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Image Texture Based Classification Methods to Mimic Perceptual Models of Search and Localization in Medical Images

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Abstract

This study explores the validity of texture-based classification in the early stages of visual search/classification. Initially, we summarize our group's prior findings regarding the prediction of signal detection difficulty based on second-order statistical image texture features in tomographic breast images. Alongside the development of visual search model observers to accurately mimic search and localization in medical images, we continue examining the efficacy of texture-based classification/segmentation methods. We consider both first and second-order features through a combination of texture maps and Gaussian mixture model (GMM). Our aim is to evaluate the advantages of integrating these methods at the early stages of the visual search process, particularly in scenarios where target morphological features may be less apparent or known, as in clinical data. By merging knowledge of imaging physics and texture based GMM, we enhance classification efficiency and refine localization of regions suspected of containing target locations.

Keywords

Accuracy; classification; GLCM; GMM; segmentation; signal detection; texture feature maps; visual search model observer

1. INTRODUCTION

Recently, our group has shown that certain second-order statistical image texture features can predict signal detection difficulty in tomographic breast images [1]. In parallel, our group has also been developing visual search model observers that accurately mimic search and localization in medical images when average target features are known to the observer (through training) [2–5]. In this paper, we focus on examining the validity of texture-based classification/discrimination methods using Gaussian mixture model (GMM) while accounting for first and second-order statistical image texture features. We compare the benefits of using this at the early stage of the visual search process when the target morphological features may be less obvious or known (such as in clinical data). Knowledge of imaging physics, when combined with GMM, should improve the efficiency of classification and narrow down regions that are more suspicious of target locations. This would help the second stage of the detection model to be efficient when target features might vary from the known average features. In the following step, we will examine if combining image texture features in our visual search observer model will help move the observer towards use with clinical data.

In our work, we explore the use of gray-level co-occurrence matrix (GLCM) texture features [6] in medical images. The GLCM constructs a matrix based on the numbers of pair pixels repeated throughout an image or volume at a specific angular direction and distance, and statistically characterizes second-order texture features with it. This technique was developed by Haralick in the early 70s, but due to its computational requirements, its full potential has not been reached yet. Recently, our group proposed the viability of using these features to predict human observer detection performance in digital images, to evaluate contributions of anatomical and quantum noise in their origins and tested its robustness in DBT images across different scenarios. In this work, we explored the modified version proposed by Löfstedt [7]. This version accounts for changes due to quantization and produces more robust texture values across different binning levels.

We employed a dataset of 2D SPECT images of simulated MCAT lungs phantom for a lesion location-unknown task in which the Visual Search model uses a two-stage strategy search and localization. We performed the search task using cross-correlation and a family of 2D Gabor functions. These provided a set of possible lesion locations, and using a statistical discriminant, we performed the localization task. In parallel, we calculated GLCM based and first-order texture feature maps to subsequently integrate them into the GMM algorithm's framework to identify the validity of a texture-based classification in the early stage of visual search/classification.

2. MATERIALS AND METHODS

2.1 Datasets

In this research, we utilized a dataset consisting of 2D SPECT images obtained from a simulated MCAT torso phantom. These images were iteratively reconstructed with a fixed number of iterations and post-smoothing level. The study images were in 8-bit format with dimensions of 256×256 pixels. We had access to the ground truth regarding the presence or absence of lesions and their locations. A set of potential lesion locations was chosen, and each lesion-present image contained a 1-cm spherical lesion.

2.2 Visual Search Model Observer

For this task, we assumed a lesion-location-unknown scenario in which the visual search model employs a two-stage strategy for search and localization [2]. In the first step (search), feature maps f_i are created by performing cross-correlation between the image and the ith Gabor function from a family of 2D Gabor functions. We consider these correlations as candidates and identify them by locating local peaks on the feature map. To identify these peaks, we use the watershed algorithm, which is known for finding local minimum points in images.

2.3 Texture Maps

Texture maps are generated by calculating Löfstedt's second-order and intensity-based first-order texture features within a 3×3 pixel^2 overlapping sliding window across the image. The first-order features describe statistics calculated for each pixel value, including mean, variance, energy, maximum, minimum, median, skewness, and kurtosis. Additionally, we employ the GLCM as a statistical characterization approach for second-order texture features. The GLCM counts pixel pairs that recur across the image at specified distances and angles. The size of the GLCM matrix depends on the quantization limits applied to the images of the dataset; if the images exhibit N grayscale levels, the GLCM dimensions will be NxN. In the normalized GLCM matrix, each entry denotes the probability of a pair of pixels with intensities (i, j) occurring in the image under a specific direction and distance combination. Below are a few examples of the texture feature maps explored in this study.

2.4 Unsupervised Clustering Algorithms

For our study, we used a highly performing unsupervised clustering algorithm. As inputs, we used the images native pixel information in combination with our texture maps. We initialized the cluster and membership centers randomly and selected eight clusters/groups for our first segmentation. We use K-means initialization assuming no previous knowledge of any sample physiological characteristics. All the texture maps were normalized to zero mean and a standard deviation of one before being used.

2.4.1 Gaussian Mixture Model - EM—As mentioned before, the GMM model provides the probabilities of a data point (pixel) belonging to a cluster where K are number of components and π_i are the weights representing the probability that a randomly selected point was generated by an ith component according to the equation:

$$p(\vec{x}) = \sum_{i=1}^{K} \pi_i f_i\left(\vec{x} \middle| \tilde{\mu}_i, \Sigma_i\right). \tag{1}$$

The number of components/clusters, means and centers of the clusters, and number of iterations are set by the user in the initial iteration. Expectation-Maximization is used to optimize the clustering probabilities, and updated the parameters for a set number of iterations per the equation:

$$p\left(C_i \middle| \vec{x}\right) = \frac{\pi_i f_i\left(\vec{x} \middle| \tilde{\mu}_i, \Sigma_i\right)}{\sum_{i=1}^{K} \pi_i f_i\left(\vec{x} \middle| \tilde{\mu}_i, \Sigma_i\right)} \tag{2}$$

3. RESULTS

In the following Image 4, we have the combination of the image intensity values, GLCM features (Mean, Cluster Shade, and Cluster Tendency) and First order statistics (Energy, Mean and Minimum); which provides the cluster prediction on the right. The prediction is color-coded based on the cluster assigned, the colors do not denote magnitude of any kind.

From our knowledge of the ground truth, we can assess that this is an accurate classification, the lesion was in fact detected with a few other components as shown in Image 5. The blue arrow points at the exact lesion location.

4. CONCLUSIONS

Second-order statistical texture features have the capability to classify regions in images that can be eliminated in the early stages of a search and localization process. This also provides additional insight into human observer perception as it relates to image texture features in search and localization tasks. Our group demonstrated the first evidence that statistical texture features can correlate with human observer performance in task-based assessment in medical images. We provided preliminary evidence that texture features contribute to visual search. The comparison between our GMM-texture-based approach and our visual search model shows promising results, considering we only required one iteration to match both. Future work will explore the convergence of these methods in model observer development for search and classification.

ACKNOWLEDGEMENTS

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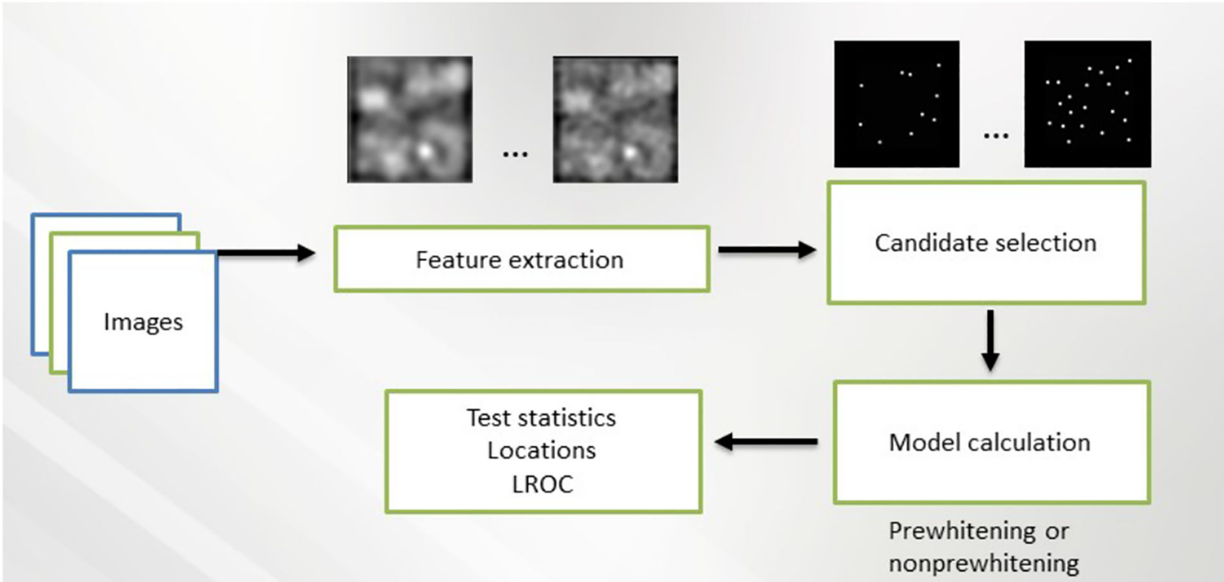

Image 1.
Visual-search model observer [8].

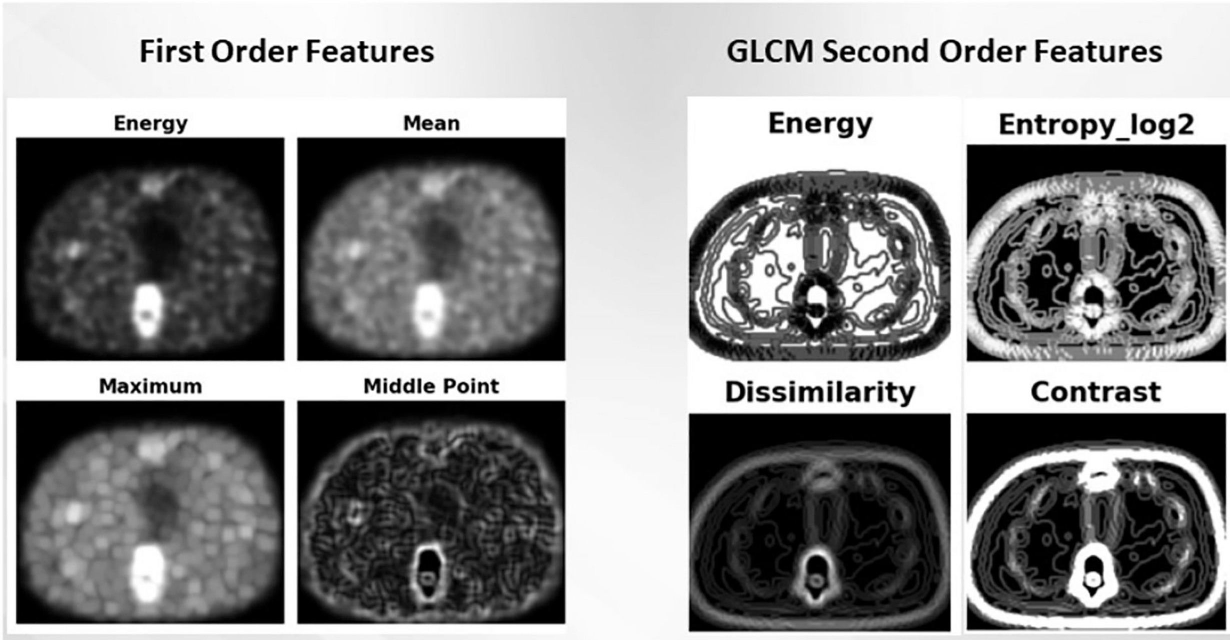

Image 2.
Texture maps.

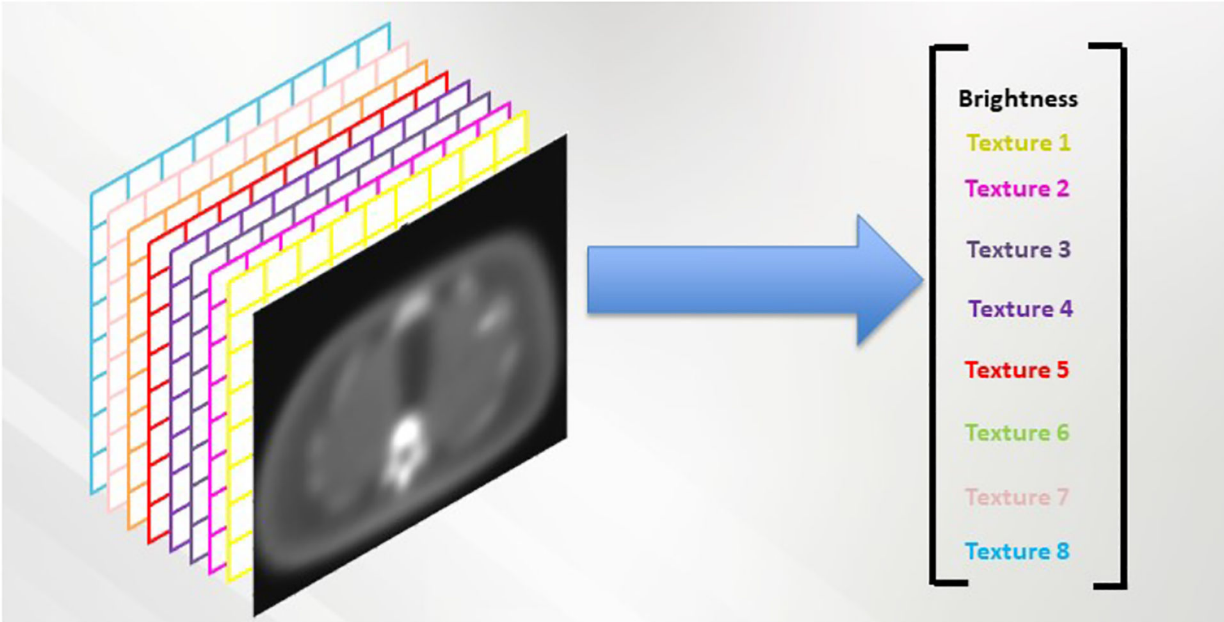

Image 3.
Representation of original image and texture features maps as inputs of GMM model.

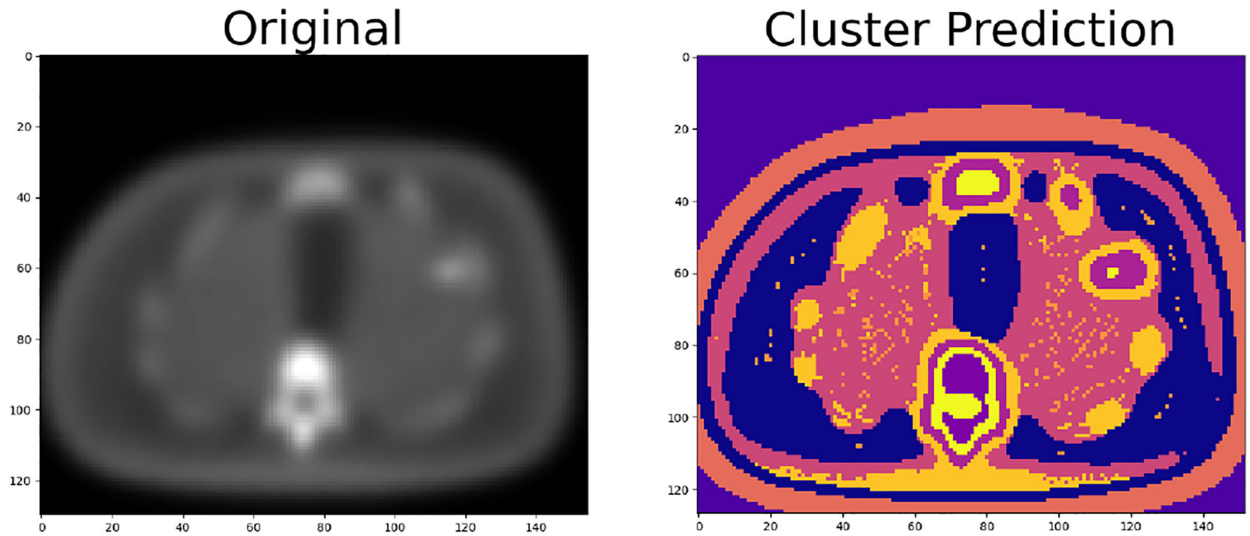

Image 4.

MCAT (Left) and GMM color-coded prediction using 8 clusters and a combination of 9 first and second order texture features.

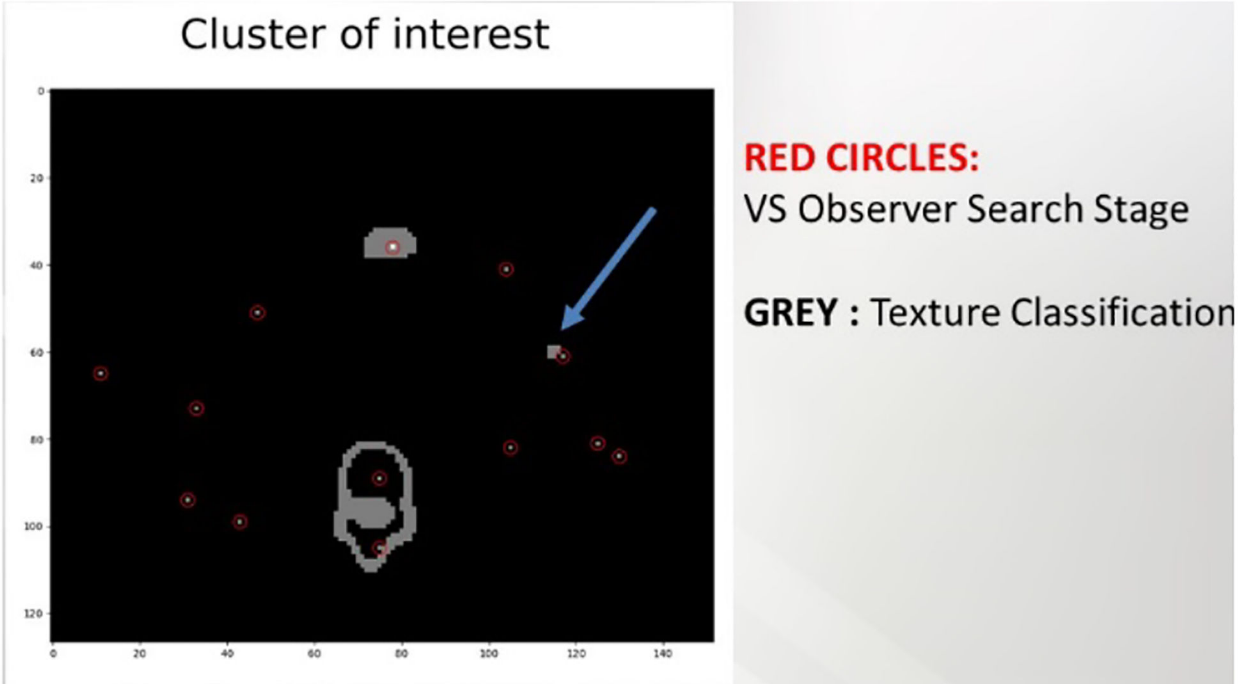

Image 5.
Cluster of interest prediction with overlapping location candidates using VS model observer approach.