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ANALYZE AND DIFFERENTIATE URIC ACID STONES AND CALCIUM STONES FROM IMAGES USING STATISTICAL PARAMETERS

G.M. Nasira[1] and M. Ranjitha[2]
[1]*Department of Computer Science, Chikkana Government Arts College, India*
E-mail: nasiragm99@yahoo.com
[2]*Department of Information Technology, CMR Institute of Management Studies, India*
E-mail: ranjitha_m@hotmail.com

Abstract

Image analysis plays a vital role in medical diagnostics. Analysing texture is a major source of discrimination in image analysis. In this paper, we have worked on and analysed images of kidney stones to differentiate between the chemical compositions of different types of stone. The most common types of stones are Calcium and Uric acid stone, hence our study focuses on these two categories. Identifying chemical composition is very crucial as it helps the patients to keep a control on their diet. A statistical comparison is made between these two categories and we have observed significant difference in various classic parameters. A new approach is presented that uses only selected statistical parameters and hence it differs from all previous approaches that differentiates the different types of stones from images without clinical interference.

Keywords:

Image Analysis, Uric Acid Stones, Calcium Stones, Entropy, Energy

1. INTRODUCTION

One of the common ailments in the modern society is kidney stone which is otherwise called as Renal Calculi. About 70% of the human population suffers from either kidney stone or gall stones. There are various factors that results in this ailment. Food habits can be considered as one of the major causes of this ailment in today's urban society. There are different types of kidney stones depending on its mineral components. The most common ones are Calcium oxalate, Calcium phosphate, Uric Acid, Struvite and Cystine stones. These stones will not be in its pure form. It can be the combination of many minerals like calcium, oxalate, phosphate etc. Calcium-containing stones are the most popular type and 80% of all cases are diagnosed with this type of stone. These stones typically contain calcium oxalate either alone or in combination with calcium phosphate in the form of apatite or brushite [1]-[3]. Some of the common factors which results in calcium stones are too much calcium absorption in the intestines, Excessive chloride (Excess chloride may lead to excess calcium), Renal calcium leak and Excessive sodium. High protein and salt intake increases the risk of calcium stone formation. Calcium that is not used by the bones and muscles goes to the kidneys. In most people, the kidneys flush out the extra calcium with the rest of the urine. Uric acid kidney stones occur because the body is unable to process the uric acid. The factors which results in uric acid stones are High Purine diets, Gout, Diabetes, Insulin resistance, Kidney abnormalities, Genetic factors, Hypocitraturia etc. Knowledge of this fact is the basis for the medical treatment of uric acid stones. People with certain metabolic abnormalities, including obesity may also produce uric acid stones [4]. Kidney stones are formed by crystal nucleation, growth and aggregation process. Stones once passed or retrieved were analyzed by Laboratory Investigation and based on their chemical composition it is classified into its different categories.

2. RELATED METHOD

A vitro study was conducted by Fung GS et al [5] by examining three protocols of dual-energy CT imaging to distinguish calcium oxalate, calcium phosphate, and uric acid kidney stones. Stone samples were placed in individual containers inside a cylindrical water phantom and imaged using dual energy CT scanner using the three protocols of different combinations of tube voltage with and without tin filter. The protocols were 80 and 140 kVp without a tin filter, 100 and 140 kVp with a tin filter, and 80 and 140 kVp with a tin filter. The mean attenuation value of each stone was recorded in both low and high energy CT images in each protocol. The dual energy ratio of these mean values was computed for each protocol. For all the three protocols, the uric acid stones were significantly different from the calciferous stones according to their dual-energy ratio values [5]. Nakada SY et al had worked on peak attenuation measurements and the attenuation/size ratio of urinary calculi from NCCT (Non Contrast Computed Tomography) to differentiate between uric acid and calcium oxalate stones [6].

3. STATISTICAL APPROACHES

There are different Statistical methods used to analyze the spatial distribution of gray values, by computing local features at each point in the image. Various statistics can be derived from the distributions of local features [7]. Spatial distribution of gray values is one of the qualities which describe the texture of an image. Various Statistical parameters can be used for the description of textures as fine or coarse. Pixels in an image are characterized by its tonal and location properties. Textures can be characterized by the average intensity, maximum intensity, minimum intensity etc. Some of the common features that can be used for texture analysis are Mean, Entropy, Homogeneity, Contrast, Energy and correlation. Among these, one of the basic statistical measure is mean. It is often used in geometry and analysis.

$$Mean = \frac{1}{N^2}\sum_{m=0}^{J-1}\sum_{n=0}^{K-1}F(m,n) \tag{1}$$

where, $F(m, n)$ is the image matrix and 'm' and 'n' are the row and column coordinates respectively for an image of size $J \times K$. Entropy is an efficient statistical measure to calculate the disorder or complexity of an image. The entropy is large when the image is not textually uniform and many GLCM (Gray Level Co-Occurrence Matrix) elements have very small values. Complex textures tend to have high entropy. Entropy is strongly, but inversely correlated to energy.

$$Entropy = -\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} F(i, j)\log(F(i, j)) \tag{2}$$

Homogeneity is also called the inverse difference moment. If weights decrease away from the diagonal, the result will be larger for windows with little contrast.

$$Homogeneity = \sum_{i=0}^{N-1}\sum_{j=0}^{M-1} \{F(i, j)\}^2 \tag{3}$$

Contrast is an indicator of local variations. For images having uniform intensity, this value is zero.

$$Contrast = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N}\sum_{j=1}^{N} F(i, j) \right\}, |i-j| = n \tag{4}$$

Energy is the sum of brightness values of all pixels in an image.

Spatial gray level co-occurrence can estimate the image properties related to second order statistics which considers the relationship among a group of pixels. Harlick [8]-[10] suggested the use of gray level co-occurrence matrices (GLCM) which have become one of the most well-known and widely used texture features. This method is based on the joint probability distributions of pairs of pixels. GLCM (Gray Level Co-occurrence Matrix) shows how often each gray level occurs at a pixel located at a fixed geometric position relative to each other pixel. Analysis or conclusions of our results are based on Mean, Standard deviation, Correlation, Covariance, Skewness and Kurtosis.

Standard deviation measures variability of diversity. It shows how much variation or dispersion exists from the mean. Low standard deviation suggests that data points tend to be very close to the mean and high values indicates that the data points are spread out over a large range of values. Standard Deviation is given by,

$$SD = \sqrt{1 \big/ MN \sum_{i=1}^{N}\sum_{j=1}^{M} (p(i, j) - \mu)^2} \tag{5}$$

Correlation measures the image linearity. In images it measures the linear dependence of gray levels of neighbouring pixels.

$$Correlation = Cov(x, y) \big/ S_x S_y \tag{6}$$

where, S_x = sample standard deviation of the random variable x and S_y = sample standard deviation of the random variable y.

Covariance indicates how two pixels are related. A positive covariance means the variables are positively related, while a negative covariance means the variables are inversely related. Covariance measures how much two variables change together [11]-[13]. When both the variables are of similar characteristics, covariance is a positive number. When both are of different behaviours, the covariance is negative. This is represented mathematically as,

$$\text{Covariance} = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \big/ n - 1 \tag{7}$$

Skewness [14]-[16] measures the asymmetry of the probability distribution that is it indicates the asymmetry about mean in the gray level distribution. In image processing it represents the asymmetry of intensity distribution. A positive skew indicates that the tail on the right side is longer than the left and most of the intensity values are on the left of mean. A negative skew indicates that the tail on the left side is longer than the right and more values lies on the right of mean. A darker and glossier surface tends to be positively skewed than the lighter and matt surface and this parameter can be used for making judgements about image surfaces.

$$Skewness = 1 \big/ MN \sum_{i=1}^{M}\sum_{j=1}^{N} [(p(i, j) - \mu)/\sigma]^3 \tag{8}$$

where, $p(i, j)$ is the pixel value at point (i, j), μ and σ are the mean and standard deviation respectively.

Kurtosis indicates the uniformity of the intensity distribution. A high kurtosis distribution has longer, fatter tails, and often (but not always) a sharper peak. A low kurtosis distribution has shorter, thinner tails, and often (but not always) a more rounded peak. Mathematically kurtosis is given as follows [17].

$$Kurtosis = 1 \big/ MN \sum_{i=1}^{M}\sum_{j=1}^{N} [(p(i, j) - \mu)/\sigma]^4 - 3 \tag{9}$$

where, $p(i, j)$ is the pixel value at point (i, j), μ and σ are the mean and standard deviation respectively.

4. RESULTS AND DISCUSSIONS

We have conducted our study on sample images of more than 200 and analysed the results based on these images. There were different types of stones in those images but we have focussed only on two types- Uric and Calcium. Entropy, Homogeneity, Contrast, Energy and Correlation were calculated for each of these stones separately for 0 degrees, 45 degrees, 90 degrees and 135 degrees (degrees represent the relationship of pixels in the respective direction). It has been observed that the mean value for Correlation, Energy, Homogeneity and Entropy is higher for Calcium stones than Uric Acid Stones whereas Contrast of calcium stone is less than uric stones. Fig.1 demonstrates our results.

We have analysed our results using some simple statistical parameters like Standard Deviation, Correlation, Covariance, Skewness and Kurtosis. This has been conducted between Calcium Stones and Uric acid stones for different properties like Entropy, homogeneity, contrast, energy and correlation which was calculated for different degrees of GLCM (for 0 degrees, 45 degrees, 90 degrees and 135 degrees). Sample result for 0 degrees is shown in Table.1 and Fig.2. We have observed significant differences in values for the various parameters under consideration which has been described earlier.

Table.1. Comparison between Calcium and Uric Acid Stones -GLCM for 0 degrees

Statistical Parameters	Entropy	Homogeneity	Contrast	Energy	Correlation
Standard Deviation	0.57669	0.06809	0.36415	0.05735	0.08963
Correlation (Uric and Calcium Stones)	-0.01273	0.05334	0.04047	0.01671	0.24804
Covariance	-0.00299	0.00019	0.00309	0.000484	0.00145
Skewness	-0.82299	-0.6065614	2.06138	0.884222	-0.52194
Kurtosis	0.73333	-0.040103	5.320126	0.045593	0.34706

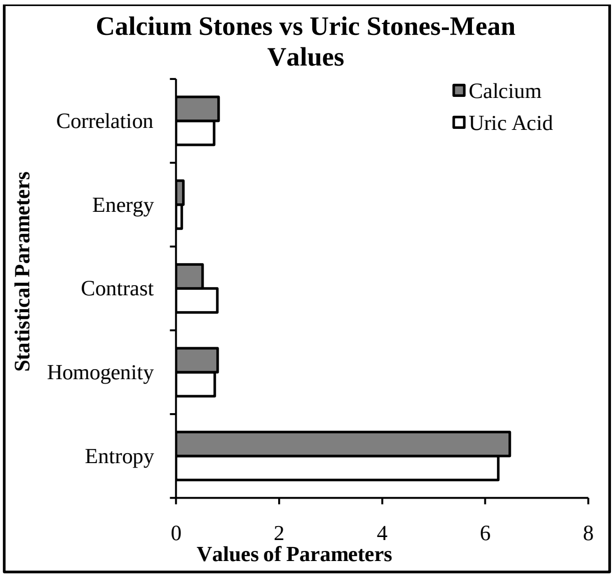

Fig.1. Comparison of Mean Values

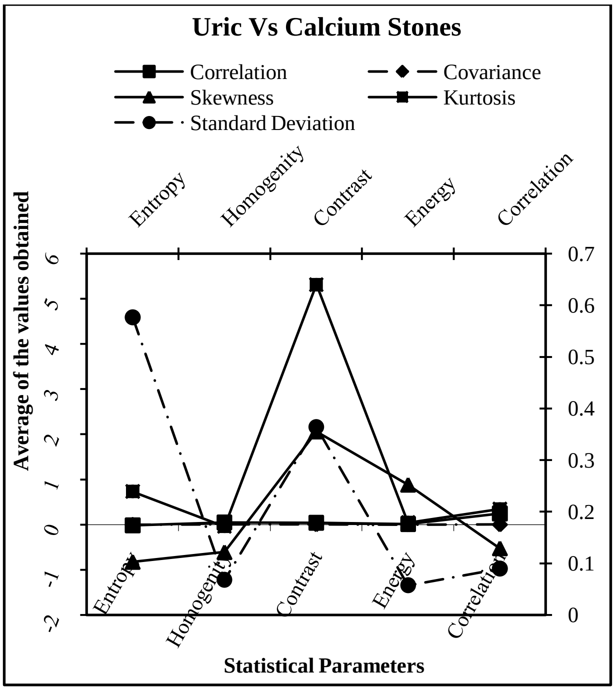

Fig.2.GLCM for 0 degrees

The Standard Deviation (the variation from mean) and Kurtosis is above 0.5 for entropy which is considered as significant. A positive kurtosis image have a moderately uniform distribution of gray levels but not many at the extreme values, while a negative kurtosis image have mid-level gray values that are quite prevailing. When kurtosis is high, we can conclude that there are more pixels with dominant gray levels and very few pixels with other gray levels. In our study Kurtosis for Entropy, Contrast, Energy and Correlation are positive which implies that gray levels are uniformly distributed for both types of images. Similarly skewness shows the asymmetry of intensity values between images which is on higher side for energy. This infers that there is trivial difference in energy values between Calcium stones and Uric stones.

5. CONCLUSION

We have conducted study on various GLCM (Gray Level Co Occurrence Matrix) parameters like Entropy, homogeneity, contrast, Energy and correlation for 0 degrees, 45 degrees, 90 degrees and 135 degrees for calcium stones as well as Uric acid stones. Significant difference in various properties like Correlation, Covariance, SD (Standard Deviation), Skewness and Kurtosis were observed. The prominent difference was in Entropy and Energy which implies that there is some substantial difference between Calcium and Uric stone Images. We have come to the conclusion that the Entropy and Energy parameters are important for the classification of different types of stones. Our study can be extended to other types of stones like Struvite and Cystine as well.

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