Automatic Target Recognition of Synthetic Aperture Radar Images Using ART Neural Networks

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ABSTRACT: This paper provides an analytical survey of the field of Adaptive Resonance Theory (ART) applied to automatic target recognition (ATR) of synthetic aperture radar (SAR) imagery. Accomplishments in the field are presented and limitations of ART neural networks are identified. With these limitations and this application area in mind, a course of action has been outlined to remedy some of these limitations and to test newly developed models.

KEYWORDS: Automatic target recognition, Synthetic aperture radar, Adaptive resonance theory neural networks

1. Introduction

Modern computers are able to operate at speeds far quicker than the human brain and are able to be much more precise than humans. Despite this speed, they perform badly solving such problems as pattern recognition and categorisation. This is due to the fact that the problem domain cannot be precisely formulated, thus a solution cannot be calculated. The only way to solve these kind of problems is to learn from experience and build up a knowledge base of previous solutions. This is essentially how the human brain works and how artificial neural networks (ANNs) work. ANNs are constructed from processing elements called neurons, and inter-neuron connections called weights. The inter-neuron connections store the long term data and are modified based on experience, Shubnikov (1996).

This paper provides an analytical survey of the field of Adaptive Resonance Theory (ART) applied to automatic target recognition (ATR) of synthetic aperture radar (SAR) imagery. Section 2 introduces Adaptive Resonance Theory neural networks. Section 3 gives a brief introduction to SAR and focuses on how ART has been adapted to suit ATR of SAR images. Section 4 includes a discussion and an outline of a research program aimed at overcoming some of the limitations of ART neural networks.

2. Adaptive Resonance Theory Neural Networks

Adaptive Resonance Theory (ART) neural networks are a family of self-organising, self-stabilising and self-scaling artificial neural network (ANN) models which implement clustering algorithms, Carpenter (1987a). ART-1 accepts arbitrarily many binary input patterns and classifies them into arbitrarily many categories or clusters in an unsupervised manner. There are many ANN models based upon the ART architecture. ART-2 generalises ART-1 to categorise both binary and continuous input patterns using a different architecture, Carpenter (1987). ART-2A is an improvement in execution speed over ART-2 by two to three orders of magnitude, Carpenter (1991). Fuzzy ART is a synthesis of ART-1 and fuzzy logic Zadeh (1965) which produces a model based upon the ART-1 architecture but which can deal with both binary and continuous input patterns, Carpenter (1991b). ARTMAP (predictive ART) is a supervised ART model which learns to classify an unspecified number of vectors into recognition categories based on predictive success, Carpenter (1991a). Fuzzy ARTMAP generalised ARTMAP in the same was as fuzzy ART generalises ART, Carpenter (1992).

3. SAR AND AUTOMATIC TARGET RECOGNITION USING ART NEURAL NETWORKS

Radar is an active sensor where resolution directly depends on the wavelength of the signal. A smaller wavelength results in a higher resolution. Optical sensors typically have a wavelength of 0.5µm whereas radar systems usually use 240000µm and because of this the optical sensor has a far greater resolution than the radar sensor for the same aperture. For the radar sensor to have the same resolution as an optical sensor with an aperture of 1m, the radar aperture would have to be 3900km. Synthetic aperture radar (SAR) increases the apparent size of the aperture, thus increasing the resolution, Sellers (1994). How this is achieved is beyond the scope of this paper.

There are few cases where ART has been applied to SAR automatic target recognition. Due to the immaturity of the field, little research has been carried out with the aim of adapting an ART network to this specific task. More often than not in this field, a previously developed ART module is used following a period of pre-processing of the input data to categorise the targets previously picked out from a SAR image. Waxman (1995) is an example of processing targets in visible, multispectral infrared and SAR imagery motivated by biological vision systems. Waxman (1995) deals mostly with different target detection techniques and explains the theory used in their modular system for learning and recognising 3-D targets from visible imagery. The objects being recognised from the SAR data are various vehicles. The task undergoes several pre-processing stages before being passed to ART-2, which is used as a single module in the modular system to quantise receptive fields into aspect categories for further processing. Thus, an unmodified ART-2 network is used in an intermediate stage in a larger processing system.

Bernardon (1995) investigates the classification results of partially obscured SAR targets. Military targets are used in this application. The required specification was to produce a system which is capable of automatic 2-D view processing and categorisation. The images underwent 3 pre-processing stages: centre-surround networks used for extracting features of locally high contrast, detection stage which locates possible target pixels, and overlapping receptive fields were used to encode spatial locations of the features. Training and testing using an unmodified ART2-A network began. Poorer results for the stripmap mode can be explained by the fact that the network was trained on spotlight data and there are inherent differences in the two types of images. Also, the system underwent on-line learning for Tank 2 and APC but as there are so few images of each class, the system did not have enough data to build a definitive category prototype for these types of input. The results give acceptable performance including a measure of confidence which reflects the goodness of match. All computations were realised in a relatively short time which indicates that this system may be suitable for real-time target recognition. Figure 1 is taken from Bernardon (1995) and shows how ART-2A networks are integrated into a larger system. Parts (a), (b) and (c) are all pre-processing stages to the classification stage.

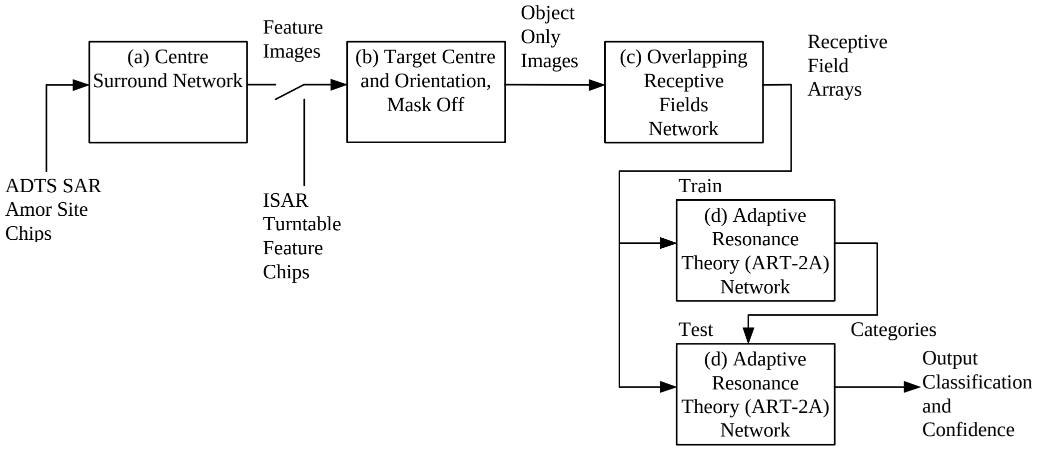

Figure 1: An example of how ART-2A networks are used in a larger system

Koch (1995) uses ART2 as a classifier and recogniser for automatic target recognition. Feature extraction was carried out by either the necognitron or generalised Hebbian learning and results were compared. The classification and recognition stage was carried out by ART2. Results indicated that ART2 is suitable for this task. However, results also indicated that as soon as targets became obscured, then the performance of ART2 to recognise the targets fell dramatically. An obscuration of more than 20% resulted in unacceptable performance. Using, what the authors call, hyperstar showed acceptable results for even 50% obscuration. Hyperstar uses ART2 but with a different, modified, distance metric, which is

$$D_*\left(\mathbf{I},\mathbf{Z}_j\right)=\frac{1}{d}\sum_{i=1}^{d} g_q\left(\left|\frac{I_i - Z_{ji}}{s_i}\right|\right) \tag{1}$$

- where $D_*(.)$ = distance between **I** and $\mathbf{Z_j}$ in R^d
- s_i = standard deviation of a feature. As it increases then the feature becomes less important
- $g_q(.)$ = threshold function = 0 if $x \leq q$, which handles arbitrary features, and is 0 otherwise, which accounts for mismatches.

ART has also been applied to the classification of ordinary Radar data. Granger (1998) compares 4 different self-organising neural network models for fast clustering of RADAR pulses. The models compared are Fuzzy ART, Fuzzy MIN-MAX clustering, Integrated Adaptive Fuzzy clustering and Self-Organising Map (SOM). The criteria examined are the clustering quality (accuracy), convergence time and computational complexity. Fuzzy ART is proven to have the lowest computational complexity, the 2nd highest accuracy and joint highest convergence time. The authors conclude that SOM and Fuzzy ART are the most suitable but for different reasons. SOM has the highest accuracy but is computationally complex. Suggested applications are long range surveillance, intelligence and targeting. Fuzzy ART may be used in time critical systems, i.e. threat alarms, due to its low convergence time. Again, this example only uses a pre-existing ART model, but Carpenter (1996a) introduces ARTMAP-FD, which is a modified ARTMAP model. The application area used to test this new ART algorithm is RADAR target recognition. The 'FD' stands for Familiarity Discrimination and is applied to prevent the standard Fuzzy ARTMAP from making guesses as to which category an input pattern may belong. Simulated RADAR profiles are used. The suitability is measured by the hit rate (percentage of input patterns classified correctly) divided by the false alarm rate (percentage of input patterns incorrectly classified). The ideal system would have a value of 1. The best observed result was 0.9989, which suggests that ARTMAP-FD is suitable to this task.

Automatic target recognition of radar range profiles using Fuzzy ARTMAP is the topic of Rubin (1995). The author found that, as is often the case, the K nearest neighbour classifier (KNN) produced results with better accuracy, but the memory requirements of Fuzzy ARTMAP make it more favourable. ART-EMAP was found to produce even better results due to its temporal evidence accumulation. ART-EMAP is an extension to Fuzzy ARTMAP and performs identification based on sequences of patterns.

The search of the literature shows that ART can be used to classify and recognise aspects of SAR and other satellite data. It is shown that its low computational complexity gives rise to the possibility that ART could be used in real-time systems. It is also shown that aspects of the ART models need to be improved to make the usage of ART more practical in a more general application. Specific limitations indicated are that the use of ART in noisy environments where the targets to be recognised may be partially obscured, and the fact that the number of true categories present in a data set cannot be known.

4. DISCUSSION

It is clear by examining the literature that Adaptive Resonance Theory has several limitations which have been addressed by several researchers. There have been varying degrees of success at eliminating each problem. ART suffers from poor noise tolerance both in recognition when a target is partially obscured, and in classification where the image suffers from speckle or other noise. This reduces the diversity of use of ART. Notably, Lee (1995), Lee (1997) and Marriott (1995) have addressed this problem. Lee (1995) change the learning equation in Fuzzy ART to incorporate a weighted sum and a fuzzy AND operation. Lee (1997) use a similar learning equation to improve noise tolerance in Fuzzy ARTMAP. And Lee (1998) discuss Lee (1997) in more detail. Marriott (1995) shows that the match tracking feature in Fuzzy ARTMAP causes over-learning. The proposed modification uses probability information in place of the match tracking feature which is shown to outperform standard fuzzy ARTMAP. Other examples of where noise tolerance has been improved are Delgado (1998), which uses a multichannel input which benefits from redundancy of information, Carpenter (1998) which introduces ARTMAP-IC ('instance counting' or 'inconsistent cases'), and ART-EMAP which uses temporal and spatial Evidence accumulation.

Without any *a priori* information, ART is able to classify an input into a number of categories which is a function of the vigilance parameter. ART is unable to give, however, an indication of how many true categories are present in a given data set because it develops its own critical feature patterns and modifies these with respect to time and new input patterns. This could be solved by using ARTMAP which is supervised training and classifying. This requires *a priori* information, i.e. information given to the system externally before the system can classify the current input pattern. Essentially, this problem occurs only when trying to establish categories in an on-line learning/classifying environment where the system is expected to map an input to an output (category) autonomously.

An indication of the correct number of categories and noise improvements to the ART model will dramatically increase the number of situations where ART could be used in place of other artificial neural network, statistical or other methods. The reason being is that once classification accuracy is achieved and such a system able to give an indication of the number of true categories present in a data set, it would be reasonable to assume that ART may replace other methods in traditionally supervised environments as ART is computationally less complex than some other models and has a far smaller memory requirement.

As noise tolerance has been identified as a key problem area for the ART models, future theoretical work should be dedicated towards the improvement of noise tolerance performance.

1. The results of Lee (1995) and Lee (1997) have proven useful with a clear improvement in the correct classification of a noisy data set. Future work will be targeted towards improving these results further still with the aim to develop a new ART NN method for the reduction of noise pollution. Assuming acceptable results, the study would then continue and investigate whether this modification could be implemented in other ART architectures.

If a neural network is trained on "crisp" data and then put into work in an application where the data is susceptible to being noisy, then one of three things may happen: an input pattern may be recognised by the network and classified into the "correct" category. If this happens, then it can be said that the network is, to a certain extent, noise tolerant. The other two possibilities are both incorrect. These are if an input pattern is recognised and miss-classified, and if an input pattern is not recognised at all. In these two cases either of the two following scenarios apply: the input pattern has activated the correct F2 'category' node but the vigilance test has failed, or no F2 node is maximally active and so a new category may be formed, depending upon whether learning is enabled.

If the input pattern is miss-classified, then the vigilance test has failed. In order to improve noise tolerance, this vigilance test has to be passed, thus it follows that to improve noise tolerance, $\frac{|\mathbf{I} \wedge \mathbf{W}_J|}{|\mathbf{I}|}$ needs to be a larger value. Thus, the investigation should be targeted at achieving this.

2. Secondly, a brief investigation into how other artificial neural network classifiers have improved noise tolerance should be carried out with the aim of developing a totally new noise tolerant algorithm for ART, or a hybrid of existing methods with any new methods found. This idea stems from the observation that problems may not be solved by one method alone, but fusing the best properties of each provide a better solution. Fuzzy ART and Fuzzy ARTMAP are examples of this: a fusion of fuzzy logic and neural network theory.

An artificial neural network which may prove useful in this investigation is Kohonen's Self-organising Feature Map (SOM) as this is a self-organising artificial neural network. Studying this neural network and how is achieves noise tolerance may reveal properties which the ART networks lack and thus a hybrid may be possible, either by modifying the architecture to include a pre- or post-processing layer to the network, or directly to the ART algorithm.

The study need only look at how other methods are noise tolerant and how noise tolerance has been improved.

3. The application area used to test the new noise tolerant ART model is Synthetic Aperture Radar and the automatic recognition of targets. The locality of the SAR data to be used as a test set has yet to be identified. Coupled with this is the investigation as to the possibility and usefulness of performing the classification on-board Surrey Satellite Technology Ltd. mini-satellites. The investigation should detail the limitations of computing on-board a mini-satellite and make aware how that would constrain any other on-board systems.

5. Conclusion

In this paper we have reviewed a number of papers relating to the application of ART neural networks to ATR of SAR data and to the limitations ART neural networks currently face. With these limitations and this application area in mind, a course of action has been outlined to remedy some of these limitations and to test newly developed models.

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