Application of Image Processing Techniques to Bone Radiograph Images for Osteoporosis Diagnosis

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Introduction

- Osteoporosis is a disease characterized by low bone mass and loss of bone tissue that may lead to weak and fragile bones. About 54 million Americans have low bone mass, placing them at increased risk of osteoporosis.
- Automated diagnosis presents a major challenge due to high visual similarity between osteoporotic and healthy images.
- We use 2D texture analysis for bone structure characterization which ensures a better fracture prediction rate than the bone mineral density tests.
- We focus on the use of various feature extraction methods with different classification techniques. We further investigate the performance of our method when subject to noise and distortion.

Methods

⇒ **Statistical features**

- Represents the texture by properties that govern the relationship between the grayscale levels of the image.
- First and second order statistical measures were extracted from the GLCM.

⇒ **Local Binary Patterns**

- Robust for grayscale and rotation invariant texture classification.
- Compares intensity values of each pixel and its neighbors and assigns an 8 digit binary number for each histogram bin.

⇒ **Fractal Analysis**

- Segmentation based fractal analysis to describe segmented texture patterns.
- Fractal dimensions, area and mean intensity constitute the feature vector.

⇒ **Gabor Filter**

- A linear filter used to analyze frequency in specific directions in a localized region.
- A set of these filters with different frequencies and orientations help in extracting useful features.

$$G_c[i,j] = Be^{\frac{-(i^2+j^2)}{2\sigma^2}} cos(2f\pi(icos\theta + jsin\theta))$$

$$G_s[i,j] = Ce^{\frac{-(i^2+j^2)}{2\sigma^2}} cos(2f\pi(icos\theta + jsin\theta))$$

⇒ **Covariance Based**

- Covariance matrix is given by:

$$C = \frac{1}{n-1}\sum_{i,j}(f_{ij} - \bar{f})(f_{ij} - \bar{f})^T$$

- We use gradient based features for each pixel:

$$f_{ij} = \Big[I^{ij}, |I_x^{ij}|, |I_y^{ij}|, |I_{xx}^{ij}|, |I_{yy}^{ij}|, \sqrt{(I_x^{ij})^2 + (I_{xy}^{ij})^2}, arctan\frac{|I_x^{ij}|}{|I_y^{ij}|}\Big]^T$$

⇒ **Non Directional Transform based**

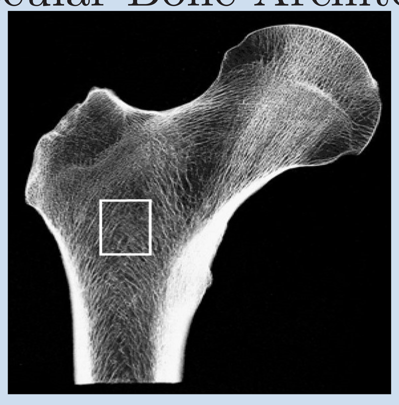
- Lower frequencies indicate coarseness and higher frequencies represent fine textures.
- Mean of the Haar high frequency wavelet coefficients along horizontal and vertical direction constitutes the feature vector.

⇒ **Directional Transform based**

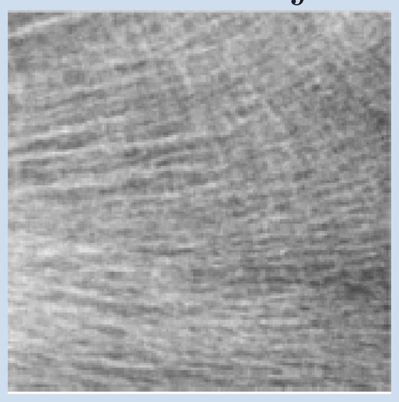
- Curvelets are an extension of wavelets where the basis functions are localized in orientation as well.
- The feature vector consists of the mean of the curvelet coefficients in the higher frequency sub-bands.

Dataset

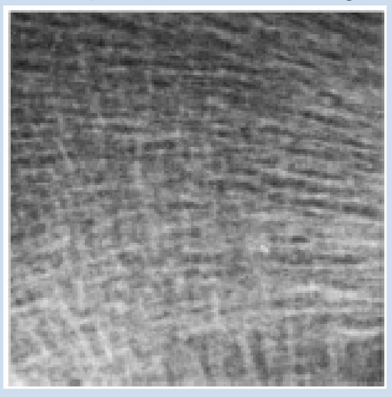
Trabecular Bone Architecture



Control Subject



Osteoporotic Subject

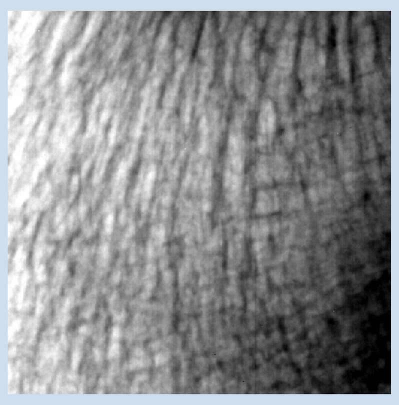


Our dataset consists of 58 osteoporotic and 58 control subjects as shown above.

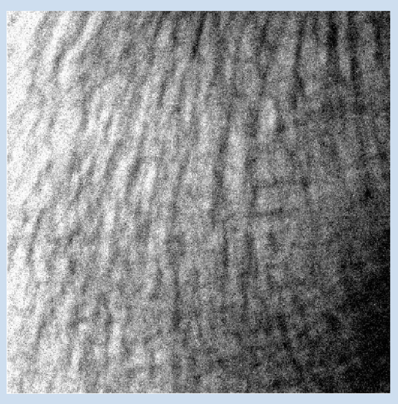
Pre-Processing

Before Pre-processing

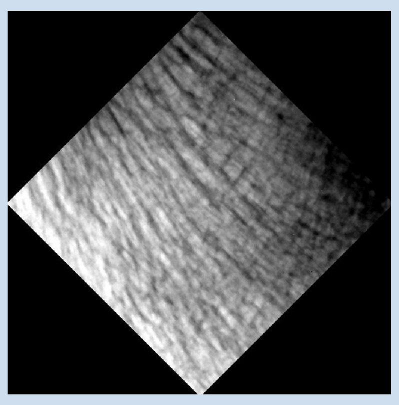
Contrast Enhanced



With Gaussian Noise



With Distortion



Our first step involves adjusting the intensity values to enhance contrast. We initially test our method assuming noiseless images. We then evaluate our methods in the case of noisy images (Gaussian Noise with 0 mean and 0.01 variance) and images with distortion (Rotation of 45°). In the latter cases, wiener filter and rotation correction measures have been implemented in the pre-processing steps as well.

Experiments and Results

Classification results using all features for Noisy & Distorted images

All Features		Noise	Angular Distortion	Noise & Distortion
SVM	TPR	0	0	5.56
	TNR	5.56	5.56	5.56
	ACC	47.22	**47.22**	50
Boosting Technique (Adaboost)	TPR	94.44	100	100
	TNR	88.89	100	100
	ACC	**52.78**	50	50
Ensemble Method (Random	TPR	50	83.33	50
	TNR	50	88.89	33.33
	ACC	50	**47.22**	**58.33**

Classification results for sets of features:

Noiseless Partition		All	Transform	Spatial	Directional	Non-Directional
SVM	TPR	0	0	22.22	5.56	0
	TNR	5.56	0	50	11.11	0
	ACC	47.22	**50**	36.11	47.22	**50**
Boosting Technique (Adaboost)	TPR	77.78	72.22	77.78	72.22	38.89
	TNR	66.66	55.56	66.66	27.78	44.44
	ACC	55.56	58.33	55.56	**72.22**	47.22
Ensemble Method (Random	TPR	50	38.89	55.56	66.67	11.11
	TNR	22.22	77.78	38.89	22.22	38.89
	ACC	63.89	30.56	58.33	**72.22**	36.11

- For SVM classifier, transform features contribute the most towards prediction.
- For AdaBoost & Random Forest classification, performance of curvelets were far superior when compared to other feature sets.
- Thus, directionality is a good measure of the textural differences between visually similar images.
- Despite disturbances, there is no change in accuracy for SVM classifier. Shows that SVM is ineffective.
- Random Forest & Adaboost tend to perform well even in the presence of noise & distortion.

Conclusion

- Our results show that degradation of the bone architecture in bone radiograph images can be identified by texture analysis.
- A prediction rate of 72.22% was achieved despite high visual similarity between the two classes.
- In future, we plan to use feature selection techniques for more robust classification and also to minimize the sensitivity of the covariance metric to outliers.

References

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[3] Yuting Hu, Zhiling Long, Ghassan AlRegib, et al. Scale selective extended local binary pattern for texture classification. 2017.