Extraction and Selection of Best Order of Zernike Moment For Small Infrared Target

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***Abstract*—Feature extraction and selection is an essential step for 'low loss dimension reduction'. The occurrence of false alarms is very high in small infrared targets due to different clutters. This paper highlights on extraction of different Zernike moments as features of small infrared target and then selection of relevant order of Zernike Moment subset is done by using forward feature selection approach that is Area under ROC curve.**

Keywords—Feature extraction,AUC(area under ROC curve) , ,Zernike moment(ZM),Feature selection.

I. Introduction

Preprocessing, dimensionality reduction, learning and testing are important steps to remove false alarms in machine learning approach. Noise filtering, Normalization and Feature extraction are approaches of Pre processing and Feature projection and Feature Selection are approaches of dimensionality reduction. Classification and recognition of an image is done by feature extraction which defines behaviour of an image.Feature extraction is the technique to collect the most relevant data from the raw data .Teague in 1934 introduced the concept of Zernike polynomials which is a is a region-based moment and orthogonal moment .The Zernike moment(ZM) also defined as a basis functions for a set of complete complex orthogonal which are square integrable and are defined upon the unit disk.The concept of Orthogonality is that there is no redudancy or overlapping of information between the moments. Moments are quantified based on their orders .With respect to rotation the magnitude of ZM remains invariant (m,n) are the ordered pair represents the order of the Zernike polynomial and the multiplicity of its phase angle.In this paper, different orders of ZM is extracted from the infrared image as a feature. The superiority of ZM to other moments is because of their insensitivity towards information content and image noise. The properties of ZM are invariance to scale, position, and rotation.The different characteristics of ZM are: 1.Reduction of noise. 2.Invariance to rotation. 3.Reducing redundancies. The Zernike moment is a series of calculations that transforms an image into vectors with real components .

Machine learning classifiers get learned from selected features.Feature vector forms through selected features. Sequential and backward elimination approaches comes under wrapper based selection[4].

After introduction,section II focuses on extraction of ZM of different orders then wrapper based forward feature selection is done by AUC (area under ROC curve) for few number of vectors.The X and Y coordinates in ROC plot represents true detection rate and false alarm rate.The value of AUC lies between 0 and 1.Experimental results are in section III and conclusion is in section IV.

II. Proposed Methodology

This section is divided into two parts. At first, ten orders of ZM are extracted as features for the appropriate feature selection then feature selection approach is applied further [2].

Feature extraction for target

Zernike moment: For two dimensional image I(x, y) Zernike moment is given by:-

$$Z = m + 1/\pi \iint I(x, y)[Vnm^*(x, y)dydx \quad (1)$$

Where,m is order of zernike moment and n is multiplicity of phase angle.

$$V_{nm}(p, \theta) = R_{nm}(p)e^{i\theta m},\ \theta \leq 1,\ p = \sqrt{x^2 + y^2} \quad (2)$$

V_{nm} is basis function of zernike moment,R_{nm} is radial polynomial, p is image pixel radial vector and θ is angle between p and x axis given as

$\theta = \arctan(y/x)$,R_{nm} is given as:

$$Rnm = \sum_{\alpha=0}^{n-m/2} (-1)^{\alpha}(n-\alpha)!(p)^{(n-2\alpha)} / \alpha!\,[(n+m/2)-\alpha]!\,[(n-m/2)-\alpha]! \quad (3)$$

The complex polynomials introduced by zernike forms an ortho-normal basis defined inside the unit disk, which means for $x^2+y^2 \leq 1$. The polynomial is defined as follow:

Where: n: a positive integer (or null).

m: an integer with |m|<=n.

r : The vector length (distance between the origin and the pixel at (x,y)).

θ: Angle formed by vectors p and x axis.

Rnm : radial polynomial.

V*(x,y) : Complex polynomial, which is the projection of f(x,y) on the complex polynomials space.

Feature selection method

Wrapper based feature selection approaches used Sequential forward feature selection and backward elimination method. Forward feature selection algorithm (AUC based) is:-

Calculate AUC for each extracted feature

Arrange features according to AUC value in decsending order.

Choose set of n highest ranking feature .

Add next ranking feature to previous subset.

Find AUC value of new subset.

If $AUC_{PREV} < AUC_{curr}$, select the added feature. III Experimental Result

Else remove the added feature.

III Experimental Results

a) Database preparation

Images of long range and mid range were collected and the database of clutter images and target images were formed for the learning purpose .Modified top- hat based filtered images used for the detection algorithm to extract the features[1].

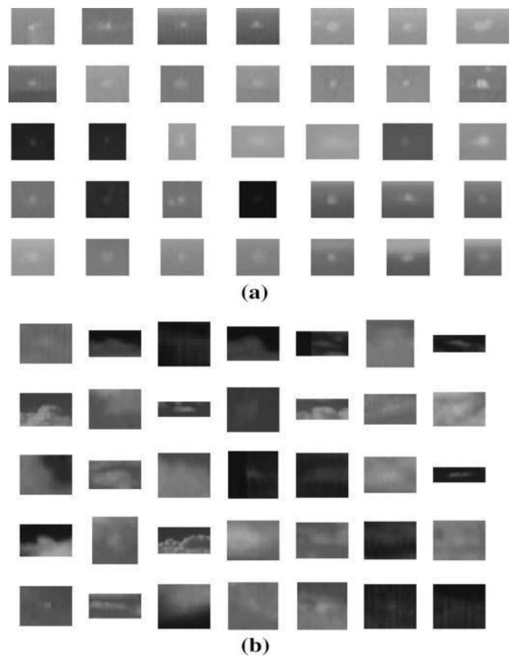

Fig.1 Dataset for the target and clutter

For target enhancement and for detection operation filtered database is obtained by modified white top hat and modified black top hat parameters operation [3][8].Fig.2 shows small infrared image with cluttered background and detection of target with modified top- hat filters.

$$MWTH(x, y) = \max(I(x, y) - I\ S(x, y), t - t \quad (4)$$

$$MBTH(x, y) = \max(I \bullet S(x, y) - I(x, y), t) - t \quad (5)$$

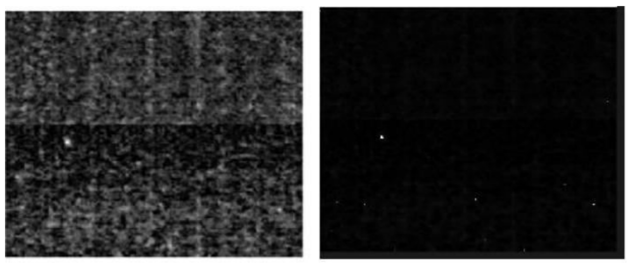

Fig.2(a) Small infrared image with target and clutter (b) Image after target detection

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(b) AUC (Area under ROC curve)based feature selection

The selection of suitable orders of ZM as a feature subset is done by AUC method.Genertaion of ROC curve is done by NN(nearest neighbor) classifier and then AUC value is calculated for each feature[7][10].NN classifier is easy simple and efficient to use[14].Finally Normalization of each order of ZM features value is done to get Stable and good results.At first, AUC value of each ZM order is shown in Fig.3.

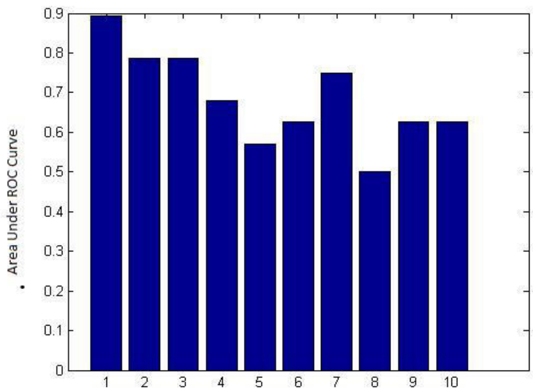


Fig.3 AUC value for each extracted feature values

According to feature selection algorithm the decreasing order of selected order is:

Order (1)> order (2) = order (3)> order (7)> order (4)> order (9) = order (10) = order (6)> order (6) > order (8).

According to algorithm Top 5 orders are selected as base feature vector. F_{base1}= [1, 2, 3, 7, 4].On finding AUC value of base feature vector, this value is more than previous AUC value of highest selected feature so, add next feature to the subset of base feature vector,F_{base2}=[1, 2, 3, 7, 4,9,10,6]. Now AUC value of new subset is less than previous subset (F_{base1} > F_{base2}).hence, F_{base1} shows the best order of Zernike moment. ROC curve for all ordered subset is explained in Fig.4 and Fig.5.Fig.6 explains comparison of AUC values for both subsets.

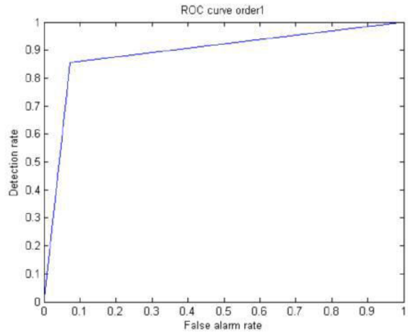
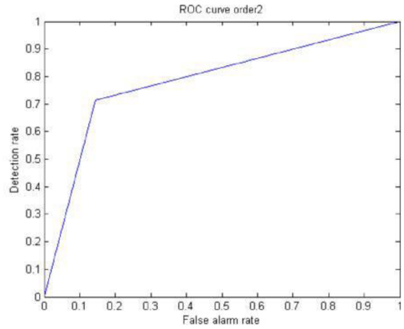
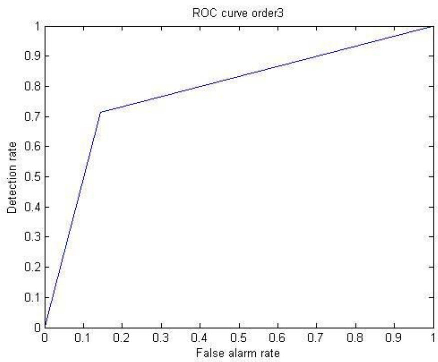


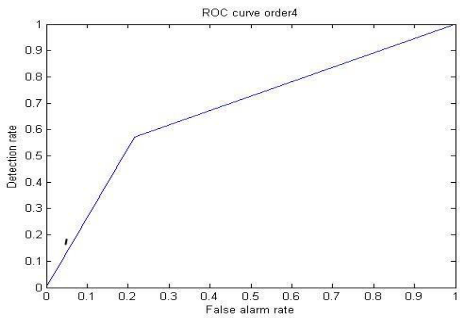
Fig.4 (a) ROC curve for order1 feature



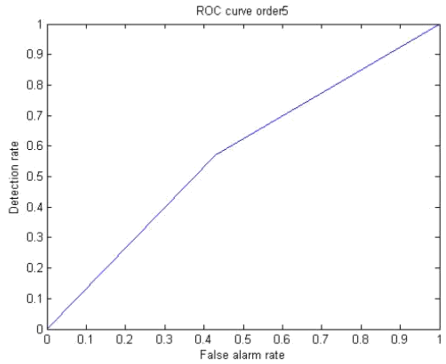
(b)ROC curve for order2 feature subset



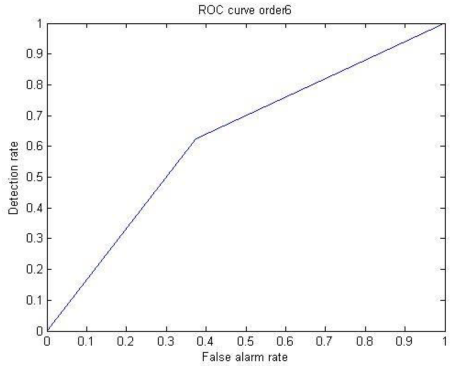
(c)ROC curve for order3 feature subset



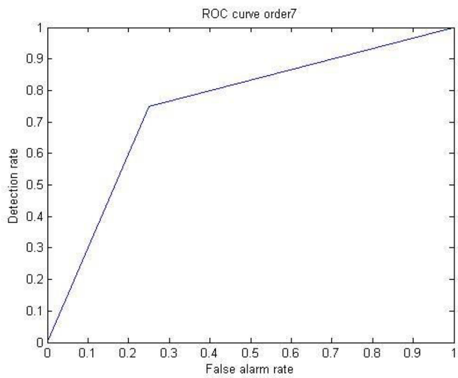
(d)ROC curve for order4 feature subset



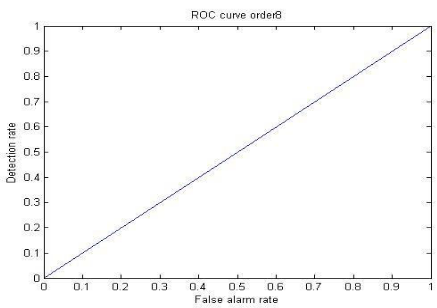
(e) ROC curve for order5 feature



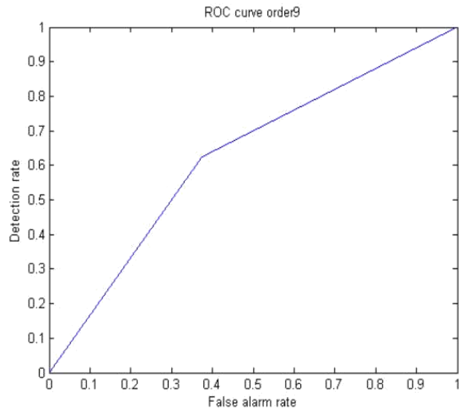
(f) ROC curve for order6 feature



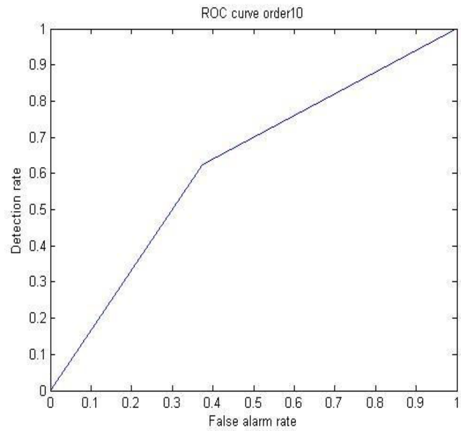
(g)ROC curve for order7 feature subset



(h)ROC curve for order8 feature subset



(i) ROC curve for order9 feature subset



(j) ROC curve for order10 feature subset

After calculation of ROC value of each order the ROC curve for F_{base1} is shown in Fig.5 and Fig.6 depicts the comparison study of both feature subsets.

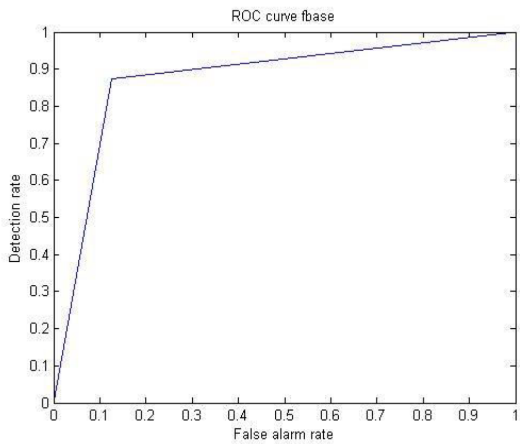


Fig5 (a) ROC curve for F_{base1}feature

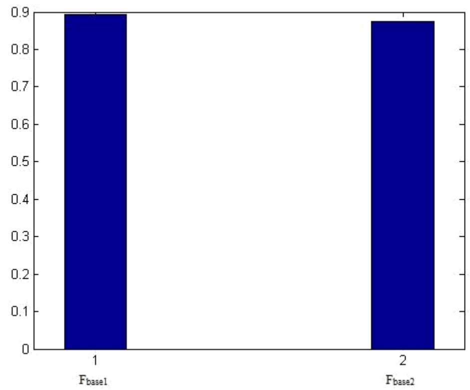


Fig.6 AUC value comparison for both feature subset

IV Conclusion

This paper focused on comparative study of different orders of zernike moment for small infrared target image.Many paper have shown the feature extarction and selection for small infrared target images and many have highlighted on Zernike moments but different orders of ZM works differently for each image.The lower order of ZM depicts the characteristic of an image properly.Order1,Order2,Order7,Order4 significantly shows the usefulness of feature extraction.Due to lesser number of feature subsets wrapper based(AUC) fature selection method is used in this paper.According to the comparative study of different orders of ZM lowers order ZM should be used for the feature extarction and selection technique for small infrared targets.

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