AUTOMATIC DETECTION OF TURBULENT BOUNDARY FLOW IN RED SEA FROM FLOCK-1 SATELLITE DATA

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ABSTRACT: A multi-objective evolutionary algorithm is utilized for the automatic detection of hydrodynamic turbulent boundaries overlying coral reefs. The procedure is implemented using sequences of Flock-1 satellite data acquired in the Red Sea. The study demonstrates that implementing Pareto - optimal solutions allows for the generation of accurate coral reef-water interface patterns. The Pareto-optimal front indicates a significant relationship between hydrodynamic turbulent boundaries, macroalgae, and coral reefs. In conclusion, MOEA which is based on Pareto optimal solutions can be used as an automatic detection tool for turbulent flow in data from the Flock 1 satellites that are excellent sensors for studying shallow coral reef zones.

1. INTRODUCTION

Until now, no study has implemented Flock-1 satellite data in oceanography applications. The Flock-1 satellite was launched on 9 January 2014, and the data holds great promise for a wide variety of Earth observations because its high spatial and temporal resolution. Consequently, this study is the first work to utilize Flock-1 data for turbulent hydrodynamic detection overlying coral reefs. Turbulent flow requires a short revisit satellite cycle and high-resolution data to provide precise information regarding turbulent hydrodynamic flow that is important for ship navigation, fishing, pollution transport and sediment transport. Nevertheless, the study of ocean turbulence is still at an early stage, and ocean turbulence studies are lost in other studies, for instance geostrophic currents, wave-current interactions, or sea surface temperature fluctuations (Rowlands et al. 2008).

In shallow waters, the coral reef cover induces a turbulent flow, since the permanent coral boundary interrelates through friction with the superimposed water column. Under these conditions, a layer of shear flow is formed that then creates a turbulent wall or boundary layer, and the hydrodynamics of the turbulent bottom boundary layer next to the coral surface governs the vertical transport of mass between the coral surface and the water column (Reidenbach et al. 2007; Stocking et al. 2016). The presence of an algal canopy increases turbulent kinetic energy within the roughness sublayer by ~2.5 times in contrasted with healthy corals while simultaneously decreasing bottom shear stress by an order of magnitude (Stocking et al. 2016).

Remote sensing techniques are powerful tools for ocean feature mapping and monitoring. The measurement of the ocean from space is a function of the electromagnetic signal. The signal reflected from the sea carries information on the primary observable quantities, including the colour, the radiant temperature, the roughness, and the height of the sea. Visible waveband radiometers depend on reflected sunlight which is a function of the local time of day. The thermal fluctuations of the sea surface are measured in the thermal infrared and microwave parts of the radiation spectrum. Hence infrared and microwave radiometers are used to measure the radiation temperature of the sea surface, and the emissivity is used to approximate the physical temperature of the ocean (Bruckner et al. 2012).

With the above concerns, we address the question of the ability of small satellites such as Flock-1 for investigating the impact of coral reefs for inducing turbulent current flow. Two hypotheses are examined: (i) low radiometric resolution data such as Flock-1 can be used for surface and benthic coral features detection, and (ii) such machine learning and intelligent algorithms are able to detect accurately the dynamic interaction between sea surface movement and benthic features such as coral reefs.

The novelty of this work is to utilize Flock-1 satellite data for the automatic detection of sea surface turbulent flow using intelligent machine learning algorithms. The main objective of this work can be divided into two sub-objectives: (1) To examine a Multi-Objective Evolutionary Algorithm (MOEA) for turbulent flow automatic detection in Flock-1 satellite data, and (2) to design a multi-objective optimization algorithm based on Pareto-optimal solutions for the automatic detection of turbulence.

2. STUDY AREA

Three study areas are selected because of the difficulty in acquiring Flock-1 satellite data. These study areas are (1) Farasan Islands, (2) Al Wajh Bank, and (3) Great Bitter Lake (Figure 1).

2.1 Farasan Islands

The Farasan Islands are located in the southern Red Sea platform of Saudi Arabia between 16° 5´–17°2´N and 41°5´–42°3´E. (Figure 1a)They are located approximately 40 km offshore Jizan City and 50 km away from the Red Sea axial trough. Within the tropical sector of the Red Sea, the Farasan Islands are the largest coral island group (about 128 islands totalling 3000 km^2 of land). Its largest islands are Farasan al-Kabir and Sajid (Douabul and Haddad 1970). The Farasan Islands have low topography (15 m a.s.l) with a maximum elevation of 75 m a.s.l.

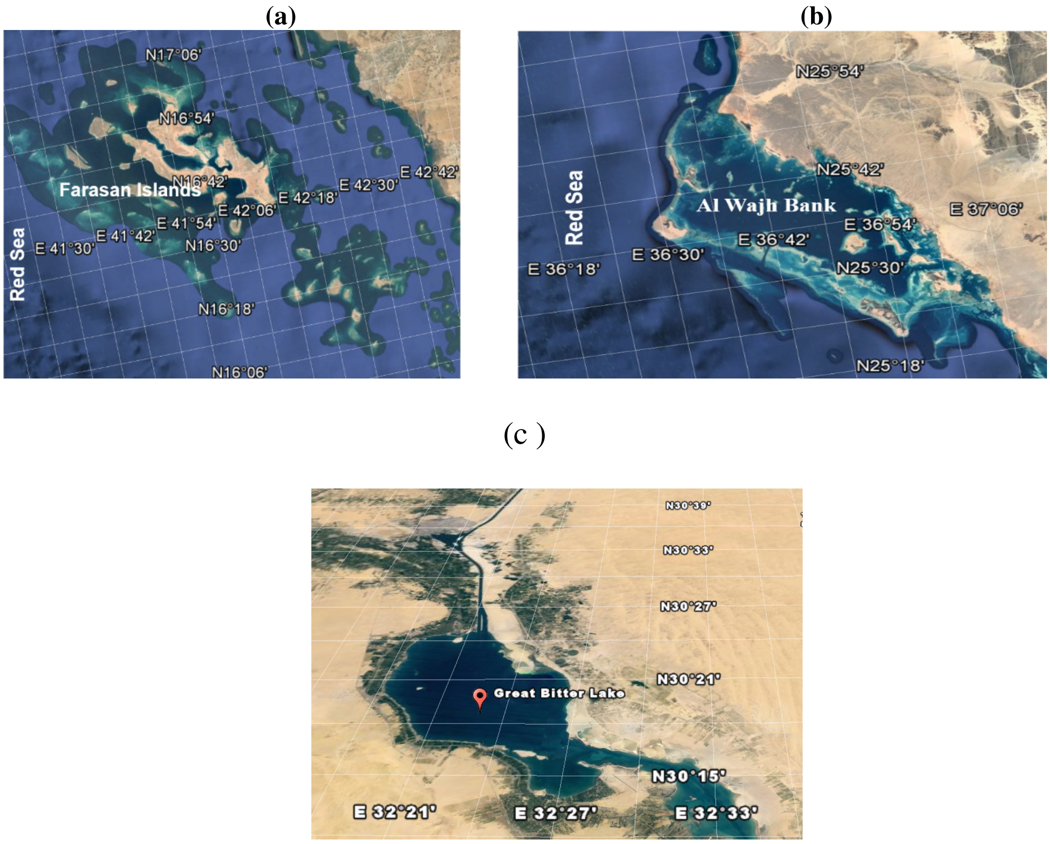


Figure 1. Geographical locations of (a) Great Bitter Lake, (b) Al Wajh Bank and (c) Farasan Island.

2.2 Al Wajh Bank

In the northeast part of the Red Sea, the Al Wajh Bank is located around 25°35'N, 36°45'E (Figure 1b), offshore Saudi Arabia. Al Wajh covers an area of approximately 2,880 km^2, 26 to 50 km offshore from the mainland and running parallel to the shoreline for approximately 50 km before turning landward at its northern and southern ends.

The Al Wajh Bank contains inshore coastal habitations, a central lagoon with shallow grass beds, algal and mangrove communities, complex reef systems, and a plethora of islands. In the western side of the bank, seaward it is bounded by a widespread deep barrier reef of 500 m. The offshore zone between Al Wajh and Umm Lujj is formed by reef islands. Inland, the coastal zone is categorised by alluvial sand flats with several saltmarsh communities on the saline sandy flats near the shoreline and a number of wide wadi drainage systems. The dominant feature is the central lagoon which covers an area of approximately 1,400 km^2, with a maximum depth of 30 to 40 m, becoming progressively shallower toward land. Extensive seagrass beds and tidal flats are found in the southern part of the Al Wajh bank. The dominant geomorphology features of the lagoon are numerous narrow channels with widths <200 m that link the inside and outside of the bank. Strong tidal currents are generated between these narrow channels and the open sea, although the tidal amplitude is less than 1 m along these channels (Rowlands et al. 2012).

2.3 Great Bitter Lake

The Great Bitter Lake (al-Buhayrah al-Murra al-Kubra) is a salt water lake which is part of the Suez Canal (Madl 1999), and is connected to the Small Bitter Lake through which the canal also runs. Before the canal was built, their site was occupied by dry salt valleys. Together, the Bitter Lakes have a surface area of about 250 km². The canal also runs through Lake Manzala and Lake Timsah, north of the Bitter Lakes (Figure 1c). As the canal has no locks, sea water flows freely into the lake from the Mediterranean and the Red Sea. In general, north of the lakes the current reverses seasonally, being north-going in winter and south-going in summer. South of the lakes, the current is tidal, reversing with the tides in the Red Sea. Fish can migrate, generally in a northerly direction, through the canal and lakes in what is known as a Lessepsian migration; by this means some Red Sea species have come to colonize the eastern Mediterranean (Hoffman et al. 2006).

3. DATA SETS

Flock 1 is a US CubeSat satellite constellation launched on 9 January 2014. Each satellite is built in 3U CubeSat bus and is equipped with a camera capable of 3 m to 5 m ground resolution, and each constellation consist of 28 satellites. Furthermore, Flock1 has high temporal resolution, that is, weekly to daily with a moderate spectral resolution of visible spectra (RGG) 400 and 660 nm and near infrared (NIR) (700-900 nm) (Boshuizen et al. 2014). The 28 satellites that make up Flock 1 measure just 12 inches long by 4 inches wide by 4 inches tall (30 by 10 by 10 centimeters), but they can take images with a resolution of 10 to 16.5 ft (3 to 5 m). The satellites use an X-Band system for the downlink of acquired images and system telemetry at data rates of up to 120 Mbit/s. Flock1 orbits the Earth at a 52° orbit, continuously collecting images as it passes over the Earth's surface which provides an insight into the dynamic changing environment (Manning et al. 2014).

4. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

Following Marghany (2013a), the entire spectral signature of Flock 1 is $\{S_1, S_2, ..., S_k\}$, where *K* is the total number of spectral signatures in the Flock 1 data. Therefore, *K* is made up of genes which represent the spectral signature $\{S\}$ of selected pixels and their surrounding environment, and genetic algorithms start with the population initializing step.

Multi-objective Optimization (Deb 2001) and (Marghany 2014b) aims at conducting optimization for a range of functions as follows:

$$\text{minimize } \vec{F} = (f_1(S), f_2(S), \ldots\ldots, f_m(S))^T \quad (1)$$

$$\text{Subject to } E(S_1 | S_2) \in I \in \Omega \quad (2)$$

where *I* is Flock 1 data and Ω is the definition domain of functions or the feasible region in decision space. In this research, two objectives are considered. One is the coral reef and second is turbulent hydrodynamics.

Pareto optimal solutions are applied to retain the discrimination of turbulent flow spectral signature diversity and its surrounding reflectance environment (Marghany 2013a). To optimize the turbulent flow spectral signature diversity automatic detection from Flock 1 data using MOEA, the turbulent flow spectral signature diversity must be coded into a Genetic Algorithm syntax form (Marghany 2014a). In this way, the turbulent flow spectral signature diversity is coded into the chromosome form. In this problem, the chromosome consists of a number of genes where every gene corresponds to a coefficient in the nth-order surface fitting polynomial that can be calculated as:

$$f(T_{i,j}) = T_0 + T_1 i + T_2 j + T_3 i^2 + T_4 ij + T_5 j^2 + \mathrm{K} + T_m j^n \quad (3)$$

where T [*0,1.....m*] are the turbulent flow spectral signature diversity parameter coefficients that will be estimated by the genetic algorithm to approximate the minimum error for turbulent flow spectra signature diversity discrimination from surrounding environment.

Lastly, the group of classified individuals is removed from the population and another layer of non-dominant individuals is considered (the remainder of the population is re-classified) (Marghany 2013b). The process continues until all the individuals in the population are classified. Since individuals in the first front have maximum fitness value, they always get more copies than the rest of the population. This allow us to search for non-dominated regions, and results in convergence of the population toward such regions. Sharing, on its part, helps to distribute the population over this region.

5. RESULTS AND DISCUSSION

Figure 2 shows the variation of the average spectral signatures of three Flock-1 data. The macroalga has the lowest reflectance value, then coral and sediment (Figure 11a). In contrast, ships have the highest reflectance value of 0.99 . Both Al Wajh Bank and the Farasan Islands have sandy shores, mangroves, and algal flats which reach their maximum extent near the coastline, with reefs restricted to offshore locations. This confirms the study of Marghany (2015). It is interesting to find that the Flock 1 satellite can imagine ships and their wakes because of its high resolution of 3 to 5 m (Manning et al. 2014).

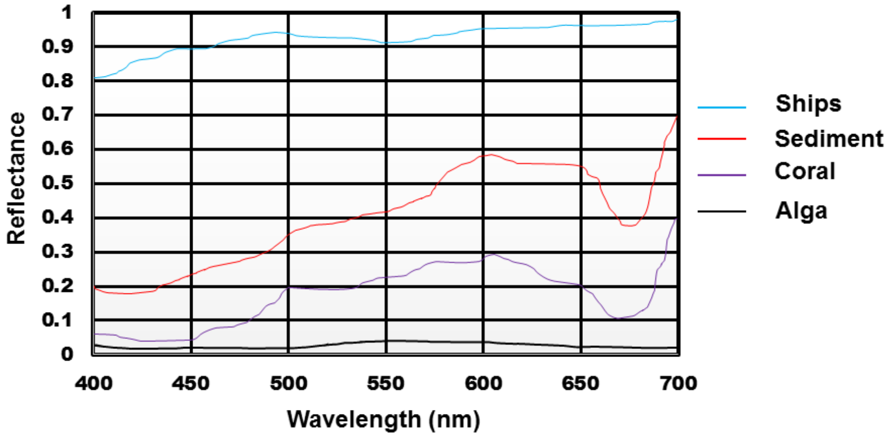
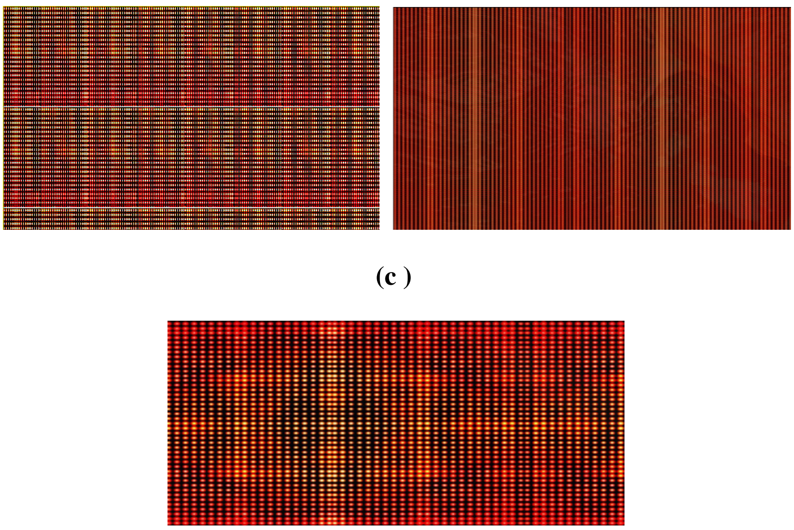


Figure 2. Spectral reflectance of Flock 1 satellite data for different features.

The proposed method for the automatic detection of turbulent hydrodynamics overlying coral reefs has been applied to generate spectral reflectance from three Flock 1 satellite data sets (Figure3). In the initial stages, the standard errors are increased with high population numbers of 35400, 24523 and 24202, respectively. At the initial stage, there are, however, no distinct features in Flock 1 data. Consequently, the random generation patterns are dissimilar among the three images due to various objects and variable spectral signatures of inconstant objects in each image. This confirms the work of Marghany (2014a).

(a) **(b)**



(c)

Figure 3. Random generation of Folck1 satellite data for (a) Great Bitter Lake, (b) Al Wajh Bank and (c) Farasan Island.

Notably, the Pareto optimal solution is able to define the turbulent hydrodynamics overlying coral reef boundaries and provides an excellent discrimination of turbulent boundary pixels. Macroalga is floating and directed by the hydrodynamics of the turbulent boundary layer (Figure 4). This is clearly shown in both Al Wajh Bank and Farasan

Island because the coral reefs exist at water depths less than 15 m. For instance, the shallow sand sheets, windward and leeward coral crests, microalgae, sponges, and sandy hardgrounds are dominant in the Saudi Arabian Red Sea. The results confirm those of Bruckner et al. (2012).

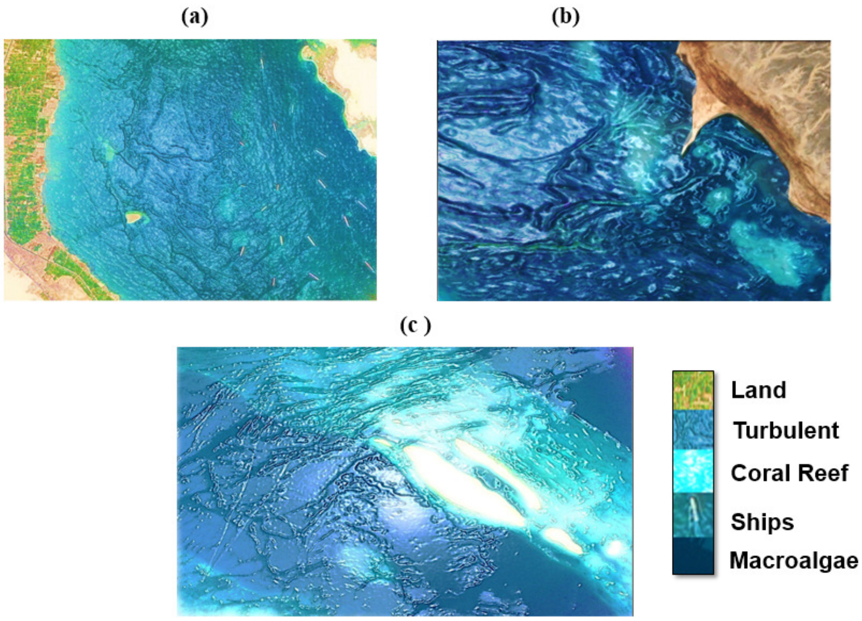


Figure 4. Pareto optimal solution for Flock1 images of (a) Great Bitter Lake, (b) Al Wajh Bank and (c) Farasan Island.

6. CONCLUSIONS

This study demonstrated the design of tools for hydrodynamic turbulent boundary detection in Flock 1 satellite data using a Multi-Objective Evolutionary Algorithm (MOEA). Flock 1 satellite data that were acquired in the Great Bitter Lake, Egypt and Red Sea in Saudi Arabia, that is, Al Wajh Bank and Farasan Island, were investigated in this study. The study demonstrated that Pareto-optimal solutions and fitness functions used in the MOEA allowed for the generation of precise hydrodynamic turbulent boundary patterns using the Flock 1 data. The MOEA exhibited excellent performance with respect to this boundary, macroalaga, and coral reef classifications in Flock 1 data.

References

Bruckner A, Rowlands G, Riegl B, Purkis S, Williams A, Renaud P (2012) Khaled bin Sultan Living Oceans Foundation Atlas of Saudi Arabian Red Sea Marine Habitats. Panoramic Press, 262 pp.

Boshuizen C, Mason J, Klupar P, Spanhake S (2014) Results from the planet labs flock constellation. http://digitalcommons.usu.edu/smallsat/2014/PrivEnd/1/ [Access on August 23, 2015].

Deb K (2001) Multi-Objective Optimization Using Evolutionary Algorithms. Wiley.

Douabul A, Haddad AM (1970) The Red Sea and Yemen's Red Sea Environments. Hassell and Assoc, AMSAT and UNOPS, pp 1-16.

Hoffman L, Van Heugten B, Dekker H (2006) Marine Mollusca collected during a journey to the Great Bitter Lake (Suez Canal) and Nile Delta, Egypt. Gloria Maris 45(1-2):30-45.

Madl P (1999) Essay about the phenomenon of Lessepsian Migration. Colloquial Meeting of Marine Biology I, Salzburg, April 1999 (revised in Nov. 2001).

Marghany M (2013a) Genetic algorithm for oil spill automatic detection from ENVISAT satellite data. In: Murgante B, Misra S, Carlini M, Torre CM, Nguyen H-Q, Taniar D, Apduhan BO, Gervasi O (eds), Computational Science and Its Applications- ICCSA 2013,7972:587-598.

Marghany M (2013b) Genetic Algorithm for Oil Spill Automatic Detection from Multisar Satellite Data. Proceedings of the 34th Asian Conference on Remote Sensing 2013, Bali, Indonesia, October 20 -24, 2013, pp SC03-671-SC0-3677.

Marghany M (2014a) Utilization of a genetic algorithm for the automatic detection of oil spill from RADARSAT-2 SAR satellite data. Marine Pollution Bull 89:20-29.

Marghany M (2014b) Multi-Objective Evolutionary Algorithm for Oil Spill Detection from COSMO-SkeyMed Satellite. In: Murgante B, Misra S, Carlini M, Torre CM, Nguyen H-Q, Taniar D, Apduhan BO, Gervasi O (eds) Computational Science and Its Applications–ICCSA 2014, Springer, pp 355-371.

Marghany M., (2015). Flock 1 data Multi-Objective Evolutionary Algorithm for turbulent flow detection. 36th Asian Conference on Remote Sensing: Fostering Resilient Growth in Asia, ACRS 2015; Crowne Plaza Manila Galleria Quezon City, Metro Manila; Philippines; 24 October 2015 - 28 October 2015.

Manning JK, Fogarty ES, Trotter MG, Schneider DA, Thomson PC, Bush RD, Cronin GM (2014) A pilot study into the use of global navigation satellite system technology to quantify the behavioural responses of sheep during simulated dog predation events. Animal Production Sci 54(10):1676-1681.

Reidenbach MA, Koseff JR, Monismith SG (2007) Laboratory experiments of fine-scale mixing and mass transport within a coral canopy. Phys Fluids 19:075107.

Rowlands GP, Purkis SJ, Riegl BM (2008) The 2005 coral-bleaching event, Roatan (Honduras): Use of pseudo-invariant features (PIFs) in satellite assessments. J Spat Sci 53:99–112.

Rowlands G, Purkis S, Riegl B, Metsamaa L, Bruckner A, Renaud P (2012) Satellite imaging coral reef resilience at regional scale. A case-study from Saudi Arabia. Marine Pollution Bull 64(6):1222-1237.

Stocking JB, Rippe JP, Reidenbach MA (2016) Structure and dynamics of turbulent boundary layer flow over healthy and algae-covered corals. Coral Reefs 35(3):1047-1059.