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Is that Portal Gothic?
A Hybrid System for Recognising Architectural Portal Shapes

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Abstract
The hybrid system described here gives an idea as to improve both neural network and symbolic reasoning performances on a recognition task, and suggests a more general approach to integrating a neural network system and symbolic reasoning.

1 Introduction

The system presented here evolved from experiments on classification of portal shapes (fig. 1) in old Italian buildings by a multi-discriminator weightless neural system [1][2]. The results obtained by a training on actual photographs of portals were not encouraging, since the multi-discriminator system could not adequately carry out the classification task [3]. The following interpretation of these experiments naturally suggested 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. In fact, the multi-discriminator system did recognise pictures representing *a* or *b*-shaped portals, but failed on items belonging to the other classes. In figure 2 the differences between some classes of portal shapes are reported. One can notice that the differences between *a*- and *b*-shaped portals are quite significant for the recognition process, while the differences between *c*- and *d*-, and between *e*- and *f*-shaped portal are not.

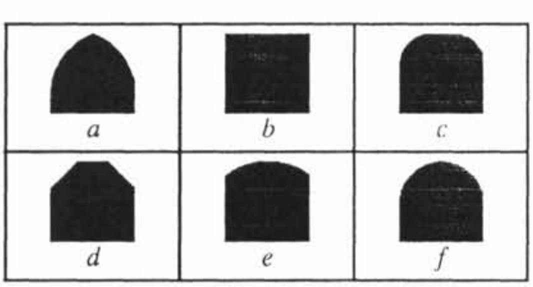

Figure 1 - *Portal shapes*

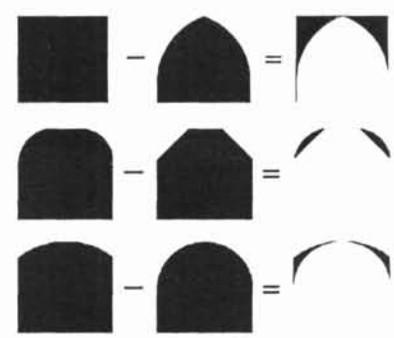

Figure 2

It seems that *reasoning* about local geometrical features can play an essential role in a successful completion of this task. 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. 3a) and secondly by putting together these features (fig. 3b) – a reasonable strategy is to combine a neural network for recognising the geometric features from portal contours and a set of production rules specialised in assembling these features.

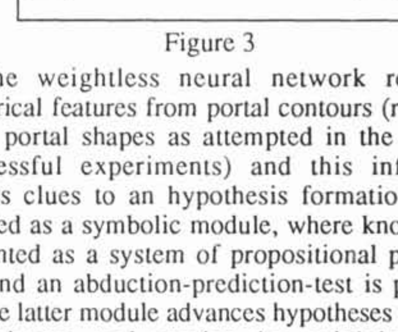

Figure 3

The weightless neural network recognises geometrical features from portal contours (rather than overall portal shapes as attempted in the previous, unsuccessful experiments) and this information provides clues to an hypothesis formation module (specified as a symbolic module, where knowledge is represented as a system of propositional production rules, and an abduction-prediction-test is performed [4]). The latter module advances hypotheses on overall portal shapes, and queries the weightless neural

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network for more information on geometrical features of portal contours in order to test these hypotheses. The process terminates with the selection of an hypothesis on the shape of the portal in input, when the system acquires sufficient confidence in that hypothesis, after one or more runs of the abduction-prediction-test cycle.

2 The Hybrid System

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 4. 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 geometric features of the portal (4, 5, 6).

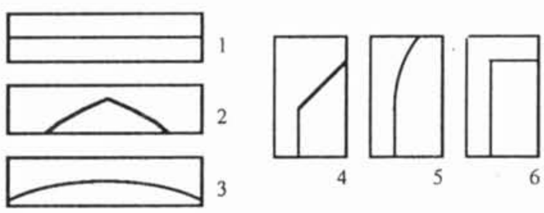

Figure 4

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. Furthermore, no thresholds are needed to evaluate the discriminator responses. The symbolic module takes into account any response and evaluates it on the basis of geometric "coherence" and plausible portal shape considerations. In fact, even if the responses are very low or close to each other, they may still contain useful information for the recognition process carried out by the symbolic module. (This situation is highlighted by the example reported in figure 6. From the results listed in table 1 one can notice that the left vertical geometric feature 5 is the lowest ranked, nevertheless the system takes it into account both on the basis of geometric "coherence" and because a plausible portal shape can be selected.)

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, part of these rules enables the system to check whether the horizontal geometric features are, on the whole, at the same height, centred with respect to the top geometric feature, etc.

The second set of rules implements an abduction-prediction-test cycle [4]. 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 horizontal features are to be detected if those hypotheses are correct, and activates the appropriate discriminators. According to which horizontal features are actually detected, 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 5 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 the system to infer the portal shape from the recognised features. For instance,

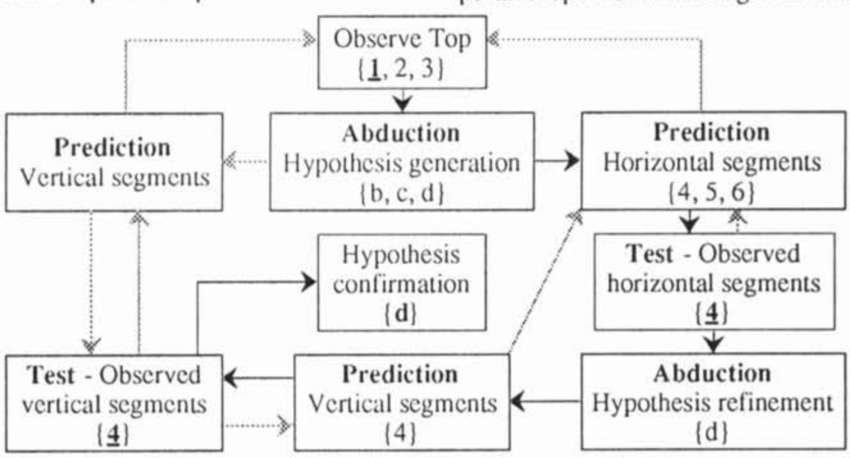

Figure 5 - *Black lines indicate the reasoning carried out by the system when either hypotheses on portal shapes are confirmed or "coherence" between geometric features is detected. Gray lines indicate failures in detecting either the predicted geometric features or the "coherence" between the observed geometric features. An example of the system reasoning is given by the numbers and the letters.*

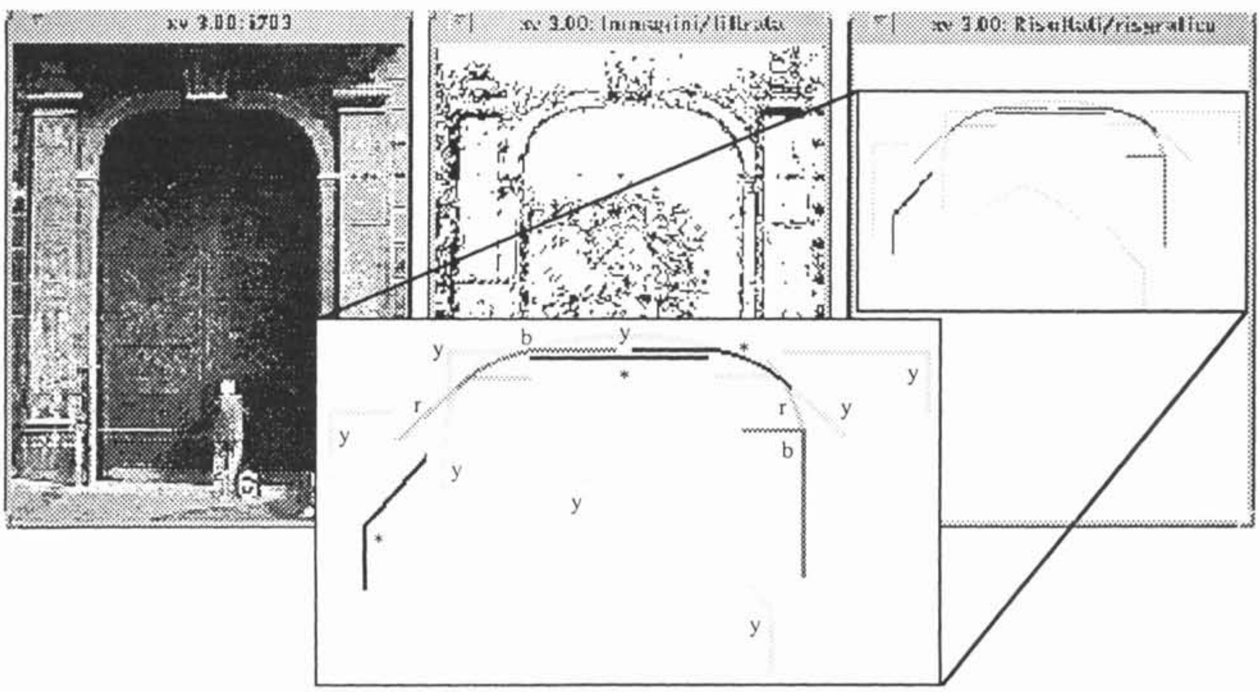

Figure 6 - * - *black*, *b* - *blue*, *r* - *red*, *y* - *yellow*

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. 4) and the vertical features are as in 5 of fig. 4. By tracing this sort of stepwise hypothetical 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.

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.

It is worth emphasising that there is a sustained interaction between the two modules (neural and symbolic) in terms of both information passing and behaviour modification. According to the hybrid system classification given by Hilario [5], "the best of both worlds" [6] is obtained by those systems in which the artificial neural network and symbolic modules are equal partners in problem-solving processes (*coprocessing functional hybrid systems*). The hybrid system presented here belongs to this class.

3 An Example

Some results obtained with the system are reported in [7]. The following example highlights 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 graphic reconstruction of that shape. The colours of the graphic output indicate: ***black***, maximum response and confidence; ***blue***, maximum response; ***red***, maximum confidence; ***yellow***, neither the response nor the confidence are maximum; ***gray***, negative confidence.

Given the photograph in the left part of figure 6, the system recognised the right portal shape (*policentrico*) after some iterations of the abduction-prediction-test cycle (looking at the darkest geometric features in figure 6 or at the first row of table 1, one can notice that by means of the neural network only, the system fails to reconstructing the portal shape).

Geometric features				
Top	Horizontal		Vertical	
	Left	Right	Left	Right
1 black	5 blue	5 black	4 black	6 blue
3 yellow	4 red	4 yellow	6 yellow	5 red
2 yellow	6 yellow	6 yellow	5 yellow	4 yellow

*The numbers denote the possible geometric features (see fig. 3), and the colours the values of the discriminator responses.

Table 1 - *Discriminator responses*

The system proceeded 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 6). The second highest response (blue) is given on the right geometric feature 6; however, as was already detected for feature 4, it turns out that feature 6 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.

4 Conclusion

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, ~7 seconds from the input to the output on a Sparc 20. These figures give a good idea of 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.

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