Using Labeling RAAM to Encode Medical Conceptual Graphs

M. de Gerlache†, A. Sperduti‡, A. Starita‡

† V.U.B., Prog Lab

Pleinlaan 2, 1050 Brussels, Belgium

‡ Department of Computer Science, University of Pisa

Corso Italia 40, 56125 Pisa, Italy

Abstract

We present a neural network based approach to the extraction of information from a medical database. Medical concepts are encoded by using *conceptual graphs*, which have been demonstrated useful for this purpose. The medical conceptual graphs are encoded into a paticular neural network architecture, i.e., the Labeling RAAM, which allows the processing of structures both using pointers (reduced descriptors) and by content. Associative *queries* to the database are implemented by Generalized Hopfield Networks, which are generated 'on the fly' by opportunely composing the weights of the LRAAM. Complex concepts are retrieved starting from basic or partial concepts conveyed by medical sentences.

Introduction

The automatic recognition of the meaning of medical texts still constitutes an unreached goal for computers. This capability, however, is strongly recommanded in order to allow automatic processing of medical texts. A first step towards this goal consists in the formalization of the concepts contained in medical texts and in defining some basic automatic procedures for their processing. The conceptual graph formalism developed by Sowa [5] is a knowledge representation language initially designed to capture the meaning of natural language, and subsequently used by several authors [1, 10, 2] to formalize medical sentences.

This paper explains how to encode in a neural network conceptual graphs describing medical concepts and how to retrieve them by using partial information. The encoding is possible because a conceptual graph (CG) is the description of a composite structure and in [6, 8] it is demonstrated that structures can be learned and retrieved by a particular neural network model named Labeling RAAM. A concrete application of the approach we propose in this paper is the search for complex concepts (stored in a large conceptual graphs database) starting from sentences containing specific or partial concepts. As result the system we propose returns the composite structures (complex concepts) containing these specific or partial concepts.

In the next section we explain the idea underlying conceptual graphs. Then, we briefly expose the access by content capabilities of the LRAAM and we introduce the

Generalized Hopfield Networks derived from the LRAAM. Eventually, we explain the link between CG's and LRAAM's information handling. A discussion on the impact of the proposed approach on knowledge extraction from a database of conceptual graphs is given in the conclusion.

Conceptual Graphs

By definition a conceptual graph CG is a finite, connected and bipartite graph. It consists of two kinds of nodes : concepts and conceptual relations. Concepts refer to discrete units of perception and are connected by conceptual relations. Each conceptual relation has n arcs (≥ 1) each of which must be linked to some concept. The meaning of a subgraph with a concept c1 that is linked by a conceptual relation r to a concept c2 is "the r of c1 is c2". Concepts and relations are typed, i.e. there is a function type that maps concepts and conceptual relations to type labels. Thus, for example, the concepts x and y are of the same type if type(x) = type(y). For any concept c and any conceptual relation r, type(c) is different from type(r). A type label may be specified or unspecified. A specific type label refers to a certain individual, an unspecified type label to a variable individual. In our medical medical CG's database, examples of concepts are: a body localization, a symptom, a point of time, a location, a diagnosis, a patient's state, an organ. Relations are the expressions of different types of links between concepts : causality of events, position in time, active or passive partnership, miscellaneous modalitites. The conceptual graph of the sentence 'The physician has shown by laryngo-fibroscopy a paralysis of the left vocal cord' is represented, in linear form, as:

```
[HUMAN-PROCESS: statement]
  → (AGENT) → [ACTOR: physician]
  → (ORIGIN) → [TEST_PROC: fibroscopy]
                  → (THEME)→ [BODY_PART: larynx]
  → (THEME) → [DISEASE: paralysis]
                  → (LOC) → [BODY_PART: vocal_cord]
                                 → (PREC) → [REGION: left]
```

Associative Data Access by Labeling RAAM

The Labeling RAAM is an extension of the Recursive Auto-Associative Memory (RAAM) by Pollack [4] which allows one to encode labeled graphs with cycles by using a variant of the Back-Propagation algorithm. The result of the encoding is that each graph represented in the training set is represented by a fixed size pattern, independently of the size of the graph. In this way it is possible to apply neural networks to structured domains, since a structure can be represented by a fixed size pattern.

In Figure 1 we have summarized some of the concepts underpinning the access by content capabilities of LRAAM. At the top of the picture, an LRAAM network with one label and two reduced descriptor fields is shown. The set of connections from the input to the hidden layer of the network implements an encoder which is able to devise a reduced descriptor of the structured pattern presented in input to the network. Since the size of a reduced descriptor is equal to the size of the reduced descriptor fields in input, reduced descriptors can be used recursively to encode complex

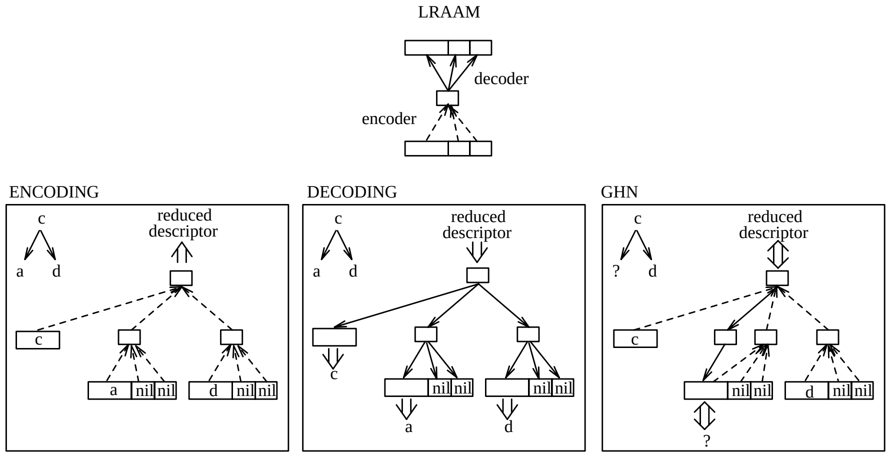

Figure 1: **Bottom left and center:** encoding and decoding of a small labeled tree using an LRAAM (top); **bottom right:** the GHN network for a partially defined tree.

structures. An example of encoding is given at the bottom left of the picture, where we have explicited the encoding process for a small tree. The information contained into a reduced descriptor can be accessed by using the decoder function implemented by the set of weights from the hidden to the output layer of the LRAAM. At the bottom center of the picture, the decoding process of the reduced descriptor devised by the encoding of the small tree is shown. Both the encoding and decoding processes are well defined only if the whole structure or a well formed reduced descriptor are given to them, respectively. If only partial information on the structure is available, then a recurrent network cyclically interleaving the encoding and decoding processes can be used to retrieve the missing information. An example of this network, that we call Generalized Hopfield Network (GHN), is given at the bottom right of the picture. A random pattern is used to initialize the field(s) for which no information is available and the network left free to relax on a stable state. A stable state represents a valid solution only if its reduced descriptor is well formed, i.e., if the decoding process applied to the reduced descriptor is consistent with the known information. In this example, the partially defined structure constitutes a *query* and each field for which no information is available can be considered as a variable of the query. We omit other implementational details which can be found in [6]. It is sufficient to point out that variables can appear not only in label fields, but also in reduced descriptor fields, i.e., the query may have a reduced descriptor field which can be instantiated either to a non-void reduced descriptor or to a void descriptor.

The access by content capability of the LRAAM can help to retrieving a fully defined conceptual graph (*context*) from a partial defined conceptual graph (*sentence*). At each query corresponds a different GHN which is built on the fly by composing the components of an LRAAM according to the topology of the query. This capability is particularly important in view of its application to a medical knowledge base of conceptual graphs.

CGs Implemented by LRAAM

In this section, we discuss how a conceptual graph is encoded in the LRAAM, how a database of conceptual graphs is represented by a single LRAAM, and finally how to build a GHN implementing a query to the database.

HUMAN_PROCESS	AG	OR	TH	Point. ACTOR	Point. TEST_PROC	Point. DISEASE

```
[HUMAN_PROCESS: statement]
   -> (AGENT) -> [ACTOR: physician]
   -> (ORIGIN) -> [TEST_PROC: fibroscopy]
                        -> (THEME) -> [BODY_PART: larynx]
   -> (THEME) -> [DISEASE: paralysis]
                        -> (LOC) -> [BODY_PART: vocal_cord]
                                    -> (PREC) -> [REGION: left]
```

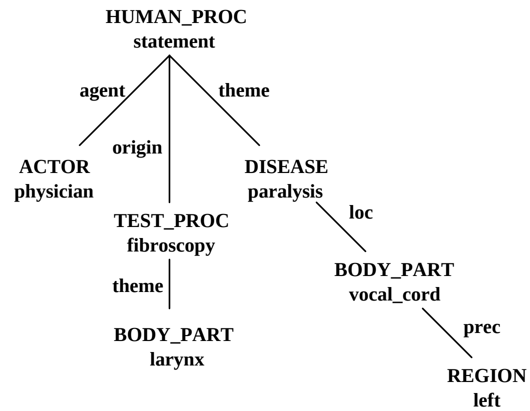

Figure 2: Input codification scheme (top side) of the root of the CG represented at the bottom of the picture both in linear form and in graphical form.

Medical CG Codification

In order to assess the applicability of the LRAAM model for encoding medical conceptual graphs, we used a database of 124 medical concepts represented as conceptual graphs. The conceptual graphs constituting the database were provided by the program developed for the AIM project "Helios" by the group of R. Baud (Geneva Hospital). Each graph has nodes with at most three outgoing arcs (relations). Both the name associated to each node and the name of the relations associated to the outgoing arcs are encoded in the label field of the LRAAM, as shown at the top of Figure 2, where the codification of the first component of the conceptual graph, represented both in linear and in graphical form at the bottom of the picture, is shown. The last tree fields are used to store the reduced descriptors corresponding to relations. The order in which the reduced descriptors are stored corresponds to the order in which the names of relations are represented in the label.

Our database was encoded by an LRAAM using symmetric sigmoids (the input was codified using bipolar values, i.e., -1 and 1), 30 units for representing the concept's name, 5 units for each relation and 35 units for each reduced descriptor field. The concepts' names where encoded by using the ICD-9 code system when a code for the name was available, otherwise we generated a new code. The LRAAM was trained with learning rate equal to 0.5 and momentum equal to 0.3 and it was stopped after 14810, when the error obtained on the labels by the decoding process was below 0.15.

Similar CGs Get Similar Reduced Descriptors

One nice property of the representations devised by an LRAAM is that reduced descriptors of similar structures are very similar. This means that similar concepts get similar reduced descriptors. We have verified this property by computing a hierarchical clustering of the reduced representations devised by the LRAAM used to encode the database. The hierarchical clustering algorithm computes the closest pair of patterns in euclidean metric and replaces the patterns belonging to the pair with a single pattern obtained by computing the mean of the pair. The algorithm is then applied recursively on the remaining patterns, including the new computed one, till only one pattern is

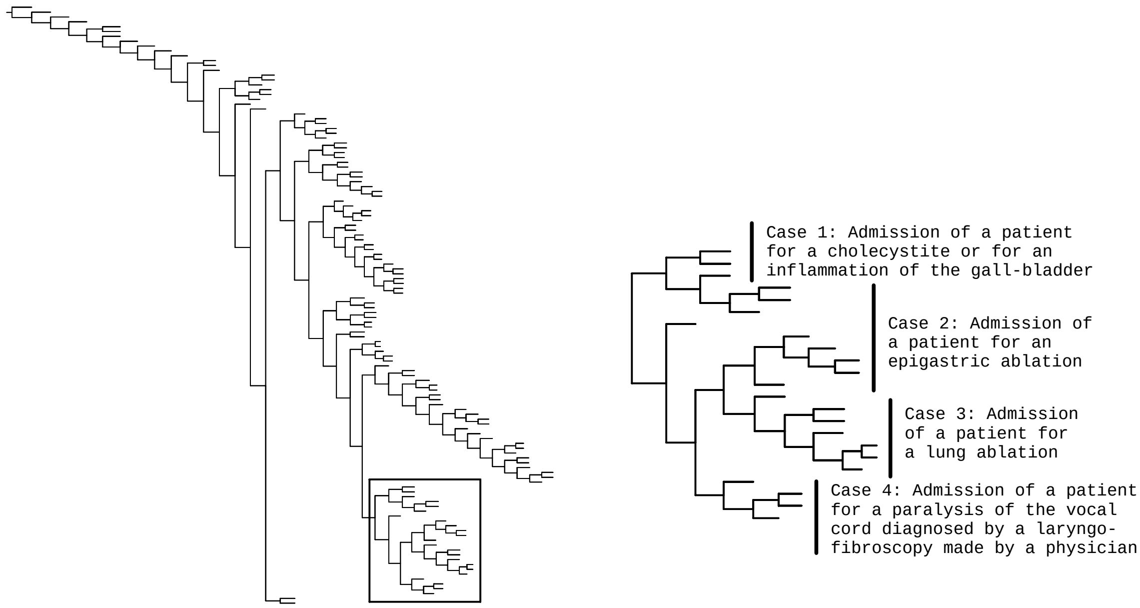

Figure 3: Hierarchical clustering of the reduced descriptors devised by the LRAAM used to encode the database.

left. Simultaneously, the algorithm builds a tree, where each node corresponds to a pattern (original or computed) discarded by the set of patterns during processing. When computing a mean pattern, the patterns used to compute it are considered as sons of the new generated pattern. Consequently, the result of the procedure is a tree which roughly represents how the original patterns are spatially related. Note that the leaves of the tree correspond to reduced descriptors, while internal nodes represent spatial relationships among reduced descriptors.

In Figure 3, we have reported the tree obtained by the hierarchical clustering algorithm (left side). An enlarged view of the boxed area is shown on the right side of the picture together with an explanation of the kind of concepts encoded by each subset of reduced descriptors. It can be noted that related concepts get related reduced descriptors. This does not mean that the GHNs have the guarantee to work properly. It only means that the network has deviced meaningful reduced representations for the conceptual graphs.

Concepts Retrieval

The retrieval of complex concepts is based on incremental queries on the database, starting from basic concepts extracted from one or more sentences. For example, when considering a sentence involving a paralysis of the vocal cord, the following linguistic query can be asked:

"Give me all the concepts speaking about paralysis of the vocal cord."

The partial concept represented by this query is shown at the top of Figure 4. The question marks represent information which has not been specified. The information which is not defined can involve both concepts' names and relations' names.

The corresponding GHN is shown at the bottom of the same figure. It must be

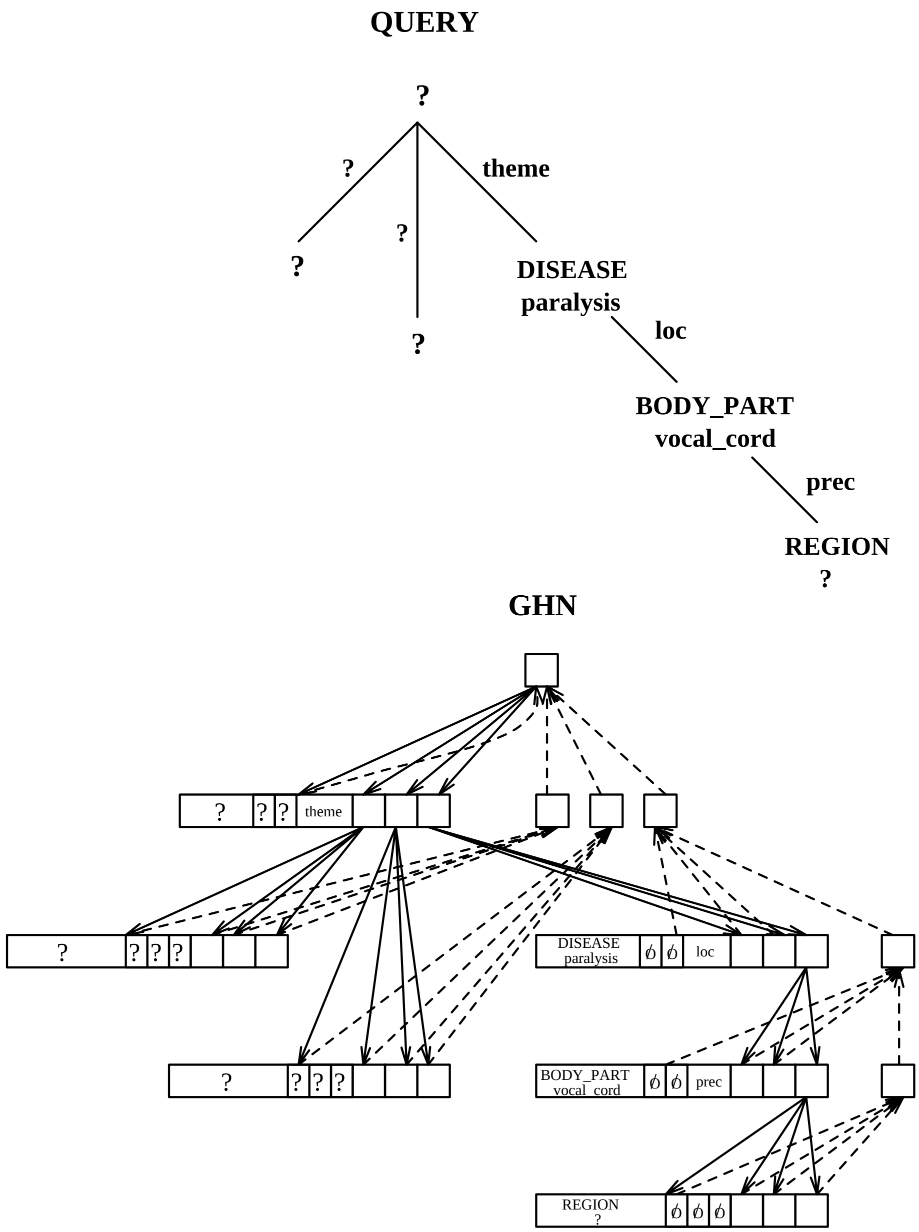

Figure 4: The GHN implementing the partial query given on the top of the picture. The question marks represent information which has not been specified.

noted that known information includes also the presence of void relations, as shown in the figure by the symbol "$\emptyset$".

The network is initialized with a random activity pattern at the top layer and left to converge to a stable state. Different solutions to the query are recalled according on how the top layer is initialized. An exaustive search for all the solutions to the query can be implemented by 'deleting' known solutions by using *terminal repellers* [11], however, this approach presents some technical problems and here we do not have space to discuss them. The interested reader can find further details in [9].

It must be pointed out that the learning algorithm for the LRAAM does not give any guarantee that each solution to a query will be an asymptotical stable state of the corresponding GHN. In practice, the probability that all the solutions are asymptotical stable states of the network is almost always 1, provided that the LRAAM is trained enough. A more serious problem is, instead, given by the difficulty to encode a very large amount of conceptual graphs into a single LRAAM. We are currently investigating a modular system [7] in order to overcome this problem.

Conclusion

In this paper, we have presented a neural network based approach for knowledge extraction from a database of medical conceptual graphs, starting from incomplete information conveyed by medical stentences. In fact, given a database of instantiated conceptual graphs encoded in an LRAAM, the technique discussed in the paper allows one to build, in real time, a GHN for each type of query the database can support by composing opportunely the weights of the LRAAM. Obviously, our proposal need to be refined in order to obtain a fully automated system. One approach we are exploring consists in the automatic generation of a set of very basic queries starting from single worlds in a sentence and subsequent synthesis of new queries by filtering the results of the previous query stage.

In conclusion, it seems appealing to encode conceptual graphs in an LRAAM, since both standard inference techniques and associative access can, in principle, be performed. Moreover, the kind of distributed representations obtained using an LRAAM are suited to be processed also by networks of different type, such as multilayer perceptrons. Multilayer perceptrons can be used to recognize conceptual graphs belonging to the same class. Different classification tasks can be defined according to the application in consideration. Learning in a multilayer perceptron can also be performed simultaneously with learning in the LRAAM model. In this way, the reduced representations of the conceptual graphs will be embedded in a metric which conforms with the particular classification task implemented by the multilayer perceptron, i.e., conceptual graphs which must be classified in the same way will get very similar reduced descriptors. Multilayer perceptrons in the context of conceptual graphs, but in a more conventional framework, has been proposed by Len daris (see, for example [3]). Moreover, the speed of processing can be potentially improved since the GHN will allows also the exploitation of analog hardware when it will be available.

References

[1] R. Baud, A. Rassinoux, and J. Scherrer. Natural language processing and semantical representation of medical texts. *Methods of Information in Medicine*, 31:117–125, 1992.

[2] J. Bernauer. Conceptual graphs as an operational model for descriptive findings. In *Proc. of Symposium on Computer Applications in Medical Care*. McGraw-Hill, 1991.

[3] G. G. Lendaris. Conceptual graph knowledge systems as problem context for neural networks. In *IEEE Second International Conference on Neural Networks*, pages 133–140, 1988.

[4] J. B. Pollack. Recursive distributed representations. *Artificial Intelligence*, 46(1-2):77–106, 1990.

[5] J.F. Sowa. *Conceptual Structures: Information Processing in Mind and Machine*. Addison-Wesley, 1984.

[6] A. Sperduti. Labeling RAAM. Technical Report 93-029, International Computer Science Institute, 1993.

[7] A. Sperduti. *Optimization and Functional Reduced Descriptors in Neural Networks*. PhD thesis, Computer Science Department, University of Pisa, Italy, 1993. TD-22/93.

[8] A. Sperduti. Encoding of Labeled Graphs by Labeling RAAM. In *Neural Information Processing Systems*, 1994. To appear.

[9] A. Sperduti and A. Starita. A Memory Model Based on LRAAM for Associative Access of Structures. In *Neural Information Processing Systems 7*, 1994. Submitted.

[10] F. Volot, P. Zweigenbaum, B. Bachimont, M. Ben Said, J. Bouaud, M. Fieschi, and J-F. Boisvieux. Structuration and acquisition of medical knowledge : Using ulms in the conceptual graphs formalism. In *Proc. of Symposium on Computer Applications in Medical Care*. McGraw-Hill, 1993.

[11] M. Zak. Terminal attractors in neural networks. *Neural Networks*, 2:259–274, 1989.