

# Multiresolution Surface Feature Analysis for Automatic Target Identification Based on Laser Radar Images

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## Abstract

*Automatic target recognition based on range image data acquired with laser radar imagers is a research topic that is of great interest to both the defense and manufacturing industries. A hybrid approach using both models and features for automatic target identification/recognition within laser radar images is presented here. The multiscale and geometrical features are developed and deployed as input parameters for the proposed classification method. The experimental results show that the proposed method has achieved a satisfactory target classification.*<sup>1</sup>

## 1 Introduction

This paper presents a hybrid approach which uses both models and features for automatic target identification/recognition within laser radar images. Automatic target cueing and recognition has a long history of research, and many algorithms and methodologies have been developed. This paper presents results from a study on target recognition based on the images acquired from infrared laser radar imagery. In our study, the targets are assumed to have already been detected in a scene and our objective is to recognize and verify the identity of an individual target.

While classification of objects is a fundamental component of human reasoning, automatic target recognition by a computer requires a task-oriented methodology for solving a specific application problem. For laser radar images, the associated range information provides a surface-geometrical description of an unknown object. As an intuitive approach, we select a number of features that more or less encapsulate the features in range images. We first introduce the features and present the connections between a human's approach to the problem of classification and the quantitative statistical properties of each of these

features. Then we discuss feature representations for our automatic target recognition application.

## 2 Multiresolution Features

The laser radar imagery used in this study is relatively low resolution. A typical image size is 40 pixels by 20 rows, as shown in Figure 1. Because of this low resolution, many physical features on the objects are unresolved. Reliable identification of objects inevitably requires a set of features that are extracted from the laser image of the object. The features we employ include moment invariants, energy and entropy, range transform invariants, cross correlation of scale functions, and morphological spatial spectrum. The object orientation features are also used for classification. Such features include Fourier descriptors, curve moment invariants, bending energy, and circularity.

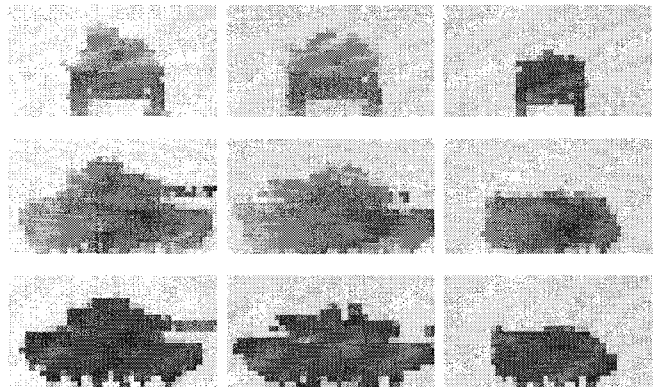


Figure 1: Range images of three targets obtained from various angles with a laser radar.

*Moment Invariants.* Let  $f(x, y)$  represent the grayscale function of a range image in region  $R$ . The moment is defined as

$$m_{p,q} = \int_R x^p y^q f(x, y) dx dy, \quad p, q = 0, 1, 2, \dots (1)$$

<sup>1</sup>THIS ARTICLE WAS PREPARED THROUGH COLLABORATIVE PARTICIPATION IN THE ADVANCED SENSORS CONSORTIUM SPONSORED BY THE U.S. ARMY RESEARCH LABORATORY UNDER COOPERATIVE AGREEMENT DAAL01-96-2-0001.

The central moments can be expressed as

$$\mu_{p,q} = \int_R (x - \bar{x})^p (y - \bar{y})^q f(x, y) dx dy, \quad (2)$$

where  $\bar{x} = m_{10}/m_{00}$ ,  $\bar{y} = m_{01}/m_{00}$ . Then the normalized central area moments are defined as

$$\gamma_{p,q} = \mu_{p,q}/m_{00}^{\frac{p+q}{2}+1} \quad (3)$$

Curve moments can be represented as setting  $f(l)$  to be 1 and

$$m_{p,q} = \int_L x^p y^q f(l) dl, \quad p, q = 0, 1, 2, \dots \quad (4)$$

With similar definition for central moments, the normalized central curve moment are defined as

$$\gamma_{p,q} = \mu_{p,q}/m_{00}^{p+q+1} \quad (5)$$

The moment invariants for both area and curve moments are expressed as follows

$$I_1 = \gamma_{20} + \gamma_{02} \quad (6)$$

$$I_2 = (\gamma_{20} - \gamma_{02})^2 + 4\gamma_{11}^2 \quad (7)$$

$$I_3 = (\gamma_{30} - 3\gamma_{12})^2 + (\gamma_{03} - \gamma_{21})^2 \quad (8)$$

$$I_4 = (\gamma_{30} + \gamma_{12})^2 + (\gamma_{03} + \gamma_{21})^2 \quad (9)$$

Eccentricity  $\epsilon$  is defined as[9]

$$\epsilon = \frac{(\mu_{02} - \mu_{20})^2 + 4\mu_{11}}{A}, \quad (10)$$

where  $A$  is the object area and the moments are defined by area moments.

*Morphological Spatial Spectrum.* Let  $S(x)$  be the area of an object  $x$ ,  $e_h(n)$ ,  $e_v(n)$ , and  $e_b(n)$  represent the structuring elements in horizontal, vertical, and both directions with scale  $n$ .  $P_h(n)$ ,  $P_v(n)$ , and  $P_b(n)$  are the features with scale less than  $n$ . Then, the Morphological Spatial Spectrum  $mss$  is defined as

$$mss = hP_h(n) + vP_v(n) + bP_b(n), \quad (11)$$

where

$$P_h(n) = \frac{S(f(x, y)) - S(f(x, y) \circ e_h(n))}{S(f(x, y))}, \quad (12)$$

$$P_v(n) = \frac{S(f(x, y)) - S(f(x, y) \circ e_v(n))}{S(f(x, y))}, \quad (13)$$

$$P_b(n) = \frac{S(f(x, y)) - S(f(x, y) \circ e_b(n))}{S(f(x, y))}, \quad (14)$$

and  $h$ ,  $v$ , and  $b$  are the weights for features  $P_h(n)$ ,  $P_v(n)$ , and  $P_b(n)$ , respectively. The features derived from boundaries and areas of objects are also used for the classification. They include the entries as follows.

*Fourier Descriptors.* A boundary function is defined by the Cartesian coordinates  $\{(x(l), y(l)), l = 1, 2, \dots, L\}$ , where  $L$  is the length of the boundary curve. Then the Fourier coefficients for the boundary function are represented as

$$a(n) = \sum_{l=1}^L x(l)e^{-2\pi nl/L}, \quad (15)$$

$$b(n) = \sum_{l=1}^L y(l)e^{-2\pi nl/L}. \quad (16)$$

Based on the Fourier coefficients, the Fourier Descriptors can be defined as follows

$$S(n) = \frac{r(n)}{r(1)}, \quad (17)$$

where  $r(n) = \sqrt{|a(n)|^2 + |b(n)|^2}$ ,  $n = 1, 2, \dots$ . These Fourier Descriptors are invariant to rotation, translation, dilation, symmetric transform, and starting point.

*Energy and Entropy.* Energy ( $E_g$ ) and Entropy ( $E_i$ ) are selected in our feature list. Energy corresponds to each pixel graylevel value weight in the object, and entropy is to calculate information measure of each pixel. They present meaningful parameters in our object classification.

*Cross Correlation of the Scale Function.* The scale function  $f(t)$  is defined as the object size in horizontal direction against the vertical coordinate. For each row  $t$  of the image,  $f(t)$  is the size of the object of along the row  $t$ . Then, the cross correlation is expressed as

$$r(\tau = 0) = \int_0^Y f(t)g(t + \tau)dt, \quad (18)$$

where  $Y$  is the image size in  $y$  direction and  $g(t)$  is the scale function of the model image.

*Bending Energy.* Let  $x_1, x_2, \dots, x_N$  be the Freeman chaincode (8-neighbor) of the boundary, the normalized bending energy  $E_N$  is defined as

$$E_N = 1 - \frac{4\pi^2}{L \sum_{i=0}^N |k(i)|^2}, \quad (19)$$

where  $L$  is the perimeter of the object,  $k(i) = \frac{x_n - x_{n-1}}{P(x_n) + P(x_{n-1})}$ , and  $P(x_i) = \frac{1}{2}$  for even  $x_i$  and  $P(x_i) = \frac{\sqrt{2}}{2}$  for odd  $x_i$  [9]. Bending energy is perimeter-independent.

*Circularity.* The normalized circularity is defined as

$$\gamma = 1 - \frac{4\pi A}{L^2}, \quad (20)$$

where  $A$  is the object area and  $L$  is its perimeter [9].

### 3 Object Recognition

To be useful, an automatic target recognition algorithm must be able to identify a target regardless its orientation. Our feature set includes entries that enable an algorithm to distinguish a target from others. Our feature selection includes (1) the target has one or more feature measures that can be employed to distinguish it from other objects at different poses, (2) the target has one or more feature measures that can be used to uniquely determine the pose of the target, and (3) the target has one or more feature measures that separate it from other possible objects at the same pose. For this purpose, we examine the features from three different targets and compare them at various angles. Figure 2 illustrates the feature measures under a certain condition: the target is 1,100 meters from the sensor, and the angles are separated by an equal increment of  $5^\circ$  from  $-90^\circ$  to  $90^\circ$ .

The classification algorithm works as follows. First a random target,  $T$ , is selected using the prior probability  $\tau_T = \text{Prob}(T = t)$ . The feature vector,  $\mathbf{X}$ , is produced by the unknown probability distribution  $h_{\mathbf{X}|T=t}(x)$ . The joint probability distribution vector  $(T, \mathbf{X})$  is  $\tau_T(t)h_{\mathbf{X}|T=t}(x)$ . A user would choose the prior distribution to represent the expected frequency. The product  $tT$  could be region and mission specific. The optimization takes advantage of any knowledge about the distribution of targets. This study used equal priors,  $\tau_T(t) = 1/3$  for  $t = 1, 2$ , or  $3$ . The classifier,  $D$ , is a function of range and the range feature vector  $\mathbf{X}$ . The preliminary form of the classifier is a range bin specific algorithm. For purposes of this study, a range bin was defined as a range plus or minus 50 meters. Feature data was generated for the range bins of 1300 and 1600 meters. The classifier,  $D$ , maps a feature vector,  $\mathbf{X}$ , into the set of targets  $\{1, 2, 3\}$ .

Once one has a classifier the question arises on how well the classifier works. The decision theory answer requires a lost function. Given a decision  $a$ , a true target  $t$ , and the cost of obtaining a feature, we define the lost function as  $l(a, t)$ . This study used the lost function

$$l(a, t, n) = (1 - \chi_{\{t\}}(a)) + cn \quad (21)$$

where  $\chi_{\{t\}}(a) = 1$  if  $t = a$  and zero otherwise, and  $n$  is the number of features required to compute the classification and  $c$  is the cost of computing each feature. If  $D(x)$  identifies the correct target the lost is  $1 + cn$ .

Given the conditional distribution of the random feature vector  $\mathbf{X}$  and the lost function, we can defined the expected risk when the target is  $t$  as

$$R(D, t) = E_{\mathbf{X}|T=t}l(D(x), t, N(D(\mathbf{X}))). \quad (22)$$

The function  $R(\mathbf{X})$  is called the conditional risk. The function  $R(D, t)$  is the conditional probability of misclassification given the target is  $t$  plus the expected number of features required for the classification function  $D$ . This function is useful in characterizing the behavior of a decision rule for a specific target. The

risk function,  $r$ , is defined for a randomly selected target as

$$r(D) = E_{\tau}R(D, T). \quad (23)$$

This shows the expected risk of using the classifier with a randomly selected target. The function  $r(D)$  is the probability of misclassification plus  $c$  times the average number of features required by  $D$ . The classification function  $D$  is defined in an iterative fashion adding a the best (with respect to the risk function  $r$ ) feature and threshold. The parameter  $c$ , the cost of obtaining a new feature, in the risk function,  $r$ , plays a major role in the classification formulation. Suppose that in the iterative procedure so far has a misclassification probability of 0.04. Suppose that by adding new features this probability can be reduced to 0.03. If  $c > 0.01$ , the risk is increased because the cost of a new feature outweighs the benefit gained by lowering the error probability. Conversely if  $c < 0.01$  the risk is decreased by the addition of the new feature.

### 4 Experimental Results

The experiments were based on a group of three targets. For each target, a collection of 37 different angles for the ranges from 1230 meters to 1380 meters with 10-meter increments in between, and from 1530 meters to 1680 meters with 10-meter increments in between. The features are listed as follows

1. Area moment invariant (range)
2. Area moment invariant (binary)
3. Curve moment invariant
4. Fourier descriptor
5. Range transform invariant
6. AutoCorrelation
7. Morph Spatial Spectra (convex)
8. Morph Spatial Spectra (concave)
9. Eccentricity 1 (with range)
10. Eccentricity 2 (with binary)
11. Circularity
12. Elongation
13. Energy
14. Entropy
15. Bending energy
16. standard deviation

Each of the listed features is associated with a group of parameters. For example, *Morph spatial spectra* has parameters of structuring element sizes, the directions of horizontal, verticle, and diagonal. The feature data set was used to construct two classification programs. One for each of the bins of 1300 and 1600 meters. Both the 1300 and the 1600 meter algorithm obtained 100% classification on the development set. The index algorithm is an ordered list of features and thresholds. The index algorithm applies each test until one is true at which time it exits with the classification. Each test is of the form

$f(\text{feature} \mid \text{parameter1}, \text{parameter2}, \text{parameter3}, \text{parameter4})$  being larger ( $>$ ) or less ( $<$ ) than the threshold, the proportion of training set covered by that test and what the classification is if the test is true.

## 5 Conclusions

We developed a variety of features for laser radar imagery which will be useful in automatic target recognition. The index procedure was applied to a set of three targets with 37 angles (from  $-90$  to  $90$  degrees) at two different range bins. A 100% correct classification was achieved in the development set. The experiment showed that the 90 features (a combination of feature functions and parameters) can be combined into a multi-feature target classifier.

The views and conclusions contained in this document are those of the authors and should not be interpreted as presenting the official policies either expressed or implied, of the Army Research Laboratory or the U.S. Government.

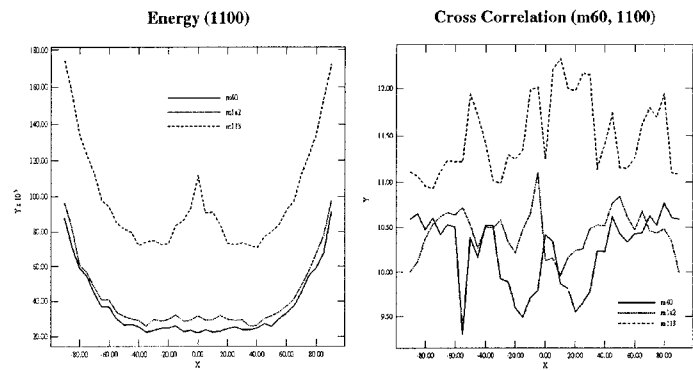
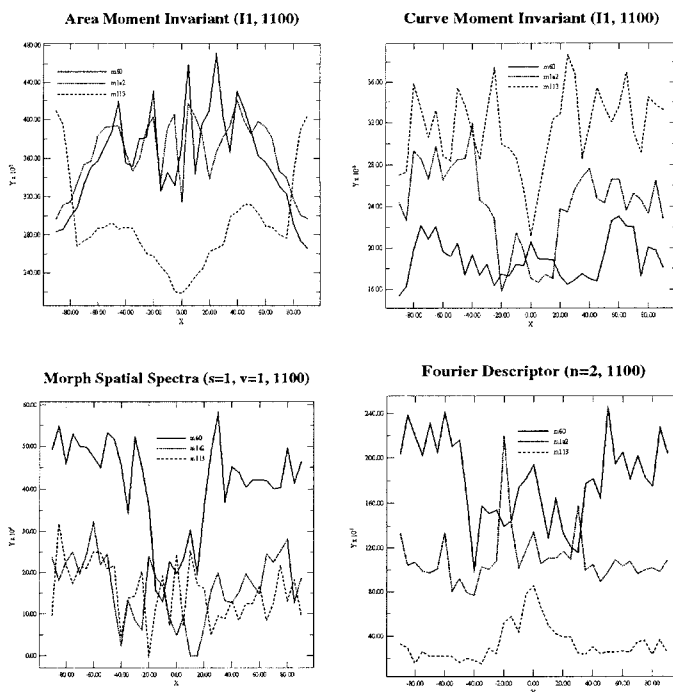


Figure 2: Selected feature measures with an angle range ( $-90^\circ, 90^\circ$ ).



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