INFRARED REGION CLASSIFICATION USING TEXTURE AND MODEL-BASED FEATURES

W. Brendan Blanton and Kenneth E. Barner

University of Delaware, Electrical and Computer Engineering, Newark, Delaware

ABSTRACT

Infrared sensors are widely utilized on manned and unmanned systems due to their ability to operate during low light conditions as well as their target discrimination capability. Machine vision algorithms that operate on infrared imagery (e.g. target detection, obstacle detection, target tracking) can significantly increase the effectiveness of platforms and the autonomy of unmanned systems. The classification of regions in infrared imagery provides a valuable input to computer vision algorithms. This paper contains an analysis of features for infrared region discrimination, feature dimensionality reduction, and classification for regions of infrared imagery. A variety of features are considered including those based on texture and a physics based model for atmospheric attenuation. An analysis of the optimal feature set and classifier combination is presented. Performance of the classifier on a database of infrared imagery is provided as well as top level contextual techniques to improve classification performance.

Index Terms—
Infrared imagery, scene analysis, feature extraction, image classification, image texture analysis.

1. INTRODUCTION

Infrared sensors are employed for a large variety of commercial and military applications. The imagery produced by these sensors provides significant information to human operators and are widely used for machine vision algorithms such as target detection. Infrared sensors are also frequently installed on unmanned systems including unmanned air vehicles (UAVs), unmanned ground vehicles (UGVs), and unattended remote sensors. In order to improve the autonomy of these systems, it is essential that the autonomous system awareness from the imagery collected by these systems be increased. A passive technique for obtaining situational awareness is the analysis of imagery for scene understanding. The first step in scene understanding is to classify imagery regions.

1.1. Background/motivation

Classification of imagery regions provides a critical first step in further analysis. In addition, the knowledge of the boundary of image regions provides significant information that can assist with autonomous navigation and collision avoidance. For instance, the boundary of the sky portions provides the horizon line that can be used to augment onboard inertial navigation. Another significant application of region classification is to provide a pre-processing step for target detection and higher level scene understanding.

This work addresses the problem of analyzing regions of infrared imagery for scene understanding. In particular, we classify regions of infrared imagery as either sky or ground. We discuss the extraction of feature sets, classification techniques and higher level methods for post processing classification results.

1.2. Related Work

Two major applications have resulted in published work related to our research; UAV autonomous navigation and automatic image retrieval. Classification of sky portions of color photographs to enable retrieval based on texture and a physics based model of blue sky was described by Gallagher *et al.* [1] and Singhal [2]. The more applicable problem of classification of regions in color UAV imagery utilizing multi-dimensional linear discriminate analysis (MDLA) was presented by Todorovic and Nechyba [3]. Other researchers have illustrated techniques of sky region classification by detection of the horizon line in UAV color imagery [4] [5]. All of these works claim high performance, but most utilize color information and have limited applicability to infrared imagery. Since tactical vehicles that may utilize our algorithm frequently operate at night or preferentially utilize infrared sensors to support targeting, it is important that an image classification technique be developed for these systems operate on infrared imagery.

1.3. Paper Organization

In this paper, we describe feature selection and analysis for infrared image region classification. The beginning of section 2 contains an overview of the features considered, methods for extraction and their potential plausibility for region classification. Section 3 discusses methods for feature selection and dimensionality reduction of a feature set. The results of feature extraction, dimensionality reduction and classification are presented in section 4. Section 5 concludes with a general discussion of results and applications for the proposed method.

2. FEATURES FOR INFRARED REGION CLASSIFICATION

There are many potential characteristics that intuitively appear likely feature candidates for classification of regions in infrared imagery. This section provides an overview of all feature types considered. The two main feature types considered are texture and sky physics-based model (PBM) features. Intensity-based features are considered because temperature characteristics of the general scene regions are a function of a myriad of environmental parameters. Without higher level knowledge (ambient temperature, diurnal conditions, weather, sensor performance, etc) it is difficult to obtain robust luminance features.

2.1. Texture Features

Infrared imagery typically is characterized by a narrow histogram concentrated around ambient temperature in which detector and atmospheric noise are present. These factors point to the desirability to consider texture features for region classification. In our previous work, we showed that wavelet-based texture features yielded excellent results when used for region dissimilarity for segementation [6]. The texture features implemented for this segmentation application serves as a starting point for texture feature based classification. These include the wavelet mean difference (MD), wavelet energy, gaussian fits for wavelet sub-band histograms and Renji's entropy. We refer the reader to [6] for the detailed computation of these features.

In addition to the wavelet-based texture measures, we considered texture features based on gray level co-occurrence. This method begins by representing how often gray-levels occur together in various orientations. A gray level concurrence matrix (GLCM) is often used to capture this information for a given image. The GLCM matrix is a two dimensional histogram with counts of various gray-level pairs for a single or set of orientations and offsets. We formed GLCM's in the horizontal(0°), diagonal(45°), and vertical(90°) orientations with offsets of one, two and three pixels.

Once the GLCM's are formed, several features can be extracted to represent texture information. Four commonly used GLCM measures are contrast, energy, correlation, and homogeneity. The region contrast is a measure of the amount of variation between a pixel and its neighboring pixel throughout an image. It is a measure of the average coarseness of texture within a region. The GLCM contrast is given by

$$GLCM_{con} = \sum_{i,j} |i-j| p(i,j) \tag{1}$$

where i and j are the row and column indices of entries in the GLCM given by $p(i,j)$. The GLCM energy is a similar measure that represents the total quantity of co-occurrence with a given GLCM. This provides a measure of the quantity of directionality within a given GLCM orientation. The energy measure is formed as the sum of squared GLCM entries,

$$GLCM_{energy} = \sum_{i,j} p(i,j)^2 \tag{2}$$

The GLCM correlation measures how correlated a pixel value is to its neighbor over a particular region. The GLCM correlation is formed as,

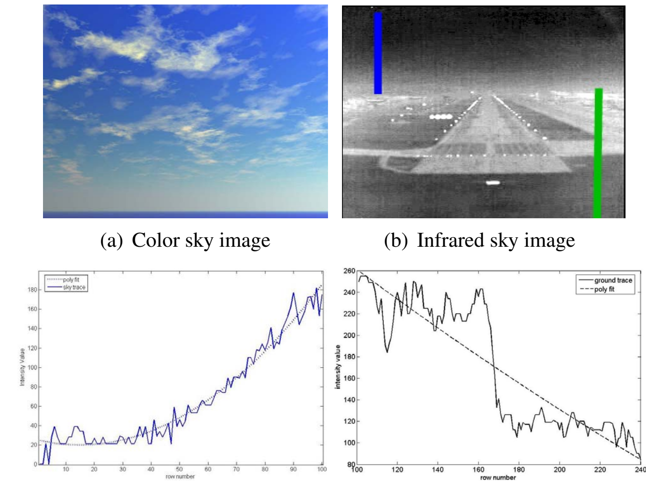
$$GLCM_{cor} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \tag{3}$$

where μ_i and μ_j are the means for a row or column given by i or j and σ_i and σ_j are the variance for a row or column given by i or j. The homogeneity measures the distribution of values in the GLCM away from the GLCM diagonal. Values closer to the diagonal correspond to similar intensity values. The homogeneity measure is formed as

$$GLCM_{hom} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{4}$$

2.2. Physics Based Features

Gallagher *et al.* [1] showed that a polynomial model applied to color traces can be used to detect sky portions of imagery. The sky is often



(a) Color sky image (b) Infrared sky image

(c) Example IR Sky Trace (d) Example IR Ground Trace

Fig. 1. Examples of vertical gradient in sky images

characterized by a blueish white along the horizon and a transition to deeper blues as elevation angle is increased. Infrared imagery does not contain the color information utilized in their work; however, a similar phenomena is present in infrared imagery. In response of infrared sensors is attenuated by numerous atmospheric effects. Atmospheric absorbtion of IR radiation, scattering of infrared radiation from emissions outside the field of view, atmospheric turbulence, and particle scattering are all additive effects that erode the target signature. Similar to the Rayleigh scattering that causes the blue sky signature in visible imagery; all of the scattering effects for infrared radiation are reduced as elevation angles are increased towards zenith largely due to the reduction in scattering contributors [7]. An example of this familiar behavior in color imagery and the analogy for infrared imagery is shown in Fig. 1. The sky and grounds sample traces and polynomial curve fits shown in Fig. 1(c) and Fig. 1(d) respectively correspond to the vertical lines overlaid on the image in Fig. 1(b).

Once a trace is extracted from a region, the least squares fit for a second order polynomial, $\hat{p}$, is formed as

$$\hat{p}(i) = a_0 + a_1 x(i) + a_2 x^2(i) \tag{5}$$

for a trace of n pixels. The least squares matrix representation is formed as

$$\begin{pmatrix} p(1) \\ p(2) \\ \vdots \\ p(n) \end{pmatrix} = \begin{pmatrix} 1 & x(1) & x(1)^2 \\ 1 & x(2) & x(2)^2 \\ \vdots & \vdots & \vdots \\ 1 & x(n) & x(n)^2 \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \end{pmatrix} \tag{6}$$

In matrix notation the equation for the polynomial fit can be written as $\mathbf{p} = \mathbf{V}\mathbf{a}$ where the least squares fit for the polynomial coefficients ($\mathbf{a}$) can be computed as

$$\mathbf{a} = (\mathbf{V}^T\mathbf{V})^{-1}\mathbf{V}^T\mathbf{p} \tag{7}$$

Once a second order polynomial is fit to a trace the coefficients are used as features for that trace. In addition, the goodness of fit is determined by calculating the mean square error of the fit,

$$E_{fit} = \frac{1}{i} \sum_{i} (p(i) - \hat{p}(i))^2 \quad (8)$$

where i is the row pixel index, p is the pixel value of the trace, and $\hat{p}$ is the fitted polynomial value.

The result is a set of fitted polynomials and errors for each trace in a given region. In order to obtain a summary for all traces in the region, the mean and variance are obtained for each coefficient and the E_{fit} across all of the traces; a set of 8 features for each region.

3. FEATURE SELECTION AND ANALYSIS

In the previous section, candidate features are described based on texture and a physics-based model(PBM) polynomial curve fitting. In this section, the methodology and results for feature set selection and performance are discussed.

The GLCM, Wavelet and PBM features were extracted from a library of infrared imagery containing 4525 regions. The result is a 101 element feature vector for each region. The next step is to determine which features lead to the highest classification performance. The purpose of feature selection is to select the optimal subset of features to reduce the feature vector dimension and eliminate non-productive and redundant features. Since the goal is to develop a highly separable feature space, the addition of non-productive features reduces classifier performance; the often referenced curse of dimensionality. In addition, the removal of non-productive features reduces computation complexity of the classifier and feature extraction.

3.1. Feature Selection

There are many methods available for selecting feature sets, but they all concentrate on two main issues: efficient search methods for the optimal feature set and methods for comparing two features sets. The following two sections provide a brief overview of these topics. Detailed discussions of common feature selection techniques are presented in many classifications texts, for example Web [8], so we provide only a brief overview of the techniques applied.

3.1.1. Feature Selection Search Methods

For a large feature set the number of combinations of features necessitates a sub-optimal search scheme. In the case of the 101 length feature vector there are approximately 10^{30} combinations. Clearly, an exhaustive search is not feasible. Perhaps the simplest method for feature selection is to measure the performance of each individual feature and select the N highest performing features. This method ignores the complementary nature of features and typically results in poor performance. Other techniques employ a sequential or tree based search scheme for evaluating features. These include forward and backward sequential, the add R takeaway L technique, and branch and bound. The branch and bound technique was employed in our work since it resulted in feature sets that have the highest performance with our test data set.

3.1.2. Feature Selection Performance Criteria

The previous section discussed schemes for searching for a desired feature subspace, but the other major consideration is determining criteria for measuring the relative performance of two feature sets.

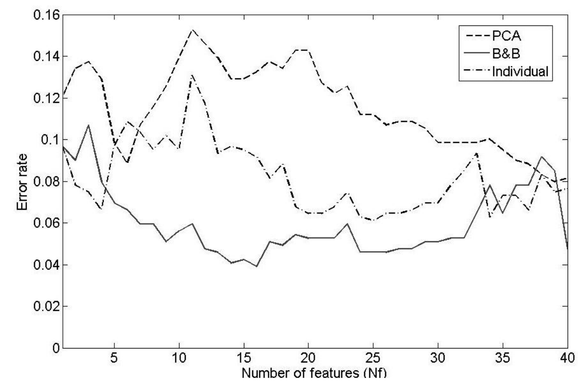


Fig. 2. Feature Selection Results

Intuitively, a desired feature set provides a major distinction or separation between features of different classes. In addition, it is also desirable if features from a like class are closely grouped together in the feature space. Popular measures utilized include the intra/inter distance and Mahanabolis distance. An alternative strategy is to test the classification performance for each candidate feature set. We chose to employ this technique with a naive Bayes classifier, since this yielded feature sets with higher performance based on trials with our infrared test data.

3.2. Feature Space Reduction

Employing the branch and bound feature set selection method with trained classifier performance yields the results depicted in Fig.2. The graph compares branch and bound feature selection with individual performance and Principle Component Analysis (PCA). As expected, the branch and bound technique exhibits the classic behavior of feature selection with a minimum error rate around 14 features and degrading performance as more features are added. The resulting features based on this selection are a mix of various wavelet, PBM, and GLCM features. Ideally, the results should show that a particular feature signature resulted in the best performance. It is not computationally conservative to produce all 101 features and then select 14; however, this result provides a excellent bound on performance that can be obtained from the features considered. In the subsequent results section we consider the practical choice for a feature set and compare against the automatic feature selection bound.

4. SIMULATION RESULTS

The proposed feature set described in section 3 was extracted from a set of 50 infrared images. This section provides performance results based on training classifiers with 34 images and testing against the remaining 16.

4.1. Classification Performance

As noted above, we can consider the 14 features determined by feature selection a reasonable approximation of the upper limit on classification performance. In addition to the overhead of computing underlying transforms to support the 101 total features, many of the features tested are inefficient to compute. For instance, there is no efficient algorithm for computing the GLCM. For this reason, we refined the feature set to exclude the GLCM features. We are using the method of infrared segmentation [6] in which the wavelet

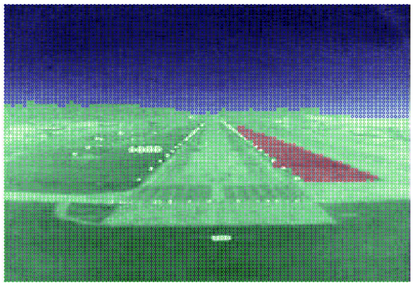


Fig. 3. Example IR Classification Result

MD is used as a dissimilarity measure. This means that the wavelet MD is already computed for each region as part of the segmentation procedure, so no additional processing is required. We also suggest utilizing the PBM features since in automatic feature selection they were observed as complementary to the texture measures. Texture is the dominate signature in cloudy conditions and PBM in clear sky conditions, hence the selection of the PBM and MD features assists in making the classification robust across clear, cloudy and overcast sky conditions.

Table 1 summarizes the results of testing 5 trained classifiers using the 14 features selected from the branch and bound process (labeled FS(14)), the combination of the wavelet MD and PBM features, and using the entire 101 features (labeled All). The classifiers evaluated include the K nearest neighbor (k=6), naive Bayes, normal density quadratic and support vector classifiers with linear and exponential kernels. As expected, the 14 selected features yield the highest performance and the entire feature set the lowest performance. The combination of wavelet MD and PBM results in a slightly lower performance than selected features, but is good tradeoff for computational complexity for most applications. It can also be observed that the linear SVM resulted in the highest performance consistently for all feature sets; therefore, it is applied to the following refinement analysis.

Table 1. Classification Error Rates

Classifier	FS(14)	MD/PBM	All
$KNN(6)$	0.066	0.122	0.136
$Bayes$	0.078	0.112	0.124
$ND(quad)$	0.048	0.098	0.127
$SVM(linear)$	0.025	0.036	0.041
$SVM(exp)$	0.126	0.128	0.124

4.2. Refining classification results

Certain classes of errors can be corrected by post processing the classification results using a higher level image analysis. These occur when an isolated region of ground is surrounded by sky and when an isolated sky region is surrounded by ground. The assumption is that the first condition is impossible and the second condition is very unlikely to occur in natural imagery. The latter condition occurs infrequently when sky is visible under a structure or terrain (e.g bridges).

The process of detecting and updating these regions is straight forward. Each region is dilated to detect the adjacent regions. If all of the adjacent regions are of dissimilar type, the classification result is toggled. This process is repeated for all classified regions.

All test results utilizing this method produced increased classification performance. In no case was a correctly classified region switched to an incorrect classification. Results of the classification refinement based on the infrared test library are depicted in table 2. Fig.3 shows a sample result of IR region classification on the image depicted in Fig.1(b). The green and blue regions show areas correctly classified as non-sky and sky respectively. The red region is a misclassified as sky, but will be corrected by suggested classification refinement method.

Table 2. Classification Refinement (linear SVM)

Feature Set	Error Rate	Refinement Error Rate
$FS(14)$	0.025	0.022
MD/PBM	0.036	0.029

5. CONCLUSIONS

We have shown that a feature set based on wavelet mean difference signatures combined with second order polynomial trace features results in excellent discrimination of sky/ground regions of infrared imagery. We also illustrated a post processing technique based on underlying assumptions of the scene structure used to improve classification results. These results will be used to extend this problem to other classes within the ground segment including vegetation, water, and structures. In addition, we plan to utilize the ground/sky classification results as a basis for development of horizon extraction, obstacle and air target detection algorithms.

6. REFERENCES

[1] A. C. Gallagher, J. Luo, and W. Hao, "Improved blue sky detection using polynomial model fit," *International Conference on Image Processing (ICIP)*, pp. 2367–2370, 2004.

[2] A. Singhal and J. Luo, "Hybrid approach to classifying sky regions in natural images," *SPIE Image and Video Communications and Processing*, vol. 5022, pp. 562–572, 2003.

[3] S. Todorovic and M. C. Nechyba, "Vision system for intelligent mission profiles of micro air vehicles," *IEEE Transactions on Vehicular Technology*, vol. 53, no. 6, pp. 1713–1725, November 2004.

[4] R. S. Timothy G. McGee and K. Hedrik, "Obstacle detection for small autonomous aircraft using sky segementation," *Proceeding of IEEE International Conference on Robotics and Automation*, pp. 4679–4683, April 2005.

[5] P. G. I. Scott M. Ettinger, Micheal C. Nechyba and M. Wasnak, "Vision-guided flight stability and control for micro air vehicles," *Proceedings of IEEE Internaltional Conference on Intelligent Robots and Systems*, pp. 2134–2140, October 2002.

[6] W. B. Blanton and K. E. Barner, "Texture-based infrared image segmentation by combined merging and partitioning," *IEEE International Conference on Image Processing*, pp. 45–48, September 2007.

[7] G. C. Holst, *Electro-Optical Imaging System Perfromance*. SPIE Optical Engineering Press, 2003.

[8] A. Webb, *Statistical Pattern Recognition*. Wiley and Sons, 2002.