BRAIN TUMOR DETECTION USING ANISOTROPIC FILTERING METHOD

A project report submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

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DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES (UGC AUTONOMOUS)

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CERTIFICATE

This is to certify that the project report entitled **"BRAIN TUMOR DETECTION USING ANISOTROPIC FILTERING METHOD"** submitted by **C. Sathya Venkata Sai (317126512071), T. Abhigna (327126512116), P. Srinivas Teja (317126512097), M. Bhargav Sai (318126512L15)** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Electronics & Communication Engineering** of Andhra University, Visakhapatnam is a record of bonafide work carried out under my guidance and supervision.

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ABSTRACT

Brain tumour is an unusual mass of tissue in which some cells multiply and grows uncontrollably. Early brain tumour diagnosis plays a crucial role in treatment planning and patients' survival rate. Manual brain tumour detection is complicated, time-consuming, and vulnerable to error. Hence, automated computer-assisted diagnosis at high precision is currently in demand. It needs to be detected at an early stage using MRI or CT scanned images when it is as small as possible because the tumour can possibly result to cancer. This paper, mainly focuses on detecting and localizing the tumour region existing in the brain by proposed methodology using patient's MRI images with the help of MATLAB. To pave the way for morphological operation on MRI image, the image is first filtered using Anisotropic Filter. It helps to reduce contrast between consecutive pixels. Anisotropic filtering is a method of enhancing the image quality of textures on surfaces of computer graphics that are at oblique(slant) viewing angles with respect to the camera. It is superior to many other filtering methods as it has a high PSNR (Peak signal to noise ratio) and low MSE (Mean Squared Error). After that the image will be resized, utilizing a threshold value. The image is then converted to a black and white image. This is done to perform processing techniques on it. Classification of MRI images is an important part to differentiate between normal patients and a patient who has tumour in brain. For this Support Vector Machine (SVM) classifier is used. After the SVM classifier, morphological operations will be applied to obtain information on areas of the possible tumour locations. Morphological operations include dilation and erosion. Dilation is making the objects more visible and Erosion is making objects less visible. Using both dilation and erosion, the tumour outline can be obtained. Then it is used to deliver final detection result, i.e., detect and isolate the region of tumour. This method can be employed to accurately locate the tumour when there is large data available. Using this can also help avoid human error during manual detection of tumour.

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LIST OF SYMBOLS

σ	Variance
η	Efficiency
∂	Partial derivative
∇	Gradient
$\triangle$	Laplacian
Σ	Summation

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CT	Computed Tomography
HPF	High Pass Filter
MRI	Magnetic Resonance Imaging
BBB	Blood brain barrier
EEG	Electroencephalography
RF	Radio Frequency
MRA	Magnetic Resonance Angiography
MRV	Magnetic Resonance venography
MATLAB	Matrix Laboratory
INU	Intensity non uniformity artifact
HSI	Hue Saturation Intensity
DSP	Digital Signal Processing
SVM	Support Vector Machine
PSNR	Peak Signal to Noise ratio
MSE	Mean squared error
MDL	Minimum Description Length

CHAPTER 1
INTRODUCTION

1.1 Project Objective

The objective of this project is to device and implement a method to locate tumour in a brain MRI scan image if it exists using digital image processing techniques. This is done to get accurate location of tumour for early detection prior to treatment of brain tumour.

1.2 Project Outline

The outline of the project is as follows. The strategy for spotting brain tumour images suggested in the research may be separated into three parts. The primary requirement is to acquire a data collection of photographs with probable brain tumours. The first step is to remove image noises. The method of filtering employed is anisotropic filtering. The next phase is segmentation with support vector machine (SVM). The area of the tumour is located in the brain in this step. In the last phase, the exact position and contour of the picture are achieved. The result is obtained with dilation and erosion, using morphological operations. A tumour in an MRI brain image can be detected and localised using this technique. This can be used for early and accurate detection of brain tumour.

CHAPTER 2

LITERATURE REVIEW

A precise picture of the brain is the initial step in brain tumour identification. In 1895, Wilhelm Roentgen discovered X-rays. X- rays were first discovered in 1895, by Wilhelm Roentgen. A German neurosurgeon began to locate the brain cancer by using x-rays. Since then, many technologies have been developed for obtaining images of brain tumour. Today, brain tumour may be identified with CT (Compute Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography) etc. Here, MRI scans are utilized in the suggested approach due to its greater quality and clearer pictures. The next step is to apply digital image processing techniques on the image. Many of these techniques were initially developed in the 1906s, for satellite-related imaging, wire-photo conversion standards, medical imaging, video-phones, character recognition & photo enhancement in the Bell Laboratory, Massachusetts Technology Institute, Maryland University and a number of other research installations. The goal of early image processing was to increase the picture's quality. The images have a great amount of noise in them which is a hindrance. There are a number of filtering techniques, such as the average filter, the wiener filter, the high pass filter (HPF), the anisotropic filter, etc. for this purpose. This study considers anisotropic filtering. It was originally formulated by Perona and Malik in 1987. Image segmentation is used to partition the image. It is necessary to classify images. Also, some techniques of data science and artificial intelligence are needed to be employed. Various researchers are utilising classical learning algorithms with diverse technologies such as thresholding, edges detection, clustering, etc. to approach this classification in different method through years. Erosion, dilation, opening and closing are the morphological operations. Originally, it was made for binary pictures, but lately it has been broadened to grayscale images.

CHAPTER 3

THEORETICAL ASPECTS

3.1 Brain Tumour

A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: cancerous (malignant) tumors and benign (non-cancerous) tumors. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which most commonly have spread from tumors located outside the brain, known as brain metastasis tumors. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. These symptoms may include headaches, seizures, problems with vision, vomiting and mental changes. The cause of most brain tumors is unknown. Uncommon risk factors include exposure to vinyl chloride, Epstein–Barr virus, ionizing radiation, and inherited syndromes such as neurofibromatosis, tuberous sclerosis, and von Hippel-Lindau Disease. Studies on mobile phone exposure have not shown a clear risk. The most common types of primary tumors in adults are meningiomas (usually benign) and astrocytomas such as glioblastomas. In children, the most common type is a malignant medulloblastoma. Diagnosis is usually by medical examination along with computed tomography (CT) or magnetic resonance imaging (MRI). The result is then often confirmed by a biopsy. Based on the findings, the tumors are divided into different grades of severity. Treatment may include some combination of surgery, radiation therapy and chemotherapy. If seizures occur, anticonvulsant medication may be needed. Dexamethasone and furosemide are medications that may be used to decrease swelling around the tumor. Some tumors grow gradually, requiring only monitoring and possibly needing no further intervention. Treatments that use a person's immune system are being studied. Outcome varies considerably depending on the type of tumor and how far it has spread at diagnosis. Although benign tumors only grow in one area, they may still be life-threatening due to their location. Glioblastomas usually have very poor outcomes, while meningiomas usually have good outcomes. The average five-year survival rate for all brain cancers in the United States is 33%. Secondary, or metastatic, brain tumors are about four times as common as primary brain tumors, with about half of metastases coming from lung cancer. Primary brain tumors occur in around 250,000 people a year globally, making up less than 2% of cancers. In children younger than 15, brain tumors are second only to acute lymphoblastic leukemia as the most common form of cancer. In Australia, the average lifetime economic cost of a case of brain cancer is $1.9 million, the greatest of any type of cancer.

Fig. 3.1 Brain metastasis in the right cerebral hemisphere shown on MRI

3.1.1 Causes

Epidemiological studies are required to determine risk factors. Aside from exposure to vinyl chloride or ionizing radiation, there are no known environmental factors associated with brain tumours. Mutations and deletions of tumor suppressor genes, such as P53, are thought to be the cause of some forms of brain tumor. Inherited conditions, such as Von Hippel–Lindau disease, tuberous sclerosis, multiple endocrine neoplasia, and neurofibromatosis type 2 carry a high risk for the development of brain tumours. People with celiac disease have a slightly increased risk of developing brain tumours. Smoking has been suggested to increase the risk but evidence remains unclear. Although studies have not shown any link between cell phone or mobile phone radiation and the occurrence of brain tumours, the World Health Organization has classified mobile phone radiation on the IARC scale into Group 2B – possibly carcinogenic. The claim that cell phone usage may cause brain cancer is likely based on epidemiological studies which observed a slight increase in glioma risk among heavy users of wireless and cordless phones. When those studies were conducted, GSM (2G) phones were in use. Modern, third-generation (3G) phones emit, on average, about 1% of the energy emitted by those GSM (2G) phones, and therefore the finding of an association between cell phone usage and increased risk of brain cancer is not based upon current phone usage.

3.1.2 Signs and symptoms

The signs and symptoms of brain tumours are broad. People may experience symptoms regardless of whether the tumor is benign (not cancerous) or cancerous. Primary and secondary brain tumours present with similar symptoms, depending on the location, size, and rate of growth of the tumor.

Headaches

Headaches as a result of raised intracranial pressure can be an early symptom of brain cancer. However, isolated headache without other symptoms is rare, and other symptoms including visual abnormalities may occur before headaches become common. Certain warning signs for headache exist which make the headache more likely to be associated with brain cancer.

Location-specific symptoms

The brain is divided into lobes and each lobe or area has its own function. A tumor in any of these lobes may affect the area's performance. The symptoms experienced are often linked to the location of the tumor, but each person may experience something different. First is frontal lobe. Tumours may contribute to poor reasoning, inappropriate social behaviour, personality changes, poor planning, lower inhibition, and decreased production of speech (Broca's area). Second one is temporal lobe. Tumours in this lobe may contribute to poor memory, loss of hearing, and difficulty in language comprehension (Wernicke's area is located in this lobe). Third is Parietal lobe. Tumours here may result in poor interpretation of languages, difficulty with speaking, writing, drawing, naming, and recognizing, and poor spatial and visual perception. Fourth is Occipital lobe. Damage to this lobe may result in poor vision or loss of vision. Fifth is Cerebellum. Tumours in this area may cause poor balance, muscle movement, and posture. Lastly, brain stem. Tumours on the brainstem can cause seizures, endocrine problems, respiratory changes, visual changes, headaches and partial paralysis.

Behaviour changes

A person's personality may be altered due to the tumor damaging lobes of the brain. Since the frontal, temporal, and parietal lobes control inhibition, emotions, mood, judgement, reasoning, and behaviour, a tumor in those regions can cause inappropriate social behaviour, temper tantrums, laughing at things which merit no laughter, and even psychological symptoms such as depression and anxiety

3.1.3 Diagnosis

Although there is no specific or singular symptom or sign, the presence of a combination of symptoms and the lack of corresponding indications of other causes can be an indicator for investigation towards the possibility of a brain tumor. Brain tumors have similar characteristics and obstacles when it comes to diagnosis and therapy with tumors located elsewhere in the body. However, they create specific issues that follow closely to the properties of the organ they are in.

The diagnosis will often start by taking a medical history noting medical antecedents, and current symptoms. Clinical and laboratory investigations will serve to exclude infections as the cause of the symptoms. Examinations in this stage may include the eyes, otolaryngological (or ENT) and electrophysiological exams. The use of electroencephalography (EEG) often plays a role in the diagnosis of brain tumors. Brain tumors, when compared to tumors in other areas of the body, pose a challenge for diagnosis. Commonly, radioactive tracers are uptaken in large volumes in tumors due to the high activity of tumor cells, allowing for radioactive imaging of the tumor. However, most of the brain is separated from the blood by the blood-brain barrier (BBB), a membrane that exerts a strict control over what substances are allowed to pass into the brain. Therefore, many tracers that may reach tumors in other areas of the body easily would be unable to reach brain tumors until there was a disruption of the BBB by the tumor.

Imaging

Medical imaging plays a central role in the diagnosis of brain tumours. Early imaging methods were invasive and sometimes dangerous because cerebral angiography and pneumoencephalography have been abandoned in favour of non-invasive, high-resolution techniques, especially magnetic resonance imaging (MRI) and computed tomography (CT) scans, though MRI is typically the reference standard used. Neoplasms will often show as differently coloured masses (also referred to as processes) in CT or MRI results.

Benign brain tumors often show up as hypodense (darker than brain tissue) mass lesions on CT scans. On MRI, they appear either hypodense or isointense (same intensity as brain tissue) on T1-weighted scans, or hyperintense (brighter than brain tissue) on T2-weighted MRI, although the appearance is variable. Contrast agent uptake, sometimes in characteristic patterns, can be demonstrated on either CT or MRI scans in most malignant primary and metastatic brain tumors. Pressure areas where the brain tissue has been compressed by a tumor also appear hyperintense on T2-weighted scans and might indicate the presence a diffuse neoplasm due to an unclear outline. Swelling around the tumor known as peritumoral edema can also show a similar result. This is because these tumors disrupt the normal functioning of the BBB and lead to an increase in its permeability. More recently, advancements have been made to increase the utility of MRI in providing physiological data that can help to inform diagnosis and prognosis. Perfusion Weighted Imaging (PWI) and Diffusion Weighted Imaging (DWI) are two MRI techniques that reviews have been shown to be useful in classifying tumors by grade, which was not previously viable using only structural imaging. However, these techniques cannot alone diagnose high- versus low-grade gliomas, and thus the definitive diagnosis of brain tumor should only be confirmed by histological examination of tumor tissue samples obtained either by means of brain biopsy or open surgery. The histological examination is essential for determining the appropriate treatment and the correct prognosis. This examination, performed by a pathologist, typically has three stages: interoperative examination of fresh tissue, preliminary microscopic examination of prepared tissues, and follow-up examination of prepared tissues after immunohistochemical staining or genetic analysis.

Classification

Tumors can be benign or malignant, can occur in different parts of the brain, and may be classified as primary or secondary. A primary tumor is one that has started in the brain, as opposed to a metastatic tumor, which is one that has spread to the brain from another area of the body. The incidence of metastatic tumors is approximately four times greater than primary tumors. Tumors may or may not be symptomatic: some tumors are discovered because the patient has symptoms, others show up incidentally on an imaging scan, or at an autopsy.

Grading of the tumors of the central nervous system commonly occurs on a 4-point scale (I-IV) created by the World Health Organization in 1993. Grade I tumors are the least severe and commonly associated with long term survival, with severity and prognosis worsening as the grade increases. Low grade tumors are often benign, while higher grades are aggressively malignant and/or metastatic. Other grading scales do exist, many based upon the same criteria as the WHO scale and graded from I-IV.

Treatment

Surgery: complete or partial resection of the tumor with the objective of removing as many tumor cells as possible.

Radiotherapy: the most commonly used treatment for brain tumors; the tumor is irradiated with beta, x rays or gamma rays.

Chemotherapy: a treatment option for cancer, however, it is not always used to treat brain tumours as the blood-brain barrier can prevent some drugs from reaching the cancerous cells. A variety of experimental therapies are available through clinical trials.

3.2 Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to form pictures of the anatomy and the physiological processes of the body. MRI scanners use strong magnetic fields, magnetic field gradients, and radio waves to generate images of the organs in the body. MRI does not involve X-rays or the use of ionizing radiation, which distinguishes it from CT and PET scans. MRI is a medical application of nuclear magnetic resonance (NMR) which can also be used for imaging in other NMR applications, such as NMR spectroscopy.

While the hazards of ionizing radiation are now well controlled in most medical contexts, an MRI may still be seen as a better choice than a CT scan. MRI is widely used in hospitals and clinics for medical diagnosis and staging and follow-up of disease without exposing the body to radiation. An MRI may yield different information compared with CT. Risks and discomfort may be associated with MRI scans. Compared with CT scans, MRI scans typically take longer and are louder, and they usually need the subject to enter a narrow, confining tube. In addition, people with some medical implants or other non-removable metal inside the body may be unable to undergo an MRI examination safely.

MRI was originally called NMRI (nuclear magnetic resonance imaging), but "nuclear" was dropped to avoid negative associations. Certain atomic nuclei are able to absorb radio frequency energy when placed in an external magnetic field; the resultant evolving spin polarization can induce a RF signal in a radio frequency coil and thereby be detected. In clinical and research MRI, hydrogen atoms are most often used to generate a macroscopic polarization that is detected by antennae close to the subject being examined. Hydrogen atoms are naturally abundant in humans and other biological organisms, particularly in water and fat. For this reason, most MRI scans essentially map the location of water and fat in the body. Pulses of radio waves excite the nuclear spin energy transition, and magnetic field gradients localize the polarization in space. By varying the parameters of the pulse sequence, different contrasts may be generated between tissues based on the relaxation properties of the hydrogen atoms therein.

Since its development in the 1970s and 1980s, MRI has proven to be a versatile imaging technique. While MRI is most prominently used in diagnostic medicine and biomedical research, it also may be used to form images of non-living objects. Diffusion MRI and Functional MRI extends the utility of MRI to capture neuronal tracts and blood flow respectively in the nervous system, in addition to detailed spatial images. The sustained increase in demand for MRI within health systems has led to concerns about cost effectiveness and overdiagnosis.

3.2.1 Mechanisms

In most medical applications, hydrogen nuclei, which consist solely of a proton, that are in tissues create a signal that is processed to form an image of the body in terms of the density of those nuclei in a specific region. Given that the protons are affected by fields from other atoms to which they are bonded, it is possible to separate responses from hydrogen in specific compounds. To perform a study, the person is positioned within an MRI scanner that forms a strong magnetic field around the area to be imaged. First, energy from an oscillating magnetic field is temporarily applied to the patient at the appropriate resonance frequency. Scanning with X and Y gradient coils causes a selected region of the patient to experience the exact magnetic field required for the energy to be absorbed. The excited atoms emit a radio frequency (RF) signal, which is measured by a receiving coil. The RF signal may be processed to deduce position information by looking at the changes in RF level and phase caused by varying the local magnetic field using gradient coils. As these coils are rapidly switched during the excitation and response to perform a moving line scan, they create the characteristic repetitive noise of an MRI scan as the windings move slightly due to magnetostriction. The contrast between different tissues is determined by the rate at which excited atoms return to the equilibrium state. Exogenous contrast agents may be given to the person to make the image clearer.

The major components of an MRI scanner are the main magnet, which polarizes the sample, the shim coils for correcting shifts in the homogeneity of the main magnetic field, the gradient system which is used to localize the region to be scanned and the RF system, which excites the sample and detects the resulting NMR signal. The whole system is controlled by one or more computers.

3.2.2 Diagnostics

Usage by organ or system

MRI has a wide range of applications in medical diagnosis and more than 25,000 scanners are estimated to be in use worldwide. MRI affects diagnosis and treatment in many specialties although the effect on improved health outcomes is disputed in certain cases.

MRI is the investigation of choice in the preoperative staging of rectal and prostate cancer and has a role in the diagnosis, staging, and follow-up of other tumors, as well as for determining areas of tissue for sampling in biobanking.

Fig. 3.2 Patient being positioned for MR study of the head and abdomen

Neuroimaging

MRI is the investigative tool of choice for neurological cancers over CT, as it offers better visualization of the posterior cranial fossa, containing the brainstem and the cerebellum. The contrast provided between grey and white matter makes MRI the best choice for many conditions of the central nervous system, including demyelinating diseases, dementia, cerebrovascular disease, infectious diseases, Alzheimer's disease and epilepsy. Since many images are taken milliseconds apart, it shows how the brain responds to different stimuli, enabling researchers to study both the functional and structural brain abnormalities in psychological disorders.

Cardiovascular

Cardiac MRI is complementary to other imaging techniques, such as echocardiography, cardiac CT, and nuclear medicine. It can be used to assess the structure and the function of the heart. Its applications include assessment of myocardial ischemia and viability, cardiomyopathies, myocarditis, iron overload, vascular diseases, and congenital heart disease.

Musculoskeletal

Applications in the musculoskeletal system include spinal imaging, assessment of joint disease, and soft tissue tumors. Also, MRI techniques can be used for diagnostic imaging of systemic muscle diseases.

Liver and gastrointestinal

Hepatobiliary MR is used to detect and characterize lesions of the liver, pancreas, and bile ducts. Focal or diffuse disorders of the liver may be evaluated using diffusion-weighted, opposed-phase imaging and dynamic contrast enhancement sequences. Extracellular contrast agents are used widely in liver MRI, and newer hepatobiliary contrast agents also provide the opportunity to perform functional biliary imaging.

Angiography

Magnetic resonance angiography (MRA) generates pictures of the arteries to evaluate them for stenosis (abnormal narrowing) or aneurysms (vessel wall dilatations, at risk of rupture). MRA is often used to evaluate the arteries of the neck and brain, the thoracic and abdominal aorta, the renal arteries, and the legs (called a "run-off").

Techniques involving phase accumulation (known as phase contrast angiography) can also be used to generate flow velocity maps easily and accurately. Magnetic resonance venography (MRV) is a similar procedure that is used to image veins. In this method, the tissue is now excited inferiorly, while the signal is gathered in the plane immediately superior to the excitation plane—thus imaging the venous blood that recently moved from the excited plane.

3.3 Image Processing

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. Image processing is one form of signal processing in which the input is a photograph or video frame; the output may be either an image or a set of characteristics or parameters related to the image. An image contains sub-images sometimes referred as regions-of-interest, or simply regions this implies that images contain collections of objects each of which can be the basis for a region. Thus, we have chosen image processing for identifying the defects on the surface of the Rexene, where the defective part will be the area of interest.

In Image science, Image processing is any form of for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. The acquisition of images (producing the input image in the first place) is referred to imaging.

Image processing is any form of signal processing for which the input is an, such as a photograph or video frame, the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most of the image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. An image may be considered to contain sub-images sometimes referred to as regions-of-interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. Thus, we have chosen image processing for identifying the defects on the surface of the Ceramics tile, where the defective part will be the area of interest.

It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps. They are, Importing the image with optical scanner or by digital photography. Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs. Output is the last stage in which result can be altered image or report that is based on image analysis.

3.3.1 Purpose of Image Processing

The purpose of image processing is divided into 5 groups. They are:

1. Visualization - Observe the objects that are not visible.
2. Image sharpening and restoration - To create a better image.
3. Image retrieval - Seek for the image of interest.
4. Measurement of pattern – Measures various objects in an image.
5. Image Recognition – Distinguish the objects in an image.

3.3.2 Basic terms in Image Processing

Digital image Processing

Digital Image Processing deals with manipulation of digital images through a digital computer. Digital Image Processing focuses on developing a computer system which is able to perform processing on an image. The input of that system is a digital image and the system process that image using efficient algorithms, and gives an image as an output.

Processing Images

Image processing has been developed in response to three major problems concerned with pictures. Picture digitization and coding to facilitate transmission, printing and storage of pictures. Picture enhancement and restoration in order to interpret easily. Picture segmentation and description as early-stage machine vision. The most requirements for image processing of images are that the images be available in digitized form, 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 using a finite number of bits. The digitized image is processed by a computer. To display a digital image, it is first converted into analog signal, which is scanned onto a display.

Pixel

Pixel is the smallest element of an image. The value of a pixel at any point corresponds to the intensity of the light photons striking at that point. Each pixel stores a value proportional to the light intensity at that particular location.

Calculation of Total Number of Pixels

We have defined an image as a two-dimensional signal or matrix. Then in that case the number of pixels would be equal to the number of rows multiply with number of columns. This can be mathematically represented as below (or) we can say that the number of (x, y) coordinate pairs is equal to the total number of pixels.
Total number of pixels = (number of rows) x (number of columns).

Resolution

The term resolution refers to the total number of count of pixels in a digital image. For example, if an image has M rows and N columns, then its resolution can be defined as M x N. If we define resolution as the total number of pixels, then pixel resolution can be defined with set of two numbers. The 1st number the pixels across columns, and the 2nd number is the pixels across its rows. We can say that the higher is the pixel resolution and the higher is the quality of the image. Size of an image = (pixel resolution) X (bits per pixel).

3.3.3 Types of Images

An image may be defined as a two-dimensional function, f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer.

Image digital processing encompasses processes whose inputs and outputs are images and, in addition, encompasses processes that extract attributes from images, up to and including the recognition of individual objects. As a simple illustration clarify these concepts, consider the area of automated analysis of text. The processes of acquiring an image of the area containing the text, preprocessing that image, extracting (segmenting) the individual characters, describing the characters in a form suitable for computer processing, and recognizing those individual characters are in the scope of what we call digital image processing in this book.

Each pixel of an image is typically associated to a specific 'position' in some 2-D region and has a value consisting of one or more quantities (samples) related to the position. An image is a stored as a matrix using MATLAB matrix convention. There are two basic types of images supported by MATLAB

Binary Image

In a binary image, each pixel assumes one of only two discrete values: 1 or 0. A binary image is stored as a logical array. Binary images are also called bi-level or two level (the name black and white, B&W used for this concept). Some input/output devices such as laser printers, fax machines and bi- level computer displays can only handle bi- level images. A binary image will be shown in the Fig. 2.1.

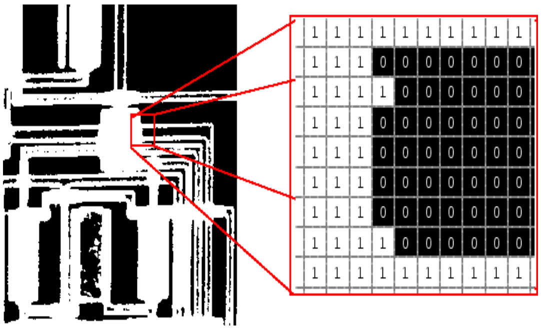

Fig. 3.3 Pixel value

Gray scale Images

A Gray scale or a gray level image in which the value of each pixel is a single sample, displayed images of this sort are typically composed of shades gray varying from black at the weakest intensity to the white at the strongest. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.). Gray scale images are often the result of measuring the intensity of images at each pixel. Gray scale images are intended for visual displays are typically stored with 8 bit per sample pixel, which allow 256 intensities (i.e., shades of gray to be recorded. A gray scale image is shown in the Fig. 5.2

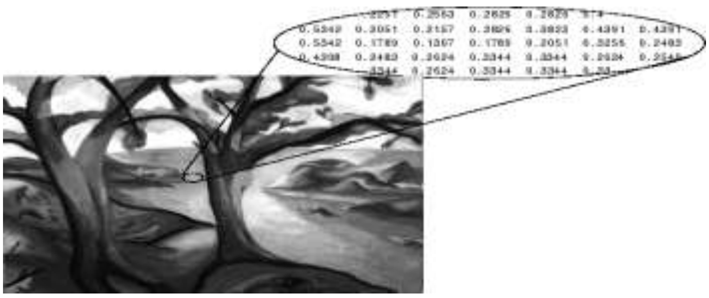

Fig. 3.4 Pixel values in a gray scale image with defined gray levels

3.3.4 Types of Image Processing

The two types of image processing used are analog image processing and digital image processing

Analog image processing

In electrical engineering and computer science, analog image processing is any image processing task conducted on two-dimensional analog signals by analog means (as opposed to digital image processing).Analog or visual techniques of image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. The image processing is not just confined to area that has to be studied but on knowledge of analyst. Association is another important tool in image processing through visual techniques. So analysts apply a combination of personal knowledge and collateral data to image processing.

Digital image processing

Digital Processing techniques help in manipulation of the digital images by using computers. As raw data from imaging sensors from satellite platform contains deficiencies. To get over such flaws and to get originality of information, it has to undergo various phases of processing. The three general phases that all types of data have to undergo while using digital technique are Pre- processing, enhancement and display, information extraction.

In this case, digital computers are used to process the image. The image will be converted into the digital form using a scanner –digitizer and then process it. It is defined as the subjecting numerical representation of objects to a series of operations in order to obtain the desired result. It starts with one image and produces a modified version of the image. It is therefore an image that takes one image into another.

The term image processing generally refers to processing of a two-dimensional picture by a digital computer, in the broader context, it implies digital processing of a two-dimensional data. A digital image is an array of real numbers represented by a finite number of bits. The principle disadvantage of digital image processing is its versatility, repeatability and the preservation of original data precision.

3.3.5 Image Processing Techniques

Digital image processing deals with manipulation and analysis of images by using computer algorithm, so as to improve pictorial information for better understanding and clarity. This area is characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem. Image processing involves the manipulation of images to extract information to emphasize or de-emphasize certain aspects of the information, contained in the image or perform image analysis to extract hidden information. The Computer Vision System aims at recognizing objects of interest from given images and helps in developing the machine, that can perform visual function parallel to human vision. Computer Vision System consists of filtering, coding, enhancement, restoration, feature extraction, analysis and recognition of objects from image. Processing of an image comprises of improvement in its appearance and effective representation of input image suitable for required application.

Image re-sizing

Re-sizing of an image is performed by the process of the interpolation. It is a process which re-samples the image to determine values between defined pixels. Thus, resized image contains more or less pixels than that of original image. The intensity values of additional pixels are obtained through interpolation if the resolution of the image is increased.

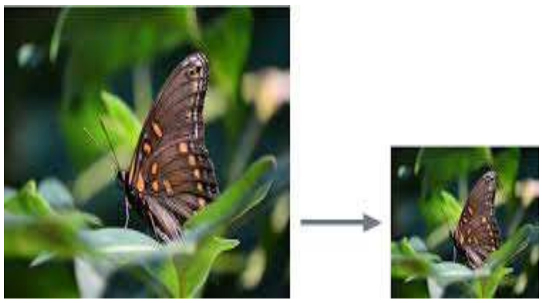

Fig. 3.5 Image resizing

Image filtering

Uncertainties are introduced into the image such as random image noise, partial volume effects and intensity non uniformity artifact (INU), due to the movement of the camera. This results in smooth and slowly varying change in image pixel values and lead to information loss, SNR gain and degradation of edge and finer details of image. Spatial filters are used for noise reduction. These filters may be linear or non-linear filters.

Fig. 3.6 Image filtering

Image segmentation

Depending on type of input image samples, segmentation can be classified as gray scale single image segmentation and Histogram based segmentation. Here the image is converted to digital form. Digitization includes sampling of image and quantization of sampled values. After converting the image into bit information, processing is performed. This processing technique may be, image enhancement, image restoration, image compression, and image segmentation. As far as our project is concerned, we used the image segmentation techniques. Image segmentation is the process of dividing or partitioning an image into multiple parts.

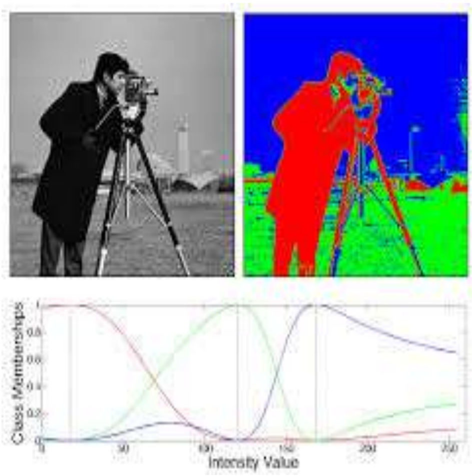

Fig. 3.7 Image segmentation

3.3.6 Applications of Image Processing

Character recognition

Optical Character appreciation, usually abbreviated to OCR, is the mechanical or electronic alteration of scanned or photo images of typewritten or printed text into machine-encoded i.e., computer-readable text. It is generally used as an appearance of records access from a little kind of original data source, whether papers, invoice, bank statement, receipts, business cards, a number of printed records or mail. It is an ordinary technique of digitizing printed manuscripts such that they can be by electronic means edited, searched, store more closely used in machine processes such as machine translation and displayed online, text-to-speech, key data extraction and text mining. OCR is a meadow of research in intelligence, pattern and computer vision. Early versions required to be automated with images of each character, and functioned on one font at a time. "Intelligent" structures with a great degree of gratitude accuracy for most fonts are now regular. Some marketable methods are skilled of duplicating formatted output that very much resembles the original scanned sheet including columns, images and other non-textual components.

Signature verification

A digital signature is a mathematical scheme for representing the legitimacy of a digital communication. A legal digital signature affords a receiver reason to consider that the message was created by a recognized sender, such that the sender cannot reject having sent the message with non-repudiation and authentication and the message was not changed in transfer. Digital signatures are commonly used for software allocation, financial communication, and in further cases where it is vital to detect imitation or tampering

Bio-metrics

Biometrics (or biometric verification) refers to the automatic identification of humans by their behaviors or characteristics. Biometrics is recycled in computer science as a type of identification and access control. It is also used to recognize individuals in groups that are under surveillance. Biometric identifiers are the exceptional, assessable characteristics used to label and describe individuals, examples include fingerprint, face recognition, Palm print, DNA, hand geometry, iris recognition, retina and odor/smell.

Agriculture

Applications towards agriculture providing the earth observation data which supports increased area under agriculture, increased crop intensity and productivity, etc. RS data can provide the data related to groundwater helping in irrigation, flood management. Applications like environment assessment and monitoring, disaster monitoring and mitigation, weather climate, village resource center etc.

Automatic target recognition

Automatic target recognition (ATR) is the skill for an algorithm or device to distinguish objects or targets stand on data gained from sensors. The function of regular target recognition technology is a serious element of robotic warfare. ATR machines are used in unmanned aerial vehicles and cruise missiles. Electric affords an ATRU (Automatic Target Recognition Unit) to the Land Attack Missile of Standoff, which processes post-launch and pre-launch aiming data, allows high quickness in video comparison, and permits the SLAM-ER i.e., Standoff Land Attack Missile-Expanded Response, "Fire-and-forget" missile. The fundamental version of an ATR system is the IFF transponder. Other applications of ATR include a proposed security system that uses active UWB radar signals to recognize objects or humans that have dropped onto channel tracks of rail. It is also possible to detect the damaged infrastructures caused by the earthquakes using satellite.

Traffic monitoring

The current disclosure relates to a number of inventions heading for, normally to the application of image processing techniques to traffic data acquisition using images/videos. The inventions exist in a system of traffic monitoring, the fundamental job of which is for acquisition of traffic data and detection of incident. Further distinctively, the application of image processing methods for the vehicle detection, from the series of video images, as well as the acquisition of traffic data and detection of traffic incident. In an individual facet, the present development provides a technique of processing images recognized from a system of traffic monitoring which is video based. In one more feature, the current development is headed to a Region of Interest.

Biomedical Application

Biomedical image processing is similar in concept to biomedical signal processing in multiple dimensions. It includes the analysis, enhancement and display of images captured via x-ray, ultrasound, MRI, nuclear medicine and optical imaging technologies. Image reconstruction and modeling techniques allow instant processing of 2D signals to create 3D images. When the original CT scanner was invented in 1972, it literally took hours to acquire one slice of image data and more than 24 hours to reconstruct that data into a single image. Today, this acquisition and reconstruction occurs in less than a second. Rather than simply eyeball an x-ray on a lightbox, image processing software helps to automatically identify and analyze what might not be apparent to the human eye.

3.4 Image Noises

Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the image sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that obscures the desired information.

The original meaning of "noise" was "unwanted signal"; unwanted electrical fluctuations in signals received by AM radios caused audible acoustic noise ("static"). By analogy, unwanted electrical fluctuations are also called "noise".

Image noise can range from almost imperceptible specks on a digital photograph taken in good light, to optical and radioastronomical images that are almost entirely noise, from which a small amount of information can be derived by sophisticated processing. Such a noise level would be unacceptable in a photograph since it would be impossible even to determine the subject.

3.4.1 Types of Noises

Gaussian Noise

Principal sources of Gaussian noise in digital images arise during acquisition. The sensor has inherent noise due to the level of illumination and its own temperature, and the electronic circuits connected to the sensor inject their own share of electronic circuit noise.

A typical model of image noise is Gaussian, additive, independent at each pixel, and independent of the signal intensity, caused primarily by Johnson–Nyquist noise (thermal noise), including that which comes from the reset noise of capacitors ("kTC noise"). Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel. At higher exposures, however, image sensor noise is dominated by shot noise, which is not Gaussian and not independent of signal intensity. Also, there are many Gaussian denoising algorithms.

Fig. 3.8 Gaussian Noise in an image

Salt-and-Pepper Noise

Fat-tail distributed or "impulsive" noise is sometimes called salt-and-pepper noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. It can be mostly eliminated by using dark frame subtraction, median filtering, combined median and mean filtering and interpolating around dark/bright pixels. Dead pixels in an LCD monitor produce a similar, but non-random, display

Fig. 3.9 Image with salt and pepper noise

Shot Noise

The dominant noise in the brighter parts of an image from an image sensor is typically that caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level. This noise is known as photon shot noise. Shot noise has a root-mean-square value proportional to the square root of the image intensity, and the noises at different pixels are independent of one another. Shot noise follows a Poisson distribution, which except at very high intensity levels approximates a Gaussian distribution.

In addition to photon shot noise, there can be additional shot noise from the dark leakage current in the image sensor; this noise is sometimes known as "dark shot noise" or "dark-current shot noise". Dark current is greatest at "hot pixels" within the image sensor. The variable dark charge of normal and hot pixels can be subtracted off (using "dark frame subtraction"), leaving only the shot noise, or random component, of the leakage. If dark-frame subtraction is not done, or if the exposure time is long enough that the hot pixel charge exceeds the linear charge capacity, the noise will be more than just shot noise, and hot pixels appear as salt-and-pepper noise.

Quantization noise (uniform noise)

The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise. It has an approximately uniform distribution. Though it can be signal dependent, it will be signal independent if other noise sources are big enough to cause dithering, or if dithering is explicitly applied.

Film grain

The grain of photographic film is a signal-dependent noise, with similar statistical distribution to shot noise. If film grains are uniformly distributed (equal number per area), and if each grain has an equal and independent probability of developing to a dark silver grain after absorbing photons, then the number of such dark grains in an area will be random with a binomial distribution. In areas where the probability is low, this distribution will be close to the classic Poisson distribution of shot noise. A simple Gaussian distribution is often used as an adequately accurate model.

Film grain is usually regarded as a nearly isotropic (non-oriented) noise source. Its effect is made worse by the distribution of silver halide grains in the film also being random.

Anisotropic Noise

Some noise sources show up with a significant orientation in images. For example, image sensors are sometimes subject to row noise or column noise.

Periodic noise

A common source of periodic noise in an image is from electrical or electromechanical interference during the image capturing process. An image affected by periodic noise will look like a repeating pattern has been added on top of the original image. In the frequency domain this type of noise can be seen as discrete spikes. Significant reduction of this noise can be achieved by applying notch filters in the frequency domain. The following images illustrate an image affected by periodic noise, and the result of reducing the noise using frequency domain filtering. Note that the filtered image still has some noise on the borders. Further filtering could reduce this border noise; however, it may also reduce some of the fine details in the image. The trade-off between noise reduction and preserving fine details is application specific. For example, if the fine details on the castle are not considered important, low pass filtering could be an appropriate option. If the fine details of the castle are considered important, a viable solution may be to crop off the border of the image entirely.

Fig. 3.10 An image injected with periodic noise

3.5 Image Filtering

Image filtering is done to improve the quality of the image. For ex- smoothing an image reduces noise, blurred images can be rectified. There are broadly two types of algorithms linear and non-linear. Linear filter is achieved through convolution and Fourier multiplication whereas Non-linear filter cannot be achieved through any of these. Its output is not the linear function of its input thus, its result varies in a non-intuitive manner. Here, the following image shows how the median filter enhances the images by reducing the noise and smoothing. In order to do further processing like image segmentation, edge detection etc. noise should be eliminated. Median filter is the most effective non-linear filtering algorithm to detect and remove salt and pepper noise. Median filter retains the edges of the while removing the noise that's why it is used most widely thus, apart from trampling the noise up to 5% to 60%, it also preserves the image details. The noisy pixels are evaluated and labelled as noisy pixels and the switching based median filter is applied to other pixels which are not noisy. Bilateral filter is a type of non-liner filter, it reduces noise by smoothing and preserves edges of the images. It takes weighted sum of the pixels which are nearby of each pixel and replaces the intensity of the pixels with the average of that weighted sum. Filtering of image is an important process done in image processing. It can be done for noise removal, blur removal, edge detection etc. Linear and non-linear filters are the algorithms which are used for filtering. Right filter should be selected for any specific purpose. If the image or input given has less amount of noise but the magnitude is high then non-linear filters are used whereas linear low-pass filter is sufficient when the input given contains noise in large amount but the magnitude of noise is low. Linear filters are the most frequently used filters as it is simplest and fastest. Unlike non-linear filters, the linear filtering is done through applying the algorithm on the neighbour pixels of the input pixels in the image. The neighbourhood pixels are identified through their locations which are relative to the input pixel. Algorithms used for linear filtering are Box blur, Gaussian, bilateral and Hann window. In box blur an image with 9x9 pixel values, can be considered having a 3x3 neighbourhood values. smoothing is achieved by averaging the neighbourhood pixel values of the particular pixel in the output image.

In this way the pixels with higher intensity gets converted into a lower valued pixel and vice-versa thus, balancing the image pixels. Gaussian filter is based on the equation of a Gaussian, it can be used to generate a kernel. A kernel is a matrix (small) which is a convoluted matrix used in various image filtering techniques for embossing, smoothing, sharpening, blurring etc. Gaussian blur can be applied for smoothing or filtering operations. The filtered image has more image details as compared to an average blur filter. It gives better results than box blur.

3.5.1 Types of Filters

Average Filter

The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used although larger kernels (e.g., 5×5 squares) can be used for more severe smoothing. (Note that a small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.)

$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

Fig. 3.11 3×3 averaging kernel often used in mean filtering

Median Filter

Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.) Fig. 7.2 illustrates an example calculation.

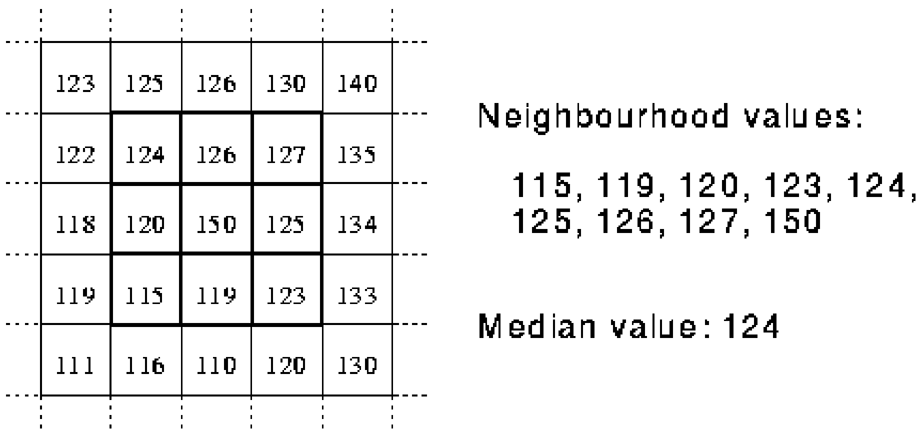

Fig. 3.12 Kernel of Median Filter

Calculating the median value of a pixel neighborhood. As can be seen, the central pixel value of 150 is rather unrepresentative of the surrounding pixels and is replaced with the median value: 124. A 3×3 square neighborhood is used here. Larger neighborhoods will produce more severe smoothing.

Weiner Filter

The goal of the Wiener filter is to compute a statistical estimate of an unknown signal using a related signal as an input and filtering that known signal to produce the estimate as an output. For example, the known signal might consist of an unknown signal of interest that has been corrupted by additive noise. The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. The Wiener filter is based on a statistical approach, and a more statistical account of the theory is given in the minimum mean square error (MMSE) estimator article.

Typical deterministic filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following

Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation

Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)

High Pass Filter

A high-pass filter can be used to make an image appear sharper. These filters emphasize fine details in the image – exactly the opposite of the low-pass filter. High-pass filtering works in exactly the same way as low-pass filtering; it just uses a different convolution kernel. In the example below, notice the minus signs for the adjacent pixels. If there is no change in intensity, nothing happens. But if one pixel is brighter than its immediate neighbors, it gets boosted.

0	-1/4	0
-1/4	+2	-1/4
0	-1/4	0

Fig. 3.13 Kernel of HPF

Unfortunately, while low-pass filtering smooths out noise, high-pass filtering does just the opposite: it amplifies noise. You can get away with this if the original image is not too noisy; otherwise, the noise will overwhelm the image. MaxIm DL includes a very useful "range-restricted filter" option; you can high-pass filter only the brightest parts of the image, where the signal-to-noise ratio is highest.

High-pass filtering can also cause small, faint details to be greatly exaggerated. An over-processed image will look grainy and unnatural, and point sources will have dark donuts around them. So, while high-pass filtering can often improve an image by sharpening detail, overdoing it can actually degrade the image quality significantly.

Anisotropic Filter

In image processing and computer vision, anisotropic diffusion, also called Perona–Malik diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family are given as a convolution between the image and a 2D isotropic Gaussian filter, where the width of the filter increases with the parameter. This diffusion process is a linear and space-invariant transformation of the original image. Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image.

3.6 Anisotropic Filtering

Noise is an omnipresent artifact in 2d and 3d meshes due to resolution problems in mesh acquisition processes. For example, meshes extracted from image data or supplied by laser scanning devices often carry high-frequency noise in the position of the vertices. Many filtering techniques have been suggested in recent years, among them Laplace smoothing is the most prominent example. In practice, denoising is still a delicate task and left to the hands of a user who carefully chooses different filtering algorithms. Anisotropic denoising concentrates on the preservation of important surface features like sharp edges and corners by applying direction dependent smoothing. For example, a sharp edge remains sharp when smoothing is avoided to happen across the edge. In geometry, different notions of curvature have been established to detect and measure the bending and the geometric disturbance of a shape. One approach to denoise a shape therefore concentrates on the removal of unwanted curvature peaks while a feature preservation simultaneously tries to keep certain curvature distributions, for example, the high curvature along sharp corners. Anisotropic mean curvature flow addresses this problem by constraining the isotropic mean curvature flow to preserve features encountered in a shape. A good knowledge of curvature is an eminent prerequisite for constrained mesh smoothing. Especially for feature constrained denoising the computation of principal curvatures on simplicial surfaces is important since it measures the individual bending of a surface in different directions. The results of this paper are based on the novel definition and explicit calculation of a shape operator and principal curvature information on a simplicial surface. These definitions rely on a smallest possible stencil for curvature calculations and are still fully consistent with the known vertex-based discrete mean curvature formulas. We incorporate these operators in new kinds of diffusion algorithms for the feature preserving denoising of meshes.

The general anisotropic diffusion equation is as follows

$$\frac{\partial I}{\partial t} = div(c(x, y, t)\nabla y) = \nabla c. \nabla I + c(x. y. t)\nabla I$$

where Δ denotes the Laplacian, ∇ denotes the gradient, div(…) is the divergence operator and c(x,y,t) is the diffusion coefficient.

For t>0, the output image is available as I(.,t) with larger t producing blurrier images. c(x,y,t) controls rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. Pietro Perona and Jitendra Malik pioneered the idea of anisotropic diffusion in 1990 and proposed two functions for the diffusion coefficient:

$$c\left(\left||\nabla I|\right|\right) = e^{-(||\nabla||/K)^2}$$

$$c\left(\left||\nabla I|\right|\right) = \frac{1}{1 + (\frac{||\nabla||}{K})^2}$$

Applications

Anisotropic diffusion can be used to remove noise from digital images without blurring edges. With a constant diffusion coefficient, the anisotropic diffusion equations reduce to the heat equation which is equivalent to Gaussian blurring. This is ideal for removing noise but also indiscriminately blurs edges too. When the diffusion coefficient is chosen as an edge seeking function, such as in Perona-Malik, the resulting equations encourage diffusion (hence smoothing) within regions and prohibit it across strong edges. Hence the edges can be preserved while removing noise from the image.

Along the same lines as noise removal, anisotropic diffusion can be used in edge detection algorithms. By running the diffusion with an edge seeking diffusion coefficient for a certain number of iterations, the image can be evolved towards a piecewise constant image with the boundaries between the constant components being detected as edges.

3.7 Image Segmentation

In digital image processing and computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different color respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

There are two classes of segmentation techniques. They are Classical computer vision approaches and AI based techniques.

Semantic segmentation is an approach detecting, for every pixel, belonging class of the object. For example, when all people in a figure are segmented as one object and background as one object. Instance segmentation is an approach that identifies, for every pixel, a belonging instance of the object. It detects each distinct object of interest in the image. For example, when each person in a figure is segmented as an individual object.

3.7.1 Segmentation Techniques

Thresholding

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, balanced histogram thresholding, Otsu's method (maximum variance), and k-means clustering.

Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image.

New methods suggested the usage of multi-dimensional fuzzy rule-based non-linear thresholds. In these works, decision over each pixel's membership to a segment is based on multi-dimensional rules derived from fuzzy logic and evolutionary algorithms based on image lighting environment and application.

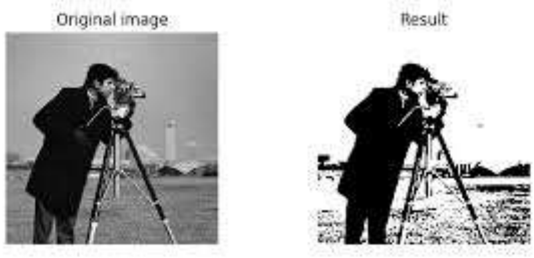

Fig. 3.14 Thresholding

Global thresholding

Suppose the histogram of an image f (x, y) is composed of light objects on a dark background. The pixel intensity levels of the object and the background are grouped into two dominant modes. In global thresholding, a threshold value T is selected in such a way that it separates the object and the background. The condition for selecting T is given as follows:

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) <= T \end{cases}$$

This Equation has no indication on selecting the threshold value T. The threshold T separates the object from the dark background. Any point (x, y) for which f (x, y) ≥ T is called an object point. After thresholding operation, the image is segmented as follows: Pixels labeled 1 corresponds to object whereas pixels labeled 0 corresponds to the background. In global thresholding, the threshold value T depends only on gray levels of f (x, y).

Threshold Selection based on Otsu's method

A segment is assumed to have relatively homogeneous gray level values, then a threshold value T can be selected in such a way that it minimizes the variance of the gray levels within the segment or T can be selected that minimizes the variance between objects and background or a method that attempts to optimize within and between segments variance. This method maximizes the between-class variance and is based on computations performed on the histogram of an image. Otsu's algorithm is as follows:
Compute the normalized histogram of the input image
Compute the cumulative sums P(k) for k=0,1, 2, … L-1.
Compute the cumulative means m(k) for k=0,1, 2, … L-1.
Compute the global intensity mean m_g.
Compute the between-class variance σ_b^2 (k) for k=0,1, 2, … L-1.
Obtain Otsu's threshold k* as the value of k for which σ_b^2 (k) is maximum.
If the maximum is not unique, obtain k* by averaging the values of k corresponding to the various maxima detected. g. Obtain the separability measure, η*, at k=k*.

Clustering methods

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is Pick K cluster centers, either randomly or based on some heuristic method, for example K-means++. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center. Re-compute the cluster centers by averaging all of the pixels in the cluster. Repeat steps 2 and 3 until convergence is attained (i.e., no pixels change clusters). In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

Fig. 3.15 Clustering Method

Motion and interactive segmentation

Motion based segmentation is a technique that relies on motion in the image to perform segmentation. The idea is simple: look at the differences between a pair of images. Assuming the object of interest is moving, the difference will be exactly that object. Improving on this idea, Kenney et al. proposed interactive segmentation. They use a robot to poke objects in order to generate the motion signal necessary for motion-based segmentation.

Compression-based methods

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modeled by a probability distribution function and its coding length is computed as follows:

The boundary encoding leverages the fact that regions in natural images tend to have a smooth contour. This prior is used by Huffman coding to encode the difference chain code of the contours in an image. Thus, the smoother a boundary is, the shorter coding length it attains.

Texture is encoded by lossy compression in a way similar to minimum description length (MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modeled by a multivariate normal distribution whose entropy has a closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize.

For any given segmentation of an image, this scheme yields the number of bits required to encode that image based on the given segmentation. Thus, among all possible segmentations of an image, the goal is to find the segmentation which produces the shortest coding length. This can be achieved by a simple agglomerative clustering method. The distortion in the lossy compression determines the coarseness of the segmentation and its optimal value may differ for each image.

Histogram-based methods

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This operation is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. Histogram-based approaches can also be quickly adapted to apply to multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per-pixel basis where the resulting information is used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in video tracking.

Edge detection

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects or spatial-taxons.

Spatial-taxons are information granules, consisting of a crisp pixel region, stationed at abstraction levels within a hierarchical nested scene architecture. They are similar to the Gestalt psychological designation of figure-ground, but are extended to include foreground, object groups, objects and salient object parts. Edge detection methods can be applied to the spatial-taxon region, in the same manner they would be applied to a silhouette. This method is particularly useful when the disconnected edge is part of an illusory contour.

Segmentation methods can also be applied to edges obtained from edge detectors. Lindeberg and Li developed an integrated method that segments edges into straight and curved edge segments for parts-based object recognition, based on a minimum description length (MDL) criterion that was optimized by a split-and-merge-like method with candidate breakpoints obtained from complementary junction cues to obtain more likely points at which to consider partitions into different segments.

Fig. 3.16 Edge based segmentation method

Dual clustering method

This method is a combination of three characteristics of the image: partition of the image based on histogram analysis is checked by high compactness of the clusters (objects), and high gradients of their borders. For that purpose two spaces have to be introduced: one space is the one-dimensional histogram of brightness $H = H(B)$; the second space is the dual 3-dimensional space of the original image itself $B = B(x, y)$. The first space allows to measure how compactly the brightness of the image is distributed by calculating a minimal clustering Kmin. Threshold brightness T corresponding to Kmin defines the binary (black-and-white) image – bitmap $b = \varphi(x, y)$, where $\varphi(x, y) = 0$, if $B(x, y) < T$, and $\varphi(x, y) = 1$, if $B(x, y) \geq T$. The bitmap b is an object in dual space. On that bitmap a measure has to be defined reflecting how compact distributed black (or white) pixels are. So, the goal is to find objects with good borders. For all T the measure $MDC = G/(k \times L)$ has to be calculated (where k is difference in brightness between the object and the background, L is length of all borders, and G is mean gradient on the borders). Maximum of MDC defines the segmentation.

Region-growing methods

Region-growing methods rely mainly on the assumption that the neighboring pixels within one region have similar values. The common procedure is to compare one pixel with its neighbors. If a similarity criterion is satisfied, the pixel can be set to belong to the same cluster as one or more of its neighbors. The selection of the similarity criterion is significant and the results are influenced by noise in all instances. The method of

Statistical Region Merging (SRM) starts by building the graph of pixels using 4-connectedness with edges weighted by the absolute value of the intensity difference. Initially each pixel forms a single pixel region. SRM then sorts those edges in a priority queue and decides whether or not to merge the current regions belonging to the edge pixels using a statistical predicate.

One region-growing method is the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparison of all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean is used as a measure of similarity. The pixel with the smallest difference measured in this way is assigned to the respective region. This process continues until all pixels are assigned to a region. Because seeded region growing requires seeds as additional input, the segmentation results are dependent on the choice of seeds, and noise in the image can cause the seeds to be poorly placed.

Another region-growing method is the unseeded region growing method. It is a modified algorithm that does not require explicit seeds. It starts with a single region the pixel chosen here does not markedly influence the final segmentation. At each iteration it considers the neighboring pixels in the same way as seeded region growing. It differs from seeded region growing in that if the minimum is less than a predefined threshold then it is added to the respective region. If not, then the pixel is considered different from all current regions and a new region is created with this pixel.

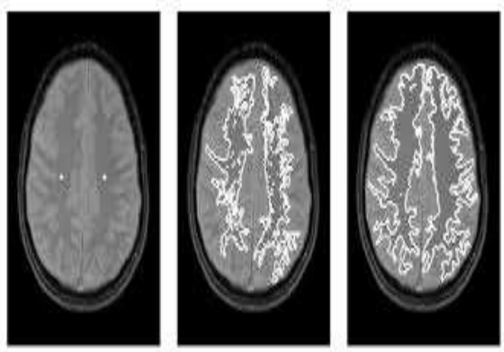

Fig. 3.17 Region growing segmentation method

3.8 Support Vector Machine

In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. Developed at AT&T Bell Laboratories by Vladimir Vapnik with colleagues, SVMs are one of the most robust prediction methods, being based on statistical learning frameworks or VC theory proposed by Vapnik (1982, 1995) and Chervonenkis (1974). Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. When data are unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups.

Motivation

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data point will be in. In the case of support-vector machines, a data point is viewed as p-dimensional vector, and we want to know whether we can separate such points with a dimensional hyperplane. This is called a linear classifier. There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So, we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum-margin classifier; or equivalently, the perceptron of optimal stability.

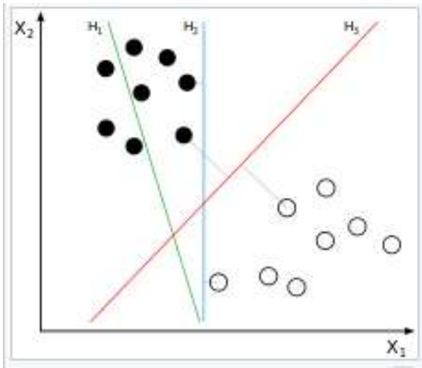

Fig. 3.18 SVM classifier working

H1 does not separate the classes. H2 does, but only with a small margin. H3 separates them with the maximal margin.

3.8.1 Definition

More formally, a support-vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks like outliers detection. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin, the lower the generalization error of the classifier.

Whereas the original problem may be stated in a finite-dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products of pairs of input data vectors may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function selected to suit the problem. The hyperplanes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant, where such a set of vectors is an orthogonal (and thus minimal) set of vectors that defines a hyperplane. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters alpha of images of feature vectors that occur in the data base. With this choice of a hyperplane, the points in the feature space that are mapped into the hyperplane are defined by a relation.

3.8.2 Applications of SVM

SVMs can be used to solve various real-world problems. SVMs are helpful in text and hypertext categorization, as their application can significantly reduce the need for labeled training instances in both the standard inductive and transductive settings. Some methods for shallow semantic parsing are based on support vector machines. Classification of images can also be performed using SVMs. Experimental results show that SVMs achieve significantly higher search accuracy than traditional query refinement schemes after just three to four rounds of relevance feedback. This is also true for image segmentation systems, including those using a modified version SVM that uses the privileged approach as suggested by Vapnik. Classification of satellite data like SAR data using supervised SVM. Hand-written characters can be recognized using SVM. The SVM algorithm has been widely applied in the biological and other sciences. They have been used to classify proteins with up to 90% of the compounds classified correctly. Permutation tests based on SVM weights have been suggested as a mechanism for interpretation of SVM models. Support-vector machine weights have also been used to interpret SVM models in the past. Posthoc interpretation of support-vector machine models in order to identify features used by the model to make predictions is a relatively new area of research with special significance in the biological sciences.

3.9 Morphological Operations

Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image. These techniques can be extended to greyscale images. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest. Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighborhood of pixels. Some operations test whether the element "fits" within the neighborhood, while others test whether it "hits" or intersects the neighborhood.

3.9.1 Dilation

The value of the output pixel is the maximum value of all pixels in the neighborhood. In a binary image, a pixel is set to 1 if any of the neighboring pixels have the value 1. Morphological dilation makes objects more visible and fills in small holes in objects. Dilation adds pixels to the boundaries of objects in an image

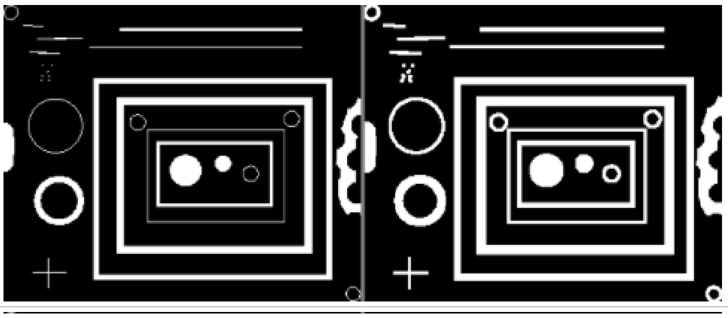

Fig. 3.19 Dilation

3.9.2 Erosion

The value of the output pixel is the minimum value of all pixels in the neighborhood. In a binary image, a pixel is set to 0 if any of the neighboring pixels have the value 0. Morphological erosion removes islands and small objects so that only substantive objects remain.

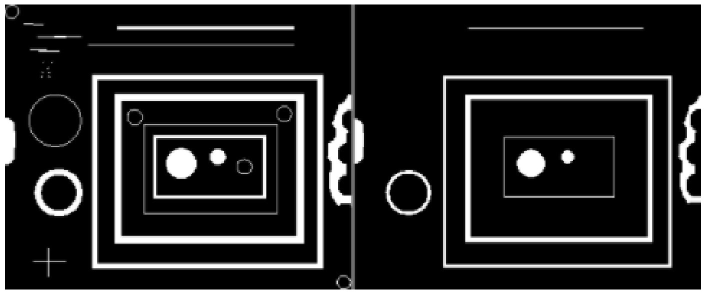

Fig. 3.20 Erosion

3.9.3 Opening

Perform morphological opening. The opening operation erodes an image and then dilates the eroded image, using the same structuring element for both operations. Morphological opening is useful for removing small objects from an image while preserving the shape and size of larger objects in the image. For an example, see Use Morphological Opening to Extract Large Image Features.

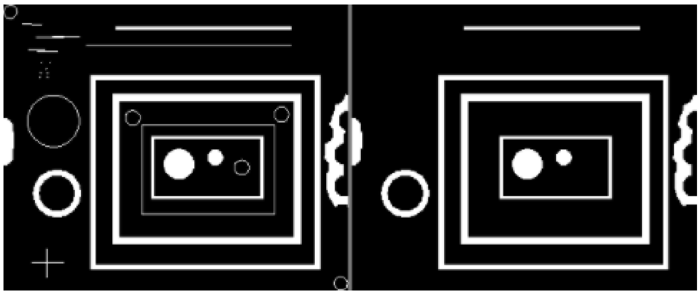

Fig. 3.21 Morphological opening

3.9.4 Closing

Perform morphological closing. The closing operation dilates an image and then erodes the dilated image, using the same structuring element for both operations. Morphological closing is useful for filling small holes from an image while preserving the shape and size of the objects in the image.

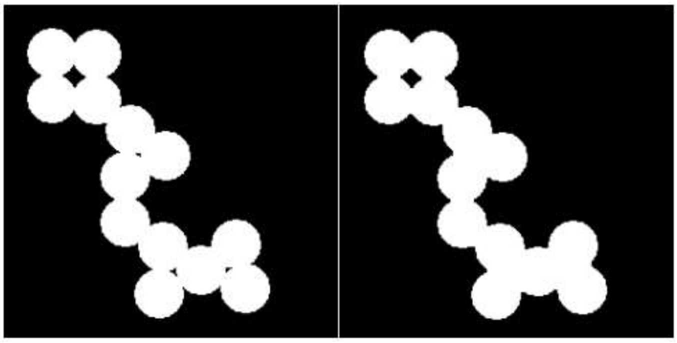

Fig. 3.22 Morphological Closing

3.10 MATLAB

MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numerical computation. Using MATLAB, you can solve technical computing problems faster than with traditional programming languages, such as C, C++, and Fortran. MATLAB is a data analysis and visualization tool which has been designed with powerful support for matrices and matrix operations. As well as this, MATLAB has excellent graphics capabilities, and its own powerful programming language. One of the reasons that MATLAB has become such an important tool is through the use of sets of MATLAB programs designed to support a particular task. These sets of programs are called toolboxes, and the particular toolbox of interest to us is the image processing toolbox. Rather than give a description of all of MATLAB's capabilities, we shall restrict ourselves to just those aspects concerned with handling of images. We shall introduce functions, commands and techniques as required.

A MATLAB function is a keyword which accepts various parameters, and produces some sort of output: for example, a matrix, a string, a graph. Examples of such functions are sin, imread, imclose. There are many functions in MATLAB, and as we shall see, it is very easy (and sometimes necessary) to write our own. You can use MATLAB in a wide range of applications, including signal and image processing, communications, control design, test and measurement financial Modeling and analysis. Add-on toolboxes (collections of special-purpose MATLAB functions) extend the MATLAB environment to solve particular classes of problems in these application areas. MATLAB provides a number of features for documenting and sharing your work. You can integrate your MATLAB code with other languages and applications, and distribute your MATLAB algorithms and applications.

When working with images in MATLAB, there are many things to keep in mind such as loading an image, using the right format, saving the data as different data types, how to display an image, conversion between different image formats.

Image Processing Toolbox provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. You can perform image enhancement, image deblurring, feature detection, noise reduction, image segmentation, spatial transformations, and image registration. Many functions in the toolbox are multithreaded to take advantage of multicore and multiprocessor computers.

3.10.1 MATLAB for image processing

Digital image processing is the use of computer algorithms to create, process, communicate, and display digital images. Digital image processing algorithms can be used to

- Convert signals from an image sensor into digital images
- Improve clarity, and remove noise and other artifacts
- Extract the size, scale, or number of objects in a scene
- Prepare images for display or printing and compress images for communication across a network.

MATLAB and Images

- An image in MATLAB is treated as a matrix
- Every pixel is a matrix element
- All the operators in MATLAB defined on matrices can be used on images: +, -, *, /, ^, sqrt, sin, cos etc.

Image formats for import/export

- BMP (Microsoft Windows Bitmap)

- GIF (Graphics Interchange Files)
- HDF (Hierarchical Data Format)
- JPEG (Joint Photographic Experts Group)
- PCX (Paintbrush)
- PNG (Portable Network Graphics)
- TIFF (Tagged Image File Format)
- XWD (X Window Dump)
- MATLAB can also load raw-data or other types of image data

Image types in MATLAB

Outside MATLAB images may be of three types i.e. black & white, grey scale and colored. In MATLAB, however, there are four types of images. Black & White images are called binary images, containing 1 for white and 0 for black. Grey scale images are called intensity images, containing numbers in the range of 0 to 255 or 0 to 1. Colored images may be represented as RGB Image or Indexed Image. In RGB Images there exist three indexed images. First image contains all the red portion of the image, second green and third contains the blue portion. So, for a 640 x 480 sized image the matrix will be 640 x 480 x 3. An alternate method of colored image representation is Indexed Image. It actually exists of two matrices namely image matrix and map matrix. Each color in the image is given an index number and in image matrix each color is represented as an index number. Map matrix contains the database of which index number belongs to which color.

Image Type Conversions

- RGB Image to Intensity Image (rgb2gray)
- RGB Image to Indexed Image (rgb2ind)
- RGB Image to Binary Image (im2bw)
- Indexed Image to RGB Image (ind2rgb)
- Indexed Image to Intensity Image (ind2gray)
- Indexed Image to Binary Image (im2bw)
- Intensity Image to Indexed Image (gray2ind)

CHAPTER 4

SYSTEM DESIGN

4.1 Introduction

Brain tumour is an unusual mass of tissue in which some cells multiply and grows uncontrollably. Manual brain tumour detection is complicated, time-consuming, and vulnerable to error. Hence, automated computer-assisted diagnosis at high precision is currently in demand. It needs to be detected at an early stage using MRI or CT scanned images when it is as small as possible because the tumour can possibly result to cancer. This paper, mainly focuses on detecting and localizing the tumour region existing in the brain by proposed methodology using patient's MRI images with the help of MATLAB. To pave the way for morphological operation on MRI image, the image is first filtered using Anisotropic Filter to reduce contrast between consecutive pixels. Anisotropic filtering is a method of enhancing the image quality of textures on surfaces of computer graphics that are at oblique(slant) viewing angles with respect to the camera. After that the image will be resized, utilizing a threshold value, the image is then converted to a black and white image. Classification of MRI images is an important part to differentiate between normal patients and a patient who has tumour in brain. For this Support Vector Machine (SVM) classifier is used. After the SVM classifier, morphological operations will be applied and information on areas of the possible tumour locations will be obtained. Then it is used to deliver final detection result, i.e., detect and isolate the region of tumour.

4.2 Methodology

The method proposed in the paper to detect brain tumor image can be divided into three steps. The primary requirement to attain a data set of images with possible brain tumour. The first step is to remove noises from the image. This is done using Anisotropic filtering method. The next step is segmentation using support vector machine (SVM). Here, the region of the tumour in the brain is detected. The final step is to obtain the accurate location and outline of the image. This is done with the help of morphological operations like dilation and erosion. With this a tumour in the MRI brain image can be located and isolated.

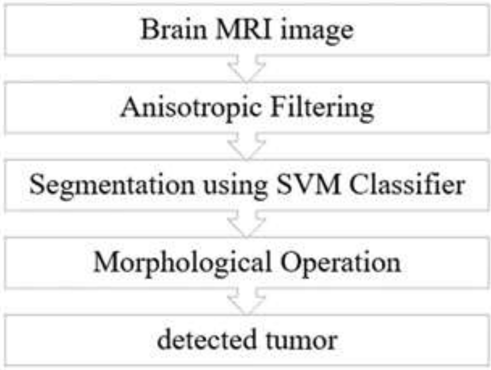

Fig. 4.1 Flow chart of proposed methodology

4.2.1 Algorithm of Proposed Methodology

Step#1: Start

Step#2: Image acquisition (MRI Image) from a file stored in a local hard disk.

Step#3: Removing Noise using Anisotropic Filtering

Step#4: Segmenting the image using Thresholding operation

Step#5: Classifying the tumour part of the image

Step#6: Outlining the tumour using Morphological dilation and erosion

Step#7: End

4.2.2 Image Acquisition

A grey scale MRI image of brain with tumour is taken as input. The input image is 256*256 pixels image and 8-bit grey scale.

4.2.3 Anisotropic Filtering

The Magnetic Resonance Imaging (MRI) images are prone to noises such as Gaussian Noise, salt and pepper noise and speckle noise. So, obtaining a clear and accurate image is extremely necessary for further diagnosis on image. The image may be corrupted by random variations in intensity, variations in illumination, or poor contrast that must be dealt with in the early stages of image processing. Image filtering is a process of removing noises from the image. There are various image filtering methods like average filter, mean filter, Weiner filter, high pass filter and anisotropic filter. Anisotropic denoising concentrates on the preservation of important surface features like sharp edges and corners by applying direction dependent smoothing. Anisotropic diffusion is a non-linear and space-variant transformation of the original image.

4.2.4 SVM for Image Segmentation

Image segmentation is process of dividing an image into parts. Among visualization techniques, no matter in which research area, such as topography visualization, medical image visualization etc., image segmentation is the key and basic technique to achieve an exact and clear object contour of the key features in the frame. Image segmentation aims at dividing an image into different sub images with different characteristics and extracts some interesting objects. SVM algorithm shows excellent segmentation performance, which has been successfully extended from basic task of classification. Unlike other methods, which minimize the empirical training error, SVM makes use of the structure risk minimization and can be combined with other methods to obtain a good performance in image segmentation.

4.2.5 Morphological Operations

Morphological opening is applied to image after segmentation. The opening operation erodes an image and then dilates the eroded image, using the same structuring element for both operations. To identify the tumor in the image, a binary tumor masked window is to be created. For this, the difference of dilated and eroded image is used. This mask is can be overlayed on the dilated image to obtain the tumor outline.

CHAPTER 5

SIMULATION RESULTS

An input image of a brain MRI image containing tumour is to be selected. Fig. 13.1 shows a grey scale MRI image of brain with tumour. The input image is 256*256 pixels image and 8-bit grey scale.

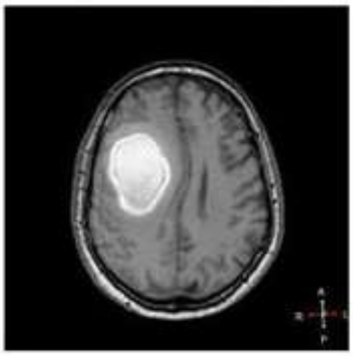

Fig. 5.1 Input Image

The MRI image consists of noises such as Gaussian Noise, salt and pepper noise and speckle noise. These noises are removed by applying Anisotropic filter which incorporates preservation of important surface features like sharp edges and corners by applying direction dependent smoothing.

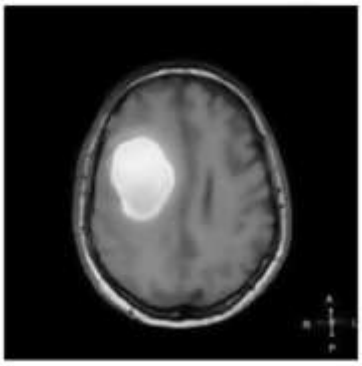

Fig. 5.2 Filtered Image

The filtered image is converted to a binary image using thresholding. This is used to select the area of interest, i.e., tumour in the image.

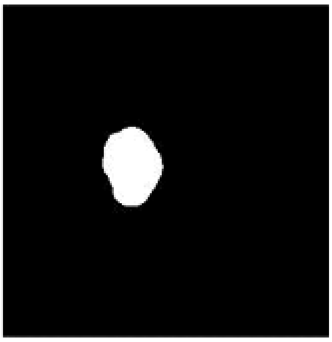

Fig. 5.3 Tumour Alone

Using SVM a bounding box is created to segment and classify brain's tumour region.

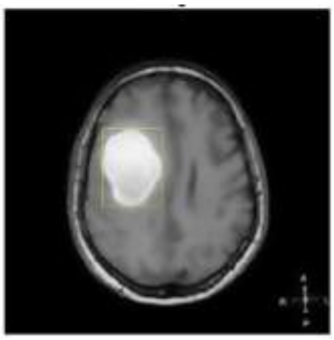

Fig. 5.4 Bounding Box

Next, on the binary tumour image, morphological opening operation is performed. This includes first eroding the image and then dilating it.

Fig. 5.5 Morphological opening

The image is then eroded. Erosion makes objects less visible. This is done to get a binary image of the tumour slightly smaller than the previous image.

Fig. 5.6 Eroded Image

Next a binary tumour masked window is created by the difference the images where dilation and erosion were carried out. This gives the outline of the tumour.

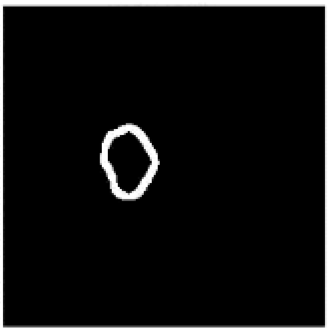

Fig. 5.7 Tumour outline

This outline is overlapped with the input image to accurately locate and outline the tumour.

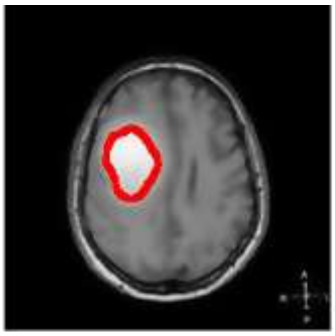

Fig. 5.8 Detected Tumour

CHAPTER 6

RESULTS AND DISCUSSIONS

A methodology to accurately detect and locate brain tumour in MRI image is proposed in the project. The process considered is to first take an abnormal brain MRI image and to remove noises using Anisotropic filtering, to segment it using support vector machine and to finally perform morphological operations to accurately locate the tumour.

6.1 Performance Analysis of Anisotropic filter

The performance of anisotropic filter is compared with the performances of other filters. The filters for comparison are Average Filter, Mean Filter, Wiener Filter, High Pass Filter (HPF), Anisotropic Filter. The performance can be compared with respect Mean-Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The noises taken into consideration are Gaussian noise, Speckle noise and salt and pepper noise.

Mean Square Error (MSE) is defined as Mean or Average of the square of the difference between actual and estimated values. It should be ideally as low as possible. The term peak signal-to-noise ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. PSNR should be ideally high. Below are the mathematical formulas of MSE and PSNR.

$$\text{MSE}=\frac{1}{pq}\sum_{i=0}^{p-1}\sum_{j=0}^{q-1}|h(i,j)-g(i,j)|^2$$

$$\text{PSNR}=20\log_{10}\left(\frac{\text{MAXf}}{\sqrt{MSE}}\right)$$

Where,

h is the matrix of original image

g is matrix of degraded image

p is the row number

i is the index of the row

q is the column number

j is the index of the column

Table 6.1 PSNR and MSE for various filters when different noises exist

Method	*PSNR value(dB)*	*MSE Value*	*Noise Type*
Average Filter	75.96504	0.00329	Gaussian Noise
	72.43547	0.00423	Speckle Noise
	75.41298	0.00287	Salt & pepper Noise
Mean Filter	71.77146	0.00432	Gaussian Noise
	71.82192	0.00427	Speckle Noise
	73.69922	0.00277	Salt & pepper Noise
Weiner Filter	72.43547	0.00371	Gaussian Noise
	72.4451	0.0037	Speckle Noise
	71.65028	0.00445	Salt & pepper Noise
High Pass Filter (HPF)	68.47065	0.00643	Gaussian Noise
	65.46914	0.00527	Speckle Noise
	67.17279	0.00608	Salt & pepper Noise
Anisotropic Filter	273.90257	0.00231	Gaussian Noise
	75.2181	0.00208	Speckle Noise
	77.92357	0.00123	Salt & pepper Noise

As the table shows PSNR value of all the considered noises is higher for Anisotropic filter and MSE value is the lowest for the same. The superior performance of anisotropic filter can be better understood with the below graphs showing PSNR and MSE values for different filters.

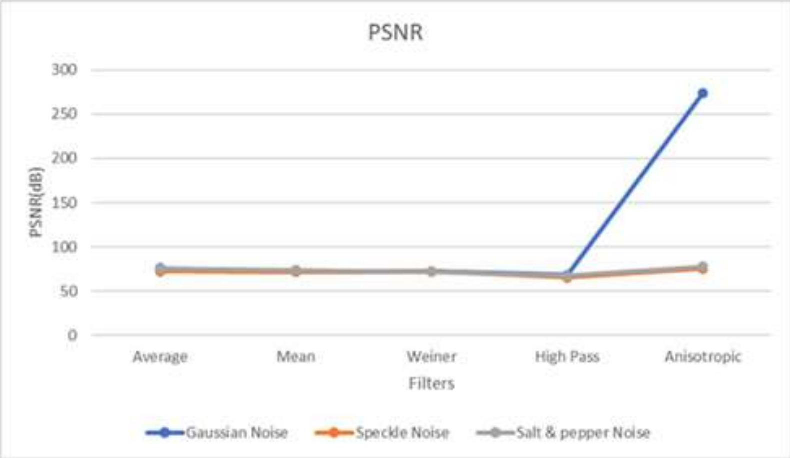

Fig. 6.1 PSNR values comparison

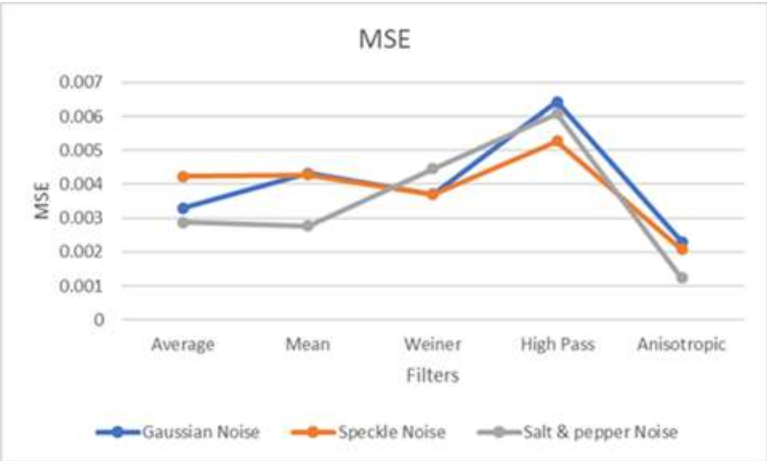

Fig. 6.2 MSE values comparison

6.2 Scope for future work

The methodology employed in the project is currently capable of detecting tumour in one MRI image at a time. This can be improved so that the system can analyze large number of images in a dataset at a time. Neural network is another booming field in the computer science and it is widely used in medical imaging filed. This can be used as another alternative to image processing for detection of life taking disease. The SVM classifier can be trained by giving large, varied and unbiased data to improve accuracy. In future, we can also be able to distinguish normal and abnormal brain images by employing some other image processing techniques and different data sets of brain abnormalities by improving the efficiency of training.

CHAPTER 7

CONCLUSION

Brain tumour is a fatal type of cancer, which needs early and accurate detection for treatment. Manual detection of tumour can be time taking and prone to error. This project proposes a method to identify tumor, if it exists, in a brain MRI image. Anisotropic filtering method is used to remove the noises in the image. It has been chosen due to its superior performance over other methods when it comes to preserving features in non-linear images. SVM classifier is proposed for segmentation to identify the tumour. In order to recognize the exact location of tumor and mark its outline, morphological operations are performed. When this proposed methodology is applied to an abnormal brain MRI image, the tumor, if any, can be accurately detected. The tumour can be exactly outlined.

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