Application-oriented approach to Texture feature extraction using Grey Level Co-occurrence Matrix (GLCM)

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Abstract: *In texture segmentation and classification using kernel-based approaches like Grey Level Co-occurrence Matrix (GLCM) and Semi-variogram, choice of window size, directionality of texture measurement and adjacency or lag criteria are important parameters and their choice is not always straight forward. In this work, experimental studies are carried out to understand how different choice of parameters affects texture feature extraction and how different applications can be associated with them. Unlike generalization approach, where common parameters are used for different applications and when information about ground features is less known, this approach is more specifically targeted towards application oriented studies.*

Through parametric studies, this work also tries to bring forth few approaches suggested by different researchers towards minimizing the computational cost of GLCM algorithm. In this work, GLCHS (Grey Level Co-occurrence Hybrid Structure) method is implemented on very high resolution satellite images to derive GLCM texture features.

Key Words: **Texture classification, Grey Level Co-occurrence Matrix (GLCM), Grey-Level Co-occurrence Hybrid Structure (GLCHS), Parameter selection**

1. INTRODUCTION

With high resolution remote sensing data frequently available and spatial resolution continuously bettering the object size, large details about individual objects and regions are visible in satellite imagery. Traditional pixel-based approaches which rely on the overall average reflectance of an object or a region suffer for intra-feature variability and non-uniformity of intensity values within that feature [2]. As a result, using higher order classification approaches like the ones incorporating texture features or object-based classification has become necessary for better classification results.

Textures are visual patterns composed of entities, or sub-patterns that have characteristic brightness, color, slope, size, etc. The local sub-patterns give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation, etc., of the texture as a whole [6]. According to [7] there is no single method of texture representation which is adequate for a variety of texture. Of all the texture classifiers GLCM is the most prominently used method by researchers.

Unlike pixel-classifiers, texture classifiers like GLCM or Semi-variogram methods are dependent on their spatial content (neighborhood) surrounding a pixel. As a result, parameter selection i.e. choice of window size, directionality of texture measurement and adjacency criteria become vital inputs to a texture classification or feature extraction algorithms.

Choice of parameters affects both computational cost and classification results as texture features derived vary. A large window size though may take time for computing probability values in GLCM, it incorporates more information. But it is also necessary to be noted that the sharpness with which a feature is captured is reduced as a result of smoothening, which beyond a certain limit must be avoided. Additionally too small a window size can result in noisy texture characteristics. Hence, an optimal choice of window size is necessary. This optimization is largely dependent on the intended application. Through this work, we try to explore how window size can be varied based on intended applications.

Unlike window size, lag-shift directionality is a less explored part of GLCM, where researchers have many times ignored the significance of directionality either because of lack of knowledge about the area or lack of applications involved. With better resolution satellite data available, this parameter can be vital in several new less explored application areas.

2. OBJECTIVES

This work intends to explore beyond the generalization approach, where uniformity of window size or omni-directional lag-shift is applied irrespective of the dataset used, image resolution, feature-type and application intended. Thus, it tries to incorporate a knowledge-based approach to carry out better texture-based feature extraction and classification.

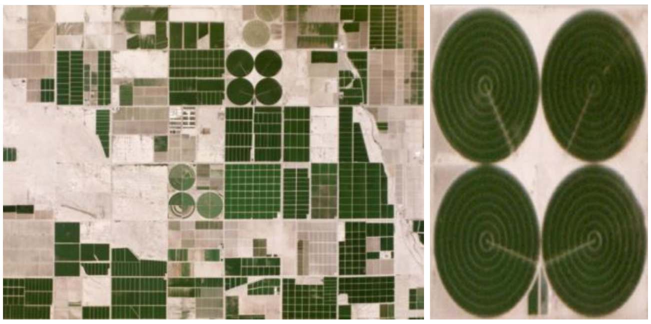
The major objectives of this work are to study the performance of texture feature extraction under varying parameters and to aid choice of appropriate parameters with the aim of minimizing over-segmentation or under-segmentation. With these objectives few experimental studies over pre-identified natural features from high resolution imagery are carried out. These experiments give an insight into different aspects of texture classification associated with texture parameters and their influence on feature extraction, texture features and image classification, correctness of the algorithms, etc. Similar studies can be very useful as preparatory process for carrying out application specific segmentation, classification or change detection studies.

3. STUDY AREAS

A number of freely available datasets are used in the experimental studies carried out. The choice of datasets is dependent on the type of experiment carried out.

Dataset-1: Circular Fields, Arizona

A natural feature, pivot irrigation, consisting of four adjacent irrigated circular lands with concentric plantation of varying diameters (Fig-1b), part of Planet imagery for the Pinal County irrigated fields, Arizona (Fig-1a) is used for checking the workability of the implemented GLCHS (Grey-Level Co-occurrence Hybrid Structure) algorithm for differing window size and lag directions.



(a) (b)

Fig-1: Pinal County, Arizona (a) Fields captured in August, 2014 (b) Pivotal irrigation field used in this work.

Table-1: Image specifications, Irrigated fields of Arizona

Parameter	Details
Image	Planet Labs satellite
Satellite	Cubesat (Dove satellite)
Multi-spectral Image	Blue: 455 - 515 nm Green: 500 - 590 nm Red: 590 - 670 nm NIR: 780 - 860 nm
Ground Sampling Distance	3.7m
Product	Ortho rectified
Image Format	GeoTIFF
Original Image Size	4005X3003
Date of Aquisition	16th August, 2014
Quantization bit	8

Dataset-2: Farm lands, Australia

Fig-2 belongs to a series of farmlands in Australia. These farmlands are typical oriented in different directions. As a result, this dataset is selected to understand how the choice of directionality in measuring different texture features affects the final outcome and might be useful in specific applications.

Fig-2: Farmlands of Australia

Table-2: Image Specifications, Farmlands of Australia.

Parameter	Details
Image	EROS-B image
Ground Sampling Distance	0.7m Nadir
Spectral Bands	0.5μm to 0.9μm
Datum	WGS-84
Coordinate System	UTM
Image Format	TIFF
Image Size	746 X 1347

Dataset-3: Chavimokic Irrigation project, Peru

Fig-3 is the part of Chavimokic irrigation project where barren land is transformed into commercial farmland in Peru. This area is used for understanding how varying window sizes affect feature extraction with respect to edge characterization associated with few markings, sea wave patterns and field edges present in the image (marked by yellow).

Fig-3: Chavimokic Irrigation project, Peru

Table-3: Image Specifications, Chavimokic irrigation

Parameter	Details
Image	Planet Labs satellite
Satellite	Cubesat (Dove satellite)
Multi-spectral Image	Blue: 455 - 515 nm Green: 500 - 590 nm Red: 590 - 670 nm NIR: 780 - 860 nm
Ground Sampling Distance	3.7m
Product	Ortho rectified
Image Size	900 X 1200

4. METHODOLOGY

4.1 Grey Level Co-occurrence Matrix (GLCM)

In this work, kernel-based texture feature extraction method of Grey Level Co-occurrence Matrix (GLCM) is used as it is widely used. GLCM works on the basic convolution principle where a window size, lag or adjacency parameters are defined to extract texture features by determining probability of pixel to pixel co-occurrence (Fig-4).

```
IMAGE

0 1 1 2 3              j=0    1     2     3
0 0 2 3 3        i= 0  1/20  2/20  1/20   0
0 1 2 2 3           1   0    1/20  3/20   0
1 2 3 2 2           2   0     0    3/20  5/20
2 2 3 3 2           3   0     0    2/20  2/20
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Fig-4: Grey-Level Co-occurrence Matrix derived from 5X5 window or image size [1]

$$Contrast = \Sigma_i \Sigma_{ij} \, (i-j)^2 * c_{ij} \text{.....................} 1$$

$$Entropy = \Sigma_i \Sigma_j \, c_{ij} * \log c_{ij} \text{..........................} 2$$

$$Dissimilarity = \Sigma_i \Sigma_j \, c_{ij} * |i-j| \text{.................} 3$$

$$IDM = \Sigma_i \Sigma_j \, c_{ij} * \frac{1}{1+(i-j)^2} \text{................................} 4$$

$$ASM = \Sigma_i \Sigma_j {c_{ij}}^2 \text{..} 5$$

The probability of co-occurrence (c_{ij}) between two grey levels i and j given a relative orientation and distance can be computed for all possible co-occurring grey level pairs in an image window. The GLCM stores these probabilities and, as such, is dimensioned to the number of grey levels available. Then, selected statistics are applied to the GLCM by stepping through the entire matrix (i.e. over all probabilities) to calculate the texture features [4] as in Equation 1 to 5.

4.2 Variants of standard GLCM

GLCM proposed by [5] is computationally demanding, majorly because of large number of redundant steps as measurements are repeated for subsequent windows and large number of unwanted zero probabilities tabulated into the co-occurrence matrix. The cost also increases with increase in window size, number of texture features per window (as many as 14 proposed by [5]) and the number of directions for which adjacency (or lag) is measured. These drawbacks drastically affect the computational performance of the segmentation algorithm, especially for large size imagery like remote-sensing datasets. With increasing image resolution, quantization bit and format size, this problem is magnified.

Therefore in order to reduce the computational cost, in this work, Grey Level Co-occurrence Hybrid Structure (GLCHS) suggested by [4] is implemented, which uses a hash table together with link list to derive GLCM. The advantage of link list is that it avoids repetitive and redundant measurement of texture features and hash table transforms an element into an address where it will be stored, which reduced exhaustive search operation for valid entries, which eliminates the time-consuming sorting operation in Grey Level Co-occurrence Linked List (GLCLL) suggested by [3].

4.3 Work Flow

In this work, parameter selection associated with individual classes is given priority instead of following a generalization approach. The work flow (Fig-5) is adopted for carrying out the experimental studies. High resolution imagery is first chosen depending on the study intended. Varying parametric inputs are used to compute co-occurrence matrices at different window sizes and lag directions. Thereafter five texture features are statistically derived using formulae in Equation 1 to 5.

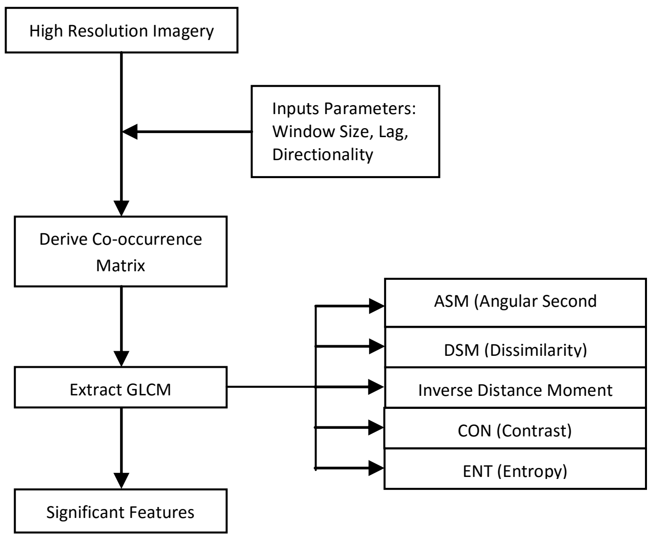


Fig-5: Flow Chart for carrying out experimental work.

The choice of texture features is another parameter that influences the computational speed. According to literature, entropy, dissimilarity, contrast, inverse distance moment (IDM) and angular second moment (ASM) are scale invariant features. Hence, these features are chosen for experimental studies instead of deriving all the texture features to reduce computational cost.

5. RESULTS & OBSERVATIONS

5.1 Parameters and Associated Feature Extraction

Parametric studies over known features are necessary to (a) identify any visual anomaly in expected result and (b) check how varying different parameters affect the results. A natural feature (Dataset-1) is used to first, extract different texture features and understand how results vary with change in window size and lag direction.

(a) Window Size

Significant to note in Fig-6 is how results for differing window sizes gradually affect the visual details extracted for each texture feature differently and how features can be smoothly extracted with a larger window than from the noisy images derived using smaller window sizes.

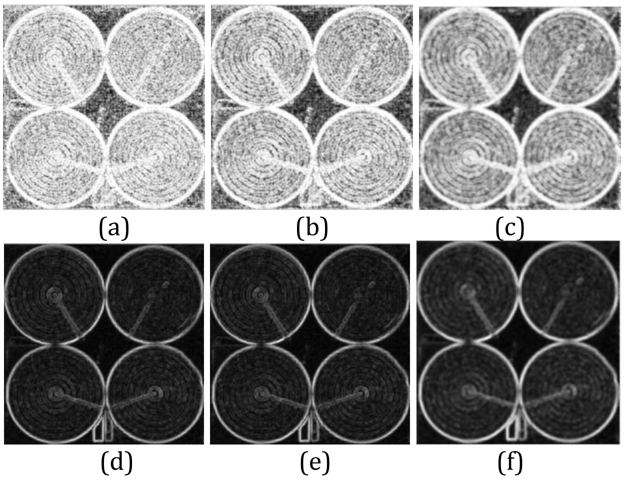
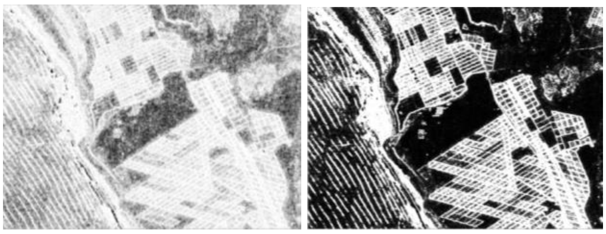


Fig-6:GLCM Texture features: Entropy (a, b, c) and Dissimilarity (d, e, f) derived using window sizes 3X3, 5X5 & 9X9 respectively.

Window size especially has a larger impact on narrow features and edge merging as evident from the result. Effect of change in window size is further elaborated in Fig-7. From results in Fig-7, one can clearly get an idea about how the choice of window size can be significant in application oriented texture feature extraction. Edges and minor variations (as in the sea portion) can be derived using smaller window size. One must also be careful that these variations might be noise due to lack of information content in 3X3 window. On the other hand, homogeneous regions are better derived using larger window sizes.



GLCM texture features (a) Entropy (b) Contrast derived using 3X3 window

GLCM texture features (c) Entropy (d) Contrast derived using 9X9 window

Fig-7: Significant Entropy (a, c) and Contrast (b, d) features derived using Window Size: 3X3 and 9X9

(b) Directionality

The directionality parameter affects the magnitude of edge detected as the strength of the edge detected is of larger magnitude when the lag direction is orthogonal to the edge direction and gradually reduces with deviation from orthogonality (Fig-8).

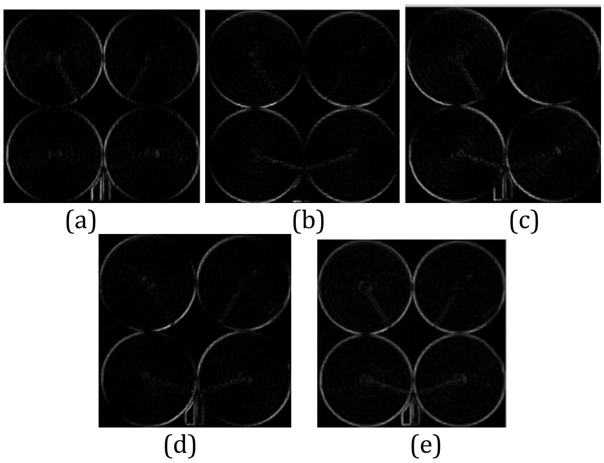


Fig-8: Significant Contrast features for different lag-shift directions (a) horizontal, (b) vertical, (c) NE-SW, (d) NW-SE and (e) omni-directions.

Also important to note is that texture magnitude derived by individual lag direction is always higher than the one derived using multiple lag directions. As a result, the markings (yellow box) detected in Fig-9d shows larger amplitude as compared to 9b. Multiple lag-directions average out the significant edges from individual lag-directions as GLCM measured is average probability. Likewise this value is almost zero for horizontal direction (Fig-9c).

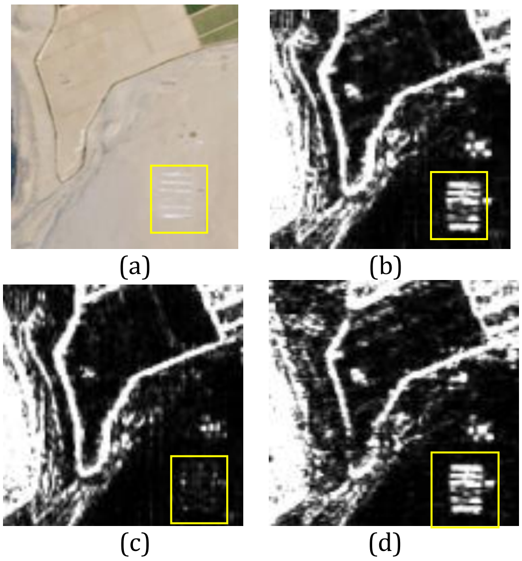


Fig-9: Contrast GLCM Feature extracted using 3X3 window using lag in (b) all direction (c) vertical direction (d) horizontal direction

The above discussed effect of change in texture feature detection with change in lag direction parameter is used in Fig-10 to demonstrate how applications can be associated with feature orientation. Most of the literatures use omni-directional lags in extracting texture features. The reason for this is that many times ground information is not available, lack of high resolution imagery available and/or classification is carried out without a specific application in mind. But directionality can be sometimes very useful as they suggest the manner in which features on ground are oriented.

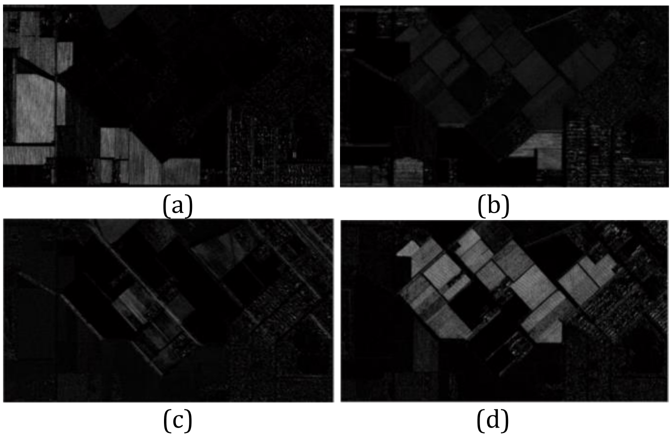


Fig-10: Field pattern from Dissimilarity GLCM feature convolved with a 3X3 window using lag-shifts in (a) horizontal (b) vertical (c) NE-SW and (d) NW-SE directions.

The results in Fig-10 show significant correlation exists between the field orientation and the direction in which a field is ploughed or sowed. Such understanding about farmlands can be useful in implementing different irrigation schemes for a set of farmland in an area or applications related to precision farming. Segmentation result using k-means approach on dissimilarity image with multi-dimensional lag-shift in Fig-11b also shows that cropping pattern might also be correlated to an extent on the orientation of the fields. Unfortunately, the field information is not available to verify the claim. Such predictive segmentation can be useful in understanding cropping patterns.

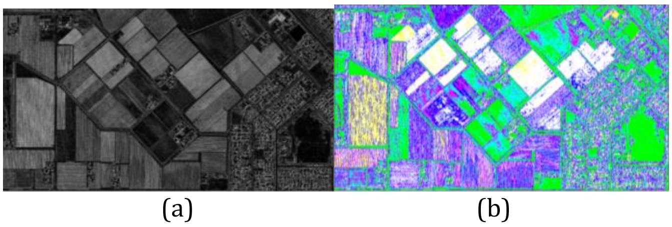


Fig-11: Omni-directional texture feature extraction and subsequent K (7)-means segmentation results (b) using dissimilarity (a) measures by GLCM (window Size 3X3).

5.2 Determining significant texture features

All GLCM texture feature described by [5] and subsequent researchers are not significant. According to [4], dissimilarity and contrast measures pertain to the degree of texture smoothness. Similarly, uniformity and entropy reflect the degree of repetition amongst the grey-level pairs.

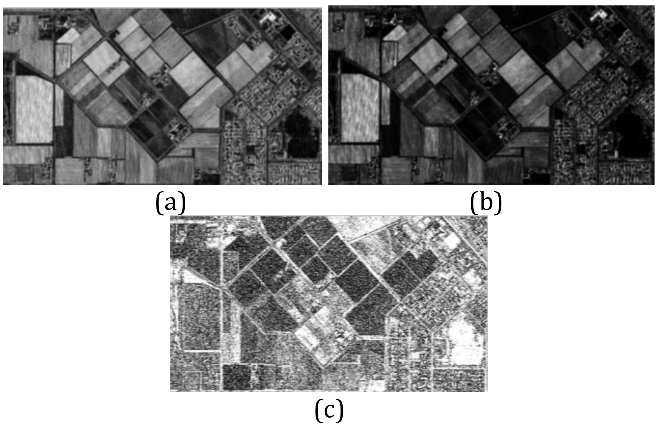


Fig-12 : Texture Features for Farmland, Australia: (a) Dissimilarity (b) Contrast & (c) Inverse Distance Moment.

Fig-12 shows similar results for dissimilarity and contrast as compared to IDM (Inverse Distance Moment). Therefore, depending on the feature type to be extracted, either dissimilarity or contrast can be chosen instead of both. Though there might be minor deviation in the result of both dissimilarity and contrast, for generic classification, either of the two can be used. This understanding about texture features and their association help reduce the computational cost of determining a number of texture values. For specific applications such choice of texture parameters can be significant in better distinguishing one class from another. For example, entropy can be more suitable in characterizing a settlement area from distinguishing from other texture features.

6. CONCLUSION

Application oriented approaches to image classification have been majorly affected due to the lack of high resolution satellite data available in public domain. With further advancements in sensor and imaging technology improvement in spatial resolution are bound to happen. Therefore, it is necessary for the users and research community to come up with new image processing approaches compatible with higher resolution images.

In this work, we have tried to address the above issue through application-oriented approaches for texture feature extraction through selective choice of parameters. We also emphasize on the use of computationally feasible methods for high resolution images through fast-computation of GLCM and selective choice of texture features for image segmentation classification to minimize redundancy.

ACKNOWLEDGEMENT

Lack of less expensive high resolution satellite data is a major hindrance to the remote sensing community. We would like to thank www.planet.com [9] and www.imagesatintl.com [8] for making available high resolution datasets online.

REFERENCES

[1] F. Albgretsen,"Statistical Texture Measures Computed From Grey Level Co-Occurrence Matrices", Nov. 2008.

[2] Chen, C. H., Pau, L. F. , Wang P. S. P. (eds.), "Texture Analysis The Handbook of Pattern Recognition and Computer Vision (2nd Edition)", pp. 207-248, World Scientific Publishing Co., 1998.

[3] Clausi, D.A. and Jernigan, M.E., "A fast method to determine co-occurrence texture features" IEEE Transactions on Geosciences and Remote Sensing 36 (1), 298–300, 1998.

[4] Clausi, D. A. and Zhao Y., "Rapid extraction of image texture by cooccurrence using a hybrid data structure", Comput. Geosci., vol. 28, no. 6, pp. 763–774, Jul. 2002.

[5] Haralick, R. M, Shanmugan, K. and Dinstein, I. "Textural features for image classification", IEEE Trans. Syst., Man, Cybern., vol. 3, pp. 610-621, 1973.

[6] Materka A, Strzelecki M (1998),"Texture analysis methods: a review", COST B11 report, Technical University of Lodz.

[7] Srinivasan, G.N., Shobha, G., 2008. "Statistical texture analysis" Proc. World Acad. Sci. Eng. Technol. 36, 1264–1269

[8] http://www.imagesatintl.com/products/very-high-resolution-satellite-imagery/

[9] https://www.planet.com/docs/spec-sheets/sat-imagery/