



An Essential Info about Image Processing and Pattern Recognition

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ABSTRACT

Advanced image processing is around the quickest developing computer innovations. Image processing and pattern recognition has exceptionally long history. In today's technology-oriented world, the term 'image processing' generally refers to the processing of a two-dimensional data set using a computer. In imaging science, image processing is any manifestation of sign transforming for which the data is a picture, for example a photo or motion picture outline; the yield of picture transforming may be either a picture or a set of attributes or parameters identified with the picture. Generally picture transforming methods include treating the picture as a two-dimensional sign and applying standard sign preparing strategies to it. In this paper we examines the basics of image handling, Mathematical preliminaries, Image improvement strategies and a portion of the Morphological procedures. While going to the pattern recognition means to arrange information (examples) dependent upon either a prior information or on measurable qualified information extricated from the patterns. The patterns to be ordered are for the most part aggregations of estimations or perceptions, demarcating focuses in a appropriate multidimensional space. This is as opposed to pattern matching, where the pattern is inflexibly specified. The discussion is continued with the components present in the pattern recognition system and its applications.

Keywords-Image,Pattern, multidimentional, pixel ,DSP

I. INTRODUCTION

An image is a subset of a signal. A signal is a function that carries information generally about the behaviour of a physical system or characteristics of some phenomenon. The characteristics of the signal may be amplitude, time duration, and so on. The world is filled with many types of signals; in case of electrical quantities, current and voltage are called electrical signals, Like that each has its own

physical meaning. In all cases the signal is contained in a different variation patterns, and they will be transmitted and received through a medium. The patterned signals represented either continuous or discrete according to their characteristics or sampling of time axis. The variables both time and amplitude are discrete that signal is said to be Digital, if both are continuous that type of signals are called Analog signals. These are processed by the computer or other devices to convert Analog to Digital and vice versa. The process of retrieving the information from the signal is called *Signal Processing*. If the processing is done on sequence of numbers or symbols are called *Digital signal processing (DSP)*. DSP includes subfields such as *digital image*, video, statistical signal processing, signal processing for communications, biomedical signal

processing, audio and speech signal processing, sonar and radar signal processing, sensor array processing, spectral estimation, and so on.

The reflected light energy from the objects can be considered as 2D intensity function. This function is commonly referred to as an *image*, and the processing of these 2D functions called *Image Processing*, again this image is divided into picture elements or *pixel*, Which the input as an Image, such as photograph, scanner, X-Ray devices, electron microscope, radar and ultrasound.

The most requirements for image processing of images is that the images be available in digitized format, that is, arrays of finite length binary words. For digitization, the given Image is sampled on a discrete grid and each sample or pixel is quantized (grey level) using a finite number of bits. The digitized image is handled by a computer. To display a digital image, it is first converted into analog signal, which is glance over a display. An image is represented by a rectangular array of integer powers of 2. The number at each pixel represents the brightness or darkness (generally called the intensity) of the image at that point. For example, Figure shows a digital image of size 8x8 with 1 byte (i.e., 8 bits/256 grey levels) per pixel. The quality of image depends on the number of grey levels or pixels. The more of those two, the better would be the image quality, but this will result in a large memory space. The storage space for an image is product of dimension of an image and number of bits required to store the grey levels. At the lower resolution, an image can result in checkerboard effect or graininess.

II. MATHEMATICAL PRELIMINARIES

Most images are recorded and processed in the time domain or spatial domain. The spatial domain refers to the aggregate of pixels composing an image, and the spatial domain processing involves operations that apply directly on these pixels. Here some of the mathematical preliminaries that are often used in image processing for converting an image from spatial domain to frequency domain are introduced. These include Laplace transform, Fourier transform, Z-transform, cosine transform, and wavelet transform.

a) Laplace Transform:

Laplace transform is named after Pierre Simon Laplace (1749–1827), a French mathematician and astronomer. Given a function $x(t)$ of the continuous-time variable t , the Laplace transform, denoted by $X(s)$, is a function of the complex variable $s = \sigma + j\omega$ defined by

$$X(s) = \int_0^{\infty} x(t)e^{-st} dt$$

The Laplace transform changes a signal in the time domain into a signal in the s -domain. It has many applications in mathematics, physics, engineering, and signal processing. It has been used for solving differential and integral equations and analysis of electrical circuits, harmonic oscillators, photosensitive devices, and mechanical systems. The Laplace transform can generally analyze any system governed by differential equations. The most powerful application of the Laplace transform is the design of systems directly in the s -domain. The Laplace transform can be used for designing a low-pass filter.

b) Fourier Transform:

In the early 1800s, French mathematician Joseph Fourier, with his studies of the problem of heat flow, introduced Fourier series for the representation of continuous time periodic signals. The Fourier series is said to be the frequency spectrum of a signal can be generated by representing the signal as a sum of sinusoids (or complex exponentials). An image is considered as a spatially varying function. The Fourier transform decomposes such an image function into a set of orthogonal functions and converts the spatial intensity image into its frequency domain. From the continuous form, one can digitize it for discrete-time images. Signal processing in the frequency domain simplifies computational complexity in filtering analysis; thus, the Fourier transform has played the leading role in signal processing and engineering control for a long time.

$$x(t) = \sum_{n=-\infty}^{\infty} \alpha_n e^{jn\omega t}$$

An example of applying the Fourier transform in optics is the diffraction of light when it passes through narrow slits. The ideas are similarly applied to auditory, X-ray, and microwave diffusion, or any other form of wave diffraction. In signal and image processing, the Fourier transform is used for frequency-domain transformation, representation, encoding, smoothing and sharpening, restoration, blur removal, noise estimation, and Wiener high-pass, low-pass, and band-pass filters.

c)Z-Transform:

In the study of time-invariant discrete-time systems, the Z-transform plays a role similar to that of the Laplace transform.

$$X(z) = \sum_{t=0}^{\infty} x(t)z^{-t}$$

By applying the Z-transform, a difference equation in the discrete variable can be transformed into an algebraic equation in **z**. usually, the algebraic equations are simpler to solve and provide more insight into the behavior of the system.

d)Cosine Transform:

Discrete cosine transforms (DCT) to transform an image to frequency domain and perform quantization for data compression. One of the advantages of the DCT is its energy compaction property; that is, the signal energy is concentrated on a few components while most other components are zero or marginally small. This helps separate an image into parts (or spectral sub bands) of hierarchical importance (with respect to the image's visual quality). A well-known JPEG compression technology uses the DCT to compress an image.

e)Wavelet Transform:

Industrial standards for compressing still images (e.g., JPEG) and motion pictures (e.g., MPEG) have been based on the DCT. Both standards have produced good results, but have limitations at high compression ratios. At low data rates, the DCT based transforms suffer from a “blocking effect” due to the unnatural block partition that is required in the computation. Other drawbacks include mosquito noise (i.e., a distortion that appears as random aliasing occurs close to object's edges) and aliasing distortions. Furthermore, the DCT does not improve the performance as well as the complexities of motion compensation and estimation in video coding. Due to the shortcomings of DCT, discrete wavelet transform (DWT) has become increasingly important. The main advantage of DWT is that it provides space–frequency decomposition of images, overcoming the DCT and Fourier transform that only provide frequency decomposition (Addison, 2002; Jensen and Cour-Harbo, 2001). By providing space–frequency decomposition, the DWT allows energy compaction at the low-frequency sub bands and the space localization of edges at the high-frequency sub bands. Furthermore, the DWT does not present a blocking effect at the low data rates.

III. IMAGE ENHANCEMENT

Whenever a picture is converted from one form to another, for example, imaged, copied, scanned, transmitted, or displayed, the “quality” of the output picture is lower than that of the input. In the absence of information about how the given picture was actually degraded, it is difficult to calculate in advance how effective a particular enhancement method will be. Image enhancement aims to improve human perception and interpretability of information in images or to provide more useful input for other automated image processing techniques. In general, image enhancement techniques can be divided into three categories:

1. **Spatial-domain** methods that directly manipulate pixels in an image.
2. **Frequency-domain** methods that operate on the Fourier transform or other frequency domains of an image.
3. **Combinational** methods that process an image in both spatial and frequency domains.

In general, the process of image enhancement involves three types of processes:

- Point Process
- Mask Process

- Global Process

In a point process, each pixel is modified according to a particular equation depending on the input only at the same pixel, which is independent of other pixel values. The input may be one or more images. For example, the difference or product of two images can be taken point by point. In a mask process, each pixel is modified according to the values of the pixel's neighbors using convolution masks. For example, an average of the pixels can be taken in the neighborhood as a low-pass filter. In a global process, all the pixel values in the image (or sub image) are taken into consideration. For example, histogram equalization remaps the histogram of the entire input pixels to a uniformly distributed histogram. Spatial-domain processing methods include all three types, but frequency domain methods, by the nature of frequency transforms, are global processes. Of course, frequency-domain operations can become mask operations based only on a local neighborhood by performing the transform on small image blocks instead of the entire image.

Here we discuss some of the commonly used image enhancement methods, containing, piecewise linear transformation, histogram equalization, histogram specification, gray scale transformation enhancement by arithmetic operations, bit plane slicing, smoothing filter, and sharpening filter. We also discuss image blur types and image quality measures.

a) Grayscale Transformation:

Gray scale transformation aims to change the gray levels of an entire image in a uniform way or intends to modify the gray levels within a defined window by a mapping function. This transformation is usually expected to enhance the image contrast, so the details of an image can be more visible, the simple operation thresholding is the simplest case to replace the intensity profile by a step function, jumping at a chosen threshold value. In this case, any pixel with a gray level below the threshold in the input image receives 0 in the output image, and above or equal to the threshold receives 255. Another simple operation, image negative, reverses the order of pixel intensities

From black to white, so the intensity of output decreases as the intensity of input increases. It is a reversed image where the image that is usually black on a white background is reversed to be white on a black background. The best example for gray scale transformation as shown in the below figure1.

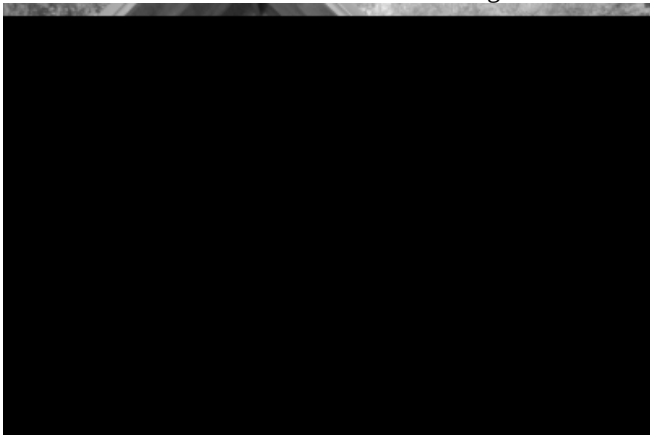


Figure1: Gray scale transformed image

b) Histogram Equalization:

Histogram equalization employs a monotonic nonlinear mapping that reassigns the Intensity values of pixels in an input image, such that the output image contains a uniform distribution of intensities (i.e., a histogram that is constant for all brightness values). This corresponds to a brightness distribution where all values are equally probable. Unfortunately, we can only achieve the approximation of this uniform distribution for a digital image.

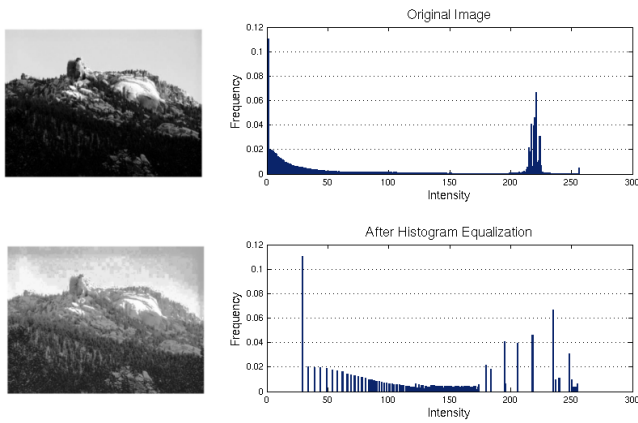


Figure2: Before and after Histogram equalization image

As shown in the above figure2 the histogram levels for different contrast images. This technique is often used in image comparison because it is effective in detail enhancement and in the correction of nonlinear effects introduced by a digitizer or a display system. In general, since the histogram equalization causes the dynamic range of an image to be stretched, the density distribution of the resultant image is made flat, so that the contrast of the image is enhanced. However, the histogram equalization method causes some problems. Since the contrast is enhanced by stretching the dynamic range, background noise is simultaneously increased by the equalization, and the image quality in a near-constant region may be degraded.

c)Enhancement by Arithmetic Operations:

Arithmetic operations (e.g., subtraction, addition, multiplication, division, and mean) are often used to combine and transform two or more images into a new image that can better display or highlight certain features in the scene. It is also possible to just use a single image as input and perform arithmetic operations on all the pixels to modify brightness and enhance contrast. The image subtraction operator takes the difference of two input images. It usually uses the absolute difference between pixel values, rather than the straightforward signed output. Image subtraction can be used to detect changes in a series of images of the same scene or recognize a moving object. Image averaging works if the noise in the image pixels and the associated noise are not correlated and the noise has a zero averaging value. These conditions are necessary because the image averaging method relies on the summing of N different noisy images. If the noise did not average out to zero, then artifacts of the noise would appear in the averaged image.

Similarly, frame averaging provides a way to average multiple video frames to create a more stable image. This module can be used to eliminate pixel vibrations or high-frequency image changes. It works by adding each frame into a moving average of frames. This effectively creates the same effect of averaging many frames without the significant memory and time that averaging hundreds of frames would take.

d)Smoothing Filter:

A simple mean smoothing filter or operation intends to replace each pixel value in an input image by the mean (or average) value of its neighbors, including itself. This has an effect of eliminating pixel values that are unrepresentative of their surroundings. Like Other convolution filters, it is based around a kernel, which represents the shape and size of the neighborhood to be sampled in calculation. Often a 3×3 square kernel is used, as shown below, although larger kernels (e.g., a 5×5 square) can be used for more severe. Another method of image smoothing convolves an input image by the **Gaussian filter**. The Gaussian filter, representing the shape of a Gaussian (bell-shaped) hump, will screen noise with the high spatial frequencies and produce a smoothing effect. In image processing, a discrete representation of the Gaussian function is required for conducting the convolution. Another smoothing filter, called a **median filter**, is used to reduce noise in an image, somewhat like a mean filter. However, it performs better than a mean filter in the sense of preserving useful details in the image. It is especially effective for removing impulse noise, which is characterized by bright and/or dark high-frequency features appearing randomly over the image. Statistically, impulse noise falls well outside the peak of the distribution of any given pixel neighborhood, so the median is well suited to learn where impulse noise is not present, and hence to remove it by exclusion. The median of a distribution is the value for which larger and smaller values are equally probable. To compute the median of a list of sample values, we category them in a descending or ascending order, and then select the central value. An example of applying a median filter on an added salt-and-pepper noisy Lena image is shown in below figure3.



Figure3: Applying filters for Noisy image

e) Sharpening Filter:

Sharpening filter is used to enhance the edges of objects and adjust the contrast of object and background transitions. They are sometimes used as edge detectors by combining with thresholding. Sharpening or high-pass filter allows high-frequency components to pass and delete the low-frequency components. For a kernel to be a high-pass filter, the coefficients near the center must be set positive and in the outer periphery must be set negative. Sharpening filter can be categorized into four types: high-pass filter, Laplacian of Gaussian filter, high-boost filter, and derivative filter. The below figure shows the filter output



Figure4: The image after applying Sharpening filter

IV. MATHEMATICAL MORPHOLOGY

Image processing techniques have been tremendously developed during the past decades, and among them, mathematical morphology has been continuously receiving a great deal of attention. It is because mathematical morphology provides quantitative description of geometric structure and shape, as well as mathematical description of algebra, topology, probability, and integral geometry. Mathematical morphology has been proved to be extremely useful in many image processing and analysis applications.

In image processing, a well-known general approach is provided by mathematical morphology, where the images being analyzed are considered as sets of points and the set theory is applied on the morphological operations. This approach is based upon logical relations between pixels, rather than arithmetic relations, and can extract geometric features by choosing a suitable structuring shape as a probe.

Here some of the mathematical morphology methods they are: binary morphology, opening and closing, hitler-miss transform (HMT), grayscale morphology.

1) Binary Morphology:

Mathematical morphology involves geometric analysis of shapes and textures in images. An image can be represented by a set of pixels. Morphological operators work with two images. The image being processed is referred to as the active image, and the other image is a kernel, is denoted as the structuring element. Every structuring element has a particular shape, which can be thought of as a probe or a filter of the active image. The active image can be modified by probing it with various structuring elements. The elementary operations in mathematical morphology are dilation and erosion, which can be combined in sequence to produce other operations, such as opening and closing.

1.1) Binary dilation combines two sets using vector addition of set elements. It was first introduced by Minkowski and is named Minkowski addition. Let A and B denote two sets in E^N with elements a and b , respectively, where $a = (a_1, a_2, \dots, a_N)$ and $b = (b_1, b_2, \dots, b_N)$ being N -tuples of element coordinates. The binary dilation of A by B is the set of all possible vector sums of pairs of elements, one coming from A and the other from B . Since A and B are both binary, the morphological operators applied

On the two sets are called binary morphology.

Binary Erosion is the morphological dual to dilation. It combines two sets using vector subtraction of set elements. If A and B denote two sets in EN with elements a and b, respectively, then the binary erosion of A by B is the set of all elements x, for which $x + b \in A$ for every $b \in B$.

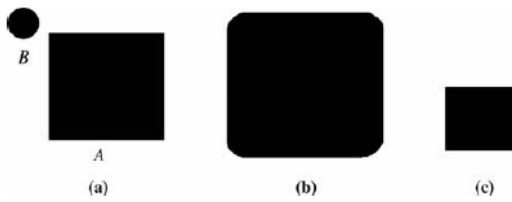


Figure5: An example of binary morphological operations. (A) A and B, (B) $A \oplus B$, and (C) $A \ominus B$.

1.2) Opening And Closing Morphology:

In practical applications, dilation and erosion pairs are combined in sequence, either the dilation of an image followed by the erosion of the dilated result, or vice versa. In either case, the result of iteratively applying dilations and erosions is an elimination of specific image details whose sizes are smaller than the structuring element without the global geometric distortion of unsuppressed features. The properties were first explored by Matheron (1975) and Serra (1982). Both of their definitions for opening and closing are identical to the ones given here, but their formulas appear different because they use the symbol $\ominus$ to mean Minkowski subtraction rather than erosion.

The opening of image A by structuring element B, denoted by $A \circ B$, is defined as

$$A \circ B = (A \ominus B) \oplus B$$

The closing of image A by structuring element B, denoted by $A \bullet B$, is defined as

$$A \bullet B = (A \oplus B) \ominus C$$

The opening and closing can be interpreted as follows: The opening will remove all of the pixels in the regions that are too small to contain the probe. The opposite sequence, closing, will fill in holes and concavities smaller than the probe. Such filters can be used to suppress object features or discriminate against objects based on their shape or size distribution.

2) Grayscale Morphology:

Mathematical morphology represents image objects as sets in a Euclidean space. In morphological analysis, the set is the primary notion and a function is viewed as a particular case of a set (e.g., an N-dimensional, multivalued function can be viewed as

a set in (N+1)-dimensional space). Then in this viewpoint, any function- or set processing system is viewed as a set mapping (transformation) from one class of sets into another class of sets. The extensions of the morphological transformations from binary to gray scale processing by Serra (1982) and Sternberg (1986) introduce a natural morphological generalization of the dilation and erosion operations.

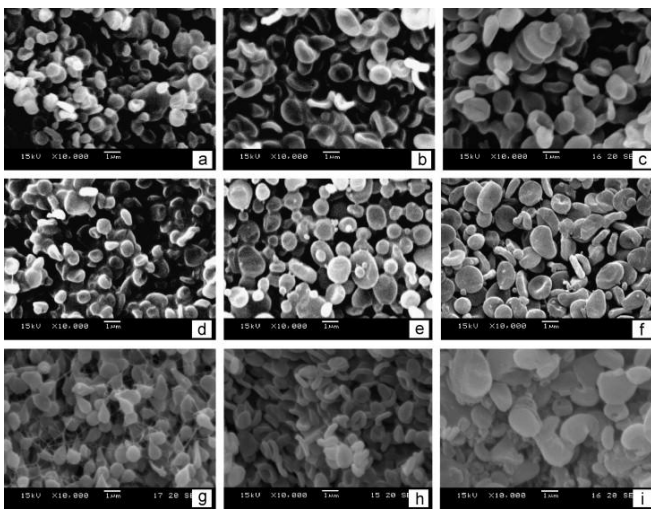


Figure6: An example of gray scale morphological operations

Note that the gray scale dilation and erosion are similar to the convolution operator, except that addition/subtraction is substituted for multiplication and maximum/ minimum is substituted for summation. Unlike convolution, morphological

operations are, however, highly nonlinear. Let a structuring element be a 3_3 square with all values 0. An example of gray scale dilation, erosion, opening, and closing is shown in the above figure5

V. PATTERN RECOGNITION

An English dictionary defines a “pattern” as an example or model—something that can be copied. A pattern is also an imitation of a model. A pattern, which describes various types of objects in the physical and abstract worlds, is any distinguishable interrelation of data (analog or digital), events, and/or concepts, for example, the shape of face, a table, the order of musical notes in a piece of music, the theme of a poem or a symphony, the tracks made on photographic plates by particles.

Pattern recognition can be defined as, it is a field whose objective is to assign an object or event to one of a number of categories, based on features derived to emphasize commonalities.

Pattern recognition is concerned primarily with the description and classification of measurements taken from physical or mental processes. Many definitions of pattern recognition have been proposed. In order to provide an effective and efficient description of patterns, preprocessing is often required to remove noise and redundancy in the measurements. Then a set of characteristic measurements, which could be numerical and/or non numerical, and relations among these measurements, are extracted for the symbol of patterns. Classification and/or description of the patterns with respect to a specific goal is performed on the basis of the representation.

In order to determine a good set of characteristic measurements and their relations for the representation of patterns so good recognition performance can be expected, a careful analysis of the patterns under study is necessary. Knowledge about the statistical and structural characteristics of patterns should be fully utilized. From this point of view, the study of pattern recognition includes both the analysis of pattern characteristics and the design of recognition systems.

The pattern recognition process can be viewed as a twofold task, namely, developing decision rules based on human knowledge (learning) and using them for decision making regarding an unknown pattern (classification). The problem of pattern recognition is divided into two parts. The first part is concerned with the study of recognition mechanism of patterns by human and other living organisms. This part is related to the disciplines such as physiology, psychology, biology, and so on. The second part deals with the development of theory and techniques for designing a device that can perform the recognition task automatically.

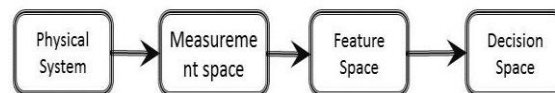


Figure7: Operating stages in a recognition system

The operating stages necessary for developing and implementing the decision rule in a practical pattern recognition system are indicated in blocks of Figure7.

There are three main pattern recognition methodologies:

- 1) Statistical Pattern Recognition; which assumes the underlying model as a set of probabilities, but ignores the structure.
- 2) Syntactic Pattern Recognition; which concentrates on the interrelation between Primitives that build the whole pattern (which are not easy to find).
- 3) Neural Pattern Recognition; which imitates human neural system.

VI. COMPONENTS OF A PATTERN RECOGNITION SYSTEM

A classifier model and its associated training algorithm are all that are usually associated with pattern recognition. However, a complete pattern recognition system consists of several components, shown in Fig. 4, of which selection and training of such a model is just one component.

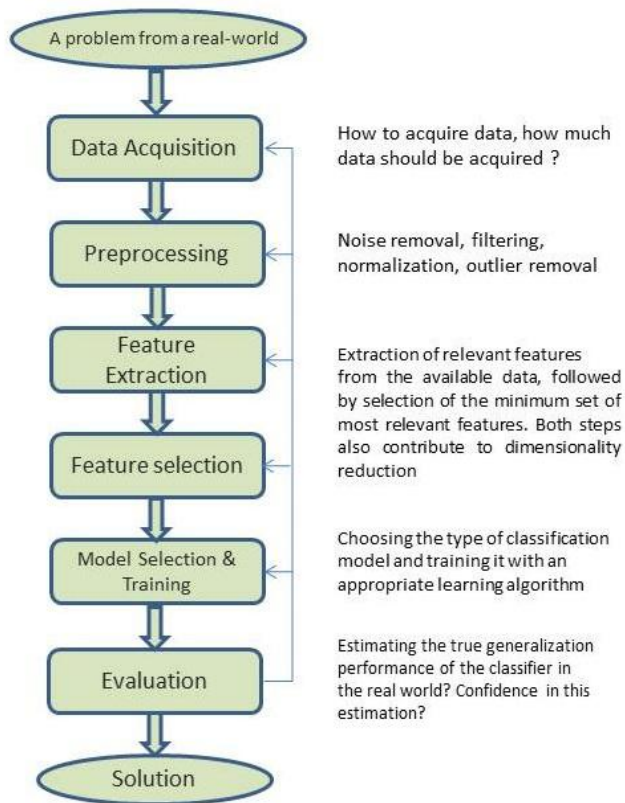


Figure8: Components of a pattern recognition system.

the above figure8 shows the contents of the pattern recognition system, the initial stage of the system having the problem that can we take from the real world. And the next section will be the data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems (abbreviated with the acronym **DAS** or **DAQ**) typically convert analog waveforms into digital values for processing. The mechanisms of data acquisition systems include:

- Sensors that convert physical factors to electrical signals.
- Signal habituation circuitry to convert sensor signals form into converted digital values.
- Analog-to-digital converters, which convert conditioned signals to digital values.

Data acquisition applications are controlled by softwareprograms developed using various programminglanguages such as BASIC, C, Fortran, Java, Lisp, Pascal.

In the section of **preprocessing** An essential, yet often overlooked step in the design process is preprocessing, where the goal is to condition theacquired data such that noise from various sources areremoved to the extent that it is possible.. For example, ifthe measurement environment is known to introduce high(low)-frequency noise, an appropriate low (high)-pass DIGITAL FILTER may be employed to remove the noise.The goal of **Feature extraction**is to findpreferably small number of features that are particularlydistinguishing or informative for the classification process, and that are invariant to unrelated transformationsof the data. Consider the identification of a cancerous tissue from an MRI image: The shape, color contrast ratio ofthis tissue to that of surrounding tissue, 2D Fourier spectrum, and so on are all likely to be relevant and distinguishing features, but the height or eye color of the patientare probably not.Feature extraction is usually obtained from a mathematical transformation on the data. Some of the mostwidely used transformations are linear transformations,such as PRINCIPAL COMPONENT ANALYSIS and linear discriminant analysis.

In **Feature selection**, this author specifically means selection of m features that provide the most discriminatoryinformation, out of a possible d features, where $m < d$. Inother words, by feature selection refers to selecting a subset of features from a set

of features that have already been identified by a preceding feature extraction algorithm. The main question to answer under this setting is then “which subset of features provide the most discriminatory information?”

Model selection & training is done Only after acquiring and preprocessing adequate and representative data and extracting and selecting the most informative features is one finally ready to select a classifier and its corresponding training algorithm. As mentioned earlier, one can think of the classification as a function approximation problem: find a function that maps a d -dimensional input to appropriately encoded class information (both inputs and outputs must be encoded, unless they are already of numerical nature). Once the classification is cast as a function approximation problem, a variety of mathematical tools, such as optimization algorithms, can be used. Some of the more common ones are described below. Although most common pattern recognition algorithms are categorized as statistical approaches vs. neural network type approaches, it is possible to show that they are in fact closely related and even a one-to-one match between certain statistical approaches and their corresponding neural network equivalents can be established.

For an example in the section of medical imaging the AUTOMATIC TISSUE PROCESSING for lot of algorithms for automatic processing of tissue images according to the following modules

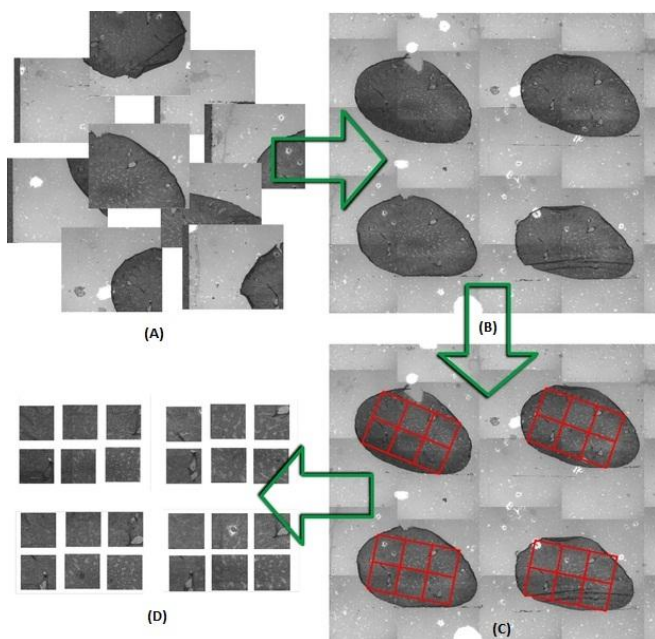


Figure8: Pattern Recognition for Automatic tissue processing

The following are the modules involved corresponding to the above figure in the automatic tissue processing

- A. Image enhancement to remove inhomogeneous illumination and image noise.
- B. Image stitching to obtain complete cell images,
- C. automatic detection of valid cell regions, and
- D. Classification of cell regions.

A large number of applications benefit from current and near future research in pattern recognition. Some of these areas are in fact very closely related to active research areas, such as follows.

Applications of pattern recognition:

1. *Man-machine communication:* automatic speech recognition, speaker identification, Optical character recognition (OCR) systems, Cursive script recognition, speech understanding, and image understanding.
2. *Biomedical applications:* electrocardiogram (ECG), electroencephalogram (EEG),
3. Electromyography (EMG) analysis, cytological, histological, and other stereological applications, X-ray analysis, and diagnostics.

4. *Applications in physics:* high-energy physics, bubble chamber, and other forms of track analysis.
5. *Crime and criminal detection:* fingerprint, handwriting, speech sound, and photographs.
6. *Natural resources study and estimation:* (a) agriculture, (b) hydrology, (c) forestry, (d) geology, (e) environment, (f) cloud pattern, and (g) urban quality.
7. *Stereological applications:* (a) metal processing, (b) mineral processing, and (c) biology.
8. *Military applications:* These include the above six areas of applications plus
 - (a) Detection of nuclear explosions,
 - (b) Missile guidance and detection,
 - (c) Radar and sonar signal detection, (d) Target identification, (e) Naval submarine detection, and
 - (f) Reconnaissance.
9. *Industrial applications:*
 - (a) computer-assisted design and manufacture,
 - (b) Computer graphics simulation in product testing and assembly, (c) Automatic Inspection and quality control in factories, (d) nondestructive testing, and (e) information systems for the handicapped.
10. *Robotics and artificial intelligence:*
 - (a) Intelligent sensor technology and (b) Natural language processing.

VII. SOME FINAL THOUGHTS

Literally hundreds of image processing and pattern recognition approaches and algorithms exist, and it is often asked whether any one of them is consistently better than the others. A cleverly named theorem, called the no-free lunch theorem, tells us that no algorithm is universally superior to all others in the absence of any additional information. In fact, it can be proven that problems exist for which random guessing will outperform any other algorithm. Although such problems may not be of much practical interest, there is still a lesson to be learned: The choice of the appropriate algorithm almost invariably depends on the nature of the problem, the distribution that provides the data for that problem, and the prior knowledge available to the designer.

References:

1. Cheng, C. and Parhi, K. K., "Low-cost fast VLSI algorithm for discrete Fourier transform," IEEE Trans. Circuits Syst. I, vol. 54, no. 4, pp. 791–806, Apr. 2007.
2. Sheridan, P., "A method to perform a fast Fourier transform with primitive image transformations," IEEE Trans. Image Process., vol. 16, no. 5, pp. 1355–1369, May 2007.
3. Addison, P. S., The Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine and Finance, CRC Press, 2002.
4. Broughton, S. A. and Bryan, K. M., Discrete Fourier Analysis and Wavelets: Applications to Signal and Image Processing, Wiley, Nov. 2008.
5. Agaian, S. S., Silver, B., and Panetta, K. A., "Transformcoefficient histogram-based image enhancement algorithms using contrast entropy," IEEE Trans. Image Process., vol. 16, no. 3, pp. 741–758, Mar. 2007.
6. L. J. Wang and Y. C. Huang, "Non-linear image enhancement using opportunity costs," in Proc. of the Second International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN 2010), Liverpool, UK, 28-30 July, 2010.
7. Wang, Q. and Ward, R. K., "Fast image/video contrast enhancement based on weighted thresholded histogram equalization," IEEE Trans. Consumer Electron., vol. 53, no. 2, pp. 757–764, May 2007.

8. Liu Yucheng ,Liu Yubin, “An Algorithm of Image Segmentation Based on Fuzzy Mathematical Morphology” IEEE conference Publications(Volume 2), 517-520, 15-17 May 2009.
9. Wang Shou-Jue , Chen Xu, “Biomimetic (topological) pattern recognition - a new model of pattern recognition theory and its application” IEEE Conference publications, 2258 - 2262 vol.3, 20-24 July 2003.