Sketching Interfaces for 2D Animation of Simple Objects

Jimmy Ho
Department of Computer Science
Brown University

Submitted in partial fulfillment of the requirments for the Degree of Master of Sciences in the Department Computer Science at Brown University.

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Signature (Prof. John Hughes, Project Advisor)

5/22/00
Date

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Jimmy Ho[*]

Computer Science Department, Brown University,
Providence, RI 02912-1910

Abstract

This report describes efforts to apply sketching interfaces to animation. We deal with the problem of sketching 2-D motion paths for objects to produce animations for applications like Microsoft PowerPoint, Macromedia Flash or Director. We worked on the core problem of editing a sketched motion curve, using the approach of blending newly sketched motion paths with older paths to allow for successive refinements of an animation. We describe various methods used to edit motion curves and their results.

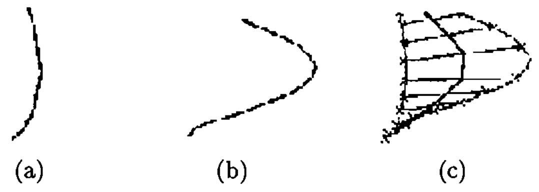


Figure 1 An example of blending two curves. (a) first curve drawn (b) second curve (c) blended curve shown in red.

1 Introduction

1.1 Background

This paper deals with building a gestural interface for the two-dimensional animation of simple objects. There are many applications that use 2-D animations, such as Macromedia's Flash, Director and Shockwave applications, or even Microsoft's PowerPoint presentation software, which deliver traditional 2-D graphic art with movement and sound. This sort of animation can also be seen in fast paced commercials that use moving textual messages to make their point. Thus, in our context, "simple objects" can be imagined as pictures, text or simple shapes (as opposed to animating Bugs Bunny or some other articulated figure). Animation of these objects include both linear and angular motion, as well as having these objects fading in/out, changing size, morphing into other objects, or even physically-based animation, all within a 2-D space.

There are already methods for producing animations, including key-framing, physically-based animation, and just manually specifying all the relevant functions ($x(t)$, $y(t)$, $\theta(t)$, $shape(t)$, $transparency(t)$, etc.). The last approach is obviously tedious. Key-framing, while not as tedious, especially in 2-D, can still be painstakingly slow. [1] Physically-based techniques work well only for things that seem to simulate a physical process, such as a bouncing ball. Even then, a user could much more quickly sketch the motion with a mouse or pen device and achieve a reasonable imitation, which is sufficient given the types of applications that we are looking at (i.e., PowerPoint or Flash animations with objects moving in an abstract space where people don't expect completely realistic physics). What we need then is an intuitive way to sketch animations without a lot of excess point-and-click, typing and arithmetic.

A sketching, or gestural, interface is characterized by "gestures," which are hand-drawn marks that issue a command to the computer. Gestures are different from buttons and pull-down menus because they often specify the operator, operands, and parameters with a single stoke or two. One can easily imagine an animator's interface in which these gestures invoke templated actions. For instance, drawing a rough spiral could produce a mathematically precise spiral with approximately the same size as the hand-drawn stroke. Similarly, straight line strokes or hand-drawn arcs might generate line segments or smooth splines. This is the more traditional use of gestural interfaces, as seen in CAD modelling tools such as SKETCH[8]. One can imagine other types of strokes used to invoke fades, size changes, etc. Gestures are often touted because they are less cumbersome than WIMP[2] interfaces and can provide intuitive, efficient ways of specifying tasks. What's interesting about using a sketching interface for animation is that there is a *temporal* aspect to the objects being manipulated.

We use concepts derived from sketching interfaces to produce an interaction model where gestures are the primary means of expressing and modifying the geometric and temporal aspects of the animation of an object.

1.2 Problem Definition

In our research, our gestures are used to specify the *free-form* motion of an object. That is, instead of mapping gestures onto a finite, fixed set of template curve types, we let the gestures themselves be the curves. We do not address the problem of specifying angular motion or other effects such as fades, morphing, or size-changes, so our objects do not spin and do not change size or shape.

This *sounds* easy: When the user clicks on and drags an object, we could simply record the points along with the timing information and replay that motion when prompted. This is the method used in a children's program called KidPix by Broderbund. The complexity arises when the user attempts to *edit* an existing curve. Taking the example of a PowerPoint animation, it becomes obvious that users of such an interface may not be skilled artists. Even so, it is oftentimes too clumsy to simply replace a curve with a newly-drawn one (it's easy to see this by trying this out for yourself). Rather, it is better to take the previous curve as a base curve and

[*]jkh@cs.brown.edu

[1]"Painstakingly slow:" Taking more than 30 seconds to create and fine tune, say, a winding, three-inch-long, S-shaped path with a pause at the first bend and a little wiggle at the end

[2]Windows, Icons, Menus and Point-and-click

modify it by drawing another curve. This involves blending two curves in an intuitive way (see Figure 1). Unfortunately, "editing" a curve not only involves editing the shape of the curve, but the timing information as well: a user may like the shape just fine, but might want some part of the animation to move at a different speed, or to elongate a pause, etc. The obvious approach (and the one that we use) is to just have the user redraw the curve at the desired speed. Obviously, the user cannot and should not have to redraw the prior curve exactly and thus, it is up to the computer to figure out how to relate the two curves so that the timing information from the second curve is appropriately overlayed onto the first curve. This process is complicated by the fact that the source for the curves is a collection of discrete samples with non-uniform sampling rates and unevenly-spaced points.

Therefore, we let a user specify a free-form 2-D motion path by successively refining it. This is done by blending new curves with previously drawn curves, which requires that we establish a good point-to-point correspondence between pairs of curves. That is, given two discrete curves $\underline{u}(r)$ and $\underline{v}(r)$, we want to find a curve $\underline{z}(r)$ which gives an intuitive blend of $\underline{u}(r)$ and $\underline{v}(r)$. r is an arbitrary parameter. In the course of describing different algorithms, we will parameterize the curve using path length, time, and point index. This ability to match curve points allows us to do some general tasks that an algorithm can perform when the user draws two successive motion curves by clicking and dragging the same object twice:

1. Blend the shapes of both curves to produce a new curve, but keep the timing information of the old curve.
2. Keep the old shape but use timing information of the new curve.
3. Both of the above.

In the course of our research, we focused mainly on case 1, since case 2 can be implemented once a correspondence is established, which is a necessary result of solving the shape blending problem. We designed and implemented various methods, with varying degrees of success. The discussion of these methods constitute the rest of the paper.

1.3 Related Work

Trying to establish a point-to-point correspondence between two discrete curves has been a problem in many fields. Research in gestural interfaces contribute to the solution in the form of gesture-recognizers. However recent research in gesture recognizers seem focused on extracting specific interesting features that are not general enough to use to match a pair of curves whose shapes are arbitrary but similar to one another[6], while others use "training sets," which are not applicable here since the user produces the two curves that require matching in real time[3][4].

Handwriting recognition researchers have long sought ways to match hand-written letters and words to a finite alphabet. The difference between our research and that of handwriting recognition is that there is no fixed set of curves or training set to take advantage of (via preprocessing, using Hidden Markov Models, etc.).

One other method is elastic matching. This usually involes treating one curve as a metal wire that is stretched and bent to match the other curve. Choosing some sort of least energy solution, one finds a correspondence along with a set of stretches and bends to interpolate a blend. Uses include 2-D morphing[2]. While this method has its merits, we did not investigate these algorithms in depth.

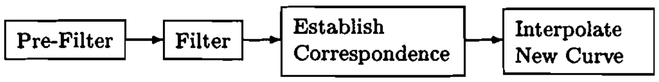
1.4 Notation and Terminology

When a user draws a stroke that specifies a free-form animation curve, we will refer to that as a "curve" or "path." The naming conventions in the source code tend to use these conventions as well. Unless otherwise noted, distances are in pixels and units of time are in milliseconds.

To establish better correspondence between the concepts in this report and the code written to implement it, references to Java packages and classes are represented by `classname`, `packagename`, or `packagename.classname`. For instance, `PathEditFactory` or `pathedit.PathEditFactory`.

2 Overall Methodology and Algorithm Structure

Similar to techniques used in gesture and handwriting recognition, we have preprocessing phases for the strokes in order to weed out noise and irrelevant details. Then we apply some algorithm which establishes a correspondence. Once a correspondence if found, it is a simple matter to interpolate the new curve. Thus, after two successive motion paths are drawn, the following steps occur:



In the Pre-Filter step, we apply a special filter to both $\underline{u}(r)$ and $\underline{v}(r)$ that deletes points that are spaced too closely together (usually less than a few pixels) and adds points where they are spaced too far apart. Points that are spaced only a few pixels apart are often too noisy and reduce the efficiency of our algorithms. Also, during animation, such closely spaced points often slow down the animation, producing an unfaithful reproduction of the user's stroke. Because we often interpolate the two motion paths by using all the points of $\underline{u}(r)$ but not necessarily all the points of $\underline{v}(r)$ (to retain the original timing information), it is essential that we start with lots of points, so that the resultant blended curves are not too coarse. This is the rationale for adding points where they are spaced too far apart. For more details, see `filter.FilterPreFilter`.

Next, the Filter step tries to reduce and eliminate irrelevant details of the shapes of the curves that would otherwise interfere with subsequent algorithms. Currently, nothing is done to the timing information. Typically, the filters will smooth out noise and resample the points so that they are evenly spaced. Some filters will, instead, take out points until only a few essential points remain (Figure 2); the Haar wavelets filter is an example of this approach if we choose the wavelet parameter to be very high ($\sim 95\%$). For some correspondence algorithms, the Filter step is skipped.

In the next step, some algorithm is applied to either or both of the original and filtered curves to link the paths. After a correspondence is established, the points are interpolated linearly between the two original (unfiltered) curves to pro-

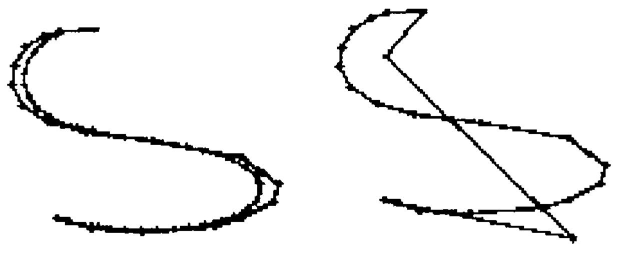


Figure 2 (a) A smoothing filter that resamples the points evenly and more closely spaced. (b) A Haar wavelet filter that extracts out only the important features by combining/eliminating the other points.

duce a final result.

The Pre-Filter is fixed and does not change. Different algorithms in the Filter step can be combined with different correspondence algorithms to achieve different results. The actual blending of the curves, once a correspondence has been established, is straightforward. Most of this paper deals with the "Establish Correspondence" step.

3 ASketch

In the course of doing our research, we have developed an application to implement and test our ideas. The project, named ASketch (for Animation Sketch), was conceived and engineered during the 1999-2000 school year. ASketch contains the implementation of the algorithms discussed in this report. (See Figure 3)

The application has a main window with a "Sketching Area." A user can add, delete, duplicate and move widgets, as well as specify motion curves by dragging these widgets around. Animations can be played by clicking a single button. The objects' animation curves can be edited via different algorithms. There is unlimited undo and redo, and the we use a marking-menu interface. There are also separate windows to view results from filters and feature detection algorithms.

More details of how the application works can be found in the Users' Manual and Programmers' Reference (if they get written).

4 Early Algorithms

In the course of our research, we tried different algorithms. We begin by detailing our early efforts, most of which failed, and finish with our more successful algorithms.

All the algorithms listed below describe the method by which a correspondence was found between two curves based on their geometric shape. We do not discuss how to actually interpolate between the curves because in all cases the method is straightforward.

4.1 Closest Point Matching Algorithm

At the outset, it seemed reasonable that since the user is likely to draw the two paths roughly alike, a point in one curve would be the closest point to its corresponding point in the other. Therefore, our first algorithm matched each point on one curve to the closest point on the other curve.

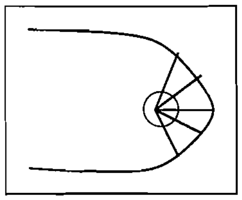
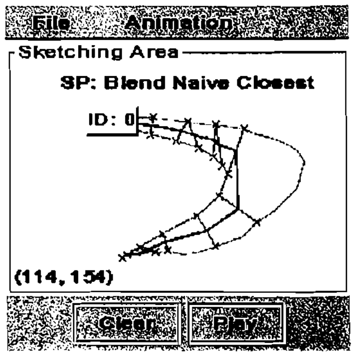



Figure 4 (a) Red circle indicates the intersection of the radii of curvature. (b) Pathlogical case for Closest Point Matching Algorithm. Blue line is the first curve, green line is the second curve and the red is the final interpolated blend.

The new blended curve keeps the timing information of the first curve. More specifically, if we let u_i and v_j be the ith and jth points of the curves $\underline{u}(r)$ and $\underline{v}(r)$, respectively, we have

```
CLOSEST-POINT($\underline{u}(r), \underline{v}(r)$)
 1  $\underline{C} \leftarrow \emptyset$ // This is our list of correspondences.
 2  $n \leftarrow$ Number of points in $\underline{u}(r)$
 3  $\underline{C}$.APPEND(($\underline{v}_0, \underline{u}_0$))
 4  $p \leftarrow -1$
 5  for $i = 0$ to $n-2$
 6  do Find $\underline{v}_j$ such that $j \geq p$ and $\|\underline{u}_i - \underline{v}_j\|$ is minimized
 7       $\underline{C}$.APPEND(($\underline{v}_j, \underline{u}_i$))
 8       $p \leftarrow j$
 9  $\underline{C}$.APPEND(($\underline{v}_{last-point}, \underline{u}_{last-point}$))
10  return $\underline{C}$
```

It should be noted that the above algorithm corresponds every point in $\underline{u}(r)$ to some point in $\underline{v}(r)$. Thus, if $\underline{v}(r)$ has fewer points, then the correspondence is many-to-one ($\underline{u}(r)$ to $\underline{v}(r)$). If the latter curve has more points, then some points in $\underline{v}(r)$ are dropped. Moreover, it could still be the case that two or more adjacent points in $\underline{u}(r)$ curve will correspond to the same point in $\underline{v}(r)$.

There is no filtering step when this algorithm is used.

One pathological case that causes numerous problems involves one curve not being within a certain distance of the other. The reason for this can be found in 4(a). Notice that the spokes that represent the radii of curvature intersect within the red circle. When the second curve drawn does not fall between the red circle and the first curve, the correspondence skips over a large section of the first curve because the next point that should be taken is farther than a point near the end of the arc. This is what happened in Figure 4(b). Not only does this cause an unexpected deformity in the blended curve, the object will also move much faster in that section of the curve. Since such a case can happen almost anywhere, we find that this algorithm is not robust enough for our needs.

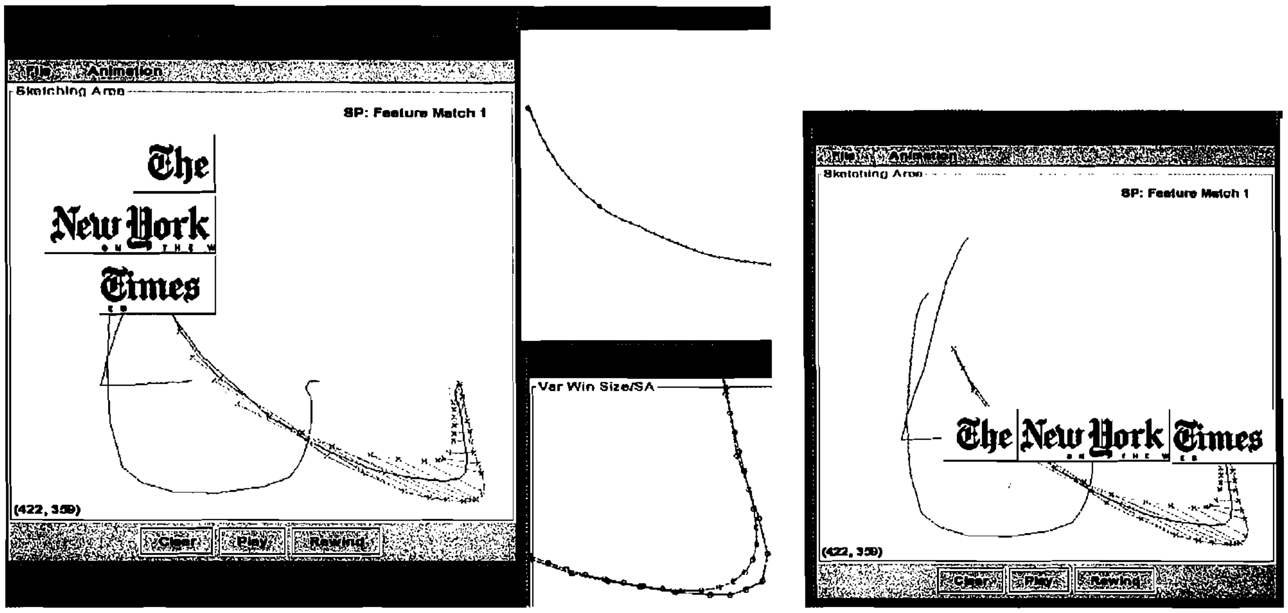


Figure 3 Screenshots of ASketch

4.2 Randomized Hill-Climbing Algorithm

In randomized hill-climbing, we use the same technique that is used to tackle some NP-complete problems. First, we use the Closest-Point algorithm to establish an initial correspondence. Then we randomly propose small incremental modifications which take effect if the resultant correspondence helps to minimize a weighted function, K, described as

$$K = \gamma \alpha K_1 + (1-\gamma)\beta K_2, \quad \alpha, \beta \geq 0 \text{ and } 0 < \gamma < 1. \quad (1)$$

γ, α, and β are arbitrary constants used to fine tune the algorithm and normalize/vary the relative importantance of K_1 and K_2, which we now describe.

Let C consist of the set of correspondences, with each correspondence being denoted by a pair of 2-D points $(\underline{u}_i, \underline{v}_j)$. Then

$$K_1 = \sum_{(\underline{u}_i, \underline{v}_j) \in C} \|\underline{u}_i - \underline{v}_j\|^2 \quad (2)$$

Thus, K_1 is smaller if we use pairs that are closer together, again, keeping with the notion that if the user draws two curves that resemble one another, the correspondence pairs should be pretty close to one another.

For K_2, we define the correspondence as a mapping function

$$r(i) = j \text{ such that } (\underline{u}_i, \underline{v}_j) \in \underline{C} \quad (3)$$

Thus, $r(i)$ maps every point in $\underline{u}(r)$ to some point in $\underline{v}(r)$. Given this, we have

$$K_2 = \sum_i \|r''(i)\|^2 \quad (4)$$

Thus, K_2 is the sum of the second derivatives of the mapping function $r(i)$. For example, a correspondence of $\{(1,1),(2,2),(3,3),(4,4)\}$ would produce $K_2 = 0$, but $\{(1,1),(2,4),(3,8),(3,15)\}$ would give $K_2 > 0$.

Since the goal of the algorithm is to essentially minimize both K_1 and K_2, we see that the K_1 term keeps the corresponding point-pairs from drifting too far apart. At the same time, the K_2 term forces the the algorithm not to skip too many points between $(\underline{u}_i, \underline{v}_j)$ and $(\underline{u}_{i+1}, \underline{v}_k)$, so that j and k are reasonably close together. This addresses the problem found in the previous Closest-Point algorithm where just finding the points closest often resulted in whole sections of a path being skipped over. The various arbitrary constants help to normalize the two variables and lend different relative weights to them.

There is no filtering step when this algorithm is used.

Unfortunately, our results showed that the algorithm would get stuck in a local minimum that often would not produce good results for many cases, despite trying a wide range of values for γ. Problems similar to ones encountered in the Closest Point Matching algorithm showed up (Figure 5. These have to do with the γ skewed too far in favor of K_1. When the gamma is skewed in favor of K_2, we get closer to

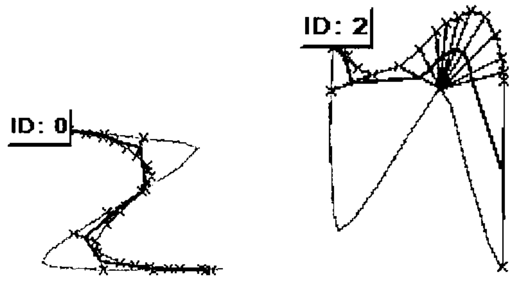


Figure 5 Hill-Climbing Algorithm Results. Blue curve is the first curve, green is the second and the red is the final blended curve.

the Path Length Fraction Algorithm to be described later (Section 4.3).

There are variations we have not yet tried in favor of moving on to other approaches. For instance, instead of choosing the initial correspondence set using the Closest-Point algorithm, we could have made the initial choice more random. In order to avoid local minimum problem, we run multiple iterations of the minimizing K, choosing a different random starting configuration. This is what is often done in variants of the Hill-Climbing algorithms (such variants can be found in artificial intelligence textbooks, page 111 of Russell[7], for example). Even with this modification, it could still be that the choice of γ may not be robust enough to handle most reasonable cases. Moreover, it is unclear how to to dynamically detect difficult cases and change γ on the fly for every pair of curves.

Another option is to simply calculate the absolute minimum by trying all possible correspondences, but we found this to be combinatorically implausible.

4.3 Path-Length and Time Fraction Matching Algorithms

This set of algorithms attempts to correspond points by looking at how far, percentage-wise, a point is from the starting point, either by looking at the time index (in milliseconds) or by path length (in pixels). That is, a point that is in the middle of the first curve, when measured by length, is assigned a corresponding point in the middle of the second curve. To be more specific, we first need to define some terminology.

Let $N_{\underline{u}}$ be the total number of points and $L_{\underline{u}}$ be the total path length of the curve $\underline{u}(s)$. $L_{\underline{u}}$ is measured by summing all the straight line segments that make up the discretely sampled curve. Let $T_{\underline{u}}$ be the total time it takes to draw the curve (i.e. time index of last point – time index of first point). Let $\underline{u}(s)$ be the linearly interpolated point that is length s away from the starting point of the curve $\underline{u}$, as measured by summing the line segments previous, plus the last partial segment leading up to $\underline{u}(s)$. Similarly, let $\underline{u}(t)$ be a point at time index t, interpolated by looking at the timing information. Lastly, we define $l_{\underline{u}_i}$ to be the path length from the starting point to $\underline{u}_i$ and let $t_{\underline{u}_i}$ be the analogous point for time.

Given this, these algorithms produce the following sets of correspondences:

$$C_L = \left\{ \left(\underline{u}_i, \underline{v}\left(\frac{l_{\underline{u}_i}}{L_{\underline{u}}} L_{\underline{v}} \right) \right) \mid 0 \le i < N_{\underline{u}} \right\} \tag{5}$$

$$C_{TL} = \left\{ \left(\underline{u}_i, \underline{v}\left(\frac{t_{\underline{u}_i}}{T_{\underline{u}}} L_{\underline{v}} \right) \right) \mid 0 \le i < N_{\underline{u}} \right\} \tag{6}$$

$$C_T = \left\{ \left(\underline{u}_i, \underline{v}\left(\frac{t_{\underline{u}_i}}{T_{\underline{u}}} T_{\underline{v}} \right) \right) \mid 0 \le i < N_{\underline{u}} \right\} \tag{7}$$

where C_L corresponds points of the same path length fraction and C_{TL} is this rather odd correspondence scheme that matches the time index fraction of one curve with the path length fraction of another. C_{TL} produced bad results for certain pathological cases and did not really produce better results than C_L for the rest of the cases. C_T was never implemented but, in theory, such a correspondence really doesn't make sense. This becomes obvious once you think about the two cases of 1) drawing $\underline{v}(r)$ to change the shape and 2) drawing to just change the timing information.

The algorithms for these correspondence algorithms are straightforward and can be found in `pathedit.PathEdit-NaivePathLengthRatio` for C_L and `pathedit.PathEdit-NaiveTimeLengthRatio` for C_{TL}. `pathedit.PathEdit-TimingPathLengthRatio` does the same thing as C_L, but transfers the new timing information to the old curve, whereas the previous two classes edit the shape of the curve only, keeping the original timing information.

It turns out that C_L produces the best results of all the early algorithms (Figure 6(a)-(c)). It still has inherent weaknesses, as shown in Figure 6(d), but works pretty well overall. In fact, we use this algorithm as a subroutine in the feature matching algorithms later.

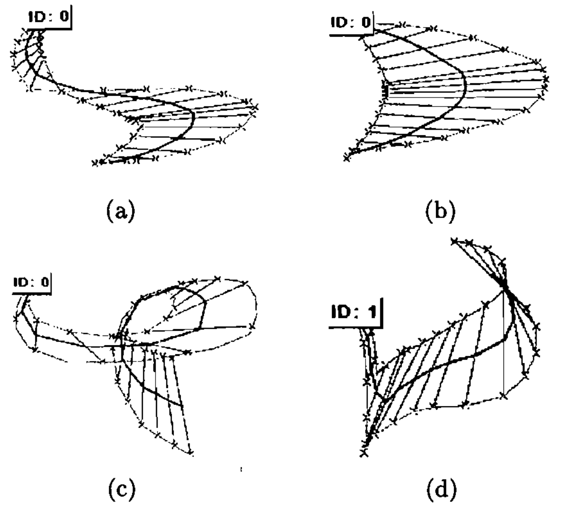


Figure 6 (a), (b) and (c) are good cases for path length fraction matching while (d) illustrates a bad case.

The problem in Figure 6(d) is subtle. Note that the sharp corner in the blue and green curves are not matched up properly. Suppose we divided up the curves into reasonable subsections, delimited by "interesting points," where there's sharp turn or significant pause. We find that the subsections for the timing and geometric information to be misaligned. For instance, suppose the user who drew Figure 6(d) put a significant pause in that first corner point. That pause will now have shifted slightly since the corner points from either curve are not corresponded to each other. In this example, the shift is probably not noticeable in the final curve, but if successive refinements are made, timing and geometric features can fall out of alignment quite easily.

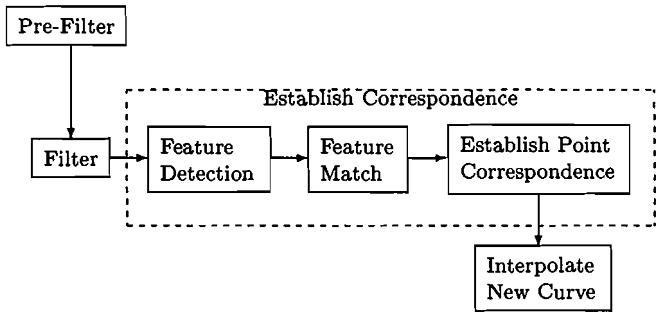
4.4 Summary

Out of these early algorithms we began to see that it was insufficient to find some global algorithm to correspond the points. There were distinct places on the curves where a user would significantly slow down, pause, or speed up the velocity, and as the user drew successive editing curves, these points would drift away from their correct places. Also, tying the correspondence to such global parameters such as the path length would often produce bad results for long paths because the latter half of the second path, while being almost exactly the same as the latter half of the first path, would be altered because the first half involved some significant differences. It is with these issues in mind that we move on to feature matching algorithms.

5 Later Algorithms

In these later algorithms, we focused more on subdividing curves into more manageable pieces, which resulted in better correspondence algorithms.

These algorithms utilize feature matching and feature detection techniques to correspond points. Thus, we attempt to subdivide a motion curve into pieces and find correspondences for each piece. In general, the correspondence algorithm attempts to detect the "interesting" features for both $\underline{u}(r)$ and $\underline{v}(r)$. It then tries to match up the features from both curves, thus setting up a correspondence between the features. After this step, the curves will have corresponding subsections for which we use a simple Path Length Fraction correspondence algorithm (C_L or C_T) to link. Thus, the general flow of execution now looks like



At the Filter step, we apply a variety of filters, described below. The feature detection algorithms then use curvature data that is derived from the filtered curve to find features that produce curvature extrema. The curvature data consists getting the direction change as we move from one line segment to another along the discretized motion path (Figure 7). Curvature extrema are detected by examining a plot of the curvature data and noticing those parts of the plot that deviate beyond a calculated threshold value from zero.

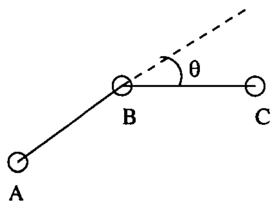


Figure 7 A, B and C are consecutive points on some curve. The curvature info for point B is θ (radians).

When establishing a point-to-point correspondence, we correspond the points in the original curves (not the filtered curves). Thus, each feature found in Feature Detection has a time index that links back to a point on the original curve.

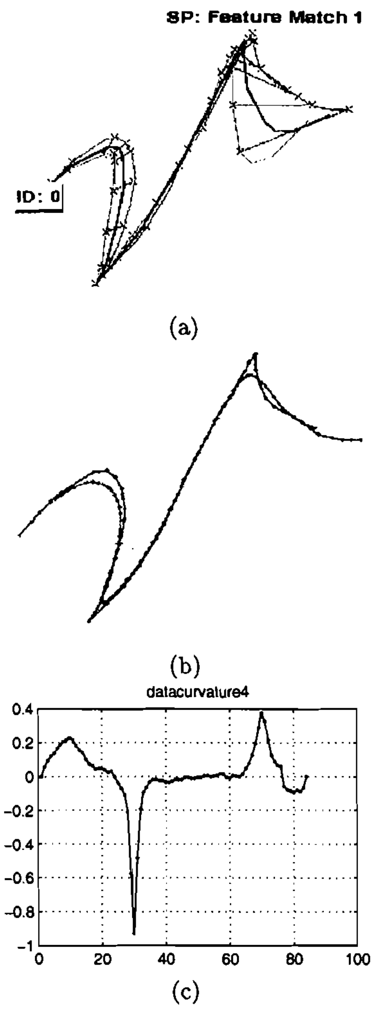


Figure 8 (a) The original two curves drawn, with blended result in red. (b) Filter results of the green (second) curve. Blue represents the original curve and red is the filtered curve. (c) A plot of the curvature data for the filtered curve, direction change (radians) vs. point index.

5.1 Filters

This section presents an overview of the filters we used and their results. More information can be found in the source code in the `SketchingAnimation.filter` package. As before, let the path $\underline{u}(s)$ be parameterized by the path length s, where s is a measure of length (in pixels).

5.1.1 Regularization (a.k.a. Sliding Average) Filter

Let $\underline{x}$ be an ordered vector of all the x values in a curve. Similarly for $\underline{y}$. The regularization filter essentially runs a box filter on $\underline{x}$ and $\underline{y}$ separately, for each motion path. Nothing is done to the timing info. This has the effect smoothing out small kinks and irregularities. The box height is 1.0, and the box width and sampling interval can be found as constants in the various `FeatureDetect` subclasses and as default values in the `Filter` subclasses, which is usually around forty to sixty pixels.[3] An example is shown in figure 8 This algorithm

[3]The box widths in the source code are often suffixed with `_RADIUS`, which means that the number assigned is half of the

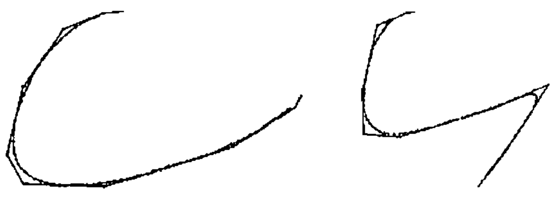
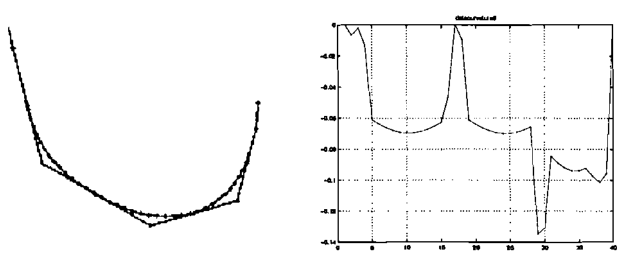


Figure 9 Blue represents the original curve and red is the filtered curve.



(a) (b)

Figure 10 (a) Blue represents the original curve and red is the filtered curve. (b) A plot of the curvature data for the filtered curve, direction change (radians) vs. point index.

is discussed by Duda[1].

While this produces fabulously smooth curves (Figures 9 and 10(a)), the major limitation of this algorithm is that the box width is fixed. Sometimes the width is too small (this happens when the user speeds up the stroke). This causes the filter to integrate over a single line segment between two points, thus producing a series of points along a line. So while the curvature may really be a non-zero number, we find that the curvature drops towards zero in some places where it should not. Notice how in Figure 10 the curvature plot spikes towards zero even though it is intuitively obvious from Figure 10(a) that the plot should be smooth and gradually changing. This produces erratic curvature plots from which it becomes harder to detect features from. If the interval of integration is expanded, then we risk smoothing away features that we would want to detect. Moroever, the box width can expand to the point where it starts encompassing the entire length of the shorter curves, which causes additional problems.

5.1.2 Regularization Filter with Dynamic Window Sizes

This is the same as a Regularization Filter except that we use a calculated box width (i.e. window size) for each curve. This is done by looking at the average length of the line segments in the input curve. Then a minimum and maximum cut-off is applied to keep the width from becoming unreasonable. This alleviates the problem of the original Regularization Filter somewhat, but problems still arise when the user draws very slowly one subsection of a stroke and speeds up significantly on another, which causes the first set of points to be spaced close together and the latter set to be spaced far apart.

A possible fix to this is to change the window width as the window slides along the curve. However, this seems to cause small kinks in the output curve which also add noise to the output.

Despite its problems, this regularization filter produces the best results to date.

5.1.3 Haar Wavelet Filter

This filter takes the x and y values and applies a Haar Wavelet transform to each vector. Then, some percentage of the values closest to zero are removed from both $\underline{x}$ and $\underline{y}$, where, once again, $\underline{x}$ and $\underline{y}$ are the vectors of the x and y values, respectively. An inverse transform is then applied to produce the final output curve. Some results are shown in Figure 11. The major problem with Haar wavelets is that it favors the x and y axes. Thus, what happens is that some points will have their x values merged but their y values won't have (and vice-versa). This produces a "stair-stepping" effect that wreaks havoc on the curvature data (Figure 11(b)).

However, when the threshold percentage is raised to around 90%, most of the points are merged so that what remains are just the "vital" points. The features can be easily discerned from the output curve since almost every point is a feature point (see Figure 11(d)). The difficulty arises from trying to pick the perfect threshold percentage. Sometimes a five percentage point difference in the threshold percentage would produce vastly different results. At least, vastly different from the point of view of a feature detection algorithm that has to then intepret the filter output. Thus, this percentage must necessarily change for each curve, but how does one figure out which one to use or know when the right one was chosen? We have not had time to investigate these questions deeply. Also, we have not investigated other wavelet transforms that are less biased towards the coordinate axes.

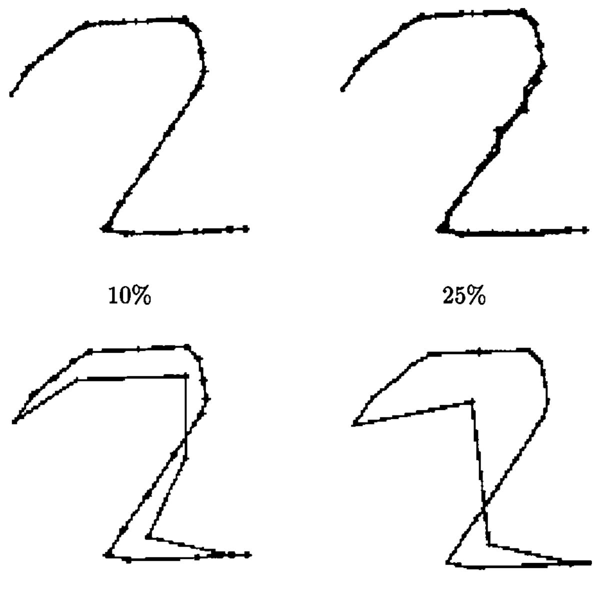


Figure 11 Same curve, filtered with a Haar wavelet filter using different threshold percentages. The blue represents the original curve and the red is the filter result.

total width

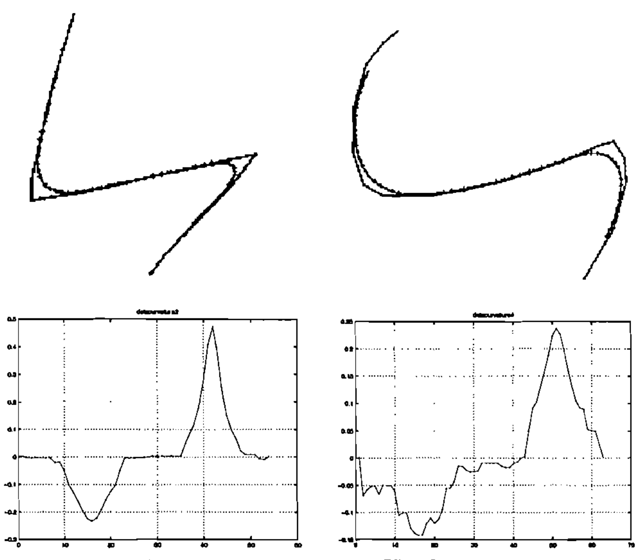

Easy to interpret. Harder to interpret

Figure 12 Two examples of the types of curvature plots that the algorithm has to process.

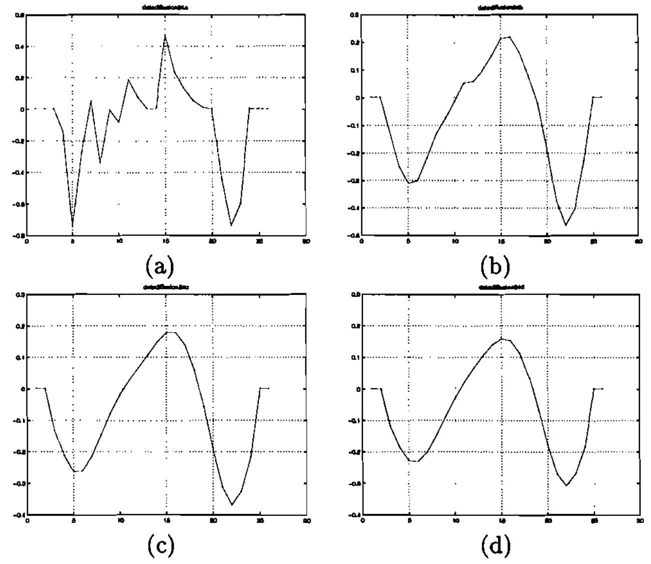


Figure 13 Results of cumulative iterations of the triangle filter.

5.1.4 Other Filters

The Evenly-Spaced Filter doesn't really "filter" anything. It just samples the points so that they are evenly spaced. Duda, in his book, also talks of a hysteresis filter[1], but we never implemented that because it was obvious that the output curves would not satisfy our needs for clean curvature data.

An Angle Filter[4] is like the Haar Wavelet Filter with a high threshold. It subtracts points away until only the relevant "hot points" are remaining. We never got around to implementing this one. The algorithm also had a large set of adjustable parameters, leading one to believe that either it would take a lot of effort to produce a set that would be general enough or that a specific set of parameters would be good only for a small subset of cases, causing the problem of having to dynamically adjust those parameters. Despite this, we believe such filters are worth exploring at a later time.

5.2 Feature Detection

5.2.1 Curvature Extrema Detection

After filtering, the curvature data is plotted. Let $\underline{c}$ be the vector of direction change values (in radians) for every point on the filtered curve. We take the average of the absolute values of $\underline{c}$ to to be our threshold value (there is a minimum cut-off for this, currently at 0.008 radians). Any cluster of curvature values that deviate from zero by more than the threshold can be considered to comprise a feature. The specific feature point is picked out by taking the point from the cluster that has the highest curvature value. Since the regularization filters do not produce completely clean curvature data, there are programmer-level tweaks that make the detection algorithm more robust. For instance, if the we encounter just one isolated point that is above the threshold, we consider that to be noise. If, after several points above the threshold, we encounter one or two points that dip below before coming back up, we also consider that noise. Check out the `feature.FDExtremal.getNextFeaturePt()` function for more details on this.

5.2.2 Curvature Extrema Detection with Diffusion Preprocessing

Basically, this is the same as the above Curvature Extrema algorithm but we have taken the curvature data and "diffused" it just before we run our feature detection routine on it. Diffusion works by treating the curvature plot like a viscous fluid with gravity pointing towards zero radians. Thus, if we take a plot of the absolute values of the curvature data and allow it to "flow" like a reasonably viscous fluid, we get a new plot that has many of the smaller kinks smoothed out. An example is shown in Figure 13. Thus, even if we get noise after filtering, such as in the second curve of Figure 12, we can smooth those out by applying diffusion.

Instead of solving partial differential equations, we simply approximated a gaussian filter with a triangle filter and ran that across the data points several times. The diffusion works because the all of the filters output curves whose points are, for the most part, evenly spaced. The triangle filter we currently use takes the curvature at a point $\underline{u}_i$ (call this $c(\underline{u}_i)$) and resets the value to the weighted average of $c(\underline{u}_{i-2})$, $c(\underline{u}_{i-1})$, $c(\underline{u}_i)$, $c(\underline{u}_{i+1})$, and $c(\underline{u}_{i+2})$, with weights $\{0.4, 0.8, 1.0, 0.8, 0.4\}$. We run the filter for six iterations over the curvature data. (see `StatUtil.diffuseValues()`) This feature detection algorithm, combined with the dynamic regularization filter, produces the best results thus far.

5.3 Feature Matching

Feature matching is done in the same way that GNU diff is implemented UNIX systems. It uses an optimized, mostly linear algorithm that minimizes the edit distance between the two sets of features[5]. Thus, we reduce the problem of corresponding feature points to that of string matching. Let the feature points of the first and second curves drawn be represented by $\underline{a}$ and $\underline{b}$. These two strings have an alphabet of three symbols: Clock-Wise Curvature Extrema

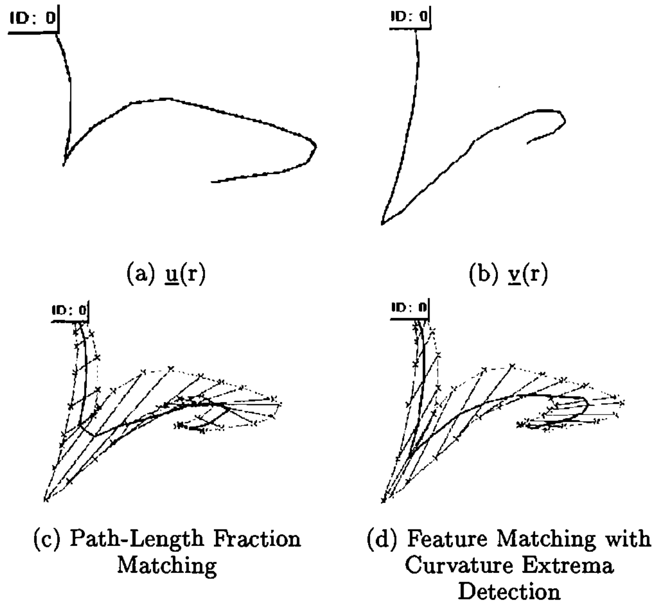

ID: 0
(a) u(r)
(b) v(r)
(c) Path-Length Fraction Matching
(d) Feature Matching with Curvature Extrema Detection

Figure 14 Comparing Path-Length Fraction Matching and Feature Matching Results. The red in (c) and (d) represent the final blended result.

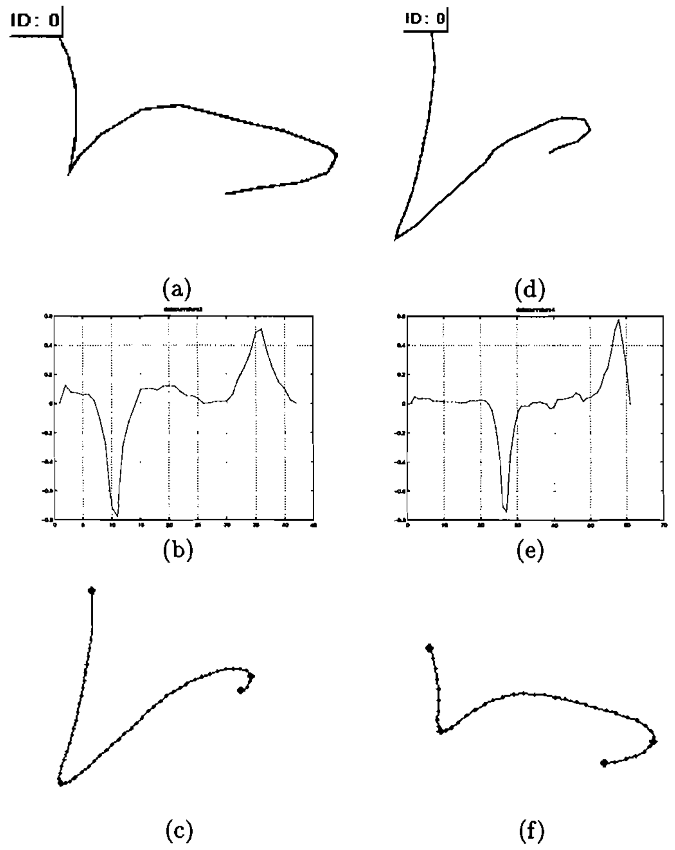


Figure 15 Feature Matching without Diffusion. Y-axis is 0.2 radians per grid-line for (b) and (e).

Point, Counter-Clockwise Curvature Extrema Point, and Endpoint. The algorithm attempts to minimize the number of DELETE and INSERT operations that would transform $\underline{a}$ into $\underline{b}$. While the resulting edit distance is the same for transforming $\underline{b}$ into $\underline{a}$, it should be noted that the correspondence set that results may be different. There are always two Endpoint feature points for every curve, one at each end. The algorithm always ends up corresponding the endpoints correctly.

For the most part, this algorithm works well. However, it might be interesting to change the measurement of the edit distance so that deleting a feature of more severe curvature would require more than the usual one unit of edit distance. This might help correspond the correct features with each other. We have not had the time to implement such an algorithm. This would probably require doing the full-blown quadratic time algorithm for minimizing the edit distance, but the number of features is usually less than ten so efficiency does not seem like a problem.

5.4 Establishing Point Correspondence

After the feature points are matched up, we correspond the segment between each pair feature points using the C_L or C_T version of the Path-Length/Time Fraction Matching Algorithms in section 4.3. This method works quite well, assuming the right feature points were found and were matched up reasonably well.

In summary, the feature matching approach requires that we first do some filtering, analyze curvature data on the filtered curves to detect the relevant features, correspond the features, and lastly, correspond the points of the original curves.

5.5 Results

We now present our results for feature matching, analyzing how they work in more depth and comparing them with our earlier approaches.

5.5.1 Comparing Path Length Fraction and Feature Matching

Here we compare results from the Path-Length Fraction Matching Algorithm and the feature detection algorithm (without diffusion). In Figure 14, we draw two curves ((a) and (b)) and try to blend them. Note that, relative to the first curve, the second curve has longer path in its first subsection and a shorter path in the second subsection.[4] It is clear that since both $\underline{u}(r)$ and $\underline{v}(r)$ contain a sharp "V" dip, the blended curve should as well. However, due to the slight shifting caused by the different arc lengths, the two corner points are not corresponded to each other in Figure 14(c). However, it's clear that in 14(d), the feature matching algorithm was able to find that critical point (because it's obviously a curvature extrema) and correspond the points properly. Not only is the blended shape better, but it could be that the user put a significant pause at the corner point. Using the Path-Length Fraction Matching scheme, a replayed animation would result in the widget pausing a few millime-

[4]A "subsection" is loosely defined to be however the "average" user would intuitively segment a motion path. In this example, there seem to be two subsections.

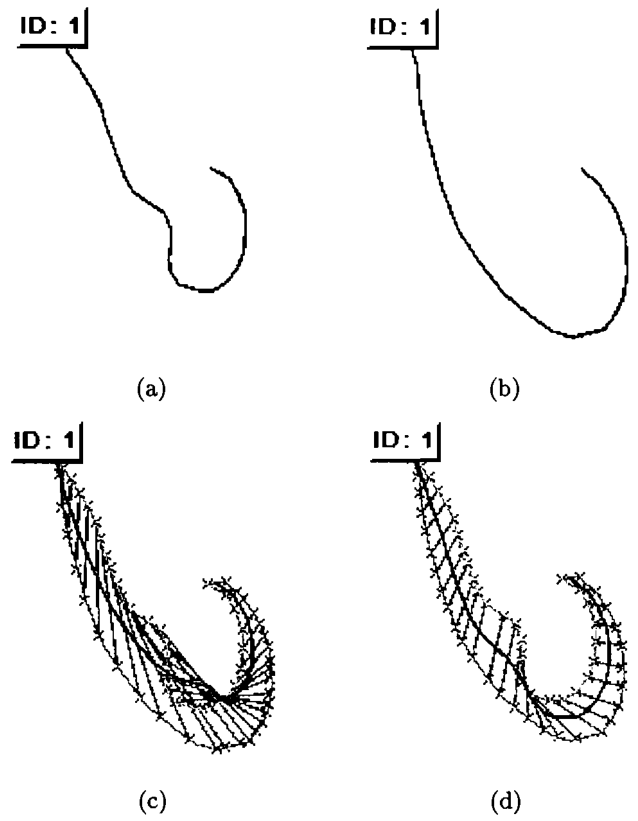


Figure 16 Feature Detection with and without diffusion. (a) $\underline{u}(r)$ (b) $\underline{v}(r)$ (c) without diffusion (d) with diffusion.

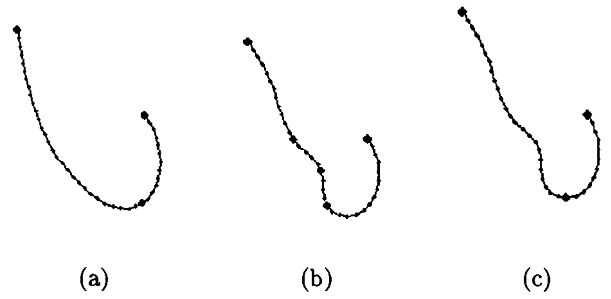


Figure 17 Feature Points (a) First curve (with and without diffusion, (b) second curve without diffusion, and (c) second curve with diffusion.

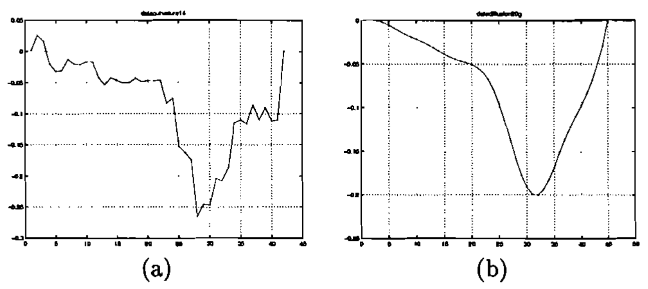


Figure 18 Curvature plots for feature detection (a) without diffusion and (b) with diffusion.

ters before the (now non-existent) corner point, and then doing a little "hook" before resuming upward motion.

The inner workings of the feature matching algorithm are shown in Figure 15. The first set in the figure show the original curves that were drawn. The second set shows the curvature plots of the *filtered* curves (No diffusion is applied in this example). The last set shows the filter output with feature points identified. Counter-clockwise-turning curvature extrema points are shown in red and clockwise-turning extrema points are shown in green. Dark gray circles mark the endpoints, which are considered their own category of feature point by the feature detection algorithm. Notice how, in this case, the feature points of two curves exactly match. The thresholds for the feature detection were 0.15 and 0.10, respectively

Therefore, we see that in some ways the Feature Detection/Matching algorithms have significant advantages over previous algorithms in there ability to subdivide a curve and correspond the subdivisions.

5.5.2 Adding Diffusion to Feature Detection

Adding a diffusion pre-processing step before feature detection allows us to filter out more noise from the curvature data. The advantage of this can be seen in Figure 16. The original curves are shown in (a) and (b). (c) and (d) show two different blends for this pair of curves. It should be clear that the diffusion improves the blending noticeably. In Figure 17, we see that the feature detection algorithm finds the same feature points for the first curve, as seen in 17(a). However, the second curve gives differing results. The extra red feature point in 17(b) forces the feature matching routine to choose between the two red points since there is only one in the other curve. This choice is basically arbitrary and dependent primarily on which curve was drawn first, and has to do with the subtleties of the edit-distance algorithm that we use. But with the diffusion thrown in, we find that only one red feature point is found in the second curve and is shifted closer to where it should intuitively be. To see why, look at the two curvature plots in Figure 18.

Thus, we find that the diffusion pre-processing gives cleaner curvature plots, which produces less extraneous points from the feature detection step. This of course helps the feature matching which improves the overall correspondence between the curves and produces better blends.

5.5.3 Weaknesses of Feature Detection/Matching

One of the weaknesses inherent in looking at curvature extrema is that sometimes, interesting features do not produce curvature extrema or non-interesting features produce unwanted curvature extrema points.

A good example of this is a circle. An imperfectly drawn circle, or arc that has approximately constant curvature, can produce extraneous feature points, as in Figure 19(d). The feature points for the first curve are as expected (Figure 19). The example given did not utilitize diffusion, but even diffusion will not eliminate this since there will be small swells and dips that exceed the threshold. This is because the threshold is calculated by averaging the curvature plot values. Therefore, there will always be such values. There is however a minimum cut-off threshold which eliminates this

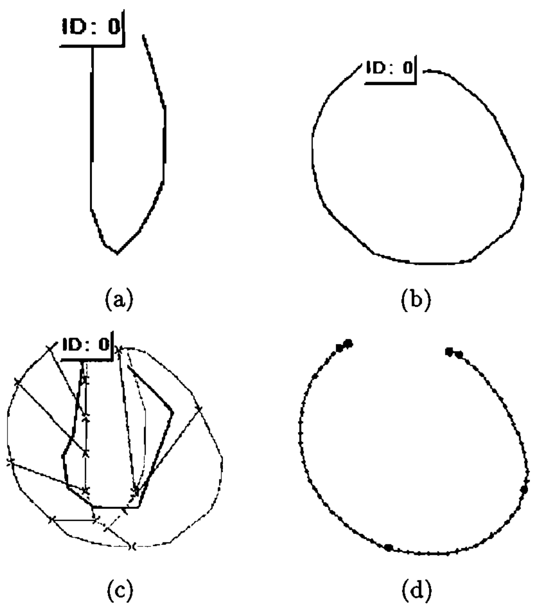


Figure 19 (a) $\underline{u}(r)$ (b) $\underline{v}(r)$ (c) blended curve (d) feature points for $\underline{v}(r)$.

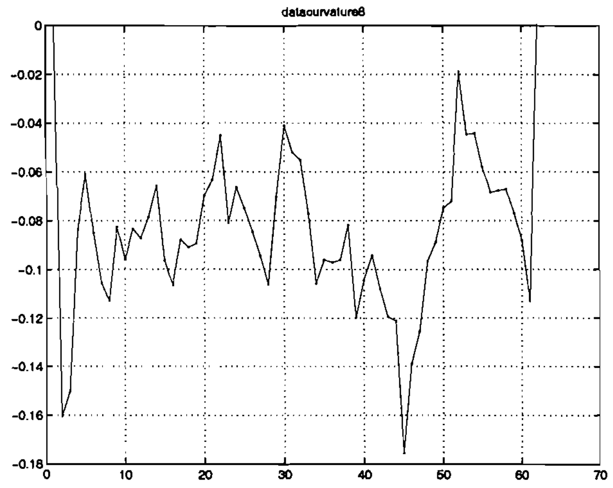


Figure 20 Curvature plot for 19(d)

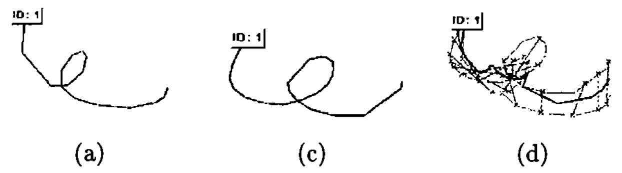


Figure 21 Loops (a) $\underline{u}(r)$ (b) $\underline{v}(r)$ (c) blended curve

problem for straight lines (which are essentially curve segments of constant curvature near zero).

Another case is where a user draws certain features in one section of the curve but fails to draw them in another. In other words, the user eliminates or adds features when drawing the second one, sometimes throwing off the feature matching algorithm.

Last, the curvature extrema points for when a user draws loops can produce odd results (Figure 21) about half of the time. Although we have not done formal studies on this, from experience, we find that the way users draw loops tend to produce inconsistently placed extrema points from one curve to the next.

6 Conclusions & Future Work

The above correspondence algorithm, using feature detection/matching with diffusion, works for many typical cases. However, it still has its weaknesses, especially when the user happens to draw the arc of a circle (i.e. constant curvature) or when the user draws small loops. In fact, any features that have ambiguous or erratic curvature data after filtering will produce unpredictable results. But overall, of the cases that seem to work, the blending seems intuitive.

As for future work, most of the opportunities for further exploration were mentioned previously throughout the various sections. The feature detection scheme could use some special case optimizations for certain pathological cases. The feature matching algorithm could be better, to help accommodate any errors or hard-to-interpret user input. Thus far, we have only used one feature matching algorithm. The diffusion algorithm could be more elegant, and could implemented to work directly on the original curve, skipping the filter step.

Another completely different avenue is to not look at curvature extrema to find different features, but to abstract away irrelevant points until only the a few important points remain. If such a filter could be implemented, then the feature detection algorithm becomes relatively easy. An example of this could be a good wavelet filter or the Angle Filter, mentioned previously.

Beyond the scope of this report, there is also the issue of angular motion and other forms of animation. In addition, providing an intuitive and elegant interface that successfully coordinates and synchronizes multiple animations may prove to be a challenge. A surface-level view shows that it could just be a "programming problem," where we define some gestures for some obvious feature set. Yet, we hesitate to endorse that view until someone actually implements such an interface.

7 Acknowledgements

I liked to acknowledge my advisor, John F. Hughes, who has been an invaluable collaborator and encouraging advisor. Thanks to Jayashree Subrahmonia at IBM Research, for taking the time to share her insights on handwriting recognition research.

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