An Adaptive Novelty Detection Approach to Low Level Analysis of Images Corrupted by Mixed Noise

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Abstract. We propose a new adaptive novelty detection based algorithm for the primary local recognition of images corrupted by multiplicative/additive and impulse noise. The purpose of primary local recognition or low level analysis such as segmentation, small object and outlier detection is to provide a representation which could be potentially used e.g. in context based classification or nonlinear denoising techniques. The method is based on the estimation of mixing parameters (priors) of probabilistic mixture models along a small sliding window. A novelty score is defined by the mixing parameters and this is utilized by the procedure for determining the corresponding class of image patch with the aid of a lookup table. Numerical simulations demonstrate that the proposed method is able to improve upon previously employed techniques for the same task. In addition, the computational demand required by the proposed method is clearly inferior to some of the recently applied techniques as expert systems or neural networks.

1 Introduction

A number of methods of novelty detection have been proposed using nonparametric [1,2], semi-parametric and parametric [2,3] statistical approaches, support vector techniques [4,5] and neural networks [6].

The main idea behind these approaches is to estimate either the unconditional probability density function or directly the support of the data distribution from a training set. Then based on this information it is tested to what extent the new data do fit to the model by calculating some measure or score of novelty. If the score exceeds some previously set threshold then the corresponding test samples are considered as outliers or novelty [1-6].

Note however that in practice data could be inhomogeneous and so the location of the support of the data distribution may change. In these cases the support of the data is rather a local feature as the global support becomes meaningless.

The approach proposed in this paper provides a solution by adapting the parameters of the model to small space-time domains. This is achieved by local analyses of the image with small sliding windows and by updating a parameter of the novelty model itself. We also show real-world examples where the proposed method is useful for low level analysis of images such as segmentation, small object and outlier detection.

The paper is organized as follows. The image models are described in Section 2. A new adaptive novelty detection method is proposed in Section 3. Simulation results are presented in Section 4. And conclusions are provided in Section 5.

2 Models of Noisy Images

Two main noise models have been considered in the image processing literature: a) an image obtained by Ka-band side look aperture radar (SLAR) is corrupted by a mixture of Gaussian multiplicative noise and outliers [7]; b) an image is influenced by a mixture of Gaussian additive noise and outliers. The main difference between these two models is that in the first case the noise is *multiplicative* or data-dependent while in the second case the noise is *additive* or signal-independent [7,8].

Let index *n* denote both the index of the pixel under consideration and the location of the central pixel in the scanning window. With the probability P_{im} of the occurrences of outliers A_n the model of SLAR image x_n corrupted by outliers can be written as $x_n = A_n$ and in the other cases x_n is corrupted by signal dependent noise, $x_n = I_n(1+\sigma\xi_n)$, [7,8,9] where $I_n \in \{\mu_1, \mu_1, ..., \mu_J\}$, I_n denotes the value of the *n*-th pixel of the image without noise. Further, ξ_n denotes standard Gaussian noise, σ^2 is the relative variance of the multiplicative noise with mean equal to 1, $\mu_1, \mu_2, ... \mu_J$ denote the different intensity levels, J is the number of different intensity levels in the noise-free image. The multiplicative noise can be easily transformed to additive noise using an appropriate homomorphic transformation, e.g., the natural logarithm [8,9].

Then the transformed image model can be written as $y_n = sI_n^h + \sigma_s\xi_n$, where $\sigma_s^2 = s^2\sigma^2$, $I_n^h \in \{\mu_1^h, \mu_2^h, ..., \mu_J^h\}$ and $\mu_j^h = \ln \mu_j$. Further, y_n, I_n^h are the *n*-th pixels of x_n, I_n^h after homomorphic transform, respectively; *s* is a scaling parameter - in our experiments we set $s = 46$ for our convenience (in this case $x_n, y_n \in [0,255]$). In the above approximation we have made use of the Taylor expansion of the natural logarithm function i.e., $\ln(1+x) = \sum_{k=1}^{\infty}(-1)^{k+1}\frac{x^k}{k}$ when $|x| < 1$, by truncating it to the linear term. Observe that after the homomorphic transform the probability density function $p(y_n)$ of the image y_n can be approximated by the mixture of Gaussians with shared variance σ_s^2, mixing parameters π_j and means μ_j^h, $p(y_n) = \sum_{j=1}^{J}\pi_j N(y_n, \mu_j^h, \sigma_S^2)$ where $0 < \pi_j \leq 1$ and $\sum_{j=1}^{J}\pi_j = 1$ [10]. Thus we now have a model with $2J+1$ unknown parameters (π_j, μ_j^h and σ_s^2) which could be estimated using a gradient-like method or Expectation-Maximization (EM) algorithm [10]. However, this still does not provide any information about the local changes of intensity (what Marr has called as 'primal sketch' [11]). The next section is concerned with developing a method for this purpose.

3 Locally Adaptive Novelty Detection Method

Our algorithm is based on the following intuitive idea. If an observer is trained to see just one homogeneous region at a time with different light intensity or texture then it is unusual for him to see: 1) two large homogeneous regions (edge) at a time; or 2) small objects or outliers with a homogeneous region in the background.

Similar to [9,12,13], we consider six classes for primary local recognition: 1) homogeneous region (H); 2) edge neighborhood between large objects or two homogeneous regions (E); 3) neighborhood of a spike (outlier) - by this we mean that there is one or no more than 3 spikes elsewhere than in the central pixel (NS); 4) spike in the central pixel of the scanning window (S); 5) the central pixel belongs to a small sized object (a small sized object is characterized by compactness of pixels belonging to it as well as by homogeneity of the pixel values) (O); 6) neighborhood of a small sized object (NO).

Because the scanning window should be small enough to ensure locality of the analysis (e.g., 5x5 pixels) and also for keeping our model as simple as possible [4] then it is reasonable to assume that there are not more than two Gaussian components appearing in the scanning window. Therefore, we will model the image fragment in each small scanning window as a mixture of two Gaussians with the mixing parameters π_i^n and π_j^n ($\pi_i^n + \pi_j^n = 1$, $0 \leqslant \pi_i^n, \pi_j^n \leqslant 1$) for the *i*-th and *j*-th component of the mixture distribution

$$p(y_n) = \pi_i^n N(y_n, \mu_i^h, \sigma_s^2) + \pi_j^n N(y_n, \mu_j^h, \sigma_s^2)\,,\ i \neq j\,,\ i,j \in \{1,2,...,J\}\ . \qquad \textbf{(1)}$$

The model (1) has only 5 free parameters but it is necessary to estimate these parameters for each location of the scanning window. Therefore, for the entire image we end up having as many models as pixels in the image. Because we employ small scanning windows and because the image is contaminated by outliers, it would be inefficient to apply a statistical estimation such as an EM algorithm, for example.

Obviously, for $i \neq j$ knowing one of mixing parameters we can find another one ($\pi_i^n = 1 - \pi_j^n$) and a small reduction in the number of free parameters is possible. Note that there are three distinct possibilities: 1) $\pi_i^n < \pi_j^n$; 2) $\pi_i^n > \pi_j^n$; 3) $\pi_i^n = \pi_j^n$. Therefore, we can find a Gaussian component that has a mixing parameter that is not less than the other one. All we need to do then is to estimate $\pi_{max}^n = \max\{\pi_i^n, \pi_j^n\}$ for each location of the scanning window.

In order to estimate π^n_{max} we will employ a well-known technique, the so-called 3-sigma rule, which states that with probability 0.997 the random value y will lie within the interval $[\mu - 3\sigma_s, \mu + 3\sigma_s]$ if it belongs to the Gaussian distribution with mean μ and standard deviation σ_s, $P(|y - \mu| \geqslant 3\sigma_s) \leqslant 0.003$ [14]. We introduce a new notation here, let N^μ_n denote the number of pixels of the scanning window in the neighbourhood of y_n which are inside the interval $[\mu - 3\sigma_s, \mu + 3\sigma_s]$. For grey-scaled images with 255 grey levels $\mu \in [0,255]$.

In summary, the proposed algorithm will consist of two steps: 1) calculate π^n_{max} where the estimate of π^n_{max} is equal to the maximal value of N^μ_n given the location of the scanning window and an estimate of σ^2_s divided by the number of points in the scanning window L (e.g., if the size of the scanning window is 5x5 then L=25 and, $\pi^n_{max} = \max_\mu N^\mu_n \; / 25$); 2) based on the estimate of π^n_{max} (or $\max N^\mu_n$ or novelty score $N_{score} = 1 - \pi^n_{max}$) and on the information about either the central pixel being inside of the selected interval $[\mu - 3\sigma_s, \mu + 3\sigma_s]$ corresponding to $\max N^\mu_n$ look up the class from the table (e.g., see Table 1). The method is *locally adaptive* because an estimate of the dominant mixing parameter of the mixture model π^n_{max} is calculated for each position of the small scanning window but not for the entire image.

For 5x5 scanning window when $L = 25$, e.g., the first row of Table 1 corresponds to $\max N^\mu_n = 25$, the second (third) one relates to $\max N^\mu_n = \{23,24\}$ ($\max N^\mu_n = 22$). Similar tables were proposed for the classification of noise-free images in order to obtain a target image using a genetic algorithm to correct misclassifications (see Table 1,2 in [13]). Thus, if the image fragment in the scanning window is not novel, then we get a novelty score $N_{score} \approx 0$. If the image fragment is not just one homogeneous region or is unusual to the observer then $N_{score} > 0$. In practice N_{score} is never exactly equal to one because even if pixels are uniformly distributed in [0,255] then $\max N^\mu_n$ is equal at least 1 ($1 \leqslant \max N^\mu_n \leqslant L$ and $0 \leqslant N_{score} \leqslant 1 - 1/L$).

4 Experiments

In this section, we demonstrate the performance of the proposed algorithm for both an artificial image corrupted by Gaussian multiplicative noise (Fig.1,a) and a real Ka-band SLAR image (see Fig.2,a). We start with a noise-free image containing small and large objects with intensity levels from the set $\{10,15,20,80,120,160\}$ i.e., six different positive and negative contrasts and a background of 40. This image was then corrupted by multiplicative (data-dependent) noise with a mean equal to 1 and relative variance $\sigma^2 = 0.003$ (see Fig.1,a).

Table 1. Example of novelty score table to select class based on N_{score}

N_{score}	A central pixel of scanning window belongs to the interval $[\mu - 3\sigma_s, \mu + 3\sigma_s]$	A central pixel of scanning window does not belong to the interval $[\mu - 3\sigma_s, \mu + 3\sigma_s]$
0..0.04	H	H
0.04..0.08	NS	S
0.08..0.16	NS	O
0.16..0.32	NO	O
0.32..0.64	E	E
0.64..1.0	O	NO

After applying the homomorphic transform to the noisy test image and setting the scaling factor ($s = 46$) the variance of the additive noise becomes $\sigma_s^2 \approx s^2\sigma^2 = 6.348$. We use this setting to compare three different methods: 1) the method of supervised primary local recognition based on radial basis neural network (NN) with 10 inputs (features are the bins of modified histograms of the image in the small scanning window, see [8] for details), 50 nodes in the hidden layer, and 6 outputs (6 classes). We will refer to this method as NN-Hi; 2) the second method uses a similar NN except that the number of inputs has been reduced to 6 local statistical parameters which have been calculated for each position of the scanning window (see [8,9]). This method will be referred to as NN-SP; 3) finally we will refer to our new method as ND. An equal window size of 5x5 has been chosen for all three methods in this comparison.

Results are shown in Table 2. The analysis of this table highlights that the proposed method produced a superior recognition performance for all the main classes (H,E,O,NO) when compared to NN-Hi and NN-SP. In addition, our simulations demonstrate that the superiority of the proposed method holds also for images with different contrasts than those utilized in the training process for NN-Hi and NN-SP. Fig.1,b shows the novelty scores N_{score} for noisy test image pixels: pixels in black color belong to homogeneous regions (not novel) while the white pixels are edges or highly novel. In Fig.1,c we can see that if the central pixel belongs to the interval $[\mu - 3\sigma_s, \mu + 3\sigma_s]$ this information is useful in classifying patches like S and O. Fig. 1,d shows how the information presented in Fig.1,b,c can be combined to recognize all classes (we use different colours to represent different classes).

Fig.2,a depicts results for a real Ka-band SLAR image where Fig.2,b,c,d correspond to Fig1,b,c,d, respectively. The size of the scanning windows was 5x5 and the relative variance was equal to 0.004. These values have been chosen according to a human expert analysing the homogeneous regions of the real image (see Fig.2,a). Visual inspection also demonstrates that the proposed method presents encouraging performance and is able to distinguish between important components of the image such as edges, small objects, outliers and homogeneous regions.

5 Conclusions

In this paper we have proposed a locally-adaptive novelty detection method for the primary local analysis in image data corrupted by mixed noise. The recognition results have outperformed those obtained with an RBF classifier on both artificial images and real Ka-band SLAR images.

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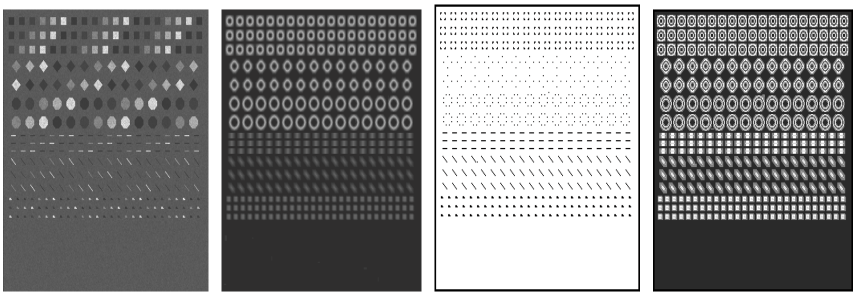
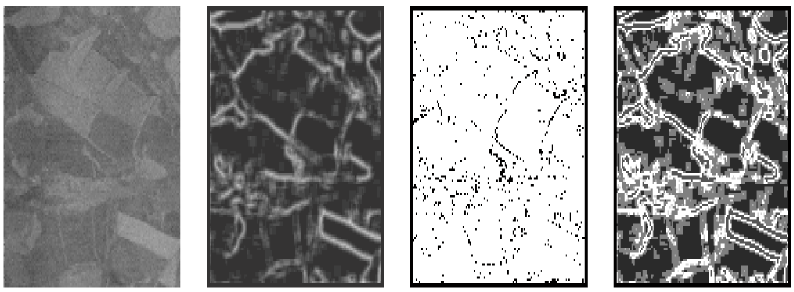
Table 2. Results of correct image classifications by NN-Hi, NN-SP and ND

	Recognized classes			
Methods	H	E	O	NO
ND	**99.94** %	**99.99** %	**99.99** %	**99.99** %
NN-Hi	99.5 %	93.6 %	99.6 %	90.6 %
NN-SP	99.1 %	91.8 %	94.7 %	85.8 %



a) b) c) d)

Fig. 1. Illustrations of primary image recognition for the artificial image: a) the artificial Ka-band SLAR image; b) novelty score mapping; c) central pixel mapping; d) classification mapping



a) b) c) d)

Fig. 2. Real radar image processing: a) real Ka-band SLAR image; b) novelty score mapping; c) central pixel mapping; d) classification mapping