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Applying Artificial Intelligence to the Identification of Variegated Coloring in Skin Tumors

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In a previous article [1], the initial results of an automatic color segmentation algorithm for identifying variegated coloring in skin tumors were presented. In this article, further results of that study are examined. These significant new results accrue from the application of artificial intelligence (AI) methods— specifically, the use of automatic induction to generate classification rules.

Induction Methods

Induction is the process of producing a general classification algorithm from a set of specific examples. It is a reasoning process that allows the formulation of theories from limited and specific experience in order to predict future events [2], such as the results of an experiment. In the context of this research, automatic induction was used to generate a classification rule to determine if a specific feature, variegated coloring (VC), was present in a given skin tumor image. Variegated coloring is a feature of great interest due to its predictivity regarding the diagnosis of malignant melanoma, which is the fastest growing in incidence and the deadliest of all skin cancers [3]. Three major methods of induction exist. These include:

- Heuristics, i.e., rules that human beings have developed as a direct result of their own experiences. These rules provide for the prediction of future events based on past experience. The induction mechanisms that are involved in human thought are not well understood. In the development of an expert system, the human expert is often called upon to provide heuristics to the system developer, so that the experience of the expert can be codified into the expert system. This process of translating the expert information into a formal system is usually the most difficult task facing the expert system developer.
- Formal Induction Methods. The concept of machine intelligence is closely related to the concept of automatic learning [4]. In order for a machine to learn, it must be able to generate concepts and apply these concepts to new situations [2]. This is where formal, or automatic, induction methods are used. Many of the formal induction methods that have been developed are based on first order, or higher order, predicate calculus that has been extended to allow for inductive inferences. Some of these extensions are based on heuristics that human beings have applied effectively in specific domains. Some of these methods are known as interference matching, maximal unifying generalizations, conceptual clustering, and constructive induction [2].
- Neural networks. Currently the subject of much research, neural network approaches have their foundations in statistical analysis, through the use of discriminant functions, and are conceptually extended to first the perceptron [5] and then on to more complex neural network structures. Neural networks are based on the concept of finding the best set of coefficients, or weight vectors, that minimize a given error function. The main unifying concept for all these different methods is that they all can be made to "learn," classify input patterns into output patterns, and to perform induction.

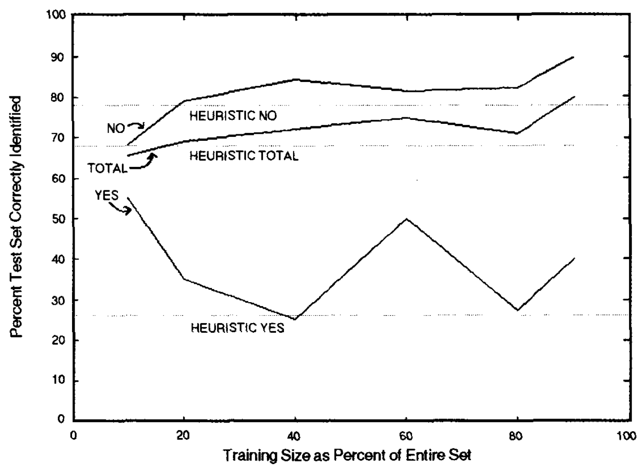
The mechanism used in this research, as first incorporated into the 1st Class Fusion [6] software, is based on an algorithm known as ID3. The ID3 algorithm operates by generating decision trees that are based on the input example data [7]. These decision trees are then coded as rules in the C programming language and are incorporated into the software developed to classify skin tumors and skin tumor features. ID3 was specifically designed to handle large masses of data. The processing time grows only linearly with the complexity of the problem [7]. This feature makes ID3 appropriate for use on a personal computer system.

All of the formal induction methods may result in an expert system tool that the human expert may not fully comprehend. That is, rules may be based on numbers that the expert would never use in practice. For example, the expert may use a heuristic rule such as "If it is red and blue, then consider variegated coloring." The automatic induction system, on the other hand, may generate the rule "If angle A in the color space is greater than 4.33, and angle B is less than 2.113, and the variance in color 4 is greater than 17.9, then consider variegated coloring." These type of data-derived expert systems have been termed implicit expert systems, in contrast to the explicit expert systems based on expert defined heuristics.

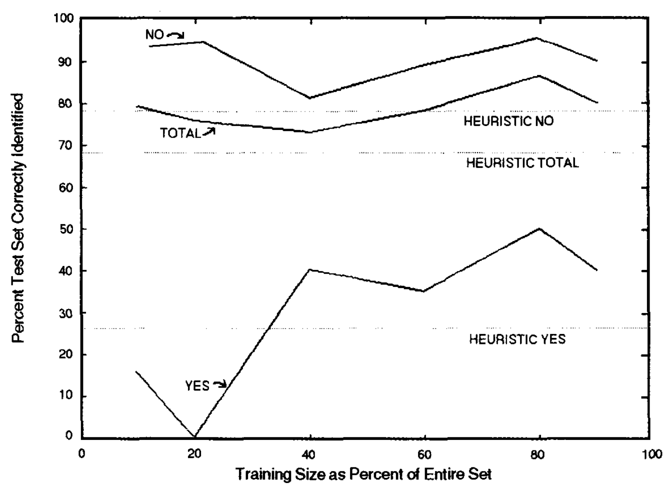
Training/Test Set Paradigm

The training/test set paradigm is used extensively in statistical studies [5]. This paradigm, simply stated, consists of separating the data or examples into two distinct sets. One set is used for training, or developing, the algorithms; and the other is used for testing the algorithms. This separation allows for unbiased results to be reported on the test set. These two sets should be statistically independent. The sets should also satisfy the minimum requirement that they are different [5].

This requirement was rigidly met for the results reported here. This concept is often neglected [8] in practice. Very often in image processing research, especially in the area of image segmentation, results are reported on the same set of images that was used to develop (train) the algorithm. Use of a single data set is sometimes necessary due to the limited availability of



1. Results from training sets with 13 inputs, primarily raw color data. Erratic behavior in the Yes plot indicates that the input data is not consistent or complete.



2. Results from training sets with 15 inputs, raw color data and higher level data. The results are better than without the higher level information, but still somewhat erratic.

images, the extensive processing time required, and the limited methods that are available for measuring success. Although convenient, this method of using the same set to train and test an algorithm, known as the resubstitution method, provides at best, results that are biased and possibly meaningless [5]. This method is best used to compare the performance of similar algorithms, but may have little utility in predicting future performance.

The problem of selecting the training set and the test set is complex. In order to generate the best classification algorithm possible, the size of the training set should be minimized, but in order to have high levels of confidence in the results as an estimate of future performance, the size of the test set should be maximized [5]. This dilemma leads many researchers to arbitrarily use 50 percent of the set for training, and 50 percent for testing. For this research, results are reported with various sizes of training and test sets. This method provides more complete information than would be obtained with a fixed set size and allows for observation of trends in the data.

Feature Files

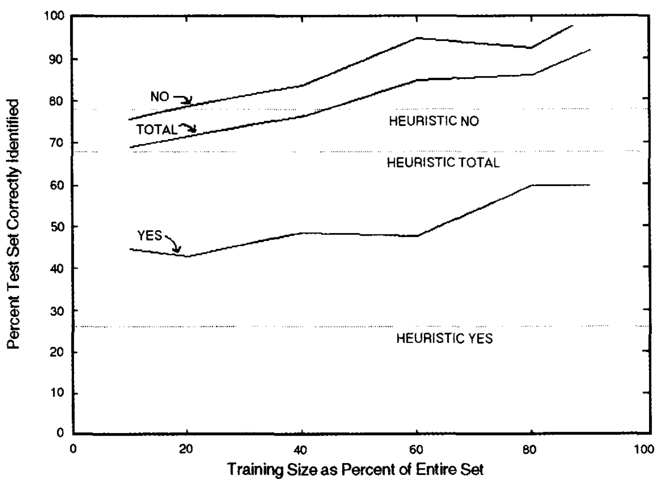
In addition to the digitized images, a database of feature information has been created by a dermatologist using software developed by the research team. This software allows the user to display an image and mark certain blocks (in this case 32 x 32 pixel blocks) that contain a specific feature. Through the use of these feature files, specific sections of an image may be selected for processing by the masking out of blocks within the image that are not of interest.

Feature masking served an important role in the development of the feature identification software modules in this project. With the feature marking software that was developed, the research team was able to proceed independently on each module. The development of the feature marking software, and the feature data base, proved its utility in the development of the software for this research. This model may be used for any large image processing/expert system project, because without it there would be no way to test each module independently. Much effort could then be wasted enhancing modules that are already functioning properly.

In addition to using the feature files to mask out unwanted portions of the image, the feature files were used to obtain a success measure for the image segmentation algorithms developed. Each feature was marked on a block-by-block basis as either containing the feature completely, marked as a full block, or containing the border of this feature, marked as a partial block. If the feature was not present in a given block, then nothing was marked for the feature in that block. Thus, the feature files provided a data base that could be used to test the success of a feature identification module and provided the necessary information to a module under development. In the final system, this information will be provided by other software modules that are currently under development.

Segmentation Algorithm

The Spherical Coordinate Transform/Center 2-D Split (SCT/2-D Split), was developed specifically for the identification of variegated coloring. The C programming language was chosen to



3. Results from training sets with 18 inputs, raw color data, higher level data, and normalized, relative to flesh color data. Monotonically increasing plots indicate consistency and completeness in the input data.

implement the algorithm, because of its ease of transportability, as the target system is a microprocessor-based computer. Each of the steps in the processing chain was implemented by a separate program. These programs communicated by writing their outputs to disk files, which were then read as inputs to the next program in the processing chain. This technique proved efficacious for development, as it allowed intermediate results to be grown into full-size images and viewed. Intermediate results could then be used to determine what should be done next or, in some cases, what modifications should be made to the existing programs.

The spherical coordinate transform was selected for this segmentation method. This transform uses the original RGB data, and transforms it into a two-dimensional color space, defined by angle A and angle B; and a one-dimensional brightness space, defined by the vector length length, L. The algorithm utilizes the two-dimensional color space defined by angle A and angle B [1].

The segmentation algorithm consists of six steps: 1) color averaging, 2) feature masking, 3) color space segmentation, 4) object filtering, 5) object labeling, and 6) feature identification. The first feature to be masked out was the feature called nonskin. This was done to eliminate artifacts such as rulers, which were present in the slides used in the research but will not be present in the final system. These artifacts were masked out by filling those portions of the image with zeros, as there are no real zeros in the image. Other portions of the image may also be masked out, depending on the feature being examined.

After the image has been segmented, and different color objects labeled, the final step was the identification of features, e.g., variegated coloring. Two approaches were taken to solve this problem: the use of heuristics, and the use of automated induction to generate classification rules.

Applying Automatic Induction to VC Identification

Variegated coloring (VC) is believed to be one of the most predictive features in the identification of malignant melanoma [9,10]. The incidence of this deadly form of skin cancer is on the rise. This is due to many factors, including the depletion of the ozone layer caused by pollution, and by excessive exposure to the sun. The high mortality rate associated with this cancer would not occur if the tumors were identified in the early stages. If caught early enough, the survival rate is near one-hundred percent [9,10].

Unfortunately, VC is not very well defined. Roughly, variegated coloring refers to a tumor that has more than one color, and these colors are swirled together. The precise definition of variegated coloring, that is, one that relates to numbers of digitized blocks and number of colors, was refined as this research was carried out. Thus it was difficult to generate consistent results. To help alleviate this problem, we called upon two experts to help identify VC. The tumors on which the two experts could not agree were not included in this study. As a basis for comparison, the two experts (dermatologists) agreed on 88 percent of the tumors considered for use in this research.

Heuristic Approach

The first method used expert information to generate heuristics that would be programmed to identify variegated coloring. This method consisted of applying the SCT/2-D Center Split color segmentation algorithm to a small set of images. These results were viewed by a dermatologist. Using the knowledge the expert had acquired by viewing "about one million tumors, although only about ten thousand interesting ones" [11], heuristics were defined.

As for defining the training set used in this research, only 10 tumor images were viewed to define the algorithm used, although the entire expert's experience and body of knowledge was utilized. In this sense, the training set consisted of about one million tumors.

The specific algorithm was first implemented in [12], and later was used in a larger study [13]. The major differences between the present study and the previous ones are as follows: 1) a different camera was used, one without automatic gain; 2) two dermatologists' opinions were included, thus many of the difficult tumors that were omitted from the previous work because of questionable status as VC were now included; 3) 250 tumor images were used for this study; previously the largest set was 160.

The features that were initially masked out were nonskin, ulcer, crust, scale, and shiny. The heuristic developed was a simple two-step algorithm:

1) If the ratio of the area of the tumor (excluding ulcer, crust, scale, and shiny areas) to the entire tumor was less than 0.5, then variegated coloring was absent.
2) If the set of objects that are greater than 10 blocks, approximately 2 mm^2, contains two or more colors, then variegated coloring was present.

This algorithm was chosen because of its simplicity and the fact that it worked on our training set of 10 images. Applying this algorithm to the test set showed an overall success of 68 percent of the tumors being correctly identified regarding variegated coloring. Of the tumors that did not exhibit this feature, 78 percent were

Table I: VC Results Using Feature Vector Methods

	Percent Correct		
Category	Error Measure— Feature Mean Ratio	Error Measure— Euclidean Distance	Error Measure— Normalized Euclidean Distance
Total	47.4	62.3	64.6
Positive VC	88.7	60.4	62.3
Negative VC	36.2	62.8	65.3

correctly identified. However, of the tumors that did exhibit variegated coloring, only 26 percent were correctly identified. This low success rate was not acceptable.

We believe that the information necessary to identify VC is contained in the color data. The human vision system, of which the brain is a part, can readily identify VC. But presenting this knowledge in a form that the computer can use proved to be very difficult. At any given time, on the conscious level, it seems that the human visual system can only store and process a small number of images. For this problem, it was necessary to explicitly process as many of the images as possible. This technique naturally leads to the use of automatic induction.

Automated Induction

The expert system development tool, 1st Class Fusion, was used as an automatic induction engine to generate classification rules. The initial example data contained 13 inputs and 1 output. The inputs were statistics gathered from the color segmentation algorithm. These inputs were selected because it was believed that the information required to identify VC was contained in the color data. Specifically, for each of the four colors into which the image was segmented, the variance of angle A, variance of angle B, and number of pixels were included as input data. The final input was the number of objects that were greater than the minimum object size, and the output for these data examples was simply yes or no, meaning either the tumor did exhibit VC or it did not.

Various sizes of training sets were used; specifically, training sets that were 10 percent, 20 percent, 40 percent, 60 percent, 80 percent, and 90 percent of the entire set. The entire set consisted of 250 tumor images, of which 50 exhibited variegated coloring. This distribution is not typical of tumors, in general, which have only a very small percentage (less than 1 percent) that exhibit this feature. However, it was necessary to include as many VC tumors as possible to provide a representative sample set for the automatic induction software.

The results are presented in Fig. 1. Along with the plots for success of the rule generated for various training set sizes, shown by solid lines, the dotted lines show the success rate that was achieved by using the heuristic technique alone. Only at the very lowest end, less than 20 percent on the abscissa, does the heuristic alone achieve better results than the AI induced rule. The erratic behavior of the Yes plot indicates that the information provided to the rule generator is probably not consistent or complete.

For the next run of this experiment, two additional inputs were added to the previous 13. These two additions were the same as were used in the heuristic: the tumor ratio and the number of different colors contained in the set of objects that were greater than minimum object size. The results from this run are shown in Fig. 2. Here, the AI-induced rule provides better results across the entire range for both the Total and the No plot. The Yes plot shows better results when the training set size is above about 30 percent of the entire set. Still, with the best case at the 80 percent training set size, total success results are only about 86 percent.

The third, and final, run of this experiment had three more inputs. These were added when the dermatologist indicated that specific colors may also be important. Using the information gained from a previous tumor color study [13], the normalized, relative to flesh, average tumor color was used; i.e., average RGB values mapped to their chromaticity coordinates, with the normal flesh chromaticity coordinates subtracted.

The resulting success plots are given in Fig. 3. The nearly monotonic increases shown in all plots indicate that consistency, and a certain degree of completeness, is contained in the input data. At the 90 percent training set size, an overall success rate of 92 percent was achieved. This very positive result is contrasted with the best success rate of only 60 percent with the set of tumors that were variegated. This low success rate may be due to this variegated (Yes) image set not being large enough; the No set had 200 tumors, while the Yes set had only 50 tumors. Overall, the success rates achieved with the automatic induction method were much better than those achieved by the heuristic alone.

Feature Vectors

Feature vectors are a standard technique for classifying objects, where each object is defined by a set of attributes in a feature space. The 18 inputs that were used to generate the AI rules were considered for this application. Of these 18, five were selected for the feature vector experiment. These five represented higher level data, as opposed to the raw color statistics, and were the same as the last five added to the input data for the aforementioned rule generation.

These five inputs were selected for three reasons: the expert selected these as being the most important; the AI induced rule study indicates the importance of these five; and the variance was large. It is a basic principle in pattern recognition theory that features with large variances will have the greatest discriminatory power.

The basic concept in using feature vectors to classify objects consists of finding 1) a representative object for each class; 2) defining an error measure; and 3) classifying the object by calculating the error measure for each class and assigning the object to the class with the smallest error measure. This basic concept can be extended to include higher order statistical information based on the distributions of the examples in the general population. However, for this study, only the first order statistics (means) were utilized. Three different error measures were utilized: 1) Euclidean distance, 2) ratio deviation, and 3) normalized Euclidean distance.

In order to find representative objects for each class, we used the entire set of 250 images to calculate averages for each of these five features for both the Yes class (variegated coloring present), and the No class (variegated coloring absent). In this sense, the training set and the test set were the same, so that optimal results were achieved. The bias that can result from combining the two sets was not a problem, since the averages stabilized after less than half of the images were included in the calculations. Thus, similar results could have been achieved by using 50 percent training set size.

The first error measure, the Euclidean distance, is defined as follows [14]:

$$E = \sum_{i=1}^{5} \sqrt{(x_i - y_i)^2}$$

where x_i is the ith sample, and y_i is the population mean. This error sum was then calculated for each of the two possible classes, variegated or not variegated, and each sample was assigned to the class with the smallest error sum. Using this error measure, an overall success rate of 62.3 percent was achieved. The tumor images without VC variegated coloring had 62.8 percent success, while the set that did exhibit VC had 60.4 percent success.

The second error measure, ratio deviation, was defined as follows:

$$E = \sum_{i=1}^{5} \left| 1 - \frac{x_i}{y_i} \right|$$

where x_i is the ith sample and y_i is the population mean. This error sum was then calculated for each of the two possible classes, variegated or not variegated, and each sample was assigned to the class with the smallest error sum. Using this error measure, an overall success rate of 47.4 percent was reached. The tumor images without VC had 36.2 percent success, while the set that did exhibit VC had 88.7 percent success. This last value was the highest success reached for the variegated coloring positive set of tumor images.

The third error measure, normalized Euclidean distance, was defined as:

$$E = \sum_{i=1}^{5} \sqrt{(x_i - y_i)^2}\, N_i$$

where x_i is the ith sample and y_i is the population mean, and $N_i = 1/\text{Range}_i$, where Range_i is the total range of this variable in the population.

This error sum was then calculated for each of the two possible classes, variegated or not variegated, and each sample was assigned to the class with the smallest error sum. Using this error measure, an overall success rate of 64.6 percent was achieved. The tumor images without VC had 65.3 percent success, while the set that did exhibit VC had 62.3 percent success.

The result obtained by use of the three error measures are summarized in Table I.

Conclusion

This research has demonstrated the importance of color information for the automatic diagnosis of skin tumors by computer vision. The utility of the relative color concept was proven by the results in identifying variegated coloring. The feature file paradigm was shown to provide an effective methodology for the independent development of software modules for expert system/computer vision research. The automatic induction tool was used effectively to generate rules for identifying the feature called variegated coloring.

The SCT/Center 2-D Split color image segmentation method was used effectively for the identification of variegated coloring. This feature can be identified at rates as high as 92 percent when using the automatic induction technique in conjunction with the color segmentation method. This rate compares with 68 percent correct identification, using expert heuristics and the color segmentation method. The feature vector methods, at 65 percent success, were about equally successful as using the expert heuristics. However, the maximum rate for the true positives was achieved by using the feature mean ratio as an error measure. This feature vector technique provided about 89 percent correct results for the set of tumors that exhibited VC.

Studies are underway in cooperation with the National Library of Medicine to compare the rule-based induction generated results, with those obtained by neural network methods. In the domain of skin tumors, the results obtained from implicit expert systems are consistently superior to that achieved by explicit, heuristic-based expert systems.

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Biographies

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Dr. Moss' research interests are in machine vision, image processing, and pattern recognition. He is especially interested in medical applications of machine vision, vision systems for industrial robots, and automatic visual inspection. He currently serves as associate editor for both *Pattern Recognition*, and *Computerized Medical Imaging and Graphics*. He is a member of IEEE and the Pattern Recognition Society. Dr. Moss has served as president of the UMR Chapter of Sigma Xi, and for two years as Secretary Treasurer of the Rolla Subsection of the IEEE. He can be reached at the Electrical Engineering Department, University of Missouri-Rolla, Rolla, MO 65401.

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Academy of Dermatology Task Force on DERM/DDX, which has developed an on-line differential diagnosis system for dermatologists. He is president of Stoecker Moss & Co., which develops medical computer vision systems. His research interests include artificial intelligence in medicine, computer vision in medicine, and diagnostic problems in dermatology. Dr. Stoecker is an associate editor of *Computerized Medical Imaging and Graphics*. He is a member of the UMR Chapter of Sigma Xi.

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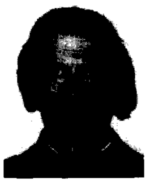
Safety in Medical Signal Analysis
(continued from page 56)

safety of signal analysis techniques proposed for medical equipments or systems; devising safer signal analysis techniques; developing corrective measures for existing techniques to improve the overall safety; and providing guidance to medical personnel in the use of complex medical equipment.



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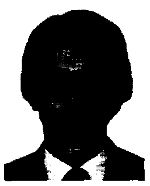

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