CHAPTER 1

INTRODUCTION

1.1 BONE STRUCTURE AND ITS FUNCTION

Bone is a unique mineralized tissue that is the building material of the skeleton of all vertebrates. It performs multiple functions such as locomotion and protection of internal organs, and also serves as the body’s major calcium store. Bone is composed of an organic substrate consisting largely of type I collagen (40% by volume) interspersed with mineral crystals composed of non-stoichiometric calcium hydroxy apatite (45%). The remaining volume (15%) is occupied by water that is either bound to collagen or resides in the spaces of the lacuna canalicular system. This combination confers to bone its unique mechanical properties in terms of tensile and compressive strength and is responsible for the material’s viscoelastic properties (Linde 1994).

Bone adapts to continuously varying loading conditions to maintain the skeletal integrity. Bone must also be flexible enough to absorb energy by deforming, to shorten and widen when compressed, and to lengthen and narrow in tension without cracking. If bone is too stiff and unable to deform a little, the energy imposed during loading will be released by structural failure initially by the development of microcracks and then by complete fracture. If bone is too flexible and deforms beyond its peak strain, it will crack. To facilitate movement, bone should serve these contradictory needs of stiffness, flexibility, lightness and strength (Seeman and Delmas 2006).
Human bone is generally classified into two types called cortical bone, also known as compact bone and trabecular bone, also known as cancellous or spongy bone. These two types are classified on the basis of porosity and the microstructure. Cortical bone is much denser with a porosity ranging between 5% and 10%. It is found primarily in the shaft of long bones and forms the outer shell around trabecular bone at the end of joints and the vertebrae. Trabecular bone consists of a network of interconnected plates and struts fused to and encased by a thin cortex. It is predominant in the axial skeleton, the joints of long bones and in flat bones like the pelvis. It is much more porous with porosity ranging from 50% to 90%. In the human skeleton, trabeculae are typically 100–150 μm thick, whereas the thickness of cortical bone varies between 1 and 5 mm (Wehrli 2007).

1.1.1 Femur Bone Structures

Figure 1.1 shows the anatomy of femur bone. It is the largest, longest, and strongest bone of the human skeleton and has the ability to support up to 30 times the weight of an adult. It is strong under compression (Huang et al. 2012).

Figure 1.1 Anatomy of the human proximal femur (Voo et al. 2004)
The femur, or thigh bone, extending from the hip to the knee, is the most proximal bone of the leg in vertebrates capable of walking or jumping. The rounded, smooth head of the femur fits into a socket in the pelvis called the acetabulum to form the hip joint. The head of the femur is joined to the bone shaft by a narrow piece of bone known as the neck of the femur. The neck is a point of structural weakness and a common fracture site. The lower end of the femur hinges with the tibia to form the knee joint. A typical femur structure includes cortical bone, trabecular bone, medullary cavity, yellow marrow, periosteum and articular cartilage (Huang et al 2012). The femur conforms to the cantilever beam theory. When vertical stress is put on the proximal femur, tensile stresses act on the femoral neck which may lead to fracture if not properly buttressed. The beam, on the medial end, is supported by pelvic reaction forces. On the lateral end, the beam is supported by the femoral shaft and the greater trochanter. When the femur undergoes bending stress, it is protected from fracturing by the shaft and by the pelvic reaction force (Mizrahi et al 1984).

Femur trabecular bone is highly metabolically active and is therefore most susceptible to the bone loss which occurs during osteoporosis diseases. The loss of trabecular density occurs through a series of changes to the trabecular microstructure. The first abnormality signaling the onset of a change in bone structure is likely to be a reduction in bone formation at the cellular level (Nishida et al 1999, Stenderup et al 2001). Trabecular bone formation follows a regular pattern of distribution. Until one year of age, trabecular bone in the proximal femur is arranged in straight bars that run parallel to the sagittal plane. The muscles of the hip contract more often as age increases. The parallel trabeculae begin to be absorbed and are replaced with the more vault-like pattern that is characteristic of mature bone. This pattern of trabeculae remains basically the same, undergoing only minor revisions, as the individual grows. After epiphyseal closure, bone continues to
thicken as the individual reaches adulthood. The bone then enters a period of relative stability. Following the period of stability, the individual enters a period of bone loss. Bone resorption continues, and indeed the volume of bone may decrease as age advances, even though at midlife there may be a temporary increase in the volume of bone resorbed within each basic multicellular unit. In this period, bone formation cannot compete with the rates of bone resorption and the overall net bone mass is reduced. The combination of continued resorption in each basic multicellular unit plus a decline in the volume of bone formed resulting in negative balance (Seeman and Dalmas 2006).

For young individuals, the processes of bone resorption and bone formation act in concert with each other to help maintain bone mass and strength (Unnanuntana et al 2010). Bone loss occurs when areas known as bone remodeling units begin to function abnormally. The high remodeling rate and deep resorption cavities produce a loss of trabecular plates and of their connection, which in turn produce a greater deficit in bone strength than does trabecular thinning. There is an inter-relationship between fatigue loading, microdamage accumulation, remodeling, bone matrix repair and fracture (Sahar et al 2005).

The mechanical behavior of the trabecular bone varies with the loading direction. These variations are interpreted as an anisotropic feature of the bone stress. Trabecular bone anisotropy corresponds to the preferential orientation(s) of trabeculae. Anisotropy is constituted under the influence of preferential oriented strength applied to bone and permits to establish resistance to these strengths in a given preferential direction. Anisotropy of the trabecular bone should be considered to predict the fracture risk (Brunet-Imbault et al 2005).
1.1.2 **Delineation of Strength Regions of Femur Bone**

Singh et al (1970) defined strength regions and structures in radiographs of the femur, which demonstrate the quality of bone. The femur trabeculae form two arches. These arches are disposed along the lines of maximum compression and tension stresses produced in the femur bone during weight-bearing. These trabeculae have been divided into principal compressive, secondary compressive, greater trochanter or ward triangle, principal tensile and secondary tensile groups forming different patterns of net-like strands varying in thickness and number as shown in Figure 1.2. These patterns are called as mechanical strength regions. Amongst all, the compressive and tensile strength components are considered important for bone strength analysis.

![Diagram representing the sub anatomical strength regions of trabeculae in the upper end of the femur](image)

**Figure 1.2** Diagram representing the sub anatomical strength regions of trabeculae in the upper end of the femur (Lin et al 1999, Singh et al 1970)

The primary compressive group is the thickest and most closely packed trabeculae in the upper end of the femur. The secondary compressive
group arises below the principal compressive group and this group is thin and widely spread. The primary tensile group, which is the thickest amongst the tensile group, curve upward and inward across the neck of the femur, to end in the inferior portion of the femoral head. The secondary tensile group, arise below the principal tensile group. The trabeculae of this group arch upward and medially across the upper end of the femur and end more or less irregularly after crossing the mid-line (Singh et al 1970, Smyth et al 1997). In the conventional planar radiographic images, all these patterns are clearly visible.

1.2 BONE STRENGTH

Bone mineral is heterogeneously distributed across different anatomical regions of the healthy skeleton, due to normal variations in functional remodelling and tissue mineralisation kinetics. The remodelling activity is variable across anatomical locations of the proximal femur (Brennan et al 2011). Predicting the strength of the bone is an important goal of current research for the diagnosis of musculoskeletal diseases such as osteoporosis and femoral fractures. The most common method of assessing bone strength is to estimate loss of bone mass by bone mineral densitometry. This is a non-invasive quantitative technique and the ability to measure Bone Mineral Density (BMD) has been one of the most significant advances in the investigation and treatment of osteoporosis. As BMD correlates strongly with bone strength, fracture risk prediction in the individual patient relies chiefly on bone BMD measurements (Donnelly 2011).

BMD reflects both bone volume and the degree of mineralization, it has been regarded as an evaluation index. The prediction of bone strength can be improved when BMD combined with measures of trabecular microarchitecture (Diederichs et al 2009). Variation in the level of bone mineral density accounts for 60% to 80% of bone strength, but it is important
to realize that bone strength depends not only on the amount of mineral measured but also on the architecture, geometric and mechanical properties of the bone (Stauber and Muller 2006, Lespessailles et al 2006, Pulkkinen et al 2008).

1.2.1 Bone Microarchitecture

Bone microarchitecture makes an important contribution to strength of the bone that may not always be captured by bone mineral density measurements. Structural analysis performed on bone demonstrates differences in their strength independently of bone mineral density (Sievanen et al 2008). The trabecular bone microarchitecture corresponds to the spatial organization and morphology of the trabecular network. In trabecular bone, the number, thickness, connectivity, orientation and thickness contribute to bone strength, whilst in cortical bone its width and porosity are the main determinants.

Trabecular structure analysis yields valuable surrogate information regarding fracture risk, bone strength, and response to therapy. Many musculoskeletal conditions such as osteoporosis are quantitatively assessed using trabecular microstructure. A variety of morphologic parameters have been introduced to quantitatively characterize the structural properties of trabecular bone. These indices include, bone volume-fraction, and metric indices such as trabecular thickness, number, and separation (Sode et al 2010). The trabecular bone is heterogeneous in nature, having varying bone strength and changes most markedly in appearance with bone loss. Thus the assessment of trabecular architecture at sub-regions of the femur may allow better predictions of osteoporosis and fracture risk in individual patients (Singh et al 1970, Nazarian et al 2007, Brennan et al 2011).
Structural changes related to trabecular bone loss include a decrease of bone density, a transformation of plate-like trabeculae into rod-like trabeculae, an increase of anisotropy, and a decrease of trabecular thickness. Generally, variations in these parameters are evaluated for all strength regions to characterize the trabecular bone. Few studies have related these variations in trabecular microstructure to the mechanical properties of the proximal femur at specific anatomic sub regions. A number of analyses have indicated that bone loss may have a different effect on different types of trabeculae, which reflects the mechanical properties of the trabecular bone (Ruijven et al 2005, Thurner et al 2006, Tabor and Rokita 2007). The bone strength declines with age which may be due to variations in macro and microarchitectural parameters. The spatial distribution of bone mass intrinsic in structural geometric properties such as diameter, area, length, and angle of the femoral neck have been recognized as a significant contributory factor in the prediction of the fracture risk (Faulkner et al 2006).

Figure 1.3 Diagram representing the different bone size, shape, orientation and spatial distribution of the femur

Bone geometry plays an important role in the prediction of mechanical strength of the bone. Geometrical measures, including bone size, predict up to 70–80% of whole bone strength. The size, shape, orientation and spatial distribution of the bones are to be optimal for their structural strength and functions shown in Figure 1.3 (Seeman and Delmas 2006). Bone fragility and susceptibility to fracture are increased not only due to changes in bone
geometry, but also to the resorption of trabecular bone. The changes in bone microstructure, loss of connectivity and removal of trabeculae can significantly decrease bone strength and increase the susceptibility to fracture (Chappard et al 2005, Hernandez and Keaveny 2006). Bone strength is also attributable to the interaction of material properties, the amount of material as well as morphological and architectural properties (Jarvinen et al 2005, Hernandez and Keaveny 2006). Factors such as age, trauma and disease process affect the tissue properties leading to changes in bone strength.

1.2.2 Osteoporosis and Hip Fractures

Osteoporosis is a disease characterized by low bone mass and deterioration of bone tissue. It results in an absolute decrease in the amount of bone to a level below that required for mechanical support of normal activity (Wahner and Fogelman 1994). This leads to increased bone fragility and risk of fracture, particularly of the hip, spine, wrist and shoulder. The increase in fracture risk is strongly related to a deterioration of bone’s mechanical competence, which itself is determined by whole bone structural properties and intrinsic material properties (Augat and Schorlemmer 2006). The bone fractures lead to pain, deformity and disability which are associated with substantial costs to the individual and to society (Cadarette et al 2000). Osteoporosis-related proximal femur fractures impose a major public health risk for the elderly, as they lead to high rates of disability and complications (Cong et al 2010). The majority of femoral fractures are sustained as a result of a lateral fall on the hip (Hayes et al 1993).

Screening for osteoporosis has been widely recommended for identifying patients at high risk before any fracture occurs. The loss of bone mass does not occur overnight. It usually occurs gradually over an extended period of time. The patients are rarely symptomatic before considerable bone loss has occurred (Kreider and Goldstein 2009). Hence, osteoporosis remains
a silent disease, reflected only in a very low bone density level. In fact, most people are not even aware that they have osteoporosis until they fracture a bone. And it’s at that time that a person finds that the disease is in its advance stages. Unfortunately, there are no symptoms associated with early signs of osteoporosis. Symptoms occurring late in the disease include fractures of the vertebrae, wrists or hips, low back pain, neck pain, bone pain or tenderness, loss of height over time and stooped posture. There is very little data on the incidence of osteoporosis in India. Indirect estimates suggest some 25 million people are osteoporotic and further 25 million are having low bone mass (Malhotra and Mithal 2008). This figure may be an underestimate of the problem as Indian women have low peak bone mass on account of low blood calcium levels due to low dietary calcium and vitamin D intake and accelerated loss due to genetic estrogen receptor polymorphism (Mitra et al 2006).

Hip fracture is recognized as the most serious osteoporotic fracture because of its association with high medical costs and its profound influence on patient morbidity, functional capacity, and mortality. A attempt to quantify the global burden of hip fracture, estimated more than 1.3 million incident hip fractures, 4.5 million prevalent hip fractures with disability associated with 740,000 deaths and 1.75 million disability adjusted life years lost(Faulkner 2006). These numbers will increase significantly over the next 50 years due to population growth and extended life expectancy. Mortality from hip fracture as high as 20% with 50% permanent loss in function has been reported (Faulkner 2006).

The World Health Organization (WHO) defines osteoporosis as BMD T-score of -2.5 and below. However, BMD only partially determines fracture risk. Many studies indicate that the decreased bone strength characteristic of osteoporosis is dependent not only on BMD, but also on
other factors, most notably bone microarchitecture. Various investigators have also suggested a role for turnover, damage accumulation and mineralization in the bone quality estimation (Hulme et al 2007). Early diagnosis may also be important since the effectiveness of treatment diminishes with disease progression. Since the disease is preventable, diagnostic techniques are of major importance (Watanabe et al 2007). Studies have demonstrated that the parameters aimed to quantify trabecular bone structure can also distinguish fracture cases from controls independently of BMD. Therefore, the diagnosis of osteoporosis would benefit from the measurement of bone microarchitecture (Huber et al 2011).

1.2.3 Imaging Techniques to Characterize Bone Quality and Quantity

Bone imaging techniques is a modality that may improve the potential for non-invasive study of bone anatomy, physiology and pathophysiology. These techniques help to detect and evaluate fractures in clinical practice which include plain radiography (X-ray), Computed Tomography (CT), Magnetic Resonance Imaging (MRI), nuclear bone scanning, and vertebral fracture assessment. There are differences in each of these in terms of imaging resolution, radiation exposure, availability, cost, and patient convenience. The objective of bone imaging in osteoporosis is to minimize fracture occurrence by identifying the osteoporotic process at an early stage, differentiate distinctive patterns of bone loss, predict fracture risk accurately and monitor treatment response precisely (Chen et al 2012).

A variety of techniques that allow characterization of bone quality and quantity have been applied at the macro, micro and nano-level (Ito et al 2011). Dual Energy X-ray Absorptiometry (DEXA) is an X-ray based technique with low radiation doses that is used to measure BMD. This method
is the basis of clinical osteoporosis assessment and monitoring. According to world health organization criteria, the diagnosis of osteoporosis in postmenopausal women is based on the BMD alone, measured with DEXA of the proximal femur or spine. A T-score which is standard deviation compared with a healthy, young reference population, of less than -2.5 is defined as osteoporotic, whereas a T-score between -1 and -2.5 is defined as osteopenic. DEXA is commonly performed at central sites such as the spine or hip. For the assessment of hip geometry, DEXA-based Hip Structure Analysis (HSA) and CT-based HSA have been developed. DEXA-based HSA is a convenient tool for analyzing biomechanical properties and for assuming cross-sectional hip geometry based on Two Dimensional (2D) data, whereas CT based HSA provides three dimension parameters which are in robust relationship with biomechanical properties (Ito et al 2011).

Quantitative Computed Tomography (QCT), permits in vivo Three Dimensional (3D) quantification of bone density separately in the trabecular and cortical bone compartments. It is based on the differential absorption of ionizing radiation by calcified tissue, and generally is performed at the lumbar spine using routine computed tomography scanners. The attenuation measurements are compared with a standard reference to calculate bone mineral equivalents. The radiation exposure in QCT is higher than for DEXA and depends on the precise imaging protocol used. Macroscopic assessment of 3D bone geometry can also be performed in vivo using QCT. These tomography outcomes include the 3D macroscopic bone geometry in which the cortical and trabecular bone are distinct. An important drawback of QCT is its delivery of ionizing radiation to patients.

The high-resolution peripheral-QCT (pQCT) scanners have facilitated in vivo imaging of 3D trabecular morphology at peripheral sites such as the distal radius. The primary advantage of this technique is that
trabecular bone can be resolved, and morphologic parameters such as bone volume fraction, trabecular thickness, trabecular separation, and trabecular number can be calculated. These measurements are largely restricted to peripheral sites but have the associated benefit of reduced radiation doses relative to those from whole-body QCT scans.

High-resolution MRI allows imaging of the trabecular network at peripheral sites. During scanning, a strong magnetic field and a series of radiofrequency pulses are applied to the specimen to generate 3D images of the hydrogen in the water within skeletal tissues. A critical advantage of this technique is its ability to generate 3D images of bone geometry and microarchitecture without ionizing radiation. The disadvantage is the long scan times required for high resolution images of trabecular bone. Also, higher spatial resolution is the trade-off with signal-to-noise ratio. As the spatial resolution increases, the signal-to-noise ratio decreases.

All these techniques produce 3D images of trabecular bone but their applicability to large populations may be limited by their cost, greater radiation exposure, lengthy time required for the analytical procedure and availability (Lespessailles et al 2007). Also, noise is significant in MRI and CT in comparison with radiography. Digital radiography is a widely available imaging modality that has the potential to reflect bone microarchitecture. Radiographs are commonly obtained at the hip, spine, and calcaneus for the purpose of analyzing trabecular bone (Corroller et al 2012).

1.2.3.1 Radiographic imaging

X-ray imaging remains a very cost-effective technique, with many applications in both the medical and material science fields. X-ray equipment is capable of spatial resolution of 50 μm when compared with the 10 μm spatial resolution of CT equipment and 1 μm spatial resolution of MRI
equipment. Standard X-ray examination allows detection of changes not only in the outer cortical part of the bone, but also changes in the inner trabecular bone microarchitecture. The 3D microarchitecture of trabecular bone is indirectly visualized in a two-dimensional X-ray projection as a pattern that can be quantified and analysed. Additionally, a significant part of the information contained in 3D images is also contained in the corresponding radiograph (Defossez et al 2003). The digital radiograph saves the image that is formed by X-rays which are more or less absorbed when passing through various tissues or materials, depending upon the substance's composition, thickness, and density.

![Radiographic image of (a) normal and (b) abnormal femur bone](image)

**Figure 1.4** Radiographic image of (a) normal and (b) abnormal femur bone
Bone structure can be estimated by observing the change of trabecular pattern in proximal femur radiograph. Trabecular bone structure is visible on standard pelvic radiographs of normal and abnormal subjects as shown in Figure 1.4. The trabecular patterns are projected as curves and straight lines oriented at various directions in the radiographic femur bone images as shown in Figure 1.5 (Ascenzi et al 2011).

Furthermore, several X-ray based techniques have been developed to evaluate, based upon the relationship between the grey level on 2D projection images and the attenuation of an X-ray beam at a single point (Podsiadlo et al 2008). The relationship between plain radiographic patterns and 3D trabecular architecture shows that the plain radiograph contains architectural information directly related to the underlying 3D structures such as porosity and connectivity (Pothuaud et al 2008). Trabecular bone structure is visible in great detail on standard radiographs and the significant parts of the information that are available in 3D images are also available in the conventional radiographs (Luo et al 1999). However, two-dimensional projection-based images do not directly portray a material's 3D
microarchitecture. Hence texture based analysis has been proposed as an indirect measurement to assess the architecture of the bone (Lespessailles et al 2007, Podsiadlo et al 2008, Corroller et al 2012).

1.3 TEXTURE ANALYSIS IN IMAGE PROCESSING

Computer-based texture analysis of digital images concerns the utilization of algorithms capable of quantifying the textural properties of an image (Christodoulou et al 2005). These properties enable quantification of the gray level patterns, pixel interrelationships, and the spectral properties of an image. In medical imaging, texture analyses are used for the extraction of diagnostically meaningful information by means of textural features that are not easily perceivable (Tourassi 1999) and are used to characterize the physiological structures (Folkesson et al 2010). Medical image analysis provides a diagnostic accuracy in digital images equivalent to that of conventional films. Both pixel size and depth are factors that critically affect the visibility of small low contrast objects or signals, which often are relevant information for diagnosis. Therefore, digital image recording systems for medical imaging must provide high spatial resolution and high contrast sensitivity (Mulemajalu and Koliwad 2009).

A variety of techniques developed for extracting texture features, have been broadly classified into the spatial and spectral methods. The spectral domain methods such as Fourier, Wavelets, Gabor filters, Radon and Hilbert transforms are most often used to extract clinical information on images recorded with different modalities (Boehm et al 2009, Gregory et al 2004, Bullmore et al 2004). Transform methods have the advantage of being insensitive to noise. Therefore, transforms have widely been used to represent image textures.
Texture analysis algorithm has a wide range of applications from random field model to multi-resolution filtering. Multi-resolution or multi-channel filtering is an effective consideration in the field of texture analysis and could mimic characteristics of the human system (Pramudito et al. 2007). The texture-based image analysis is independent of the imaging modality used, which theoretically would provide the direct estimate for individual fracture risk in terms of bone strength. Texture analysis applied to trabecular bone images offers the ability of exploiting the information present on conventional radiographs (Tourassi 1999). Several authors have reported the successful identification of osteoporotic patients from controls using texture analysis of trabecular bone derived from radiographs (Vokes et al. 2006).

Conventional radiographs are commonly used to exploit the information of trabecular texture patterns in human femur specimens (Benhamou et al. 2001). Bone structure can be estimated by observing the change of trabecular pattern in proximal femur radiograph (Pramudito et al. 2007). It has also been shown that texture analysis of X-ray radiographs could be a useful complementary tool in the investigation of bone microarchitecture and is also correlated to trabecular histomorphometry (Stauber and Muller 2006, Kreider and Goldstein 2009).

Texture and spatial pattern are important attributes of images and can be used as features in image classification. Texture metrics measure properties such as roughness or smoothness and regularity. Different methods are available to characterize the structural anisotropy on bone radiographs. In 1970, Singh et al. developed a semi-quantitative index applied to femoral neck radiographs. This index is based on the existence of several arches of trabeculae in the femoral neck. To solve the variability problem of Singh index grading system, many authors have proposed the various texture analysis methods that are robust to changes in image acquisition and
digitization. These methods should be scale invariant i.e., independent of magnification and are based on multi-scale analysis (Baduge and Dougherty 2009).

Texture analysis may use different structural or statistical approaches to extract parameters that characterize the arrangements of the patterns of the image (Apostol et al 2006). A number of image-processing techniques have been used to describe the trabecular structure. Three sets of approaches applicable to radiographic images are distinguished. The first set relies on the matrix analyses that can differentiate fractured bones, and are derived from the mean intercept length fabric tensor method. The run-length matrix method enables the inference of the trabecular direction, while the co-occurrence matrix provides texture descriptors as well as the trabecular direction. The second set of approaches is based on spatial-frequency analyses that have been correlated to bone mechanical properties. The intensity orientation method allows the inference of the dominant trabecular direction, while other power-spectrum methods allow the inference of the roughness of the trabeculae. The final set of methodologies is derived from fractal analyses where a specific feature of the image is found at different scales. The Minkowski fractal approach has the advantage of enabling the inference of the trabecular direction as well as providing a texture descriptor correlated to bone mechanical properties (Defossez 2003).

The anisotropy evaluation is possible from the texture of radiographic images. It characterizes the degree of directional organization of a material. The more preferential direction the structure has, the more important is the degree of anisotropy. The anisotropy of trabecular bone depends on the skeletal site. Several bones have already been assessed for anisotropy, such as the calcaneus, hip, vertebrae and radius. It is influenced by the main direction of strengths applied to the bone. The mean intercept length
method, fractal based texture analysis and Fast Fourier Transform (FFT) are the most currently used methods for the analysis of connectivity and architectural anisotropy (Chappard et al 2005).

Common statistical measures used in texture analysis are mean, standard deviation, energy, entropy, contrast, homogeneity, variance, correlation, maximum probability, cluster tendency and inverse difference moment (Mokji and AbuBakar 2007). Gray Level Co-occurrence Matrix (Haralick et al 1979), one of the most known texture analysis methods, estimates image properties related to second-order statistics. The description of most relevant features such as contrast, dissimilarity, inverse difference moment, energy, entropy and correlation were derived for the individual strength regions. Moment functions have a broad spectrum of applications in image analysis, such as invariant pattern recognition and object classification. However, the texture analysis methods are less sensitive to changes in spatial variation.

1.4 FRACTAL ANALYSIS

Nonlinear mathematics is used to extract texture pattern from femur bone images. The radiographic projection images are not only spectrally and spatially complex, but they often exhibit certain similarities at different spatial scales. Fractal mathematics has the power to evaluate numerically qualitative structural changes in images or signals (Huang et al 1994). They are particularly suited to characterize irregularity, complexity, roughness, and theoretically give results independent from the quantitative properties of the image. It is proved to be a useful tool in quantifying the microstructure of complex images (Lopes and Betrouni 2009). It has the property of describing such complex images by a directly computed result called Fractal Dimension (FD) (Benhamou et al 1994). The fractal dimension is a quantitative measure of self-similarity and scaling. Studies have shown that the changes in this
value are associated with changes in structural properties (Iftekharuddin et al 2003). Fractal analysis is often brought to the evaluation of the fractal dimension which allows having a global description of the inhomogeneities in the image. The applicability of this geometry in image analysis comes from the fact that the imaged object are discontinuous, complex, and fragmented (Lopes and Betrouni 2009).

Fractal geometry provides a powerful tool for the characterization and segmentation in many medical imaging applications. In recent years, fractal analysis of plain radiographs has been employed to assess the trabecular structure and to demonstrate the increased risk of fracture in osteoporosis. Assessment of trabecular microarchitecture using texture and fractal methods are shown to have potential clinical applications. It has been shown that the evaluation of structural parameters using fractals may have a complementary role in predicting bone strength. Hence, there has been considerable research interest in various fractal methods of image analysis.

The FD is very similar to the Euclidean dimension, the only difference is that Euclidean dimensions are integers and FD values are real numbers. Numerous algorithms for estimating fractal dimension have been described (Dougherty and Henebry 2001, Feltrin et al 2004). They are all based on measuring an image characteristic, chosen heuristically, as a function of a scale parameter. Generally these two quantities are linearly regressed on a log–log scale, and the fractal dimension is obtained from the resulting slope using nonparametric estimation techniques (Stein 1988). Current methods to obtain FD are surface area, semivariance, Fourier transform, and Brownian motion techniques. The method most used is the surface area, known as box counting. Box counting consists of dividing the surface image into several close square boxes until the smallest area encloses one morphologic unit which is repeated in the total image assessing trabecular
structures in radiographs of femur bone. Box Counting is combined with the gliding window method to obtain a contour map of fractal dimensions and, consequently, to provide visualization of the inhomogeneous distribution of pattern complexity (Peternell et al 2003). In normal subjects, low fractal values are obtained due to homogeneity of the trabecular patterns. The high fractal values for abnormal subjects reflect anisotropy of the trabecular structure. In Higuchi’s fractal analysis, 2-D image is preprocessed to construct two 1-D landscapes and FD values are determined from different landscapes (Klonowski et al 2010).

### 1.5 EMPIRICAL MODE DECOMPOSITION ANALYSIS

Empirical mode decomposition is a multi-scale analysis method proposed by Huang to extract texture features at multiple scales or spatial frequencies (Huang et al 1998). The decomposition method is suitable for non linear data and is based on the local characteristic of the data. Hence the method is adaptive and highly efficient. Its main idea is to decompose a given signal into a limited set of frequency components, called Intrinsic Mode Functions (IMFs). IMF is a function in which the number of extrema points and the number of zero crossings are the same or differ by one. The upper and lower envelopes of the IMF are symmetric with respect to the local mean.

The empirical mode decomposition used to analyze the two-dimensional signals is called Bi-dimensional Empirical Mode Decomposition (BEMD). BEMD is a potential image processing algorithm, which is extensively used for image enhancement as well as for feature extraction from images. BEMD can be employed for all relevant machine learning applications of image processing to enhance the performance. The BEMD method requires finding local maxima and minima points (jointly known as extrema points) and subsequent interpolation of those points at each iteration of the process. 2D extrema points are obtained using a sliding window or
various morphological operations. In the decomposition process, local maxima and minima of the image are extracted and then interpolated to form the upper and lower envelopes, respectively. Thin Plate Spline (TPS), Radial Basis Function (RBF), Hierarchical B-spline, Linear triangulation have been used as 2D scattered data interpolations for envelope surface estimation in BEMD (Nunes et al 2003, Linderhed 2009, Damerval et al 2005, Xu et al 2006).

BEMD is better than Fourier, wavelet and other decomposition algorithms in extracting intrinsic components of textures because of its data driven property. This method has been successively used for texture analysis, edge detection, texture classification, segmentation, compression and content based medical image retrieval (Nunes et al 2003). The performance of this method depends on detection of extrema points and the interpolation of the scattered extrema points.

Radial basis function based interpolation method is one of the global interpolation methods for scattered data points. RBF methods impose fewer restrictions on the geometry of the interpolation centers and are suited to problems where the interpolation centers do not form a regular grid as in the case of local maxima or minima maps appearing in the BEMD process. RBFs are well known powerful tools for high-fidelity reconstruction of surfaces from a selected set of sparse and irregular samples. Radial basis function mutliquadratic based interpolation method detects the jump discontinuities accurately.

Thin-plate smoothing spline interpolation method gives a surface with continuous second derivative everywhere. This algorithm calculates the function that minimizes the integral bending norm for given scattered data in the plane. The integral is taken over the entire image, and involves the second derivatives of function. This method turns out to successfully decompose an
image into its IMFs and a smooth residue with no or only a few extrema points. However, this implementation is extremely memory consuming and slow, because the determination of the smoothing spline involves the solution of a linear system with as many unknowns as there are data points.

Triangulation with linear interpolation works best when data are evenly distributed over the grid area. It is a very simple and fast interpolation algorithm. Hierarchical B-spline is a very fast algorithm for constructing a continuous interpolation function from arbitrary scattered data. Continuous interpolation functions are considered as the weighted average of the data, with the weights being inversely proportional to distance. In this method, high-fidelity reconstruction is achieved using a selected set of sparse and irregular samples.

Directional Empirical Mode Decomposition (DEMD), which takes image direction into account in the decomposition, and extracts feature values for each pixel. DEMD is significantly different from the classical multi-scale structure. Firstly, the distances between extrema are introduced to make the local scale. Therefore, the DEMD decomposition is self-adaptive and completely data-driven. Secondly, an iteration method is adopted to extract each component. For these reasons, the DEMD is locally self-adaptive, which is a unique advantage in extracting the content for visual perception (Zhang et al 2008).

Ensemble EMD (EEMD) defines the IMF components as the mean of an ensemble, each consisting of the signal plus a white noise of finite amplitude. The true IMF should be the result when the number of the ensemble approaches to infinity. EEMD is a noise assisted data analysis method that overcomes many drawbacks of EMD such as the sensitivity of decomposition to small perturbation of data. It will be demonstrated that, with good properties of EEMD, the inter-slice discontinuity existed in pseudo-
BEMD is no longer a daunting problem. The decompositions of image are obtained by applying EEMD to spatial data in one dimension and then followed by applying EEMD in the second dimension to the results of the decompositions of the first dimension, and then applying a new strategy of combination of appropriate components. It will be shown that this EEMD-based bi-dimensional approach can be extended to spatial data of any number of dimensions (Wu et al 2009).

1.6 SPECTRAL METHODS

Two-dimensional transforms have been used extensively in image processing to tackle problems such as image description and enhancement. Fourier transform is one of the most widely used methods. Fourier analysis can be used to study the properties of textured scenes, wherein the power spectrum reveals information on the coarseness, periodicity and directionality of a texture (Gonzalez and Woods 2001). The discrete wavelet transforms is proven to be effective in the fields of image de-noising, compression and estimation, but these transforms cannot yield an optimal discrete-time basis from the point of view of time localization.

The Hilbert-Huang transform (HHT) consists of empirical mode decomposition and Hilbert spectral analysis (Huang et al 1998). HHT have found many successful applications in analyzing a very diverse range of data sets in biological and medical sciences, geology, astronomy, engineering, and others. Hilbert-Huang transform offers much better temporal and frequency resolutions when compared to wavelet and Fourier transform analyses. This method permits analyzing 1D nonlinear and non-stationary data. EMD reflects the decomposition for the multi-texture images and Hilbert spectrum computes the local frequencies. Hilbert Transform (HT) of the IMFs lead to meaningful representations for the instantaneous frequency of the data.
HT is applied to the decomposed IMFs and the energy, frequency, time distribution, designated as the Hilbert spectrum are constructed, from which the time localities of events will be preserved.

There are some drawbacks in the application of HHT. The EMD may generate undesired low- or high-amplitude IMFs at the low-frequency region, and bring up some undesired frequency components. The first IMF may cover a wide frequency range at the high-frequency region and therefore cannot satisfy the monocomponent definition well and it contain most of the noise in the original signal and the EMD operation often cannot separate some low-energy components from the analysis signal, therefore, those components may not appear in the frequency–time plane (Ayenu-Prah et al 2010). Different approaches such as total Hilbert transform, the partial Hilbert transform, the total analytic signal and the quaternionic analytic signal (Bulow and Sommer 2001) have been proposed to a n-Dimensional (nD) analytic signal. The quaternionic analytic signal is found to overcome the problems of HHT and is compatible with the associated harmonic transform (Bulow and Sommer 2001).

Quaternion Hilbert transform, proposed by Bulow and Sommer (2001), is an important tool to analyze the frequency, amplitude, phase, direction and intrinsic dimension for the IMFs (Xu et al 2008). The QHT is the optimal selection because it can give more useful information than other HTs. QHT gives the information of the frequency, amplitude, phase, direction and intrinsic dimension of the 2D signals simultaneously. Performing QHT on every IMF is beneficial for the textural analysis. Orthonormal complex modulation can be represented mathematically by a polar representation of quaternions. Complex-valued samples are obtained using a quaternion-valued equivalent of the analytic signal obtained from a one-sided quaternion Fourier transform which refer to as the hypercomplex representation of the complex
signal. The hypercomplex representation may be interpreted as an ordered pair of complex signals or as a quaternion signal.

1.7 CLASSIFICATION TECHNIQUES

Growing interest in neural networks and learning algorithms have given the area of medical image analysis great impetus (Vani et al 2010). Conventionally, radiologists infer diagnoses on the basis of a combination of their training, experience, and individual judgment. Radiologists perceive and recognize image patterns and infer a diagnosis consistent with those patterns. It follows that there will be an inevitable degree of variability in image interpretation as long as it relies primarily on human visual perception (Kassner and Thornhill 2010). Tools for automated pattern recognition and image analysis can provide objective information to support clinical decision-making and may serve to reduce this variability.

Artificial Neural Networks (ANN) have been used successfully in prediction and classification of signals, images and data (Gaetano 2004). They are mathematical algorithms that approach the functionality of small neural clusters. ANN is trained from the input parameters and the trained network can be employed for prediction and classification of a set of information. The advantage of neural networks is that they can be used to predict one or more output types through a flexible network of weights, transfer functions and input variables (Sachin et al 2007). They have been used in a great number of medical diagnostic decision support systems (Benardos and Vosniakos 2007). ANNs are found to be efficient in the classification of non-periodic and nonlinear types of signals and are extensively used in cardiology, gastroenterology, pulmonology, oncology, neurology, ophthalmology, and radiology. ANN have also been used for classification of mechanical strength components of human femur trabecular bone using texture analysis (Christopher and Ramakrishnan 2007).
Neural networks offer a number of advantages such as ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. However, it has a characteristic of “black box” nature, greater computational burden, sometimes require thousands of epochs, proneness to over-fitting, and the empirical nature of model development (Tu 1996).

1.7.1 Support Vector Machines

Support Vector Machines (SVM) is a machine learning technique based on statistical theory. It is proposed by Vapnik in 1995. It has received considerable attention in the recent past and is extensively used for the problems of regression and classification. The merit of SVM lies in the theory of the structural risk minimization principle in estimating a function by minimizing an upper bound of the generalization error. Another key property of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimum (Andrea et al 2004, Chen et al 2008).

The principle of SVM is to find a maximum margin hyperplane for classification, which is achieved by mapping the instances to a higher dimensional space. The kernel functions allow mapping to a higher dimensional space. This reduces computational complexity and connects the input space and the higher dimensional space directly. SVM chooses a maximum soft margin separating hyperplane in this higher dimensional space that separates the training instances by their classes. The classification of a test sample will be determined by a signed function and is defined by the parameters of the hyperplane. The instances closest to the hyperplane are
called support vectors and are vital for training (Vapnik 1995, Scholkopf et al 1997).

SVM has high classification accuracy and less prediction error due to the properties such as efficient solutions, relatively few adjustable parameters and the interchangeable use of kernel functions. It discriminates the data by creating boundaries between classes rather than estimating class conditional densities and needs considerably less data to perform accurate classification. With a suitable kernel, SVM can separate the data in the feature space that was non separable in the original input space. A kernel function has a good performance if the numbers of support vectors calculated by using the corresponding transformation are few and the classification of the test data is successful. Support vector set is enriched by those training examples that cannot be classified by the model correctly (Akay et al 2009).

1.8 OBJECTIVES OF THE THESIS

The objectives of the thesis are

- To acquire radiographic images under controlled protocol
- To perform preprocessing and delineate the regions of interest
- To apply empirical mode decomposition using various interpolation methods
- To validate the intrinsic mode functions using performance metrics
- To extract the texture features and fractal dimension from intrinsic mode functions
- To extract the quaternion features of intrinsic mode functions
To analyze the extracted features based on correlation with apparent porosity and

To classify normal and abnormal femur images using support vector machines

1.9 ORGANIZATION OF THE THESIS

The work reported in the thesis is organized into five chapters. Chapter 2 gives a comprehensive review of literature on assessment of trabecular architecture using various image processing techniques. The techniques include empirical mode decomposition, fractal and quaternion Hilbert transform analyses. Chapter 3 describes the methods and protocols. Chapter 4 focuses on the results of the above mentioned methods. Chapter 5 deals with the significant conclusions and scope for future work.