A Sketch Recognition System for Recognizing Free-Hand Course of Action Diagrams

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Abstract

Military course-of-action (COA) diagrams are used to depict battle scenarios and include thousands of unique symbols, complete with additional textual and designator modifiers. We have created a real-time sketch recognition interface that recognizes 485 freely-drawn military course-of-action symbols. When the variations (not allowable by other systems) are factored in, our system is several orders of magnitude larger than the next biggest system. On 5,900 hand-drawn symbols, the system achieves an accuracy of 90% when considering the top 3 interpretations and requiring every aspect of the shape (variations, text, symbol, location, orientation) to be correct.

Introduction

Drawing with pen and paper is a common method for users to convey visual information. Sketch recognition seeks to harness the power of pen and paper by automatically understanding freehand-sketched input with a stylus and digitizing screen. Furthermore, sketch recognition attempts to recognize the intent of the user while allowing the user to draw in an unconstrained manner. This permits the user not having to spend time being trained how to draw on the system, nor will the system need to be trained on how to recognize each users particular drawing style.

The recognition of hand drawings has a variety of uses, including symbol recognition in Computer-Aided Design systems, providing automatic correction or understanding of diagrams for immediate feedback in educational settings, functioning as alternative inputs for small keyboard-less devices (such as Palm Pilots), or providing gestural interfaces. Our aim as sketch recognition researchers is to build systems using artificial intelligence techniques that recognize drawn-diagrams with human-recognizer efficiency and accuracy.

One real-world domain that has thousands of symbols is military course of action (COA) diagrams. Military commanders use COA diagrams to plan field operations, where the symbols represent troops, supplies, obstacles, and movement patterns. Currently, commanders draw COAs by hand on a map for planning purposes, and then these diagrams are entered into a computer through typical WIMP interfaces for purposes of simulation and plan communication. Previous attempts to apply sketch recognition to COAs have resulted in systems that can only recognize a handful of shapes, often require users to draw each shape with a specific gesture, and do not allow users to draw freely (Pittman et al. 1996).

In this paper, we present a first-look at an application that allows military commanders to hand-draw hundreds of COA symbols directly on a digitized map. The number of symbols we support is vastly greater than previous sketch recognition interfaces, and, by utilizing many artificial intelligence techniques, our system can rank the correct interpretation in the top three returned results 89.9% of the time, for 485 symbols.

Implementation and Methodolgy

The flowchart in Figure 1 shows the steps we take to recognize drawn course of action symbols. The following sections explain the recognition steps in more detail.

Grouping

In our framework, we have recognizers that work well for shapes and some that work well for text and decision graphics. PaleoSketch is used to recognize basic geometric shapes like rectangles, lines, and ellipses, while our handwriting recognizer (HWR) is responsible for recognizing text, decision graphics, and echelon modifiers. The job of the grouping algorithm is to make sure the right strokes go to the right recognizer. To perform grouping, we first find the largest stroke present, which is typically the boundary of a unit symbol. Next, the remaining strokes are grouped into two sets, depending on whether they are present within or outside of the bounding box of the largest stroke (Figure 2). Inside

Figure 2: Example results of the grouping algorithm. The largest stroke is found (red), and the remaining strokes are grouped based on whether they occur inside (blue) or outside (yellow) of the bounding box of the largest stroke.

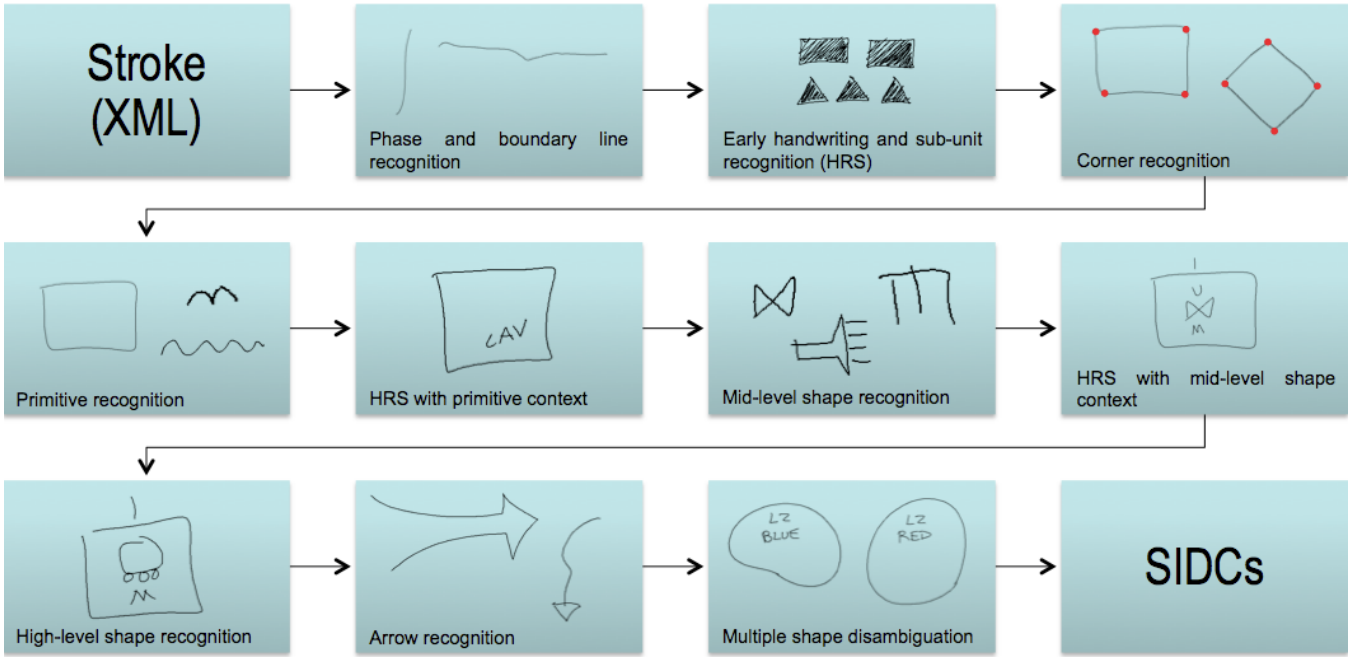


Figure 1: The recognition process, starting from a stroke represented in an XML datafile, to the final, unique symbol identifiers, SIDCs.

strokes are either going to be decision graphics, text, or type modifiers that need to be sent to the primitive recognizer. These strokes are initially run through the HWR and if the returned confidence is high enough, they are marked as text or decision graphics. If the confidence is low, then they are sent to PaleoSketch to be recognized as primitive shapes. Strokes that occur outside of the bounding box of the largest stroke are typically echelon modifiers and can recognized by the HWR.

Segmentation

Stroke segmentation involves breaking drawn strokes into a set of primitive building blocks, such as lines or arcs. In our system, we split every drawn stroke into a series of lines. These polyline representations of the stroke are then sent into our primitive recognizer, PaleoSketch.

We use a combination of multiple algorithms in order to produce a highly accurate polyline segmentation (Wolin, Paulson, and Hammond 2010; Wolin, Eoff, and Hammond 2008; Wolin, Paulson, and Hammond 2009; Sezgin, Stahovich, and Davis 2001; Kim and Kim 2006; Douglas and Peucker 1973).

Primitive Recognition

The goal of primitive recognizers is to classify individual strokes into one of a set of basic building block shapes. These primitive shapes can then be combined to form more complex symbols using high-level shape grammars like LADDER (Hammond and Davis 2005). For primitive recognition, we use an extended version of the PaleoSketch algorithm (Paulson and Hammond 2008). This version of PaleoSketch supports 13 different primitive shapes, which can be seen in Figure 3.

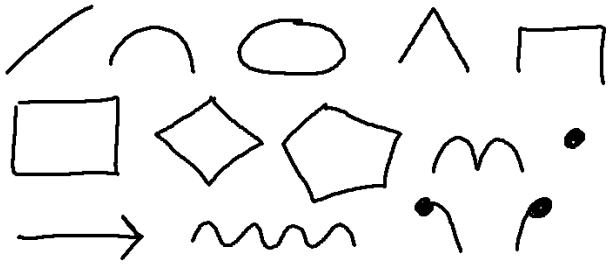


Figure 3: Primitive shapes supported by our modified version of PaleoSketch.

Dashed Primitives

Many symbols in the COA domain are "anticipated" and drawn with dashed boundaries containing an arbitrary number of lines. To search for dashed boundaries, we start by first finding instances of dashed lines. The algorithm starts by iteratively cycling through the shapes on the screen in temporal order and maintaining a stack of lines (and dots) that make up a possible candidate for a dashed line. As we encounter conditions that indicate a dashed shape is not present (e.g. large slope change, large gap between strokes), the stack is sent to a function that generates a dashed line if it contains more than one shape. Once all dashed lines have been found, they are placed into four different bins based on their orientation: those that are close to vertical (within 15 degrees), close to horizontal, or have a positive or negative slope. Next, we search within the horizontal and vertical bins for possible rectangles, and within the positive and negative bins for diamonds. For dashed ellipses, we perform a similar operation to that of dashed lines, except that we also

allow for polylines are arcs to be considered as dashes. Once we have a stack of candidate dashes for an ellipse, we generate a temporary stroke using the endpoints and midpoints of the strokes on the stack. If this generated stroke passes conditions of an ellipse test, then we group the strokes together as a dashed shape.

Decision Point Recognition

Decision points are typically drawn as 10-line stars in COA diagrams. Stars are searched for using a similar approach to dashed shapes. However, in addition to checking the spatial distances between consecutive strokes, we also verify that the angles between lines alternates between acute and obtuse angles.

Handwriting Recognition

The handwriting recognizer uses two pre-built multi-layer perceptron models from Weka to recognize inner and echelon text, respectively. Echelon text comprises of the symbols 'x', '+', '-', '1', and '*'. Inner text has the character set A-Z and 0-9, with some special symbols used in decision graphics (See **DecisionGraphics**). When strokes are passed to the handwriting recognizer, they are first grouped to combine the strokes into logical words and characters based on the stroke's spatial separation and overlap, and using the left-to-right assumptions of handwriting.

After these stroke groupings are formed, a brute-force approach is taken to compute the character and word possibilities. Our domain has no word more than seven letters, and each character is no more than five strokes, so the number of possible words is bounded. A confidence value for each possible character or word is computed using the multi-layer perceptrons, and the handwriting with the best confidence value is used for further symbol recognition.

CALVIN

CALVIN is a heuristic-driven geometric recognizer based on LADDER (Hammond and Davis 2005). It builds complex high-level shapes by combining shapes (primitves recognized by PaleoSketch (Paulson and Hammond 2008) or other high-level shapes) in different combinations. The ways that shapes can be combined are dictated by geometric constraints, such as saying that one shape `c`ontains another, or that the endpoints of two lines are `coincident`. As an example, see Figure 4 LEFT, a sketch of a mechanized infantry unit. Some of constraints that might be used to specify how the parts of this shape fit together include the lines having a `positiveSlope` and `negativeSlopve`, as well as the endpoints being `c`oincident with the corners of the rectangle.

In addition to the basic recognition capabilities found in LADDER, CALVIN has been hand-tuned using heuristics to increase the accuracy and efficiency of recognizing course of action diagrams. It re-analyzes the set of shapes for grouping purposes. Although strokes have already been grouped for recognition at earlier stages, recognition context can help us re-group strokes more accurately. For instance, if the primitive recognizer has detected a rectangle with a high degree of confidence, then we can say that certain strokes

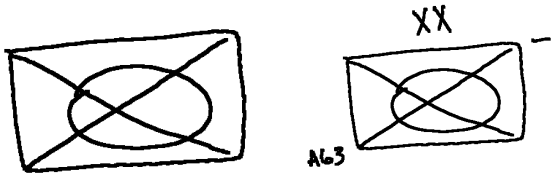


Figure 4: LEFT: Sketch of a mechanized infantry unit. The constraints for this symbol dictate that the two diagonal lines that form the X (the infantry part) are `coincident` with the respective corners of the rectangle, and that one of the lines has a `positiveSlope` and the other a `negativeSlope`. The ellipse (the mechanized part) must be contained within the rectangle, and all the centers must be roughly `coincident` with each other. RIGHT: Sketch of a mechanized infantry unit with various modifiers. After our recognition algorithms determine there is a rectangle in the sketch, it can group strokes according to contextual placement relative to the rectangle. The two Xs above the rectangle belong to the unit's echelon, the minus to the right tells us that the unit is reduced, and the alphanumeric identifier at the lower left helps us identify this particular unit. Without the context of the recognized rectangle, identifying these other pieces of information (especially differentiating the echelon X from the X in the center of the rectangle) can become difficult.

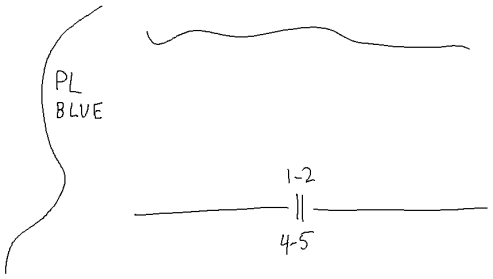


Figure 5: Examples of phase lines and boundary lines. On the left, a Phase Line, 'PL', is uniquely identified by the identifier, 'BLUE'. On the top-right, an ambiguous phase or boundary line is drawn horizontally. On the bottom-right, a Boundary Line is labeled with a company echelon, 'II', and the unique identifiers '1-2' and '4-5'.

in certain positions relative to that rectangle should go together. After grouping, it is then able to accurately put together the requisite pieces of a military symbol. In Figure 4 RIGHT, we show the same sketched unit except with modifiers. Once CALVIN determines a rectangle has been drawn, we use contextual rules to determine the inner portions of the symbol (the X and ellipse), and the different outer portions of the symbol. In this case, the user has drawn an echelon (the two Xs on top), noted that the unit is reduced (the minus on the right), and assigned an identifier (in the lower left) to the unit. Without contextual rules, identifying all these components simultaneously becomes an NP-complete search problem.

Phase/Boundary Lines

Phase lines and boundary lines define the location steps of military operations and the boundaries by which military units are confined, respectively (Figure 5). Phase and bound-

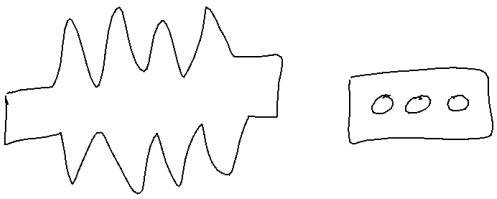


Figure 6: On the left, we have a General Belt obstacle symbol. On the right is a Minefield Static obstacle. These obstacles can be drawn with dynamic patterns, such as with more or less spikes for the General Belt, or more inner circles in the Minefield Static.

ary lines can be arbitrary contours, and they are recognized first by determining if there is a long stroke of sufficient length. If a long stroke exists, then the remaining strokes are assumed to be text and are sent to the handwriting recognizer. The handwriting recognizer looks for type identifiers, such as 'PL' or 'BL', and unique identifiers, such as 'BLUE' or 'ALPHA' that could distinguish the phase and boundary lines.

Areas

Areas are large, closed strokes that mark zones of interest, such as the landing zones ('LZ') shown in the penultimate step of the flowchart (Figure 1). The area recognizer first determines if the largest stroke in the symbol is closed. If a large, closed stroke exists, then echelon, type identifier, and unique identifier text is looked for. Echelons are located at either the top or bottom of the closed stroke, and identifier text is located inside of enclosure.

Decision Graphics

Decision graphics are type modifiers that include a combination of filled and un-filled rectangles and triangles. Because the primitive recognizer is not equipped to handle filled-in shapes, we recognize these symbols using the HWR. These shapes are included in the common dictionary that handles modifiers that occur within the bounding box of the largest shape on the screen (as determined by the grouper). If the HWR detects instances of decision graphic modifiers, it then analyzes all shape definitions that are of the type "DecisionGraphic" to find the correct symbol.

Obstacles

Some course of action shapes are drawn using similar drawing patterns, yet can contain a dynamic number of pattern repetitions (Figure 6). These symbols can be recognized by looking at the symbols on a micro-level. A set of features are computed for each symbol, and this "bag of features" is compared to a set of template patterns. Symbols with similar patterns can then be recognized.

Arrows

Arrows indicate movement of friendly or hostile forces and are allowed to have arbitrary paths. We recognize arrows by looking at the number of strokes drawn, the number of line segments the strokes can be broken into, and the type of arrow head used.

Interface

In producing our COA interface, we have identified three requirements: quick creation, simplicity, and readability.

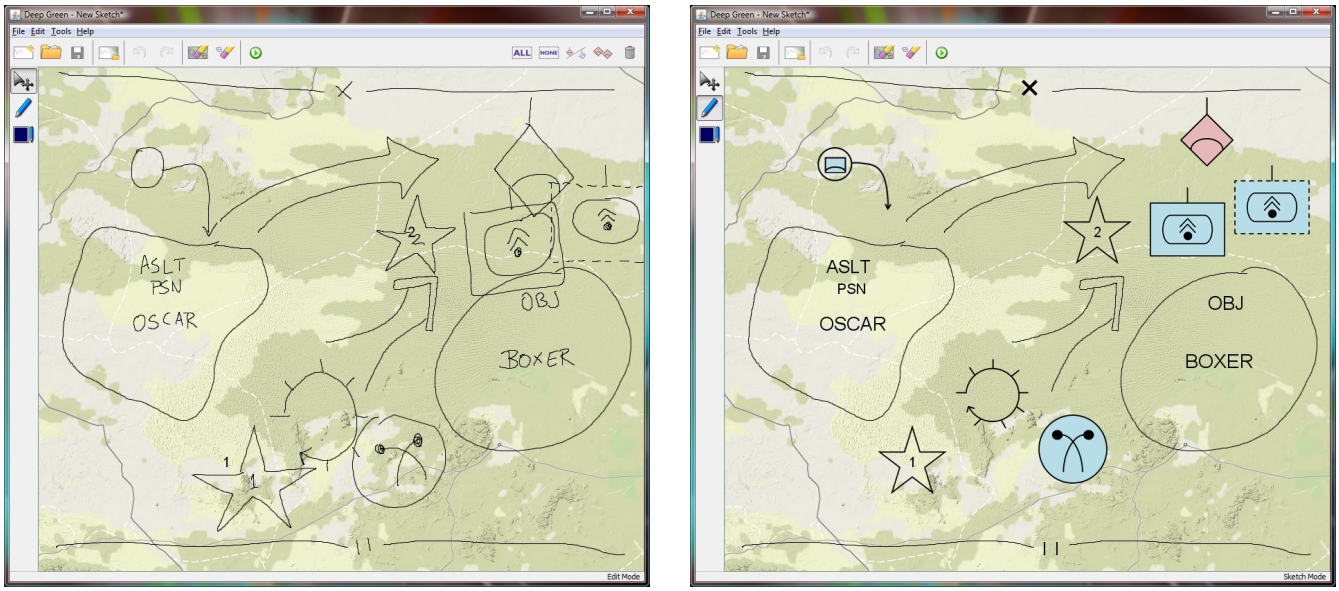
First, we must design this interface in such a way that course of action maps can be quickly created. The interface is critical because this project is intended to be used in a critical environment under time constraints. Indeed, a major goal of this project is to speed up creation of course of action maps, so its interface should facilitate this requirement. All of the recognizers reported above supply confidence values, the interface uses these to order the different results.

Second, we require simplicity. Sketch recognition, by definition, aims to simplify the user experience by allowing all or most user input in the form of sketching. This implies that our application could be extremely simple, perhaps consisting of only a drawing surface and a handful of buttons.

Finally, readability is our third requirement. The sketch recognition algorithm produces a list of interpretations ordered by probability. Usually, the desired shape is returned at the beginning of the list. However, when dealing with a large set of possible shapes, the desired interpretation may in fact be second or third in the list. We therefore have to display a few top recognition results in a way that keeps the interface simple and usable. We feel that we have successfully incorporated these requirements into the interface.

To fulfill our requirements, our interface consists of a drawing panel and a few toolbar buttons. We provide quick creation and simplicity by including few interface elements, allowing immediate creation upon launching, and automatically performing recognition and displaying results. Also, after a shape is drawn by the user, recognition automatically occurs when the hand is removed from the screen. To facilitate our readability requirement, the top results are displayed in panels once recognition finishes. These panels display textual information about the possible symbols as well as a preview image. We have displayed this information in a manner that is easily readable. While these core requirements have been implemented, we have added a few more features to enhance the creation process.

We have included a few intelligent features that help improve the user experience. First, we have included stroke beautification (Figure 7). This occurs on two levels. In many symbols, a user's strokes are replaced by a correct symbol image file. Some symbols, however, are defined by user-drawn boundaries and, therefore, do not have image files associated with them. Many of these amorphous shapes contain some text labels which are written in by the user. Our interface uses handwriting recognition to convert handwriting into text while keeping the user-defined boundary in these types of shapes. In addition to stroke beautification, we have included a set of basic editing tools including move, duplicate, and delete. These tools, while simple, provide some much needed functionality. We have also implemented a fourth tool to convert a beautified symbol to its user-drawn strokes and back again. This obviously helps us in testing our application, but it also can help users understand the sketch recognition process.



(a) The user drew COA symbols in our interface using a stylus.

(b) Drawn symbols are beautified, where some of the symbols are replaced with their recognized images, and the text becomes typed.

Figure 7: Our interface incorporates stroke beautification, which takes recognized strokes (7(a)) and turns them into cleaned images (7(b)).

Results and Discussion

We trained our recognizers on a set of 485 different symbols, collecting over 6,000 samples drawn by researchers and course of action diagram experts. We tested on a different set of data consisting of 5,900 samples drawn by 8 researchers (not that none of these users were included in the data used for the development and training of the system).

We return multiple interpretations for each symbol recognized, since many of the symbols are often similar with only minor nuances. The correct interpretation is returned as the top result 84.4% of the time, in the top three results 89.9% of the time, and in the top ten results 90.8% of the time. These recognition results are on par with current sketch recognition systems, and they are phenomenal when considering that we have an order of magnitude more symbols than other applications support.

We have not conducted large-scale user interface evaluations at this time or deployed our interface with military experts, but we hope to do so in future research. A video of the current system is posted here: http://srlweb.cs.tamu.edu/srlng/research/project/22

Related and Prior Work

Frameworks and systems have been created that either can specified to handle sketched course of action shapes, or provide alternative implementations in doing so. We discuss such works and discuss their limitations that have been improved upon by our implementation.

QuickSet System

An early system that was used for battle plans involving course of action shapes was QuickSet (Cohen et al. 1997), a multimodal system utilizing a multi-agent architecture that can be applied for a number of applications. One such application was an interface for inputting course of action shapes was LeatherNet, an interface that requires users to use a combination of speech and sketch input for drawing the shapes. The multimodal input activates an over-the-shelf speech recognizer, as well as a traditional pen-based gesture recognizer consisting of a neural network and hidden Markov models, whenever the user places the pen on screen. The system therefore listens to both speech and gesture simultaneously during interface usage. While QuickSet demonstrated that it can complete the task faster than existing CAD-style interfaces at the time (Forbus, Usher, and Chapman 2003), the necessity of speech as a modality for users using the system to describe the layout of forces in simulated exercises using course of action shapes have exhibited shortcomings. Specifically, even current speech systems are severely limited in noisy environments, and target users of such a system have repeated reported that they would not use it if it has a speech recognition requirement (Forbus, Usher, and Chapman 2003), which is the case for the QuickSet system.

nuSketch Battlespace Interface

The nuSketch Battle Interface (Forbus, Usher, and Chapman 2003) is a more recent system for handling sketched course of action shapes, and was designed to address the shortcomings of systems such as QuickSet. The first notable contrast of the nuSketch approach to previous systems is its focus on sketching and the lack of a speech modality. Despite the systems heavy emphasis on sketching for drawing up battle plans, the sketch-based interface does not utilize recognition on the users input. Instead, the system

relies on visual and conceptual understanding of the input to drive the drawing up of battle plans using sketched course of action shapes, and relies more on reasoning techniques of the sketched shapes themselves. In order to address the lack of recognition techniques, the system also depends heavily on interface mainstays such as toolbars, combo boxes, and type-in boxes to facilitate inputting the sketches.

LADDER framework

One framework that has served as the basis to our work is the LADDER framework (Hammond and Davis 2005), a domain-independent sketching language that can be used to describe how shapes and shape groups are drawn, edited, and displayed in the recognition process. The language is used as a tool to describe higher level symbols as a combination of lower-level primitives that fulfill certain geometric constraints, and is useful for recognizing symbols in a domain absent of domain-specific information. Examples of domains that have successfully utilized LADDER include biology, music notation, East Asian characters and sketch-based educational games. A limitation of LADDER though is that it does not handle symbols that are difficult to describe geometrically or are ambiguous without context, as is the case with many course of action shapes.

COA Design Interface

The COA Design Interface is a system that addresses the limitations of LADDER for sketched course of action shapes by extending that frameworks capabilities (Stolt 2007). Besides modifying LADDER to make it domain-specific to sketched course of action shapes, one significant extension is the use of the Intermediate Feature Recognizer (IFR). This recognizer serves multiple purposes such as recognizing certain shapes (e.g., variably-drawn) not handled by LADDER well, as well as provide error correction. The IFR allows a larger variety of shapes to be handled with reasonable accuracy, and thus is capable of reporting up to 247 shapes. The current implementation is still lacking components that are critical to military planners drawing battle plans, such as course of action shapes that contain text.

Conclusion

This paper describes a sketch recognition system that recognizes military course of action diagrams. The sketch recognition system recognizes 485 different military course-of-action diagram symbols, with each shape containing its own elaborate set of text labels and other variations. Even without the variations and text this is well over an order of magnitude more symbols than the next largest system. When one factors in the variations (not allowable by other systems), this system is several orders of magnitude larger than the next biggest system. On 5,900 student hand-drawn symbols, the system achieves an accuracy of 90-percent when considering the top 3 interpretations and require every aspect of the shape (variations, text, symbol, location, orientation) to be correct.

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