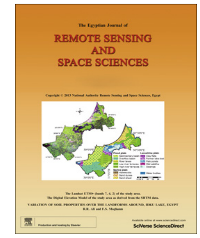
The Egyptian Journal of Remote Sensing and Space Sciences (2013) 16, 163–169

National Authority for Remote Sensing and Space Sciences

The Egyptian Journal of Remote Sensing and Space Sciences

www.elsevier.com/locate/ejrs
www.sciencedirect.com



RESEARCH PAPER

An evolutionary computing frame work toward object extraction from satellite images

P.V. Arun *, **S.K. Katiyar**

Dept. of Computer Science, National Institute of Technology, Bhopal, India

Received 9 April 2013; revised 20 May 2013; accepted 27 May 2013
Available online 17 July 2013

KEYWORDS

Cellular neural network;
Feature detection;
Interpolation

Abstract Image interpretation domains have witnessed the application of many intelligent methodologies over the past decade; however the effective use of evolutionary computing techniques for feature detection has been less explored. In this paper, we critically analyze the possibility of using cellular neural network for accurate feature detection. Contextual knowledge has been effectively represented by incorporating spectral and spatial aspects using adaptive kernel strategy. Developed methodology has been compared with traditional approaches in an object based context and investigations revealed that considerable success has been achieved with the procedure. Intelligent interpretation, automatic interpolation, and effective contextual representations are the features of the system.

1. Introduction

Earth observation data require chained transformations to become useful information products, and translation of images to interpretable form is a prerequisite in this context. However detection and identification of objects have been affected by various factors such as geometrical complexity, noise, vague boundaries, mixed pixel problems, and fine characteristics of detailed structures (Daniel et al., 2006). Efficiency of pixel based classification techniques has been limited due to increased resolution of images which popularized object based approaches (Vapnik, 1998). Different existing object extraction algorithms are specific to the features and adopt computationally complex methods (Yuan, 2009; Sunil et al., 2004; Zhang et al., 2012).

Literature reveals a great deal of recent approaches toward accuracy improvement of feature based strategies (Mladinich, 2010; Qi et al., 2010; Carlos et al., 2012). Computing techniques such as neural networks, genetic algorithms, and fuzzy logic followed by probabilistic concepts such as random field variations have been extensively applied in this context (Lari and Ebadi, 2011; Wang et al., 2009; Chi, 2004). Literature has also revealed many object enhancement filters as well as intensity-based approaches (Jenssen et al., 2003; Haralick et al., 1983). N-dimensional classifiers as well as random field concepts and different transformation techniques have been also applied for accurate detection (Hosseini and Homayoun, 2009; Kumar and Hebert, 2003; Chang and Kuo, 2006).

* Tel.: +91 4828249999.
E-mail addresses: arunpv2601@gmail.com (P.V. Arun), skatiyar1234@gmail.com (S.K. Katiyar).

Peer review under responsibility of National Authority for Remote Sensing and Space Sciences.

Production and hosting by Elsevier

1110-9823
http://dx.doi.org/10.1016/j.ejrs.2013.05.003

Contextual information is a key factor for real-time detection to avoid ambiguity; knowledge-based classification approaches such as predicate calculus have been recently used in this context (Porway et al., 2008; Harvey, 2008; Qi et al., 2010).

Different image interpretation features such as tone, texture, pattern and color are generally adopted for feature detection. Modeling of shape is less exploited in this context and is a major factor in distinguishing different entities (Lindi, 2004; Mladinich, 2010). These studies have found that inverse mapping of cellular automata (CA) using genetic algorithm (GA) can be adopted for effective modeling of feature shapes (Orovas and Austin, 1998). CA is also found to be better for context representation than predicate calculus since the latter lacks image compatible forms suitable for spatial relations (Mitchell et al., 1996; Porway et al, 2008). Spectral and spatial information can be combined using an adaptive kernel strategy to improve effectiveness of the approach. Probabilistic predicate rules in conjunction with evolutionary computing techniques are found to be effective for contextual rule representation.

In this paper we present a frame work using CNN approaches along with adaptive kernel strategy and corset optimization for accomplishing accurate detection. Automatic object modeling, adaptive kernel mapping, automatic interpretation, and intelligent interpolation are salient features of this work. Accuracy of developed methodologies has been compared with contemporary approaches using different satellite images of the study areas.

2. Theoretical back ground

2.1. Random modeling techniques

Evolutionary computing approaches such as CA, GA and their variants such as cellular neural network (CNN) and multiple attractor cellular automata (MACA), have been found to be useful for modeling random features. CNN (Orovas and Austin, 1998; Mitchell et al., 1996) is an analogue parallel computing paradigm defined in space and is characterized by locality of connections between processing elements (cells or neurons). Cell dynamics of this continuous dynamic system may be denoted using ordinary differential equations as given in Eq. (1), where vector G is the gene which determines the random nature.

$$X_k(t) = -X1 + f(G, Y_k, U_K) \tag{1}$$

CNN is effectively used for modeling object shape to facilitate feature interpretation. Random rules governing the shape of a feature can be identified by evolving the feature from a single state using CNN and GA. Abstract representations of objects are obtained by evolving features continuously until they can be separated from the background.

MACA is a special type of CA with different local rules applied to different cells and will converge to certain attractor states on execution (Sikdar et al, 2000). In an n-cell MACA with 2^m attractors, there exist m-bit positions at which attractors give pseudo-exhaustive 2 m patterns. MACA is initialized with an unknown pattern and operated for a maximum (depth) number of cycles until it converges to an attractor. PEF bits after convergence are extracted to identify the class of the pattern and are compared with stored rules to interpret the object.

2.2. Mixture density kernel

Mercer kernel functions measure the similarity between two data points that are embedded in a high, possibly infinite, dimensional feature space. mixture density kernel (MDK) is a mercer kernel that measures the number of times an ensemble agrees that two points arise from same mode of probability density function (Srivastava, 2004). It may be described using equation (2) where 'M' is the number of clusters and $P\ (C_m/X_i)$ is the probability that data point 'X_i' belongs to C_m.

$$K(X_i, X_j) = \frac{1}{Z(X_i, X_j)} \sum_{m=1}^{M} \sum_{C_m=1}^{C_m} P_m(C_m/X_i) P_m(C_m/X_j) \tag{2}$$

Mixture density kernels are used to integrate an adaptive kernel strategy to the SVRF based clustering. This approach facilitates learning of kernels directly from image data rather than using a static approach.

2.3. Support vector random field (SVRF)

SVRF (Schnitzspan et al, 2008; Lee et al., 2005) is a discrete random field (DRF) based extension for SVM. It considers interactions in the labels of adjacent data points while preserving the same appealing generalization properties as the support vector machine (SVM). The SVRF function is presented in equation (3), where $\Gamma_i(X)$ is a function that computes features from observations X for location i, $O(yi,\ i(X))$ is an SVM-based observation matching potential and $V\ (yi,\ yj,$ and $X)$ is a (modified) DRF pair wise potential.

$$P(Y|X) = \frac{1}{Z} \exp\left\{ \sum_{i \in S} \log(O(y_i, \Gamma_i(X))) + \sum_{i \in S} \sum_{j \in N_i} V(y_i, y_j, X) \right\} \tag{3}$$

SVRF is used to implement initial clustering to segment various objects for accurate detection and interpretation.

2.4. Coreset

Coreset (Agarwal et al, 2001; Badoiu et al, 2002) is a small subset of a point set, which is used to compute a solution that approximates solution of the entire set. Let μ be a measure function (e.g., width of a point set) from subsets of R^d to non-negative reals $R^+ U\{0\}$ that is monotone, i.e., for $P1\ C\ P2$, $\mu(P1) \leqslant \mu(P2)$. Given a parameter $\varepsilon > 0$, we call a subset $Q\ C\ P$ as an ε-Coreset of P (with respect to μ) if $(1 - \varepsilon)\ \mu(P) \leqslant \mu(Q)$. Coreset optimization can be adopted to reduce the number of pixels required to represent an object by preserving its shape. Hence it can be used to reduce the complexity of CA based inverse evolution.

2.5. Probabilistic decision strategy

Terrain features, specifically object parameters (tone, texture, type, and shape) are used for object specific sample point clustering as well as selection of interpolation strategies. Rules for prediction are stored in the form of grammar which constitutes of cause effect relations and are updated dynamically. Probabilistic rules are used to produce most likely predictions based on the previous experiences. This approach implements a factored product model, with separate decision strategies, whose