# A FINE MOTOR SKILL CLASSIFYING FRAMEWORK TO SUPPORT CHILDREN'S SELF-REGULATION SKILLS AND SCHOOL READINESS

A Dissertation

by

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## ABSTRACT

Children's self-regulation skills predict their school-readiness and social behaviors, and assessing these skills enables parents and teachers to target areas for improvement or prepare children to enter school ready to learn and achieve. Assessing these skills enables parents and teachers to target areas for improvement or prepare children to enter school ready to learn and achieve.

To assess children's fine motor skills, current educators are assessing those skills by either determining their shape drawing correctness or measuring their drawing time durations through paper-based assessments. However, the methods involve human experts manually assessing children's fine motor skills, which are time consuming and prone to human error and bias. As there are many children that use sketch-based applications on mobile and tablet devices, computer-based fine motor skill assessment has high potential to solve the limitations of the paper-based assessments. Furthermore, sketch recognition technology is able to offer more detailed, accurate, and immediate drawing skill information than the paper-based assessments such as drawing time or curvature difference. While a number of educational sketch applications exist for teaching children how to sketch, they are lacking the ability to assess children's fine motor skills and have not proved the validity of the traditional methods onto tablet-environments.

We introduce our fine motor skill classifying framework based on children's digital drawings on tablet-computers. The framework contains two fine motor skill classifiers and a sketch-based educational interface (EasySketch). The fine motor skill classifiers contain: (1) KimCHI: the classifier that determines children's fine motor skills

based on their overall drawing skills and (2) KimCHI2: the classifier that determines children's fine motor skills based on their curvature- and corner-drawing skills. Our fine motor skill classifiers determine children's fine motor skills by generating 131 sketch features, which can analyze their drawing ability (e.g. DCR sketch feature can determine their curvature-drawing skills).

We first implemented the KimCHI classifier, which can determine children's fine motor skills based on their overall drawing skills. From our evaluation with 10-fold cross-validation, we found that the classifier can determine children's fine motor skills with an f-measure of 0.904. After that, we implemented the KimCHI2 classifier, which can determine children's fine motor skills based on their curvature- and corner-drawing skills. From our evaluation with 10-fold cross-validation, we found that the classifier can determine children's curvature-drawing skills with an f-measure of 0.82 and corner-drawing skills with an f-measure of 0.78. The KimCHI2 classifier outperformed the KimCHI classifier during the fine motor skill evaluation.

EasySketch is a sketch-based educational interface that (1) determines children's fine motor skills based on their drawing skills and (2) assists children how to draw basic shapes such as alphabet letters or numbers based on their learning progress. When we evaluated our interface with children, our interface determined children's fine motor skills more accurately than the conventional methodology by f-measures of 0.907 and 0.744, accordingly. Furthermore, children improved their drawing skills from our pedagogical feedback.

Finally, we introduce our findings that sketch features (*DCR* and *Polyline Test*) can explain children's fine motor skill developmental stages. From the sketch feature distributions per each age group, we found that from age 5 years, they show notable fine motor skill development.

DEDICATION

I would like to thank for my precious family: my pretty lovely wife Jihee Park, my cute pink princess Isabel Hyunji Kim, and a little tiger Benjamin Sejoon Kim. Thank you Jesus for everything.

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# 1. INTRODUCTION

Children experience a major transition in environments upon entering kindergarten. They will have increased interactions with non-family members through their teachers and classmates. In order to successfully participate in classroom social and play group learning activities, they need school-readiness [151]. School-readiness is obtained through skills that support their sense of mastery and confidence or self-efficacy to engage in classroom activities and school work [153, 154]. Child development research has found that self-regulation skills, which are a set of constructive attention and behavioral skills that affect learning not only determine school readiness [151], but are also needed to complete tasks and goals even in the face of distractions and competing interests [57]. While self-regulation skills notably include abilities such as gross and fine motor control, it is fine motor control that plays a more crucial role for children to master essential basic skills required in the classroom such as writing and drawing [152]. For example, many children draw shapes in their kindergarten classes using writing implements such as crayons or pencils that demand a certain level of proficiency in fine motor skills [153]. Furthermore, children benefit for enhancing their learning and memory abilities from fine motor skills in handwriting through integrated sensory modalities such as vision, motor commands, and kinesthetic feedback [164]. From these advantages, many educational researchers found evidence that fine motor control abilities predict children's social, communication, and studying skills [14, 40, 153]. As a result, children with improved fine motor skills correspond with improved self-regulation skills that are so important to the success of their school readiness and future achievement.

Educational psychologists have thus introduced various approaches to assess chil-

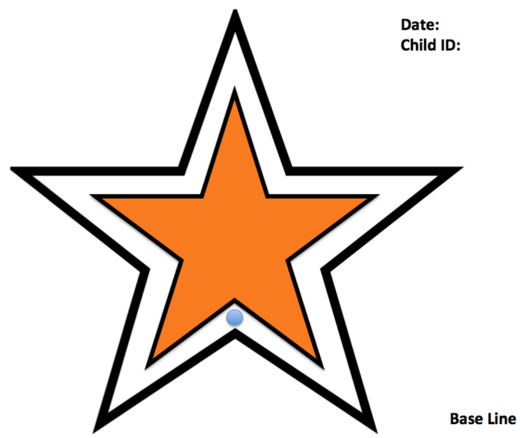



Figure 1.1: Example of a traditional assessment for fine motor skills ("star drawing test"). It asks a child to draw a star in the space between the two dark lines.

dren's fine motor abilities for evaluating their self-regulation skills [145, 167]. One approach developed and validated by Liew et al. involved a battery of assessments for behavioral self-regulation skills including fine motor control [145]. Several of these assessments required children tracing basic geometric figures such as stars or circles with a pencil (e.g. Figure 1.1). One of the assessments has the following steps [153, 167]:

1. Step 1: Trace a simple geometric shape (e.g., star, circle) without being provided additional instruction that may slow or inhibit their sketch.
2. Step 2: Draw that shape as quickly as possible.
3. Step 3: Draw that shape as slowly as possible.

From these steps, educational psychologists assess children's fine motor skills from their sketches through metrics that first calculate the time difference between slow drawing (Step 3) and normal drawing (Step 1). After that, the metrics count the number of times a child's pen crosses outside or inside the tracing lines from fast drawing (Step 2) [153]. From these assessments, Liew et al. later found a positive correlation with self-regulation skills like fine motor control and academic outcomes [152, 153]. However, the limitation of these assessments is that researchers need to manually log children's drawing durations and drawing errors (i.e., the number of times that the user accidentally traced outside the figure outlines) in order to measure children's fine motor skills. This activity is also time-consuming to educational psychologists and prone to error due to their individual bias from their manual measurements [143, 156]. Another major drawback is that the assessment does not analyze children's sketches, but instead only measures their drawing durations. As a result, regardless of their sketching skills, if the child's drawing time difference is higher than a specific threshold, the assessments determine the child's fine motor skill as "mature". Finally, as Dennis [56] discussed, high deviations from the drawing time difference exist even in the same age group. Therefore, it is challenging for setting optimal threshold of the drawing time difference that can reliably determine children's fine motor skills.

In order to overcome the limitations of existing educational psychological research approaches, sketch-recognition technology can be a solution. Furthermore, sketch recognition technology is able to offer more detailed, accurate, and immediate drawing skill information than the paper-based assessments such as drawing time or curvature difference. Because more and more children already exhibit growing familiarity with manipulating tablet computing devices [126], and so applications (e.g., [25, 88, 258]) on these devices that aim to teach children how to sketch through interesting feedback and instructions and accompanying sounds and animations. However, the applications are rarely informed by theories and research in child development and learning, and also include overly simplistic fine motor skill exercises incorporating limited binary feedback (i.e., either correct or incorrect) on children's drawing. As a result, there was no research that validates and facilitates conventional approach to assess children's fine motor skills on tablet computer.

In this research, we introduce our fine motor skill classifying framework that determines children's fine motor skills on their digital drawings. The framework includes two fine motor skill classifiers and a sketch-based educational interface.

## 1.1 KimCHI and KimCHI2: Fine Motor Skill Classifiers

To solve the limitations of the current paper-based fine motor skill assessments, we implemented two fine motor skill classifiers (KimCHI [141, 142, 143, 144] and KimCHI2). The KimCHI (Kim Computer Human Interaction) classifier determines children's fine motor skills based on their overall drawing skills. On the other hand, the KimCHI2 classifier determines children's fine motor skills based on their curvature- and corner-drawing skills. To implement the fine motor skill classifiers, we generated 130 sketch features proposed by Cali [94], Hse [131], Long [155], Paulson [177], and Rubine [215]. From the sketch features, we analyzed how children are drawing. For example, *Direction Change Ratio* (DCR) [143, 177] sketch feature can measure whether they can draw curvatures smoothly.

To implement the KimCHI classifier, we first asked twenty children (i.e. preschoolers ages 3-4 years and grade-schoolers ages 7-8 years) and four adults to draw alphabet A-F and digits 0-9, and collected a total of 725 digital sketches. After generating the 130 sketch features [94, 131, 155, 177, 215], we applied subset selection to find the best features to determine their age and gender information. From the subset selection, we found that (1) curvature-related features (e.g. DCR [143, 177]) were selected for determining their age information and (2) density (e.g. Stroke density [54, 143, 177]) and curvature related features were selected for determining their gender information. In terms of age information, when we evaluated the selected features with Random Forest + Bagging classifier, the KimCHI classifier was able to determine non-mature group (preschoolers) vs. mature group (grade-schoolers + adults) with a precision of 0.909, recall of 0.909, p-value of 0.001, and an f-measure of 0.904 with 10-fold cross-validation. In terms of gender information, when we evaluated the selected features with Bayes Net classifier, the KimCHI classifier was able to determine grade-schooler's gender information with a precision of 0.757, recall of 0.73, p-value of 0.001, and an f-measure of 0.728 with 10-fold cross-validation.

As Crosser [50] explained, older children have better dexterity and fine motor skills. We hypothesized that older children will draw curvatures and corners better than young children, and we would be able to determine their fine motor skills based on their curvature- and corner-drawings. To implement the KimCHI2 classifier that determines children's fine motor skills based on their curvature- and corner-drawings, we collected 852 digital drawings from 75 child participants including 44 preschoolers (aged 3-4 years) and 31 grade-schoolers (aged 5-8 years). For curvature-drawings, we asked the child participants to draw the letter 'C', 'circle', and 'curve'. For corner-drawings, we asked the child participants to draw the letter 'A', 'triangle', 'rectangle', and 'square'. After generating 131 sketch features [94, 131, 155, 177, 215, 271], we found that curvature-related sketch features such as *Direction Change Ratio* (DCR) [143, 177] were selected for determining children's curvature-drawing skills and line drawing-related sketch features such as *Polyline Test* [177] were selected for classifying corner-drawing skills. Using those selected features, we were able to classify children's (1) curvature-drawing skills with a precision of 0.82, recall of 0.82, and an f-measure of 0.82 with 10-fold cross-validation with Random Forest and (2) corner-drawing skills with a precision of 0.78, recall of 0.765, and an f-measure of 0.766 with 10-fold cross-validation with BayesNet.

## 1.2 EasySketch: A Sketch-based Educational Interface

After we implemented the fine motor skill classifiers, we designed and developed a sketch-based educational interface, EasySketch. The interface (1) determines children's fine motor skills based on their drawing skills using the KimCHI classifier [141, 142, 143, 144] and (2) assists children how to draw basic shapes (e.g. digits 1-3 and alphabet letter A-C) based on their learning progress by recognizing their shape drawing correctness from the the Valentine recognizer [86, 250], a modification of Stahovich's Hausdorff recognizer [136] and their sketch-gesture correctness from our sketch-gesture correctness recognizer. We evaluated our interface with 89 children. To evaluate if our interface can determine children's fine motor skills better than conventional approaches, we evaluated both our interface and the conventional approach (i.e. "star drawing test") (Figure 1.1) with 70 child participants. As a result, we found that our interface determined children's fine motor skills more accurately than the conventional methodology by f-measures of 0.907 and 0.744, accordingly. Furthermore, children improved their drawing skills from our pedagogical feedback.

## 1.3 Contributions

The contribution of our work include the following:

### *1.3.1 KimCHI: A Fine Motor Skill Classifier Based on Overall Drawing Skills*

1. We implemented the fine motor skill classifier that determines children's overall drawing skills.

2. We found that curvature-related sketch features such as *Direction Change Ratio* can determine children's age (fine motor skill) information.

3. We found that density- and curvature-related sketch features can determine

children's gender (fine motor skill) information.

4. We found that older children are able to draw curvatures better than younger children, and girls' curvature-drawing skills are better than boys. We also observed that girls are drawing more considerably than boys.

### *1.3.2 KimCHI2: A Fine Motor Skill Classifier Based on Curvature- and Corner-Drawing Skills*

1. We implemented fine motor skill classifiers that determine children's curvature- and corner-drawing skills.

2. We found that curvature-related sketch features such as *Direction Change Ratio* can determine children's curvature-drawing skills.

3. We found that line drawing-related sketch features such as *Polyline Test* can determine children's corner-drawing skills.

4. We evaluated the both KimCHI2 and KimCHI [143] classifiers, and found that the KimCHI2 classifier can determine children's curvature- and corner-drawing skills more accurately than the KimCHI classifier.

5. We validated that sketch features (*Direction Change Ratio* [143, 177] and *Polyline Test* [177]) can explain children's fine motor skill development stages. From the feature value distributions, we found that from age 5 years, they show notable fine motor skill development than younger children (i.e. 3-4 years).

### *1.3.3 EasySketch: A Sketch-based Educational Interface*

1. We employed the fine motor skill classifier (i.e., the KimCHI classifier [143]), which not only automatically determines children's fine motor skills for analyz-

ing “how they drew,” but also does not require researchers’ manual measurements. The interface also benefits parents and teachers for becoming better informed of their children’s fine motor skill levels. We implemented our fine motor skill feedback system to provide richer information of fine motor skills in three different areas (i.e., overall drawing, curved shapes, linear shapes), and adults can use this information to assist children in determining areas that they perform well and that require improvement.

2. We implemented a developmentally-appropriate interface that is capable of individualized instructions and feedback, based on children’s performance and progress while they learn to draw basic shapes such as alphabet letters and numbers. From our evaluation, we discovered that children improved their drawing skills through our interface’s pedagogical feedback.

3. We evaluated both our interface and conventional methodology (i.e., “star drawing test”) (Figure 1.1) with children between the ages of 3 and 8 years. We found that our interface can determine children’s fine motor skills more accurately than the conventional methodology by f-measures of 0.95 and 0.75, accordingly.

4. During our user study, we noticed that children ages from 5 years show notable fine motor skill development than younger children (i.e. 3 and 4 years) both on fine motor skill results from our interface and “star drawing test”. We also found that “hook” feature in drawings can explain their decision-making process.

## 1.4 Contribution Summary

To make our contributions more clear, we summarized the contributions as follows:

1. We have the world largest young children's pen-based digital drawing set (109 children with 2,258 digital sketch), and the first dataset containing pen data for children 3-8. There exist pen-based datasets [138, 178], but none with small children. Likewise, there exist published research works that include young children's drawings [7, 256], however, their study sets include only touch-based finger drawings.

2. We implemented a method to automatically classify children's fine motor skills (age and gender) information with sketch features.

3. We evaluated our computer-based fine motor skill assessment (i.e. EasySketch) with the paper-based assessment (i.e. "star drawing test" [153, 167]), and we validated that the computer-based assessment can classify children's fine motor skills more accurately than the paper-based assessment.

4. During the user study, we showed that how interface affects children's drawing learning. After following the pedagogical system in EasySketch, the child participants improved their drawing skills.

# 2. RELATED WORK

There are many child-computer interaction (CCI) researchers [1, 2, 3, 19, 20, 23, 34, 35, 41, 45, 49, 55, 77, 87, 99, 101, 124, 130, 132, 133, 135, 158, 159, 160, 163, 185, 214, 216, 217, 222, 226, 246, 247, 249, 267, 276]. Anthony [4, 5, 8, 9, 12, 13] and Brown [37, 38, 39] examined children's sketches on touch-screen. Bonsignore [27, 28, 29, 30, 31, 32, 33] and Druin [61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76], Fails [79, 80, 81, 82, 83, 84, 85], Guha [103, 104, 105, 106, 107], Subramaniam [230, 231, 232, 233], Walsh [260, 261, 262, 263, 264, 265], and Yip [279, 280]'s studies described children's role in participatory design and systems using storytelling. Dray [59, 60] described design for women. Read [190, 191, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213], Fitton [89, 90, 91, 92, 93], Horton [127, 128, 129], Mcknight [161, 162], Sim [223, 224, 225, 227, 228], and Xu [277, 278]'s works include many studies about UX for children. Foss examined children's search behaviors [95, 96, 97, 98]. Vatavu explained children's fine motor skill on touch-screen [254, 256]. The CCI researchers' common opinion is that children are not "just short adults" but entirely different user populations with their own culture [22]. To know the difference between children and adults, we will review the research from educational psychologists that describes the cognitive and physical factor differences between children and adults. After that, we will discuss the related work of children's touch and sketch gesture interaction and relevant children's sketch applications. Finally, we will review the sketch recognition algorithms.

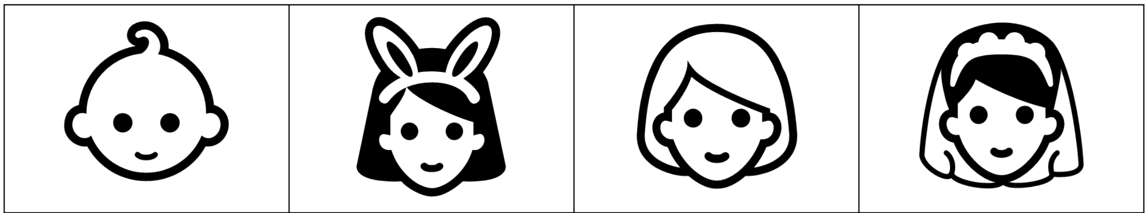
## 2.1 Children's Cognitive and Physical Factors

Children's cognitive and physical factors are widely studied in the fields of developmental and educational psychology, since these two factors contribute significantly to children's school readiness [57, 145, 153]. Piaget's Stages of Cognitive Development explain how children's understanding progresses from infancy to adolescence (Figure 2.1). According to Piaget, there are four stages of cognitive development in children: the sensory motor (from birth to 2 years), preoperational (2-7 years), concrete operational (7-11 years), and formal operational (adolescence through adulthood). From their cognitive development, children's own sensory and motor experiences contribute to their intellectual functioning[1]. The acts of sketching, drawing, and writing provide concrete experiences and engagements to construct and represent children's knowledge and mental states [164]. As Crosser[2] explained, children are developing their sketching (fine motor) skills and knowledge while they are growing. Children around 18 months first draw by scribbling as they have small muscle coordination and control. Around age 2-3 years, the scribble forms enclosures resembling primitive shapes such as circles or squares [140]. Around age 3-4 years, children attempt to make realistic drawing (e.g. draw a person).

To explore cognitive and physical factors, educational psychologists assess gross and fine motor skills. Dennis [56] introduced a gross motor skill test ("Walk-a-Line Slowly" test) that asks a child to walk along a line taped on the floor at regular speed and twice slowly. From the score of the average of the two slow trials, the test can assess the child's gross motor and self-regulation skills. The NEPSY test [146, 268] includes another fine motor skill test that asks a child to tap the thumb with the index finger 32 times in a row, as quickly as possible. Low values indicate better

[1]http://www.education.com/reference/article/importance-motor-skills

[2]http://www. earlychildhoodnews.com/earlychildhood/article_view. aspx



| 0 - 2 years | 2 - 7 years | 7 - 11 years | 11+ years |
|---|---|---|---|
| Sensorimotor | Preoperational | Concrete operational | Formal operational |
| Memory gradually increases | Gradually develop language ability to think symbolically | Able to solve concrete problem in logical fashion | Able to solve abstract problem on logical fashion |

Figure 2.1: Piaget's Stage of Cognitive Development [180, 182, 266]

dexterity. Virginia school health guideline[3] is assessing preschoolers' fine motor skills by sketch-correctness. The assessment requires children to copy a circle and make predominantly circular lines. However, the problems of these assessments are that: (1) they require researchers' manual efforts for assessments and (2) they prone to error due to their individual bias from their own manual measurements (e.g. each researcher could have different opinion that decides whether child's circle draw is predominantly circular lines).

## 2.2 Children's Touch and Sketch Gesture Interactions

To analyze touch and sketch gesture interactions, previous works have examined the usability of interactions on touch- and sketch-enabled devices [21, 257, 259]. However, most of the researchers discussed adults' interaction results without considering children's interactions. Read [192] and Ryall [218] discussed children's touch gesture interactions on tablets. However, the findings have been general conclusion rather than comparison between adults and children. There are a few researchers [7, 255] that examined touch- and sketch-gesture interactions of children and adults together,

[3] http://www.doe.virginia.gov/support/health_medical/virginia_school_health_guidelines/early_periodic_screening.pdf

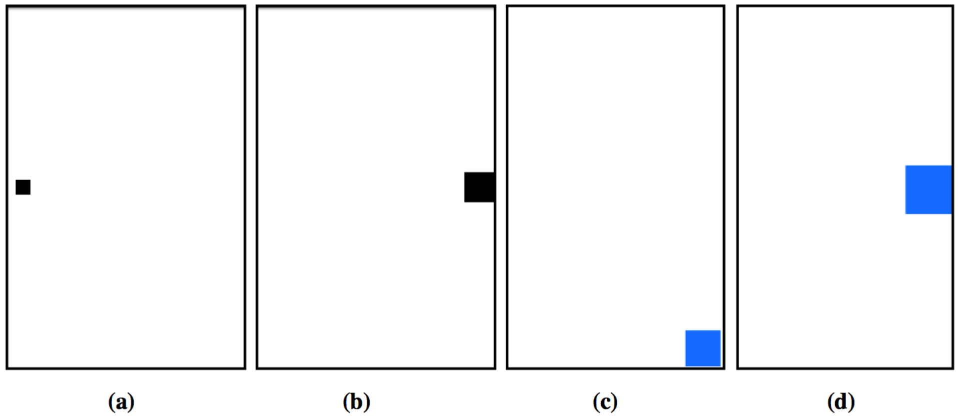



Figure 2.2: Anthony et al. had a user study that asks each participant to touch four different sized targets: (a) very small, (b) small, (c) medium, and (d) large. During the studies, all four target sizes were represented equally [7].

but it still needs more research in this area.

Anthony et al. conducted touch- and surface-gesture interaction studies with a total of 74 participants: 44 children (age 6-17) and 30 adults (age 18-30) [7]. To find the touch skills of participants, they implemented an Android app that shows four different sized targets: very small (0.125”), small (0.25”), medium (0.375”), and large (0.5”). Each participant was asked to touch the targets on screen by fingers. They found that most of the participants missed targets that are small, and young children (age 7-10) missed more targets than older children and adults (Figure 2.2). This result shows that young children have less touch skills (fine motor skill) than older people.

To find the sketching skill (fine motor skill) of participants and to know which sketch recognizer performs better, they conducted a user study that analyzes sketch recognition accuracy on touch-enabled devices. They asked the participants to draw a set of 20 gestures such as alphabets or digits by fingers on touch-enabled devices (Figure 2.3). To analyze which sketch recognizer performs better, they tested three

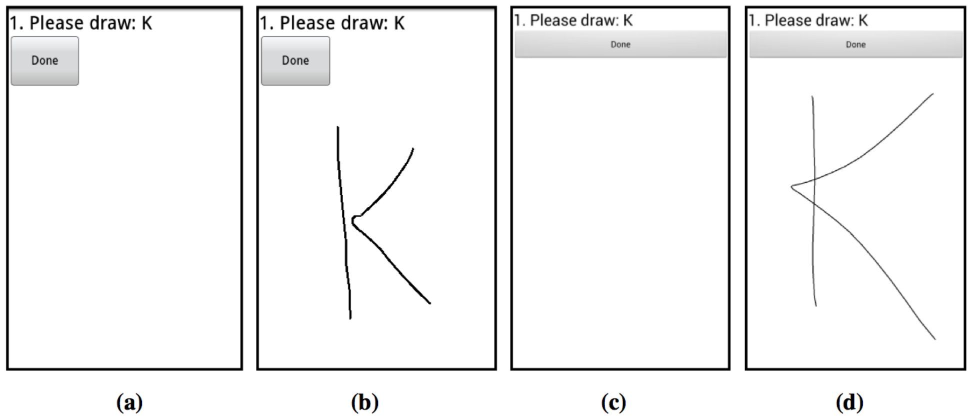



Figure 2.3: Anthony et al. conducted two studies to analyze sketch recognition accuracy on touch-enabled devices. From study 1, the interface has a small "done" button: (a) before drawing the gesture and (b) after drawing the gesture. From study 2, the interface has a larger "done" button: (a) before drawing the gesture and (b) after drawing the gesture [7].

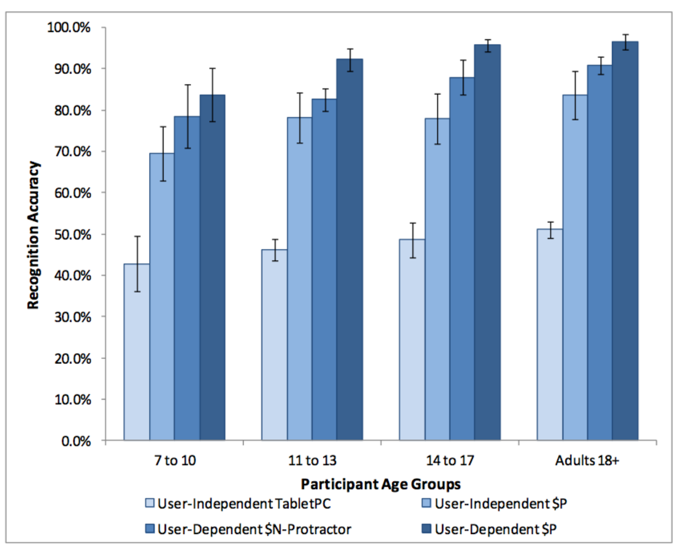



Figure 2.4: Anthony et al. compared the sketch recognition performance of three different sketch-recognizers($N-Protractor [11], $P [255], and Microsoft Tablet PC recognizer) with user-dependent and user-independent mode. They found that user-dependent $P is the best performer but still performs low (84% for young children) [7].

different recognizers ($N-Protractor [11], $P [255], and Microsoft Tablet PC recognizer). From the user study, they found that $P recognizer performs better than other recognizers, but the recognizer still performs low (84%) accuracy for young children (Figure 2.4). As a result, Anthony et al. concluded that young children (age 6-10 years) have less sketching skills (fine motor skills) than older children and adults. Furthermore, they insisted that we need to develop sketch recognizers for young children to allow them to manipulate touch-devices easily. However, the limitation of this research is that: (1) they are missing younger children (less than age 6 years), who are diligent IT consumers and need to improve their fine motor skills to prepare for kindergarten and (2) the research analyzed touch-interaction using fingers not sketch-interaction using pens. Because there are many study materials that use pens in kindergarten and we already have many sketch-enabled devices, there is a need to analyze children's sketch-interactions on sketch-enabled devices. To acknowledge children's (including younger children whose ages are under than 6) sketching skills, our research investigated the pen-based interactions on sketch-enabled device [141, 142, 143, 144].

## 2.3 Children's Sketch-based Educational Applications

As touch- and sketch-based interactions become more commonplace, interactive technologies such as surface computing or natural gesture interfaces will enable new means of motivating and engaging students in active learning in next-generation classroom and educational environments [7]. Major challenges in developing applications for children include appealing to children's interests because children tend to lose focus more easily than adults, and making the application more age-appropriate so that children do not frustrate by the difficulty of the application or by its simplicity [143]. To meet these requirements, designs need to have strong consideration in


Figure 2.5: The application includes a sketch-recognizer that can determine children's drawing correctness: (top) the application asks children to draw simple shapes with text, and children can draw the shapes on the sketch-panel and (bottom) after children draw the shape, the application determines the correctness of the shapes [173].

developing both engaging features and compelling contents.

One of the example works is *Learn Your Shape Game* [173]. The application includes study materials that ask children to draw simple shapes such as circle or line on sketch-enabled devices, and the application determines if the drawing is correct or incorrect (Figure 2.5). However, the limitation of this work is that it provides simplistic static binary feedback (correct or incorrect). If the children already know how to draw the shapes, the study material would be too simple for the children. As a result, the children may lose interest. On the other hand, if the children do not know how to draw the shapes, the application could be too complex for the children. As the application does not guide how to draw the shapes, but only returns correctness of their drawings, they could feel frustrate. To address the limitation of the previous application and encourage children to draw the shapes, *TAYouKi* [258] includes an

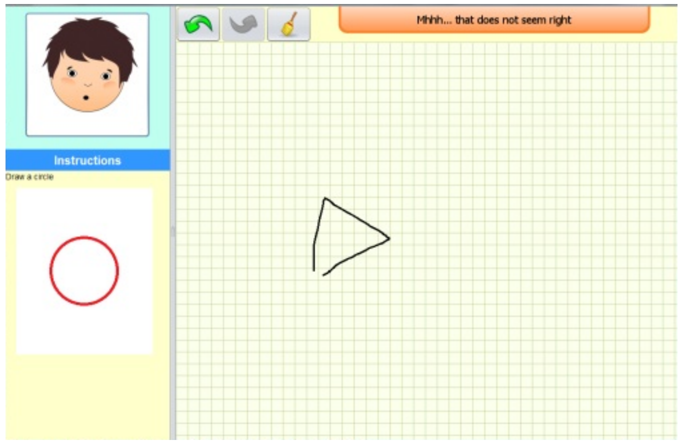



Figure 2.6: This application includes an agent system that changes emotion according to the history of children's drawing correctness. The left panel has a question and a sample shapes. When children finish their drawings, the agent system runs a sketch-recognizer and returns feedback [258]

agent system that emulates emotions based on the correctness of their drawings (Figure 2.6). The cartoon-style face changes the emotion by the user's sketch correctness history with supplementary text and sound feedback. However, the limitations of these two applications are that they are using adult-trained sketch recognizers, and they perform worse for children. Furthermore, the applications do not guide children to make correct shape drawings, but only determine the correctness of their drawings.

There are many sketch-apps on touch-based devices run on iOS or Android. The apps provide learning materials to help preschoolers to develop their fine motor skills through drawing. These applications can help the preschoolers' readiness for kindergarten. One of the examples is "Create & Learn" by Fisher-Price, which runs on iOS. The application provides a sketchpad, which looks like a sketch board, and children can follow the instructions to draw alphabets.

Another example is "Dexteria Jr. and Dexteria" by BinaryLabs [24, 25]. From

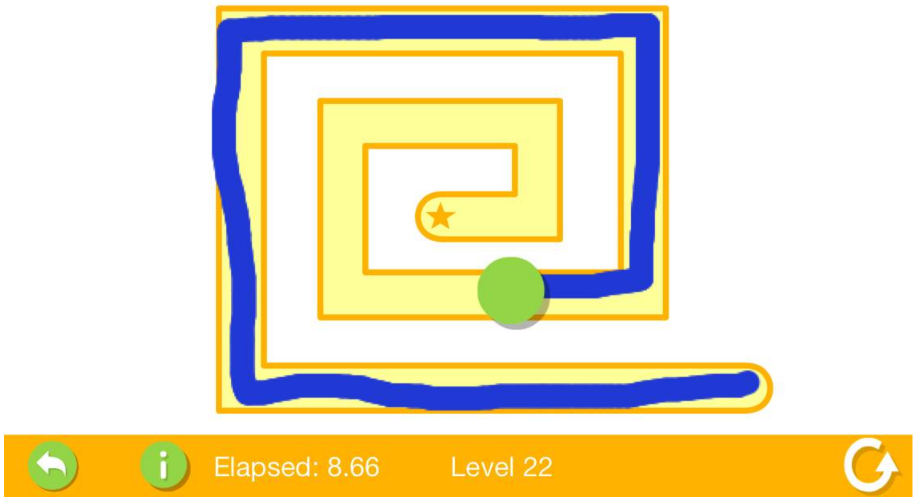



Figure 2.7: An example of "Dexteria Jr.". The app shows a mirror and children can follow the mirror to find a "star" reprinted with permission from[25].

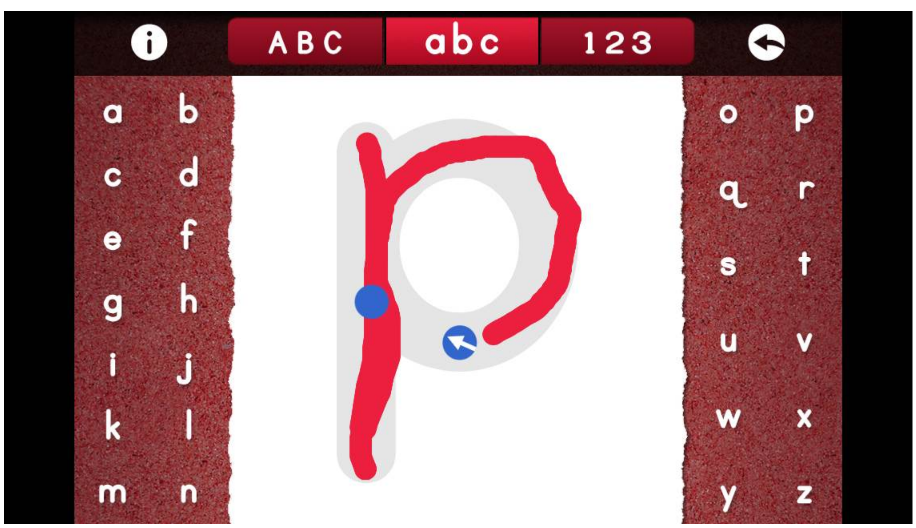



Figure 2.8: An example of "Dexteria". The app shows instructions on how to draw the letter "P", and children can follow the instructions to draw the shape reprinted with permission from[24].

the application, children can practice fine motor skills by drawing.

Finally, "PBS Parents Play & Learn" [179] provides many useful learning materials that includes simple mathematical examples and drawing examples. Children can follow instructions to draw alphabets. The application also supports drawing directions to teach children draw shapes with correct orders.

As a result, these applications provide activities that encourage children to enhance their fine motor skills by drawing. The applications also include many interesting animations to encourage children to enjoy drawing. We can hope that these practices actually enhance children's fine motor skills. Unfortunately, these applications do not recognize children's fine motor skill levels automatically, but only have simple fine motor skill activities, which cannot describe whether preschoolers' fine motor skills reached more matured level like those of grade-schoolers. To recognize children's fine motor skills, our sketch-based educational interface (EasySketch) includes the fine motor skill classifier [143] that determines sketchers' fine motor skills as *"mature"* or *"in training"* from shape drawings by digital pen.

Another deficiency of these related applications is that they have limited binary feedback that only checks whether their traces are correct or incorrect. As a result, the applications cannot tell what "shape" the children drew. To teach children how to draw digits/letters better, our interface (EasySketch) has a shape recognizer [250] that can recognize the children's shape drawings. Furthermore, the interface has a sketch-gesture recognizer to acknowledge the children's shape drawing gesture correctness and give feedback that can lead children to draw shapes correctly.

## 2.4 Sketch Recognition

Sketch recognition is the development and application of machine learning and artificial intelligence techniques to recognize hand drawn strokes [120, 183, 184].

Methods tend to be grouped either by the type of features examined or the type of algorithm used process those features [111]. The types of features include (a) vision based, focusing on the ink on the page [186, 187], (b) geometric features, which focus on the shapes created and the constraints between them [119], or (c) gesture based features, looking the path of the stroke that the hand makes while laying down the ink [46, 47, 78, 157, 221]. Algorithmic approaches include: (1) the geometric-based approaches, creating a graphical model to represent higher level shapes [238], (2) the template-matching approaches, which match one shape to another [123], and (3) the statistical feature-based approaches that send the bin of features to a SVN, linear, quadratic, decision-tree, or other classifier. Several researchers have also chosen to combine approaches to improve recognition accuracy or include the ability recognize more shapes [48, 121].

The geometric-based approach first segments the strokes and attempts to recognize primitives, such as circles and lines among the sketch. It then examines how the shapes combine together looking for certain constraints to be fulfilled in order for higher level shapes to be recognized. An early approach is the LADDER system by Hammond et al. [110, 117]. The strength of the geometric approach is that it can enlarge recognizable shapes by representing more rules of primitives in each shape, and can differentiate hundreds of shapes without needing more than a single training example for each shape. However, the approaches need to have accurate rules for representing primitives in shapes, which can be difficult for non-mathematical minds.

The template-matching approach compares the input data with data sets, which we already have, picking the closest match. The approach recognizes the best matched shapes for the input data. To compare each shape, the approach calculates the distances between input shape and the shapes in the data sets. There are many researchers who developed their algorithms with this approach. The examples are: (1) the elastic structure matching, which uses dynamic programming [42], (2) $1 and $N recognizer by Wobbrock et al. [10, 269], and (3) the vision-based recognizer by Kara et al. [136].

Our EasySketch uses a shape recognizer (the Valentine recognizer [250]) that is based on a template matching algorithm that uses vision-based features. The benefit of the template approach is that the approach does not need to represent rules of primitives in shapes. However, the template-matching approach needs many examples of each shape for comparison, which can be quite slow when there are many shapes and variations.

The statistical feature-based approach which simply applies any computed values into a numerical classifier and uses the mean and standard deviation of each class, or another statistical measure to classify each shape. Gesture based feature recognizers include Long [155], Paulson [176, 177], and Rubine [215]. Usually, the sketch features are used for determining user's drawn shape. However, we used the sketch features to decide children's fine motor skills by analyzing "how they drew".

The following sections describe in more details about these three feature types and three algorithm approaches.

### *2.4.1 Review of Gesture-based Recognition*

Gesture based features rely on the path of the stroke, rather than the ink on the page.

#### *2.4.1.1 Freeman's chain code*

Freeman's chain code uses direction of each line as a feature. Freeman's chain code is a widely used algorithm for representing shapes [100]. For example, Chan et al. used the chain code for their elastic structural matching algorithm [42, 43]. The chain code has eight values from 0 to 7, which indicates the direction from the

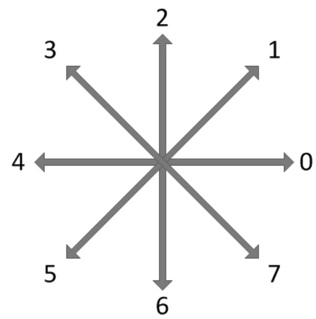



Figure 2.9: Directions in Freeman's chain code [100].

current point to the next point.

Figure 2.9 shows how the direction values are expressed in Freeman's chain code. The following formula describes the calculation of direction.

Using the directions, Chan et al. [42] described five types of primitives:

- line
- up (curve going counter clockwise)
- down (curve going clockwise)
- loop (curve joining itself at some point)
- dot ( a very short segment)

Figure 2.10 represents the example of the digit "3", and the letter has two down primitives.

However, the limitation of this approach is that it is not free from the variances of each shape.

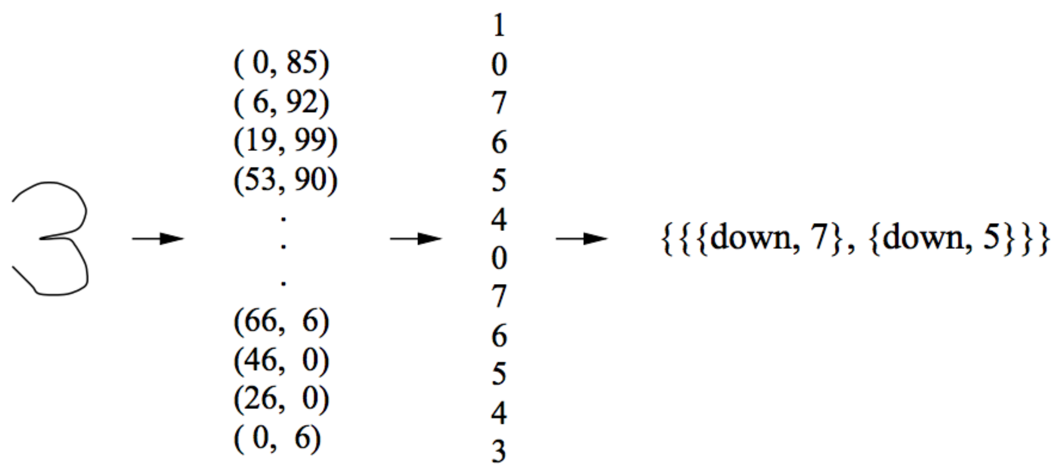



Figure 2.10: An example of directions in Freeman's chain code [42].

#### *2.4.1.2 Rubine and Long*

Statistical feature-based approach retrieves sketch features from strokes and recognizes users' drawn shapes by running classifiers such as Bayes Net. In this approach, feature sets play an important role for classifying sketches. As a result, this approach recognizes shapes by analyzing "how they were drawn".

Rubine [215] introduced one of the first gesture recognition system, GRANDMA (Gesture Recognizers Automated in a Novel Direct Manipulation Architecture). Rubine proposed thirteen features such as cosine or sine values between two points for accurately classifying simple gestures such as ellipse or dot. Long et al. [155] extended Rubine's work by introducing nine new features and proposed a more optimized feature set consisting of seventeen features (i.e., eleven and six from Rubine and Long, respectively) (Table 2.1).

| | |
|---|---|
| 1.$\star$ Cosine of initial angle | 2.$\star$ Sine of initial angle |
| 3. Size of bounding box | 4.$\star$ Angle of bounding box |
| 5.$\star$ Distance between first and last points | 6.$\star$ Cosine of angle between first and last points |
| 7.$\star$ Sine of angle between first and last points | 8. Total length |
| 9.$\star$ Total angle | 10.$\star$ Total absolute angle |
| 11.$\star$ Sharpness | 12.$\star$ Aspect [abs(45° - #4)] |
| 13.$\star$ Curviness | 14. Total angle traversed / total length |
| 15.$\star$ Density metric 1 [#8 / #5] | 16.$\star$ Density metric 2 [#8 / #3] |
| 17.$\star$ Non-subjective "openness" [#5 / #3] | 18. Area of bounding box |
| 19. Log(area) | 20. Total angle / total absolute angle |
| 21.$\star$ Log(total length) | 22.$\star$ Log(aspect) |

Table 2.1: Features examined by Long et al. [155]. The features with $\star$ are those chosen as the optimal subset through feature subset selection for their model, and features 1-11 are taken from Rubine's work [215]

### *2.4.2 Review of Geometric-based Recognition*

Geometric based recognition algorithms use the mathematical principle of the shapes to recognize the primitives drawn on the page. To help with this, strokes are segmented using corner-finding algorithms [273]. The shapes are then combined together to find higher level shapes.

#### *2.4.2.1 LADDER Sketching Language*

Hammond et al. implemented LADDER sketching language, which describes "A Language to Describe, Display, and Editing in Sketch Recognition (LADDER) [109, 112, 113, 114, 115, 116, 117, 118, 122]. LADDER describes how sketch diagrams for various domains are drawn, displayed, and edited.

To recognize user's input data, geometric methods such as LADDER, first break strokes at the corners using various segmenting approaches. Then the geometric algorithms, such as LADDER, recognize the substrokes or combinations therein as geometric primitives using the geometric mathematical definitions for each of the

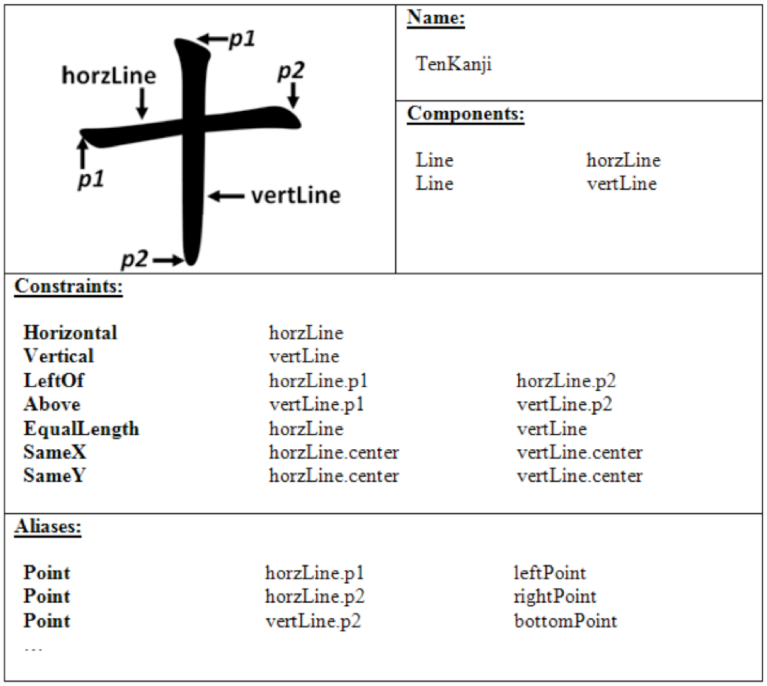



Figure 2.11: A shape description for the Chinese character ten [234].

shapes [171, 174, 176, 177]. The primitives are often used on their own in simple sketch-based applications applications [51, 52].

After recognizing the primitives, the geometric algorithm will recognize higher level shapes together by examining the constraints between the shapes and comparing them to geometric and perceptual rules [53, 58].

There are many applications that use LADDER for their recognition system. For example, the Mechanix system [15, 16, 86, 102, 139, 150, 170, 250, 251, 253] recognizes geometric shapes by LADDER system. Taele et al. [234, 235, 236, 237, 239, 240, 241, 242, 243, 244, 245] also introduced many educational systems built in LADDER for their recognition algorithms. For example, Taele [234] introduced an educational system for teaching how to draw East Asian character sets. The system teaches how to draw the characters by representing geometrical constrains per each character.

Figure 2.11 explains the Chinese character "ten". The components field explains that the character ten should have two lines: a horizontal line and a vertical line. The constraints and aliases fields explain the geometric rules for the two lines.

### *2.4.3 Review of Template-Matching Recognition*

This section explains various gesture-based template-matching recognition approaches.

#### *2.4.3.1 $1 and $N recognizer*

Wobbrock developed many gesture-based template-matching algorithms [11, 166, 255, 269] to recognize shapes. The examples are the $1 recognizer (for one-stroke shapes) [269] and the $N recognizer (for multi-strokes shapes) [10]. The $1 recognizer has preprocessing steps for the raw data. The raw data has several issues as follows:

- The number of points can be different by writing speed ratio and devices used.
- The users can have different experiences with the devices.

To alleviate the problems, the preprocessing steps in $1 and $N recognizer have the following four steps: (1) resampling points, (2) rotating once based on the "indicative angle", (3) scaling and translate, and (4) finding optimal angle for the best score [269].

The problem of the multi-strokes is that it can have various kinds of stroke orders by people. Figure 2.12 is one of the examples of multi-strokes. The "X" has two strokes and each stroke has two end points. To compare the shapes, the $N recognizer translates the multi-stroke shape into the one-stroke shape (Figure 2.13).

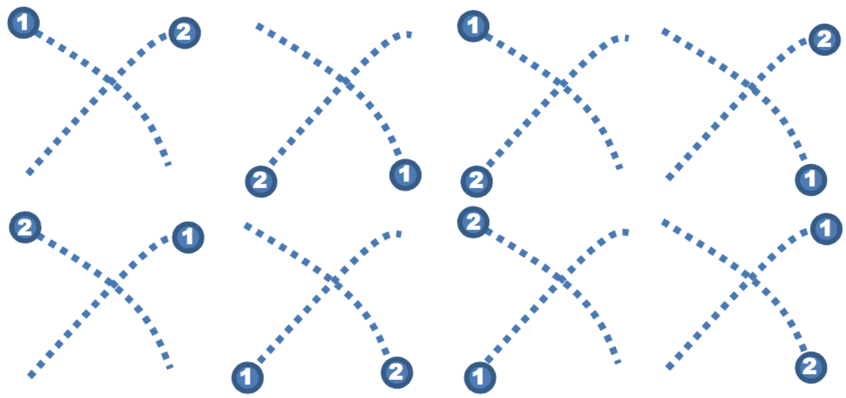



Figure 2.12: There are 8 possibilities for a two-stroke "x". The numbered dots mean the stroke order [10].

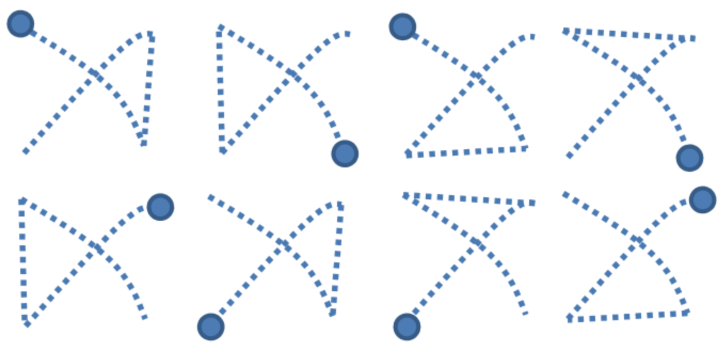


Figure 2.13: Based on the two-stroke gestures in Figure 2.12, it makes 8 uni-stroke permutations for a two-stroke "x" [10].

#### *2.4.3.2 Review of Vision-based Features*

Kara [136], Ray [189], and Valentine [86, 250] introduced algorithms that use the vision (image)-based recognition. The main idea of the features only use the ink on the page, and not any timing data. When working with stroke data, an algorithm using the vision-based features first converts the shapes into fixed pixel (Figure 2.14).

The Kara and Valentine recognizers are both template-based algorithms, which

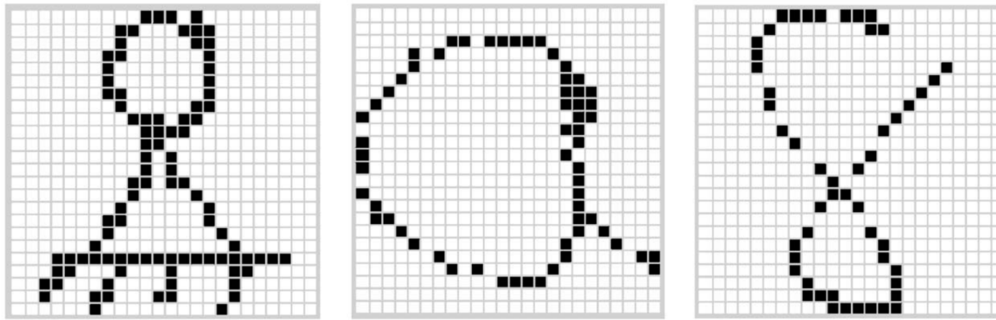


Figure 2.14: The Kara algorithm converts the shapes into fixed pixel. Left: a mechanical pivot: middle: “a”, right: “8” [136].

compare the new shape to previously classified shapes. The algorithms translate both the new and template shapes into a $40 \times 40$ ($48 \times 48$ for Kara’s recognizer [136]) bounding window to ensure both shapes are approximately the same size. Subsequently, the Valentine algorithm, used in this work, resamples the points in both shapes so each is made up of 40 equidistant points [252]. After preprocessing, the recognizer considers each point in each shape – 40 equidistant points from both shapes for a total of 80 points – and then records the distance from that point to the closest point in the other shape. From these shortest distances, it calculates three similarity metrics: the maximum of the distances (i.e., the Hausdorff distance), the average of the distances (i.e., a modified Hausdorff distance), and the ratio of points with shortest distances less than 4 pixels over the total number of points (i.e., the Tanimoto coefficient) [86, 136, 137, 252, 272]. The recognizer normalizes the distances to a value between 0 and 1, and then the three measures are averaged to form the final similarity confidence value. If that confidence value is above its empirically defined threshold of 0.65, the two shapes are deemed similar [86, 136, 252]. This error value for template matching can then be used also as an input feature for a statistical classifier in combination with other features.

Our EasySketch system employs the modified Valentine recognizer [250] for our shape recognizer. As we found that Tanimoto coefficient itself gave the best accuracy [141], we only employed Tanimoto coefficient for our measurement. The Tanimoto coefficient calculates similarity between two images. The equation is:

$$T(A,B) = \frac{n_{ab}}{n_a + n_b \text{-} n_{ab}} \tag{2.1}$$

where $n_a$ is the total number of black pixels in A, $n_b$ is the total number of black pixel in B, and $n_{ab}$ is the number of overlapping black pixels in A and B. T(A,B) describes the number of matching points in A and B, and the result is between 0.0 (minimum similarity) to 1.0 (highest similarity). The problem of this equation is that if images contain mostly black pixels, the T(A,B) value can be vanished.

To solve the problem, the following equation is used:

$$T^c(A,B) = \frac{n_{oo}}{n_a + n_b \text{-} 2\ n_{ab} + n_{oo}} \tag{2.2}$$

where $n_{oo}$ is the number of matching white pixels.

The two equations can be combined to form the Tanimoto similarity coefficient.

$$T_{sr}(A,B) = \alpha T(A,B) + (1-\alpha)T^c(A,B) \tag{2.3}$$

$\alpha$ is a weighting factor between 0.0 and 1.0.

### *2.4.4 Review of Statistical Feature-based Recognition*

Any of the methods can produce features that can then be placed in a numerical classifier.

This section explains various statistical feature-based recognition approaches.

#### 2.4.4.1 Paulson

Paulson et al. [177] introduced a hybrid approach that first proposes a larger set of forty-four features: thirteen gesture-based features from Rubine [215] and thirty-three new geometric-based features. Paulson et al. proceeded a user study with 1,800 examples to determine the optimal features from the proposed set to classify basic geometric shapes (e.g., lines, helixes), and subsequently discovered an optimal set consisting of fifteen features (i.e., fourteen geometric- and one gesture-based).

Table 2.2 explains the feature sets used, where the features with $\star$ indicate the optimal feature set through feature subset selection for primitive shape recognition. 2

As a result, the previous studies [155, 176, 177, 215] focused on generating optimized feature sets for recognizing user's drawn shape by analyzing "how the strokes were drawn" from calculated sketch features. Our research differs from Paulson in that we suggest a larger set of 130 features [94, 131, 155, 177] for analyzing sketches that help determine the sketcher's developmental stage, with the intent of eventually providing educators with a tool for gauging children's developmental progress. The following section will explain our fine motor skill classifier implementation procedures.

### 2.4.5 Extended Uses of Sketch Recognition Methods

This work shows how pen sketch data can give insight into the level of development of fine motor skills of young children. Others have used sketch data to find out the unexpected with the sketch data or sketch recognition algorithms.

Paulson et al. showed that using sketch recognition methods, he was able to recognize what objects people in an office were interacting with by the shape of their hands [172, 175]. Other work used sketch recognition features and techniques

| | |
|---|---|
| 1.⋆ Endpoint to stroke length ratio (100%) | 2.⋆ NDDE (90%) |
| 3.⋆ DCR (90%) | 4. Slope of the direction graph (20%) |
| 5. Maximum curvature (40%) | 6. Average curvature (30%) |
| 7. # of corners (30%) | 8. Line least squares error (0%) |
| 9. Line feature area error (40%) | 10. Arc fit: radius estimate (0%) |
| 11. Arc feature area error (20%) | 12.⋆ Curve least squares error (90%) |
| 13.⋆ Polyline fit: # of sub-strokes (70%) | 14.⋆ Polyline fit: percent of sub-strokes pass line test (50%) |
| 15.⋆ Polyline feature area error (80%) | 16. Polyline least squares error (30%) |
| 17. Ellipse fit: major axis length estimate (20%) | 18. Ellipse fit: minor axis length estimate (30%) |
| 19. Ellipse feature area error (10%) | 20. Circle fit: radius estimate (30%) |
| 21.⋆ Circle fit: major axis to minor axis ratio (80%) | 22. Circle feature area error (0%) |
| 23.⋆ Spiral fit: avg. radius/bounding box radius ratio (60%) | 24.⋆ Spiral fit: center closeness error (70%) |
| 25. Spiral fit: max distance between consecutive centers (20%) | 26. Spiral fit: average radius estimate (10%) |
| 27. Spiral fit: radius test passed (1.0 or 0.0) (40%) | 28.⋆ Complex fit: # of sub-fits (60%) |
| 29.⋆ Complex fit: # of non-polyline primitives (50%) | 30.⋆ Complex fit: percent of sub-fits that are lines (90%) |
| 31.⋆ Complex score / rank (50%) | 32. Cosine of the starting angle (30%) |
| 33. Sine of the starting angle (10%) | 34. Length of bounding box diagonal (20%) |
| 35. Angle of the bounding box diagonal (40%) | 36. Distance between endpoints (10%) |
| 37. Cosine of angle between endpoints (0%) | 38. Sine of angle between endpoints (10%) |
| 39. Total stroke length (20%) | 40.⋆ Total rotation (100%) |
| 41. Absolute rotation (10%) | 42. Rotation squared (10%) |
| 43. Maximum speed (20%) | 44. Total time (30%) |

Table 2.2: Features examined by [177]. The features with ⋆ are those chosen as the optimal subset through feature subset selection for primitive shape recognition. Percentage values indicate how often a feature was chosen as optimal through various folds of subset selection when attempting to recognize single-stroke shapes.

to recognize three-dimensional hand and body movements [18, 181, 188] and even musical instruments [165]. Li recognized what people were sketching by sound alone using inspiration for corner recognition methods [148, 149].

# 3. FINE MOTOR SKILL CLASSIFIER FOR OVERALL DRAWING SKILLS (KIMCHI)*

In this section, we will explain the implementation of the KimCHI (Kim Computer Human Interaction) classifier. The KimCHI classifier determines children's age and gender information based on their overall drawing skills (fine motor skills).

## 3.1 Research Question

Prior to designing the methodology of our user study, we were very interested in first defining research questions that appropriately guided the direction of the study. We therefore were particularly interested in investigating the following four specific research questions.

1. Can the sketch features classify children's age (fine motor skill) information? If it is, which sketch features can determine the information?

2. If there are fine motor skill differences between age group, what are the differences?

3. Can the sketch features classify children's gender (fine motor skill) information? If it is, which sketch features can determine the information?

4. If there are fine motor skill differences between gender group, what are the differences?

*Reprinted with permission from "KimCHI: a sketch-based developmental skill classifier to enhance pen-driven educational interfaces for children" by Kim et al., 2013. Proceedings of the International Symposium on Sketch-Based Interfaces and Modeling, Expressive 2013 - The Joint Symposium on Computational Aesthetics and Sketch-Based Interfaces and modeling and Non-Photo realistic Animation and Rendering, 33-42, Copyright 2013 by ACM.

Table 3.1: Basic demographics of participants in the user study.

| Group | Adults | 7-8 year-olds | 3-4 year-olds | Overall |
|---|---|---|---|---|
| # of volunteers | 4 | 12 | 8 | 24 |
| # of sketches | 320 | 227 | 178 | 725 |

## 3.2 User Study

To implement the fine motor skill classifier, we collected a total of 725 digital drawings from twenty young children (i.e. 3-4 years and 7-8 years) and four adults (i.e., engineering graduate students) with a sketch-based interface [142, 143, 144] (Table 3.1). The child participants were accompanied with their parents to ensure that the children felt at ease throughout the study. However, the parents did not provide feedback or instructions on their children's sketches, since we desired natural and uncoached sketches for our analysis.

To determine gender differences from digital drawings, we also analyzed sketches collected from six male and six female grade-schooler participants ages 7-8. We relied on sketch data from the grade-schooler participants for analyzing gender differences, since children of that age range have already mastered how to write digits or letters that are conventionally introduced at the kindergarten level. On the other hand, preschoolers ages 3-4 demonstrated numerous variations in their domain knowledge, since many of them did not learn how to draw the shapes from their parents or in school. Moreover, because there were many personal differences with motor skills within the preschoolers, we did not analyze the gender differences from this group (Figure 3.1).

While collecting the sketch data, we asked the adults and grade-schoolers to draw and then copy each digit (i.e., 0-9) and letter (i.e., A to F). We reduced the testing size for the preschoolers and only prompted them to draw each digit (i.e., 0-9) and

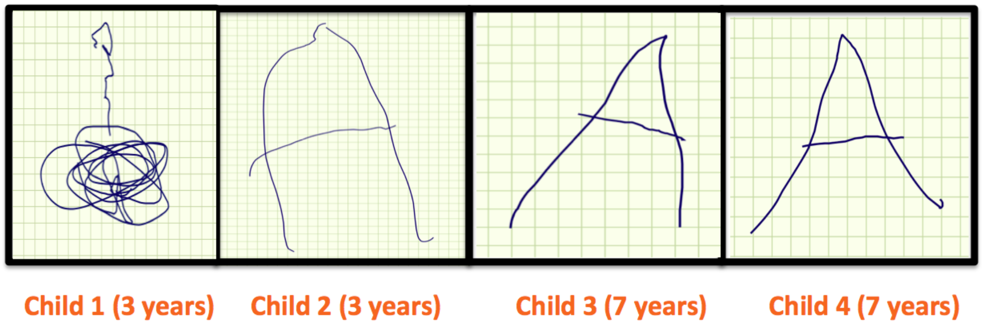



Figure 3.1: There were many variations in young children's domain knowledge (e.g. Child 1 and 2). However, older children (e.g. Child 3 and 4) knew how to draw the letter correctly.

letter (i.e., A-D) only once, since we believed that prompting this group again would cause them to lose interest in the study [125]. All of the participants were also allowed to draw the shapes naturally without restriction of stroke order.

Hanna et al. suggested that a user test involving children should be limited to 45 minutes [125], and we adhered to the recommendation in our study. All of our participants completed the study within 20 minutes using a Panasonic Touchbook and a digital stylus.

## 3.3 Implementation

This section will explain the process of implementing the KimCHI classifier. The process includes (1) preprocessing step and (2) sketch feature extraction step.

### *3.3.1 Preprocessing*

During the user study, we collected digital ink data. The data collected digital ink information of x and y coordinate points and time information. Using the information, we first generated basic feature sets such as direction value changes, stroke length overtime, and total stroke length. Algorithm 1 explains this procedure.

**Algorithm 1** Calculate the stroke direction value overtime, stroke length overtime, and total stroke length

**Input:** (1) $sketch$: the whole strokes on the screen and (2) $numberOfPoints$: the number of points in $sketch$,
**Output:** (1) $directionArray$: a stroke direction value overtime, (2) $lengthArray$: a stroke length overtime, and (3) $totalLength$: a total stroke length
**for** $i = 0$ ; $i < numberOfPoints$-1 ; $i$++ **do**
  $directionArray$ [$i$] = atan (angle whose tangent) values of X and Y values between $i$+1th point and $i$th point
  $lengthArray$ [$i$] = sqrt (square root) values of X and Y values between $i$+1th point and $i$th point
  $totalLength$ += $lengthArray$ [$i$]
**end for**

After that, we combined the strokes in their sketch into one stroke, which is required for extracting our 130 feature sets [94, 131, 155, 177] (Algorithm 2).

### *3.3.2 Sketch Feature Extraction*

As mentioned above, our goal is to determine if sketch features and classifiers can distinguish demographic data about the developmental level of the sketcher, including (1) age: between preschool age (age 3-4), school age (age 7-8), and adult, and (2) gender (within the 7-8 age group). To our knowledge, no researcher has tried to recognize age (developmental level) and gender via features of sketching style. As a result, we propose our own approach that recognizes the information. We used 130 sketch features introduced by Cali [94], Hse [131], Long [155], Paulson [177], and Rubine [215], which are generally used in the sketch recognition field to recognize shapes.

**Algorithm 2** Combine strokes into one stroke

**Input:** *strokes* in sketch
**Output:** *newStroke*: a combined stroke
**if** size of *strokes* == 1 **then**
  return *strokes*.get(0)
**end if**
*currentStroke* = *strokes*.get(0)
*dist*1 = distance between *currentStroke*.getFirstPoint and *strokes*.get(1).getFirstPoint
*dist*2 = distance between *currentStroke*.getFirstPoint and *strokes*.get(1).getLastPoint
*dist*3 = distance between *currentStroke*.getLastPoint and *strokes*.get(1).getFirstPoint
*dist*4 = distance between *currentStroke*.getLastPoint and *strokes*.get(1).getLastPoint
*min* = minimum values between *dist*1, *dist*2, *dist*3, and *dist*4
**if** *min* == *dist*1 or *dist*2 **then**
  *newStroke* = add *currentStroke* to the *newStroke* in reverse order
**else**
  *newStroke* = add *currentStroke* to the *newStroke*
**end if**
**for** $i = 1$ ; $i <$ *strokes*.size() ; $i$++ **do**
  *currentStroke* = *strokes*.get($i$)
  *dist*1 = distance between *currentStroke*.getFirstPoint and *newStroke*.getLastPoint
  *dist*2 = distance between *currentStroke*.getLastPoint and *newStroke*.getLastPoint
  **if** *dist*1 > *dist*2 **then**
    *newStroke* = add *currentStroke* to the *newStroke* in reverse order
  **else**
    *newStroke* = add *currentStroke* to the *newStroke*
  **end if**
**end for**

Table 3.2: Our optimal features for classifying preschoolers vs. grade-schoolers.

| Feature |
|---|
| Average curvature of the stroke (100%) |
| + Direction change ratio (100%) |
| + The error of the best fit line of the direction graph (100%) |
| + The maximum curvature to average curvature value (100%) |

## 3.4 Evaluation

### *3.4.1 Research Question 1: Evaluation of Classifying Age Information*

To recognize the children's developmental progress, we tried to differentiate age information by two approaches: (1) preschoolers vs. grade-schoolers and (2) preschoolers vs. matures (grade-schoolers + adults). To find the optimal subset of the 130 considered sketch features for classifying each of these groups, we used BestFirst selection built-in to the Weka system [108] with 10-fold cross-validation.

Table 3.2 and 3.3 show the selected features (each of which has a p-value <= .001). The percentage in these tables describes the percentage of selected features during the subset selection. The selected features in the tables were all curvature related features (e.g. direction change ratio). This indicates that older children (7 and 8 years) are able to draw curvatures better than younger children (i.e. 3 and 4 years), and curvature related features can be useful information to check children's developmental progress. All of the selected features were from Paulson [177].

To know the best classifier to determine their age (fine motor skill) information, we tried eight classifiers: ADTree, Bayes Net, BFTree, MultilayerPerceptron, Naive Bayes, Random Tree, Random Forest, and RBFNetwork. To find the optimal classifier for recognizing children's age (fine motor skill) by sketches, we took the selected feature sets and found that the Random Forest classifier + Bagging performed better

Table 3.3: Our optimal features for classifying preschoolers vs. matures (grade-schoolers + adults).

| Feature |
|---|
| Average curvature of the stroke (100%) |
| + Direction change ratio (100%) |
| + The angle of the major axis relative to center (100%) |
| + The error of the best fit line of the direction graph (100%) |
| + The maximum curvature to average curvature value (100%) |
| + Slope of the direction graph (100%) |

Table 3.4: Top techniques for classifying preschoolers vs. grade-schoolers.

| Classifier (Accuracy) |
|---|
| Random Forest + Bagging(82.7%) |
| Random Forest (81.51%) |
| Bayes Net (79.43%) |
| BFTree (79.43%) |
| NBTree (78.13%) |
| ADTree (77.08%) |
| Naive Bayes (77.08%) |
| Random Tree (77.08%) |
| MultiPerceptron (75.52%) |

than other classifiers (Table 3.4 and 3.5) with 10-fold cross-validation. Table 3.6 and 3.7 are the confusion matrices of the age recognition using best classifiers (Random Forest + Bagging) and selected feature sets in Table 3.2 and 3.3.

Using such identified features and differences, we were able to automatically distinguish preschoolers (ages 3-4) and grade-schoolers (ages 7-8) with a precision of .83, recall of .828, p-value of 0.001, and an f-measure of .827 with 10-fold cross-validation (Table 3.4). When distinguishing between preschool (ages 3-4) and more mature sketchers (combining children and adults), we got a precision of .909, recall of .909,

Table 3.5: Top techniques for classifying preschoolers vs. matures.

| Classifier (Accuracy) |
|---|
| Random Forest + Bagging (90.4%) |
| Random Forest (88.48%) |
| NBTree (86.63%) |
| BFTree (86.34%) |
| Bayes Net (85.63%) |
| Naive Bayes (85.35%) |
| ADTree (84.21%) |
| Random Tree (84.07%) |
| MultiPerceptron (77.81%) |

Table 3.6: Results of classifying preschoolers (p,p') vs. grade-schoolers (s,s').

| | | **Prediction outcome** | | |
|---|---|---|---|---|
| | | **p** | **s** | **total** |
| **actual value** | **p′** | 74.7 % | 25.3 % | 100 |
| | **s′** | 10.7 % | 89.3 % | 100 |

p-value of 0.001, and an f-measure of .904 with 10-fold cross-validation (Table 3.5).

### *3.4.2 Research Question 2: Contrast between Children and Adults*

As many educational psychologists [140, 164, 182] insisted, children are developing their sketching (fine motor) skills and knowledge while they are growing. As a result, generally children have less fine motor skills and dexterity than adults [6, 256].

During the user study, we found three primary contrasts between participants in the three age groups with the entire gesture set, including letters (i.e., A-D), which

Table 3.7: Results of classifying preschoolers (p,p') vs. matures (m,m').

| | | Prediction outcome | | |
|---|---|---|---|---|
| | | **p** | **m** | **total** |
| **actual value** | **p′** | 68.82 % | 31.18 % | 100 |
| | **m′** | 02.07 % | 97.93 % | 100 |

we will explain for demonstration.

The first primary contrast was that stroke lengths varied between the three groups, where stroke length was calculated from its Euclidean distance in pixels between each (x,y)-point. As seen in Figure 3.2, the stroke lengths of adults' sketches were significantly longer than the other groups, while the stroke lengths of preschoolers' sketches were shortest. We believe that the differences came from many factors including physical hand size differences, such as the preschooler participants sketching smaller shapes compared to the other groups, and existing domain knowledge, such as children drawing smaller shapes due to possible shyness with their lack of familiarity of certain shapes.

The second primary contrast was that number of points varied between the three groups. Because the number of points is dependent on the time between the pen down and pen up motions, a higher number of points means that the user took more time to draw. Figure 3.3 shows the result that the adults took the least amount of time to draw shapes (despite their tendency to draw larger shapes), presumably because they have already mastered how to draw the shapes. However, the ages 7-8

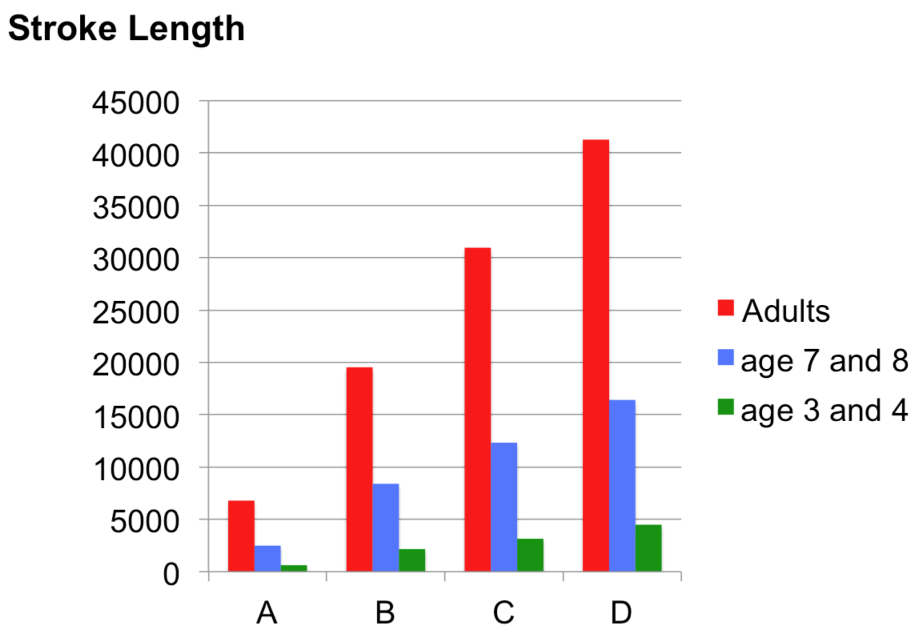



Figure 3.2: Stroke lengths for the letters ‘A’, ‘B’, ‘C’, and ‘D’. The stroke lengths of the adults’ written letters were the longest, while preschool children’s were the shortest. [141, 143]

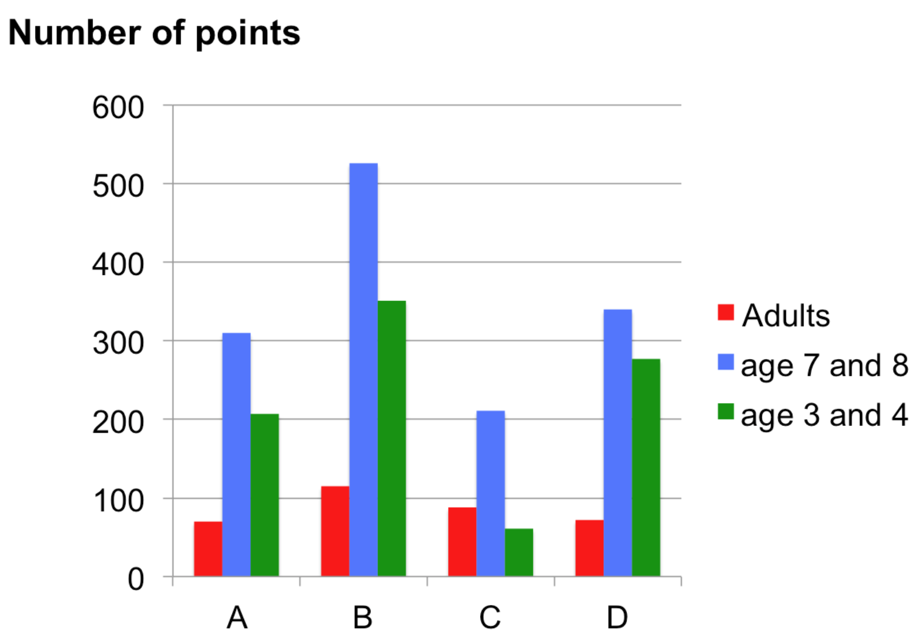



Figure 3.3: Analysis of the number of points from letters ’A’, ’B’, ’C’, and ’D’. Adults spent the least time to write the letters, while the grade-schoolers spent the most time. [141, 143]

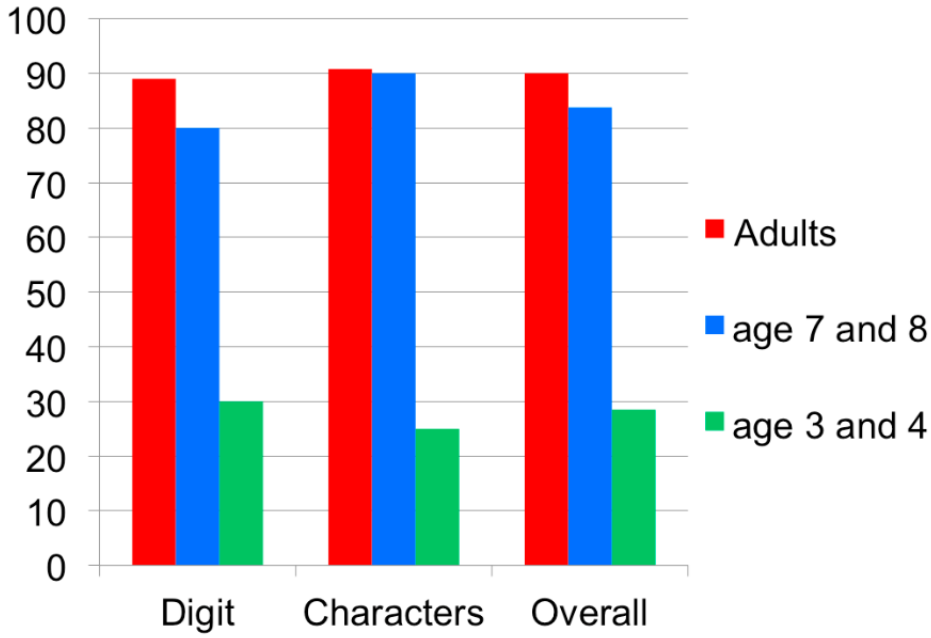



Figure 3.4: The Valentine recognizer determined adults' and grade-schoolers' shapes fairly well. However, the recognizer performed poorly on the preschoolers' shapes. [141, 143]

participants needed more time than other groups. During the user study, we found that these children drew the sketches slower and with more consideration than the adults. Some of them erased the shapes when they thought that the shapes were not drawn well enough. The preschoolers drew faster than grade-schoolers because they had little domain knowledge (i.e. digits and letters).

Finally, we analyzed the recognition accuracy for participants per each group. We measured the shape recognition accuracy using the Valentine recognizer [252]. As seen in Figure 3.4, the accuracy for adults' drawings was the highest, and the recognizer determined grade-schooler's shape drawings fairly well. However, the recognizer could not recognize the preschooler's shape drawings well. The results explain that adults and grade-schoolers have better domain knowledge than younger children (i.e. 3-4 years). To further understand which shapes proved difficulty for the

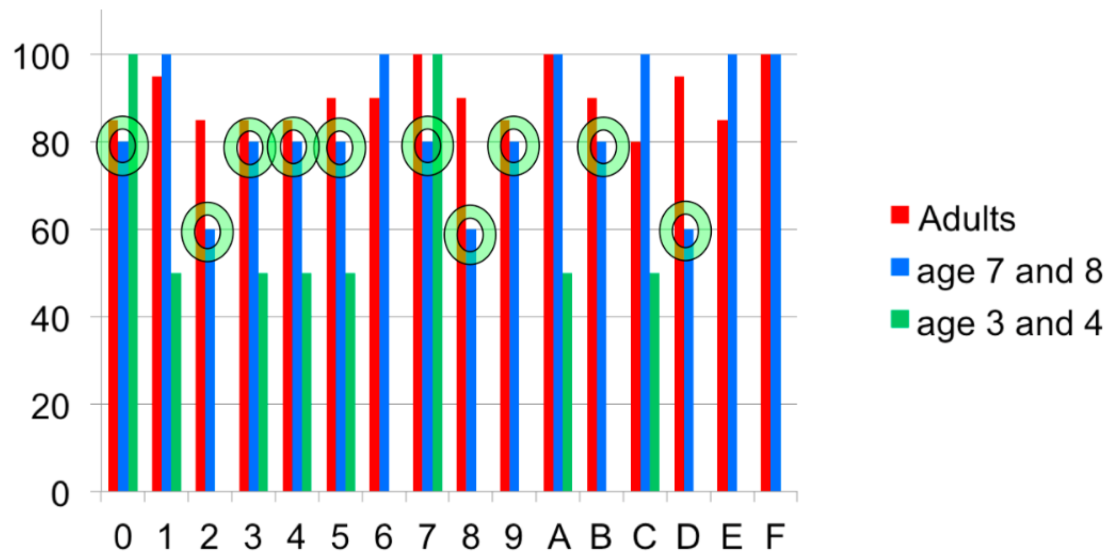



Figure 3.5: Recognition accuracy between age groups for the full gesture set, where circled areas indicate shapes that yielded numerous recognition differences. [141, 143]

preschooler participants, we analyzed the recognition accuracy for each shape (Figure 3.5) and found that both preschoolers and grade-schoolers had difficulty drawing curved shapes (e.g., digits '2' and '3'). This result can also explain the result from our age (fine motor skill) classifying result from the previous section. The selected features chosen for recognizing age information were all curvature-related features. As a result, we proved that curvature-drawing skills can determine the sketcher's developmental progress.

#### *3.4.3 Research Question 3: Evaluation of Classifying Gender Information*

When we interviewed the children's parents, most of the parents believed that girls would draw better than boys. Researchers from the educational and developmental psychology field also insist that girls possessed superior visual-motor skills over boys. For example, Brown [36] and Tennant [248] explained that girls achieved better performance with visual-motor skills than boys. However, other researchers

Table 3.8: Our optimal features for classifying genders within children.

| Feature |
|---|
| Stroke density (100%) + |
| A density metric for the gesture stroke that uses the stroke's length and bounding box size (100%) + |
| Direction change ratio (70%) |

Table 3.9: Best top techniques for classifying genders within children.

| Classifier (Accuracy) |
|---|
| Bayes Net (72.8%) |
| BFTree (69.6%) |
| Naive Bayes (68.4%) |
| Random Forest (68.2%) |
| ADTree (67.82%) |
| MultiPerceptron (63.79%) |
| Random Tree (62.64%) |
| NBTree (61.49%) |

(e.g., [156]) insist that the reverse is true. One potential reason for conflicting results may be the inconsistent use of measurements across the various studies.

An additional limitation of the prior research works involves researchers grouping all students of one gender together regardless of age within the range of ages 7-13. In order to discover any potential differences amongst genders, we tried to classify gender information within the same age group. For confirming any possible gender difference in their sketches, we employed the grade-schoolers' 227 sets of data gathered from six female children and six male children.

After retrieving 130 sketch features [94, 131, 155, 177], we found the optimal sketch features using BestFirst selection built-in to the Weka system [108] with 10-fold cross-validation.

Table 3.10: Results of classifying female children (f,f') vs. male children (m, m')

| | | **Prediction outcome** | | |
|---|---|---|---|---|
| | | **f** | **m** | **total** |
| **actual value** | **f′** | 62.11 % | 37.89 % | 100 |
| | **m′** | 13.92 % | 86.08 % | 100 |

Table 3.8 explains the best feature sets and the percentage of selected features during the subset selection from our 130 features with 10-fold cross-validation (each of which has a p-value <= .001). The selected features in the table were density and curvature related features. This indicates that girls spend more time on drawing (more careful), and girls are drawing curvatures better than boys. We also found that density and curvature related features can be useful in identifying gender. More explanation about the features can be found in [177]. Using those selected features, we found that Bayes Net classifier performed better than other classifiers (Table 3.9) with 10-fold cross-validation.

From the selected features and best classifier (Bayes Net), we could determine sketcher's gender with a precision of 0.757, recall of 0.73, p-value of 0.001, and an f-measure of 0.728 with 10-fold cross-validation. Table 3.10 is the confusion matrix of the gender recognition using best classifiers (Bayes Net classifier) and selected feature sets in Table 3.8.

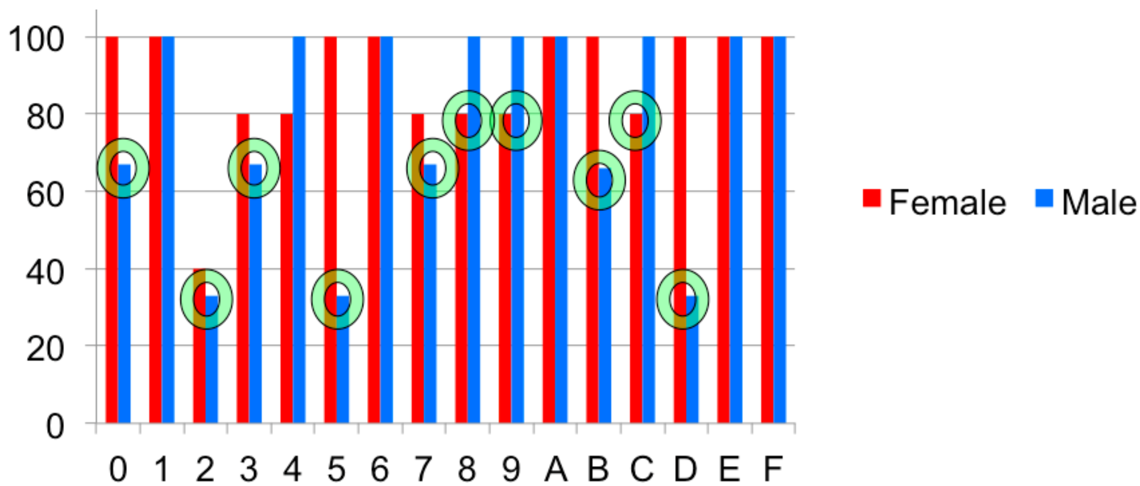



Figure 3.6: Recognition accuracy between genders in children for the full gesture set, where circled areas indicates shapes that yielded numerous recognition differences. [141, 143]

### *3.4.4 Research Question 4: Contrast between Genders*

During the user study, we found two primary contrasts between gender in the grade-schooler group.

The first primary contrast was the sketch recognition accuracy. When we compared the sketch recognition accuracy from the Valentine recognizer [252], the recognition accuracy of the girl participants was higher than the boys' on both sketched digits and letters (i.e., 88.5% and 77.8% for girls and boys, respectively). Additional insights included boy participants having greater difficulty in drawing curved shapes (Figure 3.6). As we mentioned in the previous section, density and curvature related features were selected for classifying their gender information. As a result, we found that girls have better fine motor skills than boys with better curvature-drawing skills.

The second primary contrast was the density in their sketches. During the user study, we found that females taking longer to sketch due to greater density (i.e.,

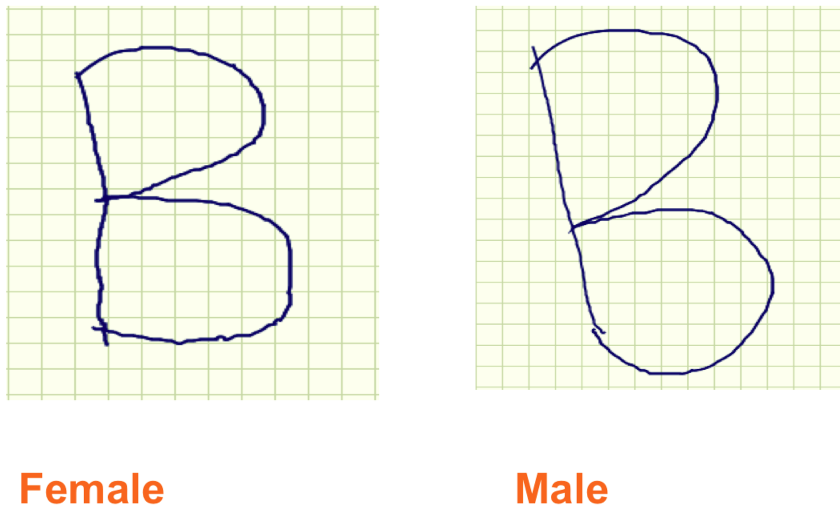



Figure 3.7: An example sketch of the letter ‘B’ from a female and male child. The female child’s sketch yielded greater density (i.e., width of the sketches) than the male child’s. [141, 143]

producing more points) in their sketches (Figure 3.7). From these observations, we believe that sketch features related to density and curvature may assist in determining the sketcher’s gender for that age range.

# 4. FINE MOTOR SKILL CLASSIFIER FOR CURVATURE- AND CORNER-DRAWING SKILLS (KIMCHI2)

The previous section explained the KimCHI classifier [142, 143, 144] that determines children's fine motor skills based on their overall drawing skills. However, the study still has limitations. One of the limitations is that the user group has many age gaps. The previous study [142, 143, 144] included age 3-4 years and age 7-8 years. As a result, the study missed age 5-6 years. According to educational psychologists, age 2-7 are rapidly developing their fine motor skills with various developmental stages including fine motor skills [50, 182]. To better assess their fine motor skill development per age, this study includes continuous age 3-8 years' sketch data.

Another limitation is that the previous study [142, 143, 144] did not determine children's fine motor skills from curvature- and corner-drawing skills, but from their overall drawing skills. As many researchers explained [6, 50, 182, 256], older children have better fine motor skills and dexterity. We specially interested in determining their fine motor skills based on their curvature- and corner-drawings, as those skills require children's dexterity and fine motor skills [50].

This section will explain the fine motor skill classifier (KimCHI2) that determines fine motor skills based on children's curvature- and corner-drawing skills. We will also introduce our findings that sketch features (*Direction Change Ratio* (DCR) [143, 177] and *Polyline Test* [176]) can explain children's fine motor skill developmental stages.

## 4.1 Research Question

Prior to designing our user study, we defined research questions that appropriately guided the direction of the study. We therefore were particularly interested in investigating the following four specific research questions:

1. Can the sketch features classify children's fine motor skills based on curvature-drawings? If it is, which sketch features can determine the information?

2. Can the sketch features classify children's fine motor skills and age information based on corner-drawings? If it is, which sketch features can determine the information?

3. Can the KimCHI2 classifier determine children's fine motor skills more accurately than the KimCHI classifier [142, 143, 144]?

4. If there are fine motor skill differences between age group, what are the differences? Furthermore, can the sketch features explain the fine motor skill differences between age group?

## 4.2 User Study

To implement the fine motor skill classifier and understand children's fine motor skill development stage per age, we collected digital drawings from 75 child participants including 44 preschoolers (aged 3-4 years) and 31 grade-schoolers (aged 5-8 years) with a sketch-enabled interface (Table 4.1). Our hypothesis was that older children who go to kindergarten (i.e., aged 5-8 years) would demonstrate better fine motor skills than younger children (i.e., aged 3-4 years), so we segmented the users into two age groups (preschoolers and grade-schoolers). We specially interested in their curvature- and corner-drawings as those skills require children's dexterity and fine motor skills [50]. For curvature-drawings, we asked the child participants to draw the letter 'C', 'circle', and 'curve'. For corner-drawings, we asked the child participants to draw the letter 'A', 'triangle', 'rectangle', and 'square'. As a result, we collected a total of 852 digital drawings (370: curvature drawings and 482: corner drawings).

Table 4.1: Demographics of user group

| Age Group | Group size | # of curvatures | # of corners |
|---|---|---|---|
| 3-4 years old | 44 | 200 | 282 |
| 5-8 years old | 31 | 170 | 200 |
| Total | 75 | 370 | 482 |

## 4.3 Implementation

This section will explain the process of implementing the KimCHI2 classifier. The process includes (1) preprocessing and (2) sketch feature extraction step.

### *4.3.1 Preprocessing*

The preprocessing step followed the same step with the previous study (the KimCHI classifier [142, 143, 144]). We first generated basic feature sets such as direction value changes, stroke length overtime, and total stroke length through the Algorithm 1. After that, we combined the strokes into one stroke (Algorithm 2), which is requirement for extracting 131 sketch features [94, 131, 155, 177, 271].

### *4.3.2 Sketch Feature Extraction*

After the preprocessing step, we extracted sketch features. In addition to the previous study, we added one more sketch feature, which can detect corners in shapes [271]. As a result, we calculated 131 state-of-the-art features [94, 131, 155, 177, 271]. We hypothesized that older children would have better cognition and fine motor skills, and they would be able to draw curvatures more smoothly than younger children. In terms of cornered shapes (e.g. square), older children would be able to draw lines and corners better than younger children. To determine curvature- and corner-drawing skills, we were especially interested in *Direction Change Ratio* (DCR) sketch feature for curvature-drawing and *Polyline Test* sketch feature for

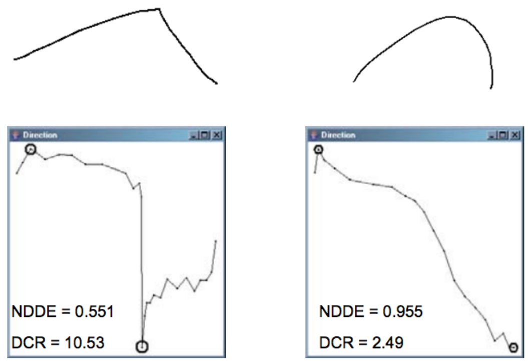



Figure 4.1: Direction graphs for a polyline (left) and arc (right). The arc has lower DCR values than the polyline, because the direction changes smoothly [176].

corner-drawing. The following sections will explain more detail about the features.

#### *4.3.2.1 Direction Change Ratio (DCR) for Curvature Drawing Skill*

*Direction change ratio* (DCR) feature calculates whether sudden direction changes are present in the direction graph [177]. This value is computed as the maximum change in direction divided by the average change in direction. During the research [176], Paulson et al. differentiated polyline and arc using the DCR feature. As seen in Figure 4.1, the arc has relatively little changes between consecutive direction values. However, the polyline has sudden direction change in its direction graph. Therefore, the arc will have lower DCR values than the polyline.

As young children have less fine motor skills and dexterity [6, 143, 256], we hypothesized that younger children may not be able to draw curvature smoothly. This will result their high DCR value, because they will have relatively higher direction changes than older children. Algorithm 3 explains the DCR calculation procedure.

$$DCR = \frac{\text{maximum of direction changes}}{\text{average of direction changes}} \tag{4.1}$$

**Algorithm 3** Calculate the *Direction Change Ratio* (DCR) (max direction change divided by overage direction change)

---

**Input:** *directionArray* from Algorithm 1
**Output:** $DCR$
$maxDirectionChange = 0$
**for** $i = 0$ ; $i <$ *directionArray.size*()-1 ; $i$++ **do**
  $tempDirectionChange$ = math.abs(*directionArray* [$i$+1] - *directionArray* [$i$])
  **if** $tempDirectionChange > maxDirectionChange$ **then**
    $maxDirectionChange = tempDirectionChange$
  **end if**
  $sumDirectionChange$ += $tempDirectionChange$
**end for**
$averageDirectionChange = sumDirectionChange$ / *directionArray.size*()
$DCR = maxDirectionChange$ / $averageDirectionChange$

---

#### 4.3.2.2 Polyline Test for Corner Drawing Skill

*Polyline Test* [176] calculates the percentage of substrokes that passed a line test. To get the value, we first divided the stroke into substrokes by analyzing corners using the algorithm from [271]. After that, we proceeded each substroke's line test by measuring average least square error of each sub-stroke and counted the number of lines that passed the line test [174, 176]. We hypothesized that younger children would have low percentage of Polyline test as they have relatively less fine motor skills than older children and may not be able to draw straight lines. Algorithm 4 explains the Polyline Test procedure.

$$PolylineTest = \frac{\#of \text{ substrokes that passed line test}}{\#of \text{ substrokes}} \tag{4.2}$$

**Algorithm 4** Calculate the *Polyline Test* (the percentage of substrokes that passed a line test)

**Input:** segmented *strokes* from *sketch* using corner-detection algorithm in [271]
**Output:** *Polyline Test*
$numLinePassed = 0$
**for** $i = 0$ ; $i < strokes$.size() ; $i$++ **do**
  $currentStroke = strokes$.get($i$)
  $linePassed$ = decide if the $currentStroke$ passed line test using Algorithm from [174, 176]
  **if** $linePassed$ = True **then**
    $numLinePassed = numLinePassed + 1$
  **end if**
**end for**
$PolylineTest = numLinePassed$ / $strokes$.size

Table 4.2: Regression output for classifying ages for curved shape.

| Feature | Multiple R-value | P-value |
|---|---|---|
| Percentage of Direction Window Passed [177] | 0.429574005 | 4.78E-18 |
| Get the percentage of the slope test that passed [177] | 0.343231139 | 1.14E-11 |
| Curve Error [177] | 0.272028581 | 1.06E-07 |
| Density of sub dot [177] | 0.270090109 | 1.32E-07 |
| The error of the best fit line of the direction graph [177] | 0.259521329 | 4.15E-07 |
| The sum of gesture intersegment angles whose absolute value is less than 19 degrees [155] | 0.247402646 | 1.45E-06 |
| Direction change ratio [177] | 0.233121645 | 5.85E-06 |
| Largest quadrilateral area / convex hull area [94] | 0.23215282 | 6.41E-06 |
| Difference of bounding boxes' largest Y value and smallest Y value / y value movement in sketch [94] | 0.180140871 | 0.000497906 |

## 4.4 Evaluation

### *4.4.1 Research Question 1: Evaluation of Classifying Curvature-drawing Skills*

To recognize the children's fine motor skills based on curvature-drawings, we tried to differentiate age information (i.e. preschoolers and grade-schoolers). We classified children's curvature drawing skills by curvature drawings (i.e. the letter 'C', 'curve', and 'circle').

To find the optimal subset of the 131 considered sketch features for classifying the age information, we first ran BestFirst selection built-in to the Weka system [108] with 10-fold cross-validation. From this step, 17 features were chosen more than 80%. After that, we proceeded linear regression analysis with each feature value (X value) and age information (Y value) (i.e. age 3-8 years). From the linear regression, we assessed how close the features and age information are fitted in a regression line. We produced multiple r-values and p-values, and sorted them by r- and p-values. Table 4.2 describes the features that have lower than p-value of 0.05. Table A.1, A.2, A.3, A.4, and A.5 in Appendix introduce the linear analysis of every 131 feature and age information. Most of the selected features were curvature related features including *Direction change ratio* (DCR). The other features included were *Density of sub dot*, which shows how the children drew the shape considerably (taking longer to sketch due to greater density) and *Largest quadrilateral area / convex hull area*, which shows whether the children drew the shape as desired. This indicates that older children (i.e. grade-schoolers) are able to draw curvatures more smoothly than younger children (i.e. preschoolers), and they are spending more time on drawing. As the selected features were mostly curvature related features, we concluded that curvature related features can be useful information to check children's fine motor skills on curvature-drawings.

When we ran the linear regression analysis with these features (X value) to age information (Y value), they were able to produce regression lines with Multiple R value of 0.53 and Adjusted R Square of 0.26 (Table 4.3), which shows high relation between the sketch features and age information.

Table 4.3: Summary output for classifying ages for curvature shape.

| | Regression Statistics |
|---|---|
| Multiple R-Value | 0.534947185137479 |
| Adjusted R Square | 0.266284605 |
| Standard Error | 1.325571201 |

To verify if those selected features can identify children's age information (fine motor skills), we labeled the age information with young (i.e. 3-4 years) and old (i.e. 5-8 years). To know the best classifier to determine their age (fine motor skill) information, we tried eight classifiers: ADTree, Bayes Net, BFTree, MultilayerPerceptron, Naive Bayes, Random Tree, Random Forest, and RBFNetwork. To find the optimal classifier for recognizing children's age (fine motor skill) by sketches, we

Table 4.4: Best top-performing techniques for classifying age for curved shape.

| Classifier (Accuracy) |
|---|
| Random Forest (81.89%) |
| Random Tree (77.3%) |
| ADTree (77.03%) |
| Bayes Net (77.03%) |
| MultiPerceptron (77.03%) |
| NBTree (76.76%) |
| BFTree (74.32%) |
| RBFNetwork (71.62%) |
| Naive Bayes (68.38%) |

Table 4.5: Results of classifying curvature-drawing skills in grade schoolers (g,g') vs. preschoolers (p,p').

| | | **Prediction outcome** | | |
|---|---|---|---|---|
| | | **g** | **p** | **total** |
| **actual value** | **g′** | 167 | 33 | 200 |
| | **p′** | 34 | 136 | 170 |

took the selected feature sets and found that the Random Forest classifier performed better than other classifiers (Table 4.4) with 10-fold cross-validation. Table 4.5 is the confusion matrix of the age recognition using best classifiers (Random Forest) and selected feature sets in Table 4.2 and 4.4.

Using those selected features, we were able to determine children's curvature-drawing (fine motor) skills with a precision of 0.82, recall of 0.82, and an f-measure of 0.82 with 10-fold cross-validation with Random Forest.

### *4.4.2 Research Question 2: Evaluation of Classifying Corner-drawing Skills*

In this section, we will discuss studies of classifying fine motor skills by differentiating age information (1) by preschoolers and grade-schoolers and (2) by their exact age information (i.e. age 3-8 years).

#### *4.4.2.1 Classifying fine motor skills*

To recognize the children's fine motor skills based on corner-drawings, we tried to differentiate age information (i.e. preschoolers and grade-schoolers). We classified children's corner drawing skills by corner drawings (i.e. the letter 'A', 'triangle',

Table 4.6: Regression output for classifying ages for corner shape.

| Feature | Multiple R-value | P-value |
|---|---|---|
| Largest quadrilateral area / convex hull area [94] | 0.473701784 | 2.83E-28 |
| Largest quadrilateral perimeter / convex hull perimeter [94] | 0.445422351 | 8.07E-25 |
| Largest triangle area / bounding box area [94] | 0.391388683 | 4.67E-19 |
| Count of corners | 0.323223271 | 3.69E-13 |
| Computes the sum of the absolute value of the angles at each mouse point [155] | 0.302459951 | 1.24E-11 |
| Get the percentage of substrokes that passed a line test [177] | 0.299690307 | 1.94E-11 |
| Number of strokes [177] | 0.295667976 | 3.69E-11 |
| Largest triangle perimeter / enclosing rectangle perimeter [94] | 0.283402153 | 2.46E-10 |
| Computes the sum of the squared values of the angles at each mouse point [94] | 0.28053494 | 3.78E-10 |
| Calculate the orthogonal distance squared error between the stroke and the ideal curve [177] | 0.265424525 | 3.37E-09 |
| Get the percentage of the slope test that passed [177] | 0.262479123 | 5.08E-09 |
| Number of points inside the triangle [94] | 0.251192224 | 2.34E-08 |
| Get the perimeter (of bounding box) to stroke length ratio [177] | 0.165534439 | 0.000266154 |
| The number of revolutions that the stroke makes [177] | 0.124237847 | 0.006367394 |

'square', and 'rectangle').

Table 4.7: Summary output for classifying ages for corner shape.

| | Regression Statistics |
|---|---|
| Multiple R-Value | 0.627853058 |
| Adjusted R Square | 0.375999447 |
| Standard Error | 1.203778371 |

To find the optimal subset of the 131 considered sketch features for classifying the age (fine motor skill) information, we first ran BestFirst selection built-in to the Weka system [108] with 10-fold cross-validation. From this step, 18 features were chosen more than 80%. After that, we proceeded linear regression analysis with each feature value (X value) and age information (Y value) (i.e. age 3-8 years). From the linear regression, we assessed how close the features and age information are fitted in a regression line. Table B.1, B.2, B.3, B.4, and B.5 in Appendix introduce the linear analysis of every 131 feature and age information. We produced multiple r-values and p-values, and sorted them by r- and p-values. Table 4.6 describes the features that have lower than p-value of 0.05. The selected features in the tables were mostly line drawing related features including *PolylinePctPassed*. *Largest quadrilateral area / convex hull area* and *Largest triangle area / bounding box area* introduce how the children can draw desired shape, which is also very relevant to their domain knowledge and cognition ability. As most of the selected features are line drawing related features, this indicates that older children (i.e. grade-schoolers) are able to draw lines more smoothly than younger children (i.e. preschoolers), and line-drawing related features can be useful information to check children's fine motor skills on corner-drawings.

When we ran the linear regression analysis with these features (X value) to age information (Y value), they were able to produce regression lines with Multiple R value of 0.63 and Adjusted R Square of 0.38 (Table 4.7), which shows high relation between the sketch features and age information.

To verify if those selected features can identify children's age information (fine motor skills), we labeled the age information with young (i.e. 3-4 years) and old (i.e. 5-8 years). To know the best classifier to determine their age (fine motor skill) information, we tried eight classifiers: ADTree, Bayes Net, BFTree, MultilayerPerceptron, Naive Bayes, Random Tree, Random Forest, and RBFNetwork. To find the optimal classifier for recognizing children's age (fine motor skill) by sketches, we took the selected feature sets and found that the Bayes Net classifier performed better

Table 4.8: Best top-performing techniques for classifying age for corner shape.

| Classifier (Accuracy) |
|---|
| Bayes Net (77.13%) |
| BFTree (76.64%) |
| Random Forest (76.3%) |
| NBTree (76.09%) |
| ADTree (76.09%) |
| MultiPerceptron (75.05%) |
| RBFNetwork (73.39%) |
| Naive Bayes (68.19%) |
| Random Tree (68.19%) |

Table 4.9: Results of classifying corner-drawing skills in grade-schoolers (g,g') vs. preschoolers (p,p') .

| | | **Prediction outcome** | | |
|---|---|---|---|---|
| | | **g** | **p** | **total** |
| **actual value** | **g′** | 221 | 60 | 281 |
| | **p′** | 46 | 154 | 200 |

than other classifiers (Table 4.8) with 10-fold cross-validation. Table 4.9 is the confusion matrix of the age recognition using best classifiers (Bayes Net) and selected feature sets in Table 4.6 and 4.8.

Using those selected features, we were able to determine children's curvature-drawing (fine motor) skills with a precision of 0.783, recall of 0.78, and an f-measure of 0.781 with 10-fold cross-validation with Bayes Net.

#### *4.4.2.2 Classifying age information*

The previous section explained our fine motor skill classifying result by dividing the age groups into young children (age 3-4 years) and old children (5-8 years). As we found that sketch features show high correlations with age information, we tried to classify children's exact age information with our 131 features [94, 131, 155, 177, 270, 271, 274, 275]. We took the same child participants from the previous section, and Table 4.10 explains more detailed information about our user demography. As the conventional fine motor skill assessment (i.e. "star drawing test" [153, 167]) assesses fine motor skills by corner-drawing, we applied corner drawing examples (i.e. 'A', 'triangle', 'rectangle', and 'square') to classify their age information.

Table 4.10: Demographics of user group

| Age Group | Group size | # of corners |
|---|---|---|
| 3 years old | 24 | 153 |
| 4 years old | 20 | 128 |
| 5 years old | 8 | 64 |
| 6 years old | 12 | 60 |
| 7 years old | 8 | 61 |
| 8 years old | 3 | 16 |
| Total | 75 | 482 |

We first applied supervised Resample filter in Weka [108] because our data set has many variations in their age group. This filter takes the class distribution into account for generating the sample with replacement or without replacement. After that, we applied BestFit selection built-in to the Weka system [108] with 10-fold cross-validation to find the optimal subset of the 131 considered sketch features. Table 4.11 describes the selected feature sets that were chosen more than 80%, and most of the selected features were from our previous study (Table 4.6). The selected

Table 4.11: Our optimal features for classifying ages within children.

| Feature |
|---|
| Curve Error (100%) [177] + |
| Number of strokes (100%) [177] + |
| Get the percentage of substrokes that passed a line test (80%) [177] + |
| Largest quadrilateral area / convex hull area (100%) [94] + |
| Largest triangle area / bounding box area (100%) [94] + |
| Largest triangle area / largest quadrilateral area (100%) [94] + |
| Absolute value of bounding box's X difference / x value movement in sketch (80%) [94] + |
| Number of points inside the triangle (90%) [94] + |
| Convex hull perimeter / stroke length (90%) [94] + |
| Largest quadrilateral perimeter / convex hull perimeter (100%) [94] + |
| A density metric for the gesture stroke that uses the stroke's length and distance between the first and last point (100%) [155] + |
| Count of corners (100%) |

features included curvature and corner drawing ability (i.e. Curve Error and Count of corners), and features from [94] determined if they drew desired shapes well (i.e. Largest quadrilateral area / convex hull area).

To know the best classifier to determine their age (fine motor skill) information, we tried seven classifiers: Bayes Net, BFTree, MultilayerPerceptron, Naive Bayes, Random Tree, Random Forest, and RBFNetwork. To find the optimal classifier for recognizing children's age information by sketches, we took the selected feature sets and found that the Random Forest classifier performed better than other classifiers (Table 4.12) with 10-fold cross-validation.

Using those selected features, we were able to determine children's curvature-drawing (fine motor) skills with a precision of 0.751, recall of 0.746, and an f-measure of 0.742 with 10-fold cross-validation with Random Forest.

From this study, we concluded that sketch features can decide exact information. However, as our study data set has many variations in age groups, we need to recruit

Table 4.12: Best top-performing techniques for classifying age using digital sketch features

| Classifier (Accuracy) |
| --- |
| Random Forest (74.64%) |
| Random Tree (73.8%) |
| BFTree (67.15%) |
| NBTree (63.83%) |
| MultiPerceptron (56.96%) |
| Bayes Net (53.22%) |
| RBFNetwork (48.65%) |
| Naive Bayes (37.0%) |

more child participants to validate this study.

### *4.4.3 Research Question 3: Better Fine Motor Skill Classification Performance than the KimCHI Classifier*

To evaluate our classifier performance over to the KimCHI classifier [142, 143, 144], we applied our sketch data set to the both classifiers and generated classifying result with the Weka system[108]. The main difference between our classifier and the KimCHI classifier is that the previous fine motor skill classifier [142, 143, 144] disregarded children's specific curvature- and corner-drawing skills, but solely focused on the overall drawing behaviors. As a result, the previous study [142, 143, 144] trained all shapes together including curvature and corner shapes and retrieved sketch features for identifying fine motor skill information. As the KimCHI2 classifier separately trained their curvature- and corner-drawings, we hypothesized that the KimCHI2 classifier will perform better than the prior study [143].

Figure 4.2 explains our classifying result. When we applied the previous study's [143] selected sketch features (e.g. Average curvature of the stroke) and their selected machine learning classifier (i.e. Random Forest and Bagging), it was able to rec-

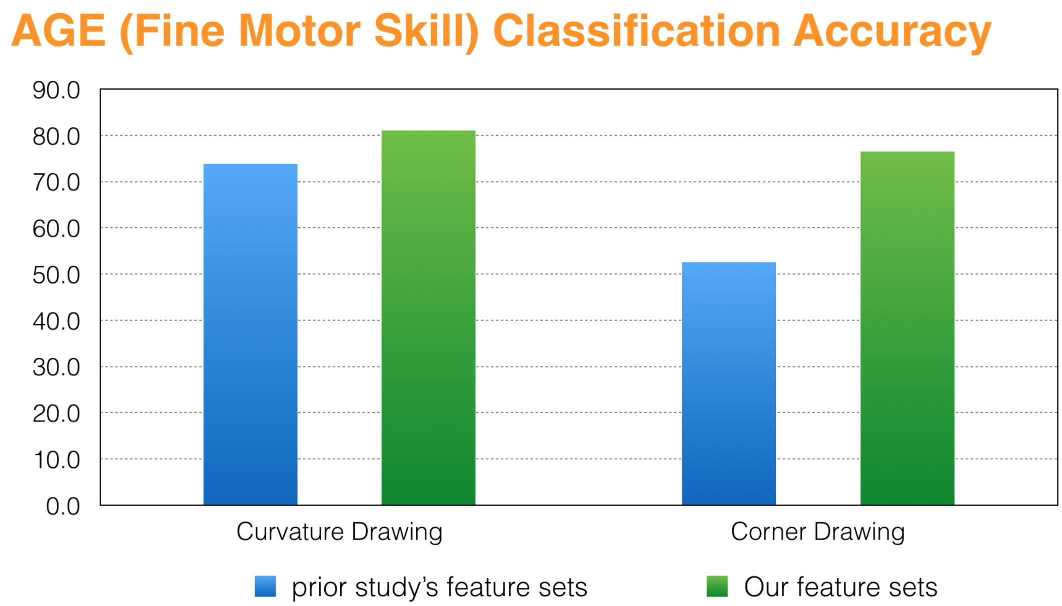



Figure 4.2: We applied our data set to the both classifiers. When we classified their fine motor skill classification results on curved- and cornered-drawings, our classifier performed better than the prior study.

ognize the curvature-drawing skills by a precision of 0.74, a recall of 0.74, and an f-measurement of 0.74 and corner-drawing skills by a precision of 0.51, a recall of 0.53, and an f-measurement of 0.53. The KimCHI2 classifier outperformed for both curvature- and corner-drawing skill recognition. Especially, the prior study's corner-drawing skill performance (f-measurement of 0.53) was much lower than this study's performance (f-measurement of 0.78). We believe that because the prior study only uses curvature-related feature sets, it was not able to determine corner-drawing skills well.

#### *4.4.4 Research Question 4: Fine Motor Skill Development Per Age*

During the user study, we observed that each age group shows different drawing skills. As seen in Figure 4.3 and 4.4, generally, younger children (i.e. 3-4 years) had lower dexterity and domain knowledge than older children (i.e. 5-8 years), which results higher DCR and lower Polyline Test values.

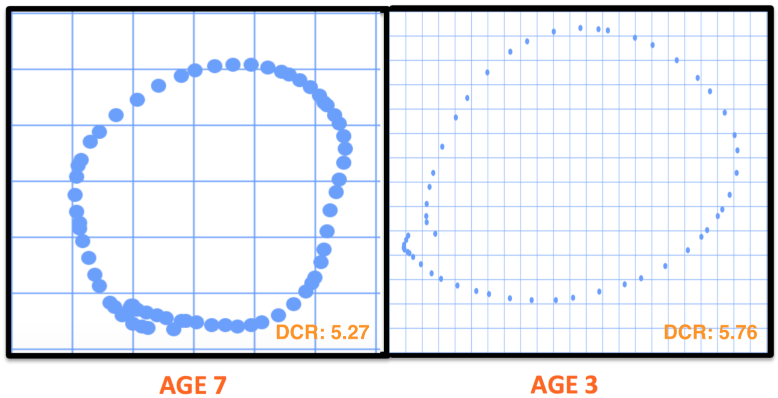



Figure 4.3: The example of a 'circle' drawing from each age group.

To find the fine motor skill stage differences between age groups, we first produced and compared their direction value changes in their drawings using the algorithm from [219, 220]. Sezgin [220] used the direction and speed values in strokes to find edges in sketch (e.g. a 'square' will have four edges and direction changes in the edges). The direction value calculating procedure can be found in Algorithm 5.

We applied the direction values to know children's fine motor skill stage differences. To understand if older children's drawing behaviors show similar values with adults (who already mastered their fine motor skills), we compared the values with an adult's sketch data. We produced each age group's direction values while drawing a 'circle' (Figure 4.5). As seen in Figure 4.6, older age group (adult and age 6 years)'s direction graph grows smoothly. However, younger age (age 3 years)'s direction graph has many direction changes.

We found the same result when we produced each age group's direction values


Figure 4.4: The older child (left) drew the lines in square better than the younger child (right) with 100% line pass rate.

while drawing a 'square' (Figure 4.7). As seen in Figure 4.8, younger age (age 3 years)'s direction graph had many variations compared to older age group's direction values.

We got an idea from these results that younger children have less fine motor skills than older ages. To find if sketch features can explain those fine motor skill stages, we generated *Direction Change Ratio* (DCR) and *Polyline Test* sketch features per each age. As we described earlier, young children will have higher *Direction Change Ratio* (DCR) values and lower *Polyline Test* as they have less fine motor skills than older children.

We generated the child participants and adult's mean values of *Direction Change Ratio* (DCR) and *Polyline Test* from curvature-drawings and cornered-drawings. As Figure 4.9 and 4.10 describe, after age 5 years, the graphs show stable values from aged 5 years to adult. On the other hand, aged 3-4 years' sketch feature values have many differences than the older ages. In terms of curvature-drawing skills, the age 3 years had highest DCR values and the age 4 years had less *Direction Change Ratio* (DCR) values, but the values were still higher than older children. In terms of

**Algorithm 5** Calculate the *Direction Value*

**Input:** *points* from sketch
**Output:** $DirectionValues$
$DirectionValues[0] = 0.0$
**for** $i = 1$ ; $i < points.size()$ ; $i{+}{+}$ **do**
  $d$ = arctac value between $points[i]$ and $points[i-1]$
  // Make sure there are no large jumps in direction - ensures graph continuity
  **while** $d$-$DirectionValues[i-1] > Math.PI$ **do**
    $d$ -= $(Math.PI * 2)$
  **end while**
  **while** $DirectionValues[i-1]$ - $d > Math.PI$ **do**
    $d$ += $(Math.PI * 2)$
  **end while**
  $DirectionValues[i] = d$
**end for**
**for** $i = 1$ ; $i < points.size()$ ; $i{+}{+}$ **do**
  $SmoothDirectionValues[i] = (DirectionValues[i-1] + DirectionValues[i] + DirectionValues[i+1])$ / 3.0
**end for**
$DirectionValues = SmoothDirectionValues$

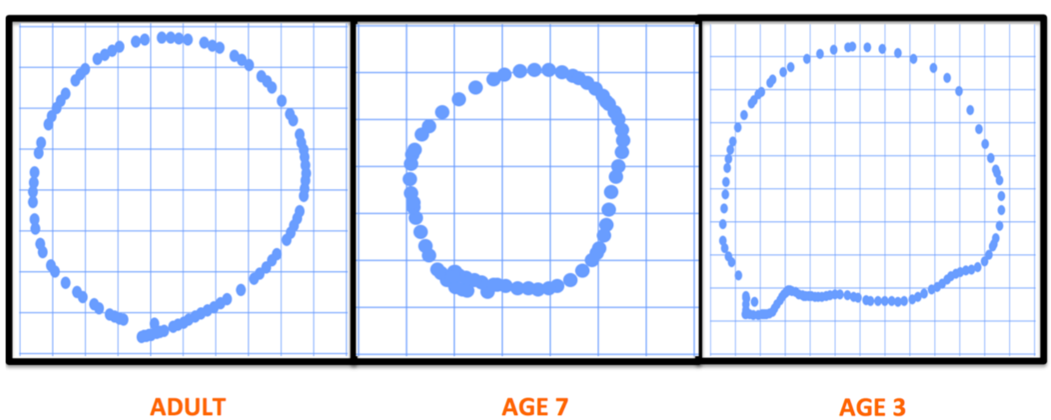



Figure 4.5: The example of a ‘circle’ drawing from each age group.

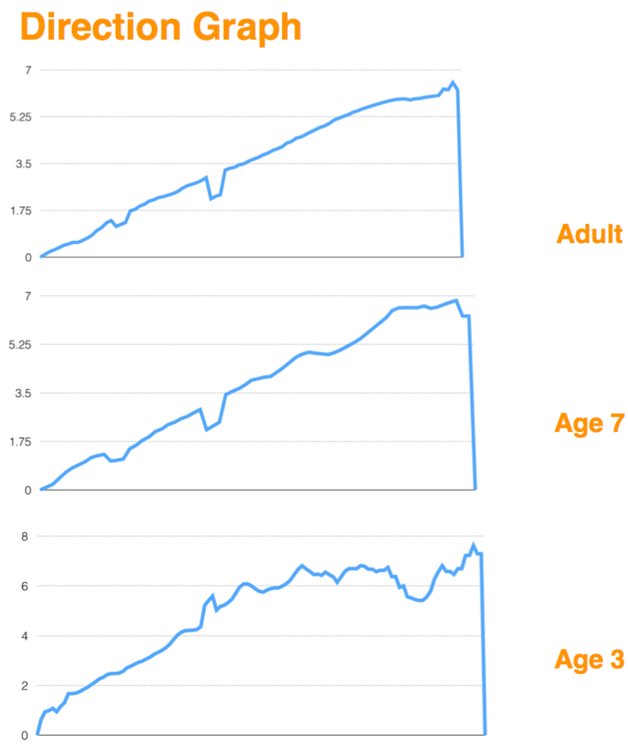



Figure 4.6: Young child could not draw curvature smoothly (many direction changes) than older child.

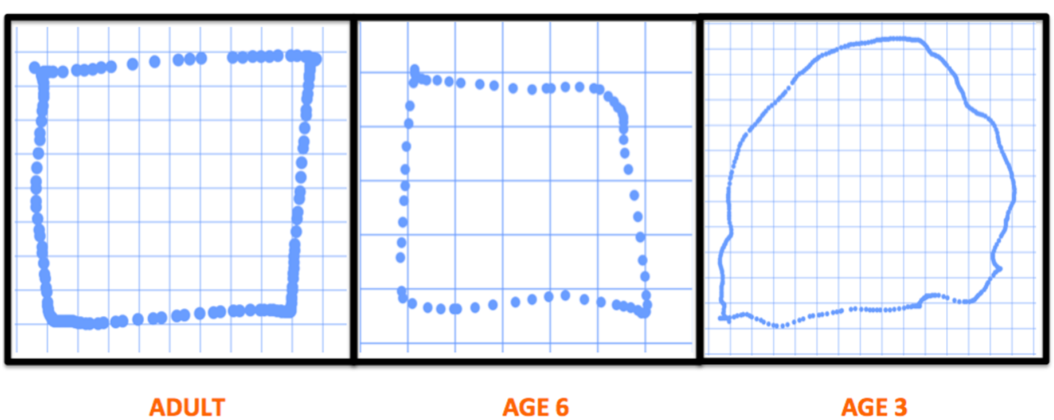



Figure 4.7: The example of a 'square' drawing from each age group.

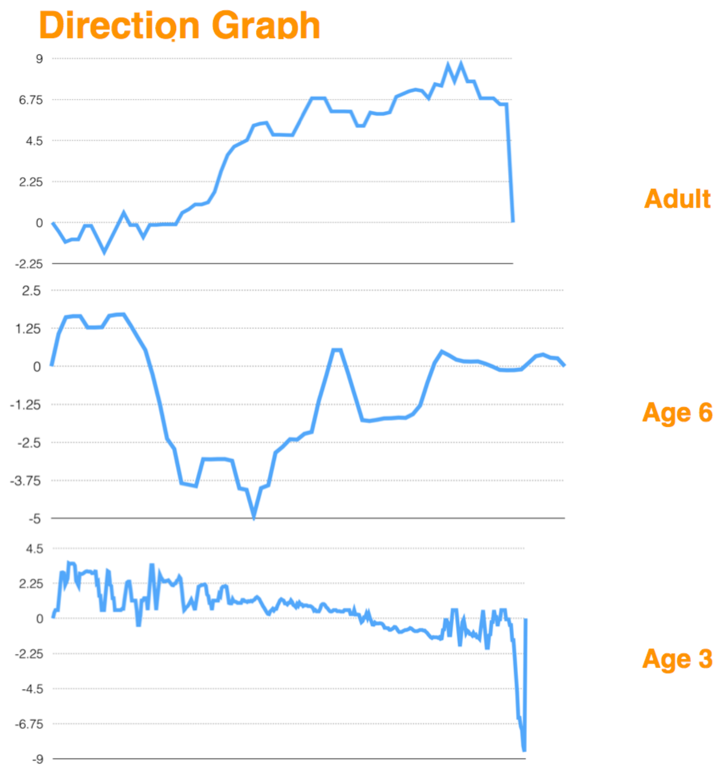



Figure 4.8: Young child could not draw line and corner smoothly (many direction changes) than older child.

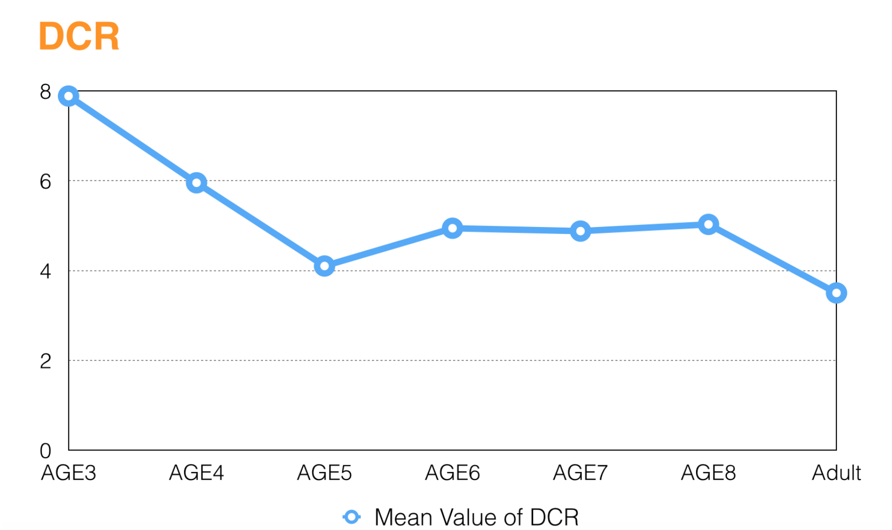



Figure 4.9: From age 5 years, they were able to draw curvature smoothly with relatively lower DCR values than younger ages (3-4 years). Younger children had higher DCR values because they had relatively higher direction changes than older children.

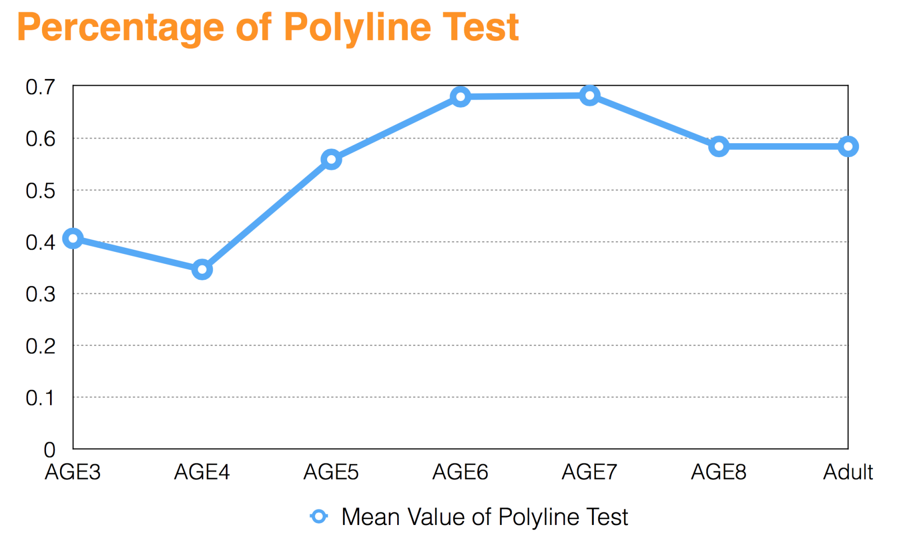



Figure 4.10: From age 5 years, they were able to draw lines better than younger ages (3-4) years with higher Polyline test percentages. Younger children could not draw lines better than older children, which results their lower Polyline test results.

Table 4.13: Standard deviations of count of strokes

| Age Group \Shape | circle | curve | square | rectangle |
|---|---|---|---|---|
| Age 3 | 0.504006933 | 0.534983081 | 2.464563668 | 1.87259546 |
| Age 4 | 0.287902241 | 2.611527476 | 1.46406754 | 1.985688546 |
| Age 5 | 0.223606798 | 0.458831468 | 0.786397516 | 0.933302004 |
| Age 6 | 0.323380833 | 0.514495755 | 0 | 0.383482494 |
| Age 7 | 0 | 0 | 0.452267017 | 0.452267017 |
| Age 8 | 0 | 0 | 0 | 0 |

corner-drawing skills, the age 3-4 years had lower *Polyline Test* than older children. We believe that because age 5 years are the ages that entering kindergarten, they will have more drawing practice and better psychical development, which will result their better fine motor skills than younger children.

To further explain their fine motor skill stages, we compared their number of strokes and drawing times. When we generated their number of strokes for curved- and cornered-shapes, we found that most of the children drew curved-shapes with

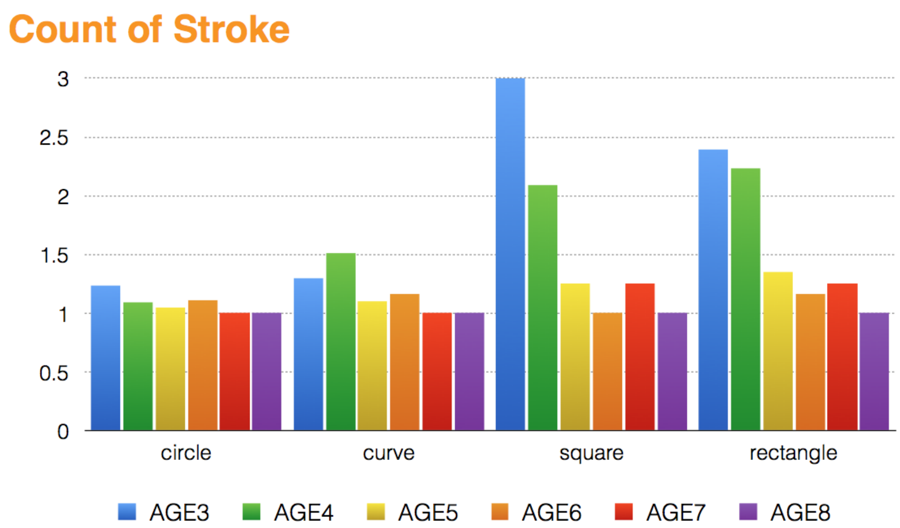



Figure 4.11: This figure explains the number of strokes per shape by age. We found that most of the children drew curved shapes with around one stroke. However, younger children (age 3-4 years) required more stroke than older children when they drew cornered shapes.

around one stroke as they were already familiar with those shapes (Figure 4.11). However, when we compared their stroke sizes of cornered-shapes, younger children (3-4 years)'s drawings had more number of strokes than older children (5-8 years). This indicated that corner-drawings require more domain knowledge than curved-shapes. When we calculated the standard deviations of stroke sizes (Table 4.13), from age 5 years, they had lower standard deviations. This indicates that from age 5 years, they would have better fine motor skills and domain knowledge.

When we generated their drawing times per each age group, we also found that younger children (3-4 years) mostly required more drawing times than older age groups (5-8 years) for both curved- and cornered-shapes (Figure 4.12). When we calculated the standard deviations of drawing times (Table 4.14), from age 5 years, they had lower standard deviations. From these findings, we concluded that older

Table 4.14: Standard deviations of drawing times

| Age Group \Shape | circle | curve | square | rectangle |
|---|---|---|---|---|
| Age 3 | 2457.624251 | 1954.997553 | 16898.24586 | 6308.21305 |
| Age 4 | 778.968364 | 2284.392067 | 3614.114208 | 4860.538499 |
| Age 5 | 631.067306 | 620.5253057 | 1567.682811 | 1195.263367 |
| Age 6 | 2337.249671 | 853.2580619 | 1103.311393 | 1136.722834 |
| Age 7 | 626.5699494 | 1489.509712 | 684.4516662 | 849.623923 |
| Age 8 | 691.3245339 | 402.7785303 | 2023.895037 | 1387.646673 |

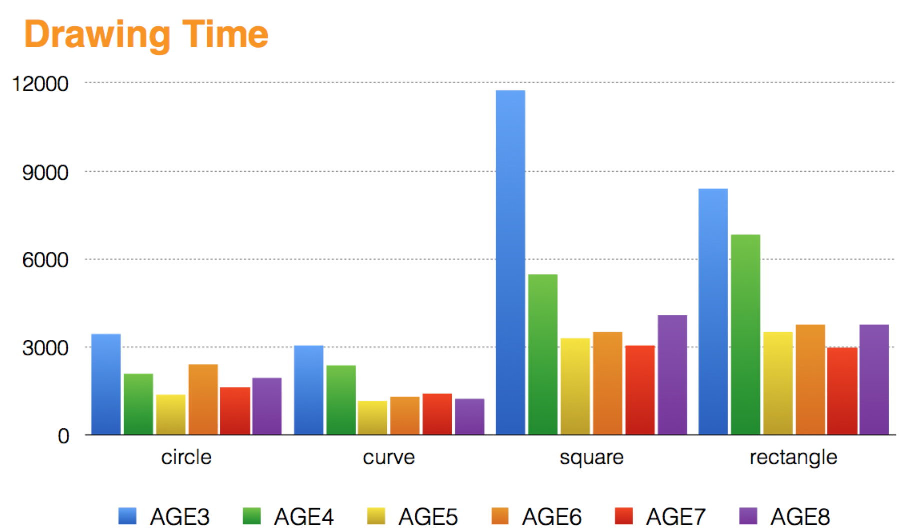



Figure 4.12: When we compared their drawing time per shape by age, younger children (age 3-4 years) took more drawing times than older children.

children have better domain knowledge and fine motor skills than younger children. Especially, around age 5 years, they have better fine motor skills and domain knowledge than younger children.

# 5. SKETCH-BASED EDUCATIONAL INTERFACE (EASYSKETCH)

After developing the fine motor skill classifiers (i.e. KimCHI and KimCHI2), we designed and developed a sketch-based educational interface, EasySketch. As we mentioned earlier, the existing educational psychological research approaches [152, 153] have many limitations when assessing children's fine motor skills. The main drawback of the approaches was that they required researchers' manual measurements to decide the fine motor skills, which are prone to human error and bias. In order to overcome the limitations of existing educational psychological research approaches, sketch-recognition technology can be a solution. There are many sketch-based educational interfaces that teach children how to sketch through interesting feedback and instructions (e.g., [25, 88, 258]). However, the interfaces are missing fine motor skill classifiers, but solely include simplistic fine motor skill exercises incorporating limited binary feedback (i.e., either correct or incorrect) on children's drawing. As a result, there was no research that validates and facilitates conventional approach to assess children's fine motor skills on tablet computer. This section will explain the sketch-based educational interface that (1) determines children's fine motor skills based on their drawing skills and (2) assists children how to draw basic shapes such as alphabet letters or numbers based on their learning progress. We will also introduce our findings that (1) our interface can determine children's fine motor skills more accurately than the conventional approach ("star drawing test") (Figure 1.1) and (2) from age 5 years, they show notable fine motor skill development.

## 5.1 Field Study

Prior to designing our interface, we engaged in an ethnographic study in a preschool classroom environment. Because ages 3-4 years are active ages in which children learn basic shapes, we specifically targeted this age group for our study. The classroom we observed included ten preschoolers and two teachers. We observed the preschool class over the course of five consecutive school days for thirty minutes per day. Prior to our study, we spent some time becoming acquainted with the children and teachers in the preschool classroom, in order for the children to be better acclimated to our presence and for the teachers to become more aware with our study approach.

Figure 5.1: After learning the letter, each child played with a piece of paper that contains the letter.

From our five-day visit, we observed one teacher spending time each day teaching the alphabet to their preschoolers. We learned from the teacher that a different letter to discuss in the class changes weekly, and that the letter that was taught as we observed was the letter 'S'. During this class time, the preschoolers were seated on the ground as the teacher taught, standing in front of them for approximately ten minutes per day to teaching concepts regarding that letter. The instructional process that the teacher followed during our visit is elaborated below.

1. The teacher shows a letter on paper and demonstrates sounding the letter out to the preschoolers. The teacher also introduces English words starting with the letter 'S' (e.g., "snake"), and the preschoolers imitate pronouncing the words.

2. The teacher demonstrates how to physically draw the letter on paper to the preschoolers.

3. The teacher draws the letter on each child's back and arm using their finger. The teacher also holds each preschooler's fingers grasping a pen, and the two draw the letter together.

4. Each child plays with a piece of paper that contains the letter (Figure 5.1).

5. Each child places a sticker containing the letter on a diagram of a letter tree (Figure 5.2).

From this instructional lesson, the preschoolers were able to learn the letter shapes using a variety of integrated sensory modalities such as vision, motor commands, and kinesthetic feedback. We also found that there were many books and posters that teach children how to draw alphabet letters with gestures using tracing dots and arrows. During an interview with the teachers, they explained that children can develop drawing skills by drawing practice, and also shared that tracing dots with drawing gestures help children to more easily follow the letters' drawing gestures and learn the letters. They also explained that there is no correct drawing gesture,

Figure 5.2: After the preschoolers learned a letter, they placed letter stickers on a diagram of an alphabet tree.

but there are common drawing gestures on digits and letters, which can also help children's school-readiness. They periodically assessed children's fine motor skills every six months by asking children to draw basic shapes (e.g. 'circle') and counted the sketch correctness manually. However, they issued the difficulty of the test that we explained in the prior section (i.e. prone to error from bias and need manual effort).

From ethnographic study, we found that (1) children like drawing; (2) tracing dots with drawing gesture can assist the children to develop their fine motor skills and school readiness; and (3) automatically assessing their sketch correctness and fine motor skills would be helpful to reduce human efforts. In order to assist children to develop their fine motor skills, we chose our application enables sketch-recognition technique and employed tracing dots with drawing gestures in the interface to assist

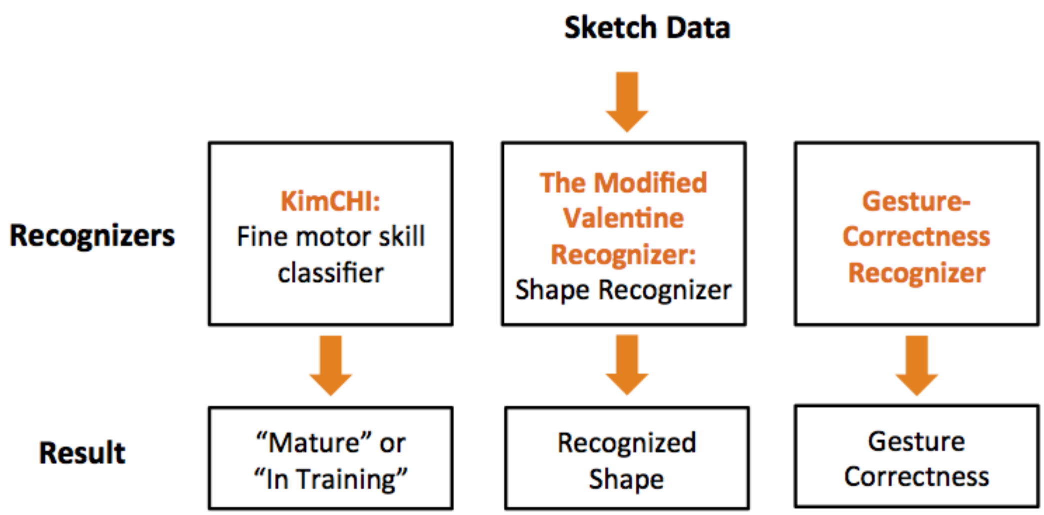



Figure 5.3: The architecture of our drawing assessment system consists of the following components (L-R): a fine motor skill classifier, a shape recognizer, and a gesture-correctness recognizer.

how to draw basic shapes.

## 5.2 Implementation

### *5.2.1 Drawing Assessment System*

Before describing our interface, we first provide information of our drawing assessment system. The system combines the capabilities of three relevant sketch recognition algorithms to assist in providing human expert-emulated assessment on children's sketches of basic shapes. Specifically, the recognizers that we incorporated specialize in providing feedback on children's (1) *fine motor skills*, (2) *shape correctness*, and (3) *gesture correctness*. Figure 5.3 explains the architecture of our drawing assessment system.

#### 5.2.1.1 Fine motor skill classifier

In order to handle classification of children's fine motor skills, we employed KimCHI [143], a gesture-based classifier. As we mentioned earlier, the major drawback of the current methodology (i.e. "star drawing test") is that the methodology does not analyze children's sketches. The KimCHI [143] classifier resolves the drawback of the current methodology by focusing on recognizing the physical act of how sketches are made (e.g. smoothness of curvature-drawing). The classifier first calculates a dimensionality-reduced subset of gesture-based sketching features (e.g., angle between important sketch points, total change in angle), derived from features in the existing sketch recognition techniques of [94, 155, 177, 215]. After that, Random Forest + Bagging machine learning technology determines the sketch's label (e.g. mature or non-mature) based on the sketch features. Since KimCHI [143] performed well in classifying the performance of children's fine motor skills, we chose to take advantage of the classifier in our interface's drawing assessment system for determining children's fine motor skill levels.

#### 5.2.1.2 Shape correctness recognizer

We assess the correctness of children's sketched shapes using the child-trained recognizer [141], which is a modified version of the Valentine recognizer [252]. The recognizer takes as input two shapes: one template shape, whose shape definition is known; and one user-generated shape, whose shape definition is unknown. The recognizer will output a value between 0 and 1 that reflects the confidence that the two shapes are similar, where 0 denotes no confidence and 1 denotes complete confidence. To calculate this confidence, the recognizer first scales and translates the shapes into a $48 \times 48$ bounding window to ensure both shapes are approximately the same size. Subsequently, the recognizer resamples the points in both shapes so each is made up of 48 equidistant points [141].

After preprocessing, the recognizer considers each point in each shape – 48 equidistant points from both shapes for a total of 96 points – and then records the distance from that point to the closest point in the other shape. From these shortest distances, it calculates similarity values from the Tanimoto coefficient [136, 252], which is the ratio of points with shortest distances less than 4 pixels over the total number of points. If that confidence value is above its empirically defined threshold of 0.65, the two shapes are deemed similar [86, 136, 141, 252]. As a result, the user's shape could be defined by the template's shape definition. The recognizer labels the user shape with the shape definition of the template with the highest similarity confidence value.

The merit of this recognizer is its extensibility. Whenever we want to add shapes to be recognized, we only need to add one sample shape as a template. Our application takes advantage of the Valentine recognizer to inform users whether they have drawn the prompted shape correctly.

#### *5.2.1.3 Gesture-correctness recognizer*

Lastly, we developed a specialized naive recognizer for handling the correctness of gestures from the set of letter and number shapes in children's sketches. For example, the recognizer can determine whether a child drew the number '3' by starting at the top and curving downward, or whether the child instead started at the bottom and curved upward. In order to do so, we first produced tracing dots, which have certain order of drawing. The recognizer calculates the distance between the tracing dots and the corresponding user's shapes, and adds a tracing dot to an ordered list if the points in the user's sketched shape lie within a certain distance threshold of that tracing dot. If the complete list of tracing dots is added and in the desired order,

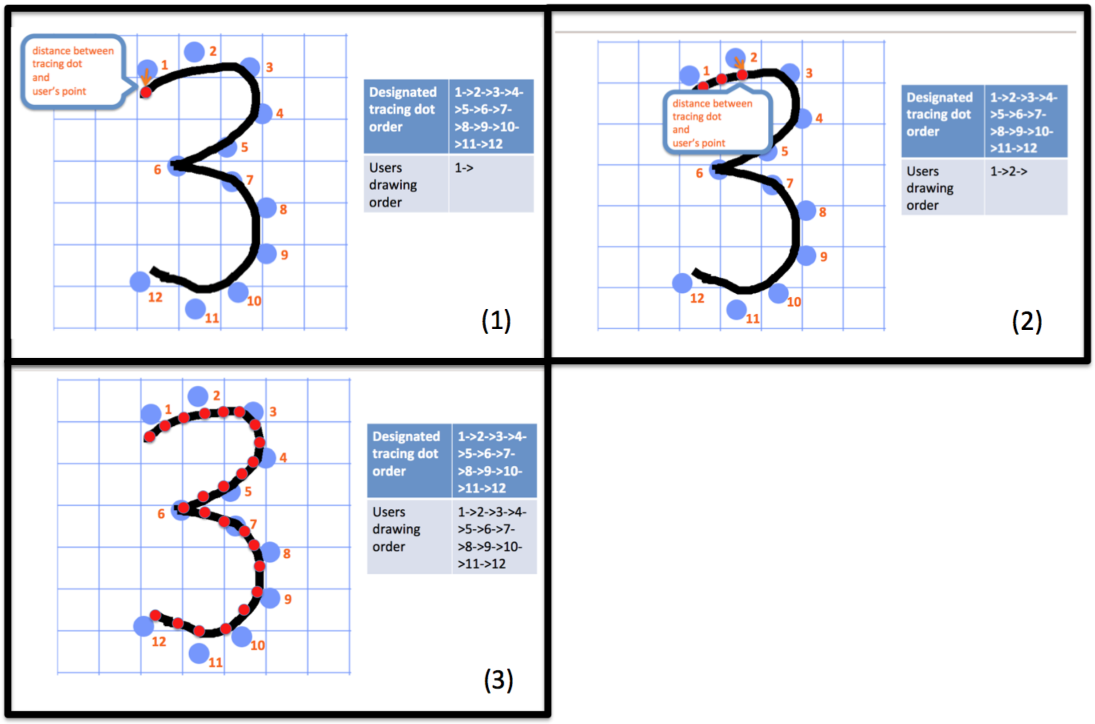



Figure 5.4: The recognizer calculates the distance between the tracing dots and the user's shape. (1) It first calculates the distance between the first desired tracing dot (number "1" in Figure) and the user's point. If the point is within distance threshold with the tracing dot, we add it to the user's drawing order list, (2) Next, it calculates the distance between the next desired tracing dot (number "2" in Figure) and the user's point. If the point is within distance threshold with the tracing dot, we add it to the user's drawing order list, and (3) Finally, when the distance comparison finishes, it compares the user's drawing order list with designated tracing dot order list. In this case, the drawing gesture was drawn correctly.

our recognizer then determines the user's shape as correct (Figure 5.4).

### *5.2.2 User Interface*

We target our interface for preschoolers, whom conventionally fall within the age group of 3-6 years in the United States, are still developing their fine motor skills, and are preparing for kindergarten. Our target user group additionally includes children whom are enrolled in kindergarten but are lacking in age-appropriate fine

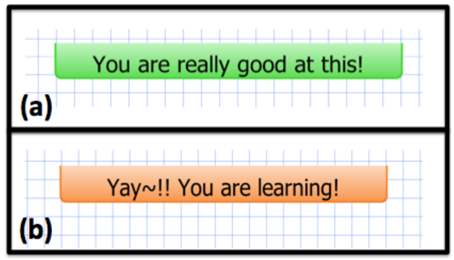



Figure 5.5: Our system provides different text feedback to children based on their shape-correctness. (a): for correct drawing and (b): for incorrect drawing, we encourage them to draw again with positive response.

motor skills compared to their peers.

Designing an interface for children has its own unique set of challenges. Interfaces for such applications should capture and maintain the interests of children that they hope to cater to, since children can easily lose their focus using applications that do not gauge their interest [125]. In order to address the challenges of maintaining children's attention, we primarily considered the following:

- **Ease of use.** Since preschoolers are one of the core target users of our application, a child should ideally be capable of independently using the sketch user interface, following an initial guided practice with a parent or teacher.

- **Ease of following.** The application should include animations and tracing dots for showing a child how to draw basic shapes and easily explore the problem space.

- **Positive and straightforward feedback.** The target users should be presented with the results of our three recognizers in a developmentally-appropriate and exciting way. Since informative and immediate feedback are crucial to children's motivation, our interface includes text feedback and audio cues that specifically cater to children. Furthermore, children can get frustrated easily from their negative outcomes. Because positive social comparative feedback was found to enhance learning of children [17], we made our feedback positive even in the face of negative outcome. For example, if a child's sketched input is incorrect, then the application reveals the text feedback of "Yay! You are learning" while simultaneously playing an audio cue corresponding to that result (Figure 5.5).

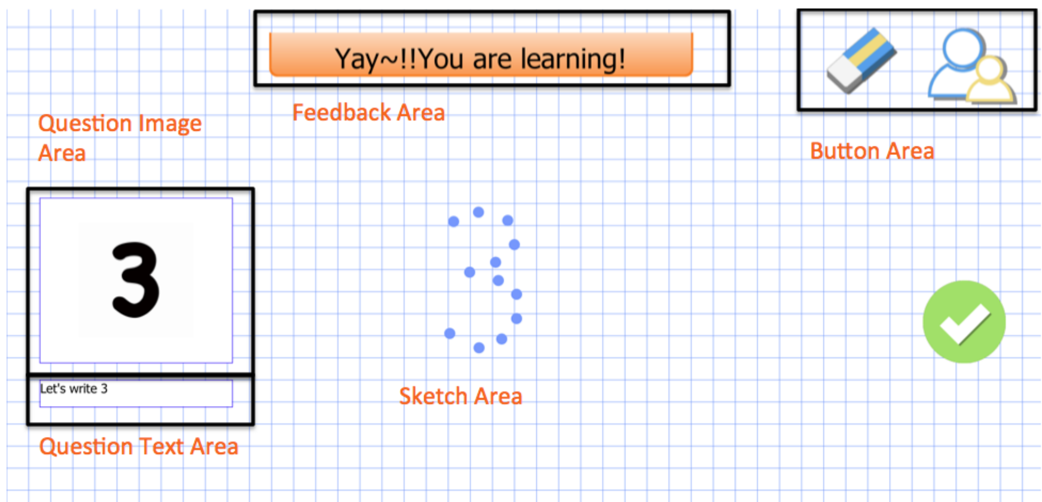



Figure 5.6: The application's sketch user interface. The interface will show the tracing dots on *sketch area* when the child could not draw the shape correctly.

Figure 5.6 depicts the user interface of our application containing the following five areas:

- **Question Text Area.** Prompts the child to sketch the shape.
- **Question Image Area.** Displays an animated image of the prompted shape, as well as instructions on how to draw that shape (Figure 5.8).

- **Feedback Area.** Displays the text feedback.

- **Sketch Area.** The space for children to sketch the shapes.

- **Button Area.** The collection of interactive buttons consisting of buttons for erasing and reporting. The report button is used to prompt the application to check the fine motor skill level from the sketch.

##### *5.2.2.1 Procedure*

Figure 5.7 explains the overall procedure of our interface. The application will let a child attempt to draw the shape correctly three times at maximum before moving on to the next question, and we designed the application as such so that the child does not feel frustrate or lose interest due to a single question. Our interface displays an animated image (Figure 5.8) that shows the correct drawing gesture in the instructions area for the child to learn or reference. When choosing "correct" drawing gestures, we referenced books recommended by our field-study preschool teachers (e.g. [229]).

##### *5.2.2.2 Pedagogical Feedback System*

As preschoolers develop their cognitive and fine motor skills, they apply these skills as they are learning at their own individual pace and approach [182]. We observed this learning contrast from the children in our user study, where many of the younger children (i.e., 3-4 years) lack knowledge of how to draw basic shapes compared to their older counterparts (i.e., 5-8 years). Due to these contrasts in domain knowledge, we developed the pedagogical feedback system of our application to support children's individual learning differences (Figure 5.7). Naka discussed that repeated hand writing facilitates children's learning [169]. To help children's learning, our pedagogical feedback system evaluates children's drawing, and asks children to

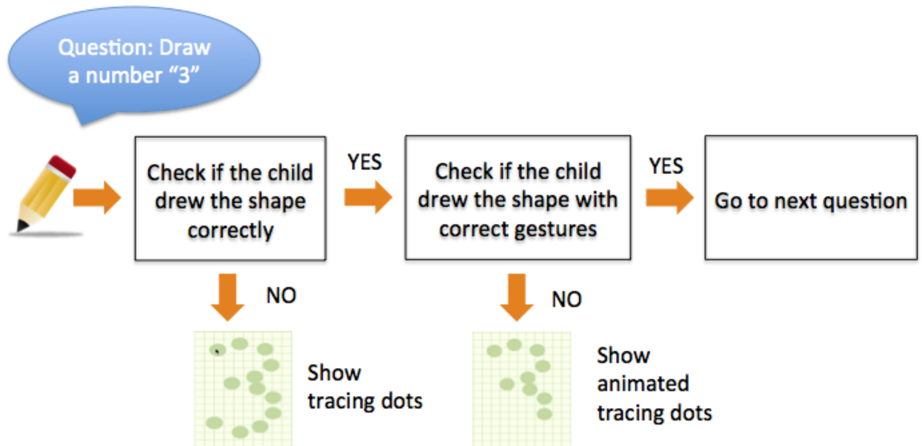



Figure 5.7: The application displays different instructions that is dependent on the the children's drawing correctness and learning progress.

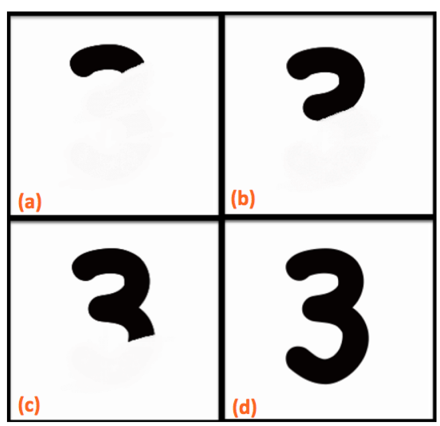



Figure 5.8: Children can see a view how a shape is drawn from an animated graphic. The animation displays the visualized model drawing at different stages from start to finish (a) - (d).

repeat drawing when they could not draw the shapes correctly. Specifically, our system first determines the shape and gesture correctness of each child's sketched input, and then provides differential instruction based on that determination. If the child sketched and gestured the shape correctly, the child will proceed to the next question with a new prompted shape (e.g., the number '4') with corresponding sound and text feedback. However, if the shape was incorrect, the application displays tracing dots of the corresponding shape for the children to guide their drawing to the correct sketching motions on *sketch area* (Figure 5.6). If instead the user drew the shape correctly but with an incorrect gesture, the child will be shown animated tracing dots (Figure 5.9) on *sketch area* (Figure 5.6). A tracing dot will appear every second in order to demonstrate to the child what the correct sketching motion is.

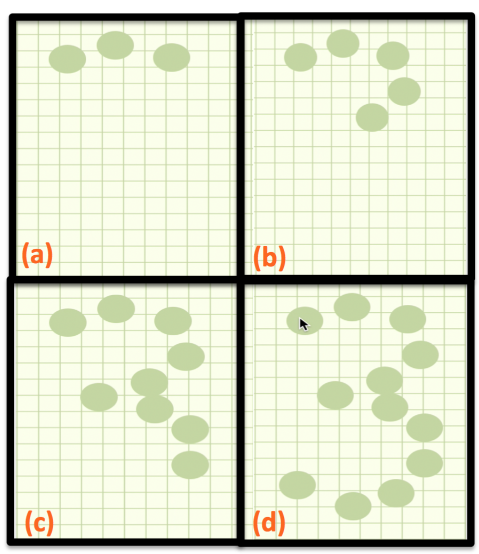



Figure 5.9: If the child drew the prompted shape incorrectly, the application displays a partial visualization of the shape with tracing dots while adding another dot every second after: (a) 3 seconds, (b) 5 seconds, (c) 9 seconds, and (d) 12 seconds.

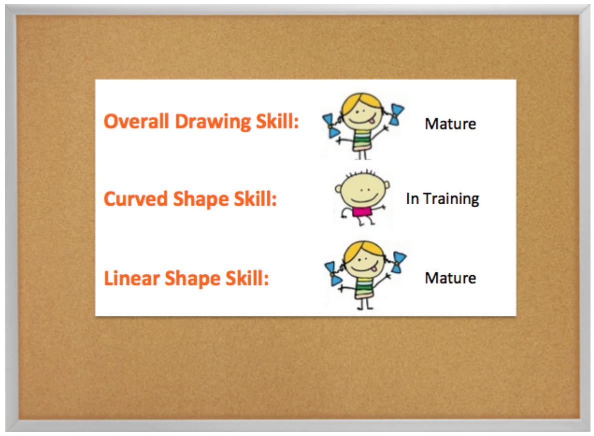



Figure 5.10: A feedback window for parents and teachers to view our system's assessment of their children's fine motor skills performance.

Once the child finishes the lesson containing the set of shapes as defined by the teacher or parent, the application automatically assesses the child's fine motor skill level. The post-lesson report screen (Figure 5.10) revealed after the child completes the lesson allows for the parent or teacher to receive an assessment of the child's fine motor skills per overall, curved (e.g. number '3'), and linear (e.g. number '1') shapes as "in training" or "mature", which provides a richer feedback rather than current manual assessments [56, 153] that only determine overall fine motor skills and automatic assessment [143] that only determines fine motor skills per drawing. Our report's information can better assist these adults in determining areas of improvement on the child's sketching performance, such as whether the child is struggling with curved or linear shapes, or whether the child is conceptually understanding or skillfully drawing the shapes.

## 5.3 Evaluation

### *5.3.1 Research Question*

Prior to designing the methodology of our user study, we were very interested in first defining research questions that appropriately guided the direction of the study. We therefore were particularly interested in investigating the following four specific research questions.

1. At what age do children show notable fine motor skill development?

2. Does our interface classify children's fine motor skills more accurately than the conventional method ("star drawing test"), and why does our method work better?

3. What are the limitations of the conventional assessment method (i.e. "star drawing test")? What are the limitations of the conventional assessment method (i.e. "star drawing test")?

4. Is there any potential way to extend "star drawing test" features into computer-based assessment?

5. Do children improve their drawing skills through our interface?

### *5.3.2 Participants*

We conducted a user study with a total of 89 children from, which we collected 1,853 sketches. Table 5.1 explains the demography of our participants. Our hypothesis was that older children (i.e., 5 years or more) would demonstrate better fine motors skills than younger children (i.e., 3-4 years), so we segmented the users into those age groups. We recruited the children by sending email with a flyer (Figure 5.11) to our university graduate students, staffs, and faculty members. We also advertized our research at Becky Gate's Children's Center and The Children's Museum of the Brazos Valley in our university area.

Table 5.1: Demographics of user group

| Age Group | Group size | Male/female | # of sketches |
|---|---|---|---|
| 3-4 years old | 54 | 24/30 | 1,082 |
| 5-8 years old | 35 | 14/21 | 771 |
| Total | 89 | 38/51 | 1,853 |

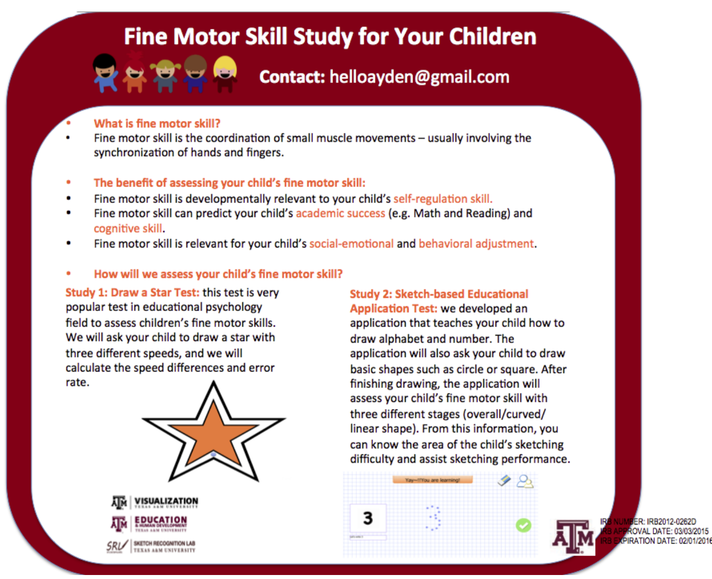



Figure 5.11: We recruited the child participants through the flyer.

### 5.3.3 Procedure

89 children completed the assessments from our interface (Figure 5.6) and 70 children (39: ages 3-4 years and 31: ages 5-8 years) volunteered to complete the

Figure 5.12: We proceeded our user study with their parents to make the children to feel comfortable.

additional conventional assessments (i.e., "star drawing test") (Figure 1.1). We communicated with the child to let them know that they can stop performing the user study at any time. However, every child voluntarily chose to complete the session and did so in approximately 20 minutes. Since our study participants consisted entirely of children, they were accompanied by their parents throughout the study (Figure 5.12).

In order to conduct the user study, we traveled either to the child's home or school/children's museum, or performed the user study at our research lab. In the case that the study took place at school/museum, we conducted the study in a private room restricted to the user study participants. Before we began each user study, we gave a brief explanation of the purpose of our study and the importance of evaluating fine motor skills.

The user study included one or two sessions. Every child (a total of 89) performed our interface test study, and 70 children volunteered to take the "star drawing test" as well. In case of they volunteered, we first conducted the "star drawing test" [153], where we asked each child to draw a star using a pencil and paper (Figure 1.1) at three different speeds – where the child was initially given no instruction, then instructed to draw fast, and then to draw slow – and measured their drawing durations manually using a stopwatch. Afterwards, we provided a Surface Pro 2 and a digital stylus to the child. With our application running on the tablet, we asked the child to draw shapes using the stylus in the presence of the parent by their side. In order to ensure that we procured the children's natural drawings and a clear understanding of the usefulness of our instruction system, we requested the parent to not help their children's drawings. In the case that a child did not know what shape to draw, the parent was allowed to explain the shapes. The interface test session had two parts: (1) *free drawing without our pedagogical feedback system*: the child first drew basic shapes (i.e., line, two lines, rectangle, square, curve, and triangle) each twice, which are generally used for assessing their domain knowledge and fine motor skills at preschool; and (2) *instructed drawing with our pedagogical feedback system* (Figure 5.7): they drew digits (1-3) and capital alphabet letters ('A','B', and 'C'), which we chose for the representative study data. Our interface assessed their fine motor skill results from each drawing – including the basic shapes – and finally saved an overview of the results to a spreadsheet.

### *5.3.4 Research Question 1: Fine Motor Skill Development Per Age*

In order to assess children's fine motor skill development per age, we introduce the result of (1) "star drawing test", (2) our interface test, and (3) hook planning evidence that we found during our user study.

#### *5.3.4.1 Star drawing test*

The "star drawing test" uses only drawing time differences for assessing fine motor skills. However, we collected both drawing time differences and error rates (i.e., the number of points that going outside the lines of the figure) for assessing children's fine motor skills that was introduced in [153], in order to determine if the children would demonstrate significant differences in both drawing time differences and error rates. We manually measured the error rates from the fast-speed drawing and calculated the drawing time difference between slow- and normal-speed drawings. As Krapp [147] discussed, children's motor skills are constantly developing, often at a rapid pace. We hypothesized that our age group (3-8 years) would have certain years that have developmental progress. Furthermore, we hypothesized that older children of 5 years or more will have greater time differences and smaller error rates compared to younger children of 3-4 years.

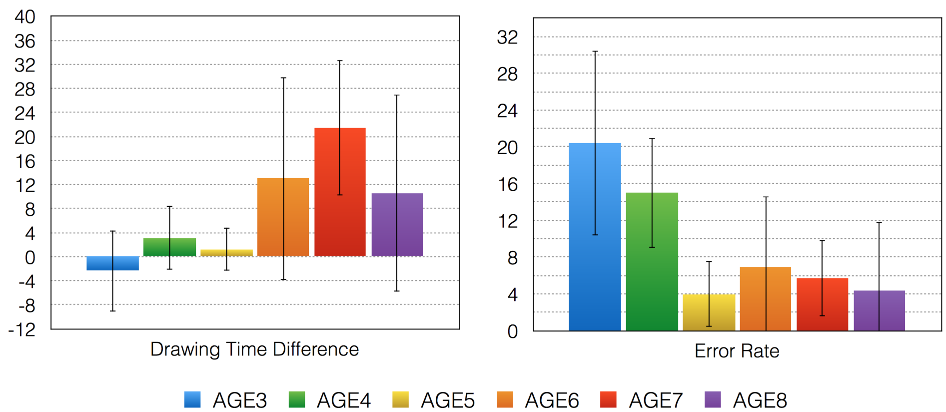



Figure 5.13: We found that after age 6 years, the drawing time difference significantly increased. From age 5 years, error rates significantly decreased. However, the standard deviations of drawing time differences and error rates of each age group were high.

Figure 5.13 explains the average values of time differences and error rates. As seen in Figure 5.13, the drawing time difference significantly increases from age 6 years and error rate significantly decreases from age 5 years (which explains better self-regulation and fine motor skills [56]). We believe the reason is that ages 5 and 6 years are the ages in which children enter kindergarten in the United States, and thus will have more drawing practices than younger children (3-4 years) and more advanced physical development. During the user study, the parents of 5- and 6-year-olds explained that they frequently practice drawing for school-readiness. We believe that their drawing practice and physical development determined the sharp changes in their fine motor skill stages.

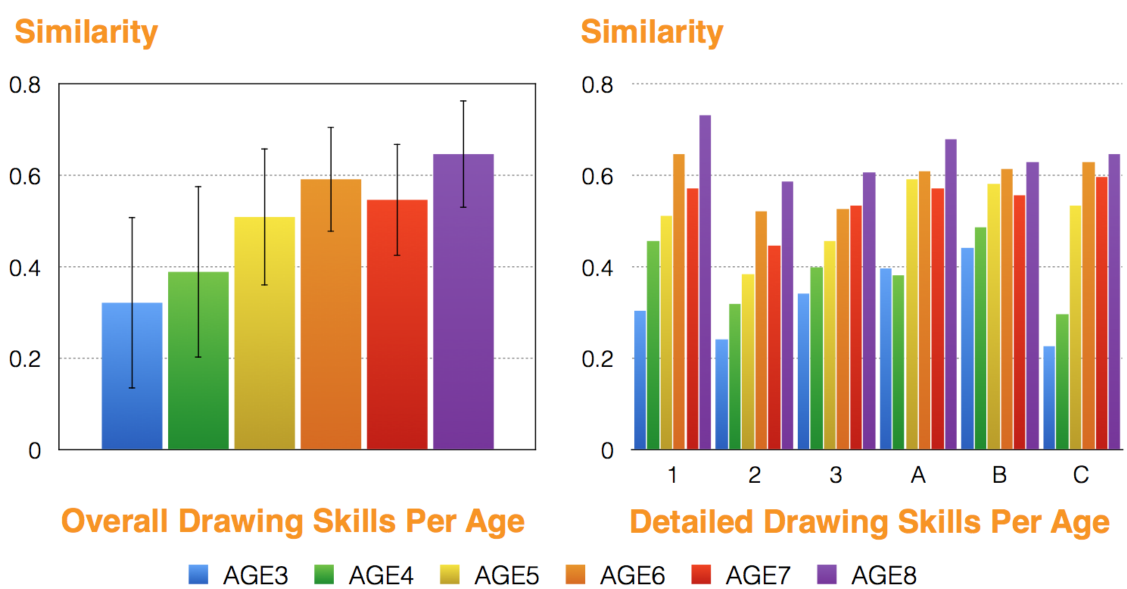



Figure 5.14: The results of similarity values per by age group (Left: overall similarity values per age and Right: detailed shape similarity values per age). When we assess the children's similarity value per age, about after 5 years, their similarity values were higher than younger children.

#### *5.3.4.2 Interface test*

To assess the fine motor skill development per age, we calculated similarity values of children's digital drawings from interface test using the modified Valentine recognizer [141, 252]. As we explained earlier, the recognizer returns a similarity value which lies in the [0..1] interval, with 1 denoting that the user's drawing is identical to the designated shape. As a result, if the similarity value of the child's drawing is closer to 1, it means the child drew a shape correctly. Figure 5.14 and Table 5.2 explains our similarity value results of the children's digital drawings from our interface test (Left of Figure 5.14: overall similarity value per each age group, Right of Figure 5.14: detailed shape (i.e. digits: 1, 2, 3, and letters: 'A', 'B', 'C') similarity values per each age group). When we assessed the children's similarity value per age, about after 5 years, their similarity values were higher than younger children. Furthermore, when we assessed each age group's standard deviations of similarity values from the overall shape drawings (Left of Figure 5.14), young children had higher standard deviations in their similarity values (0.188: age 3 and 0.203: age 4) than older children (lower than 0.15). When we assessed their detailed shape drawings' standard deviations in their similarity values (Table 5.2), young children had higher standard deviations in their similarity values than older children for most of the shapes.

As a result, we believe that the similarity value results will indicate their fine motor skills, and after ages 5 and 6 years children will have better fine motor skills than younger children, which shows the same results with our "star drawing test".

Table 5.2: Standard deviations of similarity values

| Age Group \Shape | 1 | 2 | 3 | A | B | C | Overall |
|---|---|---|---|---|---|---|---|
| Age 3 | 0.197 | 0.162 | 0.170 | 0.106 | 0.142 | 0.243 | 0.188 |
| Age 4 | 0.218 | 0.183 | 0.192 | 0.160 | 0.192 | 0.220 | 0.203 |
| Age 5 | 0.172 | 0.123 | 0.124 | 0.115 | 0.125 | 0.155 | 0.150 |
| Age 6 | 0.146 | 0.064 | 0.079 | 0.123 | 0.067 | 0.114 | 0.114 |
| Age 7 | 0.170 | 0.102 | 0.068 | 0.115 | 0.111 | 0.109 | 0.122 |
| Age 8 | 0.127 | 0.124 | 0.050 | 0.180 | 0.062 | 0.096 | 0.118 |

#### *5.3.4.3 Hook Planning Evidence in Digital Drawings*

Our user study result from "star drawing test" and "interface test" explained the fine motor skill development per each age. While we are performing our user study, we found another evidence about the fine motor skill stage. We observed that children's drawings can show their decision-making process. As Bindman et al. [26] discussed, as a child begins to write, they must first generate and articulate an idea, which reinforces vocabulary and background knowledge. In addition, the child must employ code-related skills to decide which marks to place on the page and in what order.

We hypothesized that older children would have a better grasp of this decision-making process in their sketches, because they would have more domain knowledge than younger children. To determine the level of planfulness exhibited by each child, we focused on the "hook" feature in sketches (Figure 5.15). When users draw sketches on sketch panels, the sketches contain unexpected points at the end of their strokes, which look like "hooks". Generally, sketch recognizers eliminate these hooks to avoid unexpected recognition results [141]. However, we found that hooks show their planfulness by pointing to the next stroke's start point.

To analyze the hook distributions, we assessed sketch data that has more than two strokes (i.e. '1', 'A','B', square, rectangle, and cross). During the interface test, each child drew the basic shapes (i.e. square, rectangle, and cross) two times. In terms of more complex shape drawings (i.e. '1', 'A', and 'B'), we assessed their sketches when they did not have any tracing dots to know their decision-making process. Finally, we analyzed 362 sketch data from the user study group (Table 5.1).

When we analyzed their hook features, from age 4 years, the children's sketches include hook features that show plan to the next stroke in their sketches (Figure 5.16).

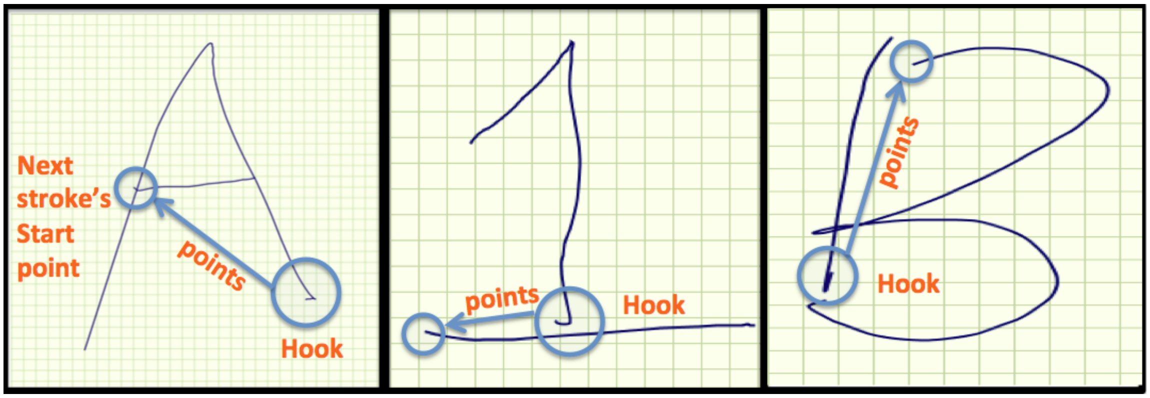



Figure 5.15: The "hook" (end point of the current stroke) points to the next stroke's start point, which explains their decision-making process.

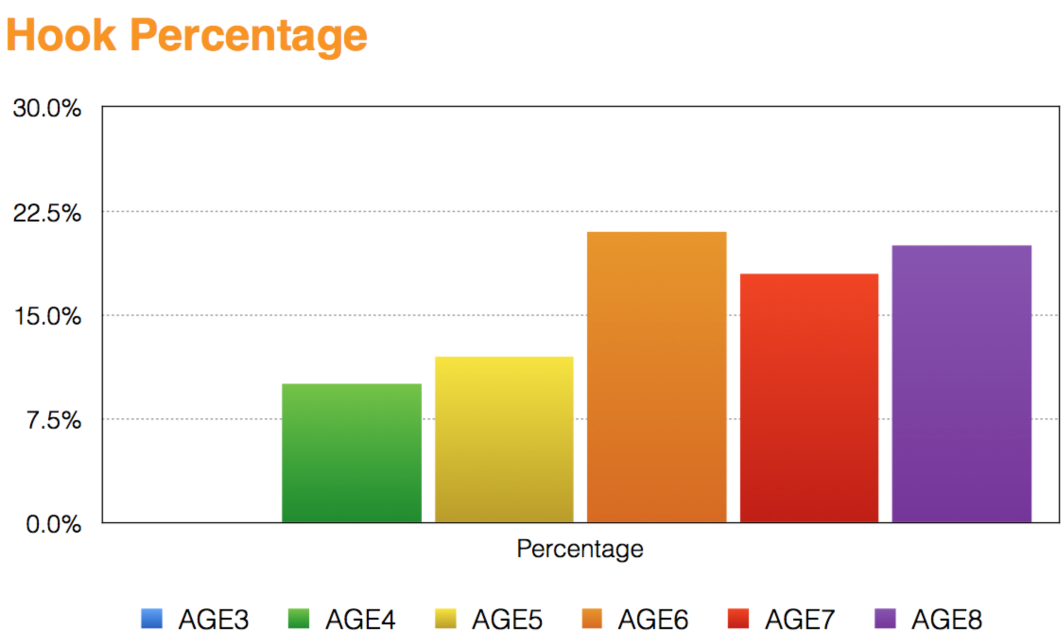



Figure 5.16: The hook features were found from age 4 years' sketches.

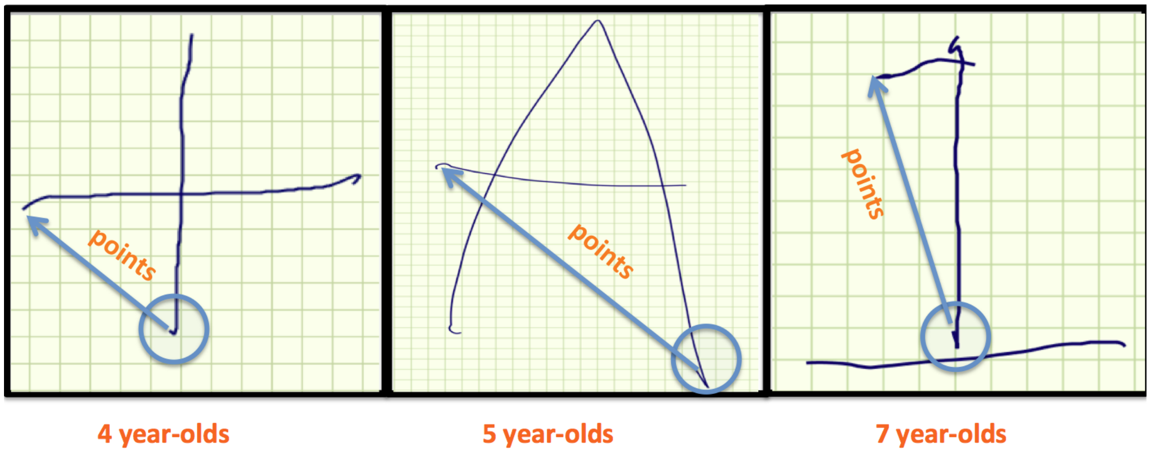



Figure 5.17: Older children (+5 years) contained hooks in more complex shapes. On the other hand, age 4 years' sketches contained hooks in basic shapes.

On the other hand, the youngest children's (age 3 years) sketches did not have hook features that show the plans. Age 6-8 years children had higher hook rates in their sketches than age 4-5 years.

Furthermore, when we analyzed their hook distributions (Table 5.3), most of the age 4 years contained hooks in basic shapes such as cross or square rather than more complex shapes (i.e. '1' and 'B'). On the other hand, older children (+5 years) contained hooks in more complex shapes. Figure 5.17 shows example of hook features in age groups. From this finding, we concluded that older children's drawings show their decision-making process by "hook" features.

When we compared the similarity values (sketch correctness values) of age 4 years, the group that contains "hook" feature in their sketches had higher similarity values than those who do not have (Figure 5.18). From this finding, we believe that "hook" features could predict their drawing skills. We also concluded that from age 4 years, they would be familiar with shape drawings and develop their decision-planning process while developing their domain knowledge.

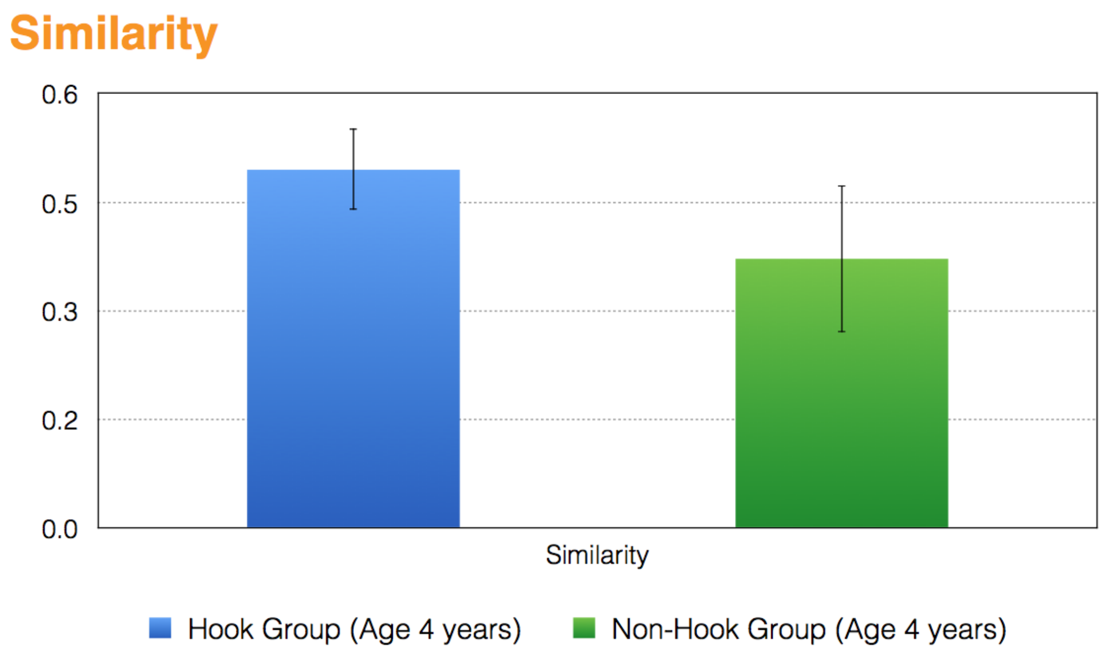



Figure 5.18: When we compared the similarity values, those who have hook feature in their sketches had better drawing skills than those who do not have hook.

### *5.3.5 Research Question 2: Better Fine Motor Skill Classification Performance than the Star Drawing Test*

As previously mentioned, a major problem with conventional assessment approaches (i.e., "star drawing test") is that it does not assess children's drawing skills, but instead only measures their drawing time differences. Since our interface's fine motor skill classifier assesses drawing skills by "how they drew", we hypothesized that our interface would perform better than the "star drawing test". Therefore, in order to compare the fine motor skill classification performance between our interface and the "star drawing test", we followed the following procedures:

1. To assess children's actual fine motor skill levels, we employed a style of measurement [44] that we used at the preschool during our initial field study. This

Table 5.3: Distributions of hooks in shapes

| Age Group \Shape | 1 | A | B | cross | rectangle | square |
|---|---|---|---|---|---|---|
| 3 years old | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 years old | 0 | 6/28 | 0 | 7/32 | 1/32 | 3/32 |
| 5 years old | 0 | 3/11 | 1/15 | 4/18 | 1/18 | 0/18 |
| 6 years old | 2/10 | 4/9 | 4/19 | 8 | 0 | 0 |
| 7 years old | 1/6 | 3/7 | 2/13 | 4/16 | 0 | 0 |
| 8 years old | 0 | 3/5 | 4/13 | 3/10 | 0 | 0 |

measure indicates that as children develop, they have proficiency in drawing increasingly more shapes. In our study, three experts (i.e., a computer scientist and two elementary school teachers who both have experience with young children's sketches) met and manually labeled the fine motor skills for each child. The experts viewed printouts of the basic shape sketches (i.e., line, two lines, circle, rectangle, square, and triangle) that were drawn on the tablet during the interface test, and the experts determined their drawing correctness and labeled their fine motor skill levels as "mature" if the children drew the every basic shape correctly, and labeled "in training" otherwise.

2. To assess children's fine motor skills from the "star drawing test", we first decided the age 6 years' mean time of time difference for our threshold, because we found that after age 6 years, they have sudden changes in drawing time difference during our study (Figure 5.13). We chose 11.5 seconds to be the threshold, which was the mean time of age 6 years from the study [56] as they included more child participants than us. If a child's drawing time difference is higher than 11.5 seconds, we then labeled their fine motor skills as "mature".

3. We assessed children's fine motor skills from our interface test that the KimCHI classifier [143] determined their skills as either "in training" or "mature".

Table 5.4: Interface Test results of classifying fine motor skills in In Training (t,t') vs. Mature (m,m').

| | | **Actual Value** | | |
|---|---|---|---|---|
| | | **t** | **m** | **total** |
| **Test Value** | **t′** | 34 kids | 5 kids | 39 kids |
| | **m′** | 2 kids | 29 kids | 31 kids |

Table 5.5: Star Drawing Test results of classifying fine motor skills in In Training (t,t') vs. Mature (m,m').

| | | **Actual Value** | | |
|---|---|---|---|---|
| | | **t** | **m** | **total** |
| **Test Value** | **t′** | 32 kids | 18 kids | 50 kids |
| | **m′** | 4 kids | 16 kids | 20 kids |

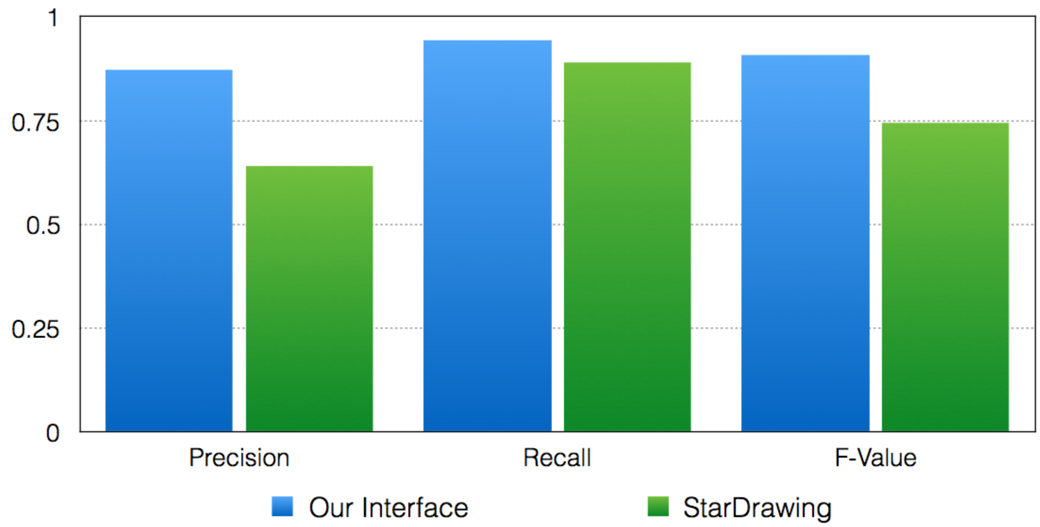



Figure 5.19: Our interface determined children's fine motor skills better than the "star drawing test"

Figure 5.19 and Table 5.4 and 5.5 show the results of our system compared with traditional assessments. Our interface classified children's fine motor skills with a precision of 0.872, a recall of 0.944, and an f-measure of 0.907. On the other hand, the "star drawing test" classified their fine motor skills with a precision of 0.64, a recall of 0.899, and an f-measure of 0.744. This verifies that our interface classifies fine motor skills better than the traditional "star drawing test" assessment.

### *5.3.6 Research Question 3: Limitation of Star Drawing Test*

During the user study, we observed the limitations of the "star drawing test". The first limitation was from high variation of drawing time differences and error rates in age group. As seen in Figure 5.13, the standard deviations of drawing time differences of each age group was high, especially in the ages of 6-8 years. Figure 5.14 also shows high variations of similarity values of children's drawings in age group. As a result, the high standard deviations make the time differences between ages statistically insignificant, except possibly in the case of 5 years, therefore indicating that time differences and error rates are not reliable features for fine motor skill evaluation.

The second limitation was from “star drawing test” only measures drawing time differences. During our user study, one 3 year old child earned a “mature” rating from the “star drawing test” because the value of the child’s drawing time difference between slow (28.32 seconds) and normal drawing (15.98 seconds) was 12.34 seconds, which is higher than our drawing time difference threshold (11.5 seconds), which was the mean time of age 6 years from the study [56]. However, when we assessed the child’s drawings, the child could not draw many of the basic shapes such as circle or square, and our interface reported that the child’s skills were “in training” not “mature”. Another example is a 6-year-old child who drew every basic shape (e.g. circle and square) correctly. The child was very careful about drawing when no speed instructions were given (i.e., normal drawing time of 20.95), so when the child was instructed to draw slowly, he drew only 4.52 seconds slower. The “star drawing test” labeled this child as “in training” because the initial conscientiousness meant that the time difference did not meet the 11.5 seconds threshold for “mature.” On the other hand, our interface determined the child’s fine motor skills as “mature”.

### *5.3.7 Research Question 4: Potential Way to Extend Star Drawing Test Features into Computer-based Assessment*

The previous section explains that “star drawing test” has limitation, because they are determining fine motor skills by drawing time difference. As there are many variations in their time drawings, determining optimal threshold for determining fine motor skill cannot be standardized.

We hypothesized that if we extend those five features (normal/fast/slow drawing times, time difference, and error rate) in "star drawing test" into computer-based classifier, we would be able to determine their fine motor skills and age information. To do this, using those features from our child participants (Table 5.6), we tried to differentiate age information with Weka system [108].

Table 5.6: Demographics of user group

| Age Group | Group size |
|---|---|
| 3 years old | 19 |
| 4 years old | 20 |
| 5 years old | 9 |
| 6 years old | 10 |
| 7 years old | 8 |
| 8 years old | 4 |
| Total | 70 |

We first calculated linear correlation values between five features used in "star drawing test" with age information (i.e. age 3-8 years). Table 5.7 describes the correlation between those features (x value) and age information (y value). Every feature except "slow drawing" had lower than 5% of p-value.

Table 5.7: Regression output for classifying ages for curved shape.

| Feature | Multiple R-value | P-value |
|---|---|---|
| Time Difference | 0.570630122 | 2.50313E-07 |
| Error Rate | 0.682180568 | 1.49732E-10 |
| Normal Drawing | 0.047115572 | 0.04711557 |
| Slow Drawing | 0.052110009 | 0.668341933 |
| Fast Drawing | 0.49958023 | 1.06857E-05 |

Next, we applied supervised Resample filter in Weka system to make their age group into equal distribution by generating the sample with replacement or without replacement. To know the optimal subset for deciding age information, we applied BestFit selection built-in to the Weka system [108] with 10-fold cross-validation from four feature sets (normal/fast drawing, time difference, error rate) used in "star drawing test" except for slow drawing time, which had higher than 5% of p-value during our linear correlation procedure. Table 5.8 shows that selected feature for determining age information was only "time difference". As the current "star drawing test" only uses time difference for assessing fine motor skills, this study validates that time difference is the optimal feature set to deciding fine motor skills and age information.

Table 5.8: Our optimal features for classifying ages within children.

| Feature |
| --- |
| normal drawing time (0%) +<br>fast drawing time (0%) +<br>time difference (100%) +<br>error rate (0%) |

To know the best classifier to determine their age (fine motor skill) information, we tried seven classifiers: Bayes Net, BFTree, MultilayerPerceptron, Naive Bayes, Random Tree, Random Forest, and RBFNetwork. To find the optimal classifier for recognizing children's age information by sketches, we took the selected feature sets and found that the Random Forest classifier performed better than other classifiers (Table 5.9) with 10-fold cross-validation.

Using those selected features, we were able to determine children's curvature-drawing (fine motor) skills with a precision of 0.762, recall of 0.743, and an f-measure of 0.743 with 10-fold cross-validation with Random Forest.

Table 5.9: Best top-performing techniques for classifying age using Star Drawing Test

| Classifier (Accuracy) |
|---|
| Random Forest (74.29%) |
| Random Tree (72.86%) |
| RBFNetwork (65.71%) |
| BFTree (52.86%) |
| MultiPerceptron (51.43%) |
| Naive Bayes (47.14%) |
| NBTree (44.29%) |
| Bayes Net (24.29%) |

From this study, we concluded that features in "star drawing test" has high potential to improve its fine motor skill assessment ability by computer-based classifier. However, as our study data set has many variations in age groups, we need to recruit more child participants to validate this study.

### *5.3.8 Research Question 5: Drawing Skill Improvement with EasySketch*

In order to assess whether or not children improved their drawing skills with our interface, we compared similarity values from the modified Valentine recognizer [141, 252] of the sketches before (i.e., their original drawing) and after following tracing dots. As we described earlier, if the similarity value of the child's drawing is closer to 1, it means the child drew a shape correctly. As a result, if the similarity value increases after following tracing dots, it means they can draw shapes better than before tracing dots (better drawing skills).

When we grouped the children as young children (age 3-4 years) and older children (age 5+ years), each group improved their drawing skills with higher similarity values after following the tracing dots (Figure 5.20). We also noticed that young children remarkably improved their drawing skills by 0.268. Their parents positively

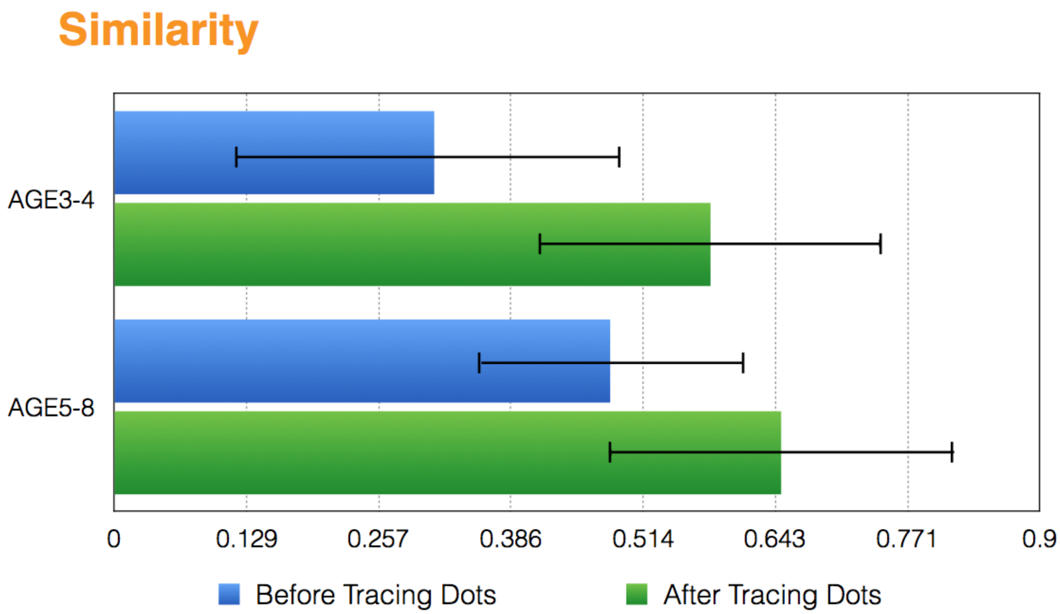



Figure 5.20: After following tracing dots, young children's similarity value enhanced by 0.268 and older children's similarity value enhanced by 0.166.

evaluated our interface that improves their children's drawing skills. The example of the feedback from their parents were:

- **Parent of child 1 (age 3 years)**: At first time, she could not draw the alphabet 'A' correctly. And, I didn't believe that she would follow tracing dots well. However, when the interface showed the tracing dots, my kid followed the tracing dots and finally drew the 'A'!

- **Parent of child 9 (age 3 years)**: It is hard to teach how to draw shapes on paper to my kid because she does not enjoy drawing. However, she enjoyed this software because it runs on computer. The tracing dots were easy to follow.

# 6. CONCLUSION

Pen-based assessments such as "star drawing test [145, 167]" have been used to assess children's fine motor skills and school readiness. However, the activities are time-consuming for researchers and prone to human error when implementing manual measurements [143]. Furthermore, the current assessment methods do not analyze children's sketches, but instead only measures their drawing durations. In order to assess children's fine motor skills more correctly and reduce the researchers' manual efforts, we introduced our digital-based assessments.

## 6.1 KimCHI and KimCHI2: Fine Motor Skill Classifiers

To solve the limitations of the current paper-based fine motor skill assessments, we introduced our fine motor skill classifiers (KimCHI [142, 143, 144] and KimCHI2). The KimCHI classifier determines children's fine motor skills based on their overall drawing skills. On the other hand, the KimCHI2 classifier determines their fine motor skills based on their curvature- and corner-drawing skills. We generated 130 sketch features proposed by Cali [94], Hse [131], Long [155], Paulson [177], and Rubine [215]. From the sketch features, we analyzed how children are drawing.

The KimCHI classifier determined children's age information with a precision of .909, recall of .909, p-value of 0.001, and an f-measure of .904 with 10-fold cross-validation and gender information with a precision of 0.757, recall of 0.73, p-value of 0.001, and an f-measure of 0.728 with 10-fold cross-validation. We found that curvature-related features such as $DCR$ were chosen for age classification and density and curvature-related features were chosen for gender classification. From the result, we concluded that better fine motor skill children can draw curvatures well, and girls are drawing more considerably than boys.

The KimCHI2 classifier determined children's curvature-drawing skills with a precision of 0.82, recall of 0.82, and an f-measure of 0.82 with 10-fold cross-validation, and corner-drawing skills with a precision of 0.783, recall of 0.78, and an f-measure of 0.781 with 10-fold cross-validation. We found that curvature-related sketch features such as *DCR* were chosen for curvature-drawing skill classification and line-drawing related sketch features such as *Polyline Test* were chosen for corner-drawing skill classification. Furthermore, we proved that sketch features (*DCR* and *Polyline Test*) can explain their fine motor skill developmental stages.

## 6.2 EasySketch: A Sketch-based Educational Interface

In order to assess children's fine motor skills more correctly and reduce the researchers' manual efforts, we designed, developed, and evaluated a sketch-based educational interface to automate assessment and provided more detailed analysis. The interface both determines children's fine motor skills and teaches children how to draw and provides children's fine motor skills and school readiness information to parents and teachers. During the user study, we found that our interface assessed children's fine motor skills better than the conventional approach (i.e. star drawing test), and the children enhanced their drawing skills through our pedagogical feedback system. Furthermore, during our user study, we found that there is a period of peak growth at age five; five year old children have markedly better fine motor skills than younger children (i.e. 3-4 years). We found another evidence that hook features in their sketches can explain their decision-making process. We believe that their drawing practice and physical development play a strong role in the sharp changes in their fine motor skill stages. As children become more exposed to using pen and touch interaction [134, 168, 192], we believe that this research can assist researchers, designers, and educators in assessing children's fine motor skill stages on digital drawings and also help children to support their self-regulation skills and school-readiness.

# 7. FUTURE WORK

This research presented our research that classifies children's fine motor skills based on digital drawings. During our user study using EasySketch, we found that our interface classified children's fine motor skills better than the conventional approach and improved children's drawing skills. To further validate the usability of our interface, we are planning to employ our interface to preschool or clinic and conducting a longitudinal study. From the study, we will further test our interface and its impact on improving young children's fine motor skills and school readiness.

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# APPENDIX A

# CURVATURE DRAWING REGRESSION ANALYSIS

Table A.1: Regression output for classifying ages for curved shape.

| Feature | R-value | P-value |
|---|---|---|
| Average distance between closest point to each corner of the bounding box [177] | 0.113682958 | 0.028784241 |
| Average curvature of the stroke [177] | 0.263677214 | 2.65925E-07 |
| The error of the best fit line of the direction graph [177] | 0.259521329 | 4.14678E-07 |
| Direction change ratio [177] | 0.233121645 | 5.85388E-06 |
| Get the distance (normalized by bounding box size) between the furthest corner and the stroke [177] | 0.173678978 | 0.00079362 |
| The endpoint to stroke length ratio of the stroke [177] | 0.110142894 | 0.034181857 |
| The angle of the major axis relative to center [177] | 0.014698795 | 0.054412247 |
| The error of the best fit line of the direction graph [177] | 0.134253699 | 0.00972667 |
| Max distance between closest point and each corner [177] | 0.173678978 | 0.00079362 |
| The error of the best fit line of the direction graph [177] | 0.277952166 | 5.45174E-08 |
| The maximum curvature to average curvature value [177] | 0.076639429 | 0.141192304 |
| Minimum distance between closest point and each corner [177] | 0.131074535 | 0.011614859 |
| The normalized distance between direction extremes [177] | 0.191202697 | 0.000215939 |
| The number of revolutions (based on direction graph) that the stroke makes [177] | 0.042240002 | 0.41787405 |
| Percentage of Direction Window Passed [177] | 0.429574005 | 4.779E-18 |
| Slope of the direction graph [177] | 0.00034616 | 0.994705281 |
| Standard deviation between closest point and each corner [177] | 0.00034616 | 0.994705281 |
| Length of the stroke [177] | 0.116469329 | 0.025066163 |
| The error of the line fit [177] | 0.084867853 | 0.103126068 |
| The least squares error of the fit / stroke length [177] | 0.019785905 | 0.704436256 |
| Get the error of the arc fit [177] | 0.062529641 | 0.230183479 |
| The estimated radius of the arc [177] | 0.065723806 | 0.207197506 |
| Get the arc to area ratio [177] | 0.058100684 | 0.264957845 |
| The angle between the endpoint [177] | 0.131360577 | 0.011432611 |
| Curve Error [177] | 0.272028581 | 1.06401E-07 |
| Get the error of the poliline fit [177] | 0.100330984 | 0.053824921 |
| Number of strokes [177] | 0.137832969 | 0.007931255 |
| Get the percentage of substrokes that passed a line test [177] | 0.010793533 | 0.836071345 |
| Get the error of the elipse fit [177] | 0.141960058 | 0.006232676 |
| Get the error of the circle fit [177] | 0.225811535 | 1.1564E-05 |
| Get the major axis to minor axis length ratio [177] | 0.205936287 | 6.58739E-05 |
| Get the error of the spiral fit [177] | 0.059328423 | 0.254975813 |

Table A.2: Regression output for classifying ages for curved shape (Continued).

| Feature | R-value | P-value |
|---|---|---|
| Get the percentage of the radius test that passed [177] | 0.037928673 | 0.467001935 |
| Get the average radius to bounding box radius ratio [177] | 0.065678965 | 0.207508267 |
| Get the max distance from a point to the center divided by the average radius [177] | 0.041794428 | 0.42280639 |
| Distance between two points that meet at the head [177] | 0.041620219 | 0.424744019 |
| Size difference between last two strokes (the head) [177] | 0.00258766489460978 | 0.960436053 |
| Number of intersections between the ends of the head and the shaft [177] | 0.016617398 | 0.750043139 |
| The error of the rectangle fit [177] | 0.117379857 | 0.023944544 |
| Get the major axis to bounding box diagonal length ratio [177] | 0.230277584 | 7.64936E-06 |
| Perimeter (of bounding box) to stroke length ratio [177] | 0.081134085 | 0.119248893 |
| Number of segmented strokes [177] | 0.100330984 | 0.053824921 |
| Stroke length to perimeter (of bounding box) ratio [177] | 0.081134085 | 0.119248893 |
| Get the width to height ratio of the square [177] | 0.1014713 | 0.051143754 |
| Get the error of the diamond fit [177] | 0.120366477 | 0.120366477 |
| Get the perimeter (of bounding box) to stroke length ratio [177] | 0.074933437 | 0.150286724 |
| Get the major axis to bounding box diagonal length ratio [177] | 0.195518717 | 0.000153868 |
| Get the width to height ratio of the square fit used for the diamond fit [177] | 0.000153868 | 2.95667E-05 |
| Stroke density [177] | 0.018029853 | 0.729593915 |
| Height to width ratio of bounding box [177] | 0.122416134 | 0.01849183 |
| Wave segment size [177] | 0.210589518 | 4.44692E-05 |
| Get the percentage of the slope test that passed [177] | 0.343231139 | 1.14392E-11 |
| Get the ratio between the smallest and largest segment of the wave segmentation [177] | 0.081090581 | 0.119447723 |
| Get the ratio between the smallest segment and the sum [177] | 0.020716072 | 0.691237739 |
| Get the angle between the middle segments [177] | 0.060179196 | 0.248213324 |
| Get the percentage of the horizontal alignment test that passed [177] | 0.03835399 | 0.462017932 |
| Get average slope of first and last segment [177] | 0.057264329 | 0.271909402 |
| Get percentage of slope test that passed [177] | 0.026332867 | 0.613631549 |

Table A.3: Regression output for classifying ages for curved shape (Continued).

| Feature | R-value | P-value |
|---|---|---|
| Ratio between largest and smallest segment [177] | 0.344785603 | 9.1113E-12 |
| Density of sub dot [177] | 0.270090109 | 1.31975E-07 |
| Number of revolutions of sub dot [177] | 0.24804383 | 1.36003E-06 |
| Convex hull area / bounding box area [94] | 0.249782597 | 0.249782597 |
| Convex hull area / enclosing rectangle area [94] | 0.111222683 | 0.032450891 |
| Largest quadrilateral area / convex hull area [94] | 0.23215282 | 6.41484E-06 |
| Largest quadrilateral area / enclosing rectangle area [94] | 0.165988905 | 0.00135385 |
| Largest triangle area / bounding box area [94] | 0.062714431 | 0.228806368 |
| Largest triangle area / convex hull area [94] | 0.145829952 | 0.004944247 |
| Largest triangle area / enclosing rectangle area [94] | 0.125800183 | 0.015467094 |
| Largest triangle area / largest quadrilateral area [94] | 0.024830167 | 0.024830167 |
| Absolute value of bounding box's Y difference / bounding box's X difference [94] | 0.096758123 | 0.096758123 |
| Enclosing rectangle's distance ratio [94] | 0.168195064 | 0.168195064 |
| Absolute value of bounding box's X difference / x value movement in sketch [94] | 0.090234379 | 0.083032138 |
| Number of points inside the triangle [94] | 0.145319772 | 0.005099109 |
| Convex hull area$^2$ / convex hull area [94] | 0.005099109 | 0.000181278 |
| Convex hull perimeter / stroke length [94] | 0.017185268 | 0.017185268 |
| Convex hull perimeter / bounding box perimeter [94] | 0.00010985 | 0.00010985 |
| Convex hull perimeter / enclosing rectangle perimeter [94] | 0.23136724 | 6.90694E-06 |
| Largest quadrilateral perimeter / convex hull perimeter [94] | 0.221780729 | 1.66732E-05 |
| Largest quadrilateral perimeter / enclosing rectangle perimeter [94] | 0.238289194 | 3.5692E-06 |
| Largest triangle perimeter / bounding box perimeter [94] | 0.090910811 | 0.080740543 |
| Largest triangle perimeter / convex hull perimeter [94] | 0.141776629 | 0.006300618 |
| Largest triangle perimeter / enclosing rectangle perimeter [94] | 0.200235333 | 0.000105355 |
| Largest triangle perimeter / quadrilateral perimeter [94] | 0.017054278 | 0.743698604 |
| Stroke Length / convex hull perimeter [94] | 0.077389987 | 0.077389987 |
| Difference of bounding boxes' largest Y value and smallest Y value / y value movement in sketch [94] | 0.180140871 | 0.000497906 |
| Zernike1 [131] | 0.135233607 | 0.009202371 |
| Zernike2 [131] | 0.249983407 | 1.11717E-06 |
| Zernike3 [131] | 0.11798451 | 0.11798451 |
| Zernike4 [131] | 0.061259981 | 0.239804171 |

Table A.4: Regression output for classifying ages for curved shape (Continued).

| Feature | R-value | P-value |
|---|---|---|
| Zernike5 [131] | 0.184072207 | 0.000372017 |
| Zernike6 [131] | 0.230124243 | 7.75975E-06 |
| Zernike7 [131] | 0.220361055 | 1.89363E-05 |
| Zernike8 [131] | 0.172071518 | 0.172071518 |
| Zernike9 [131] | 0.140079902 | 0.006961261 |
| Zernike10 [131] | 0.171806383 | 0.000905716 |
| Zernike11 [131] | 0.016671153 | 0.749261578 |
| Zernike12 [131] | 0.054624464 | 0.294661706 |
| Zernike13 [131] | 0.137700525 | 0.007992023 |
| Zernike14 [131] | 0.16088433 | 0.001906346 |
| Zernike15 [131] | 0.162294469 | 0.001736064 |
| Zernike16 [131] | 0.180474163 | 0.000485866 |
| Zernike17 [131] | 0.104514244 | 0.044529238 |
| Zernike18 [131] | 0.048602975 | 0.351189459 |
| Zernike19 [131] | 0.203125296 | 8.31719E-05 |
| Zernike20 [131] | 0.155760091 | 0.002661714 |
| Zernike21 [131] | 0.159086121 | 0.002145625 |
| Zernike22 [131] | 0.118783496 | 0.022300451 |
| Zernike23 [131] | 0.08581921 | 0.099307152 |
| Calculates the cosine of the initial angle [155] | 0.08638339 | 0.097096066 |
| Calculates the sine of the initial angle [155] | 0.053945874 | 0.300709895 |
| Get the length of the diagonal of the bounding box [155] | 0.106098436 | 0.106098436 |
| Get the angle of the diagonal of the bounding box [155] | 0.021571486 | 0.679181754 |
| Calculates the distance between the first and last point [155] | 0.143400253 | 0.005721646 |
| Calculates the cosine between the first and last point [155] | 0.102623767 | 0.048548112 |
| Calculates the sine between the first and last point [155] | 0.091324294 | 0.079365128 |
| Computes the total gesture length [155] | 0.117066326 | 0.024325768 |
| Sum of angle changes between points [155] | 0.076115769 | 0.076115769 |
| Computes the sum of the absolute value of the angles at each mouse point [155] | 0.238061488 | 3.64873E-06 |
| Computes the sum of the squared values of the angles at each mouse point [155] | 0.216312915 | 0.216312915 |
| Calculates the gesture aspect, which is abs (45 degrees - angle of bounding box) [155] | 0.096412181 | 0.063944299 |
| The sum of gesture intersegment angles whose absolute value is less than 19 degrees [155] | 0.247402646 | 1.45089E-06 |
| Returns the total angle traversed / total length of gesture stroke [155] | 0.065799778 | 0.206671759 |

Table A.5: Regression output for classifying ages for curved shape (Continued).

| Feature | R-value | P-value |
|---|---|---|
| A density metric for the gesture stroke that uses the stroke's length and distance between the first and last point [155] | 0.047378397 | 0.363472366 |
| A density metric for the gesture stroke that uses the stroke's length and bounding box size [155] | 0.077266975 | 0.137955036 |
| How "open" or spaced out is a gesture [155] | 0.165827156 | 0.001368817 |
| Get the area of the bounding box [155] | 0.092533393 | 0.075451735 |
| The log of the bounding box area [155] | 0.087223949 | 0.093874723 |
| Returns the total angle divided by the total absolute angle [155] | 0.05710878 | 0.273215875 |
| Log of the total length [155] | 0.088185703 | 0.090294239 |
| Log of the aspect [155] | 0.083870857 | 0.107252033 |
| Count of corners | 0.14279493 | 0.005931666 |
| Stroke length / bounding box area | 0.01694341 | 0.745307121 |

# APPENDIX B

# CORNER DRAWING REGRESSION ANALYSIS

Table B.1: Regression output for classifying ages for corner shape.

| Feature | R-value | P-value |
|---|---|---|
| Average distance between closest point to each corner of the bounding box [177] | 0.258645139 | 8.6129E-09 |
| Average curvature of the stroke [177] | 0.146657211 | 0.001257388 |
| The error of the best fit line of the direction graph [177] | 0.236242493 | 1.58757E-07 |
| Direction change ratio [177] | 0.102381591 | 0.024738316 |
| Get the distance (normalized by bounding box size) between the furthest corner and the stroke [177] | 0.121098502 | 0.007842449 |
| The endpoint to stroke length ratio of the stroke [177] | 0.291114495 | 7.53803E-11 |
| The angle of the major axis relative to center [177] | 0.065864085 | 0.149212062 |
| The error of the best fit line of the direction graph [177] | 0.065344127 | 0.152456167 |
| Max distance between closest point and each corner [177] | 0.121098502 | 0.007842449 |
| The error of the best fit line of the direction graph [177] | 0.071123165 | 0.119288371 |
| The maximum curvature to average curvature value [177] | 0.05989277 | 0.05989277 |
| Minimum distance between closest point and each corner [177] | 0.25386394 | 0.25386394 |
| The normalized distance between direction extremes [177] | 0.054350733 | 0.054350733 |
| The number of revolutions (based on direction graph) that the stroke makes [177] | 0.124237847 | 0.006367394 |
| Percentage of Direction Window Passed [177] | 0.011335189 | 0.011335189 |
| Slope of the direction graph [177] | 0.023770443 | 0.023770443 |
| Standard deviation between closest point and each corner [177] | 0.232989191 | 2.36808E-07 |
| Length of the stroke [177] | 0.127672957 | 0.127672957 |
| The error of the line fit [177] | 0.082924691 | 0.082924691 |
| The least squares error of the fit / stroke length [177] | 0.125817484 | 0.005723742 |
| Get the error of the arc fit [177] | 0.038356679 | 0.401274169 |
| The estimated radius of the arc [177] | 0.079574416 | 0.079574416 |
| Get the arc to area ratio [177] | 0.075271255 | 0.099173843 |
| The angle between the endpoint [177] | 0.162731439 | 0.000338881 |
| Curve Error [177] | 0.265424525 | 3.37068E-09 |
| Get the error of the poliline fit [177] | 0.264977542 | 3.58869E-09 |
| Number of strokes [177] | 0.295667976 | 3.6874E-11 |
| Get the percentage of substrokes that passed a line test [177] | 0.299690307 | 1.93999E-11 |
| Get the error of the elipse fit [177] | 0.097233513 | 0.033006603 |
| Get the error of the circle fit [177] | 0.032454389 | 0.477632547 |
| Get the major axis to minor axis length ratio [177] | 0.099534243 | 0.029057962 |
| Get the error of the spiral fit [177] | 0.07146832 | 0.11750167 |

Table B.2: Regression output for classifying ages for corner shape (Continued).

| Feature | R-value | P-value |
| --- | --- | --- |
| Distance between two points that meet at the head [177] | 0.05107491 | 0.263577453 |
| Size difference between last two strokes (the head) [177] | 0.121986336 | 0.007397089 |
| Number of intersections between the ends of the head and the shaft [177] | 0.041277095 | 0.366362988 |
| The error of the rectangle fit [177] | 0.149003396 | 0.00104652 |
| Get the major axis to bounding box diagonal length ratio [177] | 0.127499771 | 0.005103137 |
| Perimeter (of bounding box) to stroke length ratio [177] | 0.099744622 | 0.028718015 |
| Number of segmented strokes [177] | 0.264977542 | 3.58869E-09 |
| Stroke length to perimeter (of bounding box) ratio [177] | 0.099744622 | 0.028718015 |
| Get the width to height ratio of the square [177] | 0.017134903 | 0.707773884 |
| Get the error of the diamond fit [177] | 0.135217824 | 0.002963483 |
| Get the perimeter (of bounding box) to stroke length ratio [177] | 0.165534439 | 0.000266154 |
| Get the major axis to bounding box diagonal length ratio [177] | 0.221565679 | 9.21034E-07 |
| Get the width to height ratio of the square fit used for the diamond fit [177] | 0.211469835 | 2.88495E-06 |
| Stroke density [177] | 0.038999957 | 0.393418074 |
| Height to width ratio of bounding box [177] | 0.06936398 | 0.128726533 |
| Wave segment size [177] | 0.171023945 | 0.000163974 |
| Get the percentage of the slope test that passed [177] | 0.262479123 | 5.08334E-09 |
| Get the ratio between the smallest and largest segment of the wave segmentation [177] | 0.032571788 | 0.476040362 |
| Get the ratio between the smallest segment and the sum [177] | 0.107854927 | 0.107854927 |
| Get the angle between the middle segments [177] | 0.024511457 | 0.59177881 |
| Get the percentage of the horizontal alignment test that passed [177] | 0.021058697 | 0.645011925 |
| Get average slope of first and last segment [177] | 0.041985797 | 0.041985797 |
| Get percentage of slope test that passed [177] | 0.115583542 | 0.011185265 |

Table B.3: Regression output for classifying ages for corner shape (Continued).

| Feature | R-value | P-value |
|---|---|---|
| Ratio between largest and smallest segment [177] | 0.066432687 | 0.145724869 |
| Density of sub dot [177] | 0.157255699 | 0.000537227 |
| Number of revolutions of sub dot [177] | 0.137752942 | 0.002463871 |
| Convex hull area / bounding box area [94] | 0.153679689 | 0.000720127 |
| Convex hull area / enclosing rectangle area [94] | 0.035716802 | 0.434483853 |
| Largest quadrilateral area / convex hull area [94] | 0.473701784 | 2.83214E-28 |
| Largest quadrilateral area / enclosing rectangle area [94] | 0.246652074 | 4.24549E-08 |
| Largest triangle area / bounding box area [94] | 0.391388683 | 4.67116E-19 |
| Largest triangle area / convex hull area [94] | 4.24549E-08 | 0.001012074 |
| Largest triangle area / enclosing rectangle area [94] | 0.318522766 | 8.38171E-13 |
| Largest triangle area / largest quadrilateral area [94] | 0.036043575 | 0.430289216 |
| Absolute value of bounding box's Y difference / bounding box's X difference [94] | 0.023160739 | 0.612364621 |
| Enclosing rectangle's distance ratio [94] | 0.070834776 | 0.120797437 |
| Absolute value of bounding box's X difference / x value movement in sketch [94] | 0.147750943 | 0.001154644 |
| Number of points inside the triangle [94] | 0.251192224 | 2.34336E-08 |
| Convex hull area$^2$ / convex hull area [94] | 0.048396645 | 0.28947209 |
| Convex hull perimeter / stroke length [94] | 0.128263232 | 0.004842042 |
| Convex hull perimeter / bounding box perimeter [94] | 0.293175941 | 5.46204E-11 |
| Convex hull perimeter / enclosing rectangle perimeter [94] | 0.220567994 | 1.03356E-06 |
| Largest quadrilateral perimeter / convex hull perimeter [94] | 0.445422351 | 8.07107E-25 |
| Largest quadrilateral perimeter / enclosing rectangle perimeter [94] | 0.326828388 | 1.95092E-13 |
| Largest triangle perimeter / bounding box perimeter [94] | 0.359954259 | 3.68161E-16 |
| Largest triangle perimeter / convex hull perimeter [94] | 0.052587871 | 0.249675523 |
| Largest triangle perimeter / enclosing rectangle perimeter [94] | 0.283402153 | 2.45877E-10 |
| Largest triangle perimeter / quadrilateral perimeter [94] | 0.108424844 | 0.01737042 |
| Stroke Length / convex hull perimeter [94] | 0.140010758 | 0.00208493 |
| Difference of bounding boxes' largest Y value and smallest Y value / y value movement in sketch [94] | 0.070350678 | 0.123364028 |
| Zernike1 [131] | 0.142715431 | 0.001701474 |
| Zernike2 [131] | 0.201094676 | 8.81553E-06 |
| Zernike3 [131] | 0.162673384 | 0.000340566 |
| Zernike4 [131] | 0.031996227 | 0.483873921 |

Table B.4: Regression output for classifying ages for corner shape (Continued).

| Feature | R-value | P-value |
|---|---|---|
| Zernike5 [131] | 0.071299126 | 0.118374871 |
| Zernike6 [131] | 0.166304539 | 0.000248894 |
| Zernike7 [131] | 0.348197868 | 3.71645E-15 |
| Zernike8 [131] | 0.129000308 | 0.004601465 |
| Zernike9 [131] | 0.104123841 | 0.022378375 |
| Zernike10 [131] | 0.149259954 | 0.001025557 |
| Zernike11 [131] | 0.043631195 | 0.339642514 |
| Zernike12 [131] | 0.15883039 | 0.000471264 |
| Zernike13 [131] | 0.025179021 | 0.581723073 |
| Zernike14 [131] | 0.019305043 | 0.672783868 |
| Zernike15 [131] | 0.185054068 | 4.43982E-05 |
| Zernike16 [131] | 0.10485408 | 0.02144882 |
| Zernike17 [131] | 0.032605561 | 0.475582872 |
| Zernike18 [131] | 0.207655456 | 4.37873E-06 |
| Zernike19 [131] | 0.088625941 | 0.0520784 |
| Zernike20 [131] | 0.074860305 | 0.101037504 |
| Zernike21 [131] | 0.074728135 | 0.101642769 |
| Zernike22 [131] | 0.028955408 | 0.526392667 |
| Zernike23 [131] | 0.382684987 | 3.18565E-18 |
| Calculates the cosine of the initial angle [155] | 0.175474888 | 0.000109503 |
| Calculates the sine of the initial angle [155] | 0.093360801 | 0.04068688 |
| Get the length of the diagonal of the bounding box [155] | 0.085877972 | 0.059832136 |
| Get the angle of the diagonal of the bounding box [155] | 0.113592934 | 0.0126712 |
| Calculates the distance between the first and last point [155] | 0.342848352 | 1.03105E-14 |
| Calculates the cosine between the first and last point [155] | 0.082459739 | 0.07078474 |
| Calculates the sine between the first and last point [155] | 0.058443307 | 0.200713758 |
| Computes the total gesture length [155] | 0.126853584 | 0.005333964 |
| Sum of angle changes between points [155] | 0.084072333 | 0.065429012 |
| Computes the sum of the absolute value of the angles at each mouse point [155] | 0.302459951 | 1.2394E-11 |
| Computes the sum of the squared values of the angles at each mouse point [155] | 0.28053494 | 3.78126E-10 |
| Calculates the gesture aspect, which is abs (45 degrees - angle of bounding box) [155] | 0.019831779 | 0.664393113 |
| The sum of gesture intersegment angles whose absolute value is less than 19 degrees [155] | 0.300963631 | 1.57977E-11 |
| Returns the total angle traversed / total length of gesture stroke [155] | 0.035123933 | 0.442154047 |

Table B.5: Regression output for classifying ages for corner shape (Continued).

| Feature | R-value | P-value |
| --- | --- | --- |
| A density metric for the gesture stroke that uses the stroke's length and distance between the first and last point [155] | 0.088280216 | 0.053005291 |
| A density metric for the gesture stroke that uses the stroke's length and bounding box size [155] | 0.101748766 | 0.025647189 |
| How "open" or spaced out is a gesture [155] | 0.344857629 | 7.04416E-15 |
| Get the area of the bounding box [155] | 0.109644724 | 0.01614165 |
| The log of the bounding box area [155] | 0.065706415 | 0.150190194 |
| Returns the total angle divided by the total absolute angle [155] | 0.059795384 | 0.190475186 |
| Log of the total length [155] | 0.093319091 | 0.040777194 |
| Log of the aspect [155] | 0.010860388 | 0.812211379 |
| Count of corners | 0.323223271 | 3.69345E-13 |
| Stroke length / bounding box area | 0.039083681 | 0.392402463 |

# APPENDIX C

# DATA COLLECTED FROM EASYSKETCH

Table C.1: Star Drawing Test results

| | age in yrs. (Gender) | time of no instruction (seconds) | time of fast drawing (seconds) | time of slow drawing (seconds) | drawing time difference (seconds) | # of error rate |
|---|---|---|---|---|---|---|
| 1 | 3 (Female) | 26.8 | 10.53 | 29.46 | 2.66 | 34 |
| 2 | 3 (Female) | 3.76 | 4.45 | 4.51 | 0.75 | 19 |
| 3 | 3 (Female) | 23.58 | 6.48 | 17.13 | -6.45 | 16 |
| 4 | 3 (Female) | 30.3 | 13.3 | 13.11 | -17.19 | 14 |
| 5 | 3 (Female) | 16.25 | 6.18 | 16.28 | 0.03 | 15 |
| 6 | 3 (Female) | 17.66 | 10.59 | 16.21 | -1.45 | 42 |
| 7 | 3 (Female) | 13.86 | 7.53 | 19.16 | 5.3 | 20 |
| 8 | 3 (Female) | 13.85 | 16.48 | 8.75 | -5.1 | 12 |
| 9 | 3 (Male) | 15.43 | 14.53 | 18.53 | 3.1 | 17 |
| 10 | 3 (Male) | 10.61 | 3 | 14.9 | 4.29 | 15 |
| 11 | 3 (Male) | 15.03 | 8.33 | 13.31 | -1.72 | 19 |
| 12 | 3 (Male) | 27.13 | 6.53 | 12.61 | -14.52 | 33 |
| 13 | 3 (Male) | 27.46 | 13.16 | 20.45 | -7.01 | 44 |
| 14 | 3 (Male) | 25.7 | 9.13 | 16 | -9.7 | 24 |
| 15 | 3 (Female) | 12.1 | 12.98 | 20.46 | 8.36 | 14 |
| 16 | 3 (Female) | 11.7 | 4.8 | 14.08 | 2.38 | 18 |
| 17 | 3 (Female) | 28.03 | 9.28 | 24.15 | -3.88 | 16 |
| 18 | 3 (Male) | 21.05 | 8.06 | 10.28 | -10.77 | 20 |
| 19 | 3 (Male) | 25.06 | 25.45 | 36.28 | 11.22 | 14 |
| 20 | 4 (Female) | 19.18 | 8.21 | 20.4 | 1.22 | 21 |
| 21 | 4 (Female) | 14.53 | 10.63 | 20.32 | 5.79 | 8 |
| 22 | 4 (Female) | 14.33 | 5.58 | 22.18 | 7.85 | 12 |
| 23 | 4 (Female) | 23 | 13.11 | 31.7 | 8.7 | 11 |
| 24 | 4 (Female) | 19.4 | 6.9 | 24.35 | 4.95 | 11 |
| 25 | 4 (Female) | 12.75 | 5.93 | 22.95 | 10.2 | 14 |
| 26 | 4 (Female) | 20.4 | 10 | 26.53 | 6.13 | 12 |
| 27 | 4 (Female) | 15.65 | 6.33 | 14.8 | -0.85 | 10 |
| 28 | 4 (Male) | 15.98 | 14.41 | 28.32 | 12.34 | 16 |
| 29 | 4 (Male) | 18.01 | 13.35 | 14.85 | -3.16 | 13 |
| 30 | 4 (Male) | 7.88 | 7.4 | 17.88 | 10 | 28 |
| 31 | 4 (Male) | 18.75 | 7.43 | 13.85 | -4.9 | 15 |
| 32 | 4 (Male) | 21.91 | 6.21 | 24.51 | 2.6 | 17 |
| 33 | 4 (Male) | 25.73 | 3.75 | 47.23 | 21.5 | 20 |
| 34 | 4 (Male) | 15.18 | 7.46 | 56.1 | 40.92 | 7 |
| 35 | 4 (Male) | 30.77 | 10.11 | 31.23 | 0.46 | 8 |
| 36 | 4 (Male) | 14.92 | 6.85 | 30.72 | 15.8 | 16 |
| 37 | 4 (Male) | 15.4 | 9.93 | 21.35 | 5.95 | 17 |
| 38 | 4 (Male) | 11.55 | 5.4 | 9.78 | -1.77 | 13 |
| 39 | 4 (Male) | 32.68 | 17.4 | 30.17 | -2.51 | 10 |

Table C.2: Star Drawing Test results (Continued).

| | age in yrs. (Gender) | time of no instruction (seconds) | time of fast drawing (seconds) | time of slow drawing (seconds) | drawing time difference (seconds) | # of error rate |
|---|---|---|---|---|---|---|
| 40 | 5 (Female) | 8.98 | 5.75 | 13.86 | 4.88 | 10 |
| 41 | 5 (Female) | 21.81 | 5.36 | 17.18 | -4.63 | 2 |
| 42 | 5 (Female) | 26.63 | 27.28 | 29.86 | 3.23 | 2 |
| 43 | 5 (Female) | 16.05 | 7.66 | 15.91 | -0.14 | 8 |
| 44 | 5 (Female) | 22.13 | 10.25 | 23.45 | 1.32 | 3 |
| 45 | 5 (Female) | 11.86 | 8.4 | 17.52 | 5.66 | 2 |
| 46 | 5 (Female) | 16.71 | 4.1 | 26.6 | 9.89 | 17 |
| 47 | 5 (Female) | 16.76 | 14.73 | 20.86 | 4.1 | 6 |
| 48 | 5 (Female) | 15.36 | 4.31 | 49.73 | 34.37 | 16 |
| 49 | 6 (Female) | 22.81 | 8.56 | 50.8 | 27.99 | 0 |
| 50 | 6 (Female) | 20.95 | 17.46 | 25.47 | 4.52 | 0 |
| 51 | 6 (Female) | 21.36 | 11.38 | 30.97 | 9.61 | 7 |
| 52 | 6 (Female) | 20.96 | 8.2 | 26.81 | 5.85 | 14 |
| 53 | 6 (Female) | 12.68 | 6.63 | 28.67 | 15.99 | 5 |
| 54 | 6 (Female) | 18.41 | 10.48 | 33.58 | 15.17 | 7 |
| 55 | 6 (Female) | 6.81 | 3.96 | 3.51 | -3.3 | 5 |
| 56 | 6 (Female) | 19.91 | 8.9 | 68.4 | 48.49 | 0 |
| 57 | 6 (Male) | 13.35 | 7.4 | 20.91 | 7.56 | 17 |
| 58 | 6 (Male) | 26.78 | 10.4 | 75.23 | 48.45 | 2 |
| 59 | 7 (Female) | 16.71 | 9.41 | 38.13 | 21.42 | 2 |
| 60 | 7 (Female) | 17.78 | 10.05 | 37.27 | 19.49 | 0 |
| 61 | 7 (Female) | 19.76 | 8.05 | 42.48 | 22.72 | 0 |
| 62 | 7 (Female) | 16.88 | 8.28 | 57.37 | 40.49 | 0 |
| 63 | 7 (Male) | 11.71 | 8.63 | 18.85 | 7.14 | 7 |
| 64 | 7 (Male) | 24.53 | 6.56 | 68.82 | 44.29 | 9 |
| 65 | 7 (Male) | 11.53 | 5.13 | 28.52 | 16.99 | 9 |
| 66 | 7 (Male) | 20.38 | 9.23 | 38.28 | 17.9 | 8 |
| 67 | 8 (Female) | 7.58 | 4.25 | 13.38 | 5.8 | 5 |
| 68 | 8 (Male) | 36.72 | 19.53 | 66.12 | 29.4 | 0 |
| 69 | 8 (Male) | 16.41 | 7.06 | 18.61 | 2.2 | 13 |
| 70 | 8 (Male) | 17.76 | 7.3 | 48.77 | 31.01 | 0 |

Table C.3: Interface Test results

| | Age in yrs. (Gender) | Overall fine motor skill classifying result | Curvature fine motor skill classifying result | Line fine motor skill classifying result |
|---|---|---|---|---|
| 1 | 3 (Female) | In training | In training | In training |
| 2 | 3 (Female) | In training | In training | In training |
| 3 | 3 (Female) | In training | In training | In training |
| 4 | 3 (Female) | In training | In training | In training |
| 5 | 3 (Female) | In training | In training | In training |
| 6 | 3 (Female) | In training | In training | In training |
| 7 | 3 (Female) | In training | In training | In training |
| 8 | 3 (Female) | In training | In training | In training |
| 9 | 3 (Female) | In training | In training | In training |
| 10 | 3 (Female) | In training | In training | In training |
| 11 | 3 (Female) | In training | In training | In training |
| 12 | 3 (Female) | In training | In training | In training |
| 13 | 3 (Female) | In training | In training | In training |
| 14 | 3 (Female) | In training | In training | In training |
| 15 | 3 (Female) | In training | In training | In training |
| 16 | 3 (Female) | In training | In training | In training |
| 17 | 3 (Female) | In training | In training | In training |
| 18 | 3 (Female) | In training | In training | In training |
| 19 | 3 (Female) | In training | In training | In training |
| 20 | 3 (Female) | In training | In training | In training |
| 21 | 3 (Female) | In training | In training | In training |
| 22 | 3 (Male) | In training | In training | In training |
| 23 | 3 (Male) | In training | In training | In training |
| 24 | 3 (Male) | In training | In training | In training |
| 25 | 3 (Male) | In training | In training | In training |
| 26 | 3 (Male) | In training | In training | In training |
| 27 | 3 (Male) | In training | In training | In training |
| 28 | 3 (Male) | In training | In training | In training |
| 29 | 3 (Male) | In training | In training | In training |
| 30 | 3 (Male) | In training | In training | In training |
| 31 | 3 (Male) | In training | In training | In training |
| 32 | 4 (Female) | In training | In training | In training |
| 33 | 4 (Female) | In training | In training | Mature |
| 34 | 4 (Female) | In training | In training | In training |
| 35 | 4 (Female) | In training | In training | In training |
| 36 | 4 (Female) | Mature | Mature | Mature |
| 37 | 4 (Female) | Mature | In training | Mature |
| 38 | 4 (Female) | In training | In training | In training |
| 39 | 4 (Female) | In training | In training | In training |
| 40 | 4 (Female) | In training | In training | In training |
| 41 | 4 (Female) | In training | In training | Mature |

Table C.4: Interface Test results (Continued)

| | Age in yrs. (Gender) | Overall fine motor skill classifying result | Curvature fine motor skill classifying result | Line fine motor skill classifying result |
|---|---|---|---|---|
| 42 | 4 (Male) | Mature | In training | Mature |
| 43 | 4 (Male) | In training | In training | In training |
| 44 | 4 (Male) | In training | In training | In training |
| 45 | 4 (Male) | In training | In training | In training |
| 46 | 4 (Male) | In training | In training | In training |
| 47 | 4 (Male) | In training | In training | In training |
| 48 | 4 (Male) | Mature | In training | In training |
| 49 | 4 (Male) | Mature | In training | Mature |
| 50 | 4 (Male) | In training | In training | In training |
| 51 | 4 (Male) | In training | In training | In training |
| 52 | 4 (Male) | In training | In training | Mature |
| 53 | 4 (Male) | In training | In training | Mature |
| 54 | 4 (Male) | Mature | In training | Mature |
| 55 | 5 (Female) | Mature | In training | Mature |
| 56 | 5 (Female) | In training | In training | In training |
| 57 | 5 (Female) | Mature | In training | Mature |
| 58 | 5 (Female) | Mature | In training | In training |
| 59 | 5 (Female) | Mature | In training | In training |
| 60 | 5 (Female) | In training | In training | In training |
| 61 | 5 (Female) | In training | In training | In training |
| 62 | 5 (Female) | Mature | In training | Mature |
| 63 | 5 (Male) | Mature | In training | Mature |
| 64 | 5 (Male) | In training | In training | In training |
| 65 | 6 (Female) | Mature | Mature | Mature |
| 66 | 6 (Female) | Mature | In training | Mature |
| 67 | 6 (Female) | Mature | In training | Mature |
| 68 | 6 (Female) | Mature | In training | Mature |
| 69 | 6 (Female) | In training | In training | In training |
| 70 | 6 (Female) | Mature | Mature | Mature |
| 71 | 6 (Female) | Mature | In training | Mature |
| 72 | 6 (Female) | Mature | In training | Mature |
| 73 | 6 (Male) | In training | In training | In training |
| 74 | 6 (Male) | Mature | Mature | Mature |
| 75 | 6 (Male) | Mature | In training | In training |
| 76 | 6 (Male) | Mature | In training | Mature |
| 77 | 7 (Female) | Mature | In training | Mature |
| 78 | 7 (Female) | Mature | In training | Mature |
| 79 | 7 (Female) | Mature | Mature | Mature |
| 80 | 7 (Female) | Mature | In training | Mature |

Table C.5: Interface Test results (Continued)

| | Age in yrs. (Gender) | Overall fine motor skill classifying result | Curvature fine motor skill classifying result | Line fine motor skill classifying result |
|---|---|---|---|---|
| 81 | 7 (Male) | Mature | In training | In training |
| 82 | 7 (Male) | Mature | In training | In training |
| 83 | 7 (Male) | Mature | In training | In training |
| 84 | 7 (Male) | Mature | In training | In training |
| 85 | 8 (Male) | Mature | Mature | Mature |
| 86 | 8 (Male) | Mature | In training | Mature |
| 87 | 8 (Male) | Mature | Mature | Mature |
| 88 | 8 (Male) | Mature | Mature | Mature |
| 89 | 8 (Male) | Mature | In training | Mature |