



A review of Computational Intelligence techniques in coral reef-related applications



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ABSTRACT

Studies on coral reefs increasingly combine aspects of science and technology to understand the complex dynamics and processes that shape these benthic ecosystems. Recently, the use of advanced computational algorithms has entered coral reef science as new powerful tools that help solve complex coral reef related questions, which were unsolvable just a decade earlier. Some of these advanced algorithms consist of Computational Intelligence (CI) approaches, a branch of Artificial Intelligence that uses intelligent systems to address complex real-world problems yielding more robust, tractable and simpler solutions than those obtained by conventional mathematical techniques. This paper describes the most commonly used CI techniques related to coral reefs and the main improvements obtained with these methods over classical algorithms in this field. Some recommendations are given for the application of CI techniques to complex coral reef related problems, and vice-versa, for the application of novel coral reef dynamics concepts to improve the Coral Reef Optimization (CRO) algorithm, an optimization method inspired by coral reef dynamics.

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1. Introduction

Coral reefs are one of the ecologically, biologically and physically most complex ecosystems on Earth (Ferrario et al., 2014; Kline et al., 2015; Knowlton and Jackson, 2013; Lamy et al., 2015; Roberts, 2009). Corals enlarge three dimensional habitat complexity (Schoening et al., 2012) and play a key role in deep-sea epibenthic megafauna (animals > 1 cm) (Dunlop et al., 2015), which capture carbon through the redistribution of nutrients such as organic matter and oxygen (Bett et al., 2001; Dunlop et al., 2015; Ruhl, 2007; Schoening et al., 2012). Coral reefs are thus hot spots of marine biodiversity (Purser, 2015; Shantz et al., 2015; Tittensor et al., 2010), provide important ecosystem services (Dulvy and Kindsvater, 2015; Purser et al., 2013a), support the livelihood of millions of people (Ault et al., 2014; Burke et al., 2011; Chen et al., 2015; Kittinger et al., 2015), and act as early warning indicators of global climate change (Baker et al., 2008; Freeman, 2015; Mooney et al., 2009; Woodroffe and Webster, 2014). Climate change is probably the most dangerous threat to coral reefs (Baker et al., 2004; Toth et al., 2015) because of the rise of thermal stress events (which increase coral mortality (Eakin et al., 2010)) and the increment of severe storms and ocean acidity (Anthony et al., 2008; Hoegh-Guldberg et al., 2007) (which causes bleaching (Wooldridge and Done, 2004) in tropical corals, damage reef structure and reduce coral growth rates (Hoegh-Guldberg et al., 2007; Hooiconk et al., 2014; Manzello et al., 2013)). In addition to climate change, *anthropogenic* local stressors such as overfishing (which reduces – and even exhausts – key species from the ecosystem (Januchowski-Hartley et al., 2015; Mumby et al., 2006; Wilson et al., 2006)), mechanical damage from fishing (Clark and Rowden, 2009; Fossaa and Skjoldal, 2010; Orejas et al., 2009), offshore oil and gas industry (Allers et al., 2013; Gates and Jones, 2012; Larsson and Purser, 2011; Larsson et al., 2013; Pabortsava et al., 2011; Purser, 2015; Purser and Thomsen, 2012), sediments (Ban et al., 2014; Bartley et al., 2014; Kroon et al., 2014; Larsson and Purser, 2011; Yamazaki et al., 2011), and marine litter (Pham et al., 2014) are also degrading coral reef ecosystems. These combined stressors, which have undermined the resilience (Anthony et al., 2011; Hughes et al., 2003, 2007; McClanahan et al., 2012; Putra et al., 2015) of coral reef-based ecosystems (Hughes et al., 2010; Pratchett et al., 2014; Rowlands et al., 2015), operate at multiple scales (Carilli et al., 2009; McClanahan et al., 2014), which range from meters to thousands of kilometers (Hatcher, 1997). Monitoring the evolution of coral reef ecosystems at a decadal scale is necessary to understand and predict their dynamics and to design tools for coral reef management (Scopélitis et al., 2009). Monitoring is carried out via localized in situ observations, time-series of aerial photographs and remotely sensed images.

Because of the combination of all these factors, the study of coral reefs requires multi-disciplinary approaches that combine aspects of field observations (Andrew and Mapstone, 1987; Foster et al., 1991; Leujak and Ormond, 2007; Pielou, 1974; Purser, 2015; Whorff and Griffing, 1992), ecological theory (Fox and Bellwood, 2014), modeling (Harborne et al., 2006; Webster et al., 2007) and simulation (Langmead and Sheppard, 2004), and increasingly more often Computational Intelligence (CI) techniques (Bandyopadhyay et al., 2009; Beijbom et al., 2012; Benfield et al., 2007; Chang et al., 2014; Collin and Planes, 2012; Elawady, 2015; Elith et al., 2006; Gao and Hailu, 2012, 2013; Guinan et al., 2009; Halide and Ridd, 2002; Henriques et al., 2010; Huang et al., 2011a; Johnson-Roberson et al., 2006, 2007; Juillet-Leclerc, 2006, 2007, 2009; Juillet-Leclerc and Thiria, 2007, 2008; Juillet-Leclerc

et al., 2006, 2007; Knudby et al., 2010, 2013; Leslie et al., 2003; Marcos et al., 2005; Meesters et al., 1998; Mehta et al., 2007; Nagamani et al., 2012; Naveau et al., 2004; O'Connor, 2000; Padmavathi et al., 2010; Pican et al., 1998; Pittman et al., 2009; Purser et al., 2008, 2009; Ruitenbeek et al., 1999; Schoening et al., 2012; Shihavuddin et al., 2013; Tong et al., 2013; Wahidin et al., 2015; Wang et al., 2004; Watts et al., 2011; Wooldridge and Done, 2004; Yamamoto and Sugiura, 2002; Zhang, 2015). Historically, data-driven approaches have been most commonly used in coral reef research, but the rise of “big data” approaches (Kemp and Sadler, 2014) has rendered some traditional forms of data-analyses insufficient (Andrew and Mapstone, 1987; Leujak and Ormond, 2007; Pielou, 1974) and novel computational techniques are increasingly used to address this problem.

The current huge amount of coral reef data arises mainly from two technologies whose capabilities are continuously being improved: remote sensing and underwater vehicles. On the one, coral reef remote sensing techniques (Goodman et al., 2013) – both aerial imagery from satellites or aircrafts (Shihavuddin et al., 2013; Xu and Zhao, 2014) and bathymetric data via Airborne Light Detection and Ranging (LiDAR) (Pittman et al., 2009), ship-based Multi-Beam Echo-Sounder (MBES) and Sound Navigation and Ranging (SoNAR) (Costa et al., 2009) – are able to provide *repeatable* observations in *large areas* (Lucas and Goodman, 2014; Maina et al., 2008; Rowlands, 2013; Rowlands et al., 2012; Xu and Zhao, 2014) to quantify proxies of biodiversity (Shihavuddin et al., 2013; Turner et al., 2003), and has become a relevant additional tool to in situ approaches (Mumby et al., 2004a; Scopélitis et al., 2009, 2010; Shihavuddin et al., 2013; Wang et al., 2007). On the other hand, underwater vehicles – Remotely Operated Vehicles (ROVs) (Neves et al., 2014; Purser, 2015), Deep Sea Crawler (Purser et al., 2013b), autonomous underwater vehicles (AUVs), and mobile robots (Thomsen et al., 2015) – allow image acquisition at depths and over spatial scales that are not possible with divers. Underwater vehicles provide large amounts of *high spatial resolution* imagery, from which benthic organisms under study can be resolved (Shihavuddin et al., 2013), (Turner et al., 2003). Both data acquisition technologies require increasingly the use of CI techniques, not only because of the large amount of data and the difficulty to classify or detect biota from data (the classical manual analysis is both time-consuming and labor-intensive) but also because of the need to extract non-obvious relationships among the many factors that interact with each other, and which arise from the inherent complexity of coral reefs mentioned in the first paragraph.

CI is a branch of Artificial Intelligence (AI), focused on the design of robust and intelligent systems to tackle complex real-world problems for which traditional approaches fail or are inefficient. For example, in optimization problems, traditional techniques such as Newton-type algorithms need continuous and derivable objective functions to be applied, while CI techniques such as evolutionary computation (EC) algorithms do not need this requisite. There are other problems such as regression models (RMs) or classification approaches where CI techniques are known to obtain better results than traditional algorithms. For example, in regression problems, traditional regression (LR) analysis (Montgomery et al., 2012; Seber and Lee, 2012) or multi-linear regression (MLR) models (Chatterjee and Hadi, 2015) are usually considered a baseline algorithm to be beaten by CI techniques. In classification problems, the traditional naïve *k*-nearest neighbors approach (Soriano et al., 2001) is usually improved by CI techniques such as Support Vector Machines (SVMs) or neural classifiers. In this respect, note that CI is not a single technique, but a set of techniques belonging to different subfields such

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