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Fractal dimension-bound spatio-temporal analysis of digital mammograms

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Abstract. A new Fractal Dimension-based diagnosis technique for the change detection and time-series analysis of masses in the temporal digital mammogram is presented in this paper. As the digital mammograms are confirmed as a reliable source for the prognosis of breast cancer, the demand for the development of precise computer aided detection techniques is constantly on the increase. This formed the basis for the development of this method using Fractal geometry, which is an efficient mathematical approach that deals with self-similar and irregular geometric objects called fractals. This work comprises of the detection of spatial masses using Fractal Hurst bound enhancement and segmentation of those temporal masses using Fractal Thresholding. The consultant radiologist's assessment of mass lesions forms the baseline for comparison and validation of the detected masses. Further, this research work performs temporal analysis of mass lesions, detected from the mammograms of the *current* and the respective *prior* view using the principle of Fractal Dimension. The precision of Fractal-dimension based temporal texture analysis of malignant masses of digital mammograms subsequently attributes to their characterization.

1 Introduction

Medical Image Processing has evolved a new dimension in the field of medicine through computer aided diagnosis. Image segmentation has proven its potential in health diagnosis by gaining popularity in Medical image diagnostics, as it serves as a mean to extract the necessary vital objects/regions of interest by ignoring the insignificant data of an image [1–3]. Across the globe, breast cancer has become one of the prominent causes, attributing to women mortality. In India, a death rate of one in eight women has been reported, due to breast cancer [4,5].

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The early detection of breast cancer provides enormous scope in containing the death toll. Since the recent past, mammography is deemed as the most effective means of prognosis and thus the mammography screening is considered as the most popular and reliable source for the early detection of breast cancer and other abnormalities in the breast tissues. Masses or calcifications appearing as small white specks in the mammogram [6–8] indicate the presence of tumour in the breast. The breast tissues are found to have self-similarity, which is the property of fractal objects. Hence, the fractal-based methods are proved to be suitable for mammogram segmentation as well as analysis. Hence, this research work uses fractal dimension for the detection and segmentation of masses from the mammograms and in the computation of temporal changes in the mass lesions [9–13].

Fractals are of rough geometric shapes, which when subdivided into discrete parts, each possesses reduced similarities of the whole object. Fractal dimension is an important measure that characterizes the feature of fractal objects. This measure finds larger applications in the fields of image segmentation and texture analysis [14–16].

L. Bassett et al., M. Thurfjell et al. and M. Callaway et al. [17–19] assessed the outcome of the lesions using the temporal information extracted from the masses. C. Varela et al. and L. Hadjiiski et al. [20,21] characterized the mass lesions using the prior views. All these temporal data based studies found to have a significant development in the applications related to medical imaging procedures by using the prior views. Several Fractal dimension based image extraction models have been developed for medical image segmentation and classification, but no work has been as such reported on temporal data analysis, using fractal dimension. This drawback is overcome in the proposed technique by using an exclusive fractal hurst based enhancement which projects the roughest pixels, that complements efficient mass detection and segmentation using fractal thresholding on temporal mammograms.

Kostas Marias et al. [22] presented an image analysis method to detect and measure breast density from digitised mammograms and characterized the breast changes due to Hormone Replacement Therapy (HRT) based on the Standard Mammogram Form representation of tissues. Natalia Andrienko et al. [23] combined interactive visual techniques with clustering based computational methods to support analysis and modelling of large amounts of spatio-temporal data. Sheila Timp et al. [24] detected the temporal changes in masses using clustering techniques and characterized the masses by adding information about the tumour behaviour over time. The results of those methods fail to characterise the temporal changes both on a global and a local statistics, while the proposed method of temporal analysis that uses fractal dimension has the potential to aid the radiologist in temporal change detection of spatial masses.

In this paper, Sect. 2 depicts the computational methodology of the proposed technique FHMST and Sect. 3 describes the temporal analysis of the detected masses. The conclusions are drawn in Sect. 4.

2 Fractal Hurst based Mass Segmentation for Temporal mammograms (FHMST)

2.1 Fractal dimension

Fractals are of rough geometric self-similar and irregular shapes which are characterized by their Fractal dimension (defined as D_f) which is an important characteristic of fractals as it has got information about their geometric structure. In Euclidean n-space, the bounded set S is said to be self-similar when S is the union of X_t distinct non-overlapping copies of itself, each of which is similar to S, being scaled down by a ratio t. Fractal Dimension D_f of S can be derived from the relation [25–27], as

$$D_f = \frac{log(X_t)}{log(1/t)}. \tag{1}$$

2.2 Fractal hurst

The measure of long-memory dependence, Fractal hurst, is calculated by finding the difference between the topological dimension of the image and its fractal dimension. Considering the topological dimension D_t and fractal dimension D_f of the image, the fractal hurst H_f value can be calculated [27–30] as

$$H_f = D_t - D_f. \tag{2}$$

2.3 Methodology

The devised technique initially finds the fractal dimension, D_f by differential box counting method, for an input mammogram image I. Then fractal Hurst H_f is calculated by finding difference between D_f and D_t which is the topological dimension value of the image. Also, the statistical measure namely standard deviation S_d is found out for the image by calculating the variance of the image.

In many applications, the problem lies with the low contrast investigative features of the masses with respect to the neighbouring breast tissues. These features would facilitate the process of detection difficult. Hence, pre-processing techniques are needed to be applied in order to make out accuracy in the detection and diagnosis of mass lesions. There is a chance that the mammograms get affected by increased noise and inclusion of some artifacts while applying contrast enhancement techniques. Hence, since two decades, for safer side, conventional image enhancement techniques have been applied widely in the digital mammogram analysis.

Median filtering, by principle smoothens the input image, thus reduces the excessive intensity distortions such as thinning or thickening of object boundaries. Accordingly in this research study, the Median filtering is being applied on the input image I as a pre-processing step to acquire I_F which removes the digitization noise and high frequency components. On the filtered image I_F, contrast enhancement is done further using fractal hurst H_f, to acquire I_{CE}, which expands the range of intensity levels in an image so that it spans the full intensity range of the recording medium. This contrast enhancement phase modifies the levels linearly from their original range and modifies the enhancement calculation by incorporating fractal hurst as the slope value thus transforming the pixel's intensity to a value within the range corresponding to the roughness of the image, thereby enabling an efficient mass detection. Thus, the Fractal hurst based intensity transformation of the mammogram handles the space-localized distributional change which occurs over time in the temporal pairs.

Fractal thresholding value T_f is now calculated using $T_f = (H_f/S_d) * D_f$. Now by taking fractal thresholding T_f as the parameter and considering only those pixels of I_{CE}, which are greater than T_f, I_{MD} is produced that projects mass detection. The algorithmic description of the algorithms is herein under.

Algorithm: Segmentation of Masses from a Digital Mammogram

Aim: To Segment Masses from a Mammogram
Input: A 2-Dimensional Mammogram Image, I
Output: Segmented Mass from Mammogram

Phase I: Computation of Fractal Dimension

1. Read a $2-D$ input temporal mammogram I
2. Cover the image I with boxes of size t.
3. $[U, V] \leftarrow IMSIZE[I]$
4. If $U > V$ then $t \leftarrow U$
   Else $t \leftarrow V$
5. Let the minimum and maximum gray levels of the image fall in k and l boxes respectively.
6. Calculate $s_t(i,j) = l - k + 1$, where $s_t(i,j)$ is the portion at the $(i,j)^{\text{th}}$ grid.
7. Find $S_t = \sum s_t(i,j)$, where S_t is the summation of all portions of s_t with respect to t.
8. Compute Fractal Dimension D_f using Eq. (1)

Phase II: Spatial/Intensity Transformation of I

9. Smoothen the input image I, using median filtering to get I_F
10. Calculate Standard Deviation S_d of I
11. Calculate fractal Hurst $H_f = D_f - 2$
12. Enhance the I_F by fractal hurst H_f, as below, to acquire I_T
    Let M be the maximum intensity of I if $M > 235$
    fE := 1;
    elseif ($M > 220$ && $M < 235$)
    fE := $(H_f)^4$;
    elseif ($M > 210$ && $M < 220$)
    fE := $(H_f)^3$;
    elseif ($M > 200$ && $M < 210$)
    fE := $(H_f)^2$;
    else
    fE := H_f; end
    $LUT_I[i] = round([1:256].^3/(fE * M.^2))$; i := 0 ... 255
13. Transform I_F into I_T using LUT

Phase III: Segmentation of Spatial Masses in I

14. Formulate Fractal Thresholding T_f using H_f and S_d as: $T_f = (H_f/S_d) * D_f$
15. Apply T_f on I_T to produce I_{MD} that gives segmented mass
16. Stop

The proposed algorithm is implemented using Matlab 7.8. The temporal patterns of the mammogram images with masses in CC view were collected from *Basavatarakam Indo American Cancer Hospital and Research Institute, Banjara Hills, Hyderabad* to ascertain the merits of this proposed research technique. The final mass segmentation results clearly show that this proposed fractal Hurst based transformation elucidates the higher roughest portions that enable precise segmentation of masses from temporal mammograms. This algorithm is tested on the collected temporal mammograms of patients, from which, for illustrative purpose, the results of the study on 6 temporal mammograms consisting of *current* and *prior* views pertaining to 6 patients, labelled as P_ID 01, P_ID 02, P_ID 03, P_ID 04, P_ID 05 and P_ID 06, are depicted in Fig. 1.

3 Temporal analysis of spatial masses

This research work aims to evaluate the potential of the proposed FHMST on the temporal change detection of masses in the temporal mammogram pair consisting of a temporal CC image pair, as well as the characterization of the segmented masses. This research work was tried and tested on the CC view of temporal mammograms (current and prior) of six patients.

Temporal features
The temporal mass features are measured in terms of fractal dimension values for the segmented masses of the *current* and *prior* view mammograms. The change in the size of the masses of *current* and *prior* ones being perceived by the visual perception is being confirmed, by correlating it with the respective fractal dimension measure.

The segmented masses of these mammograms depicted in the last column of Fig. 1, as per radiologist's medical report, are of malignant types. By visual perception, the shapes of the masses in Fig. 1 are of more irregular shapes that justify its nature to be malignant. The change in size reduction of the masses is calculated in terms of the pixel count of the segmented mass and is tabulated in Table 1.

The tumour feature, in terms of roughness is measured through the Fractal Dimension value of the segmented masses and is tabulated in Table 1. It is observed that the fractal dimension of the malignant mass is 1.6807 on the *current* view and 1.6152 on the *prior* view for temporal pair of patient 1, 1.5936 on the *current* view and 1.5517 on the *prior* view for temporal pair of patient 2 and 1.6152 on the *current* view and 1.5228 on the *prior* view for temporal pair of patient 3.

Also, the fractal dimension of the malignant mass is 1.6839 on the *current* view and 1.6955 on the *prior* view for temporal pair of patient 4, 1.7537 on the *current* view and 1.7967 on the *prior* view for temporal pair of patient 5 and 1.5825 on the *current* view and 1.6197 on the *prior* view for temporal pair of patient 6.

From the Table 1, it is apparent that there is a reduced change in the mass size among the temporal pairs of P_ID 02, P_ID 03 and P_ID 05 and there is no obvious

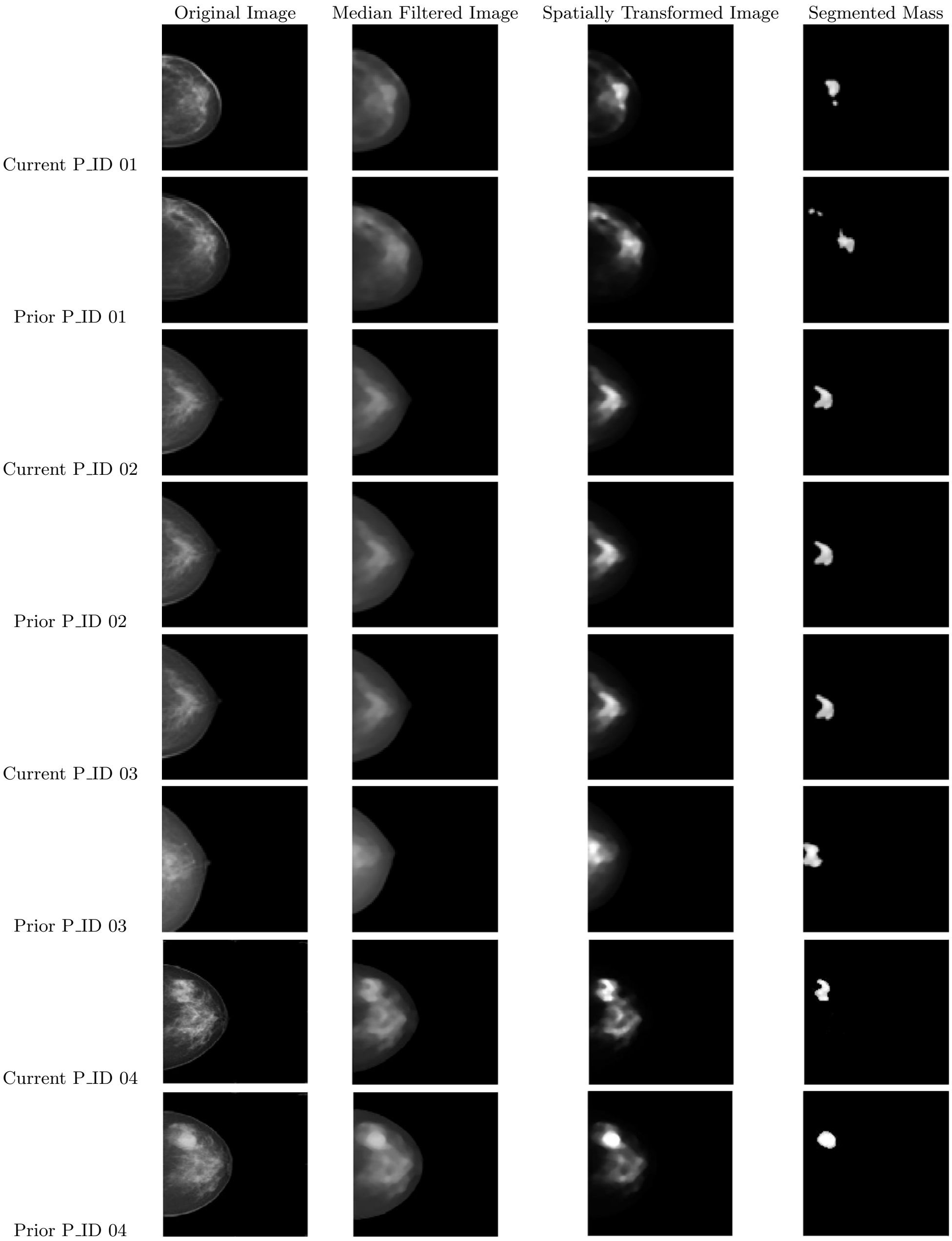

Fig. 1. Input, Intermediate and Output images of FHMST.

change reduction exhibited by the temporal pairs of P_ID 01, P_ID 04 and P_ID 06. However, there is reduction in the value of fractal dimension for all the temporal pairs of six patients indicating the reduced level of malignancy. It is apparent that the fractal dimension gives more information of changes in the masses between *prior* and *current* and hence the fractal dimension is a better qualitative measure than the quantitative data in the temporal analysis of digital mammograms.

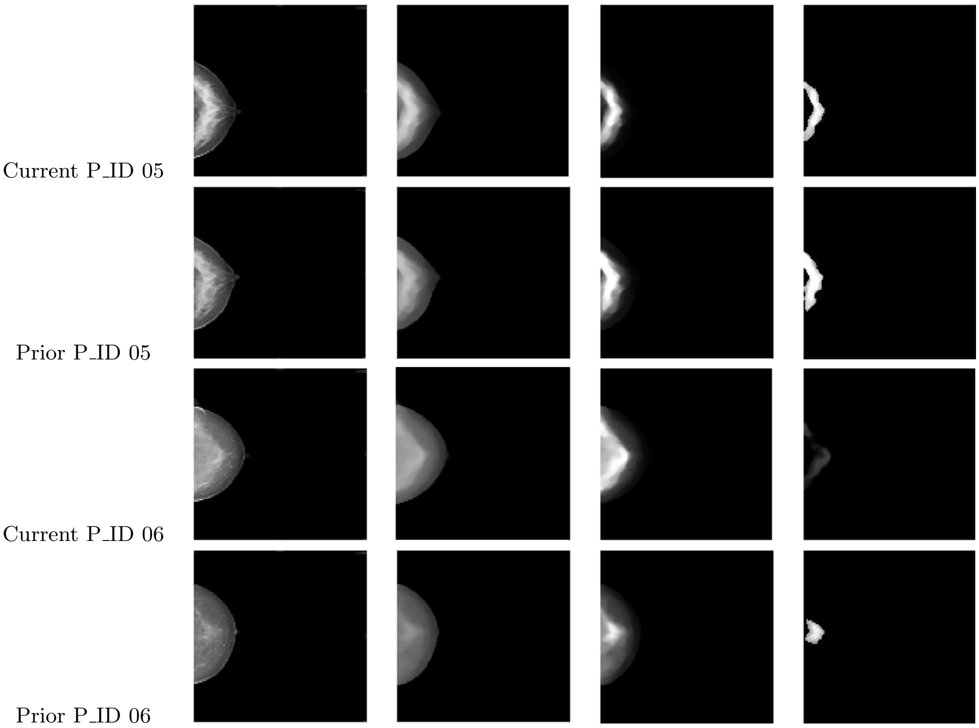

Fig. 1. Continued.

Table 1. Analysis of Reduction in Fractal Dimension and Size for Temporal Mammograms.

PATIENT	TEMPORAL	D_f	SEGMENTED PIXEL COUNT	REDUCTION IN D_f	REDUCTION IN SIZE	INFERENCES
P_ID 01	CURRENT	1.6152	569	0.0655	NO	REDUCED MALIGNANCY
	PRIOR	1.6807	321			
P_ID 02	CURRENT	1.5517	410	0.0419	YES	REDUCED MALIGNANCY
	PRIOR	1.5936	550			
P_ID 03	CURRENT	1.5228	602	0.0924	YES	REDUCED MALIGNANCY
	PRIOR	1.6152	806			
P_ID 04	CURRENT	1.6839	759	0.0116	NO	REDUCED MALIGNANCY
	PRIOR	1.6955	720			
P_ID 05	CURRENT	1.7537	1161	0.0430	YES	REDUCED MALIGNANCY
	PRIOR	1.7967	1373			
P_ID 06	CURRENT	1.5825	1195	0.0372	NO	REDUCED MALIGNANCY
	PRIOR	1.6197	693			

The pictorial plot of reduction in fractal dimension and mass size, respectively are depicted in Fig. 2 and Fig. 3.

It is evident from the inference of the study that the mass size reduction alone could not be considered as the primary parameter in the analysis and the characterization of masses, in addition to which the radiologists should also take into consideration the temporal texture measure of the masses, for the same. As the Fractal dimension

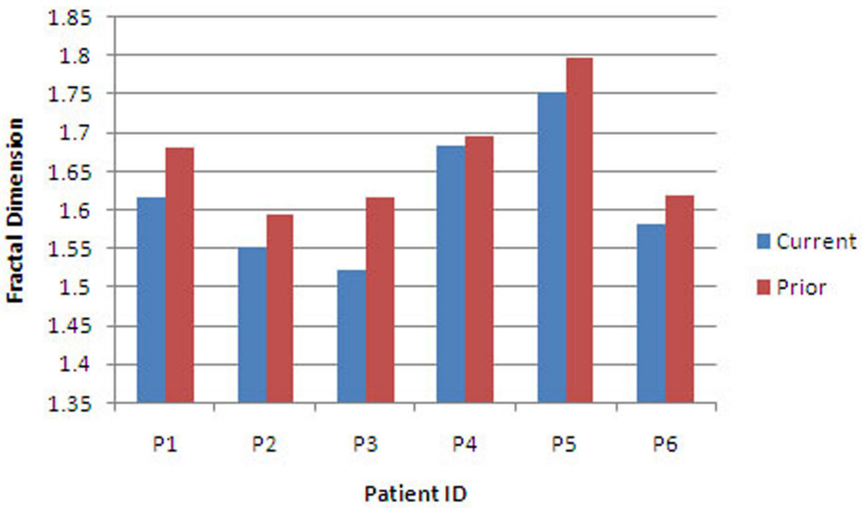

Fig. 2. Plot for Reduction in Fractal Dimension.

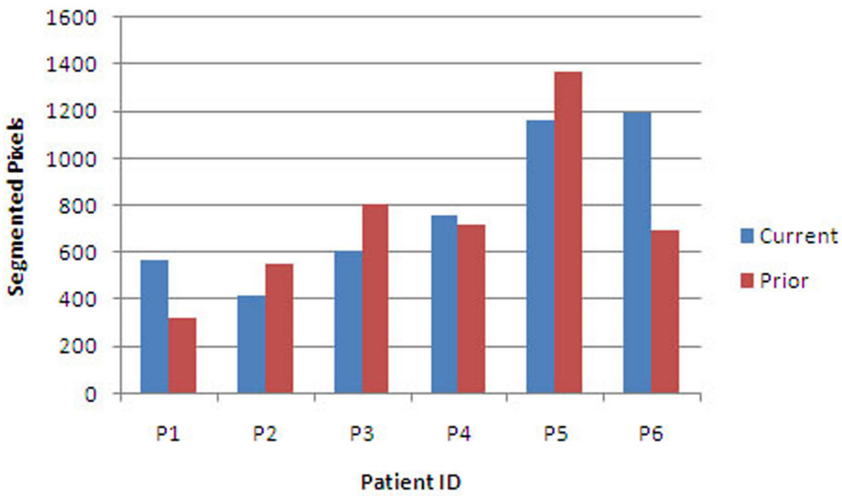

Fig. 3. Plot for Reduction in Mass Size.

values of the detected masses of temporal mammograms are highly correlated to the measure of roughness of segmented masses, this metric is strongly considered as a complimentary measure in the process of change detection and temporal analysis of malignancy. The perusal of temporal results as depicted by Fig. 1, Fig. 2, Fig. 3 and Table 1 endorses the fact that there is decrease in the degree of malignancy due to medical intervention. Furtherance of this research would lead to an automated change reduction in temporal mammogram series in order to measure the degree of malignancy and to provide suggestive remedial solutions for the follow-up. Hence this research work is proved to play a significant role in the development of an expert system for temporal analysis of mammograms as a reliable tool for radiologists.

4 Conclusion

A novel fractal dimension-bound spatio-temporal analysis for the detection, segmentation and characterization of masses from temporal pairs of digital mammograms is reported in this paper. The accuracy of the segmented mass lesions that are compared and validated with the consultant radiologist's assessment endorses the merit of this method. The FHMST corroborates that the Fractal dimension of temporal digital mammograms greatly contribute to the decision support expert system of radiologists, in medical therapy to be decided for the patients with reference to the spatio-temporal analysis of mass features.

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