

# Pattern Recognition for Imaging and Detection of Arthritis Disease

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## Abstract

Arthritis is a deadly disease which is in simple terms a bone and joint disorder causing immobility of the joints. Arthritis is occurring on ageing, genetic acquaintance, disease due to habits and external environmental factors or due to accidental damage of bones and joints. Diagnosis of the disease is difficult in the initial stages as the joints are difficult to analyse. The X-ray images obtained from the patient do not clearly demarcate the disease progress. As the nerve fibres, collagen and bone and tissue is involved in arthritis NMR imaging and X-ray imaging with a digitized image fed to an intelligent system for determining the pattern of the nerve endings for possible disease progress is the best route for detection.

The pattern recognition for arthritis is found by the disease is finally analysed and diagnosed by the following of patterns of the nerve fibres and the bone collagen and tissue structure. Pattern recognition uses various techniques like feature extraction, artificial intelligence, neural networks, fuzzy sets, expert systems, and binary and multiple search trees. Pattern recognition states the disease and its progression and thereby provides a roadmap for its treatment. In this work pattern recognition using feature extraction and image resolution using neural network topologies along with search methods are given. Various methods like K-means classifier, principal components analysis, linear classifier, curve fitting methods, pixel classifiers, are the major methods. Other advanced soft computing methods like Genetic algorithms, artificial intelligence and artificial neural networks have been tried for arthritis and in general biomedical image processing. The general commercial algorithms are PCA (Principal Components Analysis), REWIC (Rate control optimization in embedded wavelet coding), RECON (Rational Embedded Order with Constraints), REVIC (Rate control optimization in embedded Video coding), and SPIHT (system progressive Image Homogenization). These have been dealt in detail. A program for detection and data extraction from a still X-ray image has been developed, along with that program for selecting an image from a process, Image recognition (Face recognition) Image compression algorithm.

***Key words : Arthritis disease, NMR imaging, Pattern recognition, Neural network topologies***

## 1. Introduction

Diagnosis of the Arthritis disease is difficult in the initial stages as the joints are difficult to analyse. The X-ray images obtained from the patient do not clearly demarcate the disease progress. As the nerve fibres, collagen and bone and tissue is involved in arthritis NMR imaging and X-ray imaging with a digitized image fed to an intelligent system for determining the pattern of the nerve endings for possible disease progress is the best route for detection. Arthritis is a deadly disease which is in simple terms a bone and joint disorder causing immobility of the joints. Arthritis is occurring on ageing, genetic acquaintance, disease due to habits and external environmental factors or due to accidental damage of bones and joints. The pattern

recognition for arthritis is found by The disease is finally analysed and diagnosed by the following of patterns of the nerve fibres and the bone collagen and tissue structure. pattern recognition uses various techniques like feature extraction, artificial intelligence, neural networks, fuzzy sets, expert systems, and binary and multiple search trees.

In this paper we propose a new theory of bit allocation, the "bit-allocation analysis", capable of efficiently allocating a given quota of bits to an arbitrary set of different quantizers. The bit-allocation analysis discards the above concept of rate distortion function. Instead it postulates the set of bit allocation processes attainable in a given problem of quantizer based coding and then the relations of bit consumption and quantizer-based allocations are treated formally. The most important concept in this analysis is "efficient allocation process" such that no desired allocation for a particular quantizer can be increased without decreasing other desired quantizer allocation or increasing bit consumption. Application of the criterion of efficiency thus serves only to eliminate a set of clearly wasteful modes of quantizer-based allocation.

The modus operandi of bit-allocation analysis is to be through the use of set theory and the fundamental theorems of mathematical optimization. They play an important role in bit-allocation analysis just as derivatives and marginal analysis played an important role in the rate distortion theory proposed by Shannon in 1948. Based on the existence of a hyperplane that separates two disjoint convex sets, this paper characterizes the concept of efficient allocation process by profit maximization. That is, the maximization of with respect to over the set of allocation processes; where is a profit vector and represents the profit from The algorithmic solution is based on the simplex method. Then we can use the imputed profit vector at any given time in order to make a choice from the set of efficient allocations. It allows to achieve efficient allocations which may be descriptive of reality at any given time, since the profit vector can change its value over time and a user of the system may choose the appropriate strategy.

It is important to realize the basic features of the traditional rate distortion function approach in terms of the novel bit-allocation analysis terminology:

- (i) It deals with a set of allocation processes which cannot be generated from a finite number of basic allocations processes, rather a continuum of vectors is required to characterize the set of allocation processes in rate-distortion.
- (ii) (ii) the existence of a "managerial choice" is presupposed so that the combination of allocation-consumption processes always takes place to achieve some distortion constraint at the minimum bit rate which is nothing but the set of efficient allocations defined by the rate distortion function.
- (iii) The set of efficient allocations in rate-distortion constitutes a differentiable function. Instead, in the following sections, the bit allocation analysis is confined to a study of processes when the number of basic allocation processes is finite. In other words, the set of allocation processes is to be confined to a "truncated" convex polyhedral cone. However the innovative character of bit allocation analysis is not in a particular shape of the set of allocation processes. It is in the set-theoretic approach which is more fundamental and powerful than the smooth (differentiable) function approach.

A rational methodology for lossy compression - REWIC is a software-based implementation of a a rational system for progressive transmission which, in absence of a priori knowledge about regions of interest, choose at any truncation time among alternative trees for further transmission. To circumvent the lack of knowledge of what distortion measure is more suitable for optimization of the trade-off between image fidelity and coding rate, this coder shall introduce a novel mathematical

methodology for rate control by organizing the progressive transmission in accordance with coherence constraints for avoiding forms of behavioral inconsistency. A set of postulates is provided for specifying the ways in which preferences need to be made precise and fit together if illogical forms of behavior are to be avoided. We show that the rational choice for transmission at truncation time  $t$  is to select bit streams which have the maximum expected increase in utility per coding bit, where "rational" must be understood in the sense that it cannot lead the transmission system into forms of behavioral inconsistency. This method is then used within a progressive transmission scheme to produce a new compression method called rational embedded wavelet image coding (REWIC). (by *REVIC : Rational Embedded wavelet Video Coding*).

## 2.Fundamental idea of efficient allocation process

The fundamental idea of efficient allocation process as an intellectual foundation for bit allocation analysis was explored in this paper. It should serve only to eliminate a set of clearly wasteful modes of quantizer-based allocation. To this aim we replace the goal of finding efficient allocations defined by the rate distortion function (that is, to achieve some distortion constraint at the minimum bit rate) with the goal of finding an efficient combination of allocations such that an increase in one quantizer allocation can be achieved only at the cost of a decrease in some other quantizer allocation or increasing bit consumption.

The characterization theorem in this case is based on the existence of a hyperplane that separates two disjoint convex sets, which is probably the most fundamental theorem in the mathematical theory of optimization. It allows to characterize the concept of efficient allocation process by profit maximization. Hence, the fundamental theorems of mathematical optimization play an important role in bit-allocation analysis just as derivatives and marginal analysis played an important role in the rate distortion theory. Since the bit-allocation analysis is a set-theoretic approach, it is more fundamental and powerful than a differentiable function approach. An important result of this work is that the technological possibilities in bit allocation [8] can be represented in a linear model by the characterization of the set of allocation processes with resource limitations using linear inequalities. Hence the bit allocation analysis has practical and computational relevance for quantizer-based allocation. It is a typical linear programming problem, of which the computational method is well known and widely used in practice. Here we have proposed a new technique for progressive transmission following:

- (i) Attention-based quantizer formation.
- (ii) Intra-quantizer prioritization using embedded zerotree coding.
- (iii) Inter-quantizer prioritization by bit allocation analysis. One possible use of our results would be for a video codec to possess several alternative definitions of a profit vector  $p$ . By choosing the appropriate strategy for computing vector  $p$  at different bit rates, the system may attend to different parameters of interest at different bit rates within the same spatial locations. The comparative performance of the resulting technique and the MC 3D-SPIHT was explored using a perception experiment of target detection where observers were presented with the progressive transmission of moving target sequences at extremely low bit rates. The video coder using bit allocation analysis produced the lower average bit rate for achieving target detection. A key feature of the video coder developed in this paper was to avoid the use of motion compensated temporal filtering, and consequently, motion vector components did not need to be transmitted. (12)The effectiveness of a coding method can be improved through a space-varying filterbank tree representation of the image, and this property can be conveniently exploited using appropriate bit allocation strategies among the spatial segments of the image. In CORAL we examine the conditions for achieving a

rational agreement on the distribution problem by stating axioms that its solution must obey in absence of a priori knowledge about regions of interest. Firstly, a measure of benefit avoiding certain forms of behavioral inconsistency is to be assigned to each possible bit allocation in such a way that each region's preference may be inferred between any two bit allocations from their respective benefits. Secondly, individual regions are to agree on an allocation of bits which is then to be brought about by a joint strategy, but, under what conditions is their agreement rational? CORAL propose a characterization of rational agreement whose solution is an application of a general procedure for cooperative action where each may benefit only on terms which permit proportionately equal benefits to others. Experimental results are given to evaluate the performance of the strategy of COLlective Rationality for the ALlocation of bits (CORAL), based upon a validated predictor for visual distinctness from digital imagery. (by run FAST. Includes many useful vision routines, including camera calibration, homographies, fundamental matrix computation,[13] and feature detectors Dynamically reconfigurable vector, matrix and image structures in Gandalf allow efficient use of memory. Gandalf has been used to develop the "MoKey" motion editing software, released at IBC'2001 in Amsterdam. MoKey performs automatic inpainting of moving objects over an image sequence, and can also be used to compute an accurate alpha matte or outline of an object. Gandalf currently contains four packages.

### 3. Pattern matching

#### 3.1 Image Matching Using Bounded Partial Normalised Cross Correlation

Template image matching requires analysis of a template subimage into a given image for identification of known patterns in it. This technique is used in testing the existence, localizing an object in the scene and to compare portions of images against one other. Generally the template matching algorithm consists of sliding the template subimage over every pixel position in the given search image [10] and at each position calculating a measure of distortion or correlation is taken into consideration for representing the instance of the template into the image. The rate of acceptance is examined by implementing a threshold on the similarity or dissimilarity measure. The distortion measures used in template matching algorithms are the sum of absolute differences (SAD) and the sum of squared differences (SSD). Template matching approaches are computationally expensive [11] with large size images and templates. To speed up this basic approach a number of techniques are present in literature. Techniques like multiresolution scheme involve locating a coarse resolution template into the coarse resolution image and then refining the search at the higher resolution levels. Another technique like stage matching involves locating a coarse resolution template into the matching the whole template only at good candidate position. Different techniques of technology measure successive elimination algorithm and partial distortion elimination are presented for speeding up the computation required by an exhaustive search template matching process. Successive elimination algorithm is based on the evaluation of lower bound for the distortion measure. If the bounding function exceeds the current minimum then the position can be skipped without calculating the actual distortion. Whereas partial distortion elimination consists of terminating the evaluation of the distortion measure if it exceeds the current minimum. Then the position can be skipped without calculating the actual distortion whereas partial distortion elimination consists of terminating the evaluation of the distortion measure if it exceeds the current minimum [14].

### 3.2 Template Matching

Consider a gray scale image  $S(x,y)$  of size  $M \times N$  called as search image and another gray scale  $T(x,y)$  of size  $m \times n$  called as template image. The matching process moves the template image to every possible position pixel by pixel in the search image and to localize the position of best match. The matching process moves the template image to every possible position pixel by pixel in the search image and computes a numerical index to find a matching rate in that position. The sum of absolute difference (SAD) at position  $x,y$  is defined as  $SAD(x,y) = \sum_i \sum_j |S(x+i,y+j) - T(i,j)|$ -----(1)

The number of operations required to compute  $SAD(x,y)$  as determined by the dimension of the template image. Let  $lb(x,y)$  denote a lower bound function for the SAD distortion measure at every pixel position. From Li and Saari (1) we have lower bound  $lb$  related as below.

$$Lb(x,y) \leq SAD(x,y) \quad \text{Where } lb(x,y) = \sum_i \sum_j \min(S(x+i,y+j), T(i,j)) \text{-----}(2)$$

Let us denote the two sums appearing in  $lb(x,y)$  as  $S(x,y)$  and  $T(x,y)$  which represent the L norms of the sub image under examination at  $x,y$ . Since  $T(x,y)$  does not vary during the matching process, this can be computed in advance at the time of initialization and  $S(x,y)$  can be calculated very efficiently using a standard recursive technique called as box filtering. Box filtering technique is used to make its computation independent of the template area and requires only four elementary operations per image position. Successive elimination algorithm (SEA) consists in calculating  $S(x,y)$  at every position using Box filtering technique and then comparing the lower bound function against the current SAD minimum  $lb(x,y)$ .  $SAD_{min}$ ----- (3)

If the value of the lower bound function is more than or equal to minimum of the sum of absolute difference value, then the matching process can proceed with the next position without calculating  $SAD(x,y)$  but if (3) is not satisfied then the value of  $SAD(x,y)$  is compared against the minimum value of the SEA. SEA reduces the average number of calculations required to match a template into a search image by using the threshold. Threshold is used to improve the SEA's performance by computing the value of the bounding function against the lower of the threshold or the current minimum.

A partial distortion  $P_{SAD}(x,y,p,q)$  is defined as the partial distortion accumulated upto template position  $p,q$ .  $P_{SAD}(x,y,p,q) = \sum_i \sum_j |S(x+i,y+j) - T(i,j)|$ ----- (4)

The  $(x,y)$  point can be eliminated from the search without calculating the entire distortion measure if for some value of  $(p,q)$  the partial distortion value is greater than or equal to the current SAD minimum.

A partial distortion  $P_{SAD}(x,y,p,q)$  is defined as the partial distortion accumulated upto template position  $p,q$ .  $P_{SAD}(x,y,p,q) \leq SAD_{max}$ ----- (5)

PDE does not introduce any approximation in the search and it is a data dependent optimization technique that is more effective when the matching process rapidly finds low distortion points. If the template appears at multiple positions of the search image then both SEA and PDE can be applied to speed up the search work. In such cases the search image is scanned to find all the images where the distortion

### 3.3 Bounded Normalisation Cross correlation

Correlation is a measure of the degree to which the corresponding pixel values in search image and template image matches. When normalized cross correlation is used the template subimage is positioned under the search image by searching for the maximum values of the NCC function.

$$NCC(x,y) = \frac{\sum_i \sum_j (s(x+i,y+j) - \bar{s})(T(i,j) - \bar{T})}{\sqrt{\sum_i \sum_j (s(x+i,y+j) - \bar{s})^2 \sum_i \sum_j (T(i,j) - \bar{T})^2}} \text{-----}(6)$$

The numerator part of (6) represents the cross correlation  $C(x,y)$  between the search image and the template image. Let us denote the two terms appearing in the denominator as  $S(x,y)$  and  $T(x,y)$  which represent the

$L_2$  norms of the subimage under examination at  $x,y$ . Since  $T(x,y)$  does not vary during the matching process this can be compared in advance at the time of initialization and  $S(x,y)$  can be calculated very efficiently by box filtering technique and requires only 4 elementary operations per image position

Let  $ub(x,y)$  denotes an upper bound function for the  $C(x,y)$  correlation measure at every pixel position so

$$ub(x,y)C(x,y) = \frac{S(x+i,y+j) T(i,j)}{S(x,y)T} \text{-----(7)}$$

The upper bound for the normalised cross correlation function is obtained by normalization

$$ub(x,y) C(x,y) = \frac{NCC(x,y)}{S(x,y)T} \text{-----(8)}$$

$$S(x,y)T$$

**Let NCC be the current correlation maximum at point (x,y)**

$$ub(x,y) \frac{NCC(x,y)}{S(x,y)T}$$

$$S(x,y)T$$

If (0) is satisfied then the matching process can proceed with the next point without computing  $C(x,y)$  because after satisfying (9) it is clear that the position will not hold the correlation maximum value. However if (8) does not hold then  $c(x,y)$  is normalized and the following condition is verified

$$ubC(x,y,p,q) = P(x,y,p,q) + ub(x,y,p,q)$$

$$\text{where } ub(x,y,p,q) = \frac{S(x+i,y+j)^2 + T(i,j)^2}{2} + \frac{S(x+i,y+j)^2 + T(i,j)^2}{2} \text{-----(8)}$$

and the new elimination condition condition described as

$$ubC(x,y,p,q) < \frac{NCC_{max}}{S(x,y)T}$$

### 3.4 Results of the model implementation

Initially some gray scale images of different dimensions for the purpose of template matching. The proposed approach of Bounded cross correlation has been tested with several search images and templates with the program given in appendix for cross correlation. In every test conducted for matching the template image has been extracted from a different though similar image. In all the experiments a correlation threshold of more than 0.9 has been taken into consideration for obtaining best match position between the search image and the template. The results obtained for matching grayscale images of different dimensions with the correlation values after matching are represented below.

#### Experiment 1:

Matching a grayscale image of size 230x198 and a search and a template image of size 26x40. The objective of the experiment is to find and match the position of a particular letter inside the search image

### 3.5 Image coding Methods for Pattern matching

The main methods of image coding for matching of text and image pixels are

1. REWIC (Rate control optimization in embedded wavelet coding)
2. RECON (Rational Embedded Order with CONSTRAINTS)
3. REVIC (Rate control optimization in embedded Video coding)
4. SPIHT (system progressive Image Homogeniation)
5. Principal components Analysis
6. linear classifier
7. Best curvefitting algorithms
8. Kmeans classifier

### 3.5.1 (REWIC ) Rate control Optimization in Embedded wavelet coding)

A discrete wavelet transform which provides a representation of the original image, [4]. A tree structure, called Spatial Orientation Tree (SOT) in [2], naturally defines the spatial relationship on the pyramid that results from the transformation. Each node of the tree corresponds to a pixel, and its position (relation to parent node and its position). A discrete wavelet transform which provides a representation of the original image, [4]. A tree structure, called Spatial Orientation. Each node of the tree corresponds to a pixel, and its direct and direct descendants (offsprings) correspond to the pixels of the same spatial orientation in the next finer level of the pyramid. Transform coefficients over a spatial orientation tree correspond to a particular local spatial region of the original image, and thus, each SOT is associated with one spatial region. Zerotree coding and successive approximation which provide a representation of the significant wavelet coefficients, [1].

A prioritization protocol whereby the ordering of importance is determined within a rational approach that chooses at each truncation time among alternative spatial orientation trees for further transmission in such a way as to avoid certain forms of behavioral inconsistency following REWIC v 4.0. The system may exhibit either a risk seeking posture with respect to "gambles" on SOT-dependent quality of encoding or risk-averse behavior.

High levels of tolerance to risk attitude which provide an acceleration of benefit gain for quantizers of interest at very low bit rates. Risk tolerance is controlled by using a coalitional game. Any nonempty subset of the set of quantizers may be called a coalition. The coalitional game optimally transforms joint benefit gains of coalitions into payments to individual quantizers by minimizing the total dissatisfaction of important coalitions at the final payment to quantizers for being involved in the game.

### 3.5.2 Rational Embedded coder with CONstraints (RECON)

This is an algorithm which implements the rational system for transmission, at very low bit rates, with high risk tolerance.

High risk tolerance (RECON) is interrupted at 0.0625 bit/pixel by a rational embedded wavelet transmission (REWIC) with moderate risk aversion to gambles on variable-resolution compression [3,6,7], since quantizers exhibit low risk tolerance at medium and high bit rates.

#### 3.5.2.1 Adaptive arithmetic coding for entropy coding strings of symbols, [5].

Human visual system allocates different amounts of processing resources to different portions of the visual field, and in fact, features will only be perceived if they succeed in attracting attention. Hence, if the compressed images are going to be used for recognition purposes, then it is desirable to preserve the features during the progressive transmission.

In such cases, a selection of significant features might be used to guide the image transmission. To this aim, we have developed an algorithm called as "Feature-based Rational Embedded Wavelet Image Coder (FREWIC)" in which we have reformulated the rational embedded wavelet image coding to base the quantizer formation on features extracted by a local energy model which is capable of successfully explaining a reasonable number of psychophysical effects in human feature perception. REWIC2 is a software-based implementation of the codec "Rate control optimization in embedded wavelet coding" In an embedded wavelet scheme for progressive transmission, a tree structure naturally defines the spatial relationship on the hierarchical pyramid. Transform coefficients over each tree correspond to a unique local spatial region of the original image, and they may be coded bit-plane by bit-

plane through successive-approximation quantization. After receiving the approximate value of some coefficients, the decoder can obtain a reconstructed image. REWIC2 is a rational system for progressive transmission which, in absence of a priori knowledge about regions of interest, choose at any truncation time among alternative trees for further transmission. It is based on a novel mathematical methodology for rate control by organizing the progressive transmission in accordance with coherence constraints for avoiding forms of behavioral inconsistency. A set of postulates are provided for specifying the ways in which preferences need to be made precise and fit together if illogical forms of behavior are to be avoided.

The rational choice for transmission at any truncation time is to select bit streams which have the maximum expected increase in utility per coding bit, where "rational" must be understood in the sense that it cannot lead the transmission system into forms of behavioral inconsistency. Thus each spatial region of the image considers only benefits to itself (the maximum expected increase in utility per coding bit) in making the individual choice of a rational strategy for bit allocation. But, self-regarding region might also agree on an allocation of bits which is to be brought about by a joint strategy determining each region's allocation. The question is here: Under what conditions is their agreement rational? REWIC2 characterize the collective rationality by a rational agreement of just distribution reducing the inequality in the distribution of benefits among spatial regions.

### 3.5.1.2 REVIC : Rational Embedded wavelet Video Coding.

The elicitation of the optimal coding scheme consists of calculating the visual distinctness by means of the compound gain between a test image  $I$  and images reconstructed under various degrees of lossy compression. It allows us to analyze the behavior of coders, taking into account that an optimal coder tends to produce the lowest value of the compound gain.

The result of the comparison ( CG curves for every test image) show the respective 2D plots on rate-distortion as given by the CG for JPEG2000, CORAL, SPIHT, and REWIC. The compression ratio ranges from 64:1 to 16:1. The CORAL, SPIHT, and REWIC were not improved by entropy-coding their outputs, and thus, the bitstreams put out are binary uncoded (without entropy coding)."

### 2.5.1.3 Rate Control Optimization In Embedded Wavelet Coding

REWIC2 is a software-based implementation of the codec specified in the paper In an embedded wavelet scheme for progressive transmission, a tree structure naturally defines the spatial relationship on the hierarchical pyramid. Transform coefficients over each tree correspond to a unique local spatial region of the original image, and they may be coded bit-plane by bit-plane through successive-approximation quantization. After receiving the approximate value of some coefficients, the decoder can obtain a reconstructed image. REWIC2 is a rational system for progressive transmission which, in absence of a priori knowledge about regions of interest, choose at any truncation time among alternative trees for further transmission. It is based on a novel mathematical methodology for rate control by organizing the progressive transmission in accordance with coherence constraints for avoiding forms of behavioral inconsistency. A set of postulates are provided for specifying the ways in which preferences need to be made precise and fit together if illogical forms of behavior are to be avoided. The rational choice for transmission at any truncation time is to select bit streams which have the maximum expected increase in utility per coding bit, where "rational" must be understood in the sense that it cannot lead the transmission system into forms of behavioral inconsistency.



Thus each spatial region of the image considers only benefits to itself (the maximum expected increase in utility per coding bit) in making the individual choice of a rational strategy for bit allocation. But, self-regarding region might also agree on an allocation of bits which is to be brought about by a joint strategy determining each region's allocation. The question is here: Under what conditions is their agreement rational. REWIC2 characterize the collective rationality by a rational agreement of just distribution reducing the inequality in the distribution of benefits among spatial regions.

### 3.5.1.4 Image Sequences and Video

Now available are executable programs for compressing/decompressing image sequences or video using SPIHT coding of three-dimensional wavelet transforms. These programs may be used for coding sequences of multispectral or medical images or video. Please note that there is no motion compensation enacted in these programs. Programs for gray scale sequences (raw or SUN Raster (.ras) format) of 1 byte/pel images for different operating systems below are for lossy compression only. The 3D programs encode and decode a single group of frames within a sequence. The programs executable herein set the group size to 16. One can write a script for processing the sequence of groups or use the programs

## 4. Biological/Medical Signal Compression

One-dimensional **lossless** compression for biological signals, e.g., ECG, EEG, etc. Input must be raw data format consisting of series of signed short (2 bytes) integers. See included Readme.txt file. One-dimensional **progressive lossy** compression for biological signals, e.g., ECG, EEG, etc. Included are MATLAB m-files for plotting and display of waveforms. Input must be raw data format consisting of series of signed short (2 bytes) integers. Sample data files are enclosed. See included

## 4.1 Biometric Recognition Systems

The program below is for image recognition and pattern matching does the following processes. These systems are used for biometric recognition in biomedical image applications like bioimage(face/.hand/iris) recognition

## 5. Algorithm Description

The algorithm has the steps given below and executes the image pixel point  $t$  find a point and check the processed image for the input mark location  $o$  that chosen using a mouse pointer from a screen input image.

1. function `discrdatain = discretize(datain, discl)`
2. Converts any continuous dataset to a discrete dataset
3. each variable has 'discl' different discrete values
4. Calculates prior prob of each discrete value
5. Calculates entropy of each possible value
6. Finally calculates the entropy of the entire dataset (avg of variable)

Program to Separate the Processing from the Display gives the final image object independent of the image while processing is going on

For the fastest performance of a web-based application we separate the processing from the display. This demo app `selectprocess.html` loads the hibiscus image and lets the user apply successive image processing operations. The app has to keep the last processed image in memory so it will be available for the next operation. The `global.asax` file holds the global variable identifying the image as long as the session is active.

Selectprocess uses an html page as the application's main form to display the user interface and gather data from the user. When the processing is selected the image is processed and displayed by the aspx page in the browser by assignment of the aspx page to the image source: ``.

For the fastest operation of this application only the image is redisplayed, the rest of the page remains unchanged. That's the advantage of using html/css for the user interface.

If the page were built with asp.net controls, then the entire page would be resent from the server to the browser each time the image is processed. The source code for this app is contained in three main files

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## 6. Image processing interface program

**Selectprocess.html** contains the user interface containing the buttons for selection of the image processing. When a function is selected a javascript function creates the url to be set to the img src.

To find a specific mark in an image we use statistical correlation to compare a reference image that defines the mark to a test image that may contain the mark. The result image is filled with the correlation coefficient data. The pixel in the result image with the highest value is the most probable location for the mark.

This procedure supports grayscale images. Use the Victor Library conversion functions to convert color or black and white images to 8-bit grayscale.

In general, the steps are:

- determine the dimensions and pixel depth of the test and reference images
- allocate buffer space for the images
- load the images
- fill the result image with correlation coefficient data calculated between the test image and the reference image
- sort the correlation coefficient data to determine the most probable location of the mark

The result image is filled with pixel data that represent the correlation coefficient calculated between the reference image and the test image at each pixel location. The pixel values can range from zero (negative correlation) through 128 (no correlation) up to 255 (perfect positive correlation). A negative correlation would mean a good match with the negative image of the reference mark.

The brightest pixel in the result image represents the most probable location of the reference mark. In this case that is at location (84, 213).

## 6.1 Selectprocess.html source code

```

<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN"
"http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">

<html xmlns="http://www.w3.org/1999/xhtml" >
<head>
<title>Selectprocess, a Victor Library demo using asp.net, VB.NET</title>
<style>
body { font: 78%/1.5 arial, helvetica, serif }
.submit-button { width: 10em; color: #000 }
.display_box { margin-left: 1em }
.button_block { float: left; width: 11em }
</style>
</head>
<body>
<h3>ASP.NET Victor Image Processing Library Demo, VB.NET</h3>
  <span class="button_block">
    <input type="button" class="submit-button" id="refresh" onclick="selectprocess(this);"
value="Refresh" />
    <input type="button" class="submit-button" id="sharpen" onclick="selectprocess(this);"
value="Sharpen" /><br />
    <input type="button" class="submit-button" id="negative" onclick="selectprocess(this);"
value="Negative" /><br />
    <input type="button" class="submit-button" id="togray" onclick="selectprocess(this);" value="Convert
to grayscale" /><br />
    <input type="button" class="submit-button" id="kodalith" onclick="selectprocess(this);"
value="Kodalith" /><br />
    <input type="button" class="submit-button" id="flip" onclick="selectprocess(this);" value="Flip"
/><br />
    <input type="button" class="submit-button" id="mirror" onclick="selectprocess(this);" value="Mirror"
/><br />
    <input type="button" class="submit-button" id="reload" onclick="selectprocess(this);" value="Reload"
/><br />
  </span>
  <span class="display_box">
    
  </span>
<script language=javascript>
function selectprocess(sourceObject)
{
var nimage;
var func = sourceObject.id;

```

```

var anow;

anow = new Date(); // to tack on a random number so to the browser it is a new url
nimage = document.getElementById("image1");
nimage.src = "selectprocess.aspx?category=process1"
    + "&func=" + func
    + "&xtr=" + anow;
}
</script>
</body>
</html>

```

**Selectprocess.aspx** creates the jpeg in memory and defines the image source for the image control, *image1*, with the following lines:

```

If (rcode = vicwin.NO_ERROR) Then ' Set the global variables
    Session("sp_imgdes") = srcimg ' Image descriptor
    Session("sp_sessionflag") = 1 ' Flag to indicate session is active
    rcode = vicwin.savejpgtobuffer(outbuff, srcimg, 75) ' Save image to a jpg file in memory, quality =
75

```

```

If rcode = vicwin.NO_ERROR Then
    imgbytearray = buffertobytearray(outbuff) ' Omitted here for easier reading
    vicwin.freebuffer(outbuff)
    Response.ContentType = "image/jpeg"
    Response.Expires = 0
    Response.Buffer = True
    Response.Clear()
    Response.BinaryWrite(imgbytearray) ' Send the image to the browser
    Response.End()
End If

```

End If

for simpicity in this example we only use jpeg, but gif and png are other image file formats we can use and the browser will display.

### **Global.asax**

To keep track of the image in memory so that successive operations will work on the last processed image we use a global image descriptor and session flag that are maintained in global.asax.

```

<%@ import namespace="viclib" %>
<Script Runat="server">
Sub Session_Start()
    Session("sp_imgdes") = 0
    Session("sp_sessionflag") = 0
End Sub
' When the app ends, release the image buffer memory
Sub Session_OnEnd()

```

```

Dim simage As vicwin.imgdes
simage = New vicwin.imgdes()
if Session("sp_sessionflag") = 1 then
simage = Session("sp_imgdes")
vicwin.freeimage(simage)
Session("sp_sessionflag") = 0 end ifEnd Sub
</script>

```

## 7. Conclusions and Future work

Various methods of statistical coreation and image matching were studied and their suitability was tested and ranked for finding a suitable pattern in arthritis cases. For a given input vector  $t^*(12,14,72)$  the Result image, pattern mark (matching pixels) found at (84, 213) The purpose of this program is to provide resources to experienced researchers as well as new comers in the fields of pattern recognition, artificial intelligence, machine learning and other overlapping research fields.

The focus of this project was to fully describe the relationships between data characteristics and classifier behaviour, and to develop algorithms that automatically select classifiers and parameters appropriate for a given set or subset of data. Relevant publications are available from the 'Publications' link and other relevant tutorials are available at the 'Tutorials' link. It is clear from the literature that there is no best classifier for all types of problems.

Some guidelines have been proposed in the literature for classifier selection. These guidelines, however, do not provide much insight on the specific characteristics of the data that will determine the preference of classifier. An empirical comparison of classifiers on any problem can be performed by using the classification applet available at the 'Applet' link. Pattern recognition is a very active research area which overlaps with various other research fields such as Machine Learning, Artificial Intelligence, Data Mining, Probability Theory, Algebra and Calculus. Source code for various classifiers and other numerical and statistical algorithms are available at the 'Source Code' link. Terminology used in these research fields can be found at the Classifiers cover a wide range of information processing problems. These problems often have great importance and include speech recognition, classification of handwritten characters, fault detection in machinery, medical diagnosis and many other. A non-exhaustive list of pattern recognition applications is available at the 'Pattern Recognition Applications' link'. Classification algorithms have been applied to various comercial products very succesfully. Commercial Neural Network Classification, Regression, Data Analysis and many other applications are available at the linkson the left hand side. This thesis describes, proposes and evaluates methods for automated analysis and quantification of medical images. A common theme is the usage of generative methods, which draw inference from unknown images by synthesising new images having shape, pose and appearance similar to the analysed images. The theoretical framework for fulfilling these goals is based on the class of Active Appearance Models, which has been explored and extended in case studies involving cardiac and brain magnetic resonance images (MRI), and chest radiographs. Topics treated include model truncation, model compression using wavelets, handling of non-Gaussian variation by means of cluster analysis, correction of respiratory noise in cardiac MRI, and the extensions to multi-slice two-dimensional time-series and bi-temporal three-dimensional models. The medical applications include automated estimation of: left ventricular ejection fraction from

4D cardiac cine MRI, myocardial perfusion in bolus passage cardiac perfusion MRI, corpus callosum shape and area in mid-sagittal brain MRI, and finally, lung, heart, clavicle location and cardiothoracic ratio in anterior-posterior chest radiographs.

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