A MULTISTRATEGY LEARNING APPROACH FOR TARGET MODEL RECOGNITION, ACQUISITION, AND REFINEMENT

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ABSTRACT

Target recognition systems are currently unable to modify their behavior automatically in environments where processing requirements change or novel situations are encountered. Most systems can not easily adapt to varying target appearances, considerable image noise, and target occlusion. More importantly, these systems are constrained by the selection of target models used for recognition; typically, the target model database is fixed and individual features within a target model remain static as well. The incorporation of machine learning technology into the target recognition process will allow the system to use situation context, to adapt in changing environments, and to improve the system’s performance over time. This work describes an innovative approach which combines machine learning and target recognition into an integrated system. The system is called TRIPLE: Target Recognition Incorporating Positive Learning Expertise. It uses two machine learning techniques known as explanation-based learning and structured conceptual clustering, combined in a synergistic manner, which provide effective target model recognition, acquisition, and refinement capabilities. We provide an overview of the TRIPLE system and provide experimental results which illustrates the performance of the system.

1. INTRODUCTION

Prior attempts to automate target recognition systems have suffered from the lack of an ability to automatically acquire new target models, to adapt to changing environmental conditions, and to modify system behavior based on the context of the situation in which the systems are operating. In order to be effective in dynamic outdoor scenarios, a robust vision system should be able to automatically acquire necessary contextual information from the environment and react accordingly. Most target recognition systems lack this capability. Their performance begins to quickly degrade when subjected to problems such as variable target appearance, image noise, and target occlusion.

Due to recent advances in machine learning technology, some of these problems are resolvable by effectively combining machine learning and machine vision technologies. Learning allows an intelligent vision system to use situation context in order to understand images. This context, as defined in a machine learning scenario, consists of a collected body of background knowledge as well as environmental observations which may impact the processing of the scene. The resulting system dynamically reacts to the appropriate stimuli in the environment, continuously adapting its internal knowledge to improve overall performance levels. This improvement may come in the form of faster recognition times, improved recognition accuracy, and higher confidence in system results.

Machine learning technology should facilitate two main advancements in the target recognition domain: automatic knowledge base acquisition and continuous knowledge base refinement. The use of learning in the construction of the knowledge base will save the user from spending the enormous amount of time necessary to derive target models and databases. Knowledge base refinement can then be incorporated to make any necessary changes in the system’s database to improve the performance of the vision system. These two modifications, which are the focus of this paper, will serve to significantly advance the state-of-the-art in target recognition and image understanding applications.

Although machine learning has been used in many applications, very little work has been done in the computer vision domain. Refer to the earlier review by Bhanu and Ming4 for an overview of computer vision and machine learning systems. Further, within the machine learning field, very little effort has been made to combine several learning techniques together. Typically, learning methodologies are used independently to provide adaptive ability and improved system performance. Our multistrategy approach to target recognition presented in this paper, called TRIPLE (Target Recognition Incorporating Positive Learning Expertise), incorporates two powerful learning techniques, known as explanation-based learning (EBL) and structured conceptual clustering (SCC). These techniques filter and structure the information present in positive concept examples to create useful knowledge structures. While each of these learning methods, used independently, might provide some improvement in target recognition performance, they can be best put to use by combining their abilities into an integrated approach. We have synergistically combined the EBL and SCC learning methodologies in the TRIPLE system to offer a consolidated technique which employs the best features of each method to solve the target recognition problem in an efficient and effective manner.

2. TRIPLE - A MULTISTRATEGY LEARNING TECHNIQUE

The TRIPLE target recognition system integrates the EBL and SCC learning techniques to overcome the inherent limitations present in each approach. EBL,5,6 which is classified as a learning by observation technique, uses inference to construct a useful concept description from a single example of that concept. Derived from earlier learning systems which required a large number of examples in order to
generalize a target description, EBL uses a collection of applicable background knowledge to generate a useful target description from a single example. EBL's main limitation is the recognition time required when the number of target models becomes large. SCC45,7 is a method for grouping targets into classes similar to traditional numerical clustering techniques. However, instead of using predefined measures of target similarity to determine class boundaries, SCC uses a conjunction of conceptual attributes to group targets into conceptually simple classes. This process utilizes important contextual information relevant to the targets to assist in the classification process. SCC can handle complex, structural descriptions of targets, which is ideal for target recognition tasks since most targets are represented using structural descriptions. However, SCC has problems with model biases when the number of target class examples is small. Combining the ability of EBL to characterize a target using a single training example with SCC's efficient method of organizing targets once they have been properly modeled yields an integrated learning system which effectively handles the target recognition task. A more complete description of the EBL and SCC learning approaches is presented in our earlier description of the TRIPLE system.

Figure 1 shows the current configuration of the components in the TRIPLE target recognition system. The processing elements, which are indicated by rectangular boxes, transform the input image data and generate the target recognition results. The Segmentation and Symbolic Feature Extraction component segments and locates the regions of interest in the original image and then extracts the symbolic feature information from these regions. The Knowledge-Based Matching component parses the classification tree using the symbolic target features and identifies the various recognition states of the TRIPLE system. The matching component also initiates the proper learning cycle based on the target recognition results. EBL, when invoked by the matching component, selects the relevant target features from the symbolic feature information during the target model acquisition process. EBL also identifies new, pertinent target features for target models already present in the classification tree. SCC is responsible for constructing and maintaining the target classification tree using the relevant symbolic features selected by the EBL component. The Feature Value Monitor modifies the target feature values in the classification tree based on the features which are used to identify the target during the recognition cycle.

The processing elements make use of several collections of target-specific data and knowledge databases within TRIPLE, as shown in Figure 1. The image data is assumed to contain targets of interest and may include targets that are not currently in the target model database. The Symbolic Feature Definitions are used during the symbolic feature extraction process to identify important target features which are used to recognize the target. The Background Knowledge is accessed by the EBL component to select relevant target features during the model acquisition or model refinement operations. The Target Model Database stores the complete schema of each target encountered by the recognition system, including every feature (relevant or not) defined on each target. Relevant target features, which are determined by the EBL component, are tagged for future reference in the target model. SCC makes use of the Goal Dependency Network while constructing or modifying the classification tree in order to compute the optimal clustering of the targets at the current level in the hierarchy. The Target Classification Tree represents a structured hierarchy of all targets known by the TRIPLE system and is used by the matching component to identify various types of target recognition results such as complete recognition, partial recognition, occlusion, new target, target model refinement, or recognition failure.

Figure 1 also highlights the two distinct learning cycles which are present in the TRIPLE system. The first learning cycle is the target model acquisition and refinement process. The components used in this loop include the knowledge-based matching, explanation-based learning, and structured conceptual clustering processing elements as well as the target model database and the target classification tree. This learning cycle also includes the background knowledge base and the goal dependency network associated with the EBL and SCC learning components, respectively. The second learning cycle within TRIPLE is the target feature value refinement process. This operation utilizes the knowledge-based matching and feature value monitor components. The feature value monitor modifies the relevant target feature values that were used by the knowledge-based matching component to recognize the target and which are present in the target classification tree.

The various processing components of the TRIPLE system and the manner in which they interact will now be described in the following subsections.

2.1 Segmentation and Symbolic Feature Extraction

The first step in the target recognition process is to extract sufficient information from an image so that targets present in the image can be correctly identified. This process is handled by the Segmentation and Symbolic Feature Extraction component. First, the image is segmented using a set of selected parameters for a given segmentation algorithm. From the segmentation results, the target-related regions are identified and approximated using piecewise linear segments. Based on the size, shape, and relationships with neighboring regions of the border approximation, a region label is assigned to each target segment. A hypothesize-and-test approach is used to identify the rough orientation of the tar-
get during the region labeling operation.

For example, in the aircraft recognition scenario, the feature extraction process may first hypothesize a region in the image that corresponds to an aircraft fuselage based on its shape properties (narrow, elongated region). This hypothesis can then be verified by finding a symmetric pair of regions adjacent to the fuselage with wing-like properties. Similarly, the tail regions of the aircraft can also be labeled and used to support the current hypothesis.

When a hypothesis has been verified using surrounding regions as additional evidence, all contributing regions are tagged and used in the symbolic feature extraction operation. TRIPLE computes symbolic feature information from the region borders using a knowledge-based approach. Symbolic features represent conceptual descriptions of a target's properties that would be used by a human in characterizing the target's appearance. Each symbolic feature is represented by a set of production rules that are stored in the Symbolic Feature Definitions database in Figure 1. The conditions of the rule analyze the properties of the target regions and the actions define the appropriate symbolic feature when the conditions are satisfied. The rules use distances and orientations of lines, on the region borders to compute the various target features. For instance, in the aircraft recognition example, symbolic features such as fuselage length, wing span, and wing sweep angles can be obtained by examining the fuselage and wing regions of the target.

### 2.2 Knowledge-Based Matching

The knowledge-based matching component receives a target schema from the segmentation and symbolic feature extraction component, which represents the feature information obtained for the unknown target. This schema is utilized by the matching element to traverse the classification tree in an attempt to reach a leaf node of the tree. If successful, the target has been correctly identified. The classification tree represents a structured hierarchy of the target models currently known by the recognition system. The tree is constructed and maintained by the SCC component (Section 2.4).

The use of the classification tree makes the target recognition process much more effective and efficiently solves the "indexing" problem encountered in target recognition applications. And, as we shall see later, the classification tree makes it possible to identify situations such as target occlusion or incomplete target recognition that would not otherwise be possible.

The matching process begins at the root of the classification tree, matching the feature values specified in each tree branch with those in the unknown target schema. Finally, when a leaf node is reached, the matching operation terminates by matching any remaining feature values. If at any point in the tree traversal, a feature is missing from the unknown target schema, the system spawns a set of multiple viewpoints. A separate viewpoint is created for each feasible branch at the current level in the classification tree. This action allows the tree parsing process to evaluate many hypothetical alternatives. The survival of any given viewpoint is governed by the matching success that is achieved during the processing of successive tree nodes at that viewpoint. At a later time in a particular viewpoint, the tree parsing process may terminate due to feature incompatibility. This condition results in the removal of the corresponding viewpoint from further consideration. Viewpoint removal allows the search process to prune branches from the classification tree when it becomes clear further search will be useless. If a path through the entire tree to a single leaf node can be located, the unknown target has been correctly recognized as the target model present at the leaf node.

If the knowledge-based matching component is unable to parse the tree using the available symbolic feature data, the feature set is passed to the EBL component. In these situations, the failure of the matching process is due to one of two conditions. First, the feature information may represent a new target model that is not currently represented in the classification tree and which can potentially be acquired by the EBL component. Alternatively, the feature data may be faulty, incomplete, or inconsistent with the system's current target recognition domain, in which case EBL will not be able to acquire a new model. However, the matching process does not distinguish between these two cases. It merely passes the feature information to the EBL component for further investigation.

In addition, the matching component also sends the feature information to the EBL component when it detects the presence of a new feature in a correctly recognized target. By consulting the information stored in the Target Model Database, the matching component can detect when a new feature is present. It adds the new feature to the current target model and passes the revised model to the EBL component in order to determine the relevance of the new feature.

### 2.3 Explanation-Based Learning

Whenever the knowledge-base matching component is unable to process the symbolic feature information for an unknown target, the Explanation-Based Learning (EBL) component is invoked to understand the feature data. Since it makes use of a collection of domain-specific Background Knowledge (Figure 1), EBL is able to draw inferences from the symbolic feature data that are not possible for the matching process using the classification tree alone. But, because EBL and its associated knowledge base are only used in situations where the classification tree fails, the TRIPLE system remains highly efficient by accessing the information in the knowledge base only when necessary. Complete details of the EBL process are provided by Bhani and Ming.²

The EBL component is responsible for four separate tasks within the TRIPLE target recognition system:

1. Processing the training examples during system initialization.

   The TRIPLE system uses EBL to simplify the target modeling process, which has traditionally been very difficult due to the amount of work necessary to generate a correct model. EBL applies the background knowledge base (Figure 1) to each target schema using a generic target prototype to guide the explanation process. Once the explanation has been created, it is generalized to create a target model that contains the relevant target features. This model can then be used to recognize subsequent instances of the target. All target models created during system initialization are sent to the SCC component, which generates the target classification tree.

2. Acquiring new target models.

   When the target classification tree is unable to process an unknown target schema, the EBL component is given the feature data in order to determine if a new target model can be constructed from the feature data. The new model acquisition process is identical to the system training process described above. If a new model can be successfully derived, it is added to the target model database and is passed on to SCC for addition into the current target classification tree.
(3) Refining existing target models. EBL is also invoked to determine the relevance of new feature information that is present for an existing, correctly recognized target model. The presence of a new feature can be detected since EBL maintains a list of all previous symbolic features defined on each target in the target model database (Figure 1). EBL adds the new feature to the current target model feature set and replasters the feature data. If the new feature is found to be relevant, it is tagged in the target model and is sent to the SCC component for addition into the target classification tree. Otherwise, the feature is simply left in the target model database as non-relevant.

(4) Identifying recognition failures in the TRIPLE system. EBL is responsible for determining cases of recognition failure. When the knowledge-based matching component is unable to process a set of feature data, EBL is given the chance to acquire a new model using the available features. However, if EBL cannot construct an appropriate model from the feature information, the feature set is incomplete or the background knowledge is insufficient to understand the feature data. In either case, the situation is reported as a recognition failure.

2.4 Structured Conceptual Clustering

The Structured Conceptual Clustering (SCC) component of the TRIPLE system constructs the Target Classification Tree from the relevant feature data generated by EBL (see Figure 1). The classification tree represents a structured hierarchy of the targets currently stored in the recognition system. As described earlier, traversal of the classification tree allows the matching component to understand and compensate for missing information in unknown target schemata during the recognition process. The classification tree also provides efficiency in the target recognition task since the matching process does not have to compare the unknown target schemata with every target model currently in the target model database (i.e., the indexing problem is effectively handled). Thus, the SCC component plays a vital role in the TRIPLE system since it generates and maintains the structure of the classification tree.

During the construction or modification of the target classification tree, SCC accesses the information present in the Goal Dependency Network (GDN) in order to select useful target features. Global target characteristics are specified by the GDN at high levels (near the root) in the tree because they usually categorize coarse target classes. Within these classes, the GDN suggests more specialized target features that are used to determine subclass assignments. This approach to tree construction also allows the matching component to make appropriate decisions (complete recognition, incomplete recognition, target occlusion, etc) during the target recognition process.

Although the GDN suggests several features to use at a particular position in the tree, the SCC process must still select the best feature for the specific situation. To perform this task, each suggested feature is used to generate a clustering of the targets. The quality of each clustering is based on the conceptual simplicity of the clustering results. TRIPLE uses several factors in determining the conceptual simplicity of a proposed clustering including: the number of clusters into which the targets have been placed; the inter-cluster and intra-cluster distances of the clustering results; and the GDN's ranking of the selected feature at the current level in the tree. These measures of clustering quality are combined to evaluate the clustering results of each feature. The feature that provides the highest clustering quality value is selected and the current branch of the tree is defined accordingly. The SCC component continues to cluster the targets at each branch in the tree until every single target has been placed into a separate leaf node in the tree.

SCC provides an adaptive capability to the TRIPLE system since it never relies on predefined measures of class similarity, but rather, it computes the features that best distinguishes a set of targets at any given level in the classification tree. Over time, the choice of the distinguishing feature at a particular level may dynamically change as a result of the new targets and revised targets which are continually being placed in the classification tree. An analysis of the tree structure across many successive recognition cycles of the TRIPLE system shows that it dynamically responds to the targets which are added or modified by automatically restructuring the appropriate tree branches to obtain an optimal target categorization.

The SCC component performs three different jobs within the TRIPLE target recognition system:

(1) Construction of the initial target classification tree during system training. SCC takes all the target models created by the EBL component and constructs the classification tree. At each branch in the tree, the GDN is used to suggest a set of appropriate target features from which one is selected by measuring the conceptual simplicity.

(2) Addition of a new target model into the target classification tree during the target model acquisition process. SCC attempts to retain as much of the original structure of the tree as possible. SCC traverses the tree using the new target model until a branch is encountered that is not compatible with the new target's features. The tree is then reclustering at that location. If a leaf node is encountered, a new branch is created to distinguish the target model currently stored in the leaf node from the new target model.

(3) Modification of the current OCT structure during the target model refinement process. This process is similar to the new target model situation since SCC minimizes the required changes to the tree. At each node in the tree, SCC determines if the new feature produces a better clustering quality than the currently used at the current branch. If the new feature is better, the tree is reclustering at the current location. Otherwise, the appropriate branch is selected and the process continues. If a leaf node is reached, the new target model feature is simply inserted at the leaf node.

2.5 Feature Value Monitor

The Feature Value Monitor updates the quantitative feature values of a target model, if and when that model is used to recognize an unknown target. This process allows the TRIPLE system to gradually modify the feature values of a target in order to overcome any initial bias that may have been acquired during the initial construction of the target model. Changes in target models made by the feature value monitor will be very gradual compared with the changes which result from activating the EBL-SCC target model refinement process described earlier. In the latter case, symbolic features are added or removed from the relevant feature list of the target model. The feature value monitor simply modifies the relevant quantitative feature values of the target. Further, the feature value monitor does not modify any qualitative target features present in the model.

The feature values are changed by shifting the range of
numeric values produced during the EBL generalization process in the direction of the new target feature value. Each range is characterized by a central feature value with endpoints prescribed distant away from this value. For example, the central feature value for the range (100' - 106') is 103'. The feature value monitor moves the entire feature value range in the direction that more closely aligns the central value of range with the new target feature value. The width of the feature value range remains the same. To avoid wild fluctuations in the feature values ranges, the range is moved only one unit (one foot, one degree) etc during any given recognition cycle, regardless of the discrepancy size. This approach is preferable to the alternative method of aligning the numeric range on the current target's feature value because it prevents potential misclassification results from adversely affecting the actual location of the feature value range. The approach is also more in tune with the notion that adaptation should be a gradual, rather than abrupt, process.

2.6 Recognition and Learning in TRIPLE

During every recognition cycle, the TRIPLE system identifies one of the following recognition states:

1. **Complete Recognition** - The unknown target schema is correctly classified with a high degree of confidence using the classification tree. The knowledge-based matching component and the feature value monitor are involved in the complete recognition operation.

2. **Incomplete Matching** - The unknown target schema is partially classified using the classification tree. The matching component identifies multiple target models in the classification tree which meet the limited constraints imposed by the available unknown target features. A recognition confidence is produced for each matched target model. Only the knowledge-based matching component is used in this operation.

3. **Target Occlusion** - Although occluded, the identity of the unknown target schema is predicted with some confidence level using the classification tree. This operation involves only the knowledge-based matching component.

4. **Target Model Acquisition** - The unknown target schema can not be classified using the current classification tree, so the target model is acquired by the EBL-SCC learning cycle and added to the classification tree. The model acquisition process involves the knowledge-based matching, EBL, and SCC components of the TRIPLE system.

5. **Target Model Refinement** - After correctly classifying the unknown target schema using the classification tree, a new feature is identified in the unknown target schema. The target model and the classification tree are updated to indicate the relevance of this new target feature. The model acquisition process involves the knowledge-based matching, EBL, and SCC components of the TRIPLE system.

6. **Recognition Failure** - The unknown target schema can not be classified using the information in the classification tree or by EBL with the use of the background knowledge database.

Figure 2 summarizes, in a decision diagram format, the conditions which lead to each of the six recognition states.

**Figure 2:** Decision diagram specifying the conditions through which the six different recognition states of the TRIPLE system are identified.

3. EXPERIMENTAL RESULTS

We have conducted a series of experiments to test the target recognition and learning capabilities of the TRIPLE system for the recognition of 2D aircraft. The imagery used for these experiments was generated by digitizing technical diagrams of various commercial aircraft ranging in size from small single engine private aircraft (Cessna Caravan) to large passenger airliners (Boeing 747). Eleven aircraft were selected for the initial set of experiments on the TRIPLE system.

Since the technical diagrams for the aircraft are extremely precise, they do not represent the actual appearance of aircraft seen in real imagery. In order to simulate the degraded appearance of the aircraft for our experiments, we introduced noise and distortion into the border approximations for the aircraft. Gaussian noise (mean = 0, variance = 1-20) was added to each of the border points and the resultant image was then distorted using two morphological operations (erosion and dilation). Once the aircraft image was distorted, a border following routine was invoked to generate the list of pixels that comprise the outline of the aircraft. The aircraft border was then represented with a piecewise polygonal approximation using a split-merge approximation algorithm. Figure 3 provides an example of the border distortion process and the corresponding polygonal approximation results for a typical aircraft.

The polygonal approximation for an aircraft is processed by a knowledge-based algorithm to create the list of symbolic target features needed by the TRIPLE system. Given the orientation of aircraft, the knowledge-based process analyzes the line segments in the polygonal approximation to derive various symbolic features. This operation makes use of the symmetry properties of the aircraft’s shape in determining
many of the symbolic features. When feature values obtained for a specific feature (e.g., wing span or leading wing angle) vary significantly on opposite sides of an aircraft (usually due to distortion in the aircraft image), the feature is not extracted due to the ambiguity of the situation. This approach insures that target misclassification does not result from the presence of uncertain feature information. Once all possible features have been extracted from the polygonal approximation, the symbolic feature set is ready for processing by the TRIPLE system.

In the examples described below, the image distortion, border following, and polygonal approximation algorithms have all been implemented and executed on a SUN 3/60 workstation. The polygonal approximation data is transferred to a Symbolics 3670 workstation, which performs the symbolic feature extraction operation and hosts the TRIPLE target recognition system.

3.1 System Training

The first step in the target recognition process is to construct an initial collection of target models. As described in Section 2, this operation is automated in the TRIPLE system. The user merely supplies a set of training images, which are processed by the TRIPLE system to generate a set of target models. Figure 4 shows the initial set of aircraft used to initialize the TRIPLE system. These aircraft have not been distorted since most training operations utilize high quality training data to insure accuracy. Figure 5 provides the set of symbolic target features obtained for each of the aircraft in Figure 4. Missing features are due to inconsistencies in feature values or other aircraft anomalies.

Once the symbolic feature information for all training examples is available, the TRIPLE system must construct the target classification tree. To do so, the EBL component is invoked on each of the aircraft models to select the set of relevant target model features. EBL sequentially processes each of the symbolic features lists shown in Figure 5 using the information in the background knowledge base. The knowledge base for these examples consists of a generic aircraft prototype that specifies the presence of wing, fuselage, engine, and tail features in order to generate an aircraft target model. The knowledge base contains 23 different rules that are utilized to establish allowable combinations of the features to satisfy the wing, fuselage, engine, and tail requirements. Figure 6 illustrates the resulting target models created by the EBL component for the system initialization phase. Notice that the specific feature values have been generalized into ranges of values and that EBL has generated a weight associated with each feature in the target model. The weights are used during matching to compute target recognition confidence.

Following the selection of relevant target features by the EBL component, the TRIPLE system invokes the SCC process to construct the initial target classification tree. All seven target models are given to SCC, which builds the classification tree shown in Figure 7. The nodes in the tree
Figure 4: Aircraft used during the initialization phase of the TRIPLE system. (a) Boeing 747 (B-747). (b) Boeing 757 (B-757). (c) McDonnell Douglas MD-87 (MD-87). (d) Gulfstream Aerospace (Aerospace). (e) Cessna Citation (Citation). (f) Cessna Caravan (Caravan). (g) Piper Malibu (Malibu).

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<td>2.91</td>
<td>2.53</td>
<td>2.22</td>
</tr>
</tbody>
</table>

Figure 5: Symbolic features extracted from the aircraft in Figure 4.
Figure 6: EBL-generated target models for each of the symbolic feature lists shown in Figure 5. (a) B-747. (b) B-757. (c) MD-87. (d) Aerospace. (e) Citation. (f) Caravan. (g) Malibu.

Figure 7: SCC-generated target classification tree.
are labeled TN.*, which stands for TREE-NODE.*. Note that the aircraft have been effectively segmented into intuitively obvious groups by the SCC component.

3.2 Complete Recognition

The classification tree shown in Figure 7 is used by the TRIPLE system to recognize subsequent instances of the aircraft which have been modeled during training. Figure 8 shows an example of an "unknown" aircraft (Malibu) that must be recognized by the target recognition system. The aircraft image (Figure 8(a)) is moderately distorted and thus, in the polygonal approximation (Figure 8(b)), it is more irregular than the training example. The distortion of the aircraft becomes apparent by analyzing the list of extracted symbolic features, shown in Figure 8(c), and comparing this list with the previous collection of features shown in Figure 6(g). Only a few of the tail features are available due to the aircraft distortion.

The model matching component uses the list of features in Figure 8(c) to parse the classification tree in Figure 7. At the ROOT-NODE, the unknown aircraft is compatible with the leftmost branch, so the matching component traverses the tree to node TN-1. At this location, the unknown object matches the leftmost branch again, so the matching process moves to node TN-2. Here, the matching process must consider two possible alternatives due to the fact that the wing-to-tail feature is missing from the unknown aircraft. Both branches are investigated by the matching process to determine whether either of them (or possibly both) are compatible with the unknown target. The right branch of TN-2 is discounted due to differences in wing span, fuselage length, wing-to-nose, tail span, and tail leading angle. However, the left branch, TN-3, which contains the Malibu aircraft model, is found to be compatible with the unknown aircraft. The matching confidence of this target model is computed to be 74.6%. The confidence is derived using the weights assigned to each target model feature and the error between the feature values in the target model and the unknown aircraft. Even though the aircraft feature set was missing two features specified in the Malibu target model (wing-to-tail and tail leading angle), the TRIPLE system was able to correctly recognize the aircraft.

Additionally, since the recognition confidence of the aircraft is greater than the complete recognition threshold (70% for these experiments), the feature value monitor is invoked to update the values in the Malibu aircraft model. The revised Malibu model is shown in Figure 8(d).

3.3 Incomplete Recognition

The TRIPLE system is capable of partially identifying an unknown aircraft when very few symbolic features are available to describe the target. Figure 9 provides an example of an aircraft that causes the system to produce an incomplete recognition result. In this image (Figure 9(a)), the tail of the aircraft and the engine regions have been separated from the main portion of the target. This situation commonly occurs in cases where there is low contrast between the aircraft and the background or in cases where shadows or surfaces markings on the target blend in with the background. Since the border following algorithm is designed to locate only the largest target region, the system creates the polygonal approximation shown in Figure 9(b). The set of symbolic aircraft features which can be extracted from this result are indicated in Figure 9(c). Due to the lack of any tail information and discrepancies in the wing representation, very few reliable features have been obtained for this target.

**Figure 8:** Aircraft (Malibu) which illustrates the complete recognition state of the TRIPLE system. (a) Distorted aircraft image. (b) Polyonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft. (d) Revised Malibu aircraft model after complete recognition cycle.

**Figure 9:** Aircraft (B-757) which illustrates the incomplete recognition state of the TRIPLE system. (a) Distorted aircraft image. (b) Polyonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft.
The matching component begins at the ROOT-NODE of the classification tree (Figure 7) by inspecting the wing span value of the unknown aircraft. Because the wing span is missing, the matching component hypothesizes all three branches of the tree (Nodes TN-1, TN-6, and TN-11) as possible alternatives. TN-11, which contains the B-747 aircraft model, is rejected due to differences in single target model feature except wing-to-nose. At TN-7, the unknown aircraft's leading wing angle is compatible with the right branch of the node, so parsing continues down to TN-5. However, the Citation aircraft model contained in TN-5 conflicts with the unknown aircraft in every feature except the leading wing angle. Thus, this hypothesis is also rejected.

Looking at TN-6, the matching process selects the right branch and moves to the TN-8 tree node. Since the engine position feature is missing, the matching process once again considers both branches as possible alternatives. Inspecting TN-9, the model finds that the B-747 aircraft model is compatible with the unknown target (matching confidence = 25.9%). At TN-10, the unknown aircraft is also correctly matched to the MD-87 aircraft model (matching confidence = 27.5%). Since no additional feature information is available to select between these two alternatives, the TRIPLE system reports both aircraft models as possible matches.

3.4 Occluded Recognition

Target occlusion can be effectively handled by the model matching process performed in the TRIPLE system. Occluded recognition performance in TRIPLE system is very similar in nature to incomplete recognition. The difference between the two cases is that the missing target features tend to be the global features in the case of occlusion whereas, in the case of incomplete recognition, the missing features are usually the local target features.

Figure 10(a) provides an example of an aircraft image that illustrates the occluded recognition scenario. In this example, the nose and the port wing of the aircraft, which is an instance of the MD-87 target model, have been occluded. The polygonal approximation of this target is shown in Figure 10(b). The symbolic feature extraction process is still able to derive a useful set of features from the aircraft, as indicated in Figure 10(c).

The model matching component uses the list of symbolic feature information to parse the classification tree shown in Figure 7. At the ROOT-NODE, the wing span value of the unknown aircraft is compatible with the center branch, so the matching component proceeds down to node TN-6. The wing-to-nose feature is missing in the feature list, so both branches (TN-7 and TN-8) are hypothesized. Examining TN-7, the model matching process finds that the wing span and tail span feature values of the Renegade target model stored in the node, although all other features are compatible. Thus, TN-7 is discarded. At TN-8, the right branch of the node is compatible with the engine position feature in the feature list. Finally, at node TN-10, the matching process discovers that the MD-87 target model is compatible with the feature list. The recognition confidence in this example is 65.9%. No changes are made to the target model since the recognition confidence is below the complete recognition confidence threshold.

3.5 Target Model Acquisition

The machine learning capabilities of the TRIPLE system are evident in the target model acquisition and model refinement operations performed by the system. This section demonstrates several examples of the automated target model acquisition scenario.

Figure 11(a) shows an image of an unknown aircraft. In this case, the aircraft is a Lake Renegade (Renegade) which has never been seen by the target recognition system. Figure 11(b) illustrates the polygonal approximation of the aircraft image and Figure 11(c) provides the list of symbolic target features extracted from the polygonal representation. As with any other unknown object, the TRIPLE system begins by

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<td>Wing Sweep, Trailing</td>
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<td>Wing Base Chord</td>
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**Figure 10:** Aircraft (MD-87) which illustrates the occluded recognition state of the TRIPLE system. (a) Distorted aircraft image. (b) Polygonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft.

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<td>Length, Wing-to-Tail</td>
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</table>

**Figure 11:** Aircraft (Renegade) which illustrates the target model acquisition capabilities of the TRIPLE system. (a) Distorted aircraft image. (b) Polygonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft. (d) EBL-generated target model for the aircraft.
parsing the classification tree (Figure 7) using the set of symbolic target features. Traversing the tree in standard fashion, the knowledge-based matching component arrives at node TN-3 and compares the symbolic feature list with the Malibu target model. However, differences in leading wing angle, trailing wing angle, fuselage length, and tail span cause the Malibu target model to be discarded. Since no other branches in the tree were hypothesized during parsing, the current classification tree contains insufficient information to identify this aircraft.

The EBL process is subsequently invoked in an attempt to acquire the unknown aircraft as a new target model. Figure 11(d) illustrates the EBL-generated target model produced from the symbolic feature list in Figure 11(c). The new target model is then handed to the SCC component so that it can be incorporated in the classification tree structure. SCC parses the tree using the new target model in an attempt to leave as much of the tree intact as possible. SCC successfully traverses the tree until it encounters the TN-3 leaf node. The tree is reclustered at this point to distinguish between the current Malibu target model and the new Renegade target model. Tail span is found to be the best symbolic feature that separates the two target models. The revised classification tree, after insertion of the Renegade target model, is shown in Figure 12.

Figure 13 presents a second, more complex example of the target model acquisition process. Figures 13(a) and 13(b) show an image of an unknown aircraft and the corresponding polygonal approximation of this image. The aircraft in this case is a McDonnell Douglas MD-11 (MD-11). The extracted list of symbolic target features is shown in Figure 13(c). As before, the process begins by parsing the current classification tree (Figure 12). The parsing process immediately terminates since the wing span value of the unknown target is not compatible with any of the branches at the ROOT-NODE.

EBL is called upon to acquire the aircraft as a new target model. In this case, the acquisition process succeeds, as indicated by the new target model shown in Figure 13(d).

Figure 12: Revised target classification tree, after insertion of the Renegade aircraft model.

Figure 13: Aircraft (MD-11) which illustrates the target model acquisition capabilities of the TRIPLE system. (a) Distorted aircraft image. (b) Polygonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft. (d) EBL-generated target model for the aircraft.
This model is then passed to SCC so that it can be added to the classification tree. Since none of the branches at the \textit{ROOT-NODE} are compatible with the wing span of the new model, SCC is forced to recluster the tree at the root level. In doing so, the SCC process discovers that fuselage length is now a better distinguishing feature than wing span at the root node in the tree. The resulting target classification tree, after re-clustering has been completed, is shown in Figure 14. The new MD-11 target model has been included in the same branch as the B-747, with wing-to-nose used as the distinguishing feature.

3.6 Target Model Refinement

The second machine learning capability of the \textsc{TRIPLE} system is present in the automated target model refinement process described in this section. Target model refinement occurs when the presence of a new symbolic feature is detected in an aircraft that can be correctly recognized by the target recognition system. The EBL-SCC learning cycle is invoked in these instances to determine if the new feature is relevant in recognizing the aircraft and, if so, where it should be placed in the target classification tree. Several examples of target model refinement are now presented. The classification tree used in these experiments is shown in Figure 15. This tree was obtained from the tree in Figure 14 after two more aircraft models (\textit{Metro} and \textit{ Learjet}) were acquired.

The first aircraft to be refined by the \textsc{TRIPLE} system is shown in Figure 16(a). This aircraft is an instance of the MD-11 target model that was acquired in Section 3.5. The polygonal approximation and the list of symbolic target features are shown in Figures 16(b) and 16(c), respectively. The model matching process uses the symbolic features to parse the classification tree in Figure 15. The unknown aircraft is correctly identified as an MD-11 aircraft with a recognition confidence of 94.3%. In addition, the model matching process detects the presence of two new features in the unknown aircraft, wing-to-tail and leading tail angle. Both of these features were missing from the feature list in Figure 13 due to errors in the polygonal approximation of the aircraft caused by image distortion.

Since new features are present in the correctly identified aircraft, the EBL-SCC learning cycle is entered to ascertain the relevance of the features. The two new features are added to the current MD-11 target model and the entire list of features is reprocessed by the EBL component. In this example, EBL does create a new target model (Figure 16(d)) since wing-to-tail and leading tail angle were found to be significant. Further, the EBL process has selected trailing tail angle and tail-base as additional relevant features in conjunction with the presence of the leading tail angle feature.

The revised MD-11 target model is sent to the SCC component in order to update the classification tree. At the \textit{ROOT-NODE}, the four new target features are compared with the fuselage length feature to see if they produce a better conceptual clustering of the target models at that position in the tree. None of them do, so the process repeats at TN-26 by comparing the clustering quality of the wing-to-nose feature with the new relevant features. Once again, the tree node is left intact and finally, the new target features are simply added to the list of relevant features at the TN-28 leaf node.

Figure 17 provides another example of the model refinement process. The image of a \textit{Renegade} aircraft is shown in Figure 17(a) and the corresponding polygonal approximation is indicated in Figure 17(b). The list of symbolic target features obtained from this aircraft are presented in Figure 17(c). The tree is parsed using this feature information and, although the matching process must hypothesize nodes TN-36 and TN-39 during the tree traversal, the aircraft is finally identified as an instance of the \textit{Renegade} target model. The recognition confidence in this case is 86.1%. The nose shape, leading tail angle, and tail base features in Figure 17(c) are discovered to be new model features and thus, the target model refinement operation is invoked.

EBL processes the \textit{Renegade} aircraft model using the three new target features. In this case, the leading tail angle is found to be relevant along with the trailing tail angle that was present, but not relevant, in the initial \textit{Renegade} sym-

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure14.png}
\caption{Revised target classification tree, after insertion of the MD-11 aircraft model.}
\end{figure}

\textbf{Figure 14:} Revised target classification tree, after insertion of the MD-11 aircraft model.
Figure 15: Target classification tree for the target model refinement experiments.

Figure 16: Aircraft (MD-11) which illustrates the target model refinement capabilities of the TRIPLE system. (a) Distorted aircraft image. (b) Polygonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft. (d) EBL-generated target model for the aircraft.

Figure 17: Aircraft (Renegade) which illustrates the target model refinement capabilities of the TRIPLE system. (a) Distorted aircraft image. (b) Polygonal approximation of the aircraft. (c) Symbolic target features extracted from the aircraft. (d) EBL-generated target model for the aircraft.
bolic feature list. The revised target model is shown in Figure 17(d). As in the previous model refinement example, SCC is given the revised model for insertion into the classification tree. SCC finds that at TN-36, the new leading tail angle is a better distinguishing feature than the current tail span feature (Figure 15), so the classification tree is reclustered at TN-36. The final structure of the classification tree, after the target model refinement process, is shown in Figure 18.

3.7 Recognition Failure

This section presents a brief example of recognition failure in the TRIPLE system. As with any target recognition system, there will always be instances where the information processed by the system or the knowledge used to process the information is insufficient to perform the recognition task. This example demonstrates how incomplete feature information leads to recognition failure in the TRIPLE system.

Figure 19(a) provides an aircraft image (a Fairchild Merlin aircraft which has not previously been modeled) that must be identified by the recognition system. The polygonal approximation of the aircraft (Figure 19(b)) contains only the front part of the aircraft due to the separation in the fuselage portion of the image. The symbolic feature list obtained from this approximation is shown in Figure 19(c). The knowledge-based matching component uses the feature data to parse the classification tree in Figure 18. At the ROOT-NODE, the wing-span value is missing, so nodes TN-14, TN-21, and TN-26 are hypothesized. However, at each of these nodes, none of the available branches are compatible with the aircraft’s feature data, so the model matching process terminates. EBL is invoked to acquire the new aircraft, but is unable to generate an acceptable target model due to the absence of any tail features. Since EBL cannot process the available feature data, the aircraft is reported as a recognition failure.

4. CURRENT RESEARCH

The experiments performed using the TRIPLE system to date have served as a proof of concept for the integrated target recognition/machine learning approach. We are now involved in extending the capabilities of the TRIPLE system to handle complex 3D object descriptions. These changes involve modifications to the segmentation and symbolic feature extraction component to obtain valid symbolic features for 3D objects seen at arbitrary angles.

Figure 20(a) presents a typical example of an image containing an aircraft and Figure 20(b) indicates a segmented view of this image in which the aircraft regions are prominent. Due to the oblique angle imagery, the aircraft cannot be matched using a 2D target model. Instead, the symbolic feature extraction component now utilizes a generic aircraft description similar to the one shown in Figure 21. By hypothesizing various orientations of the 3D aircraft prototype and predicting the appearance of specific target features, the necessary target features can be derived from the segmentation results shown in Figure 20(b).

Once the 3D symbolic features have been obtained using this process, the TRIPLE system can process the data and recognize the unknown aircraft in a similar fashion to the matching approach described in this paper. By extending the background knowledge base to handle the additional 3D target features, the TRIPLE system can recognize, acquire, and refine complex, 3D target models. Work is currently underway to refine and implement these concepts.
5. CONCLUSIONS

We have presented the experimental results of a new target recognition system that exhibits the standard target recognition system functionalities (complete recognition, partial recognition, occluded recognition) as well as providing several new capabilities (target model acquisition and target model refinement). The machine learning components built into the TRIPLE system allow it to adapt its representation of the individual target models in order to operate effectively in an unconstrained, dynamic environment. The TRIPLE system is part of a complete multilevel machine learning system for target recognition that we are developing.1

REFERENCES


Figure 20: Typical imagery for the 3D target recognition experiments. (a) Oblique angle image of two aircraft. (b) Segmented aircraft regions used during symbolic feature extraction.

Figure 21: Generic aircraft prototype used to obtain symbolic object features in the 3D target recognition experiments.
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