

Actuation-based Shape Representation Applied to Engineering Document Analysis

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Abstract: We propose that human generated drawings (including text and graphics) can be represented in terms of actuation processes required to produce them in addition to the visual or geometric properties. The basic theoretical tool is the wreath product introduced by Leyton (Leyton, 2001) (a special form of the semi-direct product from group theory which expresses the action of a control group on a fiber group) which can be used to describe the basic strokes used to form characters and other elements of the drawing. This captures both the geometry (points in the plane) of a shape as well as a generative model (actuation sequences on a kinematic structure). We show that this representation offers several advantages with respect to robust and effective semantic analysis of CAD drawings in terms of classification rates. Document analysis methods have been studied for several decades and much progress has been made; see (Henderson, 2014) for an overview. However, there are many classes of document images which still pose serious problems for effective semantic analysis. Of particular interest here are CAD drawings, and more specifically sets of scanned drawings for which either the electronic CAD no longer exists, or which were produced by hand. We demonstrate results on a set of CAD-generated drawings for automotive parts.

1 INTRODUCTION

Our main result here is the development of a novel shape analysis method and the demonstration of its effectiveness in the text analysis of engineering CAD documents. Figure 1 shows the overall scheme for both 2D and 3D datasets.

The 2D data of interest here consists of scanned engineering drawings like those shown in Figure 2. The image analysis consists of the extraction of basic shape symmetries (represented as wreath products), followed by symmetry parsing (given as Wreath Product Constraint Sets), finally passing through a classi-

fication component where hypotheses are formed as described in the figure. We provide a formal grammar for this parsing in which the lowest level terminal symbols are simple symmetries and nonterminal symbols correspond to more complex shapes. The hypotheses produced by the system are ranked according to a Bayesian analysis based on the wreath product directed acyclic graph as well as the parse tree. Much work has been done in engineering document analysis (see (Henderson, 2014) for a detailed survey), but to our knowledge, there are few implemented systems in which shape is represented in terms of actuation primitives. One example of such work is that of Plamondon (Plamondon, 1995a; Plamondon, 1995b; Plamondon, 1998; Plamondon et al., 2014)), but that approach has a very different basis rooted in the kinematics of human rapid movement. Other recent studies of more global properties of document analysis, e.g., using deep convolutional networks (Harley et al., 2015; Kang et al., 2014), are more conventional in that they are still based on the geometric properties of the points comprising the shape, rather than exploiting how the shape is synthesized. For another survey of document analysis and recognition, see (Marinai, 2008).

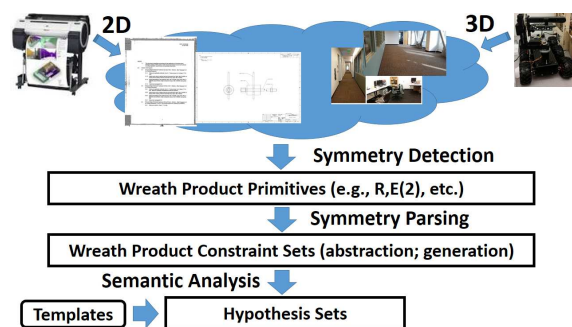


Figure 1: Overall Symmetry Analysis Flow.

Leyton (Leyton, 2001) introduced a generative theory of shape, and his key insight was that the set of points in a shape may be generated in many different ways, and that these ways can be characterized technically by a wreath product group. We propose that such a sensorimotor representation is more suitable for an embodied agent than a purely geometric or static feature method. The wreath product combines two levels of description: (1) a symbolic one based on group action sequences (i.e., strings), and (2) shape synthesis based on group actions on other groups (i.e., motion descriptions). For example, a line segment may be generated by moving a point along a line for a certain distance – represented by the wreath product: $e \wr Z_2 \wr \mathcal{R}$; however, in order to realize this for a specific line segment, an actuation mechanism in the coordinate frame of the shape must be defined and actuation commands provided whose application results in the kinematic synthesis of the points in the line segment. For example, eye motion control to move the fovea along a shape is such a system. The human arm and its motor control is another. The abstract form of the wreath product allows either of these control systems (eye or arm) to generate a line segment. Thus, shape is a sensorimotor representation, and one which supports knowledge transfer between motor systems with known mappings between them bound together through the abstraction of the wreath product. Thus, if you see a square with your eyes, you build a representation which allows the creation of that shape with your finger, say tracing it in the sand.

Henderson et al. (Joshi et al., 2014) proposed to directly incorporate and exploit actuation data in the analysis of shape. A philosophical and psychological rôle for actuation in perception has been given by Noë (Noë, 2004)

The sensorimotor dependencies that govern the *seeing* of a cube certainly differ from those that govern the *touching* of one, that is, the ways cube appearances change as a function of movement is decidedly different for these two modalities. At an appropriate level of abstraction, however, these sensorimotor dependencies are isomorphic to each other, and it is *this* fact – rather than any fact about the quality of sensations, or their correlation – that explains how sight and touch can share a common spatial content. When you learn to represent spatial properties in touch, you come to learn the transmodal sensorimotor profiles of those spatial properties. Perceptual experience acquires spatial content thanks to the establishment of links between move-

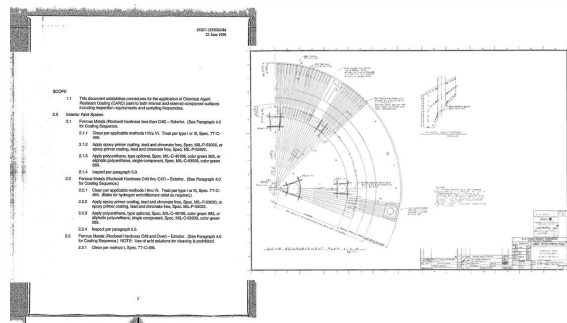


Figure 2: Two CAD Drawings; left: text image that is included with CAD to explain how to paint the structure; right: a hand-drawn design of a nuclear storage facility.

ment and sensory stimulation. At an appropriate level of abstraction, these are the same across the modalities.

For the basic description of the original work on the wreath product sensorimotor approach, see (Henderson et al., 2015). Here we go beyond their results by developing a coherent approach to the semantic analysis of large sets of CAD drawing images. Figure 2 shows examples of the types of images we analyze; on the left is a text file that accompanies an engineering drawing to explain how to paint the structure; on the right is a hand-drawn design of a nuclear waste storage facility.

The left image is a text drawing that provides information about the drawing and the image on the right is a hand drawn plan for one of the double-shell nuclear waste storage tanks at Hanford, WA. The semantic information in such drawings is needed to develop electronic CAD for automotive parts and for non-destructive examinations, respectively. The overall goal is to find the basic character strokes (defined as Wreath Product Primitives), followed by character classification (using Wreath Product Constraint Sets) and finally word recognition (by dictionary lookup) from those. Figure 3 shows the Enhanced Non-Deterministic Analysis System (NDAS) which achieves this analysis; NDAS uses agents to achieve a *parse* of the image. The levels of NDAS correspond to pre-processing, terminal symbol hypotheses, and nonterminal symbol hypotheses. Every *start symbol* represents a complete parse of the image (e.g., a *Text Image*).

2 THE ENDAS SYSTEM

Leyton proposed a generative model of shape (Leyton, 2001) based on the *wreath product* group. (Also see (Viana, 2008; Weyl, 1952) for a discussion of the

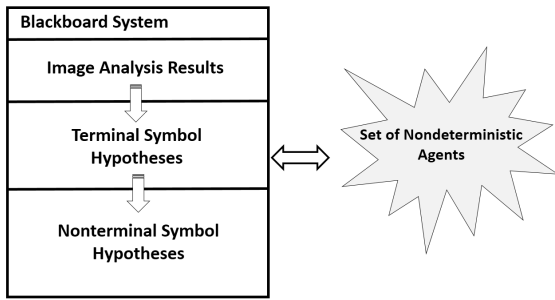


Figure 3: The ENDAS System.

key issue of invariance as a way to detect regularities in geometric objects.) The wreath product of F with C denoted $F \wr C$, is defined as the semi-direct product of two groups, F and C , where C is the *control* (permutation) group which acts on F the *fiber* group. More formally:

$$F \wr C \equiv \left(\prod_{i=1}^n F \right) \rtimes C$$

where \rtimes is the semi-direct product (the semi-direct product is explained in the next section) of n copies of F with C . C is generally a permutation group with the permutations applied to the copies of F . The key notion is that C is the control group that acts to transform the fiber group elements onto each other.

We apply this idea directly to low-level image analysis of drawings. Some examples of the types of symmetry include:

- the *translation symmetry group* denoted by \mathfrak{R} (1D): the invariance of pixel sets under translation defines a straight line segment.
- the *rotation symmetry group* denoted by $O(2)$ (2D): the invariance of pixel sets under rotation defines a circle.
- the *reflection symmetry group* denoted by Z_2 (2D): the invariance of a set of pixels under reflection about a line in the plane describes bilateral symmetry in 2D.

From these symmetry features, we apply this idea to generate the **Wreath Product Constraint Set** (WPCS) to improve the segmentation of low-level geometric primitives in engineering drawings. For example, the lowercase letter set ('b', 'd', 'p', 'q') all look similar in shape. But using symmetry analysis, each character shows that the important symmetry structure in their shape is only one circle ($O(2)$) and one straight line (\mathfrak{R}).

So, we can write a WPCS for each letter ('b', 'd', 'p', 'q') to organize the detection of their features ($O(2)$ and \mathfrak{R}) in the desired position and differentiate

between these four characters. We then create agents to search for such WPCS's.

2.1 Structural Model

In this section we introduce a structural model of technical drawings that allows an agent-based organization of the ENDAS system. We define the layout of the technical drawings in terms of structural grammar. $G = (V, \Sigma, R, S)$ where V is a set of non-terminals, Σ is a set of terminals, R is a set of rewrite rules, and S is the start symbol.

2.1.1 Terminal Structure Set

- $a|b|...|z|A|B|...|Z|0|1|...|9|\%|\$|...|\#|.|,| - |'|(|)|...|?|$
- $Space \equiv$ " " (image segment which is a white space)
- $HSpace \equiv Space$ with a nearby left and right segment
- $VSpace \equiv Space$ with a nearby up and down segment
- $Line \equiv$ image segment which is a straight solid line.
- $Arc \equiv$ image segment which is an arc.
- $Circle \equiv$ image segment which is a circle.

2.1.2 Nonterminal Structure Set

- $Letter := a|b|...|z|A|B|...|Z$
- $Digit := 0|1|...|9$
- $SpecialChar := \%|\$|...|\#$
- $Punctuation := .|,| - |'|(|)|...|?|$
- $Char := Letter | Digit | SpecialChar | Punctuation$
- $Word := Char | Char Word$
- $LineOfText := Word HSpace Word | Word HSpace LineOfText$
- $PageOfText := LineOfText VSpace LineOfText | LineOfText VSpace PageOfText$
- $Text := Word | LineOfText | PageOfText$
- $ArrowHead : Line + Line$
 $|Line + Line + Line$
- $PointerRay := Line + ArrowHead$
- $PointerLine := ArrowHead + Line + ArrowHead$
- $PointerArcRay := Arc + ArrowHead$

- $PointerArcLine := ArrowHead + Arc + ArrowHead$
- $Box := Line + Line + Line + Line$
- $PointerPair := (PointerRay + PointerRay)|(PointerLine + PointerLine)$
- $PointerArcPair := (PointerArcRay + PointerArcRay)|(PointerArcLine + PointerArcLine)$
- $Dimension := (PointerPair|PointerArcPair) + Text$
- $Graphic := Line|Box|Circle|ArrowHead|PointerRay|PointerLine|PointerArcRay|PointerArcLine|Dimension$
- $TextinBox := Text + Box$
- $Table := TextinBox TextinBox | TextinBox Table$
- $GraphicDrawing := Graphic | Graphic Table | Graphic Text$
- $TextDrawing := PageOfText | PageOfText Text | Table | Table Text$
- $Drawing := TextDrawing|GraphicDrawing$

2.2 Wreath Product

Define a *wreath product primitive* (WPP) as either a $e \setminus \mathbb{Z}_2 \setminus \mathfrak{R}$ group or a $e \setminus \mathbb{Z}_2 \setminus O(2)$ group. As a first step, a set of WPP's is fit to the pixels in each connected component and a WPP set for that component, a *minimal WPP cover set* is a combination of WPP's that cover the connected component skeleton, and if any WPP is removed, the component is no longer covered. A *wreath product constraint set* (WPCS) is a set of WPPs as well as any higher level symmetries (e.g., reflection symmetries which are described in this same coordinate frame as the WPPs).

From each WPP set, the complete set of minimal WPP cover sets is found, and they provide the initial characterization of what defines a particular shape. For example, Figure 4 shows some examples of WPP minimal cover sets.

Leyton described wreath products abstractly as symbol sequences and every $e \setminus \mathbb{Z}_2 \setminus \mathfrak{R}$ wreath product is equivalent to every other. We, however, are faced with unique, existing instances, and thus, associate a coordinate frame (generally, the rectangle containing the symbol) with each as well as descriptions of the \mathbb{Z}_2 mod group which is used to produce finite length sets (i.e., end points for line segments and angular limits for circles).

The WPP minimal cover sets shown in Figure 4 are then used to produce a WPCS which will characterize the shape. The additional information in the

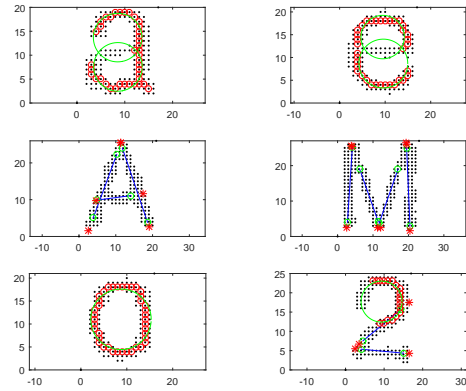


Figure 4: Example WPP Minimal Cover Sets.

WPCS over the minimal cover set includes any symmetries between WPP's in the set. For example, the two WPP's in the lowercase letters 'a' and 'e' have both vertical and horizontal reflection symmetries; the letter 'A' has a vertical reflection symmetry between the two side arms; the letter 'M' has vertical reflection symmetries on the two side arms and the two inner arms; the digits '0' and '2' do not have higher level symmetries.

We have developed a WPCS representation which is simply a list of the R WPP's, followed by the $O2$ WPP's, and then followed by the higher level wreath product symmetries found in the shape. For example, the WPCS's for the shapes in Figure 4 are characterized as:

- 'a': 'O;O;Z2O;'
- 'A': 'R;R;R;Z2R'
- 'O': 'O;Z2O'
- 'e': 'O;O;Z2O;'
- 'M': 'R;R;R;R;Z2R;Z2R;Z2R;'
- '2': 'R;O;'

The next step in the process is to associate a specific generative mechanism with the shape. Here we use the virtual sensors (pan-tilt camera) and actuators which were proposed in (Henderson et al., 2015); the pan-tilt control angles for a camera trace for each of the characters are shown in Figure 5.

Character classification for an unknown shape is started by producing the WPCS's for the shape (note there may be several). Next, these are compared at the abstract level to the character template WPCS's, and where a match is found, then the pan-tilt actuation generative data are compared. Any match at this level that is above threshold produces a character hypothesis. The final step uses the character hypotheses to produce legal word hypotheses (using a dictionary).

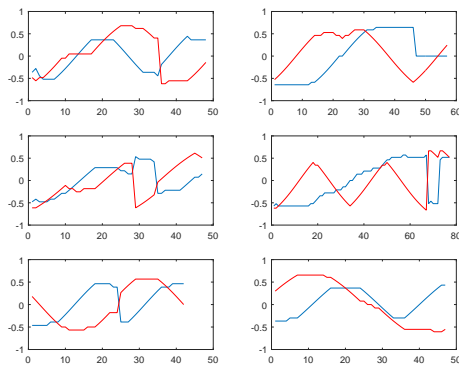


Figure 5: Pan Tilt Control Angles for the Characters in Figure 4.

3 EXPERIMENTS

The tests were run of the image shown in Figure 6 which resulted in 1,111 connected components to classify. The 62 templates for lower and uppercase letters and the ten digits resulted in 184 minimal cover WPCS's for the 62 characters. A total of 3,333 minimal cover WPCS's were generated for the 1,111 connected components. The abstract wreath product filter eliminated 67% of the unknown hypotheses; note that this check only requires comparison of their wreath product string representations.

The remaining hypotheses were matched to templates by a 2D pointwise comparison of their pan-tilt function values. An unknown is considered a match if the correct character is in the top 5 best pan-tilt distance matches. The classification rate is very good with this approach ($\sim 99\%$) when using the top five hypotheses.

4 CONCLUSIONS AND FUTURE WORK

We have demonstrated that actuation-based shape representations using the wreath product groups provide an effective tool for shape analysis, and in particular, for engineering drawing analysis. Our position is that this method works well for text analysis and can be extended to graphics and handwriting analysis.

In future work, we will:

- study the analysis of the graphics part of the CAD drawing,
- study the performance in the face of occlusion and heavy noise,
- apply the method to handwriting recognition and synthesis, and

2.3.2 Apply epoxy primer coating, lead and chromate free, Spec. MIL-P-53030, or epoxy primer coating, lead and chromate free, Spec. MIL-P-53022.

2.3.3 Apply polyurethane, type optional, Spec. MIL-C-46186, color green 383, or aliphatic polyurethane, single component, Spec. MIL-C-85089, color green 383.

2.3.4 Inspect per paragraph 5.0.

2.4 Aluminum - Exterior. (See Paragraph 4.0 for Coating Sequence.)

2.4.1 Treat per Class 1A, Spec. MIL-C-5641, except Spec. MIL-P-23377 shall not be used.

2.4.2 Apply epoxy primer coating, lead and chromate free, Spec. MIL-P-53030, or epoxy primer coating, lead and chromate free, Spec. MIL-P-53022.

2.4.3 Apply polyurethane, type optional, Spec. MIL-C-46186, color green 383, or aliphatic polyurethane, single component, Spec. MIL-C-85088, color green 383.

2.4.4 Inspect per paragraph 5.0.

2.5 Aramid Fabric Reinforced Plastic Laminates - Exterior. NOTE: Remove protective ply prior to cleaning and painting.

2.5.1 Clean with a lint free cloth dampened with thinner, type optional, Spec. TT-306.

2.5.2 Apply epoxy primer coating, lead and chromate free, Spec. MIL-P-53030, or epoxy primer coating, lead and chromate free, Spec. MIL-P-53022.

2.5.3 Apply polyurethane, type optional, Spec. MIL-C-46186, or aliphatic polyurethane, single component, Spec. MIL-C-85089, color green 383.

2.5.4 Inspect per paragraph 5.0.

Figure 6: Test Image.

- extend the method to 3D and apply it to the as-built versus as-designed problem.

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