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Master's Thesis

Augmenting Beginner's Drawing Skills with Decontextualized Methods

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Abstract

Drawing, as a carrier of culture and a form of artistic expression, has always played an important role throughout human history. It also serves as a means to enhance emotional well-being. But learning to draw presents significant challenges for beginners, as it demands strong observational skills and a solid understanding of the structural relationships of drawing targets. In recent years, with the development of digital art technologies, many artists are increasingly using software tools such as Procreate, which offers a variety of brush styles to meet diverse drawing needs. However, the use of such professional-level software usually requires professional guidance and a lot of practice, which is difficult for beginners to get started. Meanwhile, in the field of drawing education, the drawing skills are generally improved through extensive practice, using traditional drawing guidance methods may not cultivate students' observation ability, such as direct tracing and grid methods. Although these methods can produce good drawing results, they ignore the cultivation of observation ability. Existing methods, such as inverted drawing, can effectively avoid cognitive bias caused by over-familiarity, but lack systematic guidance from overall outline to local details.

This study presents a decontextualized drawing method designed to help beginners improve their drawing skills. In this method, the reference image is first inverted and fully occluded to show the contour lines. Beginners need to draw it first and unable to observe the details to ensure that their attention is focused on the proportions and contours of the image. After the contours are drawn, the occlusion is removed to show the full reference image, but keep inverted and the beginner continues to observe the details of the drawing. By dividing the drawing of the contours and details into two stages, the beginner is guided through a sequence of observation from the whole to the local, improving drawing skills.

To verify the effectiveness of this approach, a controlled experiment was conducted in which participants were asked to complete the drawing task using four different methods: the traditional upright drawing method, the inverted drawing method, the upright occlusion drawing method, and the proposed decontextualized drawing method. The experiment used eight reference images of different complexity, and each participant drew on four high-complexity and four low-complexity reference images using each of the four methods. The drawing quality was analyzed in terms of contour accuracy and similarity through subjective evaluation by five expert users with art experience and objective algorithm-based evaluation.

The experimental results show that the proposed method significantly improves the observation and drawing skills of beginners, especially in conditions where the reference image is of high-complexity. Although the traditional upright drawing method received higher subjective evaluation scores, the proposed method outperforms other methods in the case of high-complexity drawing. Compared to other drawing instruction methods, it helps beginners to first focus on the overall contour, determine the contour and then observe the local details to avoid being distracted by internal details too early.

Participants' post-experiment interviews also indicated that the proposed method provided a different viewing experience, making it easier to focus on the contours before the details. The comparison experiments confirmed that, compared to the other three methods, the proposed method enables beginners to observe and construct contours and details more effectively, while other drawing methods usually require extensive practice to achieve similar improvements.

In conclusion, this study proposes a decontextualized drawing method that guides beginners to first draw contours and then refine details, helping them to improve their observation and drawing skills. Experimental results show that the method is particularly effective for highly-complex drawings, allowing beginners to better capture structure and details. Compared to other methods, the decontextualized drawing method approach provides a clearer sequence of observation and reduces premature focus on details, providing an effective way for beginners to improve their drawing skills.

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Chapter 1

Introduction

This chapter introduces the research background and the challenges faced by beginners learning to draw in contemporary art education and digital environments. Section 1.1 discusses the cultural, educational, and technological contexts that frame the study, as well as the challenges that beginners face when learning to draw. Section 1.2 introduces some existing drawing guidance methods (such as direct tracing, grid methods, and inverted drawing) and their limitations. Section 1.3 defines the research objectives and presents the decontextualized drawing method proposed in this paper. Finally, Section 1.4 provides an overview of the thesis structure.

1.1 Background

Drawing, as a fundamental form of human expression, plays a vital role in both cultural communication and perceptual development[1]. As an important part of human culture, drawing is not only a way of artistic expression, but also an effective means of cultivating observation ability[2, 3], spatial cognition, and creative thinking [4]. It has long served as a foundational tool in education and design disciplines, encouraging visual literacy and fine motor development.

However, learning to draw is a complex process. Beginners often face many challenges when starting their journey to learn and practice the basics of drawing [5, 6]. These challenges include difficulties in accurately capturing proportions, observing fine details, and interpreting visual information into coherent forms. Conventional drawing methods are often repetitive and time-consuming, which slows progress and can diminish beginner motivation [7]. As Figure1.1 show, without adequate guidance, beginners may overlook important visual details, limiting their progress [5].

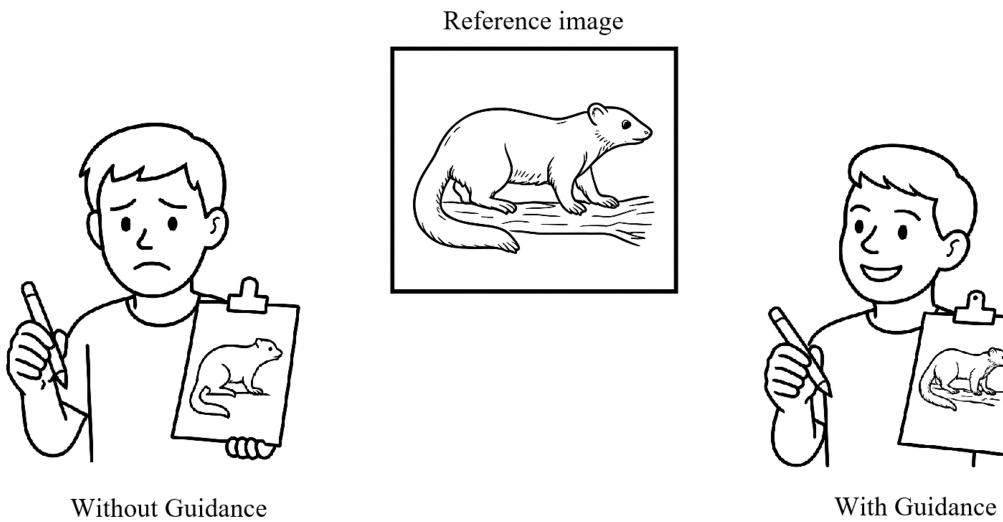

Figure 1.1: Comparison of visual detail retention between drawing without guidance and with guidance. Drawings made without assistance tend to miss fine details, while guidance helps in preserving structural features. (Image generated by the author using AI tools and manually edited.)

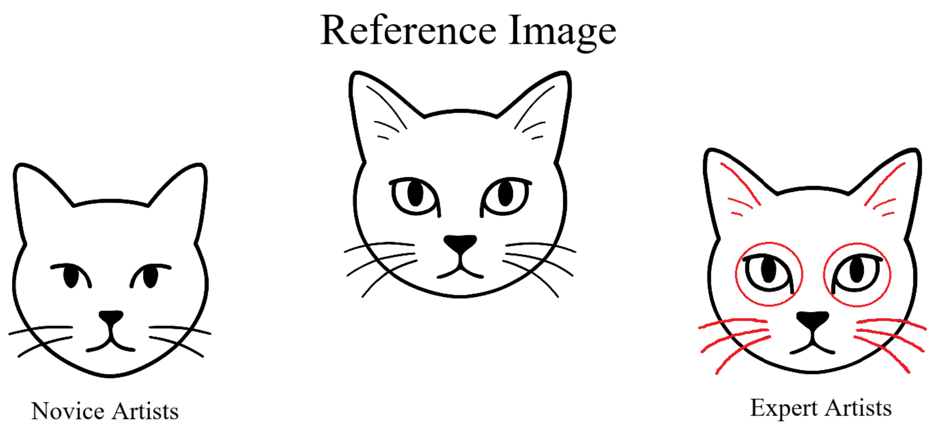

Figure 1.2: Comparison of perceptual skills between novice and expert artists. Experts are better at accurately observing and capturing the structural features and subtle visual details of objects, while novices often rely on symbolic perception, leading to simplified and less accurate drawings.

As shown in Figure 1.2, a key distinction between expert and novice artists lies in perceptual skill: experts are more adept at accurately capturing the shape and structural relationships of objects and in effectively observing and processing subtle visual information [8]. We observe that most people tend to rely on symbolic perception, describing objects based on inherent experience rather than direct observation [9]. As a result, beginners often have difficulty accurately grasping both the contours and internal details of the subject matter.

1.2 Problem Statement

To assist beginners in overcoming these challenges, various drawing assistance techniques have been developed. One such method is *Direct Tracing* (see Figure2.1), where beginners replicate reference images by tracing over translucent physical or digital layers [10, 11]. Another widely adopted technique is the *Grid Method* (see Figure2.2), which divides the reference image and canvas into identical grids, allowing beginners to copy the image section by section to improve proportional accuracy [12].

Although Direct Tracing allows beginners to get started quickly, it often overlooks the development of independent observational skills. In contrast, the Grid Method may limit creative flexibility compared to more intuitive or exploratory techniques [13]. Moreover, these traditional methods do not guide beginners in managing local and global visual information in a balanced manner. As a result, beginners are prone to premature fixation on small details while neglecting the overall structure. Therefore, how to help beginners accurately perceive structural characteristics while reducing visual interference remains an unresolved challenge in drawing pedagogy.

To mitigate symbolic interference, Betty Edwards proposed the *Inverted Drawing* method, where reference images are flipped upside down to prevent immediate object recognition and encourage perceptual analysis of shapes and lines [9]. This method has been shown to enhance attention to visual details [14], but it does not provide explicit structural guidance and lacks a systematic instructional framework.

Because the full visual content of the image remains visible, beginners' focus may depend on their personal habits—some emphasizing detail, others emphasizing general form. Without sequenced guidance or structural scaffolding, beginners may struggle to integrate local features into a coherent global composition, and observational progress may vary greatly among individuals.

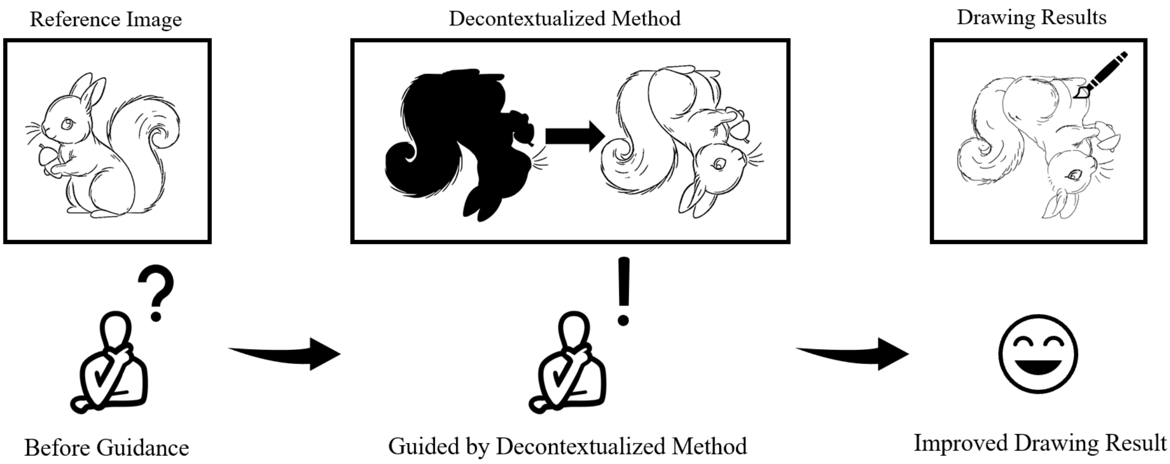

Figure 1.3: This figure shows the process of instructing a beginner in the use of decontextualized drawing methods. In the left figure, without guidance, beginners may have difficulty accurately observing and drawing complex reference images. In the middle, by first occlusion and inversion the reference image, the learner can focus on capturing the contours, and after completing the outline drawing, occlusion will be removed to show detail, and finally the beginner gets a good drawing result.

1.3 Research Objective

To address the limitations of existing methods, this study proposes a new drawing assistance approach designed to support structured observation and perceptual development in beginners. Specifically, we investigate a decontextualized drawing method based on Edwards' inverted drawing theory [9], which incorporates full occlusion to guide contour observation and structural perception (see Figure 1.3) .

The method begins with an inverted reference image in which internal details are fully occluded, allowing only the outer contour to be visible. Beginners are guided to draw the visible contour first, reducing distractions and symbolic interference. Once the contour drawing is completed, the occlusion is removed, and beginners can freely observe and refine the remaining details. This two-stage process encourages a transition from global to local processing, fostering structural awareness and focused observation. A comparison experiment was conducted to verify the effectiveness of this method. The results showed that it helped beginners better capture the contours and details of complex images compared to traditional methods.

1.4 Outline of Thesis

This thesis is structured as follows:

In Chapter 1, this chapter introduces the background and motivation for this study, describes the challenges beginners face in learning to draw, reviews existing assistance methods, and explains the purpose of proposing a decontextualized drawing method.

In Chapter 2, this chapter reviews related work on drawing education, visual perception, and drawing assistance technologies, and discusses symbolic perception, cognitive load theory, and global-to-local processing strategies that provide theoretical support for this research.

In Chapter 3, this chapter presents the proposed decontextualized drawing method in detail, explaining how inversion and full occlusion are combined to guide beginners' observation, and describes the preliminary pilot study used to refine the method.

In Chapter 4, this chapter explains the formal experimental design, including the selection of reference images, the assessments of complexity and familiarity, the allocation of drawing tasks, and the experimental procedure.

In Chapter 5, this chapter reports the experimental results based on both objective evaluation metrics (SSIM, PSNR, CW-SSIM, LPIPS) and subjective ratings by professional evaluators, and analyzes the post-experiment questionnaire feedback.

In Chapter 6, this chapter discusses the main findings of the experiment, examines the influence of image complexity and differences between methods, and outlines the limitations of the study.

Finally, in Chapter 7, this chapter summarizes the contributions and findings of this research and suggests directions for future work, including improving evaluation consistency and exploring the long-term effects of structured drawing guidance.

Chapter 2

Related Works

In recent years, research on learning to draw has garnered significant attention, with numerous methods proposed to aid beginners in improving their drawing skills. Recent advances in drawing pedagogy and assistive technologies have explored various strategies to enhance observational skills and structural understanding among beginners. This section categorizes existing approaches into traditional structural guidance, cognitive intervention methods, and technology-enhanced tools, while critically analyzing their contributions and limitations.

2.1 Drawing Guidance Methods

Traditional drawing assistance methods, such as Direct Tracing and the Grid Method, have been widely used to support beginners in learning to draw. Direct Tracing allows users to accurately replicate reference images by overlaying translucent paper or digital layers, helping beginners quickly grasp basic contours. The Grid Method improves proportional accuracy by guiding beginners to transfer reference images segment by segment using evenly spaced grids.

2.1.1 Direct Tracing

The direct tracing technique employs a semitransparent medium, either physical overlays (e.g., translucent paper) or digital layers, superimposed onto a reference image, allowing beginners to replicate visible contours through guided imitation. This approach provides instantaneous visual feedback by aligning traced strokes with underlying structural features, thereby facilitating beginner familiarity with fundamental geometric forms and proportional

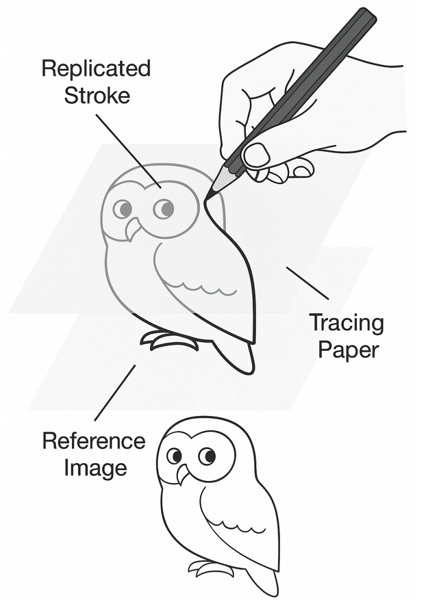

Figure 2.1: Illustration of the Direct Tracing method. Beginners replicate visible contours by tracing over a semitransparent layer placed on a reference image. (Image generated by the author using AI tools and manually edited.)

relationships[10] [11]. It is especially useful in developing confidence and motor coordination at the initial stage. However, because it bypasses the need for active observation and interpretation, it fails to cultivate the beginner's ability to analyze forms independently. Research has pointed out that this form of assistance encourages dependency and inhibits the development of visual analysis skills and structural understanding[15].As illustrated in Figure 2.1, beginners may struggle to draw accurately without such guidance.

2.1.2 Grid Method

The grid method enables beginners to complete a drawing in stages by drawing an equidistant grid over a reference image and drawing surface to break down a complex image into localized units that can be reproduced independently. The method reinforces scale accuracy through spatial segmentation, and is often used in basic instruction to train scale transformation and compositional understanding, and to assist in observational activities while drawing[12]. Figure 2.2 shows how beginners match corresponding regions between the reference and the drawing surface using grid alignment

The localized drawing strategy can significantly reduce the learning pressure of high-complexity images, and is especially suitable for structurally

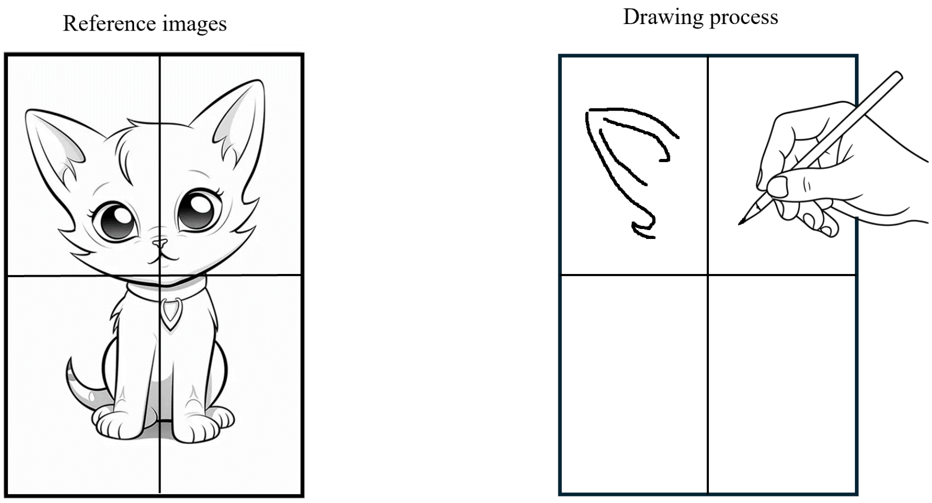

Figure 2.2: Illustration of the Grid Method. The reference image is divided into a grid, and beginners reproduce the image by copying each segment within a corresponding grid on the drawing surface. (Image generated by the author using AI tools and manually edited.)

complex drawing scenes. However, due to excessive fragmentation of overall structural cognition, beginners are prone to get caught up in the observation of local details while neglecting global morphological correlations, resulting in loose or disproportionate compositions. In addition, the over-reliance on the grid method may inhibit creative freedom[13], which is not very helpful for the subsequent improvement of drawing cognition and skills.

2.1.3 Line Simplification

Line simplification reduces complex details in reference images, enabling beginners to focus on the overall outline and more easily identify structures and outer contours [16]. This approach aims to reduce visual complexity by omitting minor or redundant information, helping beginners concentrate on fundamental forms without being overwhelmed by intricate details. Several computational approaches have been proposed for line simplification, such as the Ramer–Douglas–Peucker (RDP) algorithm [17] and the Visvalingam–Whyatt (VW) method [18], both of which simplify polylines while preserving the essential geometric structure. In the context of sketch simplification, techniques such as stroke classification and combination have also been applied to convert rough sketches into clean line drawings [19][20]. As depicted in Figure 2.3, the original image is transformed into a simplified version that highlights only the essential contours. Despite its advantages, line simplification may lead to the loss of structurally significant features, potentially causing beginners to overlook critical details necessary for accurate form construction. Over-reliance on simplified references may also impede the development of detail observation and the ability to manage complex visual information.

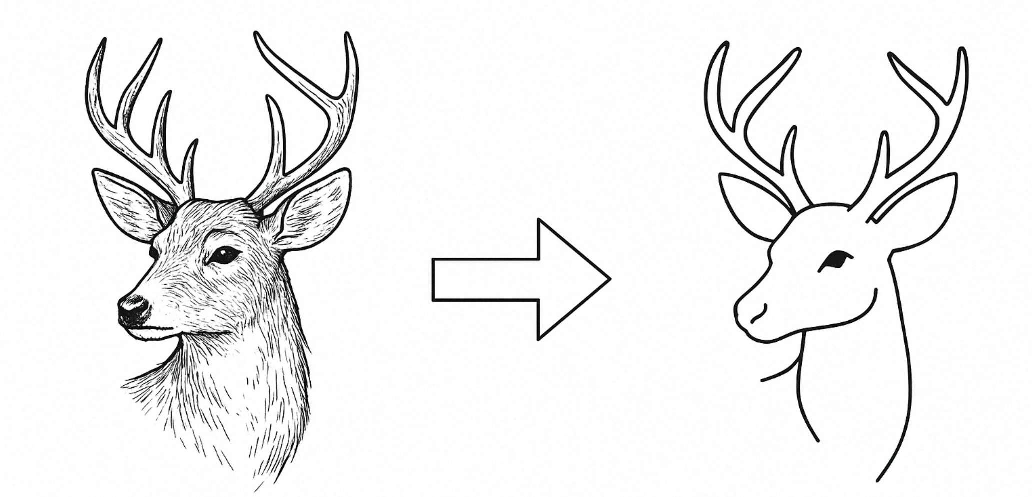

Figure 2.3: Illustration of the Line Simplification method. The original image is reduced to a simplified contour representation to help beginners focus on structural understanding. (Image generated by the author using AI tools and manually edited.)

In contrast, the inverted drawing method tackles the problem of symbolic cognition—where prior knowledge causes beginners to overlook details—by flipping the reference image, thereby reducing the immediate recognition of familiar objects. This encourages beginners to attend more closely to local details and accurate proportions rather than relying on conventional symbolic representations [9]. Although these methods contribute to improving drawing abilities to some extent, they exhibit limitations in cultivating deeper structural cognition and independent modeling capabilities. Furthermore, most existing approaches do not fully leverage the advantages of Global-to-Local processing, causing beginners to rely on individual observational habits rather than adopting a systematic learning strategy.

2.2 Observation and Perception in Drawing

In learning to draw, visual observation and perceptual processing abilities are key to beginners' ability to effectively capture the structure and form of objects. However, compared with experienced artists, beginners often have significant differences in their observation strategies and information processing styles, and are especially vulnerable to the influence of inherent cognitive habits and visual information load. In this chapter, we will explore the key mechanisms affecting the observational efficiency of drawing from the dimensions of symbolic perception and cognitive load, as well as observational sequence and structural construction, and provide a theoretical basis for the subsequent proposed decontextualized drawing approach.

2.2.1 Symbolic Perception and Cognitive Load

A key challenge in drawing instruction is that beginners frequently resort to symbolic perception, expressing objects via simplified symbols rather than faithfully rendering their true forms [21, 9]. For example, when sketching a face, beginners might depict eyes as ovals or noses as triangles, disregarding actual proportions, shading, and structural relationships.

Perceptual processing plays a crucial role in drawing ability, as highlighted by Chamberlain et al [22], yet beginners often lack the training to engage with visual stimuli in a perceptually accurate manner.

According to Cognitive Load Theory [23], human working memory has limited capacity and when beginners are presented with visually complex inputs, such as overlapping textures, blurred contours, or excessive internal detail, they may experience extraneous cognitive load. This overload distracts them from identifying essential structural features and hinders their ability to segment visual information, prioritize contours, or mentally construct coherent representations of the target form.

2.2.2 Inverted Drawing

To solve the problem of symbolic interference, Edwards proposed the inverted drawing method [9], in which the reference image is inverted. Inversion disrupts the beginner's automatic recognition of familiar forms and prompts them to shift attention to lines, angles, and spatial relationships. This method has been shown to increase beginners' attention to localized visual elements and reduce the effects of prior knowledge and symbolic bias in drawing tasks.

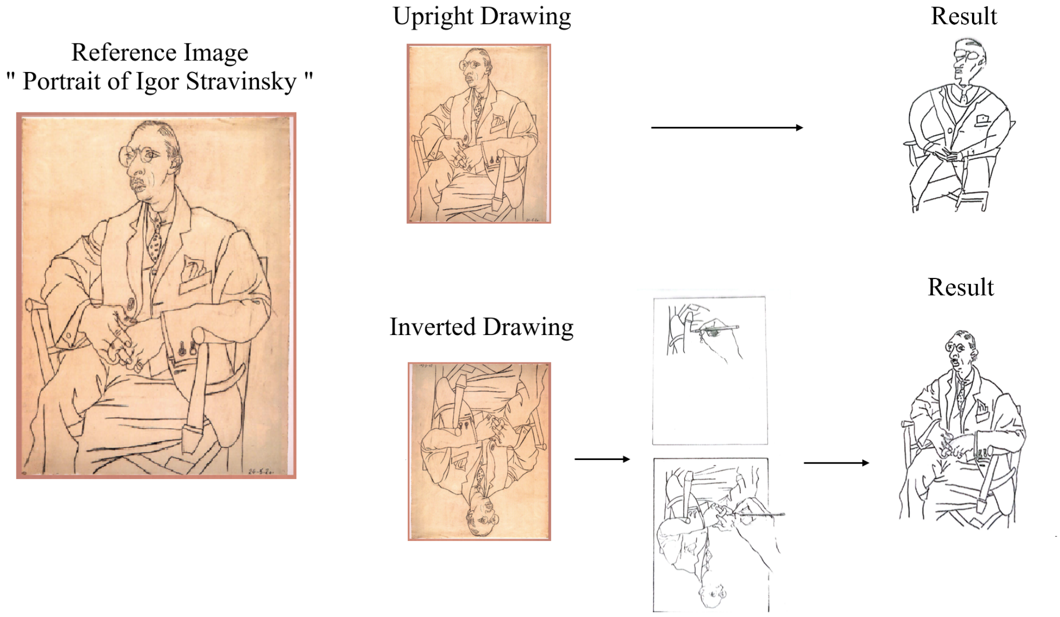

Figure 2.4: Comparison of drawing outcomes using the Upright Drawing method and the Inverted Drawing method based on the"Portrait of Igor Stravinsky" by Pablo Picasso. Two sets of drawings were made by the same participant on adjacent two days. The inverted method encourages learners to focus on lines and spatial relationships, resulting in improved structural accuracy. (Source: Edwards et al.,1997 [9])

However, it offers limited structured guidance and does not necessarily guarantee systematic observational improvement. Beginners are not guided on how to systematically organize visual information or interpret contour boundaries in a meaningful order. As a result, improvements in observational skills may not be consistent and depend on the individual beginner's ability to adapt to unfamiliar directions of observation. In addition, without structured guidance or step-by-step instructional support, some beginners may have difficulty integrating localized observations into a coherent overall structure. These limitations suggest that while inversion is effective in reducing symbolic interference, it may not be sufficient to develop a solid understanding of structure or promote transferable drawing skills [24].

2.2.3 Global-to-Local Processing

Global-to-local processing, whereby humans typically grasp the overall structure before attending to finer details [25], plays an essential role in effective learning-to-draw paradigms. As shown in Figure2.5, artists usually outline the general shape first, then progressively refine local features to ensure form accuracy. This theory aligns with our occlusion-based guidance method,

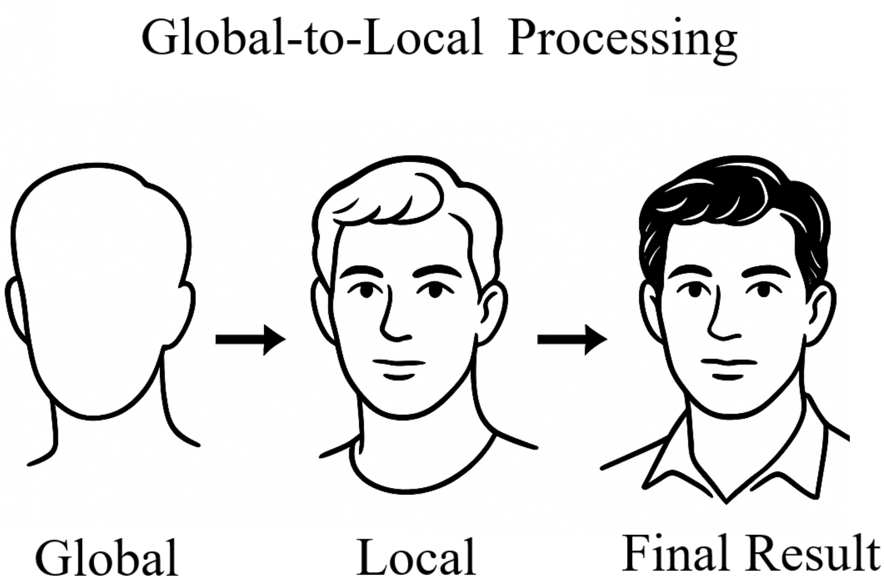

Figure 2.5: Illustration of global-to-local processing in drawing. First establish the overall structure (Global), then add localized features (Local), and finally complete detailed refinement (Final Result). (Image generated by the author using AI tools and manually edited.)

which masks non-contour regions to compel beginners to adopt a global perspective, reducing cognitive overload from fragmented details. Additionally, the DualFace system [26] further confirms that providing distinct stages for global and local visual guidance can enhance beginners' learning experiences.

Research by Li et al. [27] illustrates that beginning with an outline and then progressively refining or stylizing it into a finished piece highlights the importance of initial outline construction in the art-making process. Moreover, Wang et al. [28] investigated the relationship between reference image and canvas size on visual stimuli and drawing results, and confirmed that a canvas of the same size as the reference image gave the best results.

2.3 Drawing Guidance

Drawing assistive technologies and interface design Complementing these perceptual strategies, a number of guidance systems have also been proposed in the context of drawing assistive technologies to support structured learning through guided interfaces.

Flagg et al. [29] proposes an interactive system based on a projector and camera composition to assist artists in oil painting. The system is able to enhance structural awareness during the drawing process by providing real-time cues for auxiliary lines, shape projections and gestures during the drawing process. The research of Iarussi et al. [30] guides the user's drawing by cueing structural lines and other means to assist the user's way of seeing and to help them determine proportions and structure. These methods emphasize the embedding of visual cues into the interface to guide users to adopt a more rational observation order and composition strategy, which can effectively alleviate the burden of complex information processing on beginners.

In contrast, Kanayama's study [12] demonstrates presenting similar illustrations based on graphical features in the dataset for the user to choose from after the user inputs a sketch, and based on this, providing adjustable grid guidance to guide the user through the drawing (see Figure 2.6).

The DualFace system provides an innovative layered approach to drawing support[26]. As shown in Figure 2.7, the system draws simple face lines input by the user, matches similar face contours in the database, and generates a shadow image as a reference for drawing, which is displayed in the lower layer of the drawing board. The system thus provides a global-local drawing guidance process (see Figure 2.7), and the user completes the final drawing task in a copy-like manner, which can effectively improve the coordination of structure mastery and detail control.

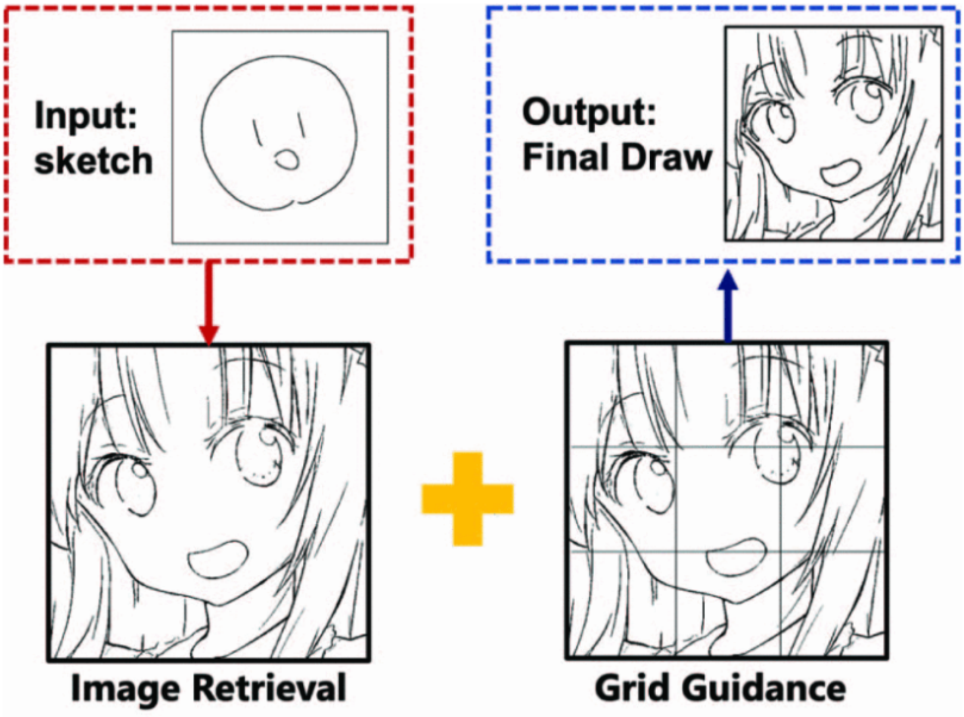

Figure 2.6: Illustration of the grid-guided drawing assistance proposed. The system first retrieves a reference image based on a rough input sketch and then overlays a grid to guide users in completing a refined final drawing (Source: Kanayama et al., 2023 [12]).

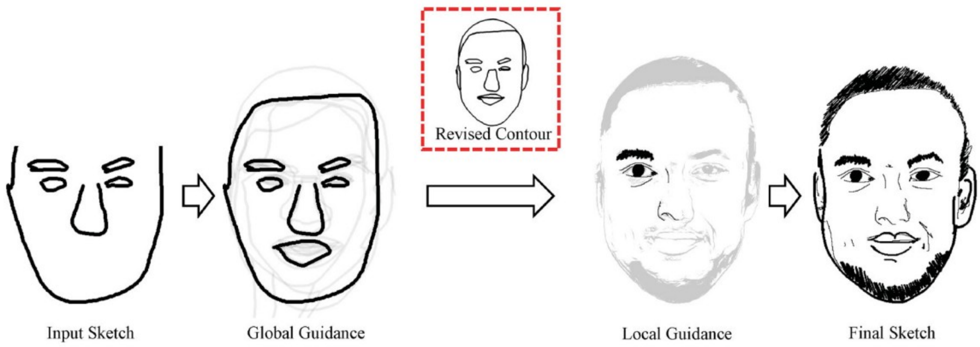

Figure 2.7: Illustration of the DualFace guidance process (Source: Huang et al., 2022 [26]).

Similarly, Alsaaran et al. proposes a tracing-based digital system that overlays reference contours, enabling users to improve line accuracy through immediate visual feedback [10]. The system provides structural path references through transparent overlays, allowing beginners to practice by imitating directly on top of the underlying guidance contours.

The DrawMyPhoto system, proposed by Williford et al. [13], decomposes the reference image into a series of structural segments. Users are guided step by step through the drawing process, progressing from rough composition to detailed depiction.

Building on these observations, this study proposes a decontextualized drawing method designed to integrate both overall structural guidance and detailed feature exploration, thus offering a more comprehensive learning strategy for developing accurate observation, robust structural understanding, and improved modeling skills.

Chapter 3

Proposed Method

This chapter introduces the proposed decontextualized drawing method, outlining its conceptual basis and implementation details. First, it briefly reviews three existing drawing guidance methods: Upright Drawing, Inverted Drawing, and Upright Occlusion Drawing. Then, it presents the design principles and step-by-step guidance process of the proposed method. Finally, the preliminary pilot study used to refine the method before the formal experiment is described.

3.1 Preliminary Study

To preliminarily assess the effectiveness of the proposed decontextualized drawing method, we conducted a Preliminary study involving three drawing conditions: (1) traditional upright drawing, (2) inverted drawing, and (3) the proposed decontextualized drawing method. To ensure consistency in visual input, a predefined set of reference images was used during the Preliminary study. These images, comprising various line drawings of fruits, flowers, and animals, are shown in Appendix A, Figure 2. A custom digital drawing interface was developed to facilitate the experiment. As shown in Figure 3.1, the interface featured a two-panel layout in which the reference image was presented on the left and the drawing canvas on the right. Basic drawing tools—including brush, eraser, undo, clear, and save—were integrated, along with a color palette and navigation buttons to switch reference images.

All tasks were performed digitally using a Wacom Cintiq Pro 16 tablet and a Pro Pen 2 stylus pen, as illustrated in Figure 3.2. Six participants (four females and two males, age of 21-34 years old) completed three sets of drawing tasks. A total of nine reference images were used in the pilot study. The drawing conditions were presented in a fixed order (upright, inverted,

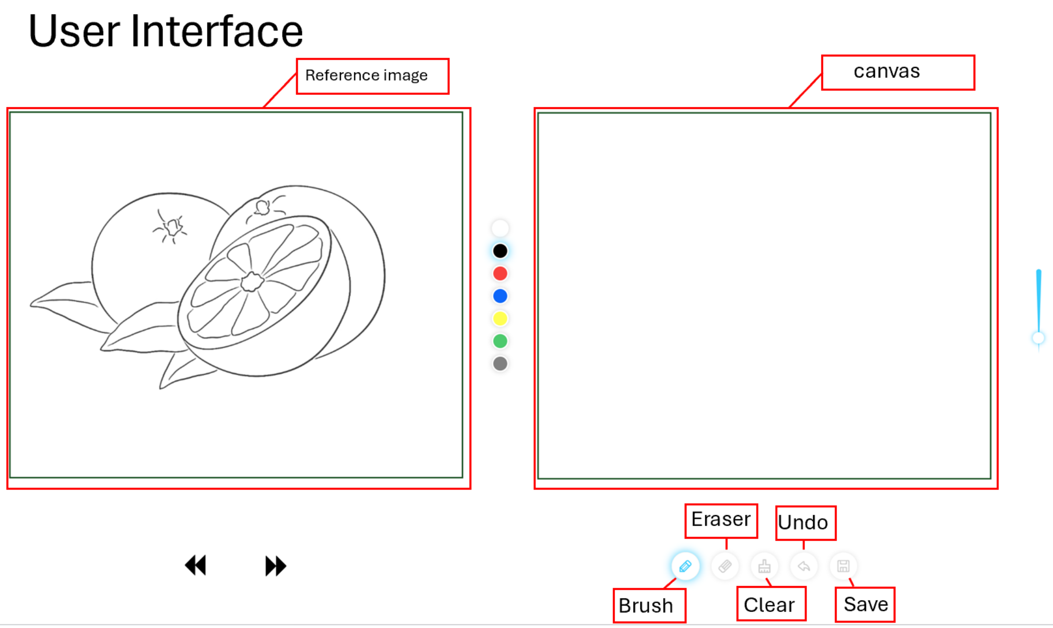

Figure 3.1: User interface of the digital drawing system. The left panel shows the reference image, while the right panel serves as the canvas for user drawing. Includes tools for brush selection, erasing, undo, clear, and save functions.

decontextualized), and each session was limited to five minutes to ensure consistency across tasks.

Figure 3.2: Participants performing drawing tasks during the preliminary study on the experimental UI by using a Wacom Cintiq Pro 16 and Pro Pen 2 stylus pen.

In the upright condition, participants observed and replicated reference images in their original orientation. The inverted condition required participants to draw from vertically flipped images to suppress symbolic recognition. In the decontextualized condition, participants first drew the outer contour based on a fully occluded, inverted image. Once the contour was completed, the occlusion was removed, and participants were allowed to refine internal details freely.

To assess the structural accuracy of the drawings, we employed the *Absolute Error (AE)* metric, a pixel-wise comparison measure widely used in image similarity analysis [31]. AE is computed as the average absolute difference between the pixel intensities of the participant's drawing I_p and a ground truth reference drawing I_r:

$$AE = \frac{1}{N}\sum_{i=1}^{N} |I_p(i) - I_r(i)| \tag{3.1}$$

where N is the total number of pixels, and i indexes each corresponding pixel in the image pair. **Lower AE values indicate higher structural fidelity and drawing accuracy.**

Figure 3.3 provides examples of drawings from the same participant using the three methods. The evaluation results revealed that the proposed decontextualized drawing method yielded the lowest average AE values among the three conditions, suggesting its superior ability to help beginner accurately capture structural and proportional features within a constrained time setting.

3.2 Experiment Results

Although the overall results of the Preliminary study indicated that the proposed decontextualized drawing method achieved the lowest average AE value, we observed that for certain reference images with relatively simple structures, the traditional upright drawing method yielded even lower AE scores. This phenomenon led us to reconsider the relationship between the effectiveness of the proposed method and the complexity of the reference images.

In particular, it raised the question of whether the benefits of the decontextualized approach are more pronounced in high-complexity images where structural guidance plays a greater role, and potentially less effective in low-complexity conditions where such guidance may be redundant or overly restrictive.

Moreover, during the preliminary study, all participants reported that the use of a digital stylus on the Wacom tablet interface lacked sufficient responsiveness and precision. This technical limitation significantly impacted the quality of their drawing experience and, by extension, their performance across all three methods. And due to the five-minute drawing time limit, some participants were unable to complete more complex drawings, making the drawing results impossible to detect and compare.

In response to these observations, we designed and conducted a formal experiment using traditional print paper and pen drawing, and removed the time limit to ensure a more natural and accurate drawing process and results. The goal was to eliminate input-related interference and more reliably evaluate the true impact of each drawing method under controlled and realistic conditions.

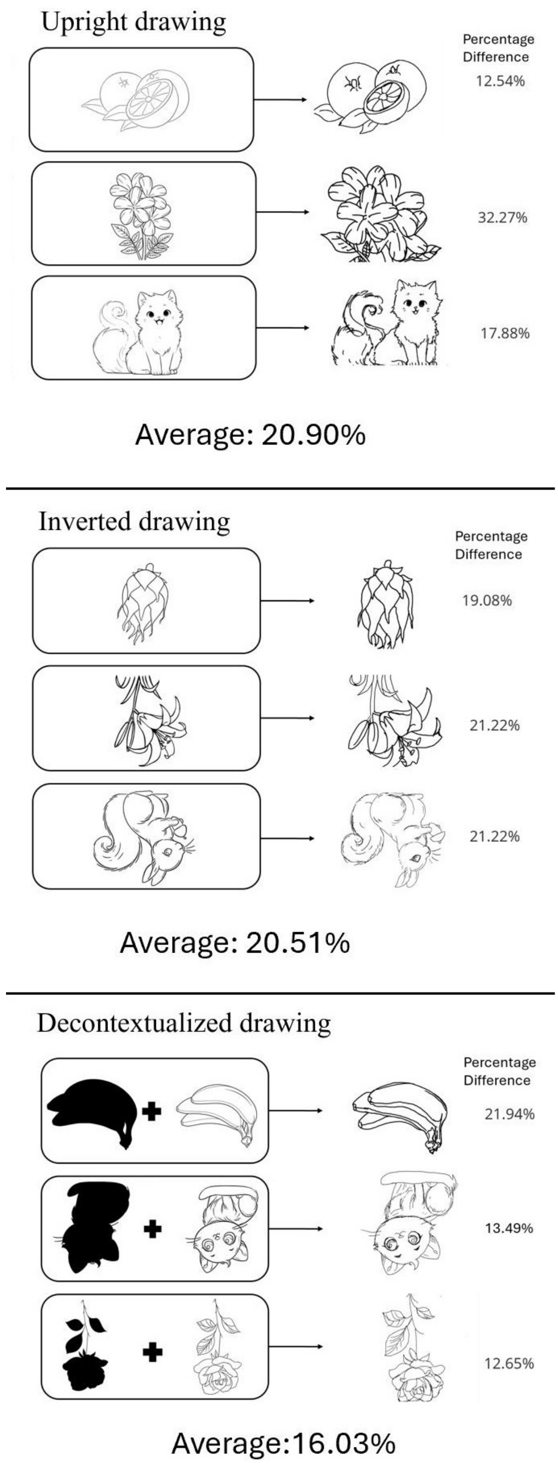

Figure 3.3: Drawing results and AE-based percentage differences across three conditions: upright drawing, inverted drawing, and the proposed decontextualized drawing. The decontextualized method yielded the lowest average error (16.03%) compared to upright (20.90%) and inverted (20.51%) conditions.

3.3 Decontextualized Drawing

To further explore the distinct contributions of image inversion and visual occlusion, we extended the Preliminary study design in the formal experiment by introducing a condition: the upright occlusion drawing method. This adjustment allowed us to isolate and compare the effects of inversion and occlusion individually, in addition to evaluating their combined implementation in the proposed decontextualized approach.

In total, the formal experiment compared four drawing methods: (1) upright drawing, (2) inverted drawing, (3) upright occlusion drawing, and (4) decontextualized drawing. We compare three existing representative drawing methods and summarize their features and limitations. Next, we introduce the proposed decontextualized drawing method, detailing its core principles and implementation. Finally, we describe how the effectiveness of the four methods is experimentally validated.

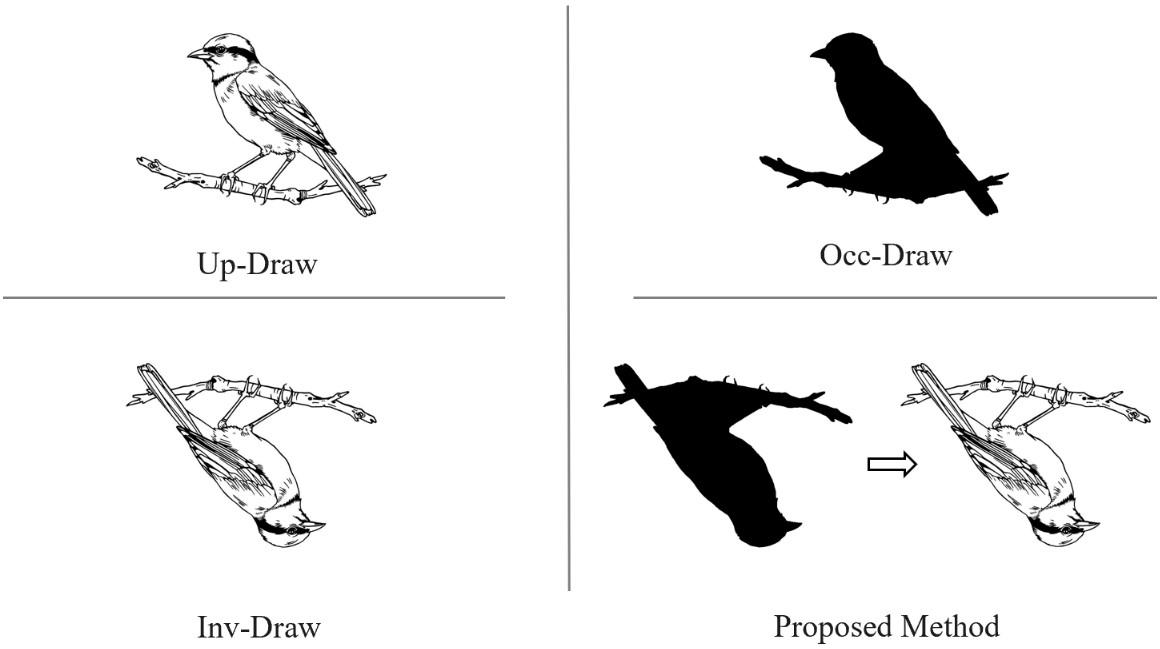

Figure 3.4: Comparison of participants' drawing process using different methods. Up-Draw: Upright Drawing; Occ-Draw: Upright Occlusion Drawing; Inv-Draw: Inverted Drawing; Proposed: Decontextualized Drawing.

Our proposed method is decontextualized drawing, which is designed to address the limitations of existing drawing assistance techniques. This method is used to guide beginners in drawing by inverted and full occlusion of the reference image. For reference images, Upright Drawing refers to the condition in which participants observe and draw an image in its upright orientation without any occlusion. Upright Occlusion Drawing builds upon this by incorporating full occlusion, revealing only the contours for guidance. Once the contour is completed, the occlusion is removed, allowing participants to freely refine the details. Inverted Drawing involves flipping the reference image upside down for observation and drawing. Decontextualized Drawing combines full occlusion and image inversion. Based on the inverted reference image, full occlusion is used to guide the drawing of the outline. After the outline drawing is completed, the occlusion is removed, allowing participants to freely refine details until the drawing is finished. We will experimentally test the effectiveness of these four methods (see Figure 3.4).

Chapter 4

Experiment Design

To control experimental variables and minimize interference from differences between object categories, we standardized the reference images by selecting animal subjects for all drawing tasks. A preliminary pool of 50 black-and-white line drawings of animals was curated as the initial set. To ensure visual diversity and systematically investigate the effects of complexity, the selected materials included images with both high and low levels of complexity.

4.1 Familiarity Evaluation of Reference Images

To minimize the cognitive bias caused by the influence of prior experience, we conducted a familiarity assessment before the main experiment. We designed a questionnaire to assess people's subjective familiarity with candidate reference images. The images depicted different animals in a black-and-white line drawing style (see Appendix B, Figure 7.2). To verify the sensitivity and accuracy of the familiarity assessment, we purposely included three visually distinct images of squirrels of varying complexity in this set.

Participants were asked to rate the familiarity of each animal using a 7-point Likert scale, where 1 means"not familiar at all" and 7 means "very familiar". The version of the familiarity questionnaire can be found in Appendix C, Figure 3.

On the 7-point Likert scale, the average familiarity ratings for these three images were 5.61, 5.48, and 5.47, respectively. The minimal differences in scores suggest that participants' familiarity ratings were stable and based primarily on conceptual recognition of animal categories rather than being influenced by differences in image complexity. This result demonstrates the reliability of the familiarity questionnaire in measuring category recognition.

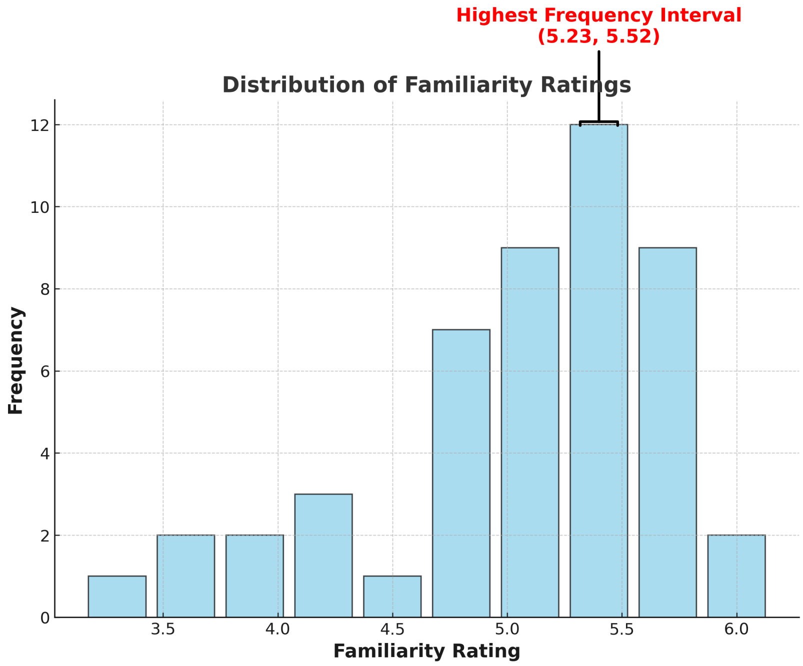

Figure 4.1: Distribution of the frequency of the 66 familiarity questionnaire results for 50 images.

Finally, we collected 66 valid questionnaires, For each image, we calculated the distribution of all scores and the average score. To ensure a balanced range of familiarity and avoid images that are too unfamiliar or too familiar, we prioritized images with a medium-high level of score distribution and selected images with moderate familiarity concentration, that is, images that are clustered around the middle of the Likert scale and are not extremely skewed.

Based on this analysis, 12 images were finally selected from the original dataset(see Figure 4.1). These images showed consistent and representative familiarity levels across participants and were used as final reference images for subsequent experiments.

4.2 Image Complexity Assessment

To evaluate and classify the complexity of the reference images used in the experiments, we adopt Shannon entropy as a quantitative metric. Shannon entropy is a well-established metric in information theory that reflects the level of uncertainty or information content based on the distribution of pixel intensities. By calculating the entropy value of each image, we divide the image set into two categories: high complexity and low complexity. This classification provides a basis for analyzing how visual complexity affects the drawing performance of different methods.

The Shannon Entropy H of an image is defined as:

$$H = -\sum_{i=1}^{N} p(i) \log_2 p(i) \tag{4.1}$$

where $p(i)$ is the probability of intensity level i, and N is the total number of distinct intensity levels in the image. Higher entropy values indicate greater visual complexity due to a more uniform or diverse pixel distribution.

After eliminating the two images with the highest and lowest entropy values as well as the two images in the center, among the remaining images, the Shannon entropy values of the low complexity images range from 4.58 to 5.52, and the Shannon entropy values of the high complexity images range from 12.12 to 15.58. Eventually, we selected the eight images as shown in Fig.4.2.

Figure 4.2: The final selection of eight reference images, categorized into high-complexity and low-complexity.

4.3 Design of Drawing Tasks

This experiment mainly compares the effects of four drawing guidance methods on beginner's drawing results. Up-Draw is Upright Drawing, Occ-Draw is Upright Occlusion Drawing, Inv-Draw is Inverted Drawing, and Proposed Method is Decontextualized Drawing (see Figure 4.3).

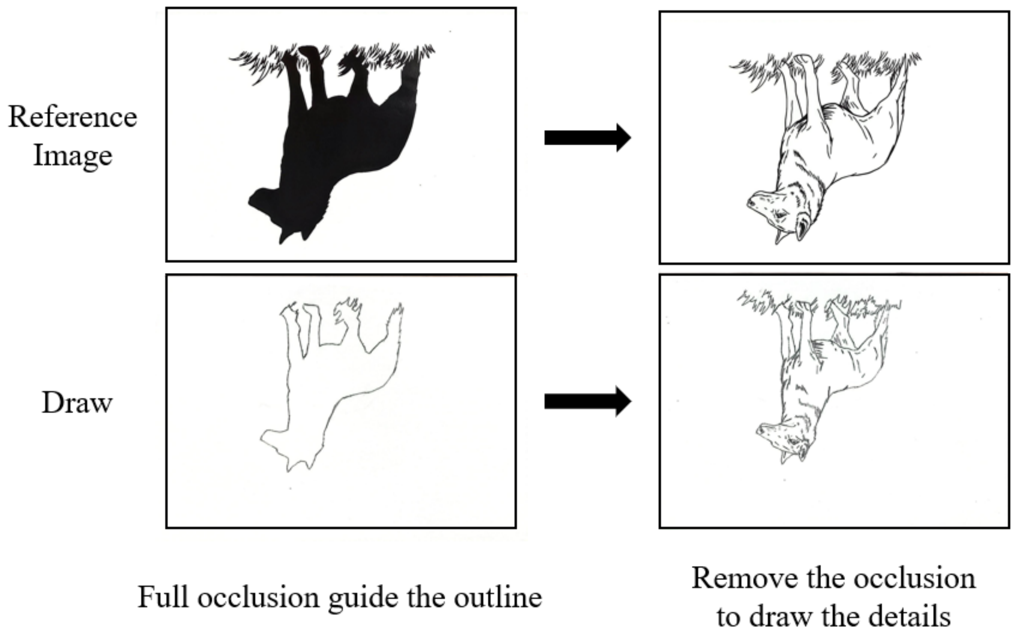

Figure 4.3: The drawing process of the proposed method.

We recruited drawing beginners (P1–P12, five females and seven males, age of 23-28 years old) to join the study, who drew 0-3 times a year. Age between 23 and 28 years old. They observed and drew 8 reference images. The reference images were given to the participants in a random order. To ensure a balanced experimental design, each method was used exactly once for each complexity level, meaning that no combination of method and complexity was repeated. For example, if Up-Draw was assigned to a high-complexity image, it was not used again for any other high-complexity image. This ensured that each drawing method was applied to both complexity levels an equal number of times, preventing bias due to repeated pairings of specific methods with specific complexity levels. The four methods were also combined with high-complexity and low-complexity images in a random order. In order to avoid the fatigue of the participants due to drawing high-complexity images all the time, high-complexity and low-complexity images were displayed alternately in this experiment. Each participant completed a total of eight drawing tasks. Upon completion of the experiment, subjects were asked to fill out a post-experiment questionnaire to evaluate their experience with each drawing method (Table 4.1).

Table 4.1: Post-Experiment Questionnaire Items

Question	**Item**
Q1	From the perspective of observing the reference image, which method do you feel was the most helpful? (Options: Up-Draw, Occ-Draw, Inv-Draw, Proposed Method)
Q2	From the perspective of executing the drawing (excluding observation), which method was the most helpful for the act of drawing? (Options: Up-Draw, Occ-Draw, Inv-Draw, Proposed Method)
Q3	Considering both observation and drawing, which method contributed the most to your overall drawing experience? (Options: Up-Draw, Occ-Draw, Inv-Draw, Proposed Method)
Q4	(Only if Q3 = Proposed Method) What aspects of the Proposed Method helped you during the drawing activity?
Q5	(Only if Q3 $\neq$ Proposed Method) What aspects of the Inverted Drawing method helped your drawing process?

4.4 Experimental Procedure

The drawing tasks were conducted using traditional media. Participants drew with pencils on A4-sized paper, and each reference image was printed at the same size as the drawing paper to ensure direct visual correspondence. During the experiment, participants observed and copied the reference images independently under different drawing guidance methods (see Figure4.4).

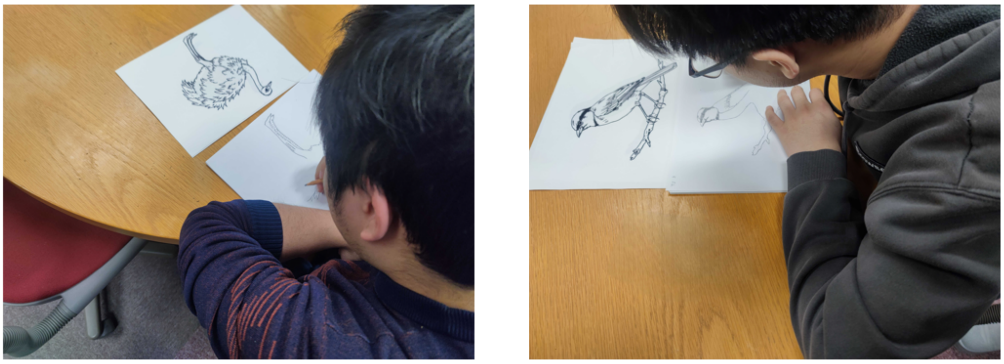

Figure 4.4: Illustration of participants performing drawing tasks under different methods in the experiment.

Each drawing method was presented in a separate session, and the reference image remained visible throughout the task. The experiment was intentionally untimed to minimize pressure and encourage natural engagement with the drawing process. Participants were instructed to begin when ready and to stop when they personally felt the drawing was complete. This self-paced approach allowed for more authentic expression and reduced interference from external constraints such as strict time limits.

No external feedback or correction was provided during the task, and participants were asked not to communicate with others to avoid cross-influence. All completed drawings were collected for subsequent evaluation.

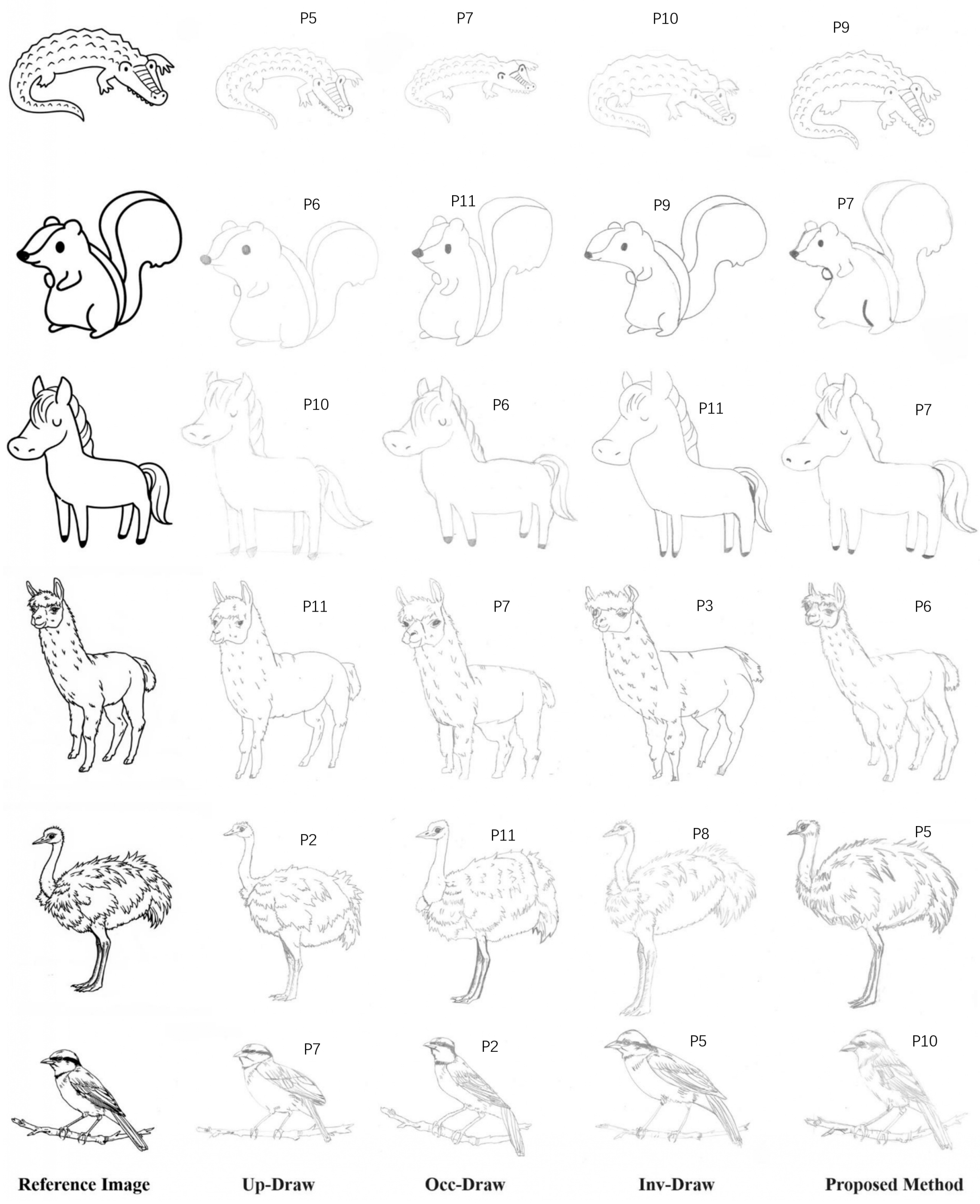

Figure 4.5: Example of the results of the pictures drawn by the participants, when drawing on a reference image of low complexity, the drawing results using the decontextualization method (Proposed Method) are worse compared to the results obtained by the other three methods, and the overall contours of the image appear to be more different. In the case of the high-complexity reference image, the results of the decontextualization method (Proposed Method) are better than the other three methods, with more accurate details and contours.

Chapter 5

Results

In total, 96 drawings were collected, and each reference image yielded results from different drawing methods. To facilitate subsequent digital processing, all paper-based drawings were scanned and converted into digital images. We performed both objective and subjective evaluations of these results.

5.1 Objective Evaluation

We employ SSIM, PSNR, CW-SSIM, and LPIPS to evaluate our experimental results: SSIM compares structural similarity between the predicted and reference images, PSNR quantifies distortion through pixel-level mean squared error, CW-SSIM incorporates wavelet transforms to further capture local phase information, LPIPS uses deep network features to measure perceptual similarity. Each metric respectively focuses on structural integrity, pixel fidelity, local phase consistency, and perceptual quality, providing complementary assessments of image quality from different perspectives. Table 5.1 presents a comparison of different methods based on objective image quality assessment metrics. Among all the evaluated methods, the proposed method consistently achieves the best performance across these metrics, demonstrating its effectiveness in preserving structural integrity, signal fidelity, local phase consistency, and perceptual quality.

The results show that the proposed method obtains the highest SSIM score (0.905), indicating that it maintains the closest structural similarity to the reference image. Since SSIM accounts for structural correlations, this suggests that our method effectively retains essential image details. Similarly, the highest PSNR value (14.968 dB) further confirms that our approach minimizes pixel-level distortions, as a higher PSNR generally corresponds to lower mean squared error (MSE) and improved fidelity. In addition, the proposed method achieves the highest CW-SSIM score (0.226), which reflects its ability to preserve local phase information, a key aspect of visual perception that helps maintain spatial coherence. Meanwhile, the LPIPS score (0.202) is the lowest among all methods, suggesting that the images produced by our method are perceptually closer to the reference images.

Overall, the results in Table 5.1 demonstrate that our proposed method outperforms the alternatives across multiple objective metrics.

Table 5.1: Comparison of different methods using subjective and objective scoring metrics. ($\Uparrow$ higher score indicates better result; $\Downarrow$ lower score indicates better result)

	Up-Draw	**Occ-Draw**	**Inv-Draw**	**Proposed Method**
Subjective scoring				
	80.292	73.000	66.960	70.083
Objective scoring				
SSIM $\Uparrow$	0.903	0.902	0.897	**0.905**
PSNR $\Uparrow$	14.862	14.758	14.690	**14.968**
CW-SSIM $\Uparrow$	0.201	0.225	0.203	**0.226**
LPIPS $\Downarrow$	0.210	0.205	0.223	**0.202**

5.2 Subjective Evaluation

We evaluated the results from multiple perspectives using five dimensions: Composition and Proportion, Structure, Details, Similarity, and Overall Impression. These dimensions not only address the overall layout and balance of the image but also examine the accuracy of finer details and how closely the work aligns with its reference, ultimately forming a comprehensive assessment of the drawings' visual quality. Five evaluators with professional drawing experience independently evaluated and scored all drawings. To compare whether the proposed method was more effective than the other methods (Up-Draw, Occ-Draw, and Inv-Draw) in assisting participants with their drawings, we analyzed the average scores for each method. The results of the subjective evaluation (Table 5.1) indicate that the average scores for these Methods were 80.291, 73.000, 66.960, and 70.083, respectively. Up-Draw achieved the highest average score, while Proposed Method was ranked third.

Table 5.2: Stability Analysis of Drawing Methods. (Total Scores)

	Up-Draw	**Occ-Draw**	**Inv-Draw**	**Proposed Method**
Mean Score	**80.29**	73.00	66.96	70.08
Standard Deviation	21.16	24.09	**14.78**	18.16
Coefficient of Variation (%)	26.36	33.00	**22.07**	25.92

Furthermore, in the area of subjective scoring, a statistical analysis of variability(Table 5.2) indicated that our proposed method (standard deviation = 18.16) achieved a better balance between scoring stability and quality compared to Up-Draw (21.16) and Occ-Draw (24.09). Although Inv-Draw demonstrated the highest stability (standard deviation = 14.78), its relatively low average score diminishes its overall effectiveness. Therefore, the proposed method demonstrates a balanced advantage, delivering consistently reliable and relatively high-quality results.

To verify whether the complexity level of the reference images affected participants' drawing results, we compared the evaluation scores of these Methods under high and low complexity conditions, the results are shown in Table 5.3.

Based on these findings, we observed that, in the subjective evaluation, under the high-complexity condition, the proposed method was rated higher than the other methods, but under the low-complexity condition, it received the lowest rating among all methods. In the objective evaluation, under the high-complexity condition, the proposed method outperformed the other methods only in the SSIM, PSNR, and LPIPS analyses. Under the low-complexity condition, the proposed method outperformed the other methods only in the PSNR and CW-SSIM analyses. Current comparisons did not attain statistical significance (paired t-test, $p>0.05$), likely constrained by the benchmark scale ($n=12$ test cases). To resolve this, we will conduct more experiments in the future.

Table 5.3: Comparison of Different Methods Based on Subjective and Objective Scoring. ($\Uparrow$ higher score indicates better result; $\Downarrow$ lower score indicates better result; “high” and “low” refer to high- and low-complexity reference images.)

		Up-Draw	**Occ-Draw**	**Inv-Draw**	**Proposed Method**
Subjective Scoring					
	high	68.146	64.625	57.513	**69.542**
	low	**69.917**	62.500	59.117	59.000
Objective Scoring					
SSIM $\Uparrow$	high	0.888	0.893	0.885	**0.900**
	low	**0.918**	0.912	0.911	0.909
PSNR $\Uparrow$	high	15.322	15.379	15.114	**15.559**
	low	14.402	14.081	14.232	**14.468**
CW-SSIM $\Uparrow$	high	0.221	**0.234**	0.211	0.223
	low	0.180	0.215	0.193	**0.229**
LPIPS $\Downarrow$	high	0.226	0.209	0.238	**0.195**
	low	**0.194**	0.209	0.207	0.208

5.3 Post-Experiment Questionnaire Analysis

All questionnaire responses are provided in Appendix D. After analyzing the post-experiment questionnaires of the 12 participants, we found that there was a clear stage-based preference across the four drawing guidance methods. When observing the reference images, 42% of participants selected the Up-Draw method, 33% chose Occ-Draw, and 25% chose the Proposed Method, indicating a general reliance on upright views for initial visual understanding.

In terms of drawing execution, 42% favored the Proposed Method, while 33% selected Up-Draw, demonstrating strong support for the two-stage workflow of the proposed method (outline to detail). Regarding overall experience, 42% again chose Occ-Draw and 33% selected the Proposed Method, suggesting that the upright occlusion strategy offers an optimal balance between perceptual familiarity and structured visual guidance.

Open-ended responses further revealed that participants who preferred the proposed method appreciated the sequence of “global observation followed by local refinement” and noted that occlusion “emphasizes contours while suppressing extraneous details". Those who did not choose the proposed approach still acknowledged that occlusion helps to quickly capture the overall shape and that inversion effectively reduces symbolic bias. However, some participants found inversion less intuitive when dealing with fine structural details.

These findings confirm that the staged structural guidance offered by the proposed method is particularly effective during execution, while Occ-Draw ranks highest in terms of general user satisfaction. Together, these insights underscore the complementary nature of subjective feedback and objective evaluation, offering actionable directions for refining our drawing assistance interface and improving step-by-step instructional design.

Chapter 6

Discussion

In this study, we explored whether our proposed method is helpful for beginners to perceive and capture form and structure in drawing copying. The results showed that it outperformed the inverted drawing method under high-complexity conditions, but performed less favorably than conventional methods when applied to low-complexity images, which contrasts with earlier findings. As illustrated in Figure 6.1, although the low-complexity image

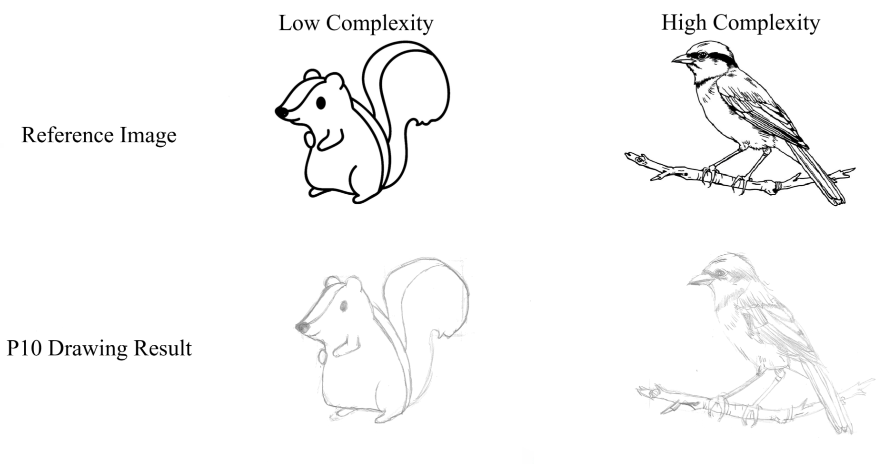

Figure 6.1: Comparison of drawing results by the same participant (P10) using the proposed method under different complexity reference images. In the low-complexity condition (left), the structure is distorted despite simplicity. In the high-complexity condition (right), the participant retained accurate proportion and detail.

contains fewer details, the participant failed to maintain structural proportion. In contrast, the high-complexity drawing preserved accurate contours and detail, This discrepancy may stem from over-simplification and cognitive overload. According to Navon's global precedence theory[25], when structural guidance is excessive for simple shapes, beginners may struggle to allocate attention efficiently, leading to impaired performance. In such cases, inversion and occlusion may hinder rather than help perceptual alignment, especially when internal details should be refined without prior contextual cues later.

To verify these phenomena, we conducted post-experiment interviews with participants to obtain subjective insights into their drawing experiences. Several participants reported that the proposed method, which combines inversion and full occlusion, helped them concentrate on the overall contour and reduced distraction from interior details. This effect was particularly beneficial in high-complexity images, where simplified visual input enhanced structural observation and drawing confidence. Conversely, under low-complexity conditions, participants noted that after completing the contour, they found it difficult to correctly locate internal features. The occlusion removed essential spatial references during the initial observation phase, making the subsequent refinement more cognitively demanding, despite the relative simplicity of the subject.

These observations indicate a potential relationship between method effectiveness and visual complexity, which aligns with trends observed in the experimental data. However, given the limited statistical significance of the subjective scores, further investigation is warranted. The impact of structural guidance on different levels of image complexity requires deeper exploration to confirm these effects. Such inquiries could help refine the proposed method and optimize its applicability across varying drawing scenarios.

Chapter 7

Conclusion

This study investigated the effectiveness of a decontextualized drawing method to improve beginners' ability to capture structural details while reducing visual distractions. This method inverts and fully occludes the reference image, letting beginners draw only its contours, once the contours are complete, the occlusion is removed to draw the details. Through a controlled experiment, we evaluated participants' drawing performance using both subjective assessments from professional evaluators and algorithm-based objective metrics. The study also examined how image complexity influenced drawing outcomes and provided insights into how structured guidance impacts observation-based learning. In addition, a familiarity screening process was introduced prior to the experiment to control for prior knowledge effect s and ensure more reliable interpretation of visual stimuli. Despite the contributions of this study, several limitations should be acknowledged, along with potential directions for future research.

7.1 Limitations

First, while this study validated inter-rater reliability among evaluators, the results showed considerable variation among individual evaluators. This suggests potential subjectivity in the scoring process, which may have influenced the subjective evaluation outcomes. Future research could explore ways to reduce scoring discrepancies, such as developing standardized evaluation criteria, conducting calibration sessions among evaluators, or integrating automated assessment tools to enhance consistency. The implementation of AI-assisted scoring systems, such as models trained on expert drawing features, may help reduce human bias and increase replicability.

Second, this study focused on short-term training effects, assessing participants' drawing performance within a single session. However, the long-term impact of the proposed method remains unclear. Future research could investigate whether the observed improvements persist over multiple training sessions, providing insights into its potential for long-term skill development. A longitudinal study design could help determine whether repeated exposure to the method enhances drawing performance over time. It would also be beneficial to examine whether the benefits of decontextualized drawing transfer to other forms of representational tasks, such as freehand sketching or figure drawing.

Third, although this study controlled for image complexity using Shannon entropy and classified reference images into two categories, complexity remains a multifaceted construct that may require additional dimensionality—such as semantic ambiguity, contour density, or structural occlusion—for more precise analysis. Future studies could explore how specific components of image complexity interact with the type of guidance provided, and how these relationships affect the allocation of visual attention during drawing.

Finally, while the current experiment was conducted using traditional pen-and-paper media, the proposed method could be adapted into digital platforms that integrate occlusion layers and inversion filters in real time. This opens up opportunities for integrating the approach into interactive art education systems, mobile drawing apps, or even augmented reality (AR)-based learning environments.

7.2 Future Works

By addressing these limitations, future studies can further refine and expand upon the findings of this research. Specifically, future work will focus on improving inter-rater reliability through standardized scoring methods, exploring AI-driven guidance systems, refining complexity classification, and further exploring the relationship between complexity and the way of seeing and the ability to capture structural detail when drawing. Additionally, the long-term effects of the method, the transferability of drawing skills across domains, and its applicability in digital and educational contexts remain promising areas for extended investigation. These efforts will contribute to a deeper understanding of effective drawing training methods and their implications for cognitive and perceptual development.

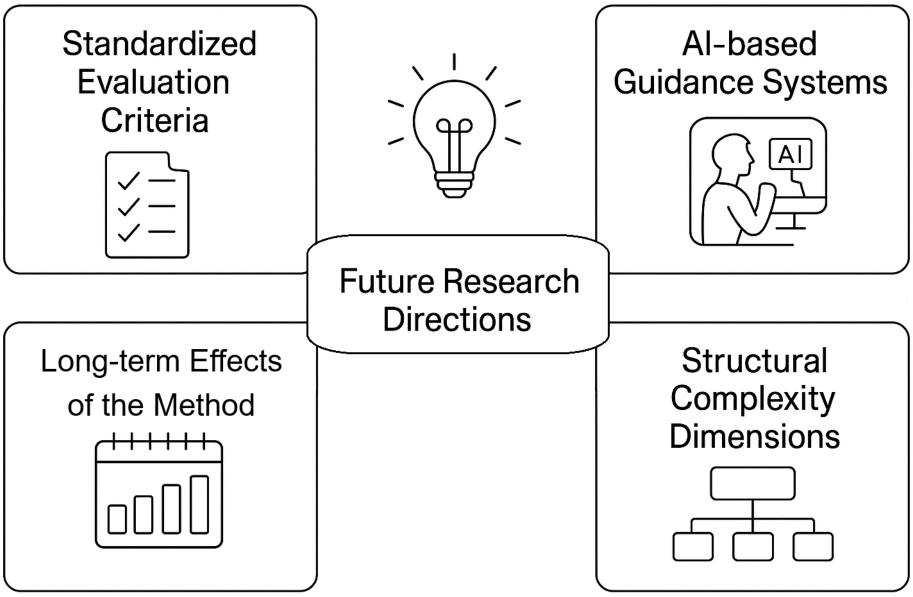

Figure 7.1: Visual summary of future research directions, including standardized evaluation criteria, AI-based guidance systems, longitudinal studies, and structural complexity dimensions.

Acknowledgment

First of all, I would like to express my sincere gratitude to my supervisor, Professor Xie, for his firm support, profound guidance and patience throughout the research process. He not only gave me careful guidance in academics, but also taught me a lot in the principles of dealing with people. He told me that it is a difficult process to go from zero to one in research, but as long as you go from zero to one, the rest of the road will be more relaxed. It is also these teachings that support and encourage me to face unfamiliar research directions and cross-disciplinary difficulties and work hard to get to where I am today. I am really grateful here. As a teacher, he is a very good mentor in different aspects, kind, responsible, serious and hardworking. The principles I learned from Professor Xie not only supported my research, but also changed my attitude towards life and the way I deal with things in life in the future. A good teacher has a lifelong impact on people. I deeply felt this sentence from my supervisor, Professor Xie. Similarly, his professional knowledge shaped the theoretical framework of this study, and his professional guidance and feedback during the repeated revision process ensured the rigor and clarity of the final paper.

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security of being accepted."

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Appendix

Notes on Figure Generation

Some of the illustrative figures were generated using ChatGPT based on author-designed prompts to aid conceptual explanation. These images are indicated in figure captions.

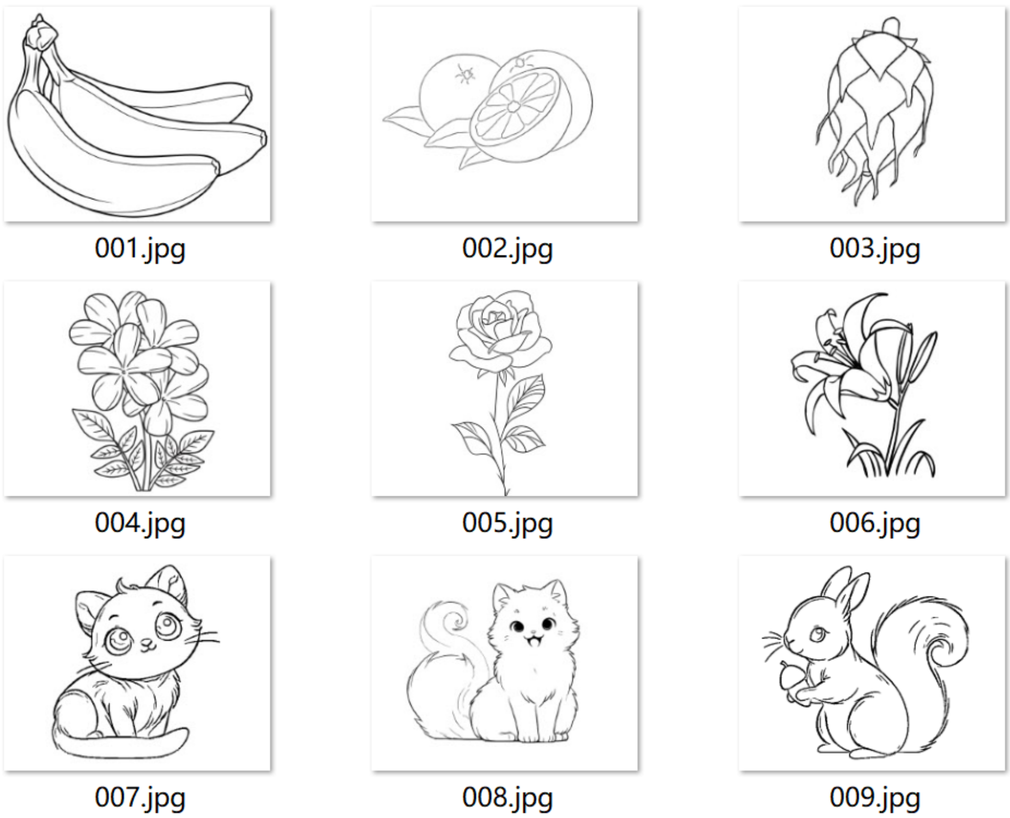

Figure 2: Reference image set used in the Preliminary study. A total of 9 black-and-white line drawings were selected, covering fruits, flowers, and animals.

Appendix A: Reference Images in Preliminary Study

Appendix B: Animal Images Used in Familiarity Test

Appendix C: Familiarity Questionnaire

Familiarity Survey

Dear Participant:

Thank you for faking part in this survey! This survey alms to understand your tamiliarity with items depicted in the following images: Below are specific instri-uctions for completing the survey, please read them carefully:

Purpose of the Survey

Through your feedback, this study seeks to gauge your recognition and familia-rity with different items presented in various images, supporting related rese-arch efforts.

Survey Content

You will view 50 images, each displaying a different item. You will be asked to rate your familiarity with each item's appearance depicted in the image.

Rating Scale

Please select most appropriate ratting, ranging from 1 to 7, via,specific 4ily, nanging from 1 to 7.

1. Not at all familiar; I have never seen or heard of the item depicted.
2. Hardly familiar: I have had very little exposure to the item depicted.
3. Somewhat familiar: I have a vague impression of the item depicted.
4. Moderately familiar; I have a basic understanding of the item depicted.
5. Fairly familiar; I have a clear awareness of the item depicted.
6. Very familiar; I have an in-depth understanding of the item depicted.
7. Extremely familiar. I am highly knowledgeable about the item depictect, and may have relevant experience.

Participation Guidelines

• Respond based on you initial instinct; there is ho need to deliberate for too long.

• There are no right or wrong answers, simply reflect your genuine responses.

Important Notes

• All data from this survey will be kept confidential and used solely for acadermic research. Completing the survey is estimated to take 10–15 minutes.

Figure 3: Familiarity questionnaire used in the experiment survey. Participants were asked to rate their familiarity with the subjects in the reference images on a 7-point Likert scale.

Appendix D: Post-Experiment Questionnaire (Blank Version)

Participant ID:

Table 1: Post-experiment questionnaire responses (blank for 12 participants)

Participant	**Q1: Best Observation**	**Q2: Best Execution**	**Q3: Best Overall**
P1	Up-Draw	Up-Draw	Up-Draw
P2	Up-Draw	Up-Draw	Up-Draw
P3	Proposed Method	Proposed Method	Proposed Method
P4	Proposed Method	Proposed Method	Proposed Method
P5	Occ-Draw	Proposed Method	Occ-Draw
P6	Occ-Draw	Up-Draw	Occ-Draw
P7	Occ-Draw	Inv-Draw	Occ-Draw
P8	Up-Draw	Up-Draw	Up-Draw
P9	Up-Draw	Occ-Draw	Occ-Draw
P10	Up-Draw	Proposed Method	Proposed Method
P11	Occ-Draw	Occ-Draw	Occ-Draw
P12	Proposed Method	Proposed Method	Proposed Method

Q4: (Only if Q3 = Proposed Method)

Participant	Response
P1	
P2	
P3	In cases where it's not clear what the pattern is under the occlusion, the Proposed Method makes it much clearer for me to observe all the details.
P4	The proposed method helps to determine the general outline of the image and facilitates stereotyping.
P5	
P6	
P7	
P8	
P9	
P10	Occlusion can better define the outline.
P11	
P12	The proposed method is two-stage drawing, first global observation drawing, then local observation drawing, two-stage effectively reduce the difficulty of observation, and two-stage with orientation, reasonable arrangement of the order of drawing, easier to draw.

Q5: (Only if Q3 $\neq$ Proposed Method)

Participant	Response
P1	Occlusion helps with drawing contour, but for complex drawings, I can't tell the contour from the rest when I draw the contour and then draw something else.
P2	Occlusion guidelines help to better define the drawing's contour.
P3	
P4	
P5	Occlusion helps to have a rough idea of what is being drawn and is more conducive to overall grasp.
P6	Occlusion shows that contours can help to better define the size as well as the structure of the drawing image, and that inversion helps to improve the completeness of the image and deepen the outlining of details when performing detail filling.
P7	Occlusion is good for grasping the general outline of a figure, inverted looks less likely to imagine what the picture is about than upright looks, whereas an upright view will easily recognize what the picture looks like and will cause the person drawing to use their imagination to fill in the details, whereas an inverted view has a low likelihood of that occurring, and instead the reference for the drawing will be more dependent on observation rather than imagination.
P8	unhelpful
P9	Occlusion allows me to focus more on the details of the drawing outline.
P10	
P11	The proposed method allowed me to remember what was being drawn, the lines were more natural, the occlusion helped the group to define the outline, and the inversion rather interfered with the drawing of the details, such as the direction of the feathers, and didn't help to discover more details.
P12	

Q1: From the perspective of observing the reference image, which method do you feel was the most helpful?

(Options: Up-Draw, Occ-Draw, Inv-Draw, Proposed Method)

Q2: From the perspective of executing the drawing (excluding observation), which method was the most helpful for the act of drawing?

(Options: Up-Draw, Occ-Draw, Inv-Draw, Proposed Method)

Q3: Considering both observation and drawing, which method contributed the most to your overall drawing experience?

(Options: Up-Draw, Occ-Draw, Inv-Draw, Proposed Method)

Q4: If you chose the Proposed Method in Q3, what aspects of this method helped you during the drawing activity?

Q5: If you did not choose the Proposed Method in Q3, what aspects of the Inverted Drawing method helped your drawing process?