Intermediate Features Improve Incremental Analogical Mapping

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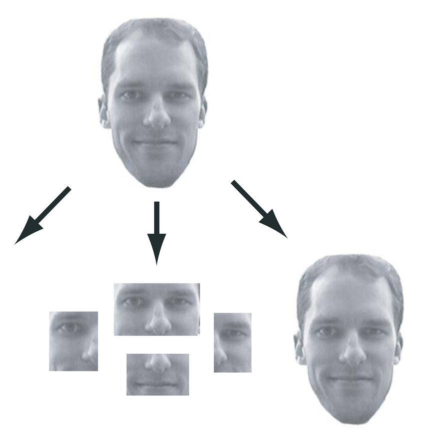
Intermediate Features

(Ullman *et al*, 2002)

Suppose that you want to identify an image such as a face by comparing it with a database of pre-classified images. Ullman's strategy was to break the image into subimages (*features*) of different sizes and see how often you find those subimages in a particular class.

Breaking an image into features of small (left), intermediate (middle) and large (right) sizes.



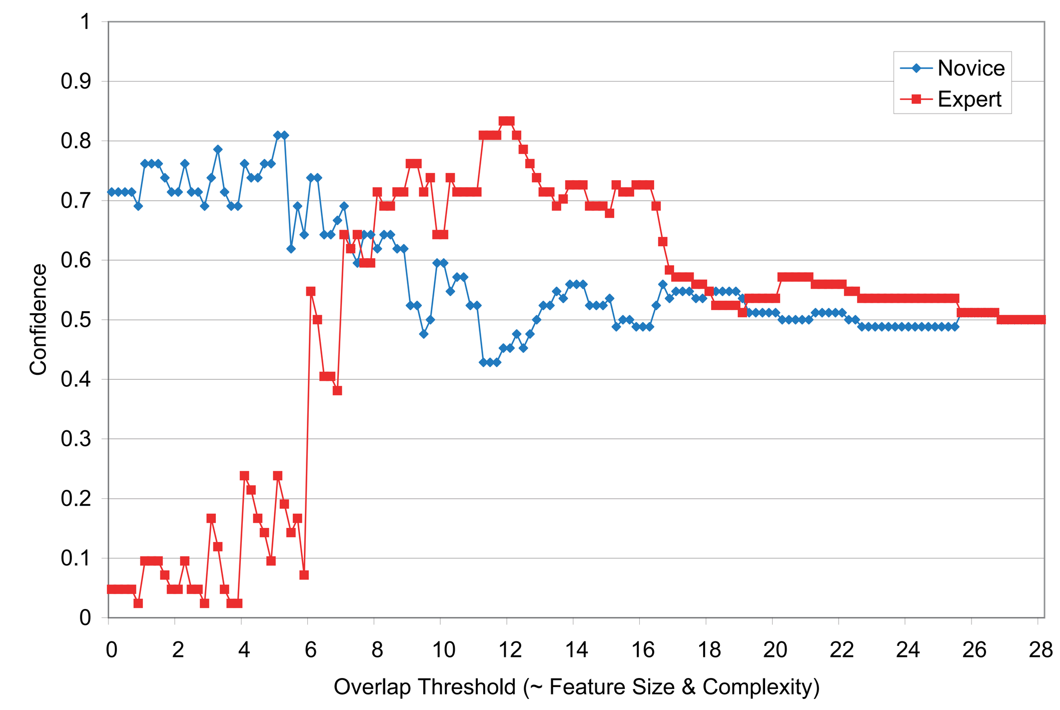
Ullman discovered that small features are found in nearly all images, regardless of class. Large features, on the other hand, are rarely found even in a set of pictures of the same class. The most informative features, those found most often in pictures of the same class, are those of intermediate size and complexity.

In other words, small features are too general, and large features are too specific. What best identifies an image within a class are features of an intermediate size and complexity.

Intermediate Features are Useful in Symbolic Processing

(Finlayson & Winston, 2005)

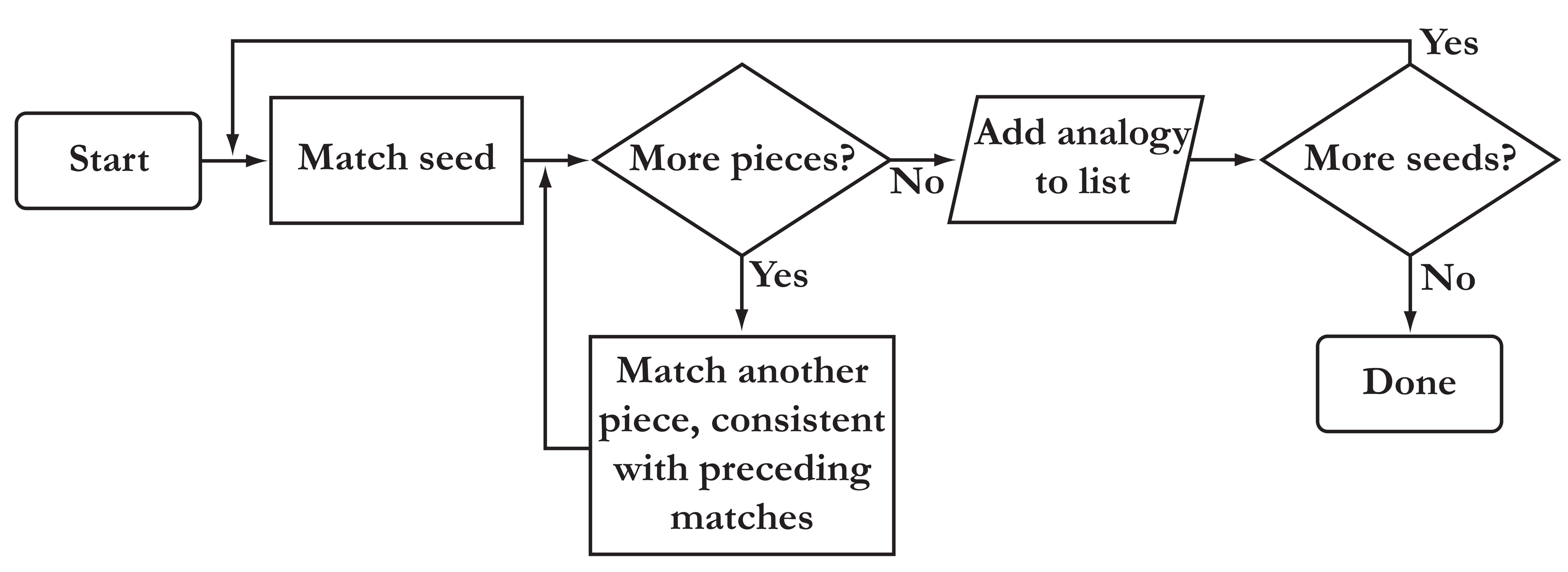
We demonstrated the utility of intermediate features in the symbolic domain by showing that they facilitate the retrieval of analogs. The graph below shows how well retrieval matches both novice-like and expert-like behavior at various average feature sizes. When features of an intermediate size are used, the behavior of the retrieval algorithm is most like that of experts.



From (Finlayson & Winston, 2005), which shows that when features of an intermediate size and complexity are used, retrieval is most expert-like.

Bridge Incremental Analogizer

Incremental mappers differ from 'single-shot' analogical mappers in that they attempt to quickly narrow the possible field of analogies and produce the best analogies first, rather produce many (or all) analogies in parallel. Algorithmically, incremental mappers can be seen as producing a list of analogies as their output, with analogies deemed best produced earlier, and analogies deemed poorer produced later. A generic incremental algorithm is shown below.



This generic incremental matching algorithm has a number of free parameters. To construct our Intermediate-Features-based mapper, which we call the *Bridge Incremental Analogizer*, or BIA, we made the following choices for those free parameters within a general implementation of an incremental matching algorithm, based closely on Keane's 1994 implementation of IAM:

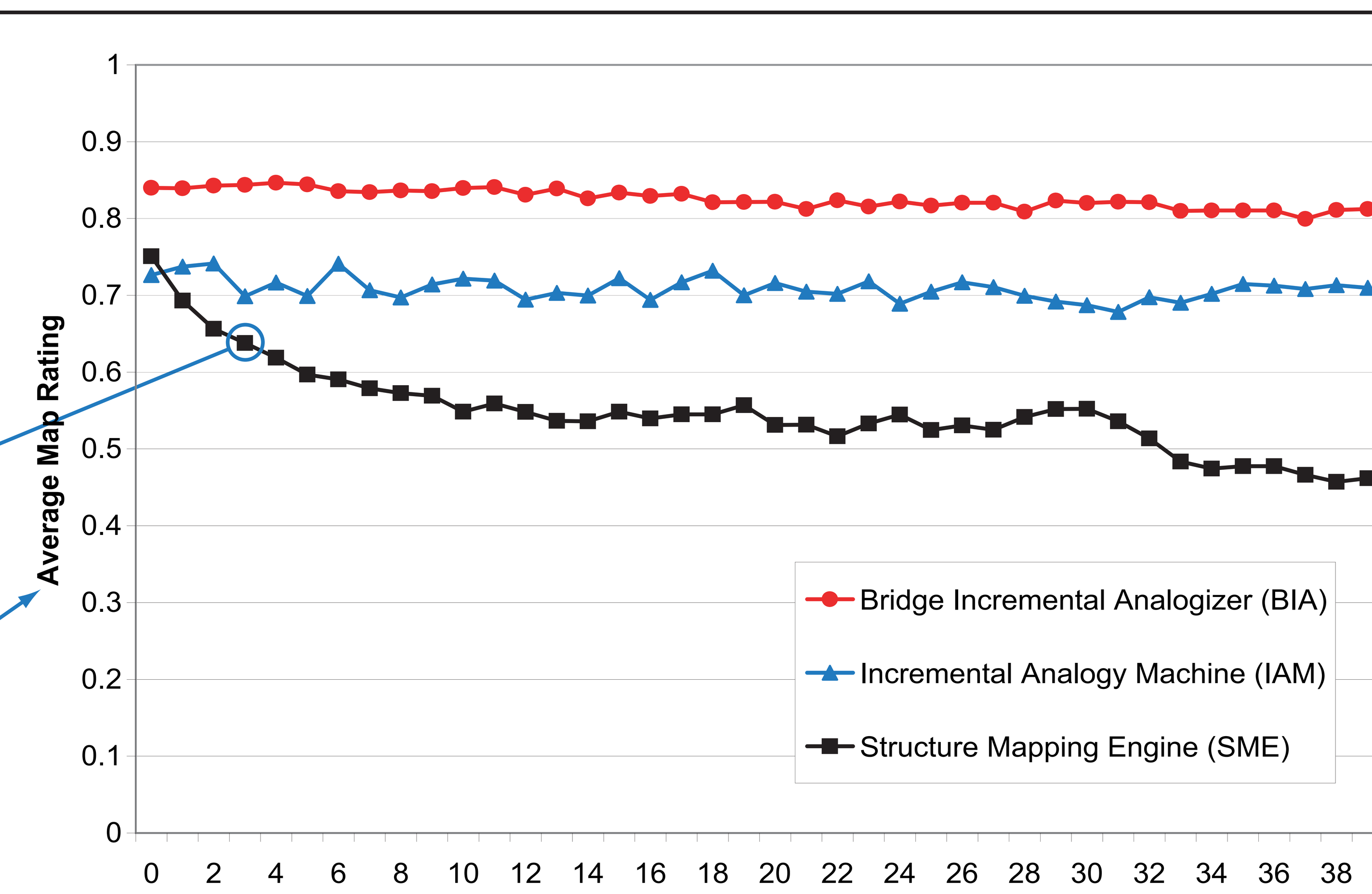
Free Parameter	BIA Implementation
Piece Definition	A piece is a node in the symbolic description and all of its children
Choice of Initial Matches (seed)	A set of assignments of intermediate features to intermediate features
Piece Preference Order	Rank according to estimated mutual information

Results

We implemented both the SME and IAM incremental analogical mappers from their descriptions in the literature (Falkenhainer *et al.*, 1989; Keane *et al.*, 1994). To produce the comparison we used a dataset of our own construction that consists of 14 descriptions of international and civil conflicts. As can be seen, the BIA performs on average much better than SME or IAM.

Each mapper was run with all description pairs (except self-self pairs), for 14x13=182 analogies per datapoint.

Each analogy was scored using a standardized rating method (Falkenhainer *et al.*, 1989) and the results were normalized against the highest-rated analogy for each index from all three queues.



Comparison of the first forty analogies produce by BIA, IAM, and SME, averaged and normalized for 182 analogies.

References

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Acknowledgements

This work is supported in part by the National Science Foundation under Grant Numbers 0218861 and IIS-0413206.

27th Annual Meeting of the Cognitive Science Society; July 2005; Stresa, Italy

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