Integrating Inference and Neural Classification in a Hybrid System for Recognition Tasks

Massimo De Gregorio
Istituto di Cibernetica - CNR
80072 Arco Felice (NA) - Italy
e-mail: massimo@sole.cib.na.cnr.it

Abstract

While the coupling of artificial of neural networks (ANN) and symbolic AI (SAI) is a strategy adopted in many hybrid systems, a real integration of the two methodologies has not been thoroughly investigated yet: so far, most hybrid systems have been viewed as just an engineering shortcut to solve complex problems in which one methodology alone seems too weak.

In this paper, an approach to integrating ANN and SAI is presented. The basic idea explored here is that there is much more to hybrid models than a coupling of methodologies for the sake of avoiding engineering problems.

1 Introduction

The problem of integrating ANN and SAI methodologies is appealing because of the complementary characteristics of these methodologies. On one hand, symbolic processing are suitable for deductive reasoning, knowledge representation, recursive structure, sequential control and has good justification capabilities. However, it can hardly deal with associative retrieval, noise resistance, generalisation and learning. The latter are easily handled by ANN processing [1]. When dealing with different levels of knowledge representation, the potential for cross-fertilisation between ANN and SAI is obvious [2].

Many hybrid systems can be replaced by a sufficiently powerful representational system in which one of the modules emulates the other's behaviour [3, 4, 5], but a real integration of the two paradigms can lead to hybrid systems with behavioural properties different from and better than a unified system based on one paradigm [6]. According to the hybrid system classification given by Hilario [7], "the best of both worlds" [6] is obtained by those systems in which the ANN and SAI modules are equal partners in problem-solving processes (*coprocessing functional hybrid systems*). The hybrid system presented here belongs to this class. This claim is better specified and supported by the following description of the hybrid system, the two modules (ANN and SAI), their co-operative behaviour, and some experimental results.

2 A recognition task

Work on designing expert systems for ancient building analysis [8][9][10] (in particular, one capable of dating parts of a building from information on, e.g., shape and building materials of portals, windows, balconies, and other architectural components [10]), suggested the possibility of designing a system capable of automatically extracting, from photographs, the relevant information about the building architectural components.

Portal shapes are the most important architectural component for the dating of a building. Fig. 1 shows the different classes the system has to deal with.

Figure 1

A first attempt at resolving this recognition task was made by adopting a multi-discriminator system [11][12]. The multi-discriminator system was formed by six discriminators, each trained on a set of drawings representing one of the classes $a - f$. Each training set contained a certain number of drawings, varying from a standard representative of the class only in the way of their position and size.

The results obtained in recognising a set of 85 actual photographs of portals were not encouraging [13]. In fact, the multi-discriminator system could not adequately discriminate between these shapes: it did recognise pictures representing a or b-shaped portals, but failed on items belonging to the other classes. The following interpretation of this experiment naturally suggests itself: multi-discriminator systems seem unable to discriminate between (classes of) images that are very similar with respect to the position of the area occupied by the object in the image, no matter how different their geometrical features are. It seems that reasoning about geometrical features plays a crucial role for recognising portal shapes.

In order to introduce this reasoning capability, a hybrid system composed of a neural module and a symbolic module has been adopted. If a portal shape can be classified by a two-step process - that is, firstly by looking at its geometric features (fig. 2a) and secondly by putting together these features (fig. 2b) - a reasonable strategy is to combine a neural network for recognising the geometric features and a set of production rules specialised in assembling these features.

The discriminating geometric features of the portal shapes are the top, the horizontal, and the vertical parts (as shown in fig. 2). It can be seen that the horizontal parts are not essential for non-linear portal arches (a, e, and f in fig. 1).

Figure 2

In this hybrid system, as we shall see, there is a sustained interaction between the two modules (neural and symbolic) in terms of both information passed and behaviour modification. For instance: the neural network receives information from the symbolic module modifying its behaviour, and on the basis of its processing feeds back new information that affect the other's behaviour.

3 System components

The system is composed of a neural network capable of discriminating geometric features of the portal shapes, and a symbolic module in which the reasoning for recognising the portal shape takes place.

In the following subsections a brief overview of the two modules is given.

3.1 The artificial neural network adopted

A multi-discriminator system has been adopted as neural module of the system. Six discriminators were trained with simple drawings representing the six different geometric features shown in figure 3. Three of them discriminate the top geometric features of the portal (1, 2, 3), while the other three discriminate both the horizontal and the vertical features of the portal (4, 5, 6).

Figure 3

For each pixel of the picture that has to be recognised, the system stores the coordinates, the responses and the respective confidence values of each discriminator in an ordered list.

The discriminators do not act at the same time and do not always run together: they are activated by the symbolic module when necessary.

3.2 The symbolic module and the system behaviour

In the symbolic module one can distinguish between three different sets of production rules.

The first one evaluates the geometric “coherence” of the discriminator responses and confidences. For instance, suppose that “straight angle” and “obtuse angle” are respectively the best and the second response for both left and right horizontal parts; the set of rules verifies whether the left and right recognised features are: almost at the same height; almost aligned with the top; symmetric with respect to the top. If the “straight angle” responses do not satisfy these conditions while the “obtuse angle” responses do, the system selects the “obtuse angle” ones as possible responses because they are geometrically “coherent”.

The second set of rules implements an abduction-prediction-test cycle [14]. From the ordered list of responses of the top feature, the first response is selected to start the cycle. The system abduces the possible portal shapes (hypotheses) by looking at the shape of the top feature. Given these hypotheses on overall portal shapes, the system predicts which shapes of horizontal features are to be detected if those hypotheses are correct, and activates the appropriate discriminators. If one of these horizontal features is detected (test), one of the abduced hypotheses will be ranked higher than the other ones and subjected to further scrutiny: the system activates the relevant discriminator to test again the soundness of that hypothesis with respect to the vertical features.

Figure 4 shows the abduction-prediction-test cycle for linear portals. The letters denote the class a linear portal belongs to, while the numbers are associated to the possible geometric features. Once the cycle ends, the third set of rules enables one to infer the portal shape from the recognised features. For instance, the rule for the round arch (*tuttosesto*) has the following structure: 'the portal is a *tuttosesto* arch if the top is part of a circle (as in 3 of fig. 3) and the vertical features are as in 5 of fig. 3. By tracing its reasoning, the system is capable of offering an explanation for its choices: it justifies why a given portal shape was recognised and the other possibilities were rejected.

Figure 4

To sum up, the first set of rules in the symbolic module evaluates the discriminator responses, the second one selects and tests hypotheses on portal shapes, while the third one arrives at a final classification, if any.

Figure 5

One of the most interesting properties of the system is "rapid learning" [15]. Suppose one wants to train the system in recognising a new class of portal shapes, for instance the one shown in figure 5. Then a new discriminator is to be trained to recognise the new element, and a new composition rule is to be added to the third set of rules. The system now is ready to recognise the new portal shape.

3.3 Results

Some results obtained with the system are reported here. Three different examples have been chosen in order to highlight significant aspects of the system behaviour.

In addition to the symbolic explanation that the system offers after having recognised a portal shape, it also outputs a graphical reconstruction of that shape. The colours of the graphical output indicate: black, maximum response and confidence; blue, maximum response; red, maximum confidence; yellow, neither the response nor the confidence is maximum; gray, negative confidence.

Figure 6

As shown in figure 6, the system reconstructed the right portal shape (*architrave*) using black features.

Figure 7

$|l|l|l|l|l|l|l|l|l|l|\_|10\mathbf{GeometricFeatures}|\_|2Top|4Horizontal|4Vertical|\_|"|2Left|2Right|2Left|2Righ$

Table 1 - Discriminator responses

Given the photograph in the left hand side of figure 7, the system recognised the right portal shape (*policentrico*) after some iterations of the abduction-prediction-test cycle. The system reasoned in the following way: it classified the top geometric feature as linear (see table 1) and selected $\{b, c, d\}$ (see figure 1) as the set of possible portal shapes; this set is reduced to $\{c\}$ after the system classified both horizontal geometric features as round angles. Being $\{c\}$ the only surviving hypothesis to be tested, the system analysed the discriminator responses on vertical geometric features. The highest discriminator response (black) is given on the left geometric feature 4, but the corresponding right geometric feature is geometrically incoherent (left and right features are not at the same height and not symmetric with respect to the position of the top geometric feature - see figure 7). The second highest response (blue) is given on the right geometric feature 6, however, as for feature 4, it is geometrically incoherent with respect to the left one. The only plausible discriminator responses found by the system are those on feature 5. In fact, they are geometrically coherent with one another and with the same horizontal geometric features. At this point, the system confirmed the hypothesis $\{c\}$, and provided a stepwise justification for its choice.

Figure 8

Given a photograph taken from an unusual angle, the system graphically reconstructed the right shape of the portal but was unable to classify it because of the geometric incoherence of the geometric features.

This example shows that if it were possible to have in the image pre- processing an algorithm capable of discovering the perspective, a set of geometric coherence rules could be adopted in which the perspective direction is taken into account without changing anything else.

4 Conclusion

The system presented here might seem complex, with high computational and design costs. The following figures specify the technical characteristics of the system:

- 10 second training time;
- ~30 production rules;
- 20.1 Kb of memory for the discriminators.

These figures summarise the system complexity and show that the approach is practically interesting. With a small amount of memory and production rules very good results are obtained, which seem to go beyond the current powers of purely neural or purely symbolic systems.

Adopting hybrid systems for problems that might otherwise be hard to solve seems to be a good approach. Furthermore, the right choice of system components and merging of technologies leads to results which are of interest outside software engineering alone.

5 Acknowledgements

I would particularly like to thank Guglielmo Tamburrini, who initially encouraged me to pursue the ideas presented in this paper, and who provided momentum to me when I was flagging.

6 References

[1] Lehnert W.G., "Symbolic/Subsymbolic sentence analysis: exploiting the best of two worlds", *Advances in connectionist and neural computation theory, 1, High-level connectionist models*, Eds. Barnden J.A., Pollack J.B, Ablex Publishing Corporation, Norwood, New Jersey, 1991.

[2] Fu Li-Min, "Integration of neural heuristics into knowledge- based inference", Connection Science, Special issue: *Hybrid systems (symbolic/connectionist)*, 1, n. 3, 325-340, 1989.

[3] Burattini E., Tamburrini G., "Purely Neural, Rule-Based Diagnostic Systems. Part I: Production Rules", 735-750, "Purely Neural, Rule- Based Diagnostic Systems. Part II: Uncertain Reasoning", 751-769, *International Journal of Intelligent Systems*, Vol.10, N.8, Wiley ed., 1995.

[4] Lima, P.M.V., "Resolution-based inference with artificial neural networks", *Workshop on Logic and Reasoning with Neural Networks, International Conference on Logic Programming*, Santa Margherita, Italy, 1994

[5] Sun R., *Integrating Rules and Connectionism for Robust Commonsense Reasoning*, John Wileay, New York, 1994.

[6] Rose D.E, "Appropriate uses of hybrid systems", *Connectionist models, Proc. of the 1990 Summer School,* Eds. Touretzky D.S., Elman J.L., Sejnoski T.J., Hinton G.E., Morgan Kaufmann Publishers Inc., 277- 286.

[7] Hilario M., "An overview of strategies for neurosymbolic integration", *Connectionist-Symbolic integration: from unifies to hybrid approaches,* Working Notes, IJCAI '95, Montral, 19-20 August, 1995.

[8] Burattini E., De Gregorio M., Pagano M., "An Expert System for the Diagnosis of Building Statical Wearout", *The World Congress on Expert Systems,* 16-19 December 1991, Orlando, Florida, U.S.A., 1941-1949.

[9] Burattini E., De Gregorio M., Montuori A., "A Model of Symbolic Probabilistic Evaluation, with an Application", *14th IMACS - World Congress on Computational and Applied Mathematics,* Atlanta, Georgia, USA, July., 11-15, 545-553, 1994.

[10] Burattini E., Fiengo G., Guerriero L., "Expert Systems in the Building Conservation Process", in *Intelligenza Artificiale e Recupero Edilizio,* Ed. Burattini E., Istituto di Cibernetica - C.N.R., 99-108, 1994.

[11] Aleksander I., Morton E., *An introduction to neural computing,* Chapman & Hall, 1990.

[12] Aleksander I., "Neural system engineering: towards a unified design discipline?", *IEE Compl. & Cont. J.,* 1, 259-265, 1990.

[13] De Gregorio M., "Experiments with Wisard-like systems in visual data acquisition", *Tech. Rep.,* Istituto di Cibernetica C.N.R., Arco Felice (Napoli).

[14] Burattini E., De Gregorio M., "Qualitative Abduction and Prediction; Regularities over Various Expert Domains", *Information and Decision Technologies*, 19, 471-481, 1994.

[15] Barnden J.A., Pollack J.B., "Introduction: Problems for High- Level Connectionism", *Advances in connectionist and neural computation theory, 1, High-level connectionist models,* Eds. Barnden J.A., Pollack J.B, Ablex Publishing Corporation, Norwood, New Jersey, 1991.