, sobel filter images and otsu algorithm images. This technique is used to enhance the contrast between valleys and ridges of the poor, medium and best image features. The experimental results gives the enhancement of the proposed method to get high performance compared with existing techniques. *Keywords* - ***DWT*, Enhancement, Histogram equalization, SVD, Thresholding.**

I. INTRODUCTION

wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero.[1] It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including - but certainly not limited to - audio signals and images. Sets of wavelets are generally needed to analyze data fully. A set of "complementary" wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet based compression/decompression algorithms where it is desirable to recover the original information with minimal loss. Wavelets are mathematical functions defined over a finite interval and having an average value of zero that transform data into different frequency components, representing each component with a resolution matched to its scale. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts). They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Many new wavelet applications such as image compression, turbulence, human vision, radar, and earthquake prediction are developed in recent years.

In wavelet transform the basic functions are wavelets. Wavelets tend to be irregular and symmetric. All wavelet functions, $w(2kt - m)$, are derived from a single mother wavelet, $w(t)$.

II. DISCRETE WAVELET TRANSFORM

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. If the scales and positions are chosen based on powers of two, the so-called dyadic scales and positions, then calculating wavelet coefficients are efficient and just as accurate. This is obtained from discrete wavelet transform (DWT).

2.1 2-D WAVELET TRANSFORM HIERARCHY

The 1-D wavelet transform can be extended to a two-dimensional (2-D) wavelet transform using separable wavelet filters. With separable filters the 2-D transform can be computed by applying a 1-D transform to all the rows of the input, and then repeating on all of the columns

LL1	HL1
LH1	HH1

Fig1.1: Subband Labeling Scheme for a one level, 2-D Wavelet Transform

The original image of a one-level (K=1), 2-D wavelet transform, with corresponding notation is shown in Fig. 1. The example is repeated for a three level (K=*3*) wavelet expansion in Fig. 2. In all of the discussion *K* represents the highest level of the decomposition of the wavelet transform. The 2-D subband decomposition is just an extension of 1-D subband decomposition. The entire process is carried out by executing 1-D subband decomposition twice, first in one direction (horizontal), then in the orthogonal (vertical) direction. For example, the low-pass subbands (L1) resulting from the horizontal direction is further decomposed in the vertical direction, leading to LL1 and LH1 subbands.

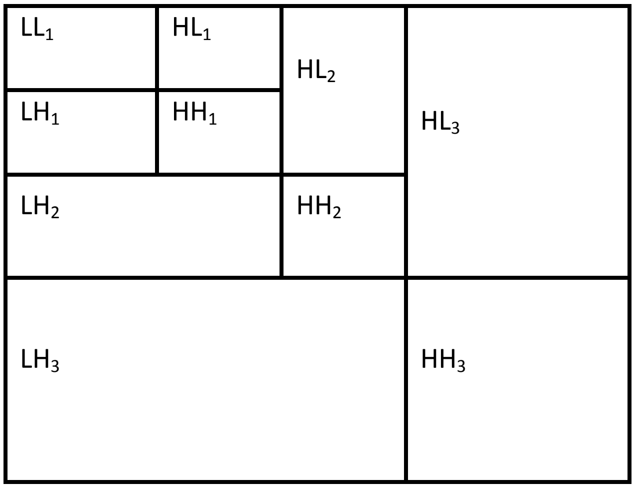

Fig 2.1: Subband labeling Scheme for a Three Level, 2-D Wavelet Transform

Similarly, the high pass subband (Hi) is further decomposed into HLi and HHi. After one level of transform, the image can be further decomposed by applying the 2-D subband decomposition to the existing LL1 subband. This iterative process results in multiple “transform levels”. To obtain a two-dimensional wavelet transform, the one-dimensional transform is applied first along the rows and then along the columns to produce four sub bands: low-resolution, horizontal, vertical, and diagonal. (The vertical sub band is created by applying a horizontal high-pass, which yields vertical edges.) At each level, the wavelet transform can be reapplied to the low-resolution sub band to further decorrelate the image.

2.2 HAAR TRANSFORM

In mathematics, the Haar wavelet is a certain sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. The study of wavelets, and even the term "wavelet", did not come until much later. As a special case of the Daubechies wavelet, it is also known asD2. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis. The Haar sequence is now recognised as the first known wavelet basis and extensively used as a teaching example in the theory of wavelets.

The Haar wavelet's mother wavelet function
$\varphi(t)$ can be described as

$$\boldsymbol{\varphi(t) = -1 \quad \frac{1}{2} \le t < 1,}$$
$$\boldsymbol{= 1 \quad 0 \le t < \frac{1}{2},}$$
$$\boldsymbol{= 0 \quad \text{otherwise}}$$

2.2.1 Propertiesi.

Any continuous real function can be approximated by linear combinations $\phi(t)$, $\phi(2t)$…….$\phi(2^k t)$,…. and their shifted functions. This extends to those function spaces where any function therein can be approximated by continuous functions.

ii. Any continuous real function can be approximated by linear combinations of the constant function, $\varphi(t), \varphi(2t) \ldots\ldots \varphi(2^k t)$…… and their shifted functions.

III. SVD

In linear algebra, the singular value decomposition (SVD) is a factorization of a real or complex matrix, with many useful applications in signal processing and statistics. Formally, the singular value decomposition of an mxn real or complex matrix M is a factorization of the form

$$M=U\Sigma V^*$$

where U is an mxm real or complex unitary matrix, Σ is an mxn rectangular diagonal matrix with nonnegative real numbers on the diagonal, and V* (the conjugate transpose of V) is an nxn real or complex unitary matrix[2]. The diagonal entries $\Sigma_{i,i}$ of Σ are known as the singular values of M. The m columns of U and the n columns of V are called the left singular vectors and right singular vectors of M, respectively.

The singular value decomposition and the eigen decomposition are closely related. Namely:

The left singular vectors of M are eigenvectors of MM^*. The right singular vectors of M are eigenvectors of M^*M. The non-zero singular values of M (found on the diagonal entries of Σ) are the square roots of the non-zero eigen values of M^*M or MM^*.

Applications which employ the SVD include computing the pseudo inverse, least squares fitting of data, matrix approximation, and determining the rank, range and null space of a matrix.

IV. FUZZY MEASURES

The discovery of useful information is the essence of any data mining process. Decisions are not usually taken based on complete real world data, but most of the times they deal with uncertainty or lack of information[3]. Therefore the real world reasoning is almost always approximate. However it is not only necessary to learn new information in any data mining process, but it is also important to understand why and how the information is discovered. Most data mining commercial products are black boxes that do not explain the reasons and methods that have been used to get new information.

However the 'why and how' the information is obtained can be as important as the information on its own. When approximate reasoning is done, measures on fuzzy sets and fuzzy relations can be proposed to provide a lot of information that helps to understand the conclusions of fuzzy inference processes.

Those measures can even help to make decisions that allow to use the most proper methods, logics, operators for connectives and implications, in every approximate reasoning environment. The latest concepts of measures in approximate reasoning is discussed and a few measures on fuzzy sets and fuzzy relations are proposed to be used to understand why the reasoning is working and to make decisions about labels, connectives or implications, and so a few useful measures can help

to have the best performance in approximate reasoning and decision making processes.

Before some measures on fuzzy sets and fuzzy relations are proposed, this chapter collects all the latest new concepts and definitions on measures, and shows a few graphics that make a clear picture on how those measures can be classified. Some important measures on fuzzy sets are the entropy measures and specificity measures. The entropy measures give a degree of fuzziness of a fuzzy set, which can be computed by the premises or outputs of an inference to know an amount of uncertainty crispness in the process. Specificity measures of fuzzy sets give a degree of the utility of information contained in a fuzzy set.

Other important measures can be computed on fuzzy relations. For example, some methods to measure a degree of generalisation of the MODUSPONENS property in fuzzy inference processes are proposed.

4.1 Concept of fuzzy measures

The concept of measure is one of the most important concepts in mathematics, as well as the concept of integral respect to a given measure. The

classical measures are supposed to hold the additive property. Additivity can be very effective and convenient in some applications, but can also be somewhat inadequate in many reasoning environments of the real world as in approximate reasoning, fuzzy logic, artificial intelligence, game theory, decision making, psychology, economy, data mining, etc., that require the definition of non additive measures and a large amount of open problems.

For example, the efficiency of a set of workers is being measured, the efficiency of the same people doing teamwork is not the addition of the efficiency of each individual working on their own.

The concept of fuzzy measure does not require additivity, but it requires monotonicity related to the inclusion of sets. The concept of fuzzy measure

can also be generalized by new concepts of measure that pretend to measure a characteristic not really related with the inclusion of sets. However those new measures can show that "x has a higher degree of a particular quality than y" when x and y are ordered by a preorder (not necessarily the

set inclusion preorder).

The term fuzzy integral uses the concept of fuzzy measure. There are some important fuzzy integrals, as Choquet integral in 1974, which does not require

an additive measure (as Lebesgue integral does).

4.2 Fuzzy set theory

Fuzzy set theory defines set membership as a possibility distribution. The general rule for this can expressed as:

$f : [0,1]^n \longrightarrow [0,1]$

where n some number of possibilities. This basically states that we can take n possible events and us f to generate as single possible outcome. This extends set membership since we could have varying definitions of, say, hot curries. One person might declare that only curries of Vindaloo strength or above are hot whilst another might say madras and above are hot[4]. We could allow for these variations definition by allowing both possibilities in fuzzy definitions. Once set membership has been redefined we can develop new logics based on combining of sets etc. and reason effectively.

The membership degree can be expressed by a mathematical function that assigns, to each element in the set, a membership degree between 0 and 1.

The -function is used for modeling the membership degrees. This type of function is suitable to represent the set of bright pixels and is defined as

$$\mu_{AS}(x) = S(x;a,b,c) = \begin{cases} 0, & x \le a \\ 2\left\{\dfrac{(x-a)}{(c-a)}\right\}^2, & a \le x \le b \\ 1-2\left\{\dfrac{(x-a)}{(c-a)}\right\}^2, & b \le x \le c \\ 1, & x \ge c \end{cases}$$

where b=(1/2)(a+c) The -function can be controlled through parameters a and c. Parameter is called the crossover point where $\mu_{AS}(b)=0.5$.The higher the gray level of a pixel (closer to white), the higher membership value and vice versa. A typical shape of the Z-function is presented in Fig. 1.

The -function is used to represent the dark pixels and is defined by an expression obtained from -function as follows:

$$\mu_{AZ}(x)=Z(x;a,b,c)=1-S(x;a,b,c)$$

Both membership functions could be seen, simultaneously, in Fig. 2. The -function in the right side of the histogram and the Z-function in the left.

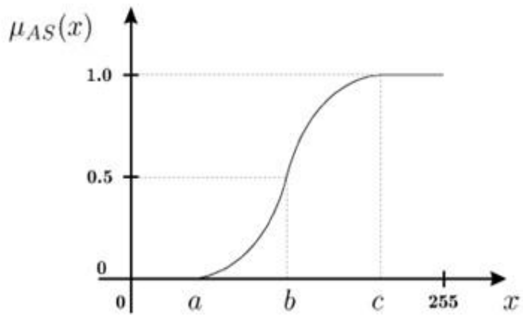

Fig3.1: Typical shape of the S-function

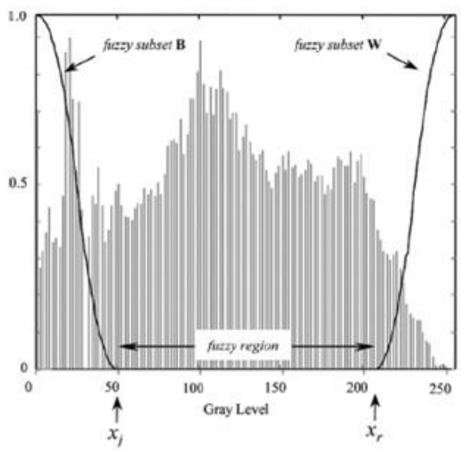

Fig3.2: Histogram and functions for the seed subsets

V. MATLAB RESULTS AND GRAPHS

In this section, simulation results for different images (64x64) are shown. Their histogram measure graphs are also included. Considered the images fingerprint.jpeg form the MATLAB library

Fig 4.1:original Image

Fig 4.2 :Red Image

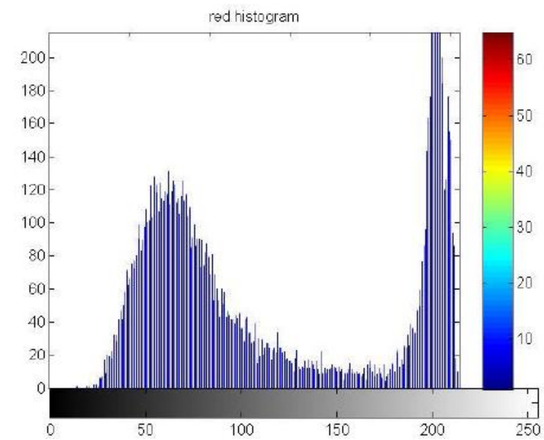

Fig 4.3: Red histogram
Histogram measuring pixel values

Fig 4.4: Blue Image

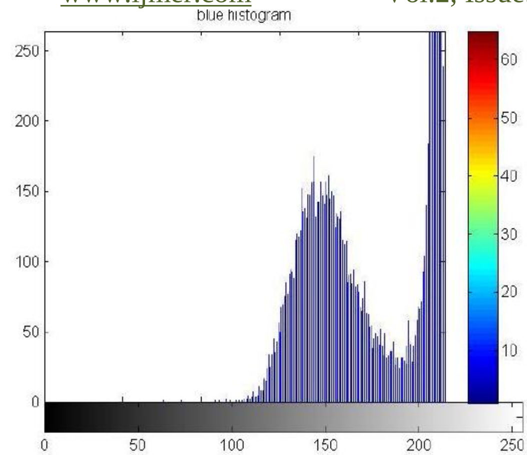

Fig 4.5:Blue histogram

Fig4.6 Green Image

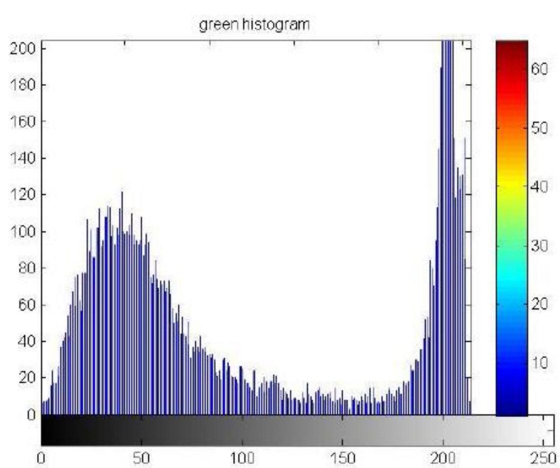

Fig 4.7:Green histogram

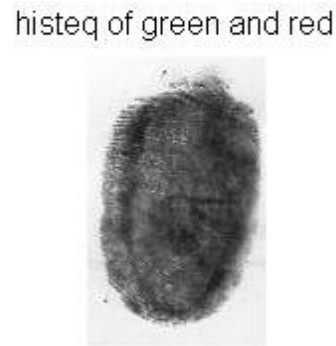

Fig 4.8: Histogram of green and red

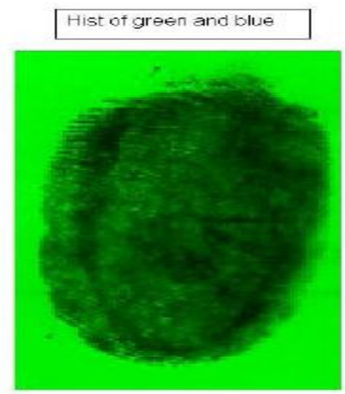

Fig 4.9:Histogram of green and blue

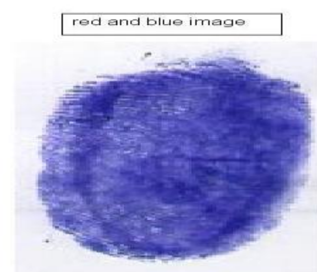

Fig 4.10:Histogram of red and blue

Fig 4.11: Canny Image

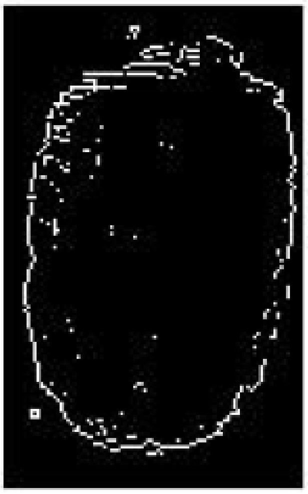

Fig 4.12: Sobel Image

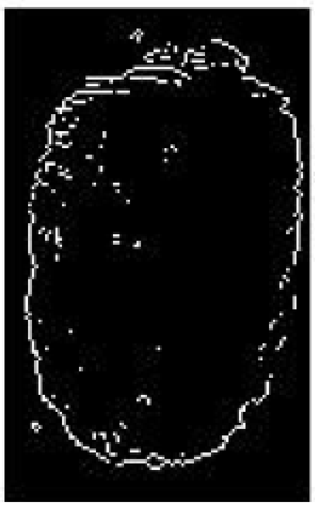

Fig 4.12 Prewitt Image

5. CONCLUSION

Our method gives the better performance, compare with existing algorithms. it is applicable for Dry finger images and blurred images.

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