A Novel Approach to Robust Blind Classification of Remote Sensing Imagery

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Abstract

In this paper we propose a novel method for the robust classification of blurred and noisy images that incorporates ideas from data fusion. The technique is applicable to blind *situations in which the exact blurring function is unknown. The approach treats differently deblurred versions of the same image as distinct correlated sensor readings of the same scene. The images are fused during the classification process to provide a more reliable result. We show analytically that the various restorations can be treated as images acquired from different but correlated sensor readings. Experimental results demonstrate the potential of the method for robust classification of imagery.*

1 Introduction

Classification is an information processing task in which specific entities are mapped to general categories. For the classification of remote sensing multispectral images, the specific goal is to assign each vector-valued pixel of the multispectral image to its appropriate category using tonal and/or textural data. When the classification process is complete, the multispectral images are transformed into a single colour-coded image showing the several types of classes in the scene.

The performance of a classification scheme depends on the quality of the images used in the classification process. The inaccuracy of many classification strategies result from fusing imagery that exhibit blurring. Compensation for image blurring is inherently sensor-dependent and is non-trivial as the exact blur is often time-varying and unknown [1]. Blind image restoration methods, which attempt to deblur the data without explicit knowledge of the blur, may be used for preprocessing prior to restoration. However, many existing techniques suffer from noise amplification [2] which reduces the accuracy of the classification process. The development of a method of robust classification would benefit such situations.

In the next section we describe the general technique and discuss specific implementation issues. Section 3 provides simulation results of the technique and comparisons to the standard classification approach. We discuss limitations of the proposed method in Section 4, and conclude with final remarks in Section 5.

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2 The Proposed Approach

2.1 General Overview

For simplicity, we consider the classification of a single noisy blurred image, although the method can easily be extended to the situations in which other sensor imagery are available. The first stage of the technique involves the blind restoration of the image. It has been shown that such algorithms are susceptible to noise amplification [2]; regularization techniques are used to make the restoration well-conditioned. However, regularization can be imposed in a variety of degrees on the image estimate. Each estimate exhibits a compromise between the amount of blur removal and noise suppression. If several image estimates of varying degrees of regularization can be used in the classification procedure, then it is reasonable to expect that there will be an overall regularizing effect on the classification.

The second stage *fuses* the various image estimates into a classified image. The data fusion process takes into account the correlation in the noise among the various image estimates. Data fusion refers to the acquisition, processing and synergistic combination of information from various knowledge sources and sensors to provide a better understanding of the situation under consideration. There are many applications and architectures for data fusion [3]; in this paper we make use of a centralized intermediate-level fusion scheme for the classification of imagery. Figure 1 gives an overview of the proposed technique.

2.2 Algorithm Specifics

We concentrate on the classification of remote sensing imagery. In such applications, the degradation of an image can be represented by the following linear equation:

$$g(m,n) = f(m,n) * h(m,n) + w(m,n), \qquad (1)$$

where $g(m,n)$ is the degraded image, $f(m,n)$ is the true image, $h(m,n)$ is the unknown blur, and $w(m,n)$ is additive white Gaussian noise with variance σ_w^2. The operator $*$ represents two-dimensional linear convolution.

To perform blind image restoration, we make use of the NAS-RIF algorithm which uses support and nonnegativity information about the original image to perform restoration. The algorithm recursively filters the signal g with a two-dimensional variable FIR filter u to produce an estimate of the original image f. At each iteration the value of

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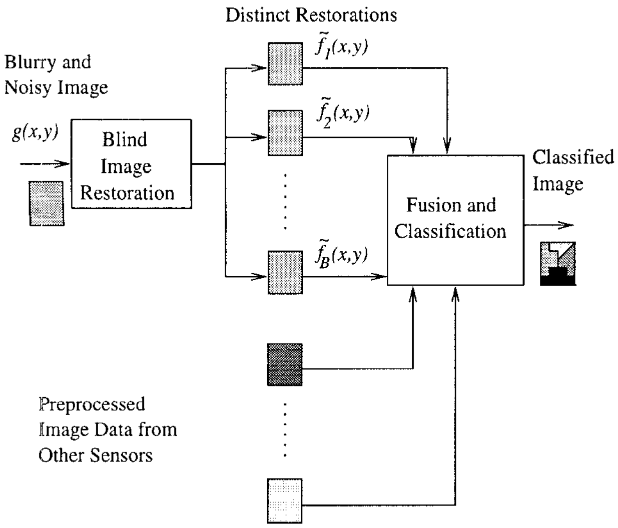

Figure 1: Proposed Robust Classification Scenario.

u is updated to minimize a specified convex cost function. The relevant details may be found in [2]. It has been shown that the NAS-RIF algorithm exhibits noise amplification at moderate and low SNRs. To regularize the problem, premature algorithm termination is employed so that one obtains a partially blurred image with low noise amplification. The main obstacle is in deciding when to terminate the algorithm such that a reliable classification can be obtained.

We propose using several image estimates, which exhibit various degrees of blur removal and noise amplification, to produce a more reliable classified output. Assuming that we use the restorations at B different iterations of the NAS-RIF algorithm, each image estimate can be represented as:

$$\begin{aligned} \tilde{g}_k(m,n) &= u_k(m,n) * g(m,n) \\ &= f(m,n) * h(m,n) * u_k(m,n) + \qquad (2) \\ &\quad\ w(m,n) * u_k(m,n) \\ &= \tilde{f}_k(m,n) + \tilde{w}_k(m,n) \qquad (3) \end{aligned}$$

where $k = 1, 2, \ldots, B$, $\tilde{f}_k = f * h * u_k$ is the partially restored image and $\tilde{w}_k = w * u_k$ is the filtered additive noise. We can interpret each image $\tilde{g}_k$ as originating from a different band of a hypothetical sensor. If we assume that most of the blurring remaining after filtering is negligible, then it follows that $\tilde{f}_k \approx f$ for all $k = 1, 2, \ldots B$, and we can treat $\tilde{w}_k$ as the associated additive noise of the sensor band k. The noise of the image bands are correlated according to the following covariance matrix:

$$E\left\{\tilde{\mathbf{w}}(m,n)\tilde{\mathbf{w}}(m,n)^T\right\} = \sigma_w^2 \mathbf{R}_u, \qquad (4)$$

where $\tilde{\mathbf{w}}(m,n) = [\tilde{w}_1(m,n)\tilde{w}_2(m,n)\cdots\tilde{w}_B(m,n)]^T$ and $\mathbf{R}_u$ is the covariance matrix of u_k, $k = 1, 2, \ldots, B$ whose elements are given by:

$$[\mathbf{R}_u]_{ij} = \sum_{\forall(m,n)} u_i(m,n)u_j(m,n), \qquad (5)$$

for $i, j = 1, 2, \ldots, B$. By taking into account the correlation in the noise, we can exploit both the redundancy and complementarity of the image estimates.

To test our approach, we implement a successful statistical classification algorithm by Schistad Solberg *et. al.* [4] which accounts for the correlation of the noise in different bands of the same sensor. The algorithm was chosen because of its flexibility and generality; it links spatial, spectral and temporal correlations in a uniform Markov random field framework. The method works well for classifying images with non-Gaussian noise characteristics. As blurring can be considered to be a form of non-Gaussian noise, this classification method is well-suited for blind image fusion. The method fuses different images into a fully classified output image by using information about the statistics of the noise in each image. The mean radiance values of the different classes as well as the covariance matrices of the noise processes for each of the sensor images are required for fusion. These values are often estimated. However, if the blurred signal-to-noise ratio (BSNR) of the degraded image is known a priori (and thus σ_w^2 is known) then the covariance matrix of the associated noise processes can be obtained from Equation 4.

The relevant details about the classification method are found in [4]. In the next section we present simulation results to validate our approach to robust classification.

3 Simulation Results

We provide the results for two sets of image data. The first set consists of synthetic image data of an island-like scene. The second set is comprised of a photographic colour image of crayons. The results of the classification processes are evaluated based on classification accuracy (CA). CA is defined as the percentage of correctly classified pixels in the entire image. That is,

$$CA \triangleq \frac{\#\text{ of correctly classified image pixels}}{\text{Total }\#\text{ of pixels in the classified image}} \times 100. \qquad (6)$$

Figures 2(a)-(d) show the original image, the degraded image, the restoration at the 6th iteration of the NAS-RIF algorithm, and the restoration at the 7th iteration, respectively. The degraded image was formed by blurring the original image with a Gaussian PSF and adding white Gaussian noise to produce a blurred signal-to-noise ratio (BSNR) of 40 dB. The mean value of the radiance for each class was assumed to be known a priori; since the data was synthetic this information was easily known. The covariance matrix was estimated from Equation 4 using the fact that the BSNR for the original blurred image was 40 dB. Figure 3 shows the classification results; four distinct classes are assumed. The white, black, light grey and dark grey colours denote classes 1, 2, 3 and 4, respectively. The classification accuracies of fusing the various image estimates are shown in Table 1.

Table 1 shows that the fusion of two different restorations of an image opposed to a single restoration can increase the classification accuracy. No additional sensor readings or information are required for this improvement. Rows 6–9 of Table 1 demonstrate how fusing two image estimates with other registered simulated sensor readings of the same scene also gives an improvement in the classification accuracy.

Figure 4 shows the photographic data used in the second set of simulations. The degraded image was formed by convolving the original red band of the photographic image (Figure 4(a)) with a 7×7 separable blur. Additive white Gaussian noise was added to the result to produce a BSNR of 40 dB. The synthetic blur was generated using vv^T where v is a 7×1 column vector linearly decreasing from the center. Restoration I corresponds to the restoration at the first iteration of the NAS-RIF algorithm and restoration II corresponds to the restoration at the eleventh iteration. The mean value for each of the classes was estimated using another unblurred photograph of the scene; in practice it is often determined this way. In addition the texture for the different classes was modeled as being additive noise (additional to w). Due to numerical problems involving matrix inversion in the implementation, the noise of the individual restorations were treated as being independent of one another (i.e, any off-diagonal entries of $\mathbf{R}_u$ were assumed to be zero).

The classification results are provided in Figure 5. There are five different classes in the scene corresponding to each of the four differently coloured crayons and the background (shown in black); classes 1, 2, 3, 4 and 5 are represented by black, dark grey, medium grey, light grey and white, respectively. Table 2 presents the classification accuracies; it demonstrates the potential of the proposed approach.

4 Limitations of the Approach and Future Work

Although the proposed approach often improves CA, experience with simulation results reveal that the method is not always successful. For example, fusing a restoration which produces a high CA with one which produces a poor CA can result in a slight reduction in CA over that of the successful restoration. It is not straightforward how to determine which combination of restorations can improve CA.

The authors also observed that if complementary non-blurred, but possibly noisy information of the scene was available, then the degree of improvement of the proposed approach was diminished. The complementary information, which could be in the form of another image of the scene, raised the overall CA. However, the improvement in CA by fusing two or more restorations (instead of just one) with the additional imagery was diminished; for example, instead of a 1% improvement in CA, a 0.1% improvement was found. The authors believe that future work should involve defining a quantitative figure of merit to assess the potential of a restoration to give good CA.

5 Conclusions

In this paper, we propose an approach for the robust classification of blurred and noisy images for situations in which the blur is unknown. Due to the ill-posed nature of the restoration procedure, we can regularize the problem by fusing many image estimates exhibiting varying degrees of blur removal and noise amplification. Simulation results demonstrate the potential of the approach for improved robust classification without the need for additional sensor readings or information.

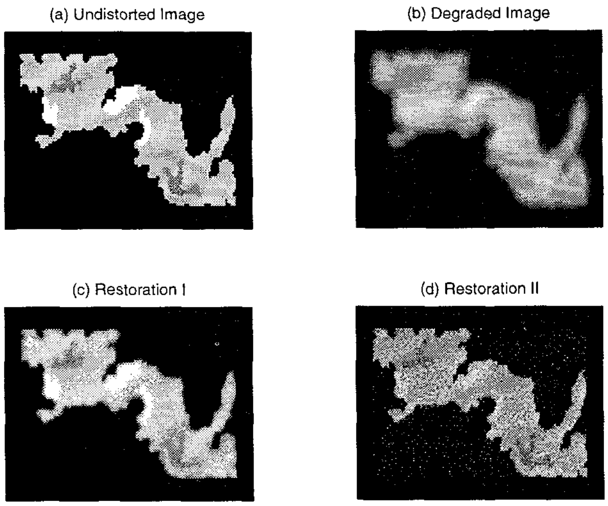

Figure 2: Synthetic Image Data. The grey-levels represent the actual simulated radiance of the scene. (a) Original, (b) Degraded image with BSNR of 40 dB, (c) Restoration at 6th iteration, (d) Restoration at 7th iteration.

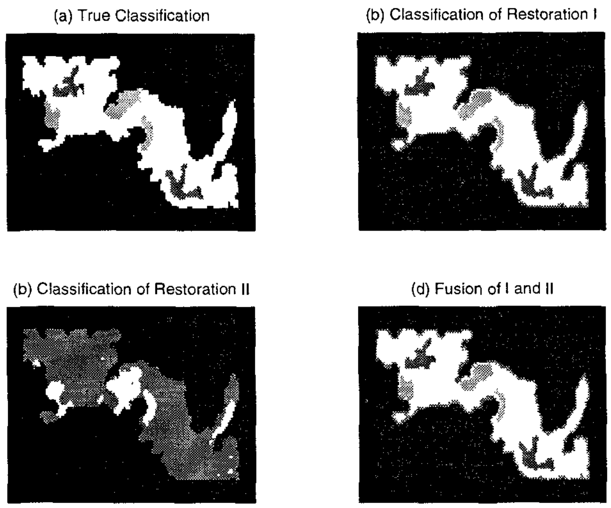

Figure 3: Classification Results for Synthetic Data. The four different grey-levels represent each of the different classes in the image. The white, black, light grey and dark grey colours denote classes 1, 2, 3 and 4, respectively.

References

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Table 1: Percentage classification accuracies for the synthetic data. Image 2 is an additional registered image of the same island-like scene which is degraded solely by additive white Gaussian noise with a SNR of 20 dB. The **boldface rows** represent the results of the proposed approach.

Image(s) Fused	Overall	Class 1	Class 2	Class 3	Class 4
Blurred Image (Fig. 2(b))	74.7	61.3	63.3	1.6	88.6
Rest. I (Fig. 2(c))	91.4	86.1	90.9	75.4	96.0
Rest. II (Fig. 2(d))	62.6	9.2	100.0	0.0	99.3
Rest. I & II	**93.8**	**88.1**	**95.2**	**75.0**	**98.7**
Image 2 (not shown)	92.2	83.7	98.5	49.5	100.0
Rest. I & Image 2	98.1	97.2	99.2	76.0	100.0
Rest. II & Image 2	96.2	98.3	100.0	0.0	100.0
Rest I & II, & Image 2	**98.3**	**98.8**	**98.5**	**65.7**	**100.0**

Table 2: Percentage Classification Accuracies for the photographic data. The **boldface row** represent the results of the proposed approach.

Image(s) Fused	Overall	Class 1	Class 2	Class 3	Class 4	Class 5
Blurred Image (Fig. 4(b))	85.2	99.4	58.8	64.4	50.7	100.0
Rest. I (Fig. 4(c))	85.2	99.4	58.8	64.4	50.7	100.0
Rest. II (Fig. 4(d))	84.4	91.7	38.0	93.6	72.8	92.5
Rest. I & II	**86.4**	**95.0**	**46.6**	**95.6**	**61.0**	**93.8**

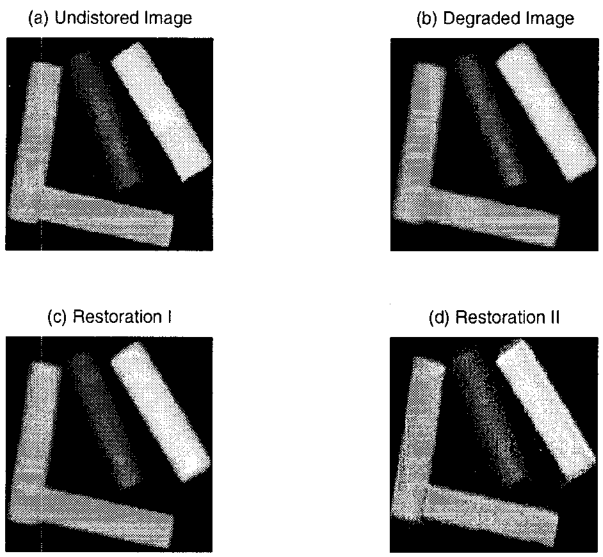

Figure 4: Photographic Image Data. The images represent the red band of a colour photograph of crayons. (a) Original, (b) Degraded image with BSNR of 40 dB, (c) Restoration at 6th iteration, (d) Restoration at 7th iteration.

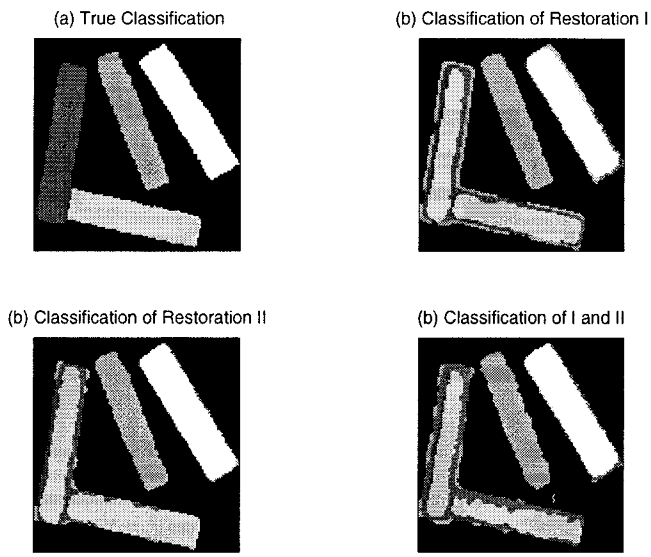

Figure 5: Classification Results for Photographic Data. The five different grey-levels represent each of the different classes in the image. The white, light grey, medium grey, dark grey and black colours denote classes 1, 2, 3, 4 and 5, respectively.

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[4] A. H. Schistad Solberg, Torfinn Taxt and A. K. Jain, "A Markov Random Field Model for Classification of Multisource Satellite Imagery," *IEEE Trans. Geoscience and Remote Sensing,* vol. 34(1), pp. 100-113, January 1996.