Journal of Intelligent and Robotic Systems **29:** 309–315, 2000.

Editorial: Neural-Fuzzy Applications in Computer Vision

1. What is Neuro-Fuzzy?

Neural networks and fuzzy logic are two bio-mimetic techniques that are used to provide approximations to real-world problems. While for some people this biological plausibility provides some justification for their use, for others the important point is that, regardless of their origins, both approaches are known to be robust alternatives to conventional deterministic and programmed models. However, the two paradigms have distinct application domains. Fuzzy logic is used to represent qualitative knowledge, and provides interpretability to system models. By this we mean that a system model is explicit and is understandable to a knowledge or systems engineer. This facilitates inspection of the model, and therefore simplifies and encourages its validation and maintenance. Zadeh [14] has summarised fuzzy logic as a body of concepts and techniques for dealing with imprecision, information granulation, approximate reasoning and computing with words. Neural networks, on the other hand, are used to induce knowledge or functional relationships from instances of sampled data. This is useful when it is not possible to develop analytic models from first principles but the system is observable. However, in contrast to fuzzy systems, this knowledge is not readily understandable to the system designer because it is encapsulated in the so-called black box. Another contrasting feature of neural and fuzzy techniques is that while traditionally fuzzy knowledge is obtained from human experts, neural network relationships are usually automatically learned from a training process that iterates through a sample data. In consideration of this, the combination of fuzzy and neural systems provides a synergy such that the marriage of each of their strengths overcomes some of their individual drawbacks and can lead to greatly enhanced systems. In particular, fuzzy system design does not incorporate any learning, while neural networks do not possess mechanisms for explicit knowledge representation.

Fuzzy processing is desirable in computer vision because of the uncertainties that exist in many aspects of image processing. These uncertainties include additive and non-additive noise in low-level image processing, imprecision in the assumptions underlying the algorithms, and ambiguities in interpretation during high-level image processing. For example, for computational convenience, the common process of edge detection usually models edges as intensity ridges. Nevertheless, in practise this assumption only holds approximately, leading to some of the deficiencies of these algorithms. As an example of the third case, the fact that all interpretation of 3D scenes based on 2D images is under-constrained means that interpretation is necessarily ambiguous since there are an infinite number of 3D scenes that project onto the same 2D image (although most would be unlikely or infeasible). Similarly, given the complexity of visual information and the attendant difficulty of determining the fundamental underlying models despite much research in a wide range of areas such as physics, physiology, and psychophysics, neural networks are useful to computer vision for learning image classification, image recognition and general image processing. Neural network and fuzzy logic, together with genetic algorithms, have in fact emerged as the basis for so-called intelligent systems [14].

Neural-fuzzy or fuzzy-neural hybrid systems exist in two predominant forms. First, there are implementations designed to represent a fuzzy linguistic algorithm in a multi-layered network [6]. Second, there are implementations that aim to explicitly replicate the processes of fuzzy inference and reasoning through the use of connectionist structures [10]. In the first approach neural networks are used to improve the performance of fuzzy systems by tuning the rules or their membership functions. In the second approach, fuzzy concepts, such as linguistic attributes, can be built into neural networks to enable knowledge-based interpretation. There is also a third approach in which disparate fuzzy and neural systems are cascaded in any order to achieve one objective or another. Unfortunately, the terminology is not consistently applied and hence, often in the literature the terms neural-fuzzy and fuzzy-neural refer to the same type of system approach. We suggest that where a neural network is used to aid a fuzzy algorithm then the hybrid system should be referred to as neural-fuzzy, whereas if the objective is to use fuzzy concepts to aid a neural system then it should be referred to as fuzzy-neural.

2. What is Computer Vision?

Over the last few decades the volume of interest, research, and development of computer vision systems has increased enormously. Nowadays they appear to be present in almost every sphere of life, from surveillance systems in carparks, streets, and shopping centres, to sorting and quality control systems in the majority of food production. In part due to the substantial increase in digital images that are produced on a daily basis (e.g., from radiographs to images from satellites) there is an increased need for the automatic processing of such images. Thus, there are currently many applications such as computer-aided diagnosis of medical images, segmentation and classification of remote sensing images into land classes (e.g., identification of wheat fields, vinyards and illegal marijuana plantations, and estimation of crop growth), optical character recognition, closed loop control, content-based retrieval for multimedia applications, image manipulation for the film industry, identification of registration details from car number plates, and a host of industrial inspection tasks (e.g., detecting defects in textiles, rolled steel, plate glass, etc.).

Historically much data has been generated as images to facilitate human analysis (it is much easier to understand an image than a comparable table of numbers!). And so this has encouraged the use of image analysis techniques over other possible methods of data processing. In addition, since humans are so adept at understanding images, image based analysis provides some aid in algorithm development (e.g., it encourages geometric analysis) and also helps informally validate results.

While the role of computer vision can be summarised as a system for the automated (or semi-automated) analysis of images, many variations are possible. The images can come from different modalities beyond normal gray-scale and colour photographs, such as infrared, X-ray, as well as the new generation of hyper-spectral satellite data sets. Second, many diverse computational techniques have been employed within computer vision systems such as standard optimisation methods, AI search strategies, simulated annealing, genetic algorithms. This openness has naturally led to experimentation with neuro-fuzzy approaches too.

One reason that so many appraches have been tried out is because computer vision tasks are usually problematic and complex in many respects. First, the goals of some tasks cannot be quantified precisely and can vary with time. For example, in an automated vision-application to classify fruit, experts may not agree on exact distinctions between ripe and unripe fruit, and the classification criteria may vary from orchard to orchard and from season to season. Second, characteristics of the application are often highly nonlinear and dynamic, and so traditional modelling and problem solving techniques become complex, suboptimal, and inefficient. Third, the data is typically incomplete and imprecise, which also gives traditional approaches difficulties.

3. Review of State of the Art

One area that demonstrates the potential for computer vision systems based on fuzzy logic and neural networks is robotic applications, typically involving recognition and manipulation of objects. Lee and Qian [4], for example, describe a two-component system for picking up moving objects from a vibratory feeder. The first component is a fuzzy system that selects an object of interest and tracks it. The second component is a neural network estimator that predicts the position at which the robot picks up the object. This sort of problem involves nonlinear dynamics that are often impractical to model accurately. Neural-fuzzy approaches have a distinct advantage in such problems because they can be used to approximate the nonlinear dynamics, rather than computing the inverse Jacobian as in the usual feature-based feedback control [9]. Another area of emerging significance in computer vision is image classification, especially allied to bio-medical problems. Examples of neuro-fuzzy application in this area include tissue identification from magnetic resonance imaging (MRI) data, a system that utilises features extracted from colour images of poultry viscera to categorise them into normal and abnormal classes [1], and neuro-fuzzy vision system developed to monitor cell populations during fermentation.

A challenge to the use of computer vision is the uncertainty associated with the environments within which the systems have to operate. This often requires a reasoning approach in order to cope with these uncertainties. In such cases multiple sources of information are used, from which the final solution is derived through information aggregation. As an example, a system for identification of machine–tool wear was reported by Li et al. [5], which uses a neural network embedded with fuzzy classifiers to analyse several images obtained by laser scattering from the machined surfaces of the work-piece. The robotic die polishing system reported by Kuo [3] similarly uses multiple images of the die texture to determine the polishing direction. Each image is analysed using a neural network and then the multiple decisions from different networks are integrated together by using an additional network. Furthermore, the learning of the networks is also controlled using fuzzy models. Mirhosseini et al. [7] describe a face recognition system in which eyes, mouth, and nose locations are detected and each facial feature provides evidence for neural classifiers with varying degrees of reliability. The decisions of individual classifiers are then combined using a fuzzy information fusion technique.

One of the advantages of image analysis is that it enables noncontact measurements to be made. Thus, in one of the most common application of neuro-fuzzy techniques, the field of feedback control, recently computer vision has been incorporated into feedback control schemes in which direct contact-based instrumentation is not feasible or convenient. We give here three examples. In the first, images of flames are analysed using image processing techniques and then a neuro-fuzzy network generates a feedback signal to control combustion [11]. Second, Chen et al. describe a neuro-fuzzy control system for real-time control of arc welding, that relies on image analysis of the arc. Third, Daxwanger and Schmidt [2] describe a system for the acquisition and transfer of an experienced driver's skills to an automatic parking controller. The neuro-fuzzy controller processes input information from a video sensor and generates the corresponding steering commands. The variety of applications is not exhaustive, and many other applications exist, such as, an automatic IC chip inspection and recognition system that determines the orientation of IC chips and recognises the printed symbols on the surface of the chips [12], neuro-fuzzy enhancement of images from a polarimetric radar navigation system [13], and a fuzzy SOM system for face processing that also combines wavelet analysis.

4. Review of the Special Issue

Although general neuro-fuzzy systems have been around for over a decade neuro-fuzzy vision systems are still in their infancy. This special issue brings together five papers which have been selected to show some of the diversity of neuro-fuzzy approaches and to demonstrate their applicability to tackling computer vision tasks. Each article is devoted to a specific application and has been selected to highlight a novel feature of the integration of fuzzy logic and neural networks.

One of the central issues in neural network research over the years has been the development of better architectures and learning algorithms in order to improve their effectiveness and efficiency. The first paper by Canuto et al. presents a variation of the well-known fuzzy-ARTMAP by the addition of reinforcement learning. They show that the architecture referred to as RePART offers general improvement over the fuzzy multilayer perceptron in terms of the training time required. By way of example they evaluate their system on handwritten numeral classification.

Continuing on this theme Hou et al. have proposed a new training algorithm which combines gradient descent and least mean squares learning. The system presents an interesting combination of image feature extraction, fuzzy C-means clustering, and RBF classification for the unusual application of automatically counting bullet holes in paper targets.

Knowledge acquisition and representation are two of the open issues in neuro-fuzzy systems. In the paper by Shanahan et al. they describe a system for learning compact models, which are also understandable. This is made possible by a combination of evolutionary learning and Cartesian granule feature modelling offering the advantage of adapting models to changing environments. The system is applied to object recognition in outdoor scenes.

The final two papers show how neuro-fuzzy techniques can be applied to benefit two diverse image analysis problems. Fisher and Kohlhepp perform the reconstruction of 3D models from multiple range maps and cope with uncalibrated data sets, occlusion, and noise. This is achieved by employing an evolutionary algorithm to generate correspondences between surface patches which are evaluated by neuro-fuzzy similary measures. These are generated by taking a set of fuzzy rules provided by a human expert, and training a neural network to have the same transfer function. The advantage of this latter step is that in the advent of environmental changes the neural network can be automatically updated by simply extending training with new data without recourse to the expert.

Foody's work is in the area of remote sensing, in particular, the classification of image pixels into land cover types. Given the nature of the data a crisp classification is not always appropriate. In this paper the author focusses on the interpretation of the neural network outputs to provide a soft classification of data. The concept of entropy is applied in combination with the maximum and summed neural network outputs to indicate the appropriateness of crisp versus fuzzy class assignments.

These papers highlight the variety of neuro-fuzzy combinations. For instance, Canuto et al. combine the fuzzy and neuro aspects within a single integrated architecture. Hou et al., on the other hand, present a fuzzy clustering component which then provides a configuration for the neuro component. Yet another variation is given by Foody who provides a neural classifier followed by a fuzzy interpretation stage. At present there appears to be no consensus on what is a good neuro-fuzzy approach and hence the architecture chosen normally only reflects the researcher's preferences and previous experience.

5. Conclusion

An obvious and important question to ask is whether a neuro-fuzzy approach is useful. Even just from the papers in this issue, we can see that the answer is yes; that we can see benefits of neuro-fuzzy approaches as compared against the many other available competing techniques. First, a system operating in a dynamic and uncertain environment needs to be adaptable to changes. The paper by Fisher and Kohlhepp demonstrates this capability by transcribing a fuzzy rule base into a neural network which can be updated in response to new data. Second, ensuring understandability of a system is important on several fronts: user interaction to ensure acceptance of the output, and system development is simplified in terms of debugging, verification, and maintenance. Shenahan et al. have shown that system accuracy comparable with competing techniques can be achieved while maintaining transparancy. Compactness of the system model is beneficial both in terms of improving computational efficiency as well as understandability. Shenahan et al. again demonstrate that their neuro-fuzzy model development results in more compact models compared to decision trees, neural and Bayesian networks. Finally, it is clear that even a simple noncrisp interpretation of neural network outputs can provide insight into the network's classification, as shown by Foody's paper.

In terms of effectiveness, from current research it is not clear that neuro-fuzzy are any better than competing techniques. In fact, the evidence shows that similiar accuracies of performance are achievable by all of the techniques so long as they are tuned appropriately. Again, during operation the various techniques generally have similar computational efficiencies. However, compared to some of them neuro-fuzzy approaches suffer from slow learning. Nevertheless, this is an area of continual research, and papers such as Canuto et al. and Hou and Song show that significant improvements in learning can be made.

What are the advantages of neuro-fuzzy techniques in computer vision? Understanding visual stmuli is difficult – both for man and machine. Biological vision systems have evolved and improved over millions of years, and part of their success lies in a set of heuristics or so-called "short-cuts" developed to provide economical and robust solutions to difficult visual tasks [8]. A well-known example is insect visual navigation which can be achieved by combining simple rules such as "slow down when approaching an object". We can abstract from the biological systems by representing such heuristics using fuzzy reasoning. Likewise, the many nonlinear relationships inherent in vision which are difficult to represent analytically can be more easily expressed within neural networks.

HENRY O. NYONGESA
Computing Research Centre
Sheffield Hallam University
United Kingdom

PAUL L. ROSIN
Department of Computer Science
Cardiff University
United Kingdom

References

1. Chao, K., Chen, Y. R., Early, H., and Park, B.: Color image classification systems for poultry viscera inspection, *Appl. Engrg. Agriculture* **15**(4) (1999), 363–369.
2. Daxwanger, W. A. and Schmidt, G.: Neural and fuzzy approaches to vision-based parking control, *Control Engrg. Practice* **4**(11) (1996), 1607–1614.
3. Kuo, R. J.: A robotic die polishing system through fuzzy neural networks, *Comput. Industry* **32**(3) (1997), 273–280.
4. Lee, K. M. and Qian, Y. F.: Intelligent vision-based part-feeding on dynamic pursuit of moving objects, *J. Manufacturing Sci. Engrg.–Trans. ASME* **120**(3) (1998), 640–647.
5. Li, X. Q., Wong, Y. S., and Nee, A. Y. C.: Intelligent tool wear identification based on optical scattering image and hybrid artificial intelligence techniques, *Proc. Inst. of Mechanical Engineers Part B* **213**(2) (1999), 191–196.
6. Lin, C. T. and Lee, S. G.: Reinforcement structure/parameter learning for neural network based fuzzy logic systems, *IEEE Trans. Fuzzy Systems* **2**(1) (1994), 46–63.
7. Mirhosseini, A. R., Yan, H., Lam, K. M., and Pham, T.: Human face image recognition: An evidence aggregation approach, *Computer Vision Image Understanding* **71**(2) (1998), 213–230.
8. Srinivasan, M. V., Chahl, J. S., Weber, K., Venkatesh, S., Nagle, M. G., and Zhang, S. W.: Robot navigation inspired by principles of insect vision, *Robotics Autonom. Systems* **26**(2/3) (1999), 203–216.
9. Suh, I. H. and Kim, T. W.: Fuzzy membership function-based neural networks with applications to the visual servoing of robot manipulators, *IEEE Trans. Fuzzy Systems* **2**(3) (1994), 203–220.
10. Takagi, H., Suzuki, N., Koda, T., and Kojima, Y.: Neural networks designed on approximate reasoning architecture and their applications, *IEEE Trans. Neural Networks* **3**(5) (1992), 752–760.
11. Tao, W. J. and Burkhardt, H.: Vision-guided flame control using fuzzy-logic and neural networks, *Particle Particle Systems Characterization* **12**(2) (1995), 87–94.
12. Tsai, M. J. and Chiou, S. D.: Recognition of ic chips via machine vision, *J. of the Chinese Institute of Engineers* **18**(3) (1995), 397–409.
13. Ukrainec, A. M. and Haykin, S.: A modular neural network for enhancement of cross-polar radar targets, *Neural Networks* **9**(1) (1996), 143–168.
14. Zadeh, L. A.: Roles of soft computing and fuzzy logic in the conception, design and deployment of information/intelligent systems, in: O. Kaynak, L. A. Zadeh, B. Turksen, and I. J. Rudas (eds), *Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications*, NATO ASI Series F: Computer and Systems Sciences, Vol. 162, 1998, pp. 1–9.