

Feature-based Image fusion scheme for satellite recognition

Han Pan

Institute of Aerospace Science and Technology,
Shanghai Jiao Tong University,
Shanghai 200240, China
hanpan@sjtu.edu.cn

Gang Xiao, Zhongliang JING

School of Aerospace Science and Technology,
Shanghai Jiao Tong University,
Shanghai 200240, China
Xiaogang@sjtu.edu.cn

Abstract - Despite the variety of technologies and algorithms studied, satellite recognition is not fully researched in the uncontrolled space environments. In this paper, a low complexity and efficient satellite recognition scheme by fusing infrared and visible image features for recognition was brought forward. Invariant moments are taken to represent the characteristics of satellites' pictures. Unlike optimal image feature fusion by classic intelligent computing algorithms, a low computation and efficient fusion rules are developed to improve the performance of recognition. Due to the compute power of space-based computer, a new fusion method by associating combined blur and affine moments invariant (CBAI) with Zernike moments is introduced. The experiments results with Semi-physical simulation images indicate that the recognition consistently demonstrated better performance than others solely based on either infrared or visible image.

Keywords: satellite recognition, fusion based feature, combined blur and affine moment, zernike moments, PCA.

1 Introduction

In recent years satellite recognition has received some attention, but still arose some problem in some application, especially in an uncontrolled space environment. In the past, infrared and visible image fusion has been successfully applied to face recognition [1][2] and security monitoring area. Despite the limit of visible light camera, Infrared imagery is nearly invariant under all lighting conditions including partial or total darkness [3]. Recently, a number of research have been devoted to satellite recognition. Several satellite recognition schemes have been proposed. Du Xun et al. [4] presented an efficient algorithm based on distinct structural relationships to index satellite images, which didn't need image segmentation. Liu Xiankang et al. [5] employed central moments to satellite recognition, which was extracted from denoised radar high resolution range profile (HRRP) data. These proposed schemes may not provide with an effective recognition performance because of the unfavorable and changing lighting conditions in an uncontrolled space environment.

In this paper, we show a new fusion and recognition scheme in feature-level. First, two images respectively was obtained from visible and infrared sensors, and then extracted independent features from both images. A group of important features vectors were created, and at last were used to classify or recognize. Recognition rate was used to evaluate the scheme's performance solely compared with either infrared or visible image. The experimental results illustrate the effectiveness of this proposed scheme.

The rest of the paper is organized as follow: In Section 2, basic algorithms or methods was reviewed in the paper. The fusion and recognition scheme is described in details in Section 3. The simulation platform and experimental structure used to evaluate the scheme is given in Section 4. Experimental results are discussed in Section 5. Finally, Section 6 contains our conclusions and plans for future research.

2 Review of image moment invariants and classification methods

2.1 Combined Blur and Affine Invariants

The affine moment invariants is widely employed in image processing and pattern recognition [6][8][9]. In image processing scopes, an image moment is a kind of useful image features to describe the object after extracting of the interested area. The moment invariants can be flexible to express the nature trait of the two-dimension shape, including area, centroid, and orientation. In other word, image moment can depict the characterization of the region of interested object. In order to recalling a brief of image moments, geometric moments and central moments are showed as follow:

For a grayscale image $I(x, y)$, geometric image moments

M_{ij} of order $(p + q)$ were displayed:

$$M_{pq} = \sum_x \sum_y x^p y^q I(x, y) \quad (1)$$

where $p, q = 0, 1, 2, \dots$ and so on, $I(x, y)$ denote grayscale image.

According to the geometric moments, central moments were defined as follow:

$$u_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q I(x, y) \quad (2)$$

Where $\bar{x} = \frac{M_{10}}{M_{00}}$ and $\bar{y} = \frac{M_{01}}{M_{00}}$, and \bar{x}, \bar{y} denote the

centroid of the object. The order of Central moments can be up to 3 orders, which are translational invariants.

Moment invariants is firstly derived by Hu[8] and is a power tools[9] for pattern recognition. Flusser[10] applied affine moment invariants to pattern recognition. Blur invariants [11] is an invariant technique that can be insensitive to image blurring, spatial degradations, and random noise. Combined blur-affine invariants (CBAI) was primarily deduced and presented by Tomas Suk[12][13], which was an efficient math tools to improve the performance of objects recognition in the images without any pre-process and restoration, especially suitable for an uncontrolled space environment.

To illustrate the CBAI in a plain way, six formulas of CBAI covering affine moment invariants of third, fifth and seven orders were presented as follow:

$$I_1 = (u_{30}^2 u_{03}^2 - 6u_{30} u_{21} u_{12} u_{03} + 4u_{30} u_{12}^3 + 4u_{21}^3 u_{03} - 3u_{21}^2 u_{12}^2) / u_{00}^{10} \quad (3)$$

$$I_2 = (u_{50}^2 u_{05}^2 - 10u_{50} u_{41} u_{14} u_{05} + 4u_{50} u_{32} u_{23} u_{05} + 16u_{50} u_{32} u_{14}^2 - 12u_{50} u_{23}^2 u_{14} + 16u_{41}^2 u_{23} u_{05} + 9u_{41}^2 u_{14}^2 - 12u_{41} u_{32}^2 u_{05} - 76u_{41} u_{32} u_{23} u_{14} + 48u_{41} u_{23}^3 + 48u_{14} u_{32}^3 - 32u_{32}^2 u_{23}^2) / u_{00}^{14} \quad (4)$$

$$I_3 = (u_{30}^2 u_{12} u_{05} - u_{30}^2 u_{03} u_{14} - u_{30} u_{21}^2 u_{05} - 2u_{30} u_{21} u_{12} u_{14} + 4u_{30} u_{21} u_{03} u_{23} + 2u_{30} u_{12}^2 u_{23} - 4u_{30} u_{12} u_{03} u_{32} + u_{30} u_{033}^2 u_{41} + 3u_{21}^2 u_{14} - 6u_{21}^2 u_{12} u_{23} - 2u_{21}^2 u_{03} u_{32} + 6u_{21} u_{12}^2 u_{32} + 2u_{21} u_{12} u_{03} u_{41} - u_{21} u_{03}^2 u_{50} - 3u_{12}^3 u_{41} + u_{12}^2 u_{03} u_{50}) / u_{00}^{11} \quad (5)$$

$$I_4 = (2u_{30} u_{41} u_{05} - 8u_{30} u_{12} u_{32} u_{14} + 6u_{30} u_{12} u_{23}^2 - u_{30} u_{50} u_{03} u_{05} + 3u_{30} u_{03} u_{14} u_{41} - 2u_{30} u_{03} u_{23} u_{32} - 2u_{21}^2 u_{41} u_{05} + 8u_{21}^2 u_{32} u_{14} - 6u_{21}^2 u_{23}^2 + u_{21} u_{12} u_{50} u_{05} - 3u_{21} u_{12} u_{14} u_{41} + 2u_{21} u_{12} u_{23} u_{32} + 2u_{21} u_{12} u_{50} u_{14} - 8u_{21} u_{03} u_{41} u_{23} + 6u_{21} u_{03} u_{32}^2 - 2u_{12}^2 u_{50} u_{14} + 8u_{12}^2 u_{41} u_{23} - 6u_{12}^2 u_{32}^2) / u_{00}^{12} \quad (6)$$

$$I_5 = (u_{30} u_{41} u_{23} u_{05} - u_{30} u_{41} u_{14}^2 - u_{30} u_{32}^2 u_{05} + 2u_{30} u_{32} u_{23} u_{14} - u_{30} u_{23}^2 - u_{21} u_{50} u_{23} u_{05} + u_{21} u_{50} u_{14}^2 + u_{21} u_{41} u_{32} u_{05} - u_{21} u_{41} u_{23} u_{14} - u_{21} u_{32}^2 u_{14} + u_{21} u_{32} u_{23}^2 + u_{12} u_{50} u_{32} u_{05} - u_{12} u_{50} u_{23} u_{14} - u_{12} u_{05} u_{41}^2 + u_{12} u_{41} u_{32} u_{14} + u_{12} u_{41} u_{23}^2 - u_{12} u_{32}^2 u_{23} - u_{03} u_{50} u_{32} u_{14} + u_{03} u_{50} u_{23}^2 + u_{03} u_{41}^2 u_{14} - 2u_{03} u_{41} u_{32} u_{23} + u_{03} u_{32}^3) / u_{00}^{13} \quad (7)$$

$$I_6 = (u_{70}^2 u_{07}^2 - 14u_{70} u_{61} u_{16} u_{07} + 18u_{70} u_{52} u_{25} u_{07} + 24u_{70} u_{52} u_{16}^2 - 10u_{70} u_{43} u_{34} u_{07} - 60u_{70} u_{43} u_{25} u_{16} + 40u_{70} u_{34}^2 u_{16} + 24u_{61}^2 u_{25} u_{07} + 25u_{61}^2 u_{16}^2 - 60u_{61} u_{34} u_{52} u_{07} - 234u_{61} u_{52} u_{25} u_{16} + 40u_{61} u_{43}^2 u_{07} + 50u_{61} u_{43} u_{34} u_{16} + 360u_{61} u_{43} u_{25}^2 - 240u_{61} u_{34}^2 u_{25} + 360u_{52}^2 u_{34} u_{16} + 81u_{52}^2 u_{25}^2 - 240u_{52} u_{43}^2 u_{16} - 990u_{52} u_{43} u_{34} u_{25} + 600u_{52} u_{34}^3 + 600u_{43}^3 u_{25} - 375u_{34}^2 u_{43}^2) / u_{00}^{18} - u_{12} u_{32}^2 u_{23} - u_{03} u_{50} u_{32} u_{14} + u_{03} u_{50} u_{23}^2 + u_{03} u_{41}^2 u_{14} - 2u_{03} u_{41} u_{32} u_{23} + u_{03} u_{32}^3) / u_{00}^{13} \quad (8)$$

Where u_{mn} denote a central moment of order (m + n) of the digital image $I(x, y)$. for the sake of computation power, I_6 would be not included in the feature vector for satellite recognition.

2.2 Zernike moment

Zernike moments are an excellent mathematical tool to describe the characteristic of the digital image, which transform the image function $I(x, y)$ into orthogonal basic functions. Zernike moments has lots of outstanding attribute in pattern classification, such as maximum information preservation, rotation invariance and insensitive to noise [14].

In briefly, the definition of Zernike moments is simply discussed as follow. The Zernike moments of order n of an image function $I(x, y)$ is given by [14]:

$$Z_{n,m} = \frac{n+1}{\pi} \sum_{x^2+y^2 \leq 1} \sum_{x^2+y^2 \leq 1} I(x, y) V_{n,m}^*(x, y) \quad (9)$$

Where $V_{n,m}^*(x, y)$ signify the complex conjugate of $V_{n,m}(x, y)$. $V_{n,m}(x, y)$ denotes orthogonal basis functions, which can make up of an orthogonal set lie in the unit circle of $x^2 + y^2 \leq 1$.

The original definition of (9) is just rotation invariant. In order to achieve the Zernike moments of a grayscale image with the invariance to scale and translation, the image center of ROI must be sat to the origin (0, 0). If the

image is rotated by an angle of α . The Zernike moments $Z'_{n,m}$ is showed as follow:

$$Z'_{n,m} = Z_{n,m} e(jm\alpha) \quad (10)$$

$$\|Z'_{n,m}\| = \|Z_{n,m} e(jm\alpha)\| = \|Z_{n,m}\| \quad (11)$$

Where $\|Z_{n,m}\|$ is the norm of $Z_{n,m}$. From the formals (10) and (11), the magnitudes of Zernike moments are invariant to the rotation.

Translation invariant can be finished by reckoning the centroid of image function $I(x, y)$.

$$I(x, y) \Rightarrow I(x + \bar{x}, y + \bar{y}) \quad (12)$$

$$\text{Where } \bar{x} = \frac{M_{10}}{M_{00}} \text{ and } \bar{y} = \frac{M_{01}}{M_{00}}.$$

In our simulation, the order of Zernike moments was four by the consideration of cutting down the computation of high order moments.

2.3 Data analysis and classification methods

1. Top-match

Top-match is a simple and efficient classification method, which is to put the input vector into the k-th class target that minimizes the Euclidian distance.

The vector z in the formals of (13) denotes the output of image feature extraction. ε_k is used to define the distance between two different image feature vector.

$$\varepsilon_k = \|z - \Omega_k\| \quad (13)$$

where Ω_k is a vector describing the k-th class target.

2. Principal component analysis (PCA) for data analysis

Principal component analysis (PCA) [15] is an excellent tool to reorganizing the sample data to be worth being analyzed and testing. PCA was firstly presented by Karl Pearson [16]. Important information is estimated from the input data by the application of PCA, and represented by a set of new orthogonal and low-dimensional vectors called principal components. The application of PCA have some limitation, and then many improvement version of PCA is proposed, for example robust PCA [17][18], generalized PCA[19]. The basic of computing principal component was presented as follow:

Given a single matrix D with dimensions $M \times N$, which has a set of N data vectors $d_1 \dots d_N$. every vector d indicate a sample data. Firstly, the mean values of the observation data are computed.

$$u[m] = \frac{1}{N} \sum_{n=1}^N D[m, n] \quad (14)$$

Where $m=1 \dots M$. $u[m]$ is the mean values of the matrix D , which has dimensions of $M \times 1$.

After obtaining the mean of the sample data, the difference between the observation data and mean value is calculated.

$$B = D - u * h \quad (15)$$

Where h is an all ones matrix with the dimensions of $N \times 1$. B is a $M \times N$ matrix of saving the mean-subtracted data.

The covariance matrix C can be obtained from formals (16).

$$C = \frac{1}{N} B * B^T \quad (16)$$

Where B^T is a transpose matrix of B .

Eigenvectors and eigenvalues can be extracted from covariance matrix C .

$$V^{-1} C V = D \quad (17)$$

Where V denote the eigenvectors taking from C , and matrix D contain all eigenvalues of C .

Some eigenvectors from the matrix of V were selected for reconstructing, a vector embody useful information can be restored from the selected eigenvectors and the corresponding eigenvalues.

In this fusion scheme, the introduction of principal component analysis is to release the redundancy information of the image feature vector produced by combining different image features. In others words, the objective of PCA is to analysis and remove redundant information in correlate or uncorrelated data. Furthermore, it is important to eliminate the outlier of the sample data which can bring in instability of recognition.

3. Support Vector machines(SVM)

Support vector machines (SVM) is the result of the development of statistical learning theory [15][20], which contains a group of supervised learning algorithms to obtaining a optimal outcome of pattern classification.

In brief, given a set of training image features vector, each input vector was grouped into one of two categories. Meanwhile a model can be created by a SVM training algorithm, which can predict and categorize following new vector.

In math, pattern classification with SVM can be completed by using an N-dimensional hyperplane. SVM has been developed into different types, such as fast SVM and so on. Some methods of SVMs have excellent performance in the case of small samples by applying special optimization theory.

In our simulation and experiment, a software package of support vector machine developed by Chih-Chung[21] was utilized.

3 Feature-Based Image Fusion and Recognition Scheme

In this section, fusion and recognition scheme is demonstrated. In the scheme, image features were separately extracted from two images. Fig 1 depicts the structure of this fusion scheme. And the main steps of this scheme are revealed:

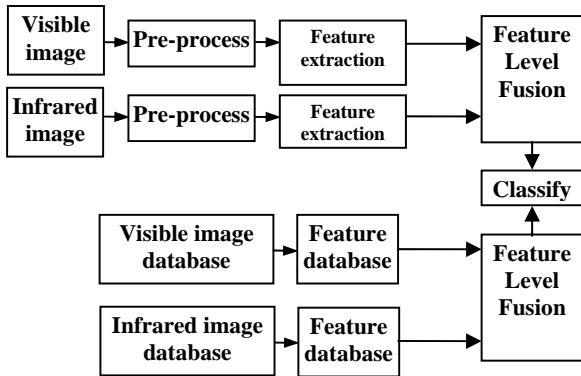


Fig 1 feature-based image fusion and recognition scheme

1. Image feature extraction
Primarily, visible and infrared images were pre-processed, for example, image enhancement, and the choice of target region. And then visible images were projected into the visible-eigenspace, meanwhile the eigenspace of infrared images is built. The procedure of constructing different eigenspace can be show by formals (18) from different modality sensor.

$$\begin{cases} [\phi_{11}, \phi_{12}, \phi_{13}, \phi_{14}, \phi_{15}, \phi_{16}, \phi_{17}] \\ [\phi_{V1}, \phi_{V2}, \phi_{V3}, \phi_{V4}, \phi_{V5}, \phi_{V6}, \phi_{V7}] \end{cases} \quad (18)$$

Where ‘V’ denotes the visible images and ‘I’ denotes infrared images, and ϕ signifies an element of satellite’s features.

2. Fusion in feature-level

The goal of fusion in feature-level is to combine or extract comprehensive important information from each eigenspace. There are two ways for fusing different eigenspace, including serial fusion, parallel fusion. Fusion in feature-level remained a challenge problem in the scope of pattern recognition.

There are a number of algorithms can be used to fusion different kinds of features, such as evolutionary algorithms, genetic algorithm and so on. In consideration of the limit space-based computer’s power and the ability to quick responsiveness, each other feature vector is directly combined into a new feature vector by merging various moments into a new eigenspace, including all information from original eigenspace. The fusing process show as follow.

$$[\phi_{11}, \phi_{12}, \phi_{13}, \phi_{14}, \phi_{15}, \phi_{16}, \phi_{17}, \phi_{V1}, \phi_{V2}, \phi_{V3}, \phi_{V4}, \phi_{V5}, \phi_{V6}, \phi_{V7}] \quad (19)$$

Denote forms (19) with (20):

$$[\phi^1, \phi^2, \phi^3, \phi^4, \phi^5, \phi^6, \phi^7, \phi^8, \phi^9, \phi^{10}, \phi^{11}, \phi^{12}, \phi^{13}, \phi^{14}] \quad (20)$$

3. Object classification

By comparing the feature vectors stored in feature database, the scheme can handle different class of satellite. In this paper, Top-match, PCA&SVM, SVM are the three methods for testing and evaluating the performance of this scheme.

In summary, the choice of image feature for representing object, the fusion rule or methods of different features, the algorithms for object recognition is the key in this scheme.

4 Semi-physical simulation platform and experiment structure

4.1 Semi-physical simulation platform

In order to simulate the uncontrolled space environment, image acquisition and processing system contain visible and infrared sensors were constructed. The Visible-Infrared Image Dynamic Acquisition System was introduced in detail in **Error! Reference source not found.** It composed of servo-system, image acquiring and processing system, such as visible and infrared sensors, video capture cards, high performance PC and so on. Fig.2 shows our hardware scheme of VIIDAS.

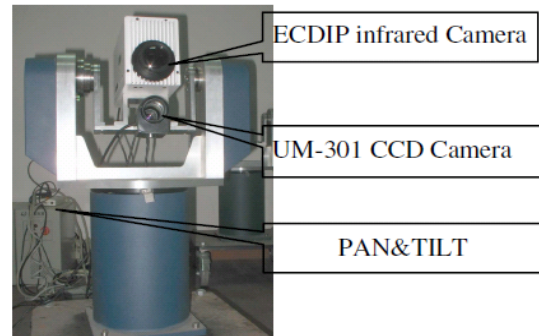


Fig.2 Picture of VIIDAS

In this system, all satellite image data was captured with different attitude and sunlight, preprocessed, collected by VIIDAS. Some sample satellite images are given in Fig 3. The visible and infrared images are grayscale images represented with 10 bits per pixel. The test set consists of 216(108 per modality) satellite images from five different satellites.

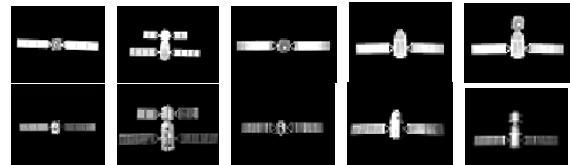


Fig.3 five satellite sample picture
(Data captured by ECDIP IR camera and UM-301 camera
size: 60 × 48 pixels)

4.2 Experiment structure

In order to measure the feasibility of this scheme, five different class of satellite were taken to test and study. And six different fusion rules and three classification algorithms were adopted to evaluate the fusion and recognition scheme. The three classification algorithms

were directly verified by matching the sample features in the feature database and the input testing vectors. These methods are classic approaches which widely were applied to different scopes. The goal of experiment is to try the scheme out by using recognition performance and employing various fusion rules to assorted eigenspace.

5 Experimental results

A training set and test set was created for evaluating six fusion rule and feature's performance overall. Table 1 shows recognition performance when several fusion rules adapted to either visible or infrared images individually. Visible images' results are reported above the corresponding infrared images' output. In contrast to row 1 and 2 of visible modality with row 3 respectively, we can get the influence of different features on the performance of satellite recognition. Discrepancy in different classification algorithms outcome greatly. Top-match was simple, but had a poor recognition rate compared to others. Redundant information in the feature vector may be removed by PCA, and then the performance of PCA&SVM sometime can lead to a decrease in recognition rate compared to SVM.

Table 1 Recognition rate of single images

Scheme	Feature	Recognition rate (%)		
		Top-match	PCA+SVM	SVM
Visible	CBAI	79.63	81.48	88.89
	Zernike	83.33	91.67	91.67
	CBAI&Zernike	84.26	91.67	91.67
IR	CBAI	73.14	75.00	85.19
	Zernike	77.78	87.95	87.95
	CBAI&Zernike	82.47	87.95	87.95

Table 2 indicates that different fusion rule with the combination of CBAI and Zernike moments have an increase in the performance of recognition. The experiments also represent that different features from different modality sensor can result in different recognition rate.

Table 2 Experimental results of feature-based fusion

Feature-based Fusion scheme				
Features		Recognition rate (%)		
Visible	IR	Top-match	PCA+SVM	SVM
CBAI	CBAI	83.33	93.51	98.15
Zernike	Zernike	87.95	97.22	98.15
Zernike	CBAI	89.81	98.15	98.15
CBAI	Zernike	88.89	97.22	98.15
CBAI&Zernike	CBAI&Zernike	95.37	99.07	99.07

6 Conclusion

A new and simple fusion recognition scheme was proposed to join different information from visible and infrared sensors for robust satellite recognition based on couple CBAI with Zernike invariant moments.

Experimental results confirm that image fusion and recognition with combining different features from various eigenspace is better than alone based on either infrared or visible image. And this fusion scheme obtains higher performance. Further research should be given to effective choosing eigenvalues in feature-level or sequence images fusion and recognition based on topology or manifold learning.

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References

- [1] Diego A. Socolinsky, Andrea Selinger, Joshua D. Neuheisel, Face recognition with visible and thermal infrared imagery, Computer Vision and Image Understanding, Volume 91, Issues 1-2, Special Issue on Face Recognition, pp.72-114.2003.
- [2] George Bebis, Aglika Gyaourova, Saurabh Singh, Ioannis Pavlidis, Face recognition by fusing thermal infrared and visible imagery, Image and Vision Computing, Volume 24, Issue 7, pp.727-742.2006
- [3] HAN Yu-ge, XUAN Yi-min, Infrared feature of the satellites, Infrared and Laser Engineering, 34(1), pp. 34-37. 2005.
- [4] Xun Du, Junshui Ma, Mohamed Qasem, and Stanley C. Ahalt, Eigen indexing in satellite recognition, Proc. SPIE 3718, 397 (1999).
- [5] Liu Xiankang, Gao Meiguo, and Fu Xiongjun, Application of HRRP even rank central moments features in satellite target recognition, IET Conference. Pub. 2007, 144 (2007).
- [6] Jan Flusser and Tomas Suk, Affine moment invariants: a new tool for character recognition, Pattern Recognition Letters, 15(4), pp.433-436. 1994.
- [7] M. R. Teague. Image analysis via the general theory of moments. J. Opt. Soc. Am., Vol. 70, Issue. 8:920-930. 1980.

- [8] M. K. Hu, "Visual Pattern Recognition by Moment Invariants", IRE Trans. Info. Theory, vol. IT-8, pp.179–187, 1962.
- [9] F. A. Sadjadi, and E L Hall, "Numerical computations of moment invariants for scene analysis," Proceedings of the IEEE Conference on Pattern Recognition and Image Processing (1978).
- [10] J. Flusser, T. Suk, Pattern recognition by affine moment invariants, Pattern Recognition 26 (1993) 167–174.
- [11] J. Flusser, T. Suk, Degraded image analysis: an invariant approach, IEEE Trans. Pattern Anal. Mach. Intell. 20 (1998)590–603.
- [12] Tomáš Suk, Jan Flusser, Combined blur and affine moment invariants and their use in pattern recognition, Pattern Recognition, Volume 36, Issue 12, pp.2895-2907.2003.
- [13] Tomáš Suk, Jan Flusser, "Blur and Affine Moment Invariants," ICPR, vol. 4, pp.40339, 16th International Conference on Pattern Recognition (ICPR'02) - Volume 4, 2002.
- [14] A. Khotanzad and Y. H. Hong. Invariant image recognition by zernike moments.IEEE Trans. on Pattern Anal. and Machine Intell., Vol. 12:489 – 498., 1990.
- [15] Jolliffe I.T. Principal Component Analysis, Series: Springer Series in Statistics, 2nd ed., Springer, NY, 2002, XXIX, 487, p.28.
- [16] Pearson, K. (1901). "On Lines and Planes of Closest Fit to Systems of Points in Space" . Philosophical Magazine 2 (6): 559–572.
- [17] C. Croux, A. Ruiz-Gazen, A fast algorithm for robust principal components based on projection Pursuit, COMPSTAT: Proceedings in Computational Statistics 1996, Physica-Verlag, Heidelberg, 1996, pp. 211-217.
- [18] C. Croux, G. Haesbroeck, Principal component analysis based on robust estimators of the covariance or correlation matrix: influence functions and efficiencies, Biometrika 87 (2000) 603-618.
- [19] R.Vidal, Y.Ma, S.Sastry, Generalized principal component analysis, in:Computer Vision and Pattern Recognition,vol.1,2003,pp.621–628.
- [20] Christopher J. C. Burges. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery, 2:121–167, 1998.
- [21] Chih-Chung Chang and Chih-Jen Lin, LIBSVM : a library for support vector machines, 2001. Software available at <http://www.csie.ntu.edu.tw/~cjlin/libsvm>.
- [22] Xiao Gang, Wei Kun, Jing Zhongliang. Improved dynamic image fusion scheme for infrared and visible sequence Based on Image Fusion System. Proceedings of the 11th International Conference on Information Fusion, FUSION 2008, Jun 30-Jul 3,2008, Cologne, Germany, PP: 1745-1750.