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Oil Spill Detection from Cosmo-Skymed Satellite Data Multi-Objective Evolutionary Algorithm

Maged Marghany

School of Humanities, Geography Section, Universiti Sains Malaysia, 11800 USM Penang, Malaysia.

Faculty Geospatial and Real Estate, Geomatika University College, Kuala Lumpur, Malaysia

***Corresponding Author:** *Maged Marghany, Faculty Geospatial and Real Estate, Geomatika University College, Kuala Lumpur and School of Humanities, Geography Section, Universiti Sains Malaysia, 11800 USM Penang, Malaysia.*

Abstract: *This study has demonstrated work to optimize the oil spill footprint detection in synthetic aperture radar (SAR) data. Therefore, Entropy-based Multi-objective Evolutionary Algorithm (E-MMGA) and non-dominated sorting genetic algorithm-II (NSGA-II) have implemented with COSMO-SkyMed data during the oil spill event along the coastal water of along the Koh Samet Island, Thailand. Besides, Pareto optimal solution is implemented with both E-MMGA and NSGA-II to minimize the difficulties of oil spill footprint boundary detection because of the existence of a look-alike in SAR data. The study shows that the implementation of a Pareto optimal solution and weight sum in E-MMGA and NSGA-II generated an accurate pattern of an oil slick. The NSGA-II has the highest performance as compared to E-MMGA, which is able to preserve the morphology of oil spill footprint boundaries i.e. thick, medium, and light. In conclusion, NSGA-II is considered as an excellent algorithm to discriminate oil spill from look-alikes and also to identify thick oil spill from the thin one within the shortest computing time.*

Keywords: *Multi-Objective Evolutionary Algorithm, Entropy-based Multi-Objective Evolutionary Algorithm, Non-dominated Sorting Genetic algorithm-II, oil spill spreading, Cosmo-SkyMed satellite.*

1. INTRODUCTION

Intelligent, learning machine algorithms such as genetic algorithm and multi-objective algorithms have been used for oil spill automatic detection from SAR data (Topouzelis et al. 2009 and Marghany 2014b). Recently, Marghany (2014a) utilized the Genetic algorithm (GA) as an automatic detection algorithm for the oil spill in RADARSAT-2 SAR data. Marghany (2014a) confirmed the work of Topouzelis et al. (2009). Further, The GA is shown to be able to identify and remove pixels that do not significantly contribute to oil slick footprint in SAR data. This conclusion has approved the findings of Mohanta and Sethi (2012); Skrunes et al. (2012) and Marghany (2014a).

Recently, there are several advanced in developing new algorithms that improve the efficiency of GA. These algorithms are an Evolutionary algorithm and non-dominated sorting genetic algorithm-II (NSGA-II). For two decades, evolutionary algorithms have played a tremendous role for accurately solving optimization problems in the area of computational engineering and image processing. One of the popular optimization algorithm is NSGA. Indeed, NSGA has the effective performance to determine the Pareto front of problems which predict low computational costs to evaluate the objective functions under the circumstance of the objective functions are explained by simple analytical models. Consequently, NSGA algorithm simulates the evolution of the evolution of a population with an internal selection of the most excellent individuals. Truthfully, NSGA has excellent performance when the evaluation of objective functions is less time-consuming, which is managing a huge number of individuals (Deb et al., 2000 and Deb 2001).

The novelty of this work is designing an optimization tool based on Pareto optimal for the real-time oil spill automatic detection by comparing between Entropy-Based Multi-objective Evolutionary algorithm and non-dominated sorting genetic algorithm-II (NSGA-II) without involving others tools such as neural network or any image processing classification tools. Indeed, previous studies have executed artificial neural networks (Topouzelis et al., 2009; Mohanta and Sethi, 2012) or post-classification techniques (Barni et al., 1995; Calabresi et al., 1999), which are considered to be semi-automatic techniques (Marghany 2001). In addition, Pareto optimal can be a new approach to determine oil spill morphology features, i.e. thick, medium and light oil spill. Yet, advanced previous work which, is based on artificial neural networks and post-classification techniques are not able to identify the oil spill morphology features. In addition, artificial neural networks and post-classification techniques are time-consuming and the probability of misclassification does not always decrease as the number of feature increases, especially when sample data are insufficient (Marghany 2014d and Marghany 2016).

2. Non-Dominated Sorting Genetic Algorithm NSGA-II

This section presents a brief description of NSGA-II relevant to this study. NSGA-II is the second version of the famous "Non-dominated Sorting Genetic Algorithm". Its main features are: (i) A sorting non-dominated procedure where all the individual are sorted according to the level of non-domination; (ii) It implements elitism which stores all non-dominated solutions, and hence enhancing convergence properties; (iii) It adapts a suitable automatic mechanics based on the crowding distance in order to guarantee diversity and spread of solutions; and (iv) Constraints are implemented using a modified definition of dominance without the use of penalty functions.

In order to sort a population of size N for $E(\beta_1),..............., E(\beta_N)$ according to the level of non-domination, each solution m must be compared with every other solution in the population to find if it is dominated. This requires comparisons $O(E(\beta_m))_N$ for each solution, where is m is the number of different pixels belongs to the oil spill, look-alikes, and sea roughness, and low wind zones.

The initialized population N of $E(\beta_1),..............., E(\beta_N)$ is sorted based on the level of non-domination for each individual $E(\beta_1)$ in the main population P do the following

Initialize $S_{E(\beta_1)} = \Phi$. This set Φ would include all the individuals of $E(\beta_n)_N$ which is being dominated by $E(\beta_1)$.

Initialize $n_{E(\beta_1)} = 0$. This would be the number of individuals that dominate $E(\beta_1)$ i.e. no individuals dominate, $E(\beta_1)$ then $E(\beta_1)$ belongs to the first front; set rank for an individual $E(\beta_1)$ to one i.e. $E(\beta_1)_{rank} = 1$. For each individual m in P if $E(\beta_1)$ dominated m then add m to the set Φ i.e. $\Phi = \Phi \bigcup \{m\}$ *else if m dominates $E(\beta_1)$ then increment for domination counter for $E(\beta_1)$ i.e. $n_{E(\beta_1)} = n_{E(\beta_1)} + 1$.o

Selection. Once the individuals $E(\beta_j)$ are sorted based on non-domination and with crowding distance $E(\beta_{d_K})$ assigned, the selection is carried out using a crowded comparison operator $\prec_n$ which is based on

(1) Non-domination rank $E(\beta_1)_{rank}$ i.e. individuals $E(\beta_j)$ in front F_i will have their rank as $E(\beta_1)_{rank}$ = i.

(2) crowding distance $E(\beta_{d_K})$

- $E(\beta_1) \prec_n m$
- -$E(\beta_1)_{rank} < m_{rank}$

- or if $E(\beta_1)$ and m belongs to the same front F_i then $F_i(E(\beta_{d_K}) > F_i(d_m)$ i.e. the crowing distance should be more.

The individuals $E(\beta_1)$ are chosen by exercising a binary contest selection with crowed comparison-operator $\prec_n$.

2.1. Recombination and Selection

The offspring population is merged with the current generation population and variety is completed to set the individuals of the next generation. Elitism is confirmed, subsequently, all best individuals are included in the population. In this context, the population is now sorted based on non-domination and function of wind speed (*V*). Subsequently, the new generation is filled by each front till the population size surpasses the existing population size. For instance, the population exceeds *N* when adding all the individuals in front F_i , then the individuals in front F_i is chosen based on their crowding distance in the descending order until the population size is *N*.

3. RESULTS AND DISCUSSION

In this study, the COSMO-SkyMed image is acquired on July 29, 2010, at 11:23:33 UTC which is implemented for oil spill detection in the Koh Samet island, Thailand. This data covered 12° 31´48" N to 12° 37´ 48" N latitude and 101° 2´24" E to 101 33 37" E longitude (Figure 1). According to Marghany (2014b), the oil spill has moved away from the mainland and has started to disperse to an extent within 6.59 km (Figure 2).

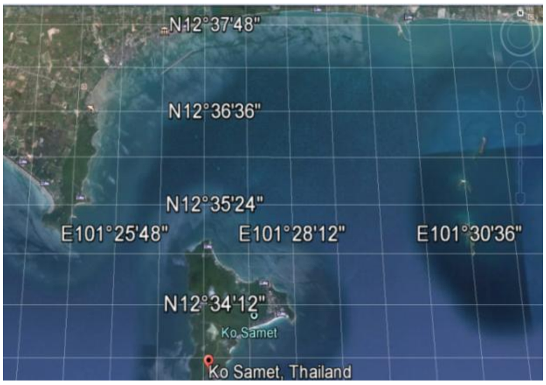


Figure1. *Geographical location of the oil spill in the Gulf of Thailand.*

Figure2. *Massive oil pollution along the coastal water of Ko Samet.*

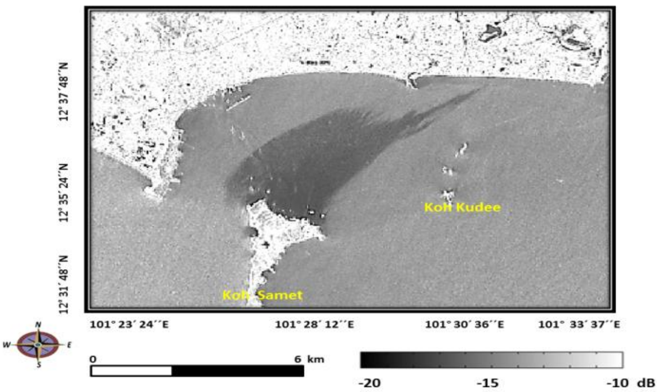
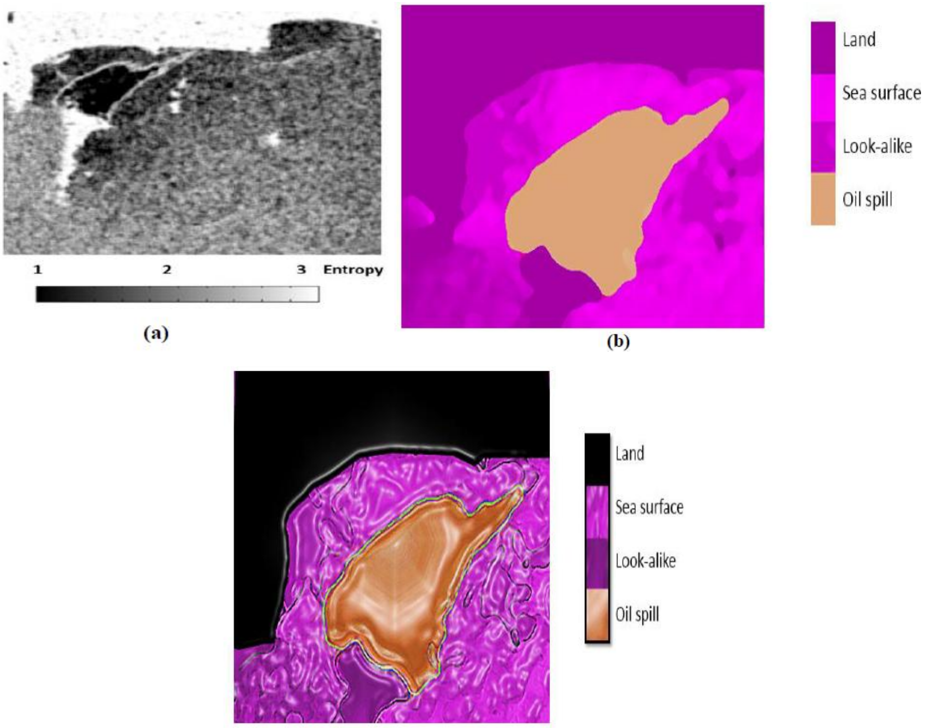


Figure3. *Average backscatter variations in COSMO-SkyMed.*

Figure 3 shows the variation in the average backscatter intensity along the oil slick footprint. The average backscatter intensity was dumped by -20 dB to -9 dB and decreased over time as the oil slick footprint gradually increased (Figure 3). Besides, the sea surface roughnesses have highest backscatter values of -10 dB than oil spill footprint pixels. Consistent with and Trivero et al., (2007) and Marghany (2014b), the wind speed is recorded on July 29, 2013, was ranged between 1 to 7 m/s. Besides, the measured reductions of backscattered radar power at X-band could be impacted by instrumental limitations, i.e. by the fact that the backscattered radar power reaches the noise floor (Trivero et al., 2007; Marghany 2014b).

Figures 4b and 4c show the output result of E-MMGA and NSGA-II. Clearly, E-MMGA is able to produce four different segmentation boundaries. However, NSGA-II can produce sharper segmentation boundaries than E-MMGA. In the NSGA-II algorithm, oil spill footprint discriminated and identified by a sharp vector that separates it from surrounding features, i.e., sea surface, look-alikes and land boundaries (Figure 4c). Besides, Figure 5a shows that the thick oil spill footprint has highest E-MMGA value of 2 than a medium and light oil spill. Nevertheless, NSGA-II is able to produce different clusters of oil spill footprint thickness as compared to E-MMGA with the highest value of NSGA-II of 2.5. This indicates that NSGA-II can identify clearly the level of oil spill footprint spreading accurately than E-MMGA due to the accurate Pareto frontier of NSGA-II.



(c)

Figure4. *Results of (a) entropy (b) E-MMGA and (c) NSGA-II for oil spill discrimination in COSMO-SkyMed.*

NSGA-II can accurately identify the sharpest morphological boundary of the oil spill and assigned by different segmentation layers in COSMO-SkyMed satellite data as compared to Entropy algorithm and E-MMGA. In fact, NSGA-II provides a set of compromised solutions called Pareto optimal solution since no single solution can optimize each of the objectives separately. The decision maker is provided with the set of Pareto optimal solutions in order to choose a solution based on the decision maker's criteria.

This sort of NSGA-II solution technique is called nondominated since the decision is taken after searching is finished. This confirms the work done by Deb (2000) and Deb et al., (2001). In this context, the Pareto-optimization approach does not require any a priori preference decision between the conflicting of the oil spill, look-alike, land, and surrounding sea footprint boundaries.

Further, Pareto-optimal points have formed Pareto-front as shown in Figure 4 in the multi-objective function of the COSMO-SkyMed data space. Finally, NGSA-II has advantages on Entropy and E-MMGA because (i) NGSA-II explicit diversity preservation mechanism; (ii) overall complexity of

NSGA-II is at most O (MN^2) and; (iii) elitism does not allow an already found Pareto optimal solution to be deleted. This agreed with Deb et al., (2001).

In general, the NSGA-II algorithm was able to automatically extract oil spill pixels from the surrounding pixels without using a separate segmentation algorithm, as was done by Skrunes et al. (2012). Further, all the algorithms have been introduced are effectively depended on wind speed conditions. Nonetheless, the NSGA-II can automatically discriminate oil spill from the surrounding pixels even under wind speed of 6 ms^{-1} . Further, the TCNNA algorithm of Garcia et al., (2013b) is based on entropy, which first introduced by Marghany (2001) as an excellent tool for oil spill detection in SAR data. In fact, entropy algorithm was automatically determined the graduate changes of sea surface backscatters along the boundary layers of the oil spill in SAR data. This helps to identify oil spill footprint in SAR data.

Indeed, the capability of a SAR satellite to differentiate between oil, low wind areas, look-alikes is restrained by the noise floor of SAR. However, NGSA-II explicit diversity preservation mechanism is involved in NSGA-II is able to overcome this issue. The Support Vector Machine (SVM) was implemented by Matkan et al., (2013) for automatic detection of the oil spill is based on thresholding. Finally, the recent work done by using a genetic algorithm (Marghany 2014c and Marghany 2017) is not able to provide any information regarding the level of oil spill footprint spatial variations from thickness to lightness levels as compared to NGSA-II.

4. Conclusion

This investigation has validated work to optimize the oil spill footprint detection in synthetic aperture radar (SAR) data. Consequently, Entropy-based Multi-objective Evolutionary Algorithm (E-MMGA) and non-dominated sorting genetic algorithm-II (NSGA-II) have applied with COSMO-SkyMed facts throughout the oil spill match along the coastal water of alongside Koh Samet Island, Thailand. Besides, the Pareto highest quality answer is carried out with each E-MMGA and NSGA-II to reduce the difficulties of oil spill footprint boundary detection due to the fact of the existence of a look-alike in SAR data. The find out about indicates that the implementation of a Pareto most reliable solution and weight sum in E-MMGA and NSGA-II generated a correct sample of the oil slick. Furthermore, the thick oil spill has the best possible rate of 2.3 NSGA-II than tiny and medium spills. The NSGA-II has the absolute best overall performance as in contrast to E-MMGA, which is capable to preserve the morphology of oil spill footprint boundaries, i.e. thick, medium, and mild the In conclusion, NSGA-II is viewed as an exquisite algorithm to discriminate oil spill from look-alike and additionally to perceive thick oil spill from the tiny one inside the shortest computing period time.

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AUTHOR'S BIOGRAPHY

Prof. Dr. Maged Marghany, (1967), is microwave remote sensing scientist. He is the author of book is titled by "Advanced Remote Sensing Technology for Tsunami Modelling and Forecasting". He was awarded the ESA Post-doctoral Fellowship by the International Institute of Aerospace and Earth Observation (ITC) in Enschede, the Netherlands, funded by the European Space Agency (ESA) from March 2000 to March 2001. He was awarded the best speaker from the Japanese Society of Remote Sensing due to his outstanding presentation at Asian Conference on Remote Sensing held in 1998 at the Terades Hotel in Manila. During his professional career, he has carried out research on the application of synthetic aperture radar (SAR) data to coastal studies. Over 18 years, he served as a lecturer in many Malaysian universities. During that period he was leading several projects related to the application of SAR to coastal waters, funded by Ministry of Science and Technology, Malaysia (MOSTE).

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