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A NOVEL METHOD OF RETRIVAL OF NOISY IMAGES BASED ON REDUCED TEXTURE SPECTRUM

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ABSTRACT
Some of the digital images in real world are intensity images that carry less information, more noise, less resolution and poor illumination levels. In such cases the existing retrieval system fails in retrieving the relevant images. This is because the chosen similarity features in those systems are not effective for the above types of image retrieval. To address these issues the present work proposed a new similarity texture feature derived from the novel idea of reduced texture unit with different lag values. Due to the advent of digital imaging the need of data storage and retrieval of medical images increased rapidly. Some difficulties in retrieving the medical images are: medical images have only intensity images that carry less information, more noise, with poor resolution and illumination levels. Therefore the records of medical images are large and complex to analyze. To address this intensified problem of medical image retrieval, the present study used the proposed novel approach of retrieval system on medical images. The increasing reliance of modern medicine on diagnostic techniques such as radiology, Computerized Tomography (CT) has resulted in an explosion in the number and importance of medical images.

INTRODUCTION
Some of the digital images in real world are intensity images that carry less information, more noise, less resolution and poor illumination levels. In such cases the existing retrieval system fails in retrieving the relevant images. This is because the chosen similarity features in those systems are not effective for the above types of image retrieval. To address these issues the present work proposed a new similarity texture feature derived from the novel idea of reduced texture unit with different lag values. Texture is an important spatial feature useful for identifying objects or regions of interest in an image. The Texture Unit (TU) extracts textural information of an image with a more complete respect of texture characteristics in all the eight directions instead of only one displacement vector. The basic TU ranges from 0 to 6561 units on a 3 x 3 mask as proposed by He and Wang. Though the basic TU represents good and efficient texture features, but the range of this basic TU which is 0 to 6561, is too large and complex measure for obtaining texture spectrum by which a similarity feature can be built. To overcome this present study reduces the texture unit range from 0 to 255 with different lag values and obtained a texture spectrum for efficient retrieval. Medical images have become the recent key investigation tools for medical

diagnosis and treatment planning. Due to the advent of digital imaging the need of data storage and retrieval of medical images increased rapidly. Some difficulties in retrieving the medical images are: medical images have only intensity images that carry less information, more noise, with poor resolution and illumination levels. Therefore the records of medical images are large and complex to analyze. To address this intensified problem of medical image retrieval, the present study used the proposed novel approach of retrieval system on medical images. The increasing reliance of modern medicine on diagnostic techniques such as radiology, Computerized Tomography (CT) has resulted in an explosion in the number and importance of medical images.

2. MEDICAL CBIR

Medical Image acquisition devices such as Computed Tomography (CT) scanners, Magnetic Resonance Imagers (MRI), Ultrasound Probes (Us) provide images with various properties in terms of resolution, contrast and signal to noise ratio. They also produce images with different information on the human body anatomy and physiology. Development of medical image indexing and retrieval tools is difficult because of certain factors such as

1. In most cases, medical images are only intensity images carrying less information than colour images. In some rare cases however, vectorial images may be produced (e.g. tensor MRI). More frequently, multimodality images of a same body may be acquired (e.g. MRI and ultrasound images of the same area). However, multiple images are usually not aligned in space and require an additional registration procedure.

2. Medical images are usually of low resolution and high noise images. They are difficult to analyze for extracting features automatically. Medical images acquired with different devices, even using the same modality, may have significantly varying properties. Some authors proposed image correction and normalization algorithms to improve image comparison.

3. Ideally, medical images should be indeed on medical criteria that are extremely variable depending on the kind of image acquisition considered (imaged body area, clinical context, etc). Moreover, automatic diagnosis in medical images is mostly impossible today except in rare specific cases. Medical images interpretation is often difficult even for trained radiologists.

As a consequence, medical CBIRs require a high level of content understanding and interpretation of images, which is possible by exploring texture features. Finally, a high level of query completion and accuracy is required by such systems to make them reliable from a clinical point of view. To overcome the difficulties caused due to medical images, the present work proposes a novel scheme based on texture unit. The proposed scheme reduces texture unit values from 0 to 6561 to 0 to 255 based on lag

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values. The similarity measures Integrated Histogram Bin matching (IHBM) are applied on the proposed texture features.

3. FEATURE EXTRACTION AND REPRESENTATION

i. The Texture

Texture is one of the crucial primitives in human vision and texture features have been used to identify content of images. Texture refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. Texture contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment. One crucial distinction between color and texture features is that color is a point, or pixel, property, whereas texture is a local-neighborhood property. As a result, it does not make any sense to discuss the texture content at pixel level without considering the neighborhood. Texture has long been an important topic in image processing. Methods of texture analysis are usually divided into two major categories. The first is the structural approach, where texture is considered as a repetition of some primitives, with a specific rule of placement. The traditional Fourier spectrum analysis and wavelet based analysis are often used to determine the primitives and placement rule. Several authors have applied these methods to texture classification and texture characterization with a certain degree of success. The second major approach in texture analysis is statistical method. Its aim is to characterize the stochastic properties of the spatial distribution of gray levels in an image. The gray tone co-occurrence matrix is frequently used for such characteristics. A set of textural features derived from the co-occurrence matrix is widely used to extract textural information from digital images. Study of patterns on textures is recognized as an important step in characterization and classification of textures. Textures are classified by various pattern methods, viz., preprocessed images, long linear patterns, and edge direction movements, avoiding complex patterns, marble texture description. Textures are also described and classified by using various wavelet transforms: one based on primitive patterns, and another based on statistical parameters.

ii. Texture Unit and Texture Spectrum

The texture image can be decomposed into a set of essential small units, called Texture Units (TU). As the TU represents the local texture aspect, the statistics of TU's in an image should reveal its texture information. The occurrence distribution of TU's is called as Texture Spectrum (TS), with the 'abscissa' indicating the type of TU and the 'ordinate' representing its occurrence frequency. This section gives a brief review of the TU and proposes different methods of calculating TU, from which TS will be constructed. The TU is introduced and described in detail by D.C. He and Li Wang. The basic concept is that a texture image can be considered as a set of essential small units termed as TU's, which characterize the local texture information for a given pixel and its neighborhood.

In a square-raster digital image, each pixel is surrounded by eight neighboring pixels. The local texture information for a pixel can be extracted from a neighborhood of 3×3

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pixels, which represents the smallest complete unit (in the sense of having eight directions surrounding the pixel). A neighborhood of 3×3 pixels is denoted by a set containing nine elements: $V = \{V_0, V_1 \ldots V_8\}$, here V_0 represents the intensity value of the central pixel and V_i $\{i = 1, 2 \ldots 8\}$, is the intensity value of the neighboring pixel i. Based on this the corresponding TU is defined by a set containing eight elements. TU = $\{E_1, E_2 \ldots E_8\}$, where E_i (i=1, 2….8) is determined by the formula given in equation 1 and the element E_i occupies the same position as the pixel i.

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i = V_0 \\ 2 & \text{if } V_i > V_0 \end{cases} \quad \text{for: } i = 1,2, \ldots 8 \qquad (1)$$

The basic TU's are labeled by using the following equation 3.2, as also represented in Fig. 1. As each element of TU has one of the three possible values, the combination of all the eight elements results in $3^8 = 6561$ possible TU's in total. The texture elements can be ordered clockwise around the centre pixel. The first element may take eight possible positions from the top left corner to the left middle. There is no unique way to label and order the 6561 TU's. These TU's are labeled and ordered in different ways.

$$N_{TU} = \sum_{i=1}^{8} E_i 3^{i-1}, \quad N_{TU} \in \{0, 1, 2 \ldots (N^{8-1})\} \qquad (2)$$

V_1	V_2	V_3		$E_1 \times 3^0$	$E_2 \times 3^1$	$E_3 \times 3^2$
V_8	V_0	V_4		$E_8 \times 3^7$		$E_4 \times 3^3$
V_7	V_6	V_5		$E_7 \times 3^6$	$E_6 \times 3^5$	$E_5 \times 3^4$

Fig.1 Representation of Texture Elements.

iii Novel Approaches of Evaluating Texture Features for Efficient Medical Image Retrieval System

For building effective image retrieval system, especially with images of noise, poor resolution and illumination levels, the most important and crucial factor is selection of the appropriate and efficient similarity feature. For this the proposed study proposed three novel methods. The method 1 is named as Reduced Texture Spectrum (RTS) and the method 2 is named as Lag value based Reduced Texture spectrum (LRTS) and the method 3 is named as Fuzzy Texture Spectrum (FTS).

4. REDUCED TEXTURE SPECTRUM RTS

A New Similarity Feature Reduced Texture Spectrum for an Effective Image Retrieval System. In Reduced Texture Spectrum (RTS), the texture unit is defined by the following equation 3.

$$E_i = \begin{cases} 0 & \text{if } V_i \leqq V_o \\ 1 & \text{if } V_i \geqq V_o \end{cases} \quad \text{for i} = 1,2,\ldots 8 \qquad (3)$$

and the element E_i occupies the same position as the pixel i. Since each element of TU in the present method has one of the two possible values, the combination of all the eight elements results in $2^8 = 256$ possible TU's in total. There is no unique way to label and order the 256 TU's. The 256 TU's are labeled by using the following equation 4:

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$$N_{TU} = \sum_{i=1}^{8} E_i \times 2^{i-1}, \quad N_{TU} \in \{0, 1, 2\ldots (2^{8-1})\} \qquad (4)$$

63	28	45
88	**40**	35
67	40	21

(a)

1	0	1
1		0
1	1	0

(b)

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(c)

1	0	2
128		0
64	32	0

(d)

Fig. 2 Transformation model of a neighbourhood to a texture unit by the proposed RTS.

Here NTU represents the TU number and E_i is the i[th] element of TU set TU = {E_1, E_2… E_8}. An example of proposed TU is given below in Fig 3.

Fig.2 Transformation model of a neighborhood to a Texture Unit by the proposed RTS: 1.2 (a) Sample Grey level Neighborhood, (b) Conversion of Fig.1.2 (a) into Binary Neighborhood, (c) Representation of Binary Weights of TU, (d) Represented Values with Binary Weights.

Fig. 2 shows an example on how to compute TU. The original 3×3 neighborhood is given in Fig. 2 (a). The central pixel value is used as a threshold in order to assign a binary value to its neighbors. Fig. 2 (b) shows the result after the thresholding the 3 X 3 neighborhood, with central pixel as specified in equation 3. The obtained values are multiplied by their corresponding weights as shown by Fig. 2 (c). The result is given in Fig. 2 (d). The sum of the resulting values gives the TU which is 227 in this case. Therefore the central pixel 40 is replaced by the obtained TU value 227. A new TU image is constructed by processing each pixel and its 3×3 neighbors in the original image. The binary weights of Fig. 2 (c) can be given in eight different ways as shown in Fig 3.

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(a)

2^7	2^0	2^1
2^6		2^2
2^5	2^4	2^3

(b)

2^6	2^7	2^0
2^5		2^1
2^4	2^3	2^2

(c)

2^5	2^6	2^7
2^4		2^0
2^3	2^2	2^1

(d)

2^4	2^5	2^6
2^3		2^7
2^2	2^1	2^0

(e)

2^3	2^4	2^5
2^2		2^6
2^1	2^0	2^7

(f)

2^2	2^3	2^4
2^1		2^5
2^0	2^7	2^6

(g)

2^1	2^2	2^3
2^0		2^4
2^7	2^6	2^5

(h)

Fig. 3 Eight Different Ways of Calculating TU on a 3 X 3 Neighbourhood

The value of the TU changes by the representation of the weights. The TU can be calculated in 8 different ways for a 3X3 neighbourhood as shown in Fig. 1.3. That is for any 3X3 neighbourhood one can generate eight TU values.

i. Texture Spectrum

The previously defined set of 255 texture units describes the local-texture aspect of a

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given pixel; that is, the relative grey-level relationships between the central pixel and its neighbors. Thus the statistics of the frequency of occurrence of all the texture units over a large region of an image should reveal texture information. The texture spectrum is the frequency distribution of all the texture units, with the abscissa indicating the texture unit number NTu and the ordinate representing its occurrence frequency. In practice, a real texture image is usually composed of two parts: Texture elements and random noise or background. The greater the proportion of texture components compared to the background, the better that texture can be perceived by human vision. In the texture spectrum the increase in percentage of texture feature components in an image will result in a tendency to form a particular distribution of peaks. In addition, different images are composed of particular texture units with different distributions in their texture spectra. In this way the texture of an image can be characterized by its texture spectrum. It should be noted that the labeling method chosen may affect the relative positions of the texture units in the texture spectrum, but will not change their frequency values in the latter. It should be also noted that the local texture for a given pixel and its neighborhood is characterized by the corresponding texture unit, while the texture aspect for a uniform texture image is revealed by its texture spectrum calculated within an appropriate window.

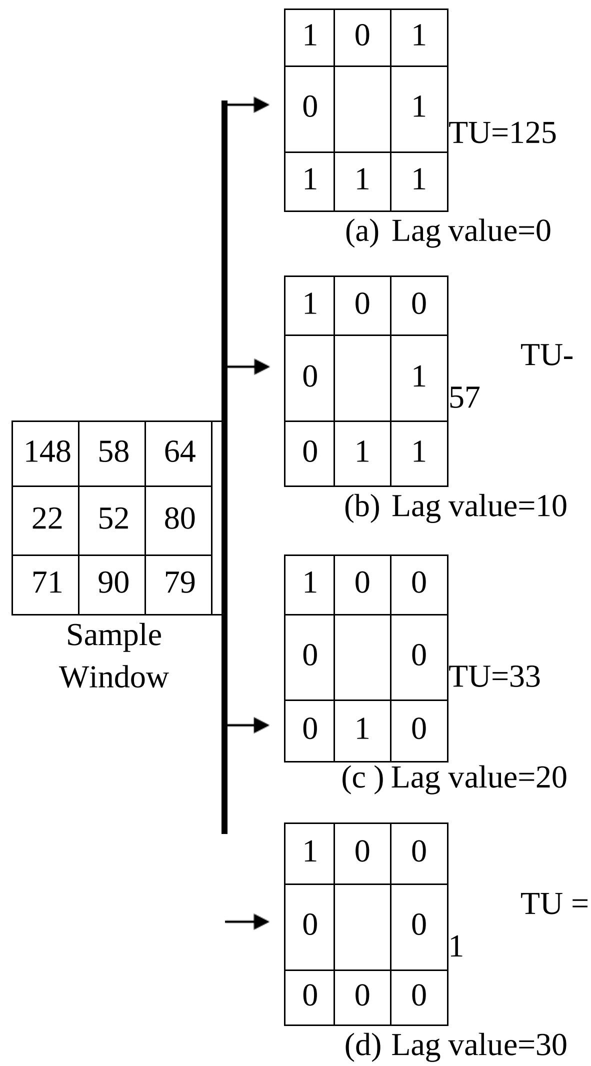

Fig. 4 Transformation model of a neighbourhood to a Texture

The size of the window depends on the nature of the texture image. The texture spectrum has discriminating performance for different textures, because different texture images will have correspondingly different spectra, where as similar texture images will have correspondingly the similar spectra.

ii. LRTS : Lag Value Based Reduced Texture Spectrum

The proposed Lag value based reduced texture Spectrum (LRTS) method retains

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discriminating power of texture elements derived by He and Wang in a better way. Because in real images two neighbouring pixels rarely have exactly the same value, due to the presence of noise and the different processes of capture like different resolution and illumination levels and digitations. To overcome this present study evaluated texture units based on different lag values. Based on the assumption that the texture is a local neighborhood property, the proposed method has given only two possible values for a TU i.e., {0, 1} based on lag values, given in equation 3.5.Whenever there is noise, or different resolution levels, or different illumination levels, the similar neighbouring pixels may not show the same value. To address this problem the present study introduced the novel concept of reduced texture unit with lag values. The lag value makes the certain range of values on either side to fall into one group. This makes two neighbouring pixels as equal even in the presence of little noise, or different illumination levels or different resolutions.

$$E_i = \begin{cases} 0 \text{ if } & V_i < V_o + L \\ 1 \text{ if } & V_i \geq V_o + L \end{cases} \qquad for \quad i = 1,2,...8 \tag{5}$$

The element E_i of equation 3.5 occupies the same position as the pixel i, L is the Lag value. If L=0, then LRTS and RTS becomes same. The present method evaluated three texture units on a 3 X 3 mask with different lag values 10, 20 and 30 as specified in equation 5. The transformation process of a TU based on LRTS with Lag value of 10, 20 and 10 for a san 3 grey level neighbourhood is shown in Fig. 4.

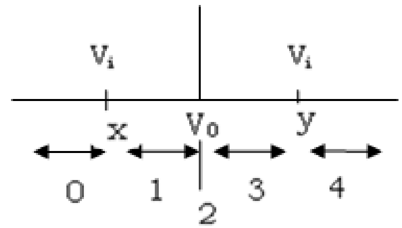

Fig. 5
Texture number (Base 5) representation

iii. FTS : A New Similarity Feature Fuzzy Based Texture Spectrum for an Efficient Image Retrieval System :

The previous approaches of TU's were unable to discriminate the differences from less, far less or greater and far greater than from the grey level value of central pixel. To incorporate this type of texture feature on a 3 x 3 mask , the present study extends the concept of LRTS , RTS, and features to FTS fuzzy texture spectrum. Given a neighbourhood of 3×3 pixels denoted by a set of nine elements: V ={V_0, V_1, V_2, ... V_8} where V_0 represents the intensity value of central pixel and V_0, V_1, V_2, ... V_8 are the intensity values of eight neighbouring pixels.

$$E_i = \begin{cases} 0 \text{ if } V_i < V_0 \text{ and } V_i < x \\ 1 \text{ if } V_i < V_0 \text{ and } V_i > V_x \\ 2 \text{ if } V_i = V_0 \\ 3 \text{ if } V_i > V_0 \text{ and } V_i > y \\ 4 \text{ if } V_i > V_0 \text{ and } V_i < y \end{cases} \quad \text{for i= 1, 2 …8} \tag{6}$$

Where x, y are user specified values.

The corresponding texture unit can be represented as a set containing eight elements, TU = {E_1, E_2, ... E_8}. The fuzzy

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texture membership function is represented as shown in Fig. 5. In Base5, the following equation 6 is used to determine the elements, E_i of texture unit. The Fuzzy Texture unit(FTU) is computed in Base5 as given in equation 7. The FTU ranges from 0 to 2020 as per equation 7

$$FT_{nu5} = \sum_{i=1}^{8} E_i \times 5^{(i-1/2)} \quad (7)$$

Therefore the range of FTU ranges in between basic texture unit and RTS and LRTS. For example the transformation model of a 3X3 neighbourhood in to FTU is shown in Fig. 6.

90	130	145
160	140	200
100	140	250

3X3 neighborhood

TU= {0,1,3,4,4,2,0,4}

0	1	3
4		4
0	2	4

Fuzzy Texture Unit

FT_{nu5}= 1292

Fig. 5 Transformation model of a neighbourhood to a Fuzzy Texture Unit

Fuzzy Texture Spectrum is termed as the frequency of distribution of all fuzzy texture units, with the abscissa indicating the texture unit number and the ordinate representing its occurrence frequency. The similarity measures IHBM is applied on the extracted texture features derived from TS, RTS, LRTS and FTS. The results are compared for the query image with database images. The principle of the similarity measure is the computation of the distance between the extracted texture features of the query image and those of the images in the database. Once all the distances are computed, the algorithm ranks the images of the database from the nearest to the furthest to the query image.

5. EXPERIMENTAL RESULTS

The above proposed methods are applied on 750 MRI and 250 other medical images. The relevant retrieved images for the query image #10 by the proposed methods TS, RTS, LRTS with different Lag values and FTS are shown in the Fig. 7, 8, 9, and 10 respectively. Table 1 shows the number of relevant images obtained and precision rate for 5 and 10 instances of the query image#10.

The relevant retrieved images for the query image #7 by the proposed methods TS, RTS, LRTS with different Lag values and FTS are shown in the Fig. 12, 13, 14, and 15 respectively. Table 2 shows the number of relevant images obtained and precision rate for 5 and 10 instances of the query image#7. The relevant retrieved images for the query image #76 by the proposed methods TS, RTS, LRTS with different Lag values and FTS are shown in the Fig. 17, 18, 19, and 20 respectively. Table 3 shows the number of relevant images obtained and precision rate for 5 and 10 instances of the query image#76. From the Tables it is clearly evident that the proposed LRTS Similarity feature with lag value 20 with IHBM Similarity measure out performs in all cases the other similarity features derived from TS, RTS and FTS. The precision V_s the number of images returned for the Tables 1, 2 and 3 are also plotted in the Fig. 11, 16, and 21 for query image #10, #7 and #76 respectively.

Fig. 7 The result of the query image and five retrieved relevant images using TS for image #10.

Fig. 8 The result of the query image and five retrieved relevant images using RTS for image #10.

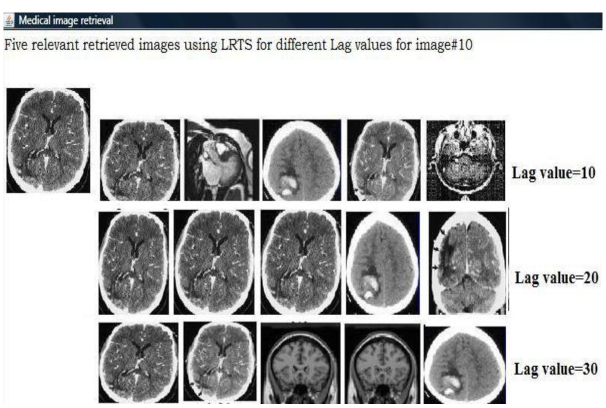

Fig. 9 The result of the query image and five retrieved relevant images using LRTS for different Lag values.

Fig. 10 The result of the query image and ten retrieved relevant images using FTS for image #10.

Table 1 : Retrieved relevant images for TOP 5 and 10 for images #10.

Query image #10	TS	RTS	LRTS			FTS
			Lag value=10	Lag value=20	Lag value=30	
5	2	2	2	3	2	3
10	4	5	4	7	4	6
Precision for Top 5 and 10 images for query image # 10						
Query image # 10	TS	RTS	Lag value=10	Lag value=20	Lag value=30	FTS
5	0.4	0.4	0.4	0.6	0.4	0.6
10	0.4	0.5	0.4	0.7	0.4	0.6

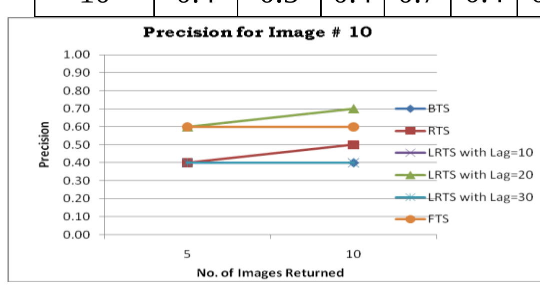

Fig. 11 Precision Vs No. of Images returned for image #10.

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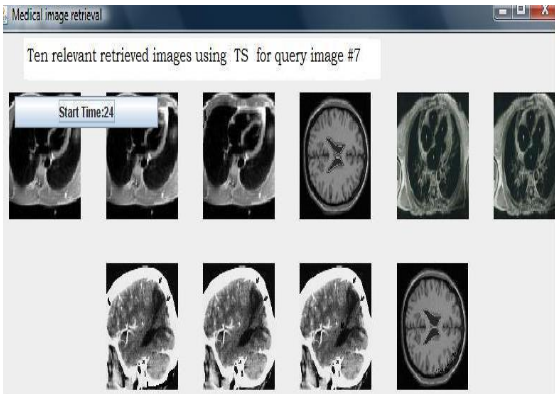

Fig. 12 The results of the query image and ten retrieved relevant images using TS for image #7.

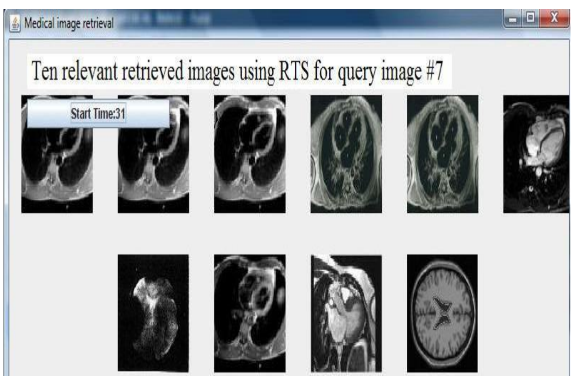

Fig. 13 The results of the query image and ten retrieved relevant images using RTS for image #7.

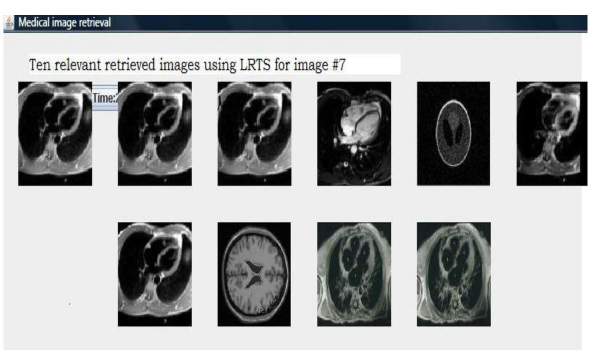

Fig. 14 The results of the query image and ten retrieved relevant images using LRTS for image #7.

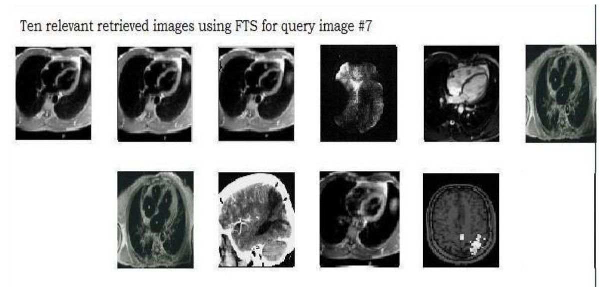

Fig. 15 The results of the query image and ten retrieved relevant images using FTS for image #7.

Query image # 7	TS	RTS	LRTS	FTS
5	4	4	4	4
10	5	7	8	7
Precision for Top % and 10 images for query image # 7				
Query image # 7	TS	RTS	LRTS	FTS
5	0.8	0.8	0.8	0.8
10	0.5	0.7	0.8	0.7

Table 2 : Retrieved relevant images for TOP 5 and 10 for images #7.

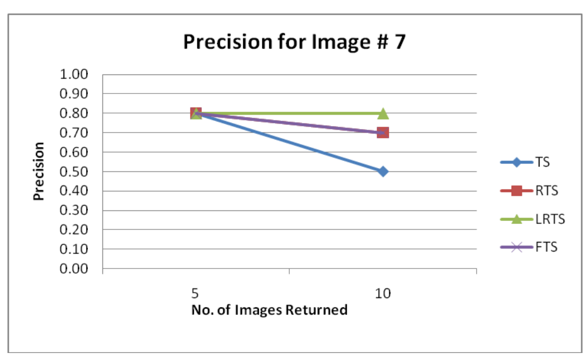

Fig. 11 Precision Vs No. of Images returned for image #7.

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Fig. 17 The results of the query image and ten retrieved relevant images using TS for image #76.

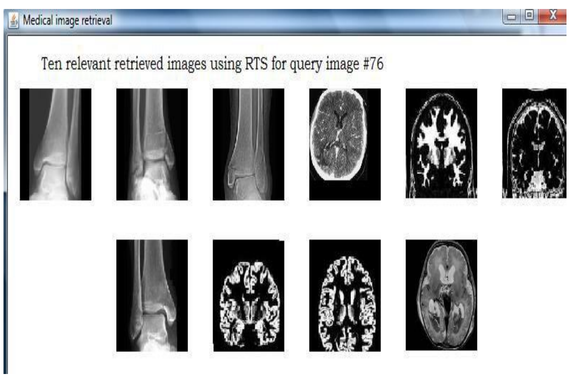

Fig. 18 The results of the query image and ten retrieved relevant images using RTS for image #76.

Fig. 19 The results of the query image and ten retrieved relevant images using LRTS for image #76.

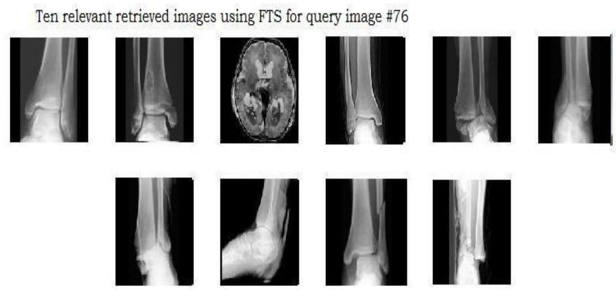

Fig. 20 The results of the query image and ten retrieved relevant images using FTS for image #76.

Query image #76	TS	RTS	LRTS	FTS
5	4	3	5	4
10	7	4	9	9
Precision for Top % and 10 images for query image # 76				
Query image #76	TS	RTS	LRTS	FTS
5	0.8	0.6	1.0	0.8
10	0.7	0.4	0.9	0.9

Table 2 : Retrieved relevant images for TOP 5 and 10 for images #76.

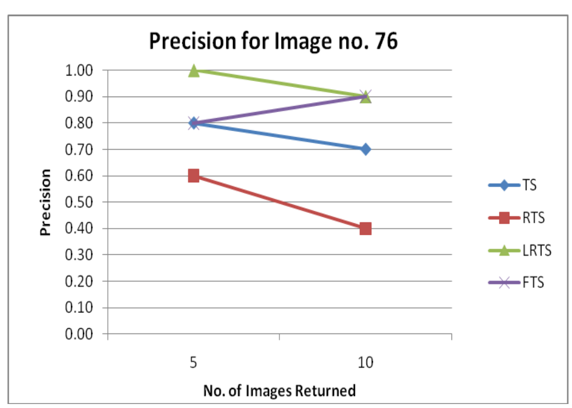

Fig. 21 Precision Vs No. of Images returned for image #76.

6. CONCLUSIONS

The present chapter derived three efficient and accurate texture based similarity features called RTS, LRTS and FTS for effective retrieval system of noisy, poor resolution and illumination images. The precision graphs, query images, retrieved instance Tables clearly indicates the proposed LRTS with Lag value 20 outperforms the other two proposed methods. The FTS and RTS similarity features have shown the similar retrieval performance between FTS and RTS similarity features, the FTS has outperformed the RTS retrieval system. However the complexity of FTS retrieval system is high when compared to RTS and LRTS because the FTU ranges from 0 to 2020 where as the in the other two proposed retrieval systems the TU ranges from 0 to 255.

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