A Statistical Approach for Multiclass Target Detection

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Abstract

Fukunaga-Koontz Transform (FKT) is a statistical technique which has many application areas for two-class classification or detection problems. In this paper, we have proposed improved target detection algorithm for hyperspectral imagery (HSI) based on enhanced FKT which gives better results for multi-class target detection problems.

Hyperspectral imagery is popular for target detection applications due to its additional properties compare to multispectral images. It presents one dimensional (spectral) and two dimensional (spatial) features of targets for detection problems. For multi-class target detection in hyperspectral images, we have selected each target’s 1D features, called signature of targets, to introduce to enhanced FKT during learning stage. After learning stage of FKT, we have applied our operators, obtained by enhanced FKT, to HSI images to detect more than one target simultaneously.

The experimental results show that multi-class FKT has satisfactory performance over 95 percent of true detection rate especially on the pixel sized targets. In addition, multi-class processing ability of the proposed enhanced FKT is very important for many applications such as classification, recognition, clustering, tracking problems in the literature.

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1. Introduction

Target detection is a challenging problem if there exist high noise and pixel sized targets on the image. However, recent advances in image sensors, with high resolution on both spectral and spatial dimensions, make people to get
interest of this area. Especially such corporations, working at military or security sectors, are paying attention to keep track of the enhancements about new methods and image types.

In particular, besides classical colored and infrared images, hyperspectral image is one of the most popular kind of image which contains information about not only spatial features but also spectral features of the targets on the image. By the spectral features, HSI is sensitive to the type of material of target instead of just color or shape. Thus, hyperspectral imagery has different applications in many areas such as agriculture, mineralogy, physics and homeland security. Although it was inconvenient method to gather HSI images in previous years, day after day these types of images have become available and easy to use.

On the other hand, HSI have some difficulties to overcome. Firstly, some of the spectral bands have too much noise before processing. Therefore, it is necessary to find these bad bands and get rid of them. Other problem is related with processing time. Since HSI have both spectral and spatial information, it needs more memory allocation and process time.

Under these considerations, a statistical approach is proposed which name Multiclass Fukunaga-Koontz Transform and suggested reasonable solutions to the problems mentioned above. For the first problem, two studies [11, 12] are selected and used their best results in order to reduce redundant spectral bands. For the second problem, we propose multiclass approach [10] in this study. Since just one training stage is enough for all the cases in the experiment, the process time is decreased remarkably.

There are various target detection studies in literature that use HSI. In 1999, A. Howard and his colleagues have studied on artificial neural network to detect pixel sized targets on HSI and get nearly 100% true detection rate on their own data [3]. In 2001, L.M Bruce and colleagues proposed wavelength transform [4], and in same year S. Chiang worked on unsupervised target detection using projection pursuit [6]. In 2003, D. Manolakis and D. Marden, published a review paper about target detection issue on HSI [2]. Some different methods such as covariance descriptors [5], extended morphological models [1,7] are also proposed for target detection on HSI.

In the following parts of the paper, the recommended method is explained in detail with training and testing stages. In training stage, data matrices for all classes are incorporated to obtain transformation operator and transform them to a lower dimensional eigenspace. Then in testing stage, transformation operator deployed to test data and transform it to same eigenspace. In this new space it is easier to classify data if it belongs to target class or not.

2. Fukunaga-Koontz Transform

Classical FKT is a statistical approach that is proposed as a novel method to feature selection of high dimensional data in 1970 [9]. It is a supervised method and according to the FKT, target and clutter data sets are transferred to a lower dimensional eigenspace to obtain most informative features. The transformation operator is created during learning stage and then it is used for transforming training and testing data to eigenspace. The transformed data involves characteristic features of targets. Consequently, this new space presents many advantages for classification, detection or recognition problems.

2.1. Multiclass Structure

Classical FKT is a classification method that based on two class, target and clutter, classification technique. If there are more than two classes, training procedure is required for each class. It means more processing time and more calculation. However, just one time training stage is enough for all cases simultaneously by multiclass approach [8].

2.2. Training Stage

Training stage is initiated with getting $K$ number of classes together. Eq.1 shows the $T_i$ matrix that contains training vectors for class $i$ and each $T_i$ matrix has $M$ number of training vectors.

$$
T_i = \{v_i^1, v_i^2, v_i^3, \cdots, v_i^M\} \quad i = 1, 2, \cdots, K
$$
Mean vectors of each $T_i$ matrix are subtracted from themselves in order to obtain mean corrected data for all class matrices. Then all $T_i$ matrices are multiplied by their transposes to get covariance matrices. In Eq. 2, $\Sigma_i$ is covariance matrix for class $i$.

$$\Sigma_i = T_i T_i' \quad i = 1, 2, \ldots, K$$  \hspace{1cm} (2)

These covariance matrices are added together as shown in Eq. 3. By getting sum matrix, we decompose eigenvalues and eigenvectors of the $\Sigma_{sum}$ matrix. In Eq. 4, $V$ represents eigenvector matrix and $D$ represents eigenvalue matrix of $\Sigma_{sum}$ matrix.

$$\Sigma_{sum} = \Sigma_1 + \Sigma_2 + \cdots + \Sigma_K$$  \hspace{1cm} (3)

$$VDV' = \Sigma_{sum}$$  \hspace{1cm} (4)

According to the FKT, training data is needed to transform to the eigenspace by deploying a transformation operator. Eq. 5 shows the formulation of $P$ transformation operator. Then, as shown in Eq. 6, both covariance matrices are multiplied by $P$ and its transpose matrix. In this way transformation operation is completed and $\phi_i$ represents transformed data matrix in eigenspace for class $i$.

$$P = VD^{-1/2}$$  \hspace{1cm} (5)

$$\phi_i = P \Sigma_i P' \quad i = 1, 2, \ldots, K$$  \hspace{1cm} (6)

Eq. 7 shows the summation of $\phi_i$ matrices, equals to $I$ identity matrix which means that all of the $\phi_i$ matrices shares the same eigenvectors and eigenvalues.

$$I = \phi_1 + \phi_2 + \cdots + \phi_K$$  \hspace{1cm} (7)

In Eq. 8, $\theta$ represents an eigenvector and $\lambda$ corresponding eigenvalue of $\phi_1$ matrix. Under this limitation, Eq. 9 indicates that $\theta(1 - \lambda)$ statement equals to sum of all other $\phi_i$ matrices multiplied by $\theta$ matrix.

$$\theta \lambda = \theta \phi_1$$  \hspace{1cm} (8)

$$\theta = \theta \phi_1 + \theta \phi_2 + \cdots + \theta \phi_K$$

$$\theta(1 - \phi_1) = \theta \phi_2 + \cdots + \theta \phi_K$$  \hspace{1cm} (9)

$$\theta(1 - \lambda) = \theta \phi_2 + \cdots + \theta \phi_K$$

As a result, we can infer from above equations that if eigenvector $\theta$ contains more information about first class, it means it contains less information about all other classes. After obtaining $I$ identity matrix and $P$ transformation matrix, training stage is completed.

2.3. Testing Stage

In testing stage, each of pixels on the image are tested to decide if they belong to target class or not. Symbol $z$ represents the selected test vector in Eq. 10. Mean of target class is subtracted from $z$ in order to have mean corrected values as performed in training stage. It is then multiplied by transpose of $P$ to go to the eigenspace.

$$z = P'z$$  \hspace{1cm} (10)
After transformation, if \( j \) is target class that we need to test, first we decompose \( \phi_j \) matrix into eigenvalues and eigenvectors. In Eq. 11, \( \Theta_j \) represents eigenvector matrix and \( \Psi_j \) represents eigenvalue matrix. Then transformed test vector \( \hat{z} \) is multiplied by transpose of \( \Theta_j \) eigenvector matrix to obtain \( \Omega_z \) result vector, as shown in Eq. 12.

\[
\Theta_j \Psi_j \theta_j' = \phi_j \\
\Omega_z = \theta_j' \hat{z}
\]

Consequently, if we use a threshold for the value of \( \Omega_z \) vector, we reach a decision about the class information of test vector. If the result value is above threshold it means that test vector belongs to target class, if the value is under threshold it means that test vector is not related to target class.

3. Target Detection on Hyperspectral Imagery

In this study, multiclass FKT algorithm is employed for multiple target detection problems on HSI. HYDICE-Urban HSI dataset [13] is selected to evaluate the performance of the proposed multiclass FKT. In this section, our goal is to classify two different types of water areas as targets on the image. RGB view of this image is shown in Fig. 1.a. It has 220 spectral bands of 307x307 resolution images and it contains various types of materials such as trees, roads, roofs or water areas.

![Figure 1: a) RGB view of HYDICE-Urban image, b) Ground-truth image of first water area, c) Ground-truth of second water area](image)

In experiments, we are only interested in water areas on HSI as shown in Fig 1.b and 1.c as a ground truth image. Figure 1.b shows first and Fig 1.c shows second type of water areas.

![Figure 2: a) Spectral Signatures for fist type of water, b) Spectral Signature for second type of water.](image)
Since the water areas have few pixels and their amount of number is less, we have added some artificial water areas to the image. In order to work with more realistic data we have added 10-20% of Gaussian noise to new regions. Fig. 2.a and 2.b show the original and artificial spectral signatures of the first water area and the second water area, respectively.

We have performed the multiclass FKT test for two kinds of water areas and the ROC curves are drawn in Fig. 3. Figure 3.a and 3.b show the detection performance of the multiclass FKT for first water area and second water area, respectively. It is easy to understand from the figures that multiclass FKT has better performance than classical FKT.

![ROC curve for first water area](image1.png) ![ROC curve for second water area](image2.png)

Figure 3: a) ROC curve for first water area, b) ROC curve for second water area

After getting the results, a thresholding operation is accomplished to determine each pixel’s class. As mentioned above, over threshold pixels are labeled as the target pixels. Best threshold results for two types of water areas are shown in Fig. 4. Figure 4.a and 4.b show detection results of first and second water areas, respectively. According to the results, the proposed multiclass FKT is very successful to detect regions for each type as 100%. However there are some missed pixels. For example, if a region has 15 pixels area, multiclass FKT is managed to detect 13-14 of them.

![Detection results for first water area](image3.png) ![Detection results for second water area](image4.png)

Figure 4: a) Detection results for first water area, b) Detection results for second water area
4. Conclusion

In this paper, we have proposed multiclass Fukunaga-Koontz Transform to detect targets on HYDICE-Urban hyperspectral images. Two different types of water areas are selected as targets. According to the test results, it is obvious that multiclass FKT is very successful for multi-target detection problems. In beside, it presents simultaneously multi-target detection possibility which is very important to decrease processing time. When we compare to classical FKT and multiclass FKT, the proposed algorithm increases the detection performance and it decreases the computational burden.

References