REVIEW PAPER FOR MULTIDIMENSIONAL PATTERN ANALYSIS AND ITS MODELING

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Multidimensional Pattern recognition techniques are often an important component of intelligent systems and are used for both data pre-processing and decision making. Broadly speaking, pattern recognition is the science that concerns the description or classification (recognition) of Measurements. The following enumerates a few of the areas where pattern recognition finds image pre processing, segmentation, and analysis.

- Computer vision
- Artificial intelligence
- Seismic analysis
- Radar signal classification/analysis
- Speech recognition/understanding
- Fingerprint identification
- Character (letter or number) recognition
- Handwriting analysis
- Electro-cardio graphic signal
- Analysis/understanding
- Medical diagnosis
- Socioeconomic
- Archaeology
- Data mining/reduction

I. INTRODUCTION TO VISUAL SYSTEM

Although object detection forms an important part of the scene information, it is not the only information that the agent might be interested in. According to the task, the agent might require to know the different objects present in the scene (not looking for a particular object), spatial organization of various objects, similarity of objects, etc. Such an entire information system can be called as a visual system.

A. Use of Neural Network: A neural network is a network of simulated neurons that can be used to recognize instances of patterns. NNs learn by searching through a space of network weights. Neural network nodes simulate some properties of real neurons

- A neuron fires when the sum of its collective inputs reaches a threshold
- A real neuron is an all-or-none device
- There are about 10^11 neurons per person
- Each neuron may be connected with up to 10^5 other neurons
- There are about 10^16 synapses (300 X characters in library of congress)

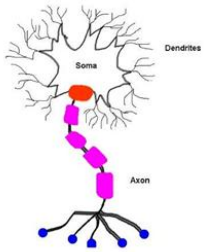

Fig 1.Basic Structure Of Neuron

The Neural Network of a mature human brain contains about 100 billion nerve cells called neurons. These neurons are the fundamental part of the Neural Network. Neurons form complex networks of interconnections, called synapses, with each other. A typical neuron can interconnect with up to 10,000 other neurons, with the average neuron interconnecting with about 1,000 other neurons.

B. USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the human like intelligence exhibited by machines or software. It is also an academic field of study. Major AI researchers and textbooks define the field as "the study and design of intelligent agents" where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success.

II. LITERATURE SURVEY

Finding an interest point and a feature vector around the interest point (describing the locality) is one of the widely used methods for solving appearance differences. Here the emphasis is to learn features which are scale, translation and illumination in variant. It essentially builds the object detection on local features. State of the art in this method include Scale Invariant feature transform (SIFTLowe [2004]), Maximally stable extremal regions (MSER Forssen and Lowe [2007]),Speeded Up Robust Features (SURF Bay et al. [2008]), etc. Most popular among these is the SIFT features. SIFT extracts a large collection of feature vectors which are invariant to image translation, scaling and rotation and partially invariant to illumination changes. Key locations are defined as maxima and minima of the result of difference of Gaussians (DOG) function, applied in scale-space to a series of smoothed and resampled images. Low contrast candidate points and edge response points along an edge are discarded. Dominant orientations are assigned to localized key points. The feature vector is formed by specifying the orientation relative to the key point, essentially making the

vector rotation invariant. Many variants to the SIFT method are also proposed like RIFT (Lazebniket al.[2004]), which is rotation invariant SIFT, PCA-SIFT (Ke and Sukthankar [2004]),GLOH (Mikolajczyk and Schmid [2005]), etc. The whole approach of building object detection on local features is challenged by researchers who have shown that extracting global features along with local features might help in better detection-accuracy and speeds (Oliva and Torralba[2006]). They argue that the ambiguity in local features can be reduced by global features of the image - gist of the scene.

III. MOTIVATION

In this work we describe an object detection system which is based on advance entropy function for a set of images. The approach is motivated by Shimon Ullman's visual routines theory (Ullman [1984]) which states that the human vision system is composed of basic visual operators which are combined in different ways for complex object detection tasks. New Entropy function detect properties like colour, shape, texture, etc.

IV. CHALLENGES INVOLVED

Object detection can be considered as a pattern recognition task, where the input representation is mapped to an output label. But the image domain makes the problem much harder to solve. A visual scene contains a lot of information. From the processing point of view it is just a collection of pixels with colour and location information. Group of such pixels forms objects or object parts. These object parts combine to form bigger objects and they together define a scene. The object itself can appear in different colour, texture, size or even shape. Many of these variation scan occur combined in a scene, which makes it harder to detect these properties.

V. EXISTING WORK

A. STATISTICAL APPROACHES TO PATTERN RECOGNITION

There are two aspects to pattern recognition - developing a decision rule and using it. The actual recognition occurs in the use of the rule; the pattern is defined in the learning process by the labeled samples. Since 'O' could be seen as a 'circle' or as a character 'O', the pattern recognition problem thus begins with class definition and labeled samples of those classes in some workable representation. The problem is solved when a decision rule is derived which assigns a unique label to new patterns. Pattern recognition is concerned primarily with the description and analysis of measurements taken from processes. For this preprocessing is often required to remove noise and measurement redundancy. An important step for any classification algorithm is feature selection and extraction from the training data.

B. SYNTACTICPATTER RECOGNITION APPROACH

Syntactic pattern recognition or structural pattern recognition is a form of pattern recognition, in which each object can be represented by a variable-cardinality set of symbolic, nominal features. This allows for representing pattern structures, taking into account more complex interrelationships between attributes than is possible in the case of flat, numerical feature vectors of fixed dimensionality, that are used in statistical classification. Syntactic pattern recognition can be used instead of statistical pattern recognition if there is clear structure in the patterns. One way to present such structure is by means of strings of symbols from a formal language. In this case the differences in the structures of the classes are encoded as different grammars.

C. NEURAL PATTERN RECOGNITION APPROACH.

In computer science and related fields, artificial neural networks (ANNs) are omputational models inspired by an animal's central nervous systems (in particular the brain) which is capable of machine learning as well as pattern recognition. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs. For example, a neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read like other machine learning methods - systems that learn from data - neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition.

VI. PROPOSED WORK

A. ENTROPY BASED SELECTION APPROACH FOR RECOGNITION TO MULTIDIMENSIONAL TECHNIQUE

In the classification task, a favorable occurrence is when an object (or signal) is correctly classified. If classification is based on given probability distribution functions, one possible approach to classify an observed signal is to evaluate pdf functions for different classes of this observed signal. The signal is classified as an object of the class with the maximum pdf value. Let us consider a two-class classification problem with pdf functions as shown in Figure 9.

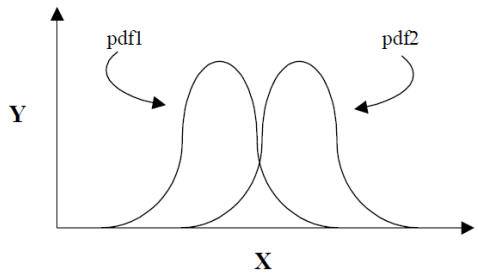

Fig. 2: Illustration of the Parzen window approach.

Probability that a signal from class 1 will be correctly classified under this scenario equals to the integral under pdf1 for all random variables X for which pdf1 > pdf2. Let us define S1 as a subspace of the input space for which pdf1 > pdf2. In order to obtain the Value of integral (pdf1) dx, a

number of schemes were used and are discussed further.

B. Cartesian Grid Method

The motivation for this approach arose from the simple way of integral approximation. The input space is divided into equally sized segments and integral over each segment is approximated by multiplying the volume of the each segment by the average value of the integrated function over this volume. Total integral is approximated by the sum of the segment integrals. Initially a unit grid centered at the origin is made. Each dimension is divided into equal number of parts given by 'num Points'. In order to map the unit grid to the actual points we multiply the original grid points by maximum standard deviation of the original points and a constant named 'varstd'. The value of this constant is chosen so that statistically almost 98% of the points are covered. Having obtained the grid of points in Cartesian coordinates we now perform QR factorization of the actual signal shifted to the origin of the coordinate system. The resulting two matrices Q and R will be used to obtain a linear transformation of the input space, where Q is the orthogonal matrix and R is the upper triangular matrix. Having Q and R we can easily obtain an N-dimensional ellipsoid which encloses the original points in the input space and can be used to describe n-dimensional probability density function (pdf) of the data points in the original input space. The original data points can be transformed to the orthogonal space by using multiplication of the input signals by R-1. In the orthogonal space, all data points are equally spread around the origin. Their distribution is approximately Gaussian with the mean value equal to zero and standard deviation equal to 1/sqrt(m-1), where m is the number of data points (also equal to standard deviation of the matrix Q). To include most of the data points in an enclosing n-dimensional sphere we multiply the standard deviation (includes close to 98% of all normally distributed samples).

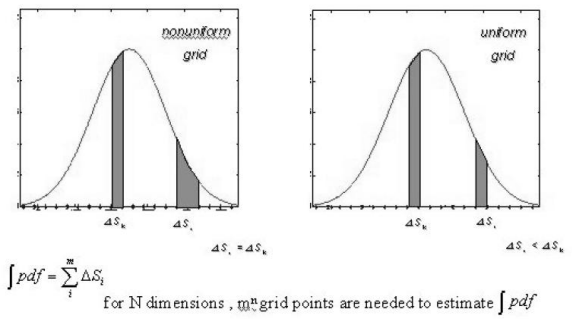

Figure 3: Illustration of Uniform and Non-uniform grid for direct integration in 1D

The enclosing sphere (and the Gaussian probability density function) can be transformed back to the original input space by taking product of vectors in the orthogonal space with matrix R. Therefore, the enclosing sphere will be transformed to enclosing ellipsoid in the input space. Subsequently, all the grid points are transformed to the orthogonal space spanned by column vectors of matrix Q and points lying outside the enclosing N-dimensional sphere are discarded. Now, we have reduced the earlier generated grid to a selected set of points over which we are going to calculate the pdf. Figure 10 illustrates the 2-dimensional grid. It shows the original points in 'o' and the original grid points with '+'. The ellipse which bounds the original set of points is shown in red with '-' and the grid points which are selected and lie within the ellipse are shown with '*'.

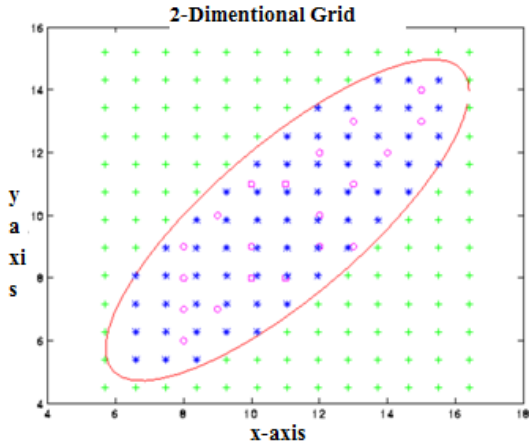

Fig. 4 -Dimensional grid red (.): ellipse bounding the signal green (+): original set of points magenta (o): original signal blue (*): selected set of points

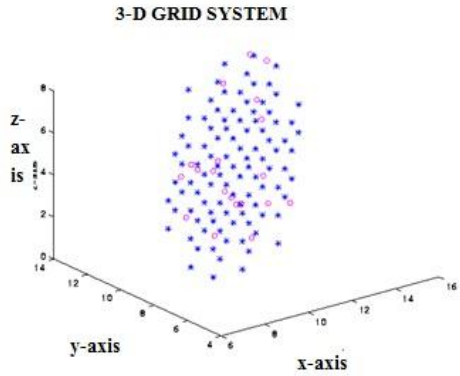

Fig.5 -Dimensional grid: Original points and the selected grid points magenta (o): original set of points blue (*): selected set of points

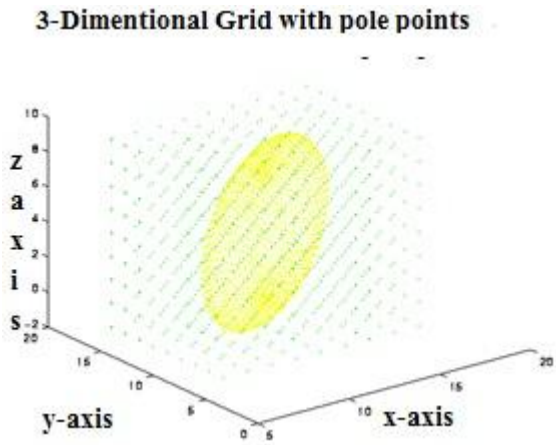

Fig 6 -Dimensional grid blue (.): original set of points yellow (.): ellipse bounding the signal

Figures 5 and 6 illustrate the 3-dimensional process. The original set of points and the selected grid points are shown in Figure 5, while the original grid points and the ellipse which bounds the original set of data points.

C. Spherical Grid Method:

Cartesian grid approach is simple to use, however it is not the most numerically efficient way of finding n-dimensional integrals. Considering specificity of Gaussian functions (exponentially declining values) significant savings in computations can be obtained. The same accuracy can be obtained with non-uniform distribution of the grid points and total number of grid points reduced. First, a regular N-dimensional grid is obtained using polar coordinates. Polar coordinates are described by specifying the radius and angles in all directions. The increment in radius Δr1 is obtained from the function instep. This function evaluates the steps for integration of normal 1-dimensional pdf under the assumption that discrete integration using selected points introduces equal increments of the integral values. Once the increments in radius are known we make the grid in polar form. The angles vary from 0 to π and radius varies from 0 to maximum value obtained from instep function. Starting from the 2- dimensional case the projection of the radius vector is used to determine the radius of next higher dimension such that the resulting grid points are equally distributed on the surface of n-dimensional sphere with radius r1.To illustrate this process let us assume that we want to obtain a radius and a number of grid points on a single circle around a 3-dimensional sphere. We assume that the sphere radius is r1 and the projection angle α1 is used.

The radius r2 is obtained from projection of r1 using

$r2 = r1 * \cos\alpha 1$ as shown in Figure 14.

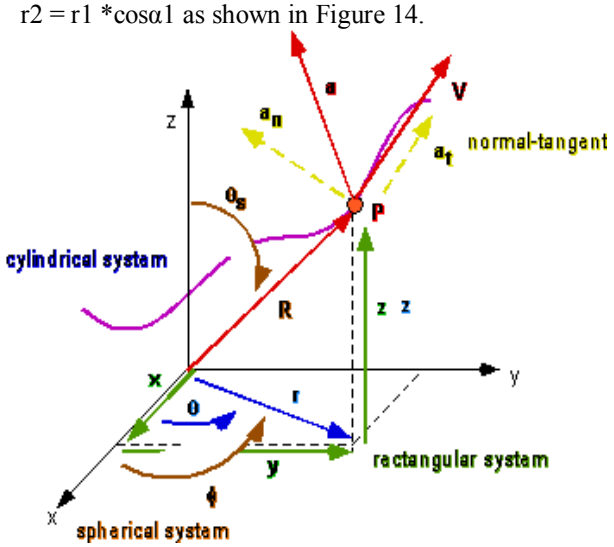

Figure 7: Radius Projection in other Direction Radius r2 is needed to determine values of α2, where α2 has the increment

$\Delta\alpha 2 = \Delta r1/r2$

α2 starts from 0 and is incremented by Δα2 until it reaches π. The number of grid points on this circle is less than or equal to 2πr2/Δr1. Subsequently r3, which is a radius of a circle around 4-dimensional sphere, is obtained using:

$r3 = r2 * \cos\alpha 2$

Values of α3 are also computed from increment in α3 which is given by:

$\Delta\alpha 3 = \Delta r1/r3$

This continues until the highest dimension is reached. Then with the radius r1 and varying angles from 0 to π in each dimension we obtain a set of grid points equally distributed on the surface of n-dimensional sphere with radius r1. A function was written which generates the entire grid points on this sphere by calling itself recursively. The procedure Ndsph is repeated for each r1 value which was determined by instep. The result is a polar grid of points that fill the upper half of n-dimensional volume. Examples of generated polar grids for 2 and 3-dimensional volumes are as shown on Figure 5 and Figure 6.

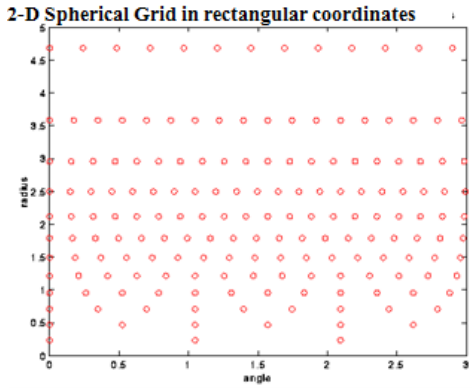

Fig. 8 -dimensional Spherical Grid in rectangular coordinates.

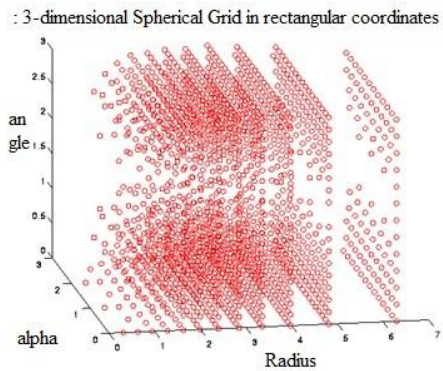

Fig. 9 dimensional Spherical Grid in rectangular coordinates.

These spherical points are then converted to the Cartesian set of points. The formulas used to convert the spherical coordinates to the Cartesian form are as follows:

$Xn = r * \sin\alpha n-1$

$Xn-1 = r * \cos\alpha n-1 * \sin\alpha n-2$

$Xn-2 = r * \cos\alpha n-1 * \cos\alpha n-2 * \sin\alpha n-3$

$X2 = r * \cos\alpha n-\alpha 1 * \cos n\alpha-2 * \cos n\alpha-3 *.....* \cos\alpha 2 * \sin\alpha 1$

$X1 = r * \cos n\alpha-1 * \cos n-\alpha 2 * \cos n-\alpha 3 *.....* \cos\alpha 2 * \cos\alpha 1$

For instance, the Cartesian form of the 2-dimensional grid shown in Figure 16 is illustrated in Figure 17. This grid

needs to be complemented to fill full n-dimensional volume by symmetrical projection around the coordinate center, as well as adding the center point. The resulting grid for 2-dimensional case is shown in Figure 16.

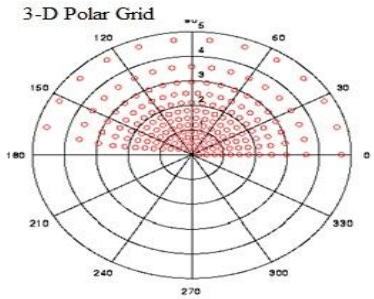

Fig. 10 - Dimensional Spherical Grid in Cartesian from, shown in Cartesian coordinates.

Once the grid is converted from polar coordinates to Cartesian form, transformation based on QR factorization is applied and the grid points lying outside the unit circle are discarded. This method of QR factorization and discarding the points outside the unit circle is the same as described in Cartesian grid described previously. The program that makes the spherical grid is called sphndmand it calls two routines instep and Ndsph. These programs are attached in Appendix. Figure above illustrates the grid selection process in which the '+' sign shows the original grid points and 'o' shows the original signal points, '*' indicate the selected grid points and '-'in red shows the ellipse which bounds the original set of points and bounds the selected grid points.

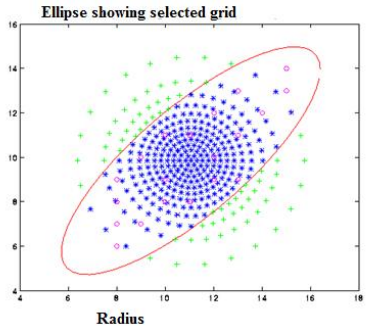

Fig.11 Dimensional Spherical grid red (-): ellipse bounding the signal green (+): original set of points magenta (o): original signal blue (*): selected set of points

Figures 11 and 12 show the 3-dimensional case. Figure below shows the ellipse and the original set of points, while last two figures shows the original grid and selected grid points.

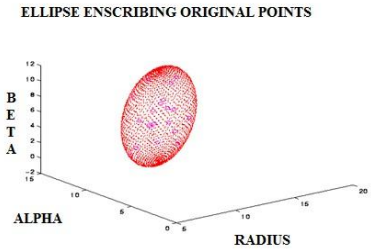

Fig.12 : Ellipse enclosing the original set of points .Magenta (o): Original Points

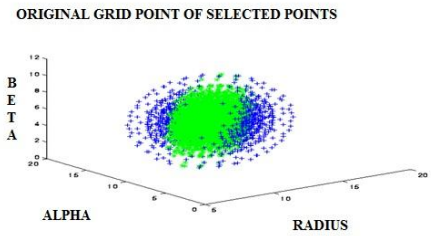

FIG 13 - 2Red (.): Ellipse enclosing the original points

D. Monte Carlo Method:

One of the major drawbacks of Cartesian and Spherical approach was that with increase in dimension, the number of grid points generated grew exponentially. Monte Carlo method eliminates this problem by generating a fixed known number of random points to approximate the integral.In Monte Carlo integration the estimate of integral.

$$\int_{S}^{1} (pdf1)\, dx$$

is obtained by counting how many random points generated by pdf1 have pdf1 > pdf2

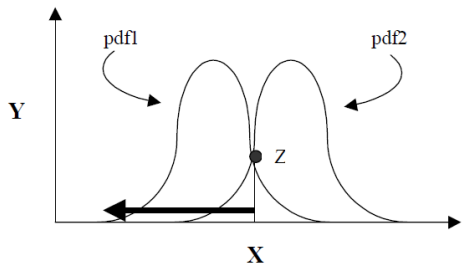

Figure 14: Probability based on pdf1>pdf2

A slight modification of the above scheme is to use weighted pdfs. Now a point is classified as a point of class 1 with the believe level determined by:

$PDf_1(x)/[pdf_1(x)+pdf_2(x)]$ and as a point of class 2 with the believe level determined by:

$PDf_2(x)/[pdf_1(x)+pdf_2(x)]$

As a result of weighted pdf functions we need to estimate their integrals with weighted Probabilities. Figure 15 shows the region of each weighted probability.

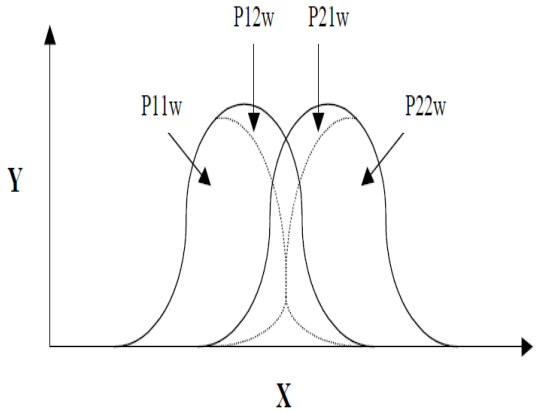

Fig. 15: Region of each weighted probability.

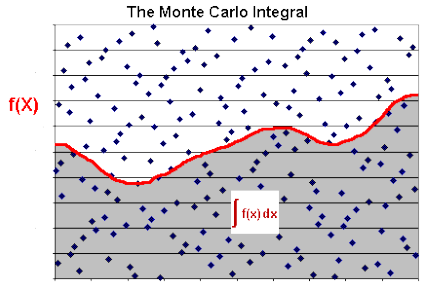

Figure 16: illustrates the Monte Carlo method integration approach – generation of points

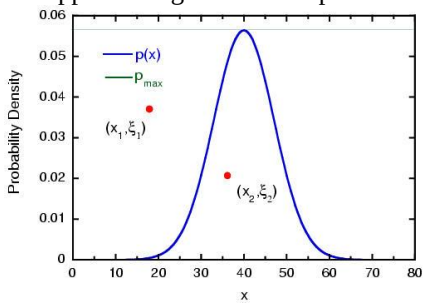

Figure 17: Illustration of Monte Carlo Integration approach – probability calculation

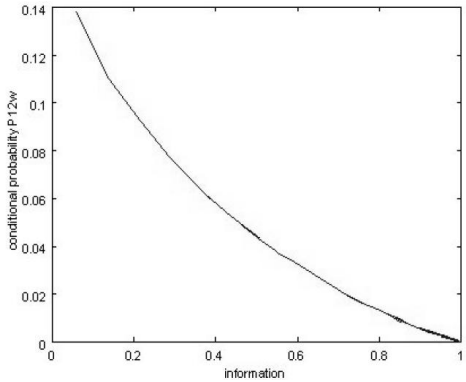

Fig 18: Relationship between information index and probability of misclassification

Relationship between information index and probability of misclassification. As it is clear from figure in order to achieve a high information index. We need to correctly classify the points i.e., probability of misclassification should be minimum.

The information is determined as

Info=1-(entr/maxentr) ------- --------- (1)

Where,

Entr=-(P1*log(P1)+P2*log(P2))+P1w.*log(P1w)+p2w.*log(P2w)+P12w.*log(P12w)
+P21w.*log (P21w) ---------- (2)

And maxentr= -(P1.*log(P1)+P2.*log(P2))+P11.*log(P11)+P22.*log(P22)+2*P12.*log(P12) -- (3)

Where,

P11=P12 /(P1+P2) P22=P22 /(P1+P2)
P12=P1*P2/(P1+P2)

VII. SIMULATION TOOLS

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical use include:

- Math and computation
- Algorithm development
- Modelling, simulation, and prototyping
- Data analysis, exploration, and visualization
- Scientific and engineering graphics
- Application development, including Graphical User Interface building

VIII. EXPECTED OUTCOME

This thesis need to find better pattern detection by trial of various multidimensional patterns as well its 3-D modelling for real time analysis of geometrical patterns

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