Performance Evaluation of Land cover change detection Algorithms using remotely sensed Data

L.Antony Jude
PG Scholar
Dept. of CSE,
M S University, Tamilnadu.
judelawre@gmail.com

Dr.A.Suruliandi
Professor
Dept. of CSE,
M S University, Tamilnadu.
suruliandi@yahoo.com

***Abstract* - Remote sensing has long been used as a means of detecting and classifying the different types of data attribute present in the land cover. In general, remote sensing is widely used across variety of real-time applications to identify the change information of geographical areas. The Objective of this work is to study three land cover change detection algorithms such as Image Differencing method, Auto-Correlation function method and Distance Analysis method. In this paper, land cover change is obtained by change detection method from the sequence of annual pattern dataset of multi-date temporal datasets. This work presents a performance comparison of change detection algorithms based on performance metrics Change data and False alarm. From the evaluated results, Auto-correlation function method performs better than other Image differencing and Distance analysis method.**

Index Terms – Change Detection Algorithms, Satellite, time series analysis, Change data, and False alarm.

I. INTRODUCTION

Remote sensing has widely used for sensing the information of land cover/land use through different types of sensors placed in the satellite [6], [1]. In general, world's resource estimation across variety of fields depends upon the observation of remote sensing data only. Among, identifying land cover change plays vital role in the estimation of city planning, vegetation growth rate, natural hazard etc [8]. The Land cover data captured by the remote sensing satellite are in the form of band sequences. Each band represents the properties of different objects like water, vegetation areas etc. with their specified DN values. Before the processing, the dataset is processed for geo-referencing and radiometric correction to reduce the noise present in it. After that, dataset will be processed for land cover change using the optimized change detection algorithm [6] with respect to change data and false alarm rate, Land Cover change observation is used to maintain the growth or system cycles of the environment [1]. To identify the land cover change information, it is necessary to know about the remote sensing which acquires the dataset of temporal annual patterns for land cover. Land cover change detection algorithms that detect the changes of multi-temporal same land cover area [11].

One of the most challenging issues in land cover change detection is the development of land cover change detection method which can efficiently finds the land cover change of different objects present in it. The limitation with only using two images is that similar land cover types can appear significantly different at various times of the year, Land cover change had been identified in past decades through direct image subtraction method [7], which is not efficient. Due to the difficulty of that like method, researchers were motivated to develop the enhanced land cover change detection method. So many methods were developed and implemented. Each one shown its own characteristics for identifying land cover change in a better way. Motivation here is to study some land cover change detection algorithms such as Image Differencing Method (NDVI) [7], Auto-Correlation Function Method (ACF) [3] [9], Distance Analysis Method [8] and analyze the above methods with metrics like Change Data, False Alarm [7] [3] [9]. In this paper, a comparative evaluation for three types of land cover change detection algorithm has been carried out and those methodologies are descripted as follows for multi-temporal landsat 30m resolution dataset.

II. METHODOLOGY

A. *Image Difference Method*

Image differencing method [7] is used to identify the land cover change based on the normalized difference vegetation index. Landsat TM Dataset of two different date of tirunelveli region is taken for performing the land cover change detection. First step of this method is to perform the NDVI for both dataset band3&band4 using the below equation [12].

$$NDVI= (NIR-RED) / (NIR+RED) \qquad (1)$$

This method is used to find change information of same region in different time periods. It includes the structural process of the method and it is shown in following Fig.1

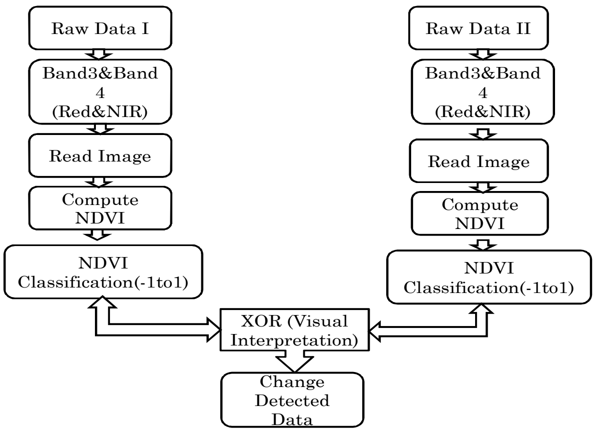


Fig. 1. Methodology of Image Differencing method

After achieving the NDVI for both dataset, it needs to be processed separately to reduce the pseudo-hikes and drops (noise) through setting up the threshold value by ≥0.15 for getting best setting to eliminate the anomalous points that cause noise to the data. For better result NDVI values greater than 0.15 treated as 1 and remaining values are treated as 0. Resultant NDVI threshold data of both dataset further processed into image subtraction i.e., using logical XOR operation. The output of the logical operation displays the land cover change information.

A.1 *Algorithm*

1. Read the image.
   (Band 3 & Band 4 from the multi-date Imagery of same location)
2. Initialize and set the threshold value ±0.15 for pre-processing.
3. Compute NDVI for both imagery bands as in (1).
4. Classify the NDVI Image of both Imagery by setting up the threshold value of 0.15 (z-score).
5. Assign value 1 if NDVI (I, J) ≥0.15 stated as vegetation area, else 0 for non-vegetation area.
6. Calculate logical operation XOR for change detection.
7. If pixel value 0 in resultant image is stated as no change area and 1 is change area.
8. Calculate the area of non-vegetation and vegetation through with pixel resolution.
9. Calculate the percentage of Change area

B. Auto-Correlation Function Method

In ACF method, by taking correlation for the sequences of annual pattern dataset pixel-by-pixel leads to get the single correlated value for entire annual period [3] [9]. Initial Correlated values are taken as threshold value for further annual pattern dataset, using that land cover change and no-change data can be easily identified. Comparison of only two images is not always reliable, as similar land cover types can appear significantly different at various stages of the natural growth [7]. To overcome this problem the temporal frequency of medium resolution remote sensing data acquisitions should be enough to distinguish change events of land-cover from natural phenological-cycles. The autocorrelation function [3] [9], in the temporal context, has been used in the spatial context. In this method the temporal ACF of a pixel’s time-series was considered. By determining suitable detection parameters like time-lag (τ), threshold (δ) it will be shown that real land cover change can be detected reliably. This method is used to find the change information of same region in different time-periods. It includes the structural process of the method and it is shown in following Fig. 2. The autocorrelation function, in the temporal context, has been used selectively in remote sensing, but is mostly applied in the spatial context. In this study the temporal ACF of a pixel’s time-series was considered. An ACF of a time-series that is stationary behaves differently from an ACF of a time-series that is non-stationary due to land cover change.

The temporal ACF method uses a two stage approach. Firstly, the simulated change dataset together with the no-change dataset are used in an off-line optimization phase to determine the appropriate parameters (band, lag and threshold selection). Second, the method is run in an unsupervised manner using the parameter-set that was determined during the aforementioned off-line optimization phase.

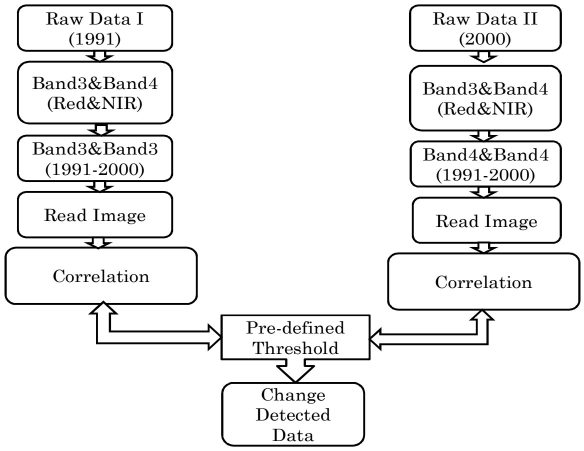


Fig. 2. Methodology of Auto-Correlation method

Off-Line Optimization Phase:

Assume that the Landsat time-series for any given band is expressed as

$$X_n^b \; n \in \{1,2,\ldots.N\} b \in \{1,2,\ldots.8\} \quad (2)$$

where 'X_n^b' is the observation from spectral band 'b' at time 'n' and 'N' is the number of time-series observations available. The ACF for time-series can then be expressed as

$$R^b(\tau) = \frac{E[(X_n^b - \mu^b)(X_{n+\tau}^b - \mu^b)}{var(X^b)} \quad (3)$$

where τ is the time-lag, mean of x^b is given as μb and the variance, which is used for normalization, is given as var (x^b). It is clear that the no-change pixel has a symmetrical form relative to the axis, whereas the change pixel shows strong asymmetry. The reason for this is the stationarity requirement of the ACF. The mean and variance of the time-series of X_n^b are required to remain constant through time to determine the true ACF of the time-series. The inconsistency of the mean and variance typically associated with a change pixel's non-stationary time-series thus becomes apparent when analyzing the ACF of the time-series. The key here is that even though reflectance time series in nature are more often than not non-stationary because of, for example, inter annual variability, the time-series of a pixel undergoing land cover change will typically have a higher degree of non-stationarity than a time-series that does not experience a land cover change. This property is thus exploited by considering the temporal correlation of a specific band (b) at a specific lag (τ) as a change index.

$$R^b(\tau) = \delta_\tau^b \quad (4)$$

By making use of a dataset of change and no-change ACF examples, the distribution of δ_τ^b could be determined for the change (p $(\delta_\tau^b|C)$) and no-change (p $(\delta_\tau^b|\bar{C})$) case respectively for different values of and .The aim is thus to determine the value of and in that will result in the most separable distributions between for the change (p $(\delta_\tau^b|C)$ and no-change (p $(\delta_\tau^b|\bar{C})$ case respectively. The value of the optimal threshold (δ_τ^b) also needs to be determined.

Operational Phase:

After the off-line optimization phase is complete, the resulting parameters are used to run the algorithm in an unsupervised manner for the entire area of interest. A pixel is labeled as having changed by evaluating the following:

$$change = \begin{cases} true \; if \; R^b\,(\tau) > \delta \\ false \; if \; R^b\,(\tau) < \delta \end{cases} \quad (5)$$

Where $R^b(\tau)$the ACF of band b is evaluated at lag τ and is the δ decision threshold.

B.1 Algorithm

1. Read the image.
   (Band 3 & Band 4 from the multi-date imagery of same location)
2. Reorder the 'b' bands of same period dataset into a single band value.
   (Band 3 & Band 4 of sequence annual pattern data separately)
3. Calculate the mean (μ) time-lag (τ) and threshold (δ) of each band. Using above parameter (μ, τ, δ), find Correlation as in(3)
4. Change index taken for every pixel, as single Correlation value for entire sequence annual pattern of each data period as in (4)
5. Calculate the overall change by finding the z-score of Correlated values through by standard normal distribution.
6. Standard score (z-score) is the set as threshold value and compared it with the Correlated data lead s to find the Change
7. Combine change in band 3 & band 4 by using NDVI method

C. Distance Analysis Method

In this method, assigned a change area is based on distance comparison of EVI values from two successive years, and a threshold was used to assign a change [10]. Distance measure is used to find the distance between the successive annual patterns of the multi-date datasets through that land cover change can be detected.

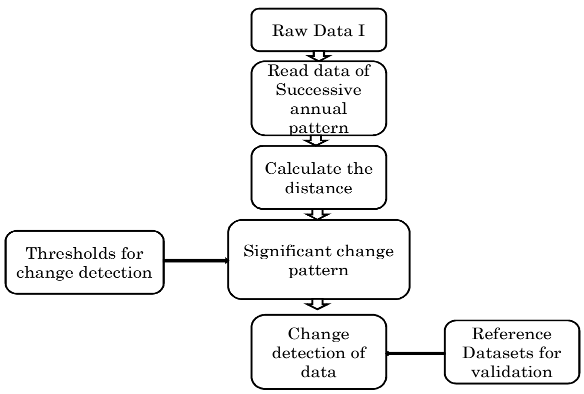


Fig. 3. Methodology of Distance Analysis method

Then created distance in two successive annual patterns. Any two successive annual segments are merged into a new segment, $R_{new}= R_k U R_l$ furthermore, the distance function between segments has a form $d_{kl} = D(R_k, R_l) \geq 0$.

$$d_{k,l} = \frac{N_k}{N_{new}} |\mu_k - \mu_{new}|^2 + \frac{N_1}{N_{new}} |\mu_1 - \mu_{new}|^2 \quad (6)$$

Where $d_{k,l}$ is distance between two successive segments, N is the number of observations $N_{new} = N_k + N_1$, and μ is the mean of a segment

$$\mu_{new} = \frac{N_k \mu_k + N_1 \mu_1}{N_{new}} \quad (7)$$

After that, perform statistical analysis using a standard normal distribution to identify pixels that had the greatest change in distance of EVI for each period [7]. Then, the change threshold was selected corresponding to a range of z-score probabilities [3], which produced appropriate estimates of annual change values.

C.1 Algorithm

1. Read the time-series dataset. (Band 3 & Band 4 from the multi-date imagery of same location)
2. Calculate the mean (μ) of each band and new mean (μ_{new}) through (7)
3. Compute the successive annual pattern pixel element distance and its happens around the entire pixel elements, where it represents distance function between the segment has a form $d_{kl} = D(R_k, R_l) \geq 0$ as in (6)
4. Calculate the distance through the above factor.
5. After that a standard normal distribution performed with data.
6. Then from that standard score or Z-score computed for distance dataset.
7. Using the Z-score a threshold has been set to identify the change pixels.
8. Combine change in band 3 & band 4 by using NDVI method.

III EXPERIMENTAL RESULTS

A. Performance Metrics

In order to perform the comparative evaluation of three types of land cover change detection method, in this project consider the following two metrics

A.1 Change Data

Change data is the amount of changes inferred in land cover of multi-date data in terms of percentage. It can be achieved through the land cover change detection method used in this project.

$$P(C|C) = \int_{\delta_\tau^b=\delta^*}^{\delta_\tau^b=\infty} p(\delta|C) \quad (8)$$

$P(C|C)$ is the probability that a change was detected given that a change was present (percentage change correctly detected)

A.2 False Alarm

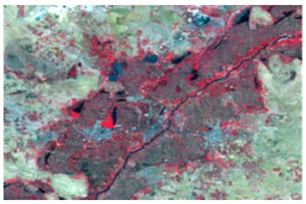
False alarm is nothing but the false detection of change in no change area, achieved through by the comparison of test change data with the reference data set using the confusion matrix (Bayesian decision error).

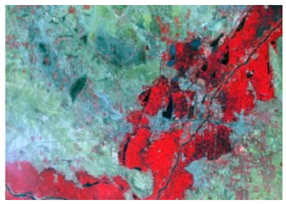
$$P(C|\bar{C}) = \int_{\delta_\tau^b=\delta^*}^{\delta_\tau^b=\infty} p(\delta|\bar{C}) \quad (9)$$

$P(C|\bar{C})$ is the probability that a change was detected given that no change was present (percentage false alarms).

B. Data description

The study area for this project is Tirunelveli region of Landsat TM data for the time-period of the Year 1991 & 2000. Among four bands, band number three and four of both year has been taken for experimentation. In this project, time-period taken is 1991 as no change data and data 2000 period taken as change data for reference.





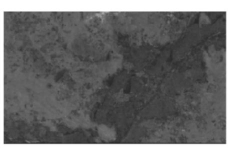
(a)TirunelveliRegion-1991 (b)TirunelveliRegion- 2000

Fig. 4 a. Input Dataset (FCC) of Tirunelveli Region-1991 and
b. Input Dataset (FCC) of Tirunelveli Region-2000

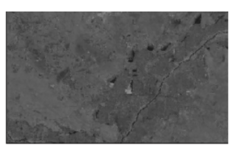
C. Results and Analysis

An input of different period (1991 & 2000) of FCC dataset is used here for Land Cover Change identification by this Image differencing method (NDVI) shown in Fig.4 and it is then split into numbers of band data. For this paper, it requires only band 3 and band 4 of the both FCC datasets, band 3 and band 4 of both FCC datasets is shown below I Fig. 5

I. FCC Dataset (1991)

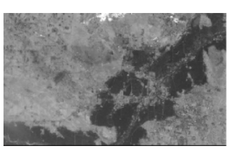


(a) band 3 (red)

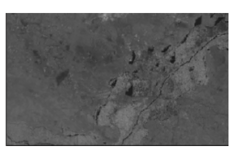


(b) band 4 (infra-red)

II. FCC Dataset (2000)



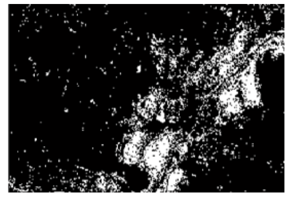
(a) band 3 (red)



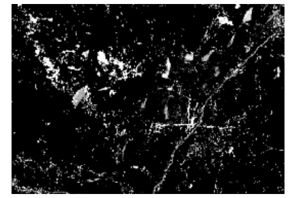
(b) band 4 (infra-red)

Fig. 5. Band3 & Band4 of FCC Datasets of 1991 & 2000

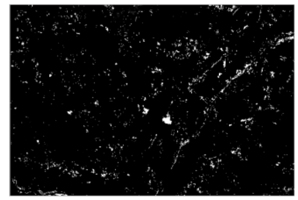
In Fig. 6 the results of Land cover change with respect to Image differencing, Auto-Correlation and Distance analysis methods are shown in fig. 6



(a) Image differencing method



(b) Auto-Correlation method



(c) Distance Analysis method

Fig. 6. Change Detection (1991-2000) using Image Differencing, Auto-Correlation and Distance analysis methods.

D. Performance Evaluation

The Performance analysis shows in tables and graphs which tells that, the best method. Comparing the three methods with respect to metrics change data and false alarm gives the better result for 312317 pixel areas.

Table 1. Evaluation of Change data

Data Period	Methods	No. of loc.	Change (%)
1991-2000	NDVI	312317	57
1991-2000	ACF	312317	80
1991-2000	Distance Analysis	312317	61

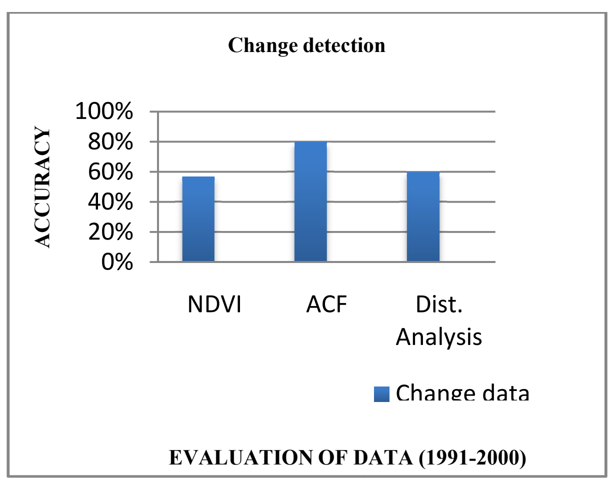


Fig. 7. Percentage of Change for NDVI, ACF and Distance Analysis method

Table 2. Evaluation of False Alarm

Data Period	Methods	No. of loc.	False Alarm (%)
1991-2000	NDVI	312317	14
1991-2000	ACF	312317	15
1991-2000	Distance Analysis	312317	20

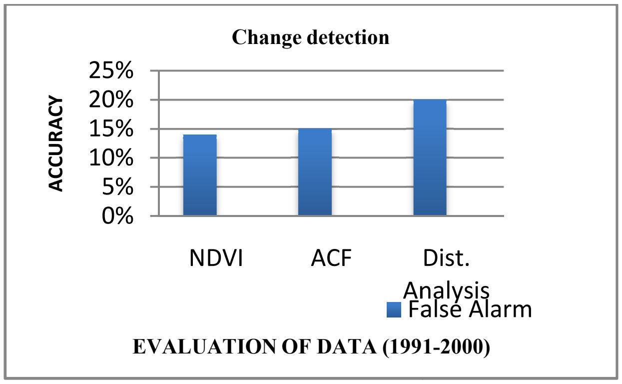


Fig. 8. Percentage of False alarm for NDVI, ACF and Distance Analysis method

Table 3. Change data and False Alarm for three land cover change detection methods.

Methods	Change data (%)	False Alarm (%)
NDVI	57	14
Auto-correlation	80	15
Distance Analysis	61	20

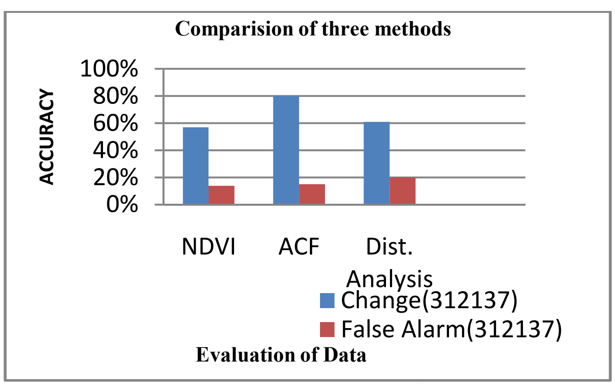


Fig. 9. Comparison of NDVI, ACF and Distance Analysis method about land cover change detection

In table 3 & fig 9, comparison of three land cover change detection algorithms are showed with number of pixel location taken as test data set. It clearly showing the best among the three methods in terms of land cover change data rate in percentage. From the Confusion matrix (Bayesian decision error) showing the best among the three methods in terms of false alarm in percentage. The minimal percentage of false alarm is chosen as best one

IV. CONCLUSIONS

In this work, Image Differencing method, Auto-Correlation Function method and Distance Analysis method that enables the process of identifying land cover change in multi-date datasets of same area and also evaluating their performance. Performance evaluation metrics for these methods are Change Data and False Alarm. The Comparative study between these three methods shows that Auto-Correlation Function method performs better than all the other in case of Change Data. The Comparative study also reveals that Image Differencing method performs better than all the other in case of least False Alarm. Overall, Auto-Correlation Function method provides better results for the land cover change detection of tirunelveli region landsat datasets. In Future, the following processes may be suggested for the above land cover change detection algorithms. Inefficiency of land cover change detection for large areas could be overcome by implementing techniques such as Extended Kalman filter [9] [10].

V. REFERENCES

[1] Coppin p et al., "Digital change detection methods in ecosystem monitoring: A review," *Int. J. Remote Sens..*, vol. 24, no. 9, pp. 1565–1596, May 2004

[2] Fraser R. H, Li Z., and Cihlar J, "Hotspot and NDVI Differencing Synergy (HANDS): A New Technique for Burned Area Mapping over Boreal Forest". *Remote Sens. Environ.* 74:362–376 (2000)

[3] Kleynhans W et al., "Land Cover Change Detection Using Autocorrelation Analysis on MODIS Time-Series Data" *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 5, no. 3, June 2012.

[4] Kleynhans W et al., “Detecting land cover change using an Extended Kalman Filter on MODIS NDVI time series data,” *IEEE Geosci. Remote Sens. Lett.*, vol. 8, no. 3, pp. 507–511, May 2011.

[5] Kleynhans W et al., “Improving land cover class separation using an Extended Kalman Filter on MODIS NDVI time-series data,” *IEEE Geosci. Remote Sens. Lett. ,* vol. 7, no. 2, pp. 381–385, Apr. 2010. vol. 19, no. 6, pp. 1635–1650, Jun. 2010.

[6] Lu D, Mausel P, Brondizio E, and Moran E, “Change detection tech-niques,” *Int. J. Remote Sens.* , vol. 25, no. 12, pp. 2365–2407, Jun. 2004.

[7] Lunetta R.S et al., “Land-cover change detection using multi-temporal MODIS NDVI data,”*Remote Sens. Environ. ,* vol. 105, pp. 142–154, Nov. 2006.

[8] Xian G, Collin H, and Fry J, “Updating the 2001 National Land Cover Database land cover classification to 2006 by using Landsat imagery change detection methods,” *Remote Sens. Environ.,* vol. 113, no. 6, pp. 1133–1147, Jun. 2009.

[9] You H, Garrison J, Heckler G, and Smajlovic D, “The auto-correlation of waveforms generated from ocean-scattered GPS signals*,” IEEE Geoscience Remote Sensing*, vol. 3, no. 1, pp. 78–82, Jan. 2006.

[10] Yudi setiawan et al.,“change detection in land-use and land-cover dynamics at a regional scale from modis time-series imagery”. *ISPRS Annals of the photogrammetry, Remote Sensing and Spatial information sciences*. vol 1-7,Nov2012.

[11] Zhan X, Sohlberg R.A., Townshend J. R. DiMiceli C., Carroll M. L., Eastman J. C., Hansen M. C., and DeFries R. S., “Detection of land cover changes using MODIS 250 m data,” *Remote Sens. Environ. ,* vol. 83, no. 1/2, pp. 336–350, Nov. 2002.

[12] Zhang B, Gao Y, Zhao S, and Liu J, “Local derivative pattern versus local binary pattern: Face recognition with higher-order local pattern descriptor,” *IEEE Trans. Image Process.*, vol. 19, no. 2, pp. 533–544, Feb. 2010.