WEED IDENTIFICATION USING A PICTURE-BASED HIERARCHICcAL CLASSIFICATION SYSTEM[1]

Urs Schulthess, Rick Ward, Joe Ritchie
Crop and Soil Sciences Department
Michigan State University
East Lansing, MI 48824
urs@psssun.pss.msu.edu
22857MGR@msu.edu
Rhines%Staff%CSSDept@banyan.cl.msu.edu

Kris Schroeder, Ahmed Kamel, Jon Sticklen
Intelligent Systems Laboratory
Computer Science Department
Michigan State University
East Lansing, MI 48824, USA
schroede@cps.msu.edu
kamela@cps.msu.edu
sticklen@cps.msu.edu

A. Salah & A. Rafea
Central Lab for Agricultural Expert Systems
Agriculture Research Center
Ministry of Agriculture and Land Reclamation
Cairo, EGYPT
ESIC%EGFRCUVX.BitNet@pucc.princeton.edu

A. Abd El-Shafy, A. Abd El-Ghani, S. Shaban
Wheat Research Department
Field Crop Research Institute
Agricultural Research Center
Ministry of Agriculture and Land Reclamation
Cairo, EGYPT
ESIC%EGFRCUVX.BitNet@pucc.princeton.edu

ABSTRACT

The goal of our work is to develop a system that will address all aspects of irrigated wheat management in Egypt including pest identification and remediation. In this paper, we present our implementation of an expert system for weed identification. The approach we take to solve the problem of weed identification is based upon the Generic Task Approach to expert systems development pioneered by Chandrasekaran et al.(Chandrasekaran, 1986) and two approaches to weed identification outlined by Hanf (Hanf, 1990) and Behrendt and Hanf (Behrendt & Hanf, 1979). We have identified weed identification as a classification problem. Therefore, Hierarchical Classification (Gomez & Chandrasekaran, 1981) is the individual GT that provides the problem solving template for our weed identification. The computer-based approach enabled us to overcome several shortcomings of traditional, dichotomous keys. Through the use of pictures, we largely avoided technical terms. Furthermore, the system allows for multiple decisions at each level. The system also enables the user to backtrack and revise decisions.

INTRODUCTION

An expert system has been built to assist with managing irrigated wheat in Egypt. The list of potential users includes researchers, government planners and, last but not least, extension agents and farmers. Apart from tillage, water and fertilizer management, weeds and their control have been

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identified as a major problem constraining wheat production in Egypt (El-Marsafy & Hassanein, 1993).

The first step in integrated pest control is the correct identification of the pest and, in the case of weeds, their density, field uniformity, and size. In wheat, chemical and mechanical weed control is possible only until wheat has reached the stem elongation stage (Detroux, 1980). No-till wheat is not common in Egypt for various reasons and weeds are eliminated during seed bed preparation. Therefore, new weeds germinate and emerge at the same time as wheat and they must be identified at the seedling stage. However, traditional taxonomy is mainly based on reproductive structures in conjunction with an exhaustive set of technical terms (Jones & Luchsinger, 1986). Most traditional keys are dichotomous. They present (mostly) two contrasting choices at each step which are indented or yoked. This helps the user to grasp the differences faster. These keys, however, have some disadvantages. Because they are text based, they require many technical terms. Due to their dichotomous nature, they do not allow for multiple choices in case of uncertainty. This can make plant identification a frustrating process, especially since they do not actively support the possibility of backtracking.

Based on work done by Hanf (Hanf, 1990) and Behrendt and Hanf (Behrendt & Hanf, 1979) and using expert systems technology we developed a new, computer-based approach that eliminates the above mentioned disadvantages.

GENERIC TASK APPROACH

The approach we take to solve the problem of weed identification is based upon the Generic Task Approach to expert systems development pioneered by Chandrasekaran et al. (Chandrasekaran, 1986). The assumption of the Generic Task (GT) approach is that knowledge takes different forms depending upon its intended function. The GT approach sets out to identify *generic tasks* — basic combinations of knowledge structures and inference strategies that perform the basic tasks that make up complex problem solving across numerous domains.Once identified, the individual generic tasks (GTs) provide the knowledge organizations and control structures specific to certain *types* of problem solving as depicted in Figure 1.

A number of GTs are currently available to perform knowledge intensive tasks. Among the most relevant in our current research are:

- **Hierarchical Classification and Structured Matching** (Chandrasekaran & al, 1979; Gomez & Chandrasekaran, 1981; Mittal, 1980). Hierarchical classification is intuitively a knowledge organization and control technique for selecting among a number of hierarchically organized options. The abstract engine used for hierarchical classification, known as CSRL, was the first TSA shell and is described in (Bylander & Mittal, 1986).

- **Routine Design** (Brown & Chandrasekaran, 1986; Chandrasekaran, Josephson, Keuneke, & Herman, 1989). Routine Design was proposed by Brown as an architecture for performing design and planning tasks in which substantial experience is available (not for design or planning in totally novel situations).

- **Abductive Assembly** (Josephson, 1987)**.** Abductive Assembly is based upon the abductive reasoning work of Josephson et al. Given a list of findings, the goal of Abductive Assembly is to form a composite hypothesis that will collectively explain the set of findings.
- **Functional Reasoning** (Sembugamoorthy & Chandrasekaran, 1986; Sticklen, Chandrasekaran, & Bond, 1989). Functional reasoning was proposed by Sembugamoorthy and Chandrasekaran initially as a means of capturing the intuition that knowing what a device is used for (i.e., its purposes/functions) yields leverage in understanding the device (Sembugamoorthy & Chandrasekaran, 1986). Later, Sticklen and Chandrasekaran extended functional representational frameworks by adding a qualitative simulation component (Sticklen, et al., 1989).

We have identified the problem of weed identification as a classification problem. Therefore, Hierarchical Classification (Gomez & Chandrasekaran, 1981) is the individual GT which provides the problem solving template for weed identification.

Figure 1: The components of a Generic Task

Hierarchical Classification

Hierarchical Classification (HC) is a knowledge organization and control strategy for selecting among a number of hierarchically organized hypotheses. Figure 1 depicts the components of the Generic Task, Hierarchical Classification. The Information Processing Task (IPT) of HC is to take as input a data description of the problem to be solved, and to produce as output all the classifications which are applicable to the data. Note that only those classifications which have been identified a priori in the hierarchy can be produced by the HC problem solver. In other words, it is not the goal of the HC problem solver to extract new classifications in the domain.

Knowledge Organization

The domain knowledge is organized into a hierarchy such that the most general hypotheses are found higher in the structure, while the most specific hypotheses are found lower in the hierarchy. Thus, the tip-level nodes in the hierarchy represent the most detailed hypotheses (i.e., complete classifications of the input data. Each specialist in the hierarchy is charged with establishing one hypothesis. Therefore, the specialist must contain the knowledge necessary to determine the degree of fit of the hypothesis (in other words, whether to establish the hypothesis or rule it out). The establishment of a hypothesis at a given level is normally accomplished by a set of table matchers that compare textual descriptions of the current case to descriptions of those cases in which the hypothesis is or is not applicable.

Control Strategy

The control strategy used by HC is *establish and refine*. In this method, the hierarchy of hypotheses is explored in a top-down manner by first establishing the top level hypothesis, then refining this hypothesis by asking the immediate subspecialists in the hierarchy to establish themselves. The establish/refine process is repeated at each level until a list of specific hypotheses is established. If a hypothesis is *ruled-out*, then the hypotheses below it in the hierarchy are also ruled-out. This allows a large section of the hierarchy (i.e., hypothesis space) to be pruned, providing a significant computation advantage over searching the entire hypothesis space.

Figure 2: The Components of Hierarchical Classification

Computational Advantages of Hierarchical Classification

The computational advantages of Hierarchical Classification stem from the distribution of domain knowledge throughout the hierarchy and the concentration of specific decision knowledge for each hypothesis at a specialist (Chandrasekaran, 1986). First, by distributing the domain knowledge across the hierarchy, only the relevant portions of the domain knowledge are examined during the establish and refine process. Figure 3 shows the result of a specialist ruling out its associated hypothesis. In this case, the entire subtree of subspecialist is pruned as shown in the figure and is not explored. Additionally, the knowledge a specialist needs to establish or rule-out its hypothesis is concentrated into a knowledge organization at the specialist.When a specialist is called upon to establish itself, it needs to only examine its own knowledge to gather sufficient evidence to confirm or deny its associated hypothesis. Thus, by concentrating knowledge at each specialist, only a small portion of the knowledge base must be examined.

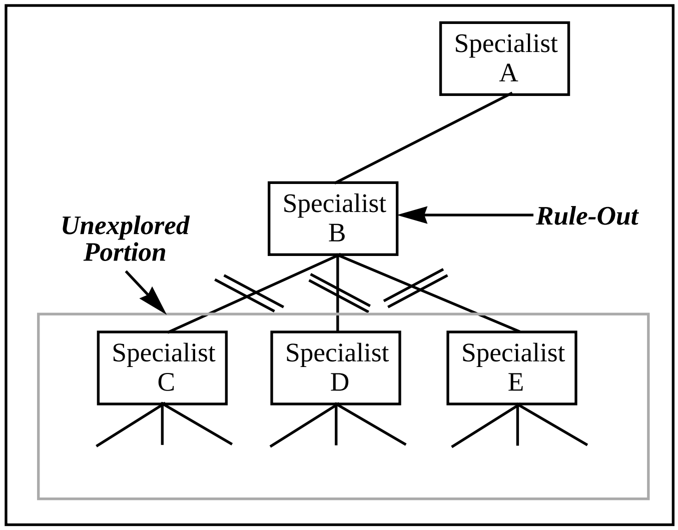

Figure 3: The computational effects of ruling-out a specialist.

Hierarchical Classification for Knowledge Acquisition

Hierarchical Classification provides significant leverage to the knowledge engineer during the knowledge acquisition process. By explicitly presenting the knowledge engineer with a knowledge organization to use for “classification” type problems, the Generic Task approach overcomes one of the biggest obstacles in knowledge based systems development, ***knowledge representation***. HC also provides the knowledge engineer with a vocabulary with which to communicate with the expert. During knowledge acquisition, the knowledge engineer speaks to the expert in terms of *hypotheses*, the *evidence* needed to *establish* or *rule-out* a hypothesis, and the *refinement* of a hypothesis into more specific subhypotheses.

HC also allows the knowledge engineer to approach the problem of knowledge acquisition from either a top-down fashion (i.e., speaking to the expert in terms of high-level hypotheses and refining each hypothesis into more detailed hypotheses) or a bottom-up fashion (i.e., staring with the most detailed hypotheses and grouping them into abstract hypotheses). Therefore, HC provides the knowledge engineer with a guiding framework to perform knowledge acquisition.

These advantages of the traditional text-based hierarchicalclassification system are maintained when we moved to a picture-based HC system for weed identification.

PICTURE-BASED HIERARCHICAL WEED CLASSIFICATION

The occurrences of weed species in field crops depends, among factors like cropping sequence and control methods, on the region and crop (Hanf, 1990). Thus, by creating a crop and region specific weed identification system for wheat grown in Egypt, we reduced the number of weeds in our system to around 50. Consequently, less criteria were required to distinguish the weeds. The system for the identification of grasses as outlined by (Behrendt & Hanf, 1979) is based on five criteria. However, we found that two criteria were sufficient to distinguish the nine grasses. The two criteria are: 1) morphology of the leaf base and 2) appearance of the leaf blade.Similarly, the outline for the identification of dicots (Hanf, 1990) could be simplified as well. They are classified according to 1) the shape of the cotyledon and 2) shape of true leaves. This has the advantage that the system can be understood more easily and the process of identification is speeded up. The nature of the hierarchical classification system allows for a dynamic expansion and adaptation of the system to the requirements of the user, i.e. it adapting the weed identification to cotton, or another crop, is easy.

As stated above, the traditional Hierarchical Classification tool used text-based matchers to determine when a hypothesis can be established or ruled-out. However, describing the weeds using text is a tedious and error-prone process that is open to misinterpretation by the end user. Therefore, we chose to extend the traditional HC tool without losing the advantages described above. Our extension added a pictorial description at each specialist, thus allowing the establishment of the specialist to be picture-based. The end user is responsible for comparing the pictures to their current case and selecting the appropriate match. Furthermore, the system records the decisions made at each node. Thus, backtracking and revision of decisions is possible. Our system even allows for jumping back to any previous decision level. This is a big improvement over traditional, printed keys, where the user could get easily lost. Because pictures represent an idealized form of the plant that not always corresponds to the forms found in nature, we added the options to select any two criteria within one level at the same time. At the next deeper level, the system presents the user the combined selection of both criteria.Thus, we overcame one of the severe limitations of the dichotomous system.

EXAMPLE FOR IDENTIFICATION OF DICOT PLANTS

In the following, we give a brief example of our implemented system. [1]At the first level (Fig. 4), the user has to decide whether the plant is broad leaved (dicot) or a grass type (monocot). The help button placed next to the pictures enables the user to get a description of the picture and an explanation of how to proceed. The user makes his selection by simply clicking on the picture.

1. The pictures of the individual weeds were provided by BASF. We use the book by Hanf (Hanf, 1990) as the source of the abstract shapes for the cotyledons and true leafs.

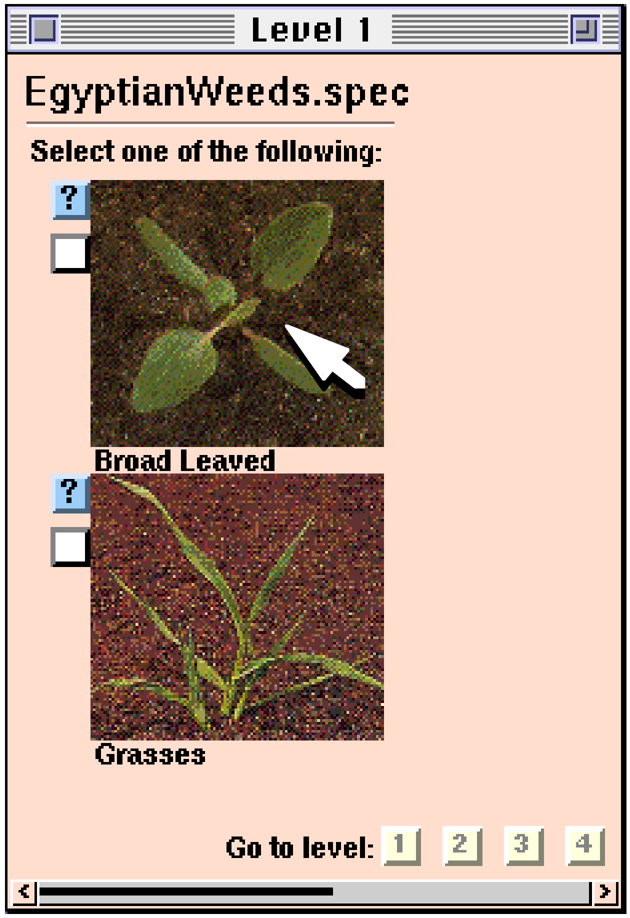

Figure 4: User selects broad leaved weeds or grasses

At the second level (Fig. 5) the user is shown a selection of possible shapes of cotyledons. The default choice is to select one shape. By first marking “select two” the user can select two cotyledon shapes before the system proceeds to the next level. The “to level” check box at the bottom gives the user the ability to jump back to the previous selection levels.

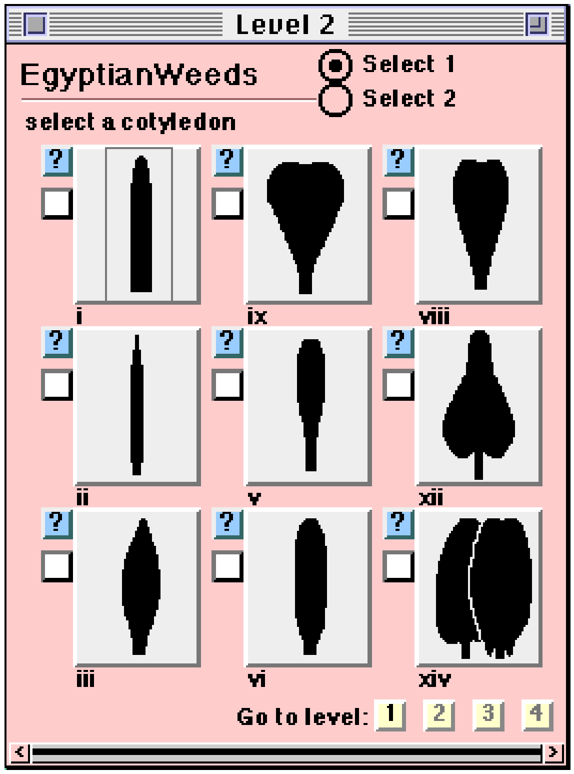

Figure 5: User selects appropriate shape of cotyledon

At the third level (Fig. 6) the user is shown a selection of true leaves that are possible with the cotyledon shape selected at the second level.

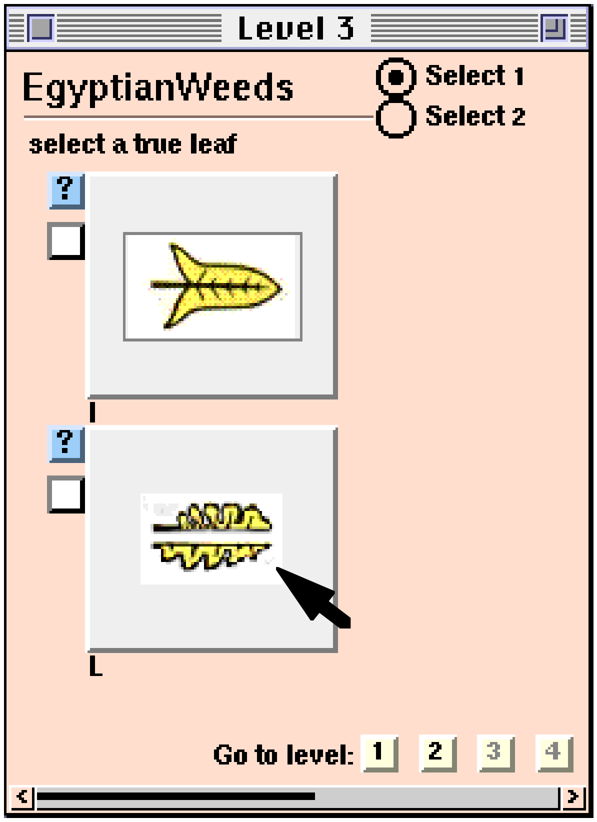

Figure 6: User selects appropriate true leaf shape

At the fourth level (Fig. 7), the user is shown the seedlings that match the combination of cotyledons and true leaves selected at the previous levels. The /button" reveals a description of the weed, and contains information on the ecology of that weed species and possible control methods

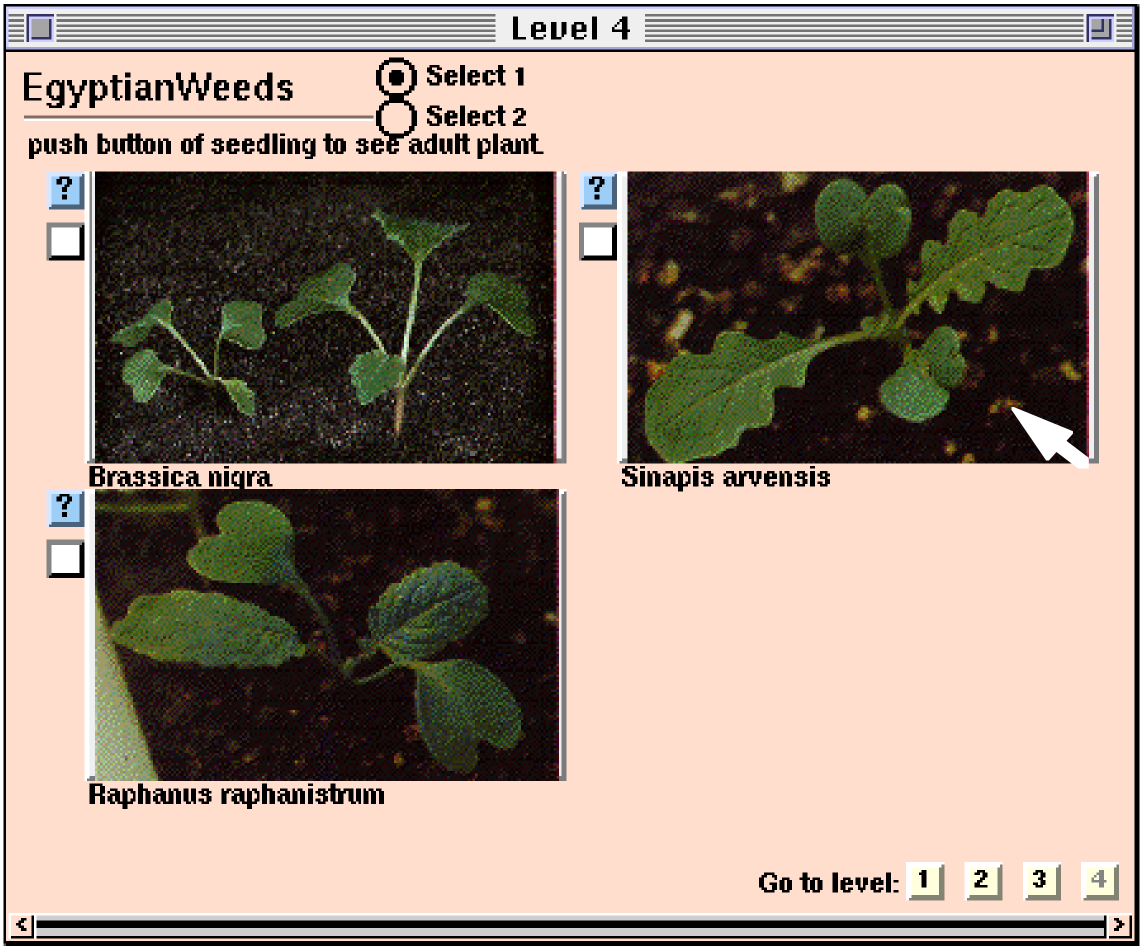

Figure 7: User selects seedling

At the last level (Fig. 8), the fifth, the user is shown a picture of the flowering plant.

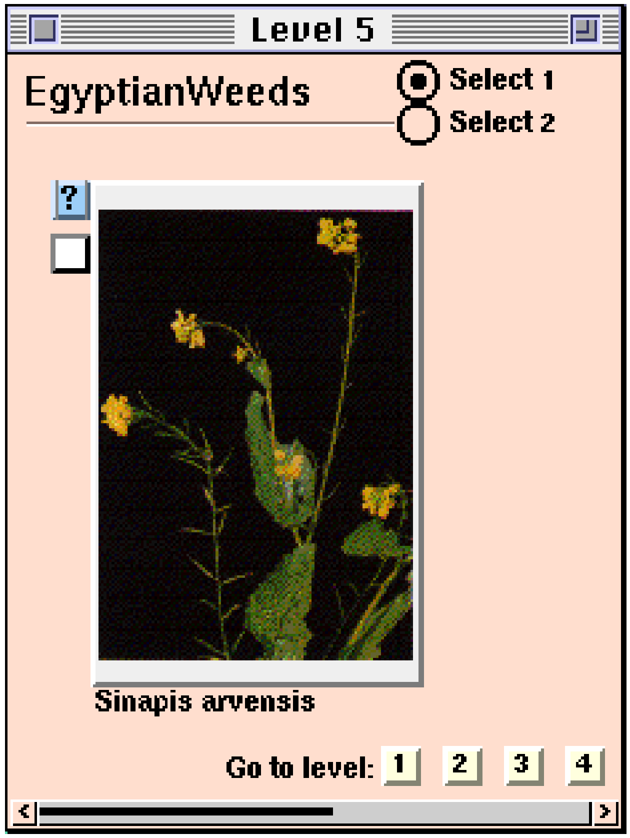

Figure 8: The flowering plant is shown

OUTLOOK AND CONCLUSION

We intend to link the identification system to a weed control module so that information on all the identified weeds in a given field can be used to generate a recommendation for control. That recommendation will be based on density, field uniformity, and size of each species.

The rate of acceptance of the weed identification system by extension agents and farmers will be the best indicator for its usefulness. Preliminary field tests in Egypt showed that the system can be readily understood by farmers and they seemed to be very keen on using this new technology.

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