Automatic Detection of Ships in Spaceborne SAR Imagery

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1 Overview

This paper examines the evolution of automatic target detection algorithms and their application to the detection of shipping in spaceborne SAR imagery.

Evolutionary Computing (EC) techniques are used to generate both Finite State Machines (FSMs) and the mathematical functions embedded within their states. These mathematical functions are evolved using Genetic Programming (GP). The GP function set used is $\mathcal{F} = \{+, -, \times, \div, \neg, max, min\}$, where $\neg$ negates its argument, and $max,\ min$ returns the maximum and minimum of its input arguments respectively. The GP terminal set used is $\mathcal{T} = \{s_0, \ldots, s_{15}\}$, where $s_0, \ldots, s_{15}$ are statistical features extracted from the image pixels. In our model, two GPs are embedded within each state of the FSM. The FSM is thus a function of the GPs embedded within its states, and hence denoted FSM(GP). In addition, each state has an associated transition level τ upon which the state transition function ϑ bases its decisions.

Let q_i, q_j, and q_n be arbitrary states, q_z be the halt state, and GP$_m$ be an arbitrary GP. Assuming that at least one state transition has taken place, the algorithm operates as follows. GP$_m \in q_n$ is evaluated and returns an output $v_m \in \mathbb{R}$. The state transition function ϑ then generates a transition

$$\vartheta : q_n \times v_m \mapsto \begin{cases} q_i & \text{if } |v_m| < \tau \text{ and } v_m \geq 0 \\ q_j & \text{if } |v_m| < \tau \text{ and } v_m < 0 \\ q_z & \text{if } |v_m| \geq \tau. \end{cases}$$

If the FSM(GP) has entered state q_z then a pixel is designated as target if $v_m > 0$ or as non-target if $v_m < 0$. If the state entered is not terminal, i.e. q_z, GPv_m is executed next. Thus, GPs are given access to results from previous states, allowing evidence to be accumulated during processing until there is sufficient upon which to base a sound decision. And significantly, processing can be terminated with minimum expenditure when a decision is clear cut. The ordering of the states can therefore have a major impact on processing overhead. This too is determined during the system's evolutionary development.

Table 1: Performance comparison of NN, two stage GP, and FSM(GP).

	FOM		
Image	NN	GP	FSM(GP)
Test 1	0.67	0.67	0.74
Test 2	0.72	0.69	0.8

2 Results

The FSM(GP) has been applied to the detection of shipping in spaceborne SAR Imagery. The results have been compared with those obtained in two independent studies: one using two stage Genetic Programming (Howard et al., 1999), and the other using a Kohonen Neural Network (Foulkes, 2000). In both cases, algorithm performance was assessed using the figure of merit FOM$= \frac{N_{tt}}{N_{fa}+N_{gt}}$, where N_{tt} is the number of true target detections, N_{fa} is the number false alarms, and N_{gt} is the total number of ships in the ground truth data set. Using the same set of ship candidates for training purposes, the performance of the three techniques on identical unseen imagery is shown in Table 1. The FSM(GP) is clearly superior.

References

Foulkes, S. B. (2000). Ship detection in ESR-1 and radarsat SAR images using self-organising neural networks. In *Procceding of the amrs workshop on ship detection in coastal waters*.

Howard, D., Roberts, S. C., and Brankin, R. (1999). Target detection in SAR imagery by genetic programming. *Advances in Engineering Software*, 30:303–311.