Streamlined and Accurate Gesture Recognition with Penny Pincher

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Abstract

Penny Pincher is a recently introduced template matching \$-family gesture recognizer that exhibits competitive accuracy with even just one template. However, our recognizer is also able to rapidly compare a candidate gesture against numerous templates in a short amount of time, as compared to other recognizers, in order to achieve higher accuracy within a given time budget. Penny Pincher achieves this goal by reducing the template matching process to merely addition and multiplication; by avoiding translation, scaling, and rotation; and by avoiding calls to expensive geometric functions. In an evaluation compared against four other \$-family recognizers, in three of our six datasets, Penny Pincher achieves the highest accuracy of all recognizers reaching 97.5%, 99.8%, and 99.9% user independent recognition accuracy, while remaining competitive with the three remaining datasets. Further, when a time constraint is imposed, our recognizer always exhibits the highest accuracy, realizing a reduction in recognition error of between 83% to 99% in most cases as Penny Pincher is able to process five times as many templates in the same amount of time as its closest competitor. Further, in this extended work, we also evaluate the effectiveness of Penny Pincher in a stressful setting using a video game prototype that makes heavy use of gestures, so that rushed and malformed gesture articulation is more likely. Our evaluation was conducted with a 24 participant between-subject user study of Protractor and Penny Pincher. Training data and in-game data collected during the user study was further used to evaluate several \$-family recognizers. Again we find that our recognizer is on par with or better than the others, reducing the recognition error by as much as 5.8% to 10.4% with just a small number of templates per gesture.

Keywords: Gesture recognition, \$-family, template matching

1. Introduction

As pen- and touch-based interfaces become ubiquitous via the widespread use of smart phones, pocket computers, and tablet computers, the need for high quality gesture recognition also continues to rise. Enabling technologies such as the iTunes Store, Google Play, and Windows Store makes it possible for individual developers to create and easily distribute small to large scale software for these devices, which has attracted numerous professionals as well as casual hobbyists. However, without expert knowledge in pattern recognition, a developer is unable to create even the simplest custom gesture-based interface for his or her software. Wobbrock et al. [1] began to address this issue in their seminal work when they introduced the \$1 recognizer. This is a straightforward, highly accessible, and easy to implement recognizer that spurred a flurry of research known as the \$-family of recognizers [1, 2, 3, 4, 5, 6], their common theme being simplicity.

The \$-family exhibits several benefits, the most obvious of those being their all around straightforwardness. This trait makes them ideal not only for rapid prototyping, but because they are also generally accurate, they are a good choice for situations where existing gesture recognition libraries cannot be

used or when licensing constraints make their use prohibitive. Since they are quick to implement, \$-family recognizers are also ideal for studies in gesture-based user interfaces. Another argument for their use, provided by Li [5], is that for custom gestures, users are unwilling to provide more than a small number of training examples, which makes statistical based methods like Rubine's [7] linear discriminator impractical. Further, each recognizer is designed to solve a different problem. For example, \$1 was designed for unistroke gestures, \$N for multistroke, \$P for memory reduction, Protractor to overcome the speed impediments of \$1, 1^c for fast recognition of rotation invariant gestures, and so on. However, all of these varieties rely on template matching and as such, tend to improve in accuracy as the number of training templates increase.

We recently introduced *Penny Pincher* [8] to address the problem of how to create a recognizer that is accurate within a time constraint. For instance, suppose that the recognizer is part of a game. The recognizer then has to share computational resources with several other components including AI, the rendering engine, animation system, physics simulator, event and message handlers, networking, scripts, and so on [9]. Therefore, a software architect may allocate only 50 microseconds to the gesture recognition task when a new stroke is collected, to ensure that the process is not disruptive to other game tasks. This constraint poses two issues. First, with such a tight constraint, certain recognizers cannot be used because they are simply too slow. Second, this limits the number of templates a rec-

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Figure 1: A candidate gesture (a) is given by the user, which is then resampled into a set of equidistance segments (b). Given a template gesture (c) we compare the corresponding between-point vectors to find the best match. In this case, the 'e' template is the best match because it minimizes the sum of the angles of the corresponding resampled input and template vectors as compared to all other templates.

80 ation to consider the accuracy of Penny Pincher and other \$-
81 family recognizers in a game environment. Specifically, we de-
82 veloped the bimodal pen and touch video game Lemarchand's
83 Prototype to evaluate the effectiveness of such recognizers in
84 circumstances where gesture articulation is likely to be rushed
85 and often malformed. This is one domain where flexible rec-
86 ognizers that can handle a great deal of variance are likely to
87 be appreciated. In Section 5, we show that Penny Pincher is
88 again on par with or better than other recognizers despite its
89 simplicity. In Section 6, we discuss and analyze our findings,
90 and future work, and finally we conclude in Section 7.

91 2. Related Work

92 Since Rubine's [7] seminal work on gesture recognition, nu-
93 merous techniques have been developed for both gesture and
94 symbol recognition. One popular branch of research focuses
95 on easy to understand and easy to implement recognizers. The
96 \$-family of recognizers started with Wobbrock et al. [1] who
97 designed the \$1 recognizer. This simple and effective unistroke
98 recognizer works by resampling strokes to a predetermined num-
99 ber of points, and then these strokes are translated and scaled to
100 the unit square centered at zero. Euclidean distance between
101 points is then used as a similarity metric to compare candidate
102 strokes with template gesture strokes. The template with the
103 least distance is assumed to be the most likely gesture. To en-
104 sure the best match possible, \$1 also uses a golden section
105 search (GSS) [11] to rotate candidate strokes into alignment
106 with the template under consideration. Anthony and Wobbrock
107 [2] extended the \$1 unistroke recognizer into the \$N multi-
108 stroke recognizer. This version is able to handle multistroke
109 gestures by combining all strokes into a single stroke so that
110 \$1 techniques can be leveraged. Given an example gesture,
111 during training when templates are constructed, all permuta-
112 tions of strokes and stroke directions are used to generate all
113 possible ways in which the gesture can be written.

114 While the previous approaches work with arcs, Vatavu et al.
115 [6] considers input as point clouds. The \$P recognizer still re-
116 samples, scales, and translates strokes and uses Euclidean dis-
117 tances as a similarity metric. However, the points are not treated
118 as a time series; instead the authors employ a greedy algo-
119 rithm that tests different permutations of points to find the over-
120 all minimum distance between candidate and template point
121 clouds. Herold and Stahovich [4], on the other hand, continue
122 to work with strokes as time series, but their 1^c recognizer gen-
123 erates a rotation invariant representation that is a time series
124 vector of one-dimensional points—normalized distances mea-
125 sured from the stroke's centroid. That is, strokes are resam-
126 pled as usual, but then each two-dimensional point is converted
127 into a one-dimensional scalar, the distance of the point from the
128 centroid normalized by the standard deviation of all distances.
129 Candidate and template strokes are then compared using the
130 one-dimensional Euclidean distance.

131 One major limitation of \$1, \$N, and \$P is that they are gen-
132 erally slow. The former two recognizers are slow due to their
133 use of the GSS. Li [5] was able to overcome this limitation. He
134 discovered a closed form equation to find the optimal rotation

of a candidate stroke to match the template. Since Li's Protractor recognizer represents each stroke as a vector and works with the angle between the two vectors (between the candidate and template vectors), it is not necessary to scale candidate strokes when matching. However, resampling and translation to the centroid are still required. Anthony and Wobbrock [3] adapted Protractor's technique to create a fast multistroke recognizer, \$N-Protractor.

To further speed up template matching, Reaver et al. [12] proposed Quick\$ to use agglomerative hierarchical clustering with a branch and bound search to cull branches that cannot contain a better match than what has already been found. Zhang et al. [13] use nonlinear embedding [14, 15] as a filter to quickly check the lower boundary of the Euclidean distance between a candidate and template using only stroke means and variances based on a low dimensional representation. Vatavu [16] developed 1F to sort all templates based on a scalar value (such as total curvature). Then the probability mass functions (*pmf*) are learned for each template. During the matching process, the best match is identified based on the 1F value, and then the *pmf* of the associated template is used to determine how far left and right of the current template to search for the best match. Except for nonlinear embedding, our Penny Pincher recognizer is orthogonal to these methods. However, such methods are not within the spirit of the \$-family because of their additional complexity in code and data structures.

Fuccella and Costagliola [17] more recently introduced a new recognizer that the authors claim is also suitable for rapid prototyping, and that outperforms other state-of-the-art recognizers. However, their recognizer is somewhat more complex than the typical \$-family recognizer, involving polyline approximation using dominant points, smoothing of polylines by segment fusion, polyline segment alignment, rotation with an optional GSS, and a final distance calculation.

Compared to other \$-family recognizers, Penny Pincher [8] is the easiest yet to understand and simplest to implement. As mentioned previously, we do not rotate, scale, or translate candidate gestures, whereas every other recognizer does at least one of these. Also, most recognizers use Euclidean distance and have to make calls to geometric functions at some point in the template matching process. We compare between-point vectors instead, so that only simple dot product calculations are required (after the gesture has been resampled). As we show in Section 4, these simple modifications improve computational performance without sacrificing accuracy. However, the main contribution of this paper is an extension of our previous evaluation, where Penny Pincher and other \$-family recognizers are put to test in a challenging video game environment. Again, we demonstrate that our recognizer is ideal for its accuracy and simplicity, as compared to the alternatives, in this tough domain—one in which players are rushed, make mistakes, and write sloppy.

3. Penny Pincher

Loosely following [16], we define a gesture as an ordered series of points as follows:

$$g = \{g_i = (x_i, y_i) \in \mathbb{R}^2\}, \quad (1)$$

where i indexes the gesture's points in time relative order. Gestures are resampled by length into n points so that the distance between each point is equal. A gesture is then converted into a series of between-point vectors:

$$v = \{v_i = g_{i+1} - g_i\}, \quad (2)$$

for $i < n$. Given two gestures v and w , their similarity is taken to be the sum of the angles between corresponding between-point vectors:

$$D(v, w) = \sum_{i=1}^{n-1} \frac{v_i \cdot w_i}{\|v_i\| \|w_i\|}. \quad (3)$$

A perfect score is therefore $n - 1$ because the normalized dot product is 1 for identical vectors. Now, let m be the number of distinct gestures and $\mathcal{T}$ the set of templates created by training the recognizer:

$$\mathcal{T} = \{t_i = (s_i, l_i) \mid l_i \in \{1 \dots m\}\}, \quad (4)$$

where t_i is the enumerate template in set $\mathcal{T}$, s_i is the gesture sample's between-point vector, and l_i is the gesture's class label. A candidate gesture c takes the classification of the template T that is most similar:

$$T = \arg \max_{t_i \in \mathcal{T}} D(t_i, c), \quad (5)$$

This already simple calculation can be simplified further. During training, let the components of the between-point vectors be normalized so that each $\|s_i\| = 1$, thus eliminating one normalization factor in Equation 3. Next, as a simplifying assumption, say that the length of each between-point vector component is equal (each $\|w_i\| = \|w_{i+1}\|$) because gestures are resampled into $n - 1$ equidistance arc lengths; this assumption is evaluated in Section 4.2. This allows us to treat $\|c_i\|^{-1}$ as a constant to be factored out of the summation of Equation 3. Further, note that this factor is the same for all evaluated templates in Equation 5—it scales each dot product result identically. Therefore the scaling factor can be eliminated entirely without affecting the final result, thus simplifying our template matching equation to:

$$T = \arg \max_{t_i \in \mathcal{T}} \sum_{i=1}^{n-1} v_i \cdot w_i. \quad (6)$$

There are a few distinct advantages to this formulation. Notice first that there are no rotation, scale, or translation operations involved. This means less overhead in preparing templates and matching. Also, template matching is reduced to merely addition and multiplication with no expensive calls to geometric library routines. This reduction in overhead compared to other recognizers means that more templates can be evaluated in the same amount of time, see Section 4. The simplicity of our approach also means Penny Pincher is the easiest to understand and implement in the \$-family.

It should be noted that Penny Pincher is not specifically a multistroke gesture recognizer. However, we leverage the same technique used by \$N\$ [2], which is to concatenate sequential strokes together into a single unistroke gesture. We find that with a sufficient number of training samples, this achieves the same effect as \$N\$'s scheme to internally generate all possible permutations of a gesture from a single sample.

3.1. Complexity

In this section we discuss the theoretical minimum asymptotic boundary of the \$-family of recognizers. Without the use of filtering or other culling techniques we make the following assumptions:

1. Candidate gestures are always resampled.
2. The resampled candidate gesture is always compared against every template in $\mathcal{T}$.
3. Each point in the resampled candidate gesture is evaluated against at least one corresponding template point.

Under these assumptions, let $r = |c|$ be the length of the candidate gesture before resampling, representing the number of raw data points. As before, n is the number of resampled data points. The cost of resampling c is the cost of first calculating the stroke length and then computing the resample points. This requires touching every raw data point twice, $\Omega(2r)$, and every resample point once, $\Omega(n)$. The latter is because each resample point is part of the path and must be considered as the resampling procedure continues. Supposing that the recognizer can match the resampled points directly (e.g., without further manipulation), then no additional processing is necessary. Template matching is subsequently carried out for each $t \in \mathcal{T}$, which is $\Omega(n|\mathcal{T}|)$. Therefore, at best, a template based recognizer as described is bounded by:

$$\Omega(2r + n + n|\mathcal{T}|). \quad (7)$$

To the best of our knowledge, Penny Pincher is the first \$-family recognizer to achieve this lower bound. Note that the complexity of several other recognizers are available in [6], however, these do not consider the cost of resampling. Of course Ω notation hides certain details that are important in practice. We have to consider that 1^c , for example, represents each point in its template as a one-dimensional point where the other methods use two-dimensional points. This means that 1^c can compare templates faster despite having a non optimal resampling strategy as is shown in the evaluation Section 4.3. Penny Pincher, on the other hand, relies on straightforward dot product calculations without having to utilize external or built-in math libraries.

4. Evaluation

We evaluate Penny Pincher using three different tests. All tests were performed on a MacBook Pro with a 2.4 GHz Intel Core i7 processor, 8 GB of 1333 MHz DDR3 memory, and an 760 GB mechanical SATA disk. In our first test we check the validity of the assumption that all between-point vector lengths

of a single gesture are of equal length. Next we evaluate the accuracy of our method compared to other \$-family recognizers when the number of templates is controlled (the standard method of evaluation). Finally we investigate the accuracy of the fastest recognizers to see how well they perform under varying time constraints. However, we first describe the various datasets used in our tests in the follow subsections.

4.1. Datasets

This subsection gives a brief description of each dataset used in our evaluation. For additional information beyond what is presented here, we refer the reader to the associated cited work.

\$1-GDS. The \$1 recognizer gesture dataset [1] is a unistroke gesture dataset comprising 16 gestures collected from 10 subjects at 3 speeds (slow, medium, and fast) on an HP iPAQ h4334 Pocket PC. Because each subject supplied 10 samples of each gesture at each speed, there are 4800 samples in aggregate.

SIGN. The Synchromedia-Imadoc Gesture New On-Line Database [18] is a unistroke gesture dataset comprising 17 classes collected from 20 writers on tablet PCs and whiteboards. Each writer supplied 25 samples over four sessions so that SIGN contains 8500 samples in aggregate.

EDS 1 and EDS 2. Two unistroke gesture datasets were collected by Vatavu et al. [19] to study gesture execution difficulty, referred to as Execution Difficulty Set #1 (EDS 1) and Execution Difficulty Set #2 (EDS 2). The first dataset contains 5040 samples in aggregate comprising 18 gestures collected from 14 participants providing 20 samples each. The latter dataset contains 4400 samples in aggregate comprising 20 gestures from 11 participants providing 20 samples each. All samples were collected on a Wacom DTU-710 Interactive Display.

MMG. The Mixed Multistroke Gestures dataset [3] comprises 16 gestures having between one and three strokes. Samples were collected from 20 participants using either a stylus or their finger on a tablet PC at three different speeds (slow, medium, and fast). In aggregate there are 9600 samples.

UJI. The UJIpenchars2 Database [20] is a multistroke gesture dataset of lowercase and uppercase letters, digits, characters with diacritics, and punctuation marks containing an aggregate of 11640 samples over 97 gesture classes. Data was collected from 60 writers each providing 2 samples of each class.

4.2. Verification of Between-Point Vector Distribution

The simplifying assumption used in Equation 6 supposes that each between-point vector is of equal length. In reality, this is inaccurate because indeed, vectors taken from collinear points are longer than those taken from curves, which in turn are generally longer than those taken from sharp cusps. However, for the purpose of an approximation, we find this assumption to be sufficient. To verify this we examine the empirical probability density distribution generated with the relative between-point vector lengths of each sample in six datasets (\$1-GDS, SIGN, EDS 1, EDS 2, MMG, and UJI). For each individual sample, the mean between-point vector length is computed and all vectors within the same sample are normalized by the

Figure 2: The empirical probability density of the distribution of between-point vector length. For each resampled gesture in the \$1-GDS, SIGN, EDS 1, and EDS 2 datasets, we normalize the between-point vectors to the average length of the vectors within the gesture. All results are combined to create this overall distribution of relative lengths. It can be seen that the majority of the density is centered around 1.0 which indicates that the majority of between-point vectors are of equal length within each sample.

mean. Then the set of all normalized vectors from all sets are combined to build the empirical probability density distribution shown in Figure 2. If all between-point vectors were truly of equal length then the full density would be located at one. We see, though, that the majority of the density is near one with the distribution being left skewed. Specifically, 85% of the distribution is contained between 0.9 and 1.15 and is left skewed -2.85 . The individual distributions of the six unique datasets are all similar to the overall distribution. They are left skewed in the same manner (-3.08 , -3.06 , -2.44 , -2.56 , -2.5 , and -2.59 respectively) and contain a similar portion of the density within the same range (87.58%, 87.43%, 79.96%, 85.83%, 78.81% and 81.06% respectively). Further, note that the observed left skewness is expected. When most vectors are of similar length but there are a small number of short vectors on sharp cusps for example, then the mean is pulled down, shifting the densest portion of the distribution right of the mean. Nevertheless, given that the majority of the density is located near one, we find our previous assumption that between-point vector lengths are approximately equal to be accurate enough for our use.

4.3. Standard Test

Using all six datasets we compared the accuracy of Penny Pincher against its predecessors \$1, Protractor, \$N, \$N-Protractor, and 1^ϵ using what we call the standard test. The resampling rate of each recognizer was set according to that given (or suggested) in each recognizer’s paper respectively: 1^ϵ , Protractor, and Penny Pincher resample to 16 points whereas \$N, \$N-Protractor, and \$1 resample to 96 points. Where applicable, we enabled bounded rotation invariance due to an observed slightly higher recognition performance. Note that we also considered \$P. However, we found that the recognizer was very slow in

practice, and based on results reported in [6], this recognizer performs similarly to \$1 for unistroke gestures. Also because we are interested in recognizers that can potentially process numerous templates in a short amount of time, \$P was not an option.

In this part of the evaluation, the template count T varies from 1 to 10 for each gesture and we consider only user independent scenarios. For each template count and for each recognizer we ran 1000 tests. That is, in each iteration we randomly select T templates per gesture from all of the available samples, and then we randomly select one remaining sample from each gesture to be the candidate gesture. Therefore each test contains g recognition tasks, where g is the number of gestures in the dataset. Throughout the following, we report on the recognition error of the various recognizers (which is equivalent to one minus the accuracy). All of the standard test results can be found in Figure 3.

Penny Pincher performs strongly on the \$1-GDS dataset. With only one template loaded, the error rate is 8.58% which drops to 1.3% by ten templates. \$1, on the other hand, also starts at 8.58% but only achieves a 1.9% error by the end. Protractor makes the most dramatic improvement in reduction of error by swinging from 12.16% to 1.55%, beating out \$1 starting at 6 templates. For the EDS 1 dataset, Penny Pincher is mostly a middle of the road yet still accurate performer, achieving a 3.3% error with one template, and dropping to below 0.7% with three templates, but reaching the best result of all recognizers at 0.11% error with ten templates loaded. With EDS 2, our recognizer starts at 2.19% and drops to .70% by the second template. For the remaining template counts, Penny Pincher maintains the highest accuracy with its best result at 9 templates (0.11% error). Both \$1 and Penny Pincher perform very well compared to \$N and Protractor for the SIGN dataset, although Penny Pincher has better overall performance. We start at a 13.41% error which drops over ten templates to 2.2%, whereas \$1 starts at 13.47% and only drops to 4.41%

MMG is a dataset designed for \$N and \$N-Protractor which were developed to handle multistroke gestures. So it is expected that Penny Pincher would not perform as well in this case. Our recognizer is approximately in line with Protractor, where with one template loaded, we see 38.31% error. This steadily decreases until the error rate reaches 8.0% using 10 templates. One thing to note, however, is that \$N internally creates a template for every possible permutation of the strokes and their directions. So although the template count is 10, for example, in reality \$N is evaluating significantly more templates. As is shown in the third part of our evaluation, Penny Pincher is also capable of achieving similar or better results when more templates are available. UJI is a large gesture dataset that has gestures with significant similarities, making it a difficult dataset for all recognizers. Our recognizer starts out at a 67.12% error rate and only achieves 41.53% error with ten templates loaded. This is approximately in line with \$1 and Protractor. \$N, however, fares less well, only reaching 45.32%

In all of the six datasets, 1^ϵ ’s accuracy was well below the other recognizers. This is likely due to the fact that 1^ϵ is completely rotation invariant, and while this turns out to be good

Figure 3: User independent error recognition test results for varying template counts. Each test, for each recognizer and template count, was performed 1000 times. 1^ϵ was also tested, though because it exhibited high error rates with these datasets, it was removed for readability.

Recognizer	Avg ns / Template	ns- σ
1^ϵ	25	4.5
Penny Pincher	33	6.2
Protractor	174	27.7
$\$N$ -Protractor	2449	650

Table 1: Average time taken in nanoseconds per template to perform the recognition task for the UJI dataset given 10 templates per gesture. The four fastest recognizers are shown alongside their standard deviations. Although 1^ϵ is the fastest recognizer, its accuracy is subpar compared to its competitors for this dataset.

one reason why Penny Pincher is able to achieve high accuracy as reported in the next subsection.

4.4. Budget Test

We refer to our final test as the budget test. In this scenario we are given a time constraint and are allowed to process as many templates as possible within the given boundary. This setup is similar to the standard test except that we vary the time constraint rather than the template count directly. For each test we first determine the number of templates the recognizer can process per second. We then start with a $10\mu s$ budget and allow the recognizer to train with as many templates as it can process within the time constraint. Using this configuration, as before, we execute 1000 randomized tests. Thereafter the budget is incremented by $10\mu s$ and the test is rerun. This continues until there are not enough remaining samples to perform a full recognition test. Since the number of templates a recognizer can train will depend on the budget, it is possible to have an uneven number of templates per gesture class. If, for example, the budget allows for 2.2 templates per gesture, we ensure that at least two templates are loaded per class and then a random 20% of the gesture classes will have a third template loaded. The results of this test are shown in Figure 4. The graphs are cropped to $100\mu s$ for readability, but the tail results are reported below.

Penny Pincher achieves high accuracy for EDS 2 right at the start with a 0.13% error and is able to process approximately 7.9 templates per gesture (tpg) within $11\mu s$. As the test continues,

Figure 4: User independent error recognition test results for varying time constraints. Each test, for each recognizer and budget, was performed 1000 times. Although the graphs are cropped to 100 μ s for readability, the tail results are reported in Section 4.4.

	20 μ s		40 μ s		60 μ s		80 μ s		100 μ s	
\$1-GDS	87%	(0.32, 2.41)	87%	(0.18, 1.39)	87%	(0.09, 0.74)	95%	(0.03, 0.66)	99%	(0.01, 0.64)
EDS 2	94%	(0.09, 1.45)	87%	(0.09, 0.71)	84%	(0.07, 0.40)	94%	(0.03, 0.44)	87%	(0.05, 0.38)
SIGN	94%	(1.26, 21.88)	95%	(0.96, 19.69)	96%	(0.75, 18.38)	96%	(0.65, 18.36)	96%	(0.69, 18.40)
MMG	69%	(2.13, 6.80)	83%	(1.25, 7.51)	85%	(0.88, 5.95)	83%	(0.79, 4.71)	—	—
UJI	26%	(45.07, 60.84)	30%	(38.04, 54.32)	30%	(35.12, 50.42)	31%	(32.99, 47.60)	31%	(31.41, 45.7)

Table 2: Reduction in percentage error for 20, 40, 60, 80 and 100 microsecond budgets. Shaded cells show the percentage reduction in error achieved by Penny Pincher compared to the second most accurate recognizer at each sample location (see the individual graphs in Figure 4 to know which recognizer this is). To the right of each percentage reduction result is the exact percentage error of Penny Pincher and its competitor, in this order. Note that with **MMG**, the dataset is exhausted before Penny Pincher reaches 100 μ s, which is why there is no entry.

the dataset is exhausted at a 111.29 μ s budget where the error rate drops to 0.06% and 208.6 tpg are processed. 1¢ initially achieves a 3.2% error with 10.4 tpg at a 11 μ s budget. This improves to only 0.53%. Protractor starts with the worst accuracy, only being able to handle 1.05 tpg at 10 μ s. As expected, Protractor takes the longest to complete where the dataset is exhausted at 701.34 μ s, though the error rate drops to 0.1%. In all budgets, Penny Pincher achieves a considerably lower error rate.

Of all our tests, 1¢ achieves its best results with the \$1-GDS budget test. Although the initial error is high (14% at 19.12 tpg), this drops to 0% by the end with 297.94 tpg at 90 μ s. Penny Pincher also reaches 0% with 219.38 tpg at 89 μ s. However, its initial error is much better, 0.85% with 19.12 tpg at 11 μ s. Starting with 2.81 tpg, Protractor only achieves a 5.3% error and at its best, cannot reach 0%. Using 297.56 tpg over

766 μ s, Protractor reaches .2% error.

UJI again is the most challenging dataset. Even at 65.81 tpg and 135 μ s, the error only drops to 49% from 69% for 1¢. Protractor is a little better, getting down to 30% from 66% but also requiring a 1152 μ s budget to do so. Penny Pincher has the best performance overall. With 3.06 tpg at 11 μ s, the initial error is 54%, which steadily drops to 28% by 183 μ s.

Initially Penny Pincher did not do as well as \$N when working with the MMG multistroke dataset. However, as discussed, \$N internally creates the various permutations of a gesture from a single template, which implies that given a specific template count, the recognizer is actually processing significantly more variations. In this scenario, that is no longer true. Each recognizer is trained with numerous examples as afforded by the budget so that most practical variations of the gestures are learned by the recognizer (whereas \$N may generate permutations that

Figure 5: Screenshot of Lemarchand’s Prototype, a game designed for pen-based gesture input. The box and wheels are rotated with touch. If the symbol in the box’s window matches the symbol on the hand of an enemy, then the player can draw the symbol to banish it. Enemies move faster and are generated faster as the game progresses.

never occur in practice). Therefore Penny Pincher working with 18.75 tpg at $11\mu s$ can achieve a 4.8% error, which declines rapidly to 1.1% (42.19 tpg) at $21\mu s$, and then to 0.79% at $86\mu s$ (183.06 tpg). Protractor and 1° also see higher accuracies but do not fare as well as Penny Pincher. Respectively their best errors rates are 2.9% and 4.7% (198 tpg at $526\mu s$ and 187 tpg at $62\mu s$).

SIGN again is where we see the most dramatic difference in performance between Penny Pincher and the other recognizers. With a budget of $9\mu s$ and 14.29 tpg, the error is already 1.9%. This continues to improve until the end where the error drops to 0.54% (with 1936 tpg over $1213\mu s$). 1° struggles initially in comparison with a 50% error that only drops to 43% near the end with $747\mu s$. Protractor is in the middle with an initial 26% error (2.41 tpg) which improves only to 14% with a $5720\mu s$ budget.

In Table 2 we provide a summary of select results from the budget test. For each sample, we compare Penny Pincher to the second best performing recognizer in the category and report the percentage reduction in recognition error. The exact errors are shown next to each result. It can be seen that in all cases, Penny Pincher significantly outperforms the other recognizers. With four datasets, the reduction in recognition error ranges between 69% and 99% with most results being above 83%. Our worst result is observed with the UJI dataset where the recognition error is only improved by 26–31%.

5. In Game Evaluation

There are a number of practical applications for pen and touch gesture recognition, though one of particular interest to

Figure 6: The 40 gestures used in Lemarchand’s Prototype. These are randomly selected samples collected from participants during training.

us is in the electronic games domain. There are two reasons for this: use cases are limited only to the imagination of game designers, and gesture recognition in games is difficult, often falling below expectation. Baseline results from offline tests, for example, are often better than those results collected in a video game environment [21, 22], which in part may be due to the induced stress associated with playing a game itself. Therefore, to evaluate the effectiveness of Penny Pincher and other \$-family recognizers in this difficult but practical situation, we developed the toy game *Lemarchand’s Prototype* shown in Figure 5, which is loosely inspired by Lemarchand’s box from Clive Barker’s novella *The Hellbound Heart* [23].

In our bimodal game, a box and four wheels that are arranged symmetrically in the center of the screen are rotated using touch, and symbols are drawn using a stylus. The box has a window in one corner that exposes symbols etched into the wheel over which the window is oriented. Upon selecting the desired wheel by rotating the box, the wheel itself is then rotated by touch to select from its different symbols. Those wheels not selected rotate automatically to ensure the player is able to see all symbols in play. Once the desired symbol is inside of the box’s window, a player can draw the symbol (gesture) anywhere on the screen. If a unistroke symbol is recognized as the selected symbol within the window, and if there is an enemy on the screen matching that symbol, then the enemy is banished to another realm. Enemies are arms that grope their way towards the box, and once close enough, shoot lightning (or “magic”) at the box in order to wreak havoc. As mentioned, each arm has a symbol on its hand which matches one of the symbols on one of the four wheels. The associated symbol on the wheel is highlighted lightly once the corresponding arm is visible on the screen to assist the player with locating matches. When a gesture is recognized and the enemy is banished, a new symbol appears on the wheel; this continues until the game ends. At the start of a round, a player has approximately 10–14 seconds to banish an enemy before it reaches the cube and is able to attack. Similarly, there is a sufficient delay between when new enemies are created so that the game pace is

leisurely. As the game progresses, enemies are generated faster and move faster (approximately 3—6 seconds to reach the box) so that not all arms can be defeated before they begin to attack. At this time, players are forced to react as quickly as possible in order to defend the box before too much damage is taken. By the end, there are usually six to twelve enemies attacking at once.

The Lemarchand’s Prototype gesture set comprises the 40 unistroke symbols shown in Figure 6, which were inspired by different sources. The star and right arrow variants, unistroke ‘x’, caret, check, pigtail variant, and curly and square brackets were derived from \$1-GDS [1], which we extended with the rounded brackets. The ‘3’, ‘6’, ‘8’, ‘a’, ‘g’, ‘m’, and triangle variant were derived from EDS 1 [19]. The ‘α’, rectangle (square), heart, curly, ‘?’, and spiral variant are due to EDS 2 [19]. The ‘2’, ‘@’, ‘b’, ‘e’, ‘h’, ‘q’, and ‘y’ gestures come from UJI [20]. We also included the division gesture (second row, second column in figure) from the Graffiti [24] gesture set. Finally, from no particular source, we also added the ‘&’, ‘∞’, ‘Σ’, ‘σ’, ‘~’, transistor, and register symbols.

5.1. Experimental Design

Since our evaluation involved a large number of direction sensitive unistroke gestures, we were only concerned with recognizers designed to solve this problem. 1^e generally does not perform well when gestures are symmetric or rotation variant; Protractor is considered to be a \$1 enhancement² because of its speedup and similar (sometimes better) accuracy; \$N as well as \$N-Protractor are extensions designed to also handle multi-stroke gestures; and \$P is a general purpose, stroke order and direction invariant recognizer. Following the cheatsheet provided by Vatavu et al. [6], we evaluated our recognizer alongside Protractor because of its support for stroke direction sensitivity, low coding complexity, and low algorithmic complexity. For the in game Protractor recognizer, we integrated the reference source code available on the \$1 project website². The standard way of evaluating \$-family recognizers is to increment the template count from 1 template per gesture to the maximum available (usually 9 or 10). In practice, however, a user is unlikely to provide more than one example of each gesture [5], or perhaps at most, two to three. Further, it would be quite time consuming to have a participant play the game 10 times, once for each count of templates per gesture from one to ten, and performance would likely deteriorate as participants become lethargic with repeated game play. As a compromise, we settled on a 3-level within-subjects design for each recognizer and between-subjects design between recognizers. That is, participants were asked to play the game three times utilizing one recognizer, each iteration with a different number of templates per gesture: 1, 3, and 10. Each recognizer was evaluated with 12 participants (24 total) recruited from the University of Central Florida, and each participant was compensated \$10 for approximately 65 minutes of time. Of the participants that utilized Protractor, 10 were male (2 female), 10 were right handed (2 left),

all but 1 had prior experience with pen and touch interfaces (2 had a lot of experience), and the ages ranged from 18—24 (average 21.3). Of the participants that utilized Penny Pincher, 7 were male (5 female), 9 were right handed (3 left), all but 2 had prior experience with pen and touch interfaces (no had a lot of experience), and the ages ranged from 14—34 (average 21.6).

5.1.1. Procedure

Each participant was first acquainted with the experiment and then asked to provide 10 samples of each gesture. Our data collection apparatus allows for five samples to be collected at a time, each in a different area on the display. Above each location, an example of the required gesture was shown. Further, the order of the 400 samples (forty gestures times ten) were randomly permuted. After the training data was collected, the participant filled out a pre-questionnaire to collect demographic information. Next the participants played a tutorial round of the game where all of the mechanics were introduced, though the recognizers were not active at this time.

After the practice round was completed, a participant played the game three times: with 1, 3, and 10 templates per gesture loaded. However, the order was randomly permuted, and since there were three levels, there were six possible permutations. Having twelve participants, we ensured that each permutation was tested twice. During a single iteration of the game, the order of the enemy gestures were randomly selected, and each symbol appeared three times so that once the experiment was completed, each gesture was attempted at least nine times. However, a single instance of a gesture can be attempted at most three times. After three unsuccessful attempts, the associated enemy is banished regardless. Note that the second and third attempts were included to allow the participant additional practice in case of bad form, though we only consider first attempts when calculating accuracy.

5.2. Baseline Results

Using the training data only, we first estimated baseline results—the highest accuracy possible when there are no additional stress factors to consider. Specifically, we examine two scenarios: user dependent accuracy and user independent accuracy. A user dependent scenario may represent a situation where a user provides templates for gestures that only he or she will write in the game. For example, this may occur when custom gestures are mapped to certain commands within a game, or when user dependent recognition is expected to be important as of game play. User independent recognition, on the other hand, may be important in a variety of different scenarios such as:

- A player borrows his friend’s mobile device to try out a game trained with his friend’s example gestures.
- A multiplayer game involves cooperative gesture creation and manipulation such that ad hoc gestures are shared amongst the players.

²See the \$1 unistroke recognizer project website: <https://depts.washington.edu/aimgroup/proj/dollar/>

Figure 7: Baseline accuracy for user dependent (left) and user independent (right) test case scenarios based on training data as candidates and templates. Note that in the user dependent case, the template count only goes up to nine. This limit is because one sample per gesture is saved as a candidate gesture to be classified in each test, and there are only ten samples collected per gesture.

- A hobbyist developer or student collects training data from his or her family and friends that are then integrated into a prototype game.
- An application does not support data collection or training, and deploys with a user independent gesture recognition interface.

Our baseline tests follow the same procedure as the standard tests where template and candidate gestures are randomly selected from the participant’s training data. Results are shown in Figure 7. Although in game data (as discussed in the next subsection) was collected and evaluated for only two recognizers, we ran this evaluation over all of the unistroke gesture recognizers. In the user dependent scenario, the \$1 and Penny Pincher recognizers perform almost identically and are the best performing recognizers. At one, two, and three templates per gesture, Penny Pincher achieves 8.8%, 4.5%, and 3.1% recognition error rates, whereas \$1 is at 9.1%, 4.6%, and 3.2%; and by ten templates per gestures, they fall to 1.4% and 1.5% respectively. Penny Pincher, therefore, sees only a very slight advantage over \$1. Protractor is also very close, starting out at 10.1%, 5.2%, and 3.7%, and drops to 1.6% for the same template counts, and \$1 is the worst performer overall with this particular dataset.

The relationship between the recognizers in user independent baseline results are similar, although, as expected, all recognition error rates are worse due to differences in style and handwriting between participants. Again, \$1 and Penny Pincher achieve close results, with Penny Pincher being slightly better. At one, two, and three templates per gesture, Penny Pincher achieves a 24.1%, 15.0%, and 11.3% recognition error rate, and by ten templates per gesture, this drops to 5.2%. \$1’s recognition error rate is not as low, but still reaches 25.2%, 15.5%, and 12.1%, and 5.8% for the same template counts. The third best recognizer is Protractor, which falls slightly behind the others

at 28.2%, 18.7%, and 14.6% for one, two, and three templates, and 7.3% by ten templates per gesture.

These initial baseline results suggest that Penny Pincher should do as well or even slightly better than Protractor in the game. Further, although \$1 was not explicitly evaluated in the game, Penny Pincher should perform almost identically.

5.3. In Game Results

The in game recognition error rates for Protractor and Penny Pincher are shown in Table 3. Considering baseline results, we noticed that Protractor and Penny Pincher were further apart in recognition error rates than expected. Upon further inspection, we found that the reference source² scales strokes for Protractor as well as \$1. However, this is not necessary with our dataset, and in fact, performance is much better without scaling. Therefore, we also include results for the in game data using Protractor without scaling, and further discussions refer to this latter result. It can be seen that the Penny Pincher recognition error rates are superior for all levels, where the error rate is decreased by 16.1%, 21.8%, and 10.5% for one, three, and ten templates per gesture respectively.

For the remaining tests in this subsection, we used samples collected during game play to evaluate user dependent and user independent scenarios for Penny Pincher, \$1, Protractor and \$1. We utilize this configuration to ensure that all recognizers are

#	Protractor			Penny Pincher	
	Baseline	Game	Without Scaling	Baseline	Game
1	11.9%	34.4%	27.4%	8.8%	23.0%
3	4.6%	24.4%	22.4%	3.1%	17.5%
10	2.1%	19.0%	13.3%	1.4%	11.9%

Table 3: Summary of baseline and in game recognition error rates for Protractor and Penny Pincher for 1, 3, and 10 templates per gesture. Because the in game protractor implementation scales strokes, we also report the error rates without scaling, which in our tests are much lower.

Figure 8: Recognition error rate of user dependent (left) and user independent (right) test case scenarios using the first in game gesture attempts as the candidate gestures and training data as the template gestures.

evaluated with the same distribution of online samples. The experimental setup is similar to the standard test (Section 4.3) except that the candidate gestures are any of those gestures that were drawn during game play by any participant. Since there are 24 participants and 9 first attempts of each gestures, there are 216 candidates per gesture to choose from in each of the 1000 iterations. Further, recall that the template gestures are chosen at random from the training data in each iteration.

With the in game data, the difference between Penny Pincher and \$1 is more pronounced than in the baseline test, see Figure 8. With one, two, and three templates, Penny Pincher achieves recognition errors rates of 24.1%, 19.2%, and 16.9% respectively, which drops to 12.7% by ten templates. \$1 sees 25.6%, 20.2%, and 18.1%, which then drops to 13.7% for the same template counts respectively. This represents a 5.8%, 4.9%, and 6.6% reduction in error rate for the first three template counts, and a 7.3% reduction for ten templates. Protractor is slightly less accurate than \$1: 27.9%, 22.2%, and 19.7%, which then drops to 14.6%. Compared to the baseline test results, the in game accuracy of Penny Pincher dropped by 16% at one template per gesture and 11.6% at nine templates per gesture in the user dependent test. \$1 accuracy also dropped by 18.2% and 12.6% for the same template counts. So, although in the user dependent baseline tests, Penny Pincher and \$1 were close in their recognition errors rates, \$1 had a larger overall drop with the in game data. Protractor’s drop was even more dramatic, 21.9% and 14.5%.

When looking at the user independent test results, it can be seen that the trends are very similar. Penny Pincher, again, is the best achiever in recognition errors rates: 35.0%, 26.4%, and 22.8% for one, two, and three templates per gesture, which drops to 16.3% by ten templates. This is followed by \$1: 36.8%, 28.4%, and 24.7% for the lower template counts, and 18.0% for ten templates. Protractor is not too far behind at 40.1%, 31.6%, 27.3%, and 20.1% for the same four template counts. Between Penny Pincher and \$1, our recognizer enjoys a 5.1%, 7.5%, and 8.3% reduction in error for up to three templates per gesture,

and by ten, the reduction reaches 10.4%. It is worth noting that the margin between \$1 and Penny Pincher is somewhat consistent in all of the charts (except the baseline user dependent test) as the template counts increase. This implies the percentage reduction in error rate continues to improve as the template count increases, even if the difference in accuracy is somewhat constant.

5.4. Misclassified Gestures

In a game where one has to quickly find a symbol, mechanically arrange components through touch, and then rapidly pen a gesture, mistakes are going to be made. This is supported by the fact that our baseline results are dramatically different from the in-game results, as is often the case [21, 22]. However, it is also important to understand the cause of these errors. In a post analysis of first attempt misclassifications, we visually examined each recorded sample that was classified incorrectly and further divided all errors into four categories: misfire, mistaken, malformed, and false negative. A *misfire* occurs when one accidentally strikes the pen against the interactive display or when one starts, but does not complete a gesture. One cause of this may be that the participant realized that he or she was about to pen an incorrect gesture. Switching between touch and pen may be another cause of misfires, and in a couple of cases, participants tried to rotate the box or a wheel with the stylus. To determine misfires, we assumed that the symbol framed by the selection window was the gesture attempted. It is possible that a participant performed a gesture without first selecting the correct symbol, and though we do not have a method to differentiate this situation, it does not seem apparent upon visual inspection of the collected gestures. A *mistaken* gesture occurs when one gesture is expected but a different gesture is drawn. A common example of this occurred when a participant should have drawn an ‘@’ gesture, but he or she drew a spiral instead. These errors may have been caused by rushed game play, where the participant did not properly observe the

#	Protractor		Penny Pincher	
	Count	Percentage	Count	Percentage
Misfire	118	10.5%	121	15.8%
Mistaken	71	6.3%	56	7.3%
Malformed	517	45.8%	329	43.1%
False Negative	423	37.5%	258	33.8%
Total	1129	—	764	—

Table 4: Distribution of misclassification error types for first attempt gestures of in game Protractor and Penny Pincher results. Note that there were 4320 first attempts per recognizer: 12 participants by 40 gestures by 9 instances.

expected gesture and mistook, by broad shape similarity, a different gesture. *Malformed* gestures occur when the stroke is readable—a human can recognize the symbol—but the form is wrong; one example of this is when a player draws an α symbol backwards, starting at the wrong end of the stroke. The \$N and \$P recognizers can handle this situation, but in our game, we do not allow stroke direction invariance. Finally, a *false negative* is simply a well formed gesture that is confused and misclassified as another.

Note that the distinction between malformed gestures and false negatives can be subjective. For instance, samples that are human readable but excessively sloppy or misshaped are classified as malformed, though there is no formal criteria. It is also important to understand that a malformed gesture can be correctly recognized, especially when the gesture exists in a “sloppiness space” [25] where its form is sufficiently far from neighboring gestures and sloppiness is less problematic, which in part depends on the recognizer’s internal representation of gestures.

The tabulated results are shown Table 4. Misfired and mistaken gestures were similar for both Protractor and Penny Pincher in raw numbers. This is not surprising given that participants were under the same level of stress and their interaction with the game was expected to be similar. On the other hand, we noticed that malformed gestures and false negatives were significantly higher with Protractor (with the in-game Protractor recognizer variant). However, the percentage distribution between malformed and false negative gestures is almost identical for both recognizers. As mentioned before, we expected participants (on average) to utilize both recognizers identically; therefore, this result is not surprising given that sloppiness is likely uniform, and because Protractor appears to be less accurate with this particular dataset, the raw number of misclassifications are accordingly higher without changing the distribution. The false negative and malformed gesture counts would likely have been lower with Protractor’s scaling removed, as previously noted. Though, despite a high number of misclassifications, especially with Protractor, users did not report being frustrated while playing the game, and most enjoyed the challenge.

6. Discussion and Future Work

Penny Pincher was designed to be as fast as possible and we took a number of steps to achieve this goal. First, we decided to base our similarity metric on the dot product of between-point

vectors. This immediately afforded us two benefits, that candidate gestures neither need to be scaled nor do they have to be translated to a common origin for comparison. Second, we worked to eliminate the need for normalization during template matching. This is accomplished by normalizing the between-point vectors of template gestures during training, and by assuming that the distance between points of resampled strokes are equal. With this approach, we reduced the recognition task down to just addition and multiplication. As a result, Penny Pincher is the simplest and easiest to understand of all \$-family recognizers. In terms of speed, only 1 ϵ is faster, but as was demonstrated, it seems that 1 ϵ is not well suited for general purpose gesture recognition. In terms of accuracy, for three datasets we achieved the lowest user independent recognition error with accuracies between 97.5% and 99.9%. Over an additional three datasets, our recognizer still remained competitive, indicating that Penny Pincher is an excellent general purpose recognizer, even without considering speed. In one case, the dataset was a multistroke dataset having varying stroke orders and directions, which is why Penny Pincher did not perform as well as \$N and \$N-Protractor with only a few templates loaded.

Computational performance, however, was initially our primary concern. Given a difficult time budget, we worked to develop a recognizer that could process as many templates as possible to achieve the highest recognition rate possible within the specified constraint. In the budget portion of our evaluation we demonstrated that Penny Pincher succeeded in this objective. With our test apparatus, Penny Pincher is able to process approximately 30.3 templates per microsecond, whereas Protractor (generally the second most accurate recognizer in the budget test) is limited to 5.7. Therefore, our recognizer is able to achieve a percentage error that is less than 1% for all but one of the tested datasets given as little as 60 μ s. When considering reduction in recognition error for the various time budgets, Penny Pincher sees an 83% or higher reduction in most cases, and in several instances, the reduction is 94% or more. The UJI dataset is by far the most difficult to work with because of the similarity in gestures (e.g, upper- vs lower-case ‘O’) and because the number of gesture classes is large (97). However, the reduction in error still ranges between 26% and 31%. This indicates that from all of the \$-family recognizers, ours is best suited for tight time budgets, when a large number of samples are available. Also note that our budgets were selected because of the number of examples available in the datasets and because of our apparatus. In other environments, such as an implementation in an interpreted language running on a mobile device, budgets would likely have to be much higher to attain the same accuracies.

Our derivation of the recognizer assumes that the between-point vectors are of equal length. While this is not strictly true, the empirical probability distribution of relative between-point vector lengths shows that as an approximation the assumption is valid. But because the distribution is left skewed, what does this really mean for shorter vectors with respect to pattern matching? In a resampled stroke, between-point vectors on straight lines will have the longest length. Relative to shorter vectors that fall on cusps, straight lines will have a larger influence

on the final estimate. Therefore, under our assumption, Penny Pincher winds up weighting straight lines with greater importance. Interestingly, in informal ad hoc testing, we saw that this had a positive impact on accuracy and as part of future work, it is worth investigating further to determine how lines, curves, and cusps impact accuracy with respect to our method.

We were surprised to see Penny Pincher perform so well as compared to the other recognizers when testing involved lower template counts. However, the majority of datasets evaluated were collected in a relaxed stress-free lab environment. This made us curious about how well our recognizer could do in a more difficult setting, again using a small number of templates as often occurs in practice, which is why we developed Lemarchand’s Prototype—to evaluate the effectiveness of Penny Pincher in a stressful game setting, one in which users are likely to be less precise in their writing. As it turns out, Penny Pincher still performs remarkably well. Compared to \$1 and Protractor, the average recognition error rates were lower with a 5.8% to 10.4% reduction in error rate. Even though in the user dependent test, Penny Pincher scored just slightly better than its closest competitor, the difference was still more pronounced in the user independent tests. These results in combination with previous tests suggest that Penny Pincher is a good general recognizer for small and large datasets, and that because of its simplicity, our recognizer will likely be preferred by many for its speed, quick implementation, and non-sacrificing accuracy.

In our evaluations we demonstrated the benefits of Penny Pincher, but it is also important to understand its various limitations. Since we compare between-point vectors, Penny Pincher is scale invariant, though unlike other recognizers it is not rotation invariant. As it turns out though, with the datasets we evaluated, this was not an issue and with more templates loaded, variations in angular displacement are well represented. Our recognizer is also not intrinsically a multistroke recognizer. Similar to \$N, we concatenate multiple strokes together to create a single unistroke gesture for template matching, but unlike \$N, we do not generate all of a sample’s various permutations. Instead, training Penny Pincher with additional examples may essentially have the same effect and therefore, it may be unnecessary to derive the numerous permutations (some of which may never occur in practice anyways) to achieve high accuracy. This is supported, in part, by the fact that we achieve over 99% accuracy in the budget test with the MMG dataset, and Penny Pincher also achieves high accuracy (relative to \$N and \$N-Protractor) with UJI.

The idea behind our work is that there are potentially hundreds of templates available per gestures for the recognizer to utilize, but this poses two possible problems. First, a large amount of memory is required to store high counts of template data. Suppose that an implementation is using double-precision floating point numbers that are 8 bytes long. Each two-dimensional point then requires 16 bytes and with a sixteen point resampling count, each template requires 256 bytes of memory (not including any overhead needed for the template structure itself). Given sixteen gestures and two-hundred samples per gesture, approximately 800 KiB of memory are needed to store all of the data. For most systems, 800 KiB is negli-

ble, but in some cases this may be impractical. The second issue is that in certain applications there are simply not that many examples available. This will occur, for instance, if a user is supplying custom gestures to a user interface. As we saw in the evaluation though, Penny Pincher provides high accuracy already with even a small number of templates. Further, over time as the system is used, additional examples can be collected and the recognizer can be continuously retrained with new data.

As part of future work, in the spirit of making things go fast, it would be interesting to look at alternatives to equidistant resampling of candidate gestures. With thousands of templates loaded, the majority of time is spent in matching, but by eliminating the last remaining geometric library calls (namely *sqrt*), there may be a small positive effect. More importantly though, not all templates give relevant additional information about the sample space. For example, if a minimum subset of the available templates are sufficient to define a portion of the sample subspace (so that if any candidate gesture falls within this subspace, it will be classified correctly), then any additional templates in this subspace are superfluous. Therefore it would be interesting to research template selection techniques that are appropriate for Penny Pincher and that are also within the theme of the \$-family. Finally, there are numerous ways in which games utilizing gesture recognition can be imagined. In order to further validate the effectiveness of Penny Pincher and other recognizers in a game environment, additional studies are warranted. One example includes a multi-player tabletop fighting game in which four or more players are interacting and as a result, numerous gestures are being produced at varying angles and orientations, which is a potentially very challenging scenario to handle.

7. Conclusion

We have presented Penny Pincher, a fast and accurate \$-family gesture recognizer that compares between-point vectors to estimate similarity. This recognizer is stripped down to the bare essentials so that after a gesture is resampled, only elementary arithmetic is required to achieve great performance. In a user independent evaluation utilizing six unique datasets of varying complexity, we demonstrated that Penny Pincher outperforms \$1, Protractor, \$N, \$N-Protractor, and 1^c in three cases with just a small number of templates (achieving 97.5%, 99.8%, and 99.9% accuracy), and remains competitive in the other cases. In a budget test where each recognizer is given a limited amount of time to perform its recognition task, Penny Pincher significantly outperforms the other recognizers, achieving a reduction in recognition error of between 83% and 99% with four datasets, and a 31% reduction with the most difficult dataset. Finally, with an online user evaluation of Penny Pincher and Protractor in a video game, we were able to demonstrate that Penny Pincher still yields higher accuracy. Utilizing the in game data we collected, we also evaluated \$1 and 1^c , varying template counts, as well as the user independent and user dependent use case scenarios. In all tests, Penny Pincher achieved the highest accuracy with our dataset.

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Appendix A. Penny Pincher Pseudocode

RESAMPLE-BETWEEN-POINTS (POINTS $points$)

```

1:  $I \leftarrow \text{PATH-LENGTH}(A) / (n - 1)$ 
2:  $D \leftarrow 0, v = \{\}$ 
3:  $prev \leftarrow points_0$ 
4: foreach  $p_i$  in  $points$  such that  $i \geq 1$  do
5:    $d \leftarrow \text{DISTANCE}(p_i, p_{i-1})$ 
6:   if  $D + d \geq I$  then
7:      $q \leftarrow p_{i-1} + (p_i - p_{i-1}) * (I - D) / d$ 
8:      $r \leftarrow q - prev$  ▷ Equation 2
9:      $r \leftarrow r / \text{DISTANCE}((0, 0), r)$  ▷ Only if template
10:     $D \leftarrow 0, prev \leftarrow q$ 
11:     $\text{APPEND}(v, r)$ 
12:     $\text{INSERT}(points, i, q)$ 
13:   else  $D \leftarrow D + d$ 
14: return  $v$ 

```

PATH-LENGTH (POINTS $points$)

```

1:  $d \leftarrow 0$ 
2: for  $i \leftarrow 1$  to  $|points| - 1$  do
3:    $d \leftarrow d + \text{DISTANCE}(points_{i-1}, points_i)$ 
4: return  $d$ 

```

DISTANCE (POINT a , POINT b)

```

1: return  $\sqrt{(a_x - b_x)^2 + (a_y - b_y)^2}$ 

```

RECOGNIZE (POINTS g , TEMPLATES $\mathcal{T}$)

```

1:  $c \leftarrow \text{RESAMPLE-BETWEEN-POINTS}(g)$ 
2:  $similarity \leftarrow -\infty$ 
3: foreach  $t$  in  $\mathcal{T}$  do
4:    $d \leftarrow 0$ 
5:   for  $i \leftarrow 0$  to  $n - 2$  do
6:      $d \leftarrow d + t_{i_x} c_{i_x} + t_{i_y} c_{i_y}$  ▷ Equation 6
7:   if  $d > similarity$  then
8:      $similarity \leftarrow d$ 
9:      $T \leftarrow t$ 
10: return  $\langle T, similarity \rangle$ 

```

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