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Digital Mammogram Image Feature Extraction Using Local Binary Patterns

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Abstract

Nowadays, breast cancer is a very common disease among women and causes many deaths world-wide. One of the most popular techniques to diagnose breast cancer is using computer-aided diagno-sis (CAD) techniques. It helps diagnose cancer in its early stages. It can show cancer in different forms, such as masses, density, or calcifications. It is important to note that breast density is not the same as density in normal cases. In mammograms, breast density is evaluated by the percentage of fatty tissue in the breast, which differs from glandular tissue. Moreover, calcifications and masses are also important for determining breast cancer, but breast density is mainly used to identify breast cancer risk. Feature extraction is very helpful and facilitates the classification process. An algorithm for mammogram feature extraction based on fuzzy clustering and histograms was proposed to en-hance the feature extraction process. The proposed algorithm was implemented using MATLAB. A set of mammogram images was selected from the MIAS database, and the features extracted for these selected images were successful. However, the same set of images was also processed using the K-means clustering algorithm to compare the obtained features.

Keywords: Digital image processing, Feature Extraction, Local Binary patterns, mammogram

Introduction

Motivation and Significance

The proposed Mammogram Feature Extraction approach using LBP

A new method is proposed based on LBP and its discriminate ability working on texture images. It was mentioned in previous chapters that many models of Local Binary Pattern were introduced. Some of these models tried to reduce dimensionality and produce less number of patterns with preserving feature quality; these models worked in many fields, one of them is the medical image field, in specific the mammogram image that is used to detect the abnormalities in the breast tissues by extracting their features to use them in classification process..

The proposed algorithm works as follows:

1. Input a mammogram image
2. Define features vector called "K".
3. For each pixel in the grayscale image, use the surrounding 8 pixels and surrounding 16 pixels,
4. Find the maximum from the 8 neighbors.
5. Find the mean value of the 8 neighbors
6. Add the max value to the mean value then divide by two.
   - If the result is less than pixel value set f 0 to 0
   - Else set f0 to 1.
7. Find the maximum from the 16 neighbors.
8. Find the mean value of the 16 neighbors
9. Add the max value to the mean value then divide by two.
   - If the result less than pixel value set f1 to 0
   - Else set f1 to 1.
10. Add the max value to the mean value then divide by two
11. Obtain the binary number which is combined of F0 & F1 will be either 0 or 1, so put them next to each other , then the code will be of two binary numbers
12. Convert f0 and f1 to decimal number.
13. Put the features in features vector "K".

This method is rotation invariant, there will be four patterns instead of 256 for the classical LBP represented in two numbers instead of eight and only the following binary numbers will be used: 00, 01, 10 and 11. So, the histogram will equal to 4 bins only.

The flowchart below demonstrates the steps of the algorithm.is shown in figure (1)

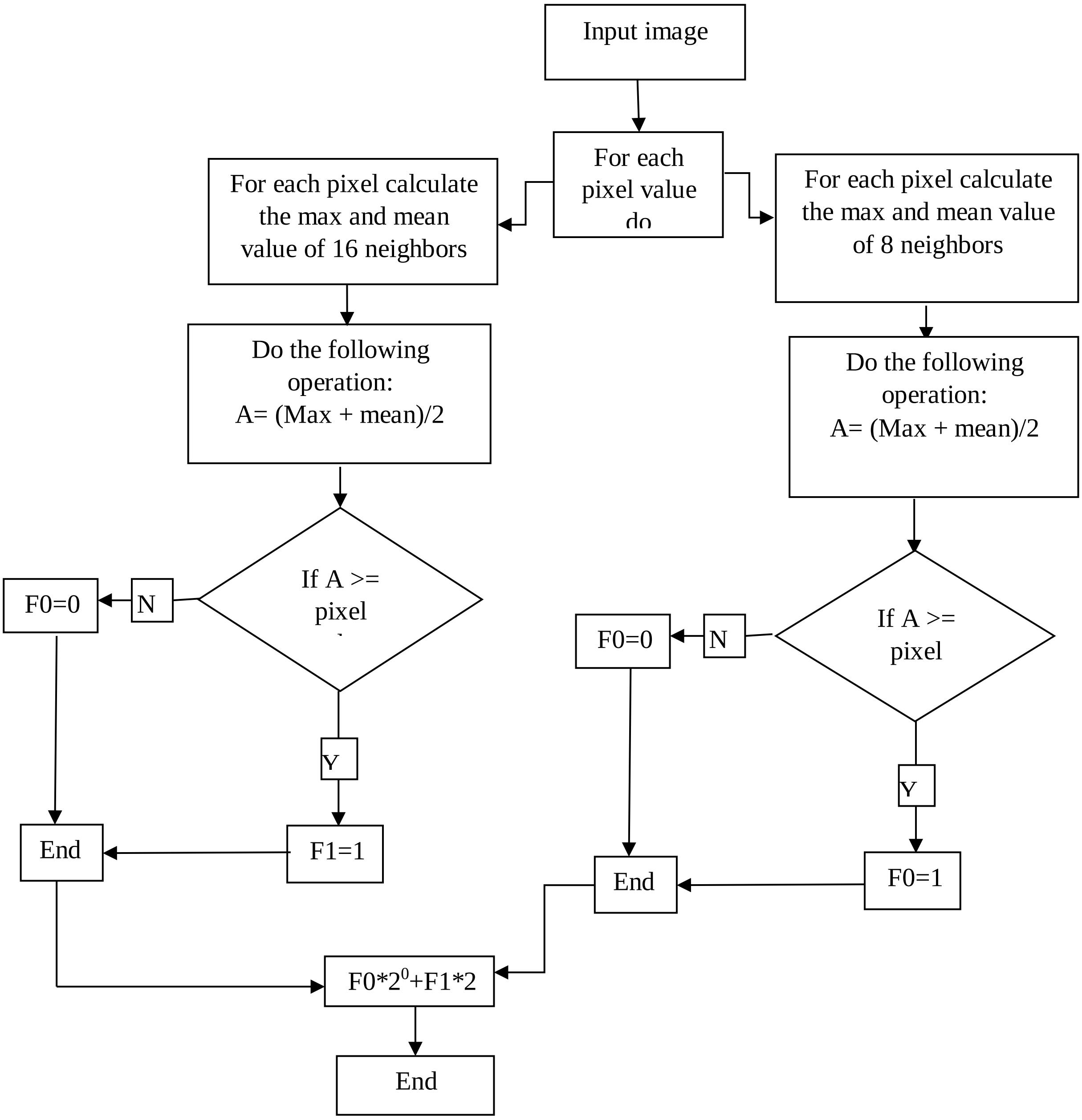

Fig. 1. Flowchart of proposed Algorithm

Implementation and Experimental Results

This algorithm will be implemented on Matlab 2013a using images from MIA's database (Mammographic Image Analysis Society), which contain 322 mammogram images representing left and right breast of 161 patients, each image of size 1024 x 1024 pixels and in portable gray map (.pgm) format, each image also contain marked positions defined by the radiologist determining the abnormality location and the database gives the coordinates of the center of abnormality.

The proposed method was implemented using the selected images; figure (2) shows one of these images and the associated histogram.

By employing the proposed algorithm on the selected mammogram images to extract the features for these mammogram. The obtained experimental results are shown in table (1).

Table 1. Proposed method results

Image	Features				Extraction time(seconds)
mdb001	628811	10752	50839	349998	7.868000
mdb002	521013	14529	69577	435281	7.952000
mdb003	512952	16331	79438	431679	8.097000
mdb004	486039	16911	78008	459442	7.927000
mdb005	453958	13369	63678	509395	8.239000
mdb006	452606	14866	62211	510717	7.977000
mdb007	547821	13439	59977	419163	8.005000
mdb008	463364	16989	68130	491917	8.075000
mdb009	454689	18333	78025	489353	7.898000
mdb010	628959	10916	46965	353560	7.938000
mdb011	492357	18408	77508	452127	7.973000
mdb012	461177	16622	74481	488120	7.867000
mdb013	596703	11263	52066	380368	8.015000
mdb014	542811	12441	58009	427139	8.061000
mdb015	616164	14720	59272	350244	7.967000
mdb016	646622	9548	38979	345251	7.913000
mdb017	685490	12449	51416	291045	7.918000
mdb018	681473	11262	47385	300280	7.897000
mdb019	482883	11060	46111	500346	7.888000
mdb020	470901	13320	57649	498530	7.969000
mdb021	443143	17573	73808	505876	8.058000
mdb022	569422	13531	56672	400775	7.841000
mdb023	434724	18054	75626	511996	8.043000
mdb024	444885	17704	79022	498789	7.933000
mdb025	450201	13663	59514	517022	7.875000
Average					7.9678

From table (1) we can see the following facts:

I. The required extraction time is small and it can be acceptable, the extraction process required in average 7.9678 seconds.

II. For each image each features victor is a unique, thus we can use it as a key to retrieve or recognize the image.

III. The features are stable and do not change from run to run.

In order to compare the effectiveness and the efficiency of the proposed algorithm. The algorithm will be compared with K-means clustering feature extraction algorithm. The same images were treated using K_mean clustering. Table (2) shows the obtained results for K-means clustering algorithm.

Table 2. K_mean clustering results

Image	Features				Extraction time(seconds)	Running processes
mdb001	1.8577	71.0629	136.9325	186.3291	10.079000	6
mdb002	2.7459	78.5317	135.0894	196.7702	9.812000	7
mdb003	1.8350	71.5252	142.4988	209.5532	7.304000	1
mdb004	2.1885	78.4900	151.0311	206.3074	7.153000	3
mdb005	2.7665	68.5085	134.0088	185.4582	5.388000	2
mdb006	2.2332	78.3863	142.3775	202.6120	4.309000	1
mdb007	2.0359	76.5203	143.8546	184.1855	4.165000	1
mdb008	2.1229	73.8039	145.1087	192.4114	4.625000	4
mdb009	2.5975	78.8095	150.3644	223.9733	9.478000	1
mdb010	1.2351	57.3308	121.3752	171.4762	2.312000	9
mdb011	2.1684	61.4191	127.5335	172.2400	10.418000	1
mdb012	2.9119	78.3389	147.5097	232.9753	5.748000	3
mdb013	1.5291	76.7896	153.5750	188.6029	6.729000	1
mdb014	1.3924	58.0811	123.5137	182.0483	6.851000	5
mdb015	1.1191	79.0042	153.2655	185.2334	3.667000	3
mdb016	0.8902	62.4187	129.0592	172.5032	5.061000	11
mdb017	Fail	Fail	Fail	Fail	Fail	Fail
mdb018	0.9009	59.2321	130.9019	179.4296	10.608000	12
mdb019	2.5663	98.3467	158.1136	195.9537	3.747000	4
mdb020	2.1950	76.2536	155.9254	205.3611	3.462000	2
mdb021	3.2370	79.9892	157.7831	201.9783	11.741000	2
mdb022	1.8697	72.0764	145.0137	186.7580	9.606000	4
mdb023	3.5494	61.5335	126.2776	178.5977	3.785000	1
mdb024	3.5550	57.1647	121.3654	170.6427	3.663000	2
mdb025	3.1017	67.2713	123.4264	195.4301	5.942000	1

From Table (2) we can see that the obtained features are unique for each image and some time the extraction time is better than time needed for the proposed method, K_mean method as shown in table (2) has a serious disadvantage, some it requires more than one run to get the features, sometime it fails, to overcome this problem we can use the proposed method.

It is clear from the obtained results on a set of features which are required during the classification process. However, the same set of mammogram images were run using K-Means clustering technique and it was shown the results of the proposed algorithm outperform the K-Means clustering. Also, the feature extraction time using the proposed algorithm is less than the K-Means clustering algorithm. The results obtained have shown that the propose algorithm is effective and the performance outperforms other techniques. Moreover, the proposed can be adopted and employed in Computer Aided Diagnosis Systems.

Conclusion

Digital mammogram is a new approach for the early detection of breast cancer. This technique basically depending on overall tissues to recognize the shadows. The mammography is considered a very important tool for detection of masses. The problem with mammogram techniques is the increase in the rate of missed cancer diagnosis. The researches have reported that amid screening, usually radiologists miss recognizing 15% of bosom diseases that are clear while reviewing them. Moreover, whenever insignificant points are believed as appraisal of missed cases increasing to 50% due to errors in observations. Searching and identification mistakes are those that committed whenever radiologists don't indicate the availability of an unmistakable cancer and diagnosing errors.

In order to find out if the breast tissue is indicating a cancer, usually a biopsy is taken where the suspected tissues from the breast is removed out from the patients for further testing. The tissues of the breast is extracted surgically and is examined by the pathological procedures. Breast tissues that are identified as normal will be further investigated to decide whether it is benign “not cancerous” or malignant “Cancerous”. Currently, Computer-Aided Diagnosis techniques are developed for automatic breast cancer detection.

Mammogram images processing generally employ image processing techniques with the objectives of deleting the artefacts and labels, removing noise from digital image and enhancing mammograms for perfect interpretation, and to detect any masses lesions. Many investigations confirmed that radiologist’s performance enhanced by using Computer-Aided Diagnosis systems by improving images to replace mammograms so that they can be imprinted or evaluated on a display.

To assist in classification of mammogram cancer and to carry out detection to improve the detection and classification process, an algorithm for digital mammograms feature extraction was proposed based on Local binary patterns technique.

The algorithm was implemented using Matlab software and run on many mammogram images that available in MIAS database. A set of features obtained which are required during the classification process. However, the same set of mammogram images were run using K-Means clustering technique and it was shown the results of the proposed algorithm outperform the K-Means clustering. Also, the feature extraction time using the proposed algorithm is less than the K-Means clustering algorithm. The results obtained have shown that the propose algorithm is effective and the performance outperforms other techniques. Moreover, the proposed can be adopted and employed in Computer Aided Diagnosis Systems.

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