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Automated Detection of Focal Skin Lesion Using Percentage Occupancy Hit and Miss Transform

[1]N.S.Shinija,[2]H.S.Anuja,[3]Mr.Anton Franklin,
[1,2]PG Student (final M.E Applied Electronics), [3]Asst. Prof.of ECE Department
Lord Jegannath College of Engineering and Technology, Ramanathichanputhoor

Abstract: *The hit-or-miss transform (HMT) is a well-known morphological transform capable of identifying features in digital medical images. When image features contain noise, texture, or some other distortion, the HMT may fail. Various researchers have extended the HMT in different ways to make it more robust to noise. The most successful, and most recent extensions of the HMT for noise robustness, use rank-order operators in place of standard morphological erosions and dilations. A major issue with the proposed methods is that no technique is provided for calculating the parameters that are introduced to generalize the HMT, and in most cases, these parameters are determined empirically. We present here, a new conceptual interpretation of the HMT which uses a percentage occupancy (PO) function to implement the erosion and dilation operators in a single pass of the ultrasonic image. The focal skin lesion can be clearly segmented from an ultrasonic image having noise.*

Index-Terms: *Bayesian estimation, Gibbs sampler, Heavy-tailed Rayleigh distribution, mixture model, Hit-or-Miss Transform.*

I. INTRODUCTION

Ultrasound imaging is a longstanding medical imaging modality with important applications in diagnosis, preventive examinations, therapy and image-guided surgery. In dermatologic oncology, diagnosis relies mainly on surface indicators such as color, shape, and texture whereas the two more reliable measures are the depth of the lesion and the number of skin layers that have been invaded. Recent advances in high-frequency transducers and 3-D probes have opened new opportunities to perform noninvasive diagnostics using ultrasound images. However, changing dermatological practices requires developing robust segmentation algorithms. Despite the extensive literature on the subject, accurate segmentation of ultrasound images is still a challenging task and a focus of considerable research efforts. Current segmentation techniques are extremely application-specific, developed mainly for echocardiography followed by transrectal prostrate examination (TRUS), kidney, breast cancer and intra vascular diseases (IVUS). The hit-or-miss transform (HMT)[1] and [8], which is capable of identifying groups of connected pixels that comply with certain geometric properties. If there is noise in a given image, or if image features are extremely textured, the standard HMT will fail to detect objects which are of interest. For the processing of binary images, the HMT is well defined. Gaussian mixture models coupled with Markov random fields were proposed to segment lesions based on their region statistics [14], [15]. Various techniques attempt to generalize the HMT for feature recognition in noisy images. In [13], Khosravi and Schafer present a formal definition of the grayscale HMT and analyze its performance in the presence of Gaussian noise.

This paper presents percentage occupancy HMT (POHMT) which allows partial fitting of SEs in a similar fashion to the partial fitting allowed by rank order filters. Furthermore, as a direct result of the plots that we use as a design tool, we show in this paper how we can make the POHMT operate as a discriminatory filter which allows objects to be selectively marked or discarded by the transform.

II. EXISTING SYSTEM

One of the important contributions is the Rayleigh region-based LS method presented in [16] that adapted the fundamental work of Chan and Vese [17] on ACs without edges to ultrasound images with Rayleigh statistics. These region-based LS should be very appropriate for ultrasound images of lesions as they are able to segment objects with smooth edges under poor signal-to-noise ratio conditions. This work was recently generalized to all the distributions from the exponential family (i.e., Gamma, Rayleigh, Poisson, etc.) in [18]. However, these methods have not yet been applied to lesion segmentation in ultrasound images.

Early lesion segmentation methods have focused mainly on thresholding [19], [20] and were superseded by texture-based techniques. Madabhushi et al. derived an active contour based on texture and boundary features. Huang et al. proposed a texture segmentation technique based on a neural network and a watershed algorithm. In addition, Gaussian mixture models coupled with Markov random fields were proposed to segment lesions based on their region statistics.

III. PROPOSED SYSTEM

The proposed mixture model is equipped with a Markov random field (MRF) that takes into account the spatial correlation inherent to biological tissues.

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A major issue with the proposed methods is that no technique is provided for calculating the parameters that are introduced to generalize the HMT, and, in most cases, these parameters are determined empirically. We present here, a new conceptual interpretation of the HMT which uses a percentage occupancy (PO) function to implement the erosion and dilation operators in a single pass of the ultrasonic image. The focal skin lesion can be clearly segmented from an ultrasonic image having noise.

IV. PROBLEM STATEMENT

This section describes the mixture model used for ultrasound image voxels.

A. Bayesian Approach

The Bayesian approach we describe bases inferences on exact posterior distributions for the parameters and latent variables estimated by Markov chain Monte Carlo. As sample sizes increase, Bayesian and frequentist estimators of the parameters should converge. However, an appealing feature of the Bayesian approach is that posterior distributions are obtained not only for the parameters, but also for the latent variables. The Bayesian approach yields estimates of the exact joint posterior distribution of the latent variables. This model requires defining the likelihood and the priors for the unknown parameters.

The likelihood of the Bayesian model can be written as

$$P(r \backslash \theta, z) = \prod_{k=1}^{k} 1 \prod\{n \backslash zn = k\} \; p_{\alpha R}(r_n \backslash \acute{\alpha}_k, \gamma_k) \quad (1)$$

The probability density function (pdf) of an α-Rayleigh distribution with parameters $\acute{\alpha}_k$ and γk and J_0 is given by

$$p_{\alpha R}(r_n \backslash \acute{\alpha}_k, \gamma_k) = r_n \int_0^{\infty} \lambda \; \exp[-(\gamma_k \lambda)^{\alpha k}] \, J_0(r_n \lambda) d\lambda \quad (2)$$

The approximation of the likelihood function involves the computation of the following indefinite integral

$$\int_0^{\infty} \lambda \; \exp[-(\gamma_k \lambda)^{\alpha k}] \, J_0(r_n \lambda) d\lambda \qquad (3)$$

The integral can be precomputed for each level and stored in a lookup table.

B. Gray Level HMT

The binary HMT transform by the pair (A,B) associates to a binary image X the set X (A,B) of positions where the translate of A fits inside X and at the same time the translate of B fits inside the complement Xc . For the gray-level HMT operator, we use a definition that assigns to A and B gray-levels a and b, respectively. Following this definition, the gray-level (GL) HMT compares at each point p the minimum intensity.

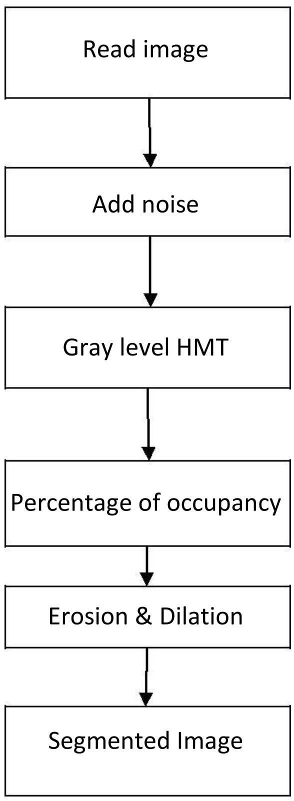

Fig1. Block Diagram of proposed system

1. Preprocessing

For the processing of binary images, the HMT is well defined [2]–[7], and involves searching an image for locations where predefined templates simultaneously fit the image. The templates, known as structuring elements (SEs) in morphology, are designed to match the geometry of objects of interest in the foreground and background of the image. In the preprocessing module we resize the image; we add additive noise and then filter it. The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity.

2. Morphological operation

Morphological operation we use Local pixel transformations for processing region shapes. It is most often used on binary images.

Here the Logical transformations based on comparison of pixel neighborhoods' with a pattern. Morphological processing is constructed with operations on sets of pixels. Binary morphology uses only set membership and is indifferent to the value, such as gray level or color, of a pixel. Morphological processing is described almost entirely as operations on sets. In this discussion, a set is a collection of pixels in the context of an image. Our sets will be collections of points on an image grid G of size N × M pixels.

3. A Percentage Occupancy HMT

In the standard HMT the foreground structuring element must fit entirely within the foreground of the object and the background SE must fit entirely within the background surrounding the object. In other words, they must be fully occupied by the foreground and background respectively. Any noise, even just one pixel, in either the foreground or background of the object can prevent an otherwise legitimate hit occurring. The idea behind the POHMT is to make the detection process less sensitive to moderate amounts of noise (or texture) in the image. We propose relaxing the constraint that the SEs must be 100% occupied and allow them to be only partially occupied and to still record a 'hit'.

Attempts at relaxing these strict constraints have been proposed in [21], [22], and [23]– [25]; however, in this paper we introduce a new design tool in order to set the appropriate level of partial (or percentage) occupancy. This tool may also be used in order to set the parameters for equivalent methods in an objective rather than an empirical way.

4. Segmentation

Segmentation is the process of partitioning a digital image into multiple segments(sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

5. Performance Analysis

In performance analysis we compare the performance of the proposed system with the existing system in an image such that pixels with the same label share certain visual characteristics.

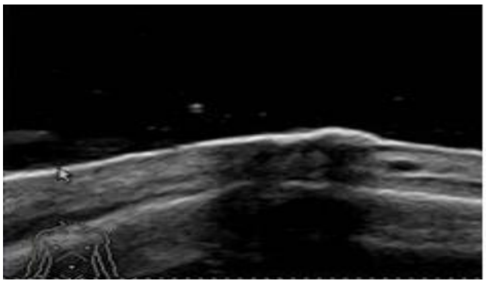

Fig2. An example of the noisy biological image

V. EXPERIMENTAL RESULTS

Here, we test the performance of the POHMT to detect a biological cell in a series of very noisy images .Firstly as it processes the image in a single pass. Second, a fast POHMT has been implemented using techniques similar to those used to optimize median filtering [26] and by observation of the data, it is evident that the shape and orientation of the cell changes between the images. The first stage in the process is to generate a PO plot for each feature of interest in the test set in order to determine an appropriate level for P. Although the cell is not a constant shape and size in all images, we can design B such that its elements corresponding to B_{FG} will fit inside it in each image. Similarly, B_{BG} was designed to encompass all of the features of interest in each image to guarantee that we can detect the cell in all possible orientations and variations of shape and size. By increasing the spatial distance between the SEs, as we are here, it can be argued that the transform may produce erroneous hits. If a problem occurs, this issue can easily be overcome by exploiting the discriminatory property of the POHMT.We also note that, although automatic techniques are available for SE design we have used a manual method here to compare our method with the one presented in [22].We have used square SEs for processing simplicity; however, this may be readily extended to arbitrarily shaped SEs using the method described in [27]. B was used to generate a PO plot for each image in the training set in order to obtain a suitable level for , such that the feature could be detected in the test set, without picking up erroneous hits. Clearly, by reference of the PO plot, setting 81% is sufficient to ensure that this feature may be detected using one composite SE for the entire test set. The POHMT was calculated for foreground and background image in the test set where the results of applying this transform and reconstructing the features of interest that have been marked are shown in fig 3. To improve visibility, we have dilated each image resulting from the opening by reconstruction.

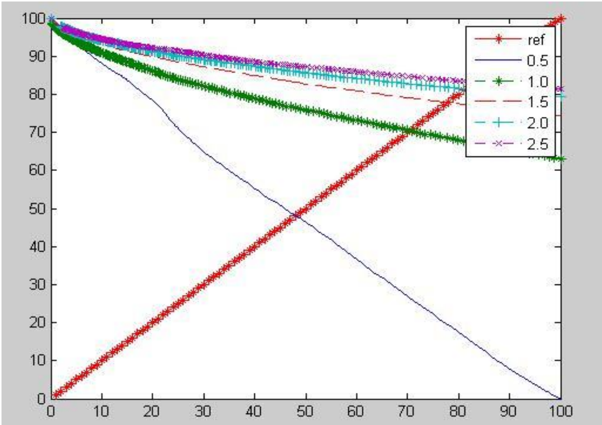

Fig3. Output of POHMT

VI. CONCLUSION

In this paper, we have presented an extension of the grayscale HMT following the definition given by Soille, although various definitions exist in the literature. We have shown the equivalences between these extensions, and we have highlighted the reasons that noise in images may cause these transforms to fail. We have presented a solution that offers improved robustness to noise, in the form of a POHMT, which relaxes the fitting criteria of the SEs making them more flexible such that they can successfully detect image features even in very noisy conditions of a POHMT, which relaxes the fitting criteria of the SEs making them more flexible such that they can successfully detect image features even in very noisy conditions In addition to the POHMT, we have shown in this paper a novel design tool in the form of a PO plot. The plot can be used to set the only parameter required by the POHMT and can be used by other researchers to set parameters for their own routines. We have given various examples of how this can be achieved, and we have used the PO plot to incorporate some suggested modifications by other researchers to make the grayscale HMT perform better in the presence of noise. When performing the HMT and using the suggested modifications, we have shown that image features can be detected in noise, but unlike the POHMT, there are also a large number of false positives in the result. Further to the PO plot being used to set parameters for grayscale HMTs in noise, we have shown that this tool provides some additional benefits. The discriminatory filter aspect of the POHMT which is a direct result of analyzing the PO plot, allows us to differentiate between objects in the image that we wish to detect and others which may appear visually similar in the spatial domain but that are not of interest. On the set of images containing the noisy biological cell, the fast POHMT executed in less than one second while detecting the image features of interest. We have shown that our method outperforms all of the grayscale HMTs that have been discussed in this paper when images are noisy and that even using the an that even using the suggested techniques for improved robustness to noise, we still achieve better results. We have also shown that our method achieves better results than the most recent extension of the HMT presented by Perret *et al.* and we have verified this using their images. Although the applications of this method have been demonstrated for images of a biological and astronomical nature, our method may be applied to any feature recognition problem. The only requirement of this routine is that we must know the spatial characteristics of pattern that we seek ,however this requirement is consistent with most morphological operations.

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