Speed Labeling: Non-stop Scrolling for Fast Image Labeling

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Abstract

This study presents "Speed Labeling", an image-labeling technique to increase the efficiency of easy binary labeling tasks where an annotator can choose a label instantly. We first conduct a formative study to identify the factors affecting the efficiency of easy image labeling: image layout and image transition. Based on these results, we designed a novel labeling technique using non-stop scrolling. In conventional image labeling, the system moves to the next image only after the user assigns a label to the previous image. To maximize efficiency, our technique continuously scrolls images without waiting for the completion of labeling, assuming that the user gives labels at a mostly constant speed. The system dynamically adjusts the scrolling speed based on the labeling speed. Subsequently, we conduct a user study to compare the proposed "non-stop scrolling" technique to the conventional "stop-and-go scrolling" technique in an easy image-labeling task. The results showed that speed labeling requires less time (faster by 7%, 305 more images labeled per man-hour) to complete the labeling task than the conventional technique without a significant increase in errors. In addition, the results showed that speed labeling makes the labeling task more enjoyable for crowd workers and makes them feel more attentive during tasks.

Keywords: Manual Image Labeling, Non-stop Scrolling, Labeling Efficiency, Human Processor.

Index Terms: • Human-centered computing~Human computer interaction (HCI)~Interactive systems and tools

1 Introduction

Data are among the most important aspects in the development of intelligent systems. However, data collection (i.e., data annotation) is always a bottleneck because it is labor-intensive and time-consuming. For data collection, a crowdsourcing platform, such as Amazon Mechanical Turk, is typically used because through it the task requesters can efficiently recruit a large number of human workers (mostly non-experts) [1]. There are two main issues in crowd-sourced image labeling: labeling quality and labeling efficiency. We focus on labeling efficiency because labeling quality has been intensively discussed in the literature [7, 8, 9, 10, 11], but labeling efficiency has been less explored. Labeling efficiency is important because it directly connected to the cost. Improvement of subjective experience (enjoyment and attentiveness) is also important to make recruitment of crowd workers easier.

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We focus on an easy binary image labeling task where we can expect almost 100% accuracy to investigate methods to improve labeling efficiency to factor out labeling accuracy. We propose that reducing the task completion time and increasing the attention of crowd workers can save time as well as the data annotation cost. This study involved cases where the annotation task was very easy and an annotator could assign a label to an image almost instantly. We assumed that annotators provide labels at an almost constant rate and rarely make errors.

First, we conducted a formative study (n = 4) to explore and discuss the effect of two factors on easy image labeling: (1) image-viewing layout (single image, single line, and grid) and (2) image-transition method (with and without animation). The results showed that single-line and grid layouts were more efficient than a single-image layout, and the efficiency of the image transition with animation was comparable to that without animation.

Based on the insights obtained from the formative study, we then proposed "Speed Labeling", an image-labeling technique for increasing the speed of easy image labeling. In conventional image labeling, the system moves from one image to the next only after the user assigns a label to the previous image. The proposed technique, assuming that the user gives labels at a mostly constant speed, continuously scrolls through the images without waiting for the user to confirm the completion of labeling, thus achieving high efficiency (Figure 1). The system dynamically adjusts the scrolling speed based on the weighted average of the past N image labeling speeds.

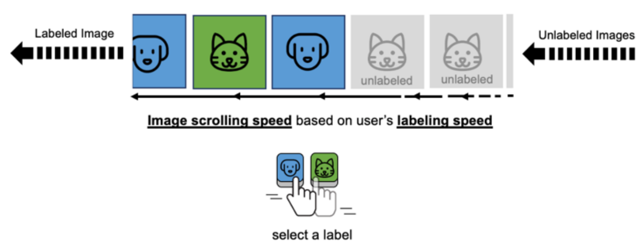

Figure 1: Workflow of speed labeling.

We conducted a user study (n = 36) on a crowdsourcing platform to compare the proposed "non-stop scrolling" labeling technique to the conventional "stop-and-go scrolling" technique in an easy binary image-labeling task. The results showed that the proposed "non-stop scrolling" labeling technique required lesser time to complete the task (7% faster, 305 more images labeled per man-hour) than the conventional technique, with a comparable label quality. In addition, the results showed that the participants enjoyed the task and felt more attentive during the labeling process when using the "non-stop scrolling" technique. The three main contributions of this study are as follows:

- We conduct a formative study that explored and identified the factors affecting image-labeling efficiency.

- We propose the speed-labeling technique that increases the labeling speed of easy manual image-labeling tasks.
- Finally, we conduct a user study comparing the speed labeling technique to the conventional “stop-and-go scrolling” technique. The results show that the proposed technique is more efficient and enjoyable and makes annotators more attentive.

2 RELATED WORK

2.1 Crowdsourcing Annotation

Collecting a sufficient amount of relevant data is always challenging, as data annotation is a labor-intensive and time-consuming process. For example, ImageNet [12] contains more than 14 million images labeled by human workers, which must have been a significant endeavor. Crowdsourcing is typically used to address this issue. In crowdsourcing, task requesters can easily recruit a large number of human workers to collect (annotate) a large amount of data. In addition, several annotation tools, such as LabelMe, a web-based annotation tool [14, 15], and VIA [16], have been developed. However, there are several issues when conducting crowdsourcing annotation tasks [13]. One critical issue is that the label quality of a crowdsourcing annotation task is unstable, often containing numerous errors [2, 3, 4, 5, 6]; these data errors can cause problems in a machine learning task [22].

Many studies have proposed solutions to improve the label quality of crowdsourced annotations. For example, Revolt [8] is a collaborative crowdsourcing image-annotation tool that applies concepts from expert annotation workflows (label check modification). This specific workflow can produce a higher label quality than a conventional labeling workflow. Involving multiple annotators in an annotation task is a popular concept for improving label quality. Fang et al. [9] proposed a two-round workflow to improve the quality of crowdsourced image labeling, and Baba [21] proposed two types of labeling workflows (parallel and interactive) that allow multiple annotators to be involved in an annotation task in different ways to improve the label quality. Spatial labeling [7] is an image-labeling tool that provides a spatial layout that allows annotators to observe and organize the similarities and differences between images before selecting an appropriate label for an image. This spatial-labeling interface is especially efficient in improving the label quality in non-expert image annotation. Pairwise HITS [10] is a labeling workflow for quality estimation that enables annotators to compare a pair of labeled data and select a better one. Kulesza et al. [45] introduced two structural labeling solutions to help annotators in defining and refining their concepts during data labeling. Zhou et al. [54] proposed “RelRoll”, a relative labeling interface highlighting emotion-changing sentences and an approach to estimating absolute labels from relative labels. Tang et al. [55] introduced “PDFChatAnnotator”, a semiautomatic human-LLM tool for document annotation. In addition, some studies applied hierarchical classification in an annotation task to increase label quality [23, 24] and interactive concept learning guides users to assign labels [47, 48, 56, 57, 58].

While most of these studies focused on improving label quality (especially for a more complicated labeling task that requires domain knowledge), the present study focuses on improving labeling efficiency in an easy binary image-labeling task (i.e., does not require domain knowledge). We propose improving labeling efficiency is as important as improving label quality, even in a very easy labeling task, because it can save time as well as money involved in data collection.

2.2 Automatic Scrolling

Scrolling is a typical approach to viewing the different parts of a document or webpage and is controlled by many forms of input device [50]. A scrollbar is the most basic function of a graphical user interface and has been used in a range of systems (e.g., Microsoft Windows). However, a standard scrollbar has various limitations [29]. Several techniques have been proposed to improve the manipulation of standard scroll bars in different tasks. For example, Alexander et al. [27] proposed the “Footprints” scrollbar that can efficiently support the task of revisiting a document with the feature of scrollbar marks and mark thumbnails. A study [30] introduced an artificial-landmark scrollbar that uses icon design on the scrollbar as marks for revisiting tasks. Brewster et al. [28] introduced an auditory scrollbar that can reduce the mental workload and have a higher preference score than a standard visual scroll bar.

Furthermore, several techniques have been proposed for browsing large documents that allow users to control the scrolling speed by dragging a knob on the scrollbar [32, 33, 34]. Igarashi et al. [26] proposed a technique that integrated rate-based scrolling with automatic zooming to browse documents. The results have shown that automatic zooming is a helpful alternative to a standard scrollbar. The similar concept “speed dependent automatic zooming” was also applied on viewing different types of documents [51] and on large [46] and small screens [52]. Kin et al. [35] introduced content-aware kinetic scrolling, a scrolling technique that dynamically applies pseudo-haptic feedback to items with high degrees of interest in a long document, whereas a study [31] showed that, for reading and counting tasks, animated vertical scrolling could improve both efficiency and user satisfaction. In addition, scrolling has been widely used as an efficient method for browsing images on mobile devices [36, 37, 38].

In this study, we share an “automatic scrolling” concept with an easy binary image-labeling task. We proposed a “non-stop scrolling” technique that can continuously scroll the images based on the user’s labeling speed. We believe that the scrolling feature can also bring benefits in the form of improved labeling efficiency.

3 FORMATIVE STUDY

We conducted a formative study (n = 4) to explore two factors that may affect the labeling efficiency and label quality of an image-labeling task: (1) the image-viewing layout and (2) the image-transition method in an image labeling task. The participants were computer science graduate students (three male and one female). We used a binary image-labeling task (dog or cat) as an example of an easy-to-label task. The participants were asked to label 100 images (50 dog and 50 cat images; the order of the images was randomized). We measured the time and accuracy of the tasks completed by the participants.

(1) Image-Viewing Layout

An image-viewing layout (e.g., the number of images that can be displayed at one time) affects the efficiency of image browsing [41]. It also affects the efficiency of image labeling, but there are no detailed studies exploring this issue in an image-labeling task. In the formative study, we compared three layouts in a binary image-labeling task (dog or cat): a single image, b) single-line, and c) grid (Figure 2).

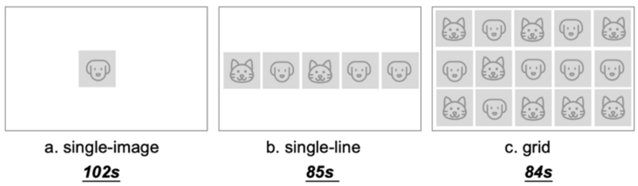

Figure 2: Image viewing layouts and the average labeling time in the formative study (100 images).

A single-image layout shows only one image at a time. The next image was shown after selecting the label for the image. The single-line layout shows five images in a line. After selecting the labels for all images, the next five images are shown. The grid layout shows three lines of images (five images per line). After selecting labels for all images, the next page of 15 images is shown. We did not use animation in this transition. The results showed that the single image required an average of 102 s to complete the labeling task, whereas the single-line and grid required an average of 85 s and 84 s to complete the task, respectively. The accuracy of all the three layouts was 100%.

This indicates that the single-line and grid layouts are more efficient than the single-image layout for displaying images during image-annotation tasks. This is probably because one can start working on the next image immediately after selecting a label for the previous image in line and grid layouts, whereas one needs to wait for labeling the previous image in the single-image layout. This shows that, by eliminating this waiting time, we can save time in image-annotation tasks. We expected the grid layout to be much more efficient than the single-line layout. However, task completion times were comparable between the single-line and grid layouts. We assumed that this was because the line and grid layouts both require significant eye movements (right to left) at the end of a line.

(2) Image-Transition Method

Animation in a user interface affects usability and the user experience [39, 40]. In the formative study, we compared a transition with and without animation in the same image-labeling task (to label 100 dog or car images) with the above three image layouts. Figure 3 shows the conditions with and without animation in the single-image layout. In the without-animation condition, the image abruptly switched (i.e., required 0 s) to the next image. In the with-animation condition, the image switched to the next image with an animated transition. The animation required 0.4 s to complete.

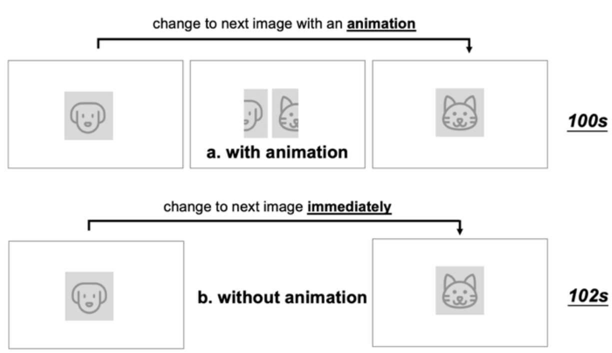

Figure 3: Image transition methods and the average labeling time in the formative study (100 images).

The results show that it takes 100 s without animation and 102 s with animation to label 100 images in a single-image layout. This is surprising, as the with-animation condition requires a total of 40 s for animation. This implies that the worker actively performs image recognition, even during animation, without wasting time. We also tested the two transition techniques in single-line and grid layouts, and the results were similar (single-line: 85 s without animation and 86 s with animation; grid: single-line: 84 s without animation and 86 s with animation). This result leads to the idea of actively exploiting transition time in animated transition in our "non-stop scrolling" technique.

4 Speed Labeling

We designed our new labeling technique based on the insights obtained from this formative study. First, we chose to use a single line layout because it was faster than single-image layout and comparable to the grid layout and more space-efficient (i.e., the single-line layout is more efficient than the single-image layout). Second, we slid the images horizontally individually after an image was annotated rather than replacing all the images after completing a line (as in the formative study) to avoid large eye movements when moving to the next set. Third, we used an animated transition to exploit the transition time. We show multiple images at a time; therefore, a sudden change without animation can take time for the annotator to identify the target image. We also devised a new technique, called "non-stop scrolling". The basic idea is to exploit the time required for the human processor [42] to perceive the incoming image and actuate a finger to press a key (Figure 4, top). We eliminate this idle time in the conventional stop-and-go technique by preemptively moving to the next image without waiting for the user's mouse click, assuming that the user provides labels to images at an almost constant speed (Figure 4 bottom). This is a reasonable assumption when the labeling task is easy, and the user can instantly assign a label without careful thinking. In reality, the labeling speed is not exactly the same; therefore, we constantly monitor the labeling speed and dynamically adjust the scrolling speed accordingly.

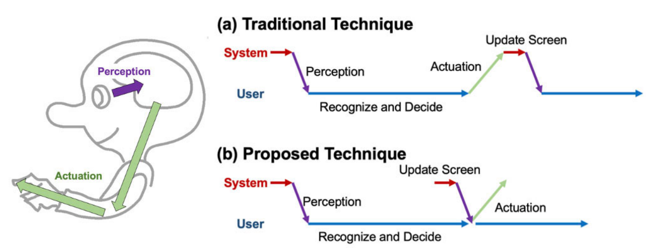

Figure 4: Basic idea of the human processor: (a) conventional technique and (b) proposed technique. The illustration on the left is inspired by [42].

4.1 Image-Labeling Interface

Figure 5 (a) shows the initial state of the speed-labeling interface. The annotator needs to press the "Begin" button to start the image-labeling task. To select a label for an image, the annotator presses arrow keys on the keyboard to select a "dog" label (left arrow key) or a "cat" label (right arrow key). After selecting a label for the first image, the images start scrolling from the right to the left. Figure 5 (b) shows the working state of the interface. Images were highlighted after being assigned a label (i.e., red border for a dog label and blue border for a cat label).

Figure 5: Speed-labeling interface: (a) initial state and (b) working state.

The images were continuously scrolled from right to left, while the annotator continually assigned labels to the incoming new (unlabeled) images. The scrolling speed was dynamically adjusted according to the annotator's labeling speed to avoid abrupt changes in speed. If the annotation selects labels quickly, the scrolling speed becomes fast; if the annotation selects labels slowly, the scrolling speed becomes slow. If the annotator spends an image that is quite long, the scroll tentatively stops when the next keyboard presses (i.e., an unlabeled image never gets scrolled out of the screen). In this prototype implementation, we did not provide a mechanism to return and fix errors during annotation.

4.2 Speed Control Algorithm

Our speed-labeling system (algorithm) always has the current target image around the center of the screen during the annotation. The center of the screen was defined as zero, and the position of the target image was defined as x. If the image is on the right side of the interface, x > 0; if it is on the left side, x < 0. The value of x constantly decreases when the images scroll automatically. x becomes x+D when the user presses a keyboard, and the target image switches to the next one (Figure 6).

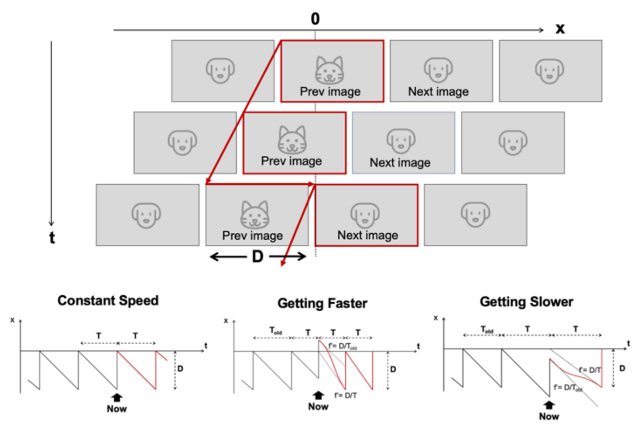

Figure 6: Algorithm for speed labeling.

The system defines time t when the user has just pressed the key (labeled) as zero (t=0) (reset the counter). The system records current position x(0) (after adding D) and current velocity x'(0). We make a plan (velocity profile) until the next key is pressed based on the values of x(0) and x'(0). If x(0) < 0, the system needs to decrease the velocity to slow down, and if x(0) > 0, the system should increase the velocity to catch up. The system also computes time interval T between the previous and current key presses, as well as the average speed D/T, where D is the distance between the positions of two adjacent images. The system assumes that the next key-press occurs after time T. It controls the velocity such that, after time T (just before the next key press), the velocity reaches the average speed D/T (x'(T) =D/T), and the position becomes − D (x(T) =− D). Specifically, the system computes a cubic function f(t) satisfying f(0) = x(0), f(T) = -D, f'(0) = x'(0), f'(T) = D/T, and computes the position of the target image using the function (x(t) = f(x)) until the next key is pressed. In the actual implementation, we take the average of recent time intervals when computing T and introduce buffer time N_buffer when computing the target position and velocity to avoid abrupt changes in speed (see Algorithm 1).

Algorithm 1:

Input: distance between two images D; the time interval between this press time and the last press time T_0; average press time interval T; a cubic function of distance x(t); a quadratic function of velocity v(t); parameters of distance and velocity function a,b,c,d; buffer time parameter N_buffer = 2;

for *each keydown* **do**
- update the average press time interval T based on the latest time interval T_0;
- $x_0 = x(t) - D$;
- $v_0 = v(t)$;
- $x_1 = N\_buffer \times D$;
- $v_1 = D/T$;
- $t = N\_buffer \times T$;
- //solve the following four equations to solve a,b,c,d;
- $at^3 + bt^2 + ct + d = x_1$;
- $3at^2 + 2bt + c = v_1$;
- $c = v_0$;
- $d = x_0$;
- update a,b,c,d in distance and velocity function;

end

4.3 Example of the Usage Scenario

Figure 7 shows an example of the usage scenario. (a) At the beginning of a labeling task, the annotator first sees several images and makes labeling decisions (dogs, dogs, and dogs) in the mind before assigning these labels to the images. (b) The annotator then assigns the labels (dog, dog, and dog) to the images without spending time considering them. This is because the annotator has already made labeling decisions at the time of seeing the images. (c) Simultaneously, new (unlabeled) images are continually coming (scrolling from the right side), and the annotator continually labels the images while seeing new images. The annotator always sees a few more unlabeled images (i.e., makes label decisions in mind) before giving labels.

Figure 7: Example of usage scenario: (a) seeing images and making labeling decisions in mind, (b) giving labels to the images and new images are continually coming, and (c) keeping seeing new images and giving labels.

5 User Study

We conducted a user study to compare the proposed "non-stop scrolling" labeling technique with a conventional "stop-and-go scrolling" labeling technique in an easy binary image-labeling task (i.e., dog or cat). "Stop-and-go scrolling" without animated transition was chosen as the baseline because most existing labeling tools use transition without animation [11, 17, 24, 25]. Our hypothesis is that the proposed "non-stop scrolling" technique can increase labeling efficiency (i.e., spend less time completing the task) without decreasing label quality. In addition, the "non-stop scrolling" technique can make the task more enjoyable and make the participants (crowd workers) feel more attentive than the conventional "stop-and-go scrolling" technique during the labeling process.

5.1 Participants

A total of 36 participants (18 men and 18 women, aged 18–59 years) were recruited using Amazon Mechanical Turk (MTurk) [1]. To control for the quality of the user study, all participants were MTurk Master Workers and had a 98% HIT approval rate [18]. None of the participants had any professional experience in image labeling. During user evaluation, participants were asked to sit in front of a desktop computer and complete the given image-labeling tasks. The participants were required to use Google Chrome with a screen resolution of 1920 × 1080 (full screen) and set their display refresh rate at 60 Hz before starting the labeling tasks. Each participant was paid $5 for participation.

5.2 Image Dataset

For image-labeling tasks, we used the dog and cat image dataset from ImageNet [12]. First, we randomly selected 100 dog and 100 cat images. Second, we created two datasets (Datasets A and B). Each dataset contained 50 dog and 50 cat images, and the images were different in the two datasets. In addition, the order of the images was randomized in the image-labeling tasks. All selected dog and car images are easy and clear enough to be recognized by humans. Figure 8 shows examples of selected dog and cat images.

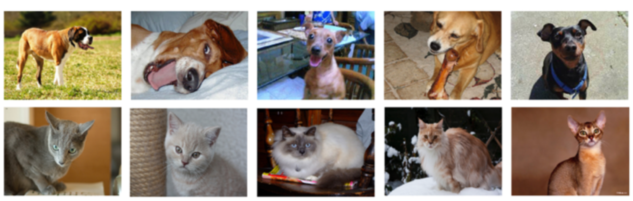

Figure 8: Examples of the selected dog and cat images.

5.3 Task and Condition

A within-subjects method was used for user evaluation. The image-labeling tasks involved labeling 100 images (50 dog images and 50 cat images) using both the proposed "non-stop scrolling" labeling technique and a conventional "stop-and-go scrolling" labeling technique, with a total of 200 images that needed to be labeled (all images were different) by each participant. Half of the participants were asked to start the labeling task by using a conventional "stop-and-go scrolling" labeling technique, and the remaining half were asked to start the labeling task by using the proposed "non-stop scrolling" labeling technique. Table 1 shows the distribution of labeling techniques and datasets for the participants.

Table 1. Distribution of annotation interfaces and datasets for the participants.

Participants	1st Task	2nd Task
P01 - P09	Stop-and-go scrolling + Dataset A	Non-stop scrolling + Dataset B
P10 - P18	Stop-and-go scrolling + Dataset B	Non-stop scrolling + Dataset A
P19 – P27	Non-stop scrolling + Dataset A	Stop-and-go scrolling + Dataset B
P27 – P36	Non-stop scrolling + Dataset B	Stop-and-go scrolling + Dataset A

The image-labeling interfaces of the proposed "non-stop scrolling" technique and the conventional "stop-and-go scrolling" technique appear exactly the same. The only difference was in the scrolling behavior. In the conventional "stop-and-go scrolling" labeling technique, the images shift to the left without transition animation (sudden change) when the user assigns a key press (i.e., focus stays at the center and five images shift to the left each time). In the proposed "nonstop scrolling" labeling technique, new images continuously come from right to left based on the weighted average of the past N image labeling speeds. If the annotator selects labels quickly, the scrolling speed of the incoming new (unlabeled) images is high. If the user selects labels slowly, then the scrolling speed is slow. The instructions for the participants before starting the task were as follows:

"*There are dog and cat images. Your task is to select a dog label or a cat label for those images using the arrow keys on the keyboard. If the image contains a dog, press the left arrow key to assign a dog label to the image. If the image contains a cat, press the right arrow key to assign a cat label to the image. After selecting a label for an image, it is not possible to change the answer (selected labels). Therefore, please select the labels as carefully as possible. Simultaneously, select a label for an image as quickly as possible.*"

5.4 Procedure

The evaluation itself consisted of three parts (in order): instruction and trial (3–5 min), two labeling tasks (3-5 min), and a questionnaire (5–10 min). The entire evaluation process was completed within approximately 30 min. The instructions (text and images) were initially presented to the participants to explain the details of the user evaluation process, labeling tasks, and labeling interfaces. This includes a step-by-step demonstration of how to use the labeling interfaces to complete the given image labeling tasks. After the instruction, the participants practiced a small labeling task (to label 20 images) using the conventional "stop-and-go scrolling" technique and the proposed "non-stop scrolling" technique before starting the main tasks. The participants were asked to select a label as carefully as possible (i.e., we informed the participants that, if their selected labels contained too many errors, their tasks may be considered failures). Participants were also asked to select a label for an image as quickly as possible. In addition, participants were required to concentrate on the tasks until they completed them. After completing the two labeling tasks, participants were asked to complete a questionnaire about the labeling tasks.

5.5 Measurement

Following the evaluation of the labeling task, the participants were asked to answer a questionnaire regarding the two techniques (i.e., "non-stop scrolling" and "stop-and-go scrolling") they used in the image-labeling tasks. The questionnaire contained the following four questions (Likert-scale questions): There is a "why" question after each question. The participants were asked to answer the "why" questions as much as they could (i.e., the participants were told they had more than enough time to do it).

Q1 Do you agree that the "non-stop scrolling" technique is more efficient than the "stop-and-go scrolling" technique during the labeling task? Why?

Q2 Do you agree that the "non-stop scrolling" technique is more enjoyable than the "stop-and-go scrolling" technique during the labeling task? Why?

Q3 Do you agree that the "non-stop scrolling" makes you more attentive than the "stop-and-go scrolling" technique during the labeling task? Why?
Q4 Which labeling technique do you prefer? Why?

6 Results

6.1 Task Completion Time

Figure 9 shows that the participants spent an average of 89 s 411 ms and 83 s 104 ms to complete the labeling tasks (label 100 images) using the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques, respectively. This is approximately 7% reduction in time (i.e., 305 more images labeled per man-hour). The analysis of paired t-test on task completion time indicates that there was a statistical significance ($p < 0.01$) between the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques. This indicates that the "non-stop scrolling" labeling technique is more efficient (i.e., requires less time to complete the task) than the "stop-and-go scrolling" labeling technique.

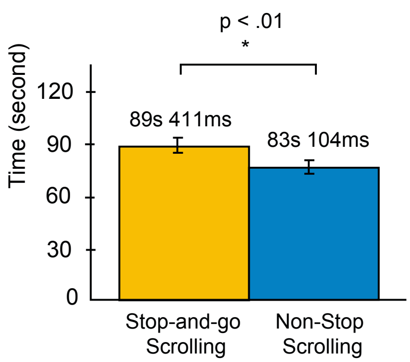

Figure 9: Task completion time. N-s: mean = 89s 411ms; SD = 23s 285ms; S: mean = 83s 104ms; SD = 19s 127ms.

The formative study showed that the "non-stop scrolling" technique required 85 s to complete the task, which was faster than the user study (89 s). We assumed that it is because the 4 participants in the formative study were not crowd workers, and they had worked on many similar tasks (i.e., got used to the image labeling tasks).

More specifically, Figure 10 shows the average time for the image labeling process for the first half (1–50 images) and the second half (51–100 images) using the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques. The results indicate that the participants spent an average of 45 s 926 ms and 43 s 420 ms to complete the first and second halves of the labeling task using the "stop-and-go scrolling" labeling technique, and an average of 42s 968ms and 40s 192ms to complete the first and second halves of the labeling task using the "non-stop scrolling" labeling technique. The analysis of paired t-test on task completion time indicates that there were statistical significances between the first and second halves of the labeling task in the "stop-and-go scrolling" ($p < 0.05$) and "non-stop scrolling" ($p < 0.01$) labeling techniques. This indicates that both proposed and conventional labeling techniques got faster as the users get used to the task.

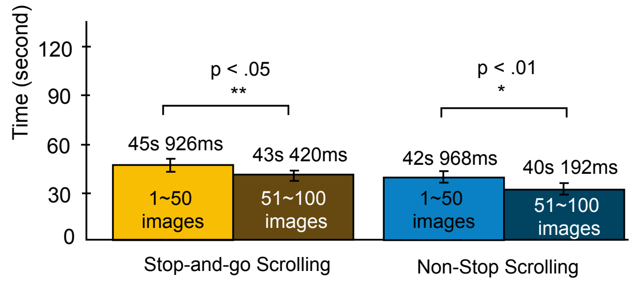

Figure 10: Average time of the first and second 50 images using the non-scrolling and scrolling labeling approaches. N-s (1–50 images): mean = 45s 926ms; SD = 12s 91ms ; N-s (51–100 images): mean = 43s 420ms; SD = 12s 359ms. S (1–50 images): mean = 42s 968ms; SD = 9s 398ms; S (51– 100 images): mean = 40s 192ms; SD = 10s 292ms.

6.2 Annotation Accuracy

Figure 11 shows the accuracy (i.e., success in selecting an appropriate label for an image) of the labeling tasks (label 100 images) completed by the participants using the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques. The results indicate that the accuracy was 98.72% and 97.94% for the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques, respectively. The accuracy analysis using a paired t-test indicates that the difference was not statistically significant ($p > 0.05$) between the two labeling techniques. These results indicate that the label quality with the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques was comparable and high (this is expected because the labeling tasks were easy).

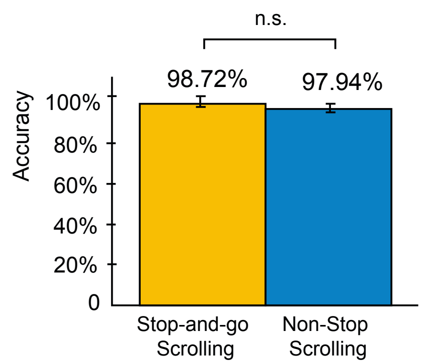

Figure 11: Annotation accuracy. N-s: mean = 98.72; SD = 1.99; S: mean = 97.74; SD = 2.38.

More specifically, Figure 12 shows the accuracy of the image labeling process in the first half (1–50 images) and the second half (51–100 images) using the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques. The results indicate that the accuracy rates were 98.11% and 99.11% in the first and second halves of the labeling task using the "stop-and-go scrolling" labeling techniques; the accuracy rates were 97.06% and 97.94% in the first and second halves of the labeling task using the "non-stop scrolling" labeling technique. The accuracy analysis using a paired t-test indicates indicate that the difference was not statistically significant ($p > 0.05$) between the first and second halves of the labeling task in the "stop-and-go scrolling" and "non-stop scrolling" labeling techniques.

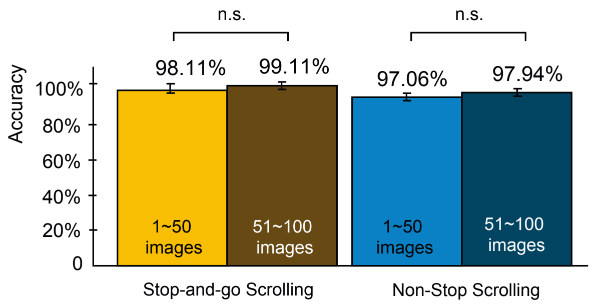

Figure 12: Annotation accuracy of the first and second 50 images using the non-scrolling and scrolling labeling approaches. N-s (1–50 images): mean = 98.11; SD = 2.74; N-s (51–100 images): mean = 99.11; SD = 2.21. S (1–50 images): mean = 97.06; SD = 3.40; S (51– 100 images): mean = 97.94; SD = 2.51.

6.3 Questionnaire

Figure 11 shows the questionnaire results. The results for Q1 show that 77.8% (n = 28) of the participants agreed (and strongly agreed) that the "non-stop scrolling" labeling technique is more efficient than the "stop-and-go scrolling" technique, while only 19.6% (n = 7) of the participants disagreed (and strongly disagree) with it. The results for Q2 showed that 72.3% (n = 26) of the participants agreed (and strongly agreed) that the "non-stop scrolling" labeling technique is more enjoyable than the "stop-and-go scrolling" technique during the annotation process, while 19.4% (n = 7) of the participants disagreed (and strongly disagree) with it. The results for Q3 showed that 69.3% (n = 15) of the participants agreed (and strongly agreed) that the "non-stop scrolling" labeling technique made them feel more attentive than the "stop-and-go scrolling" technique during the annotation process, while only 16.7% (n = 6) of the participants disagreed (and strongly disagree) with it. In addition, 75% (n = 27) and 25% (n = 9) of the participants preferred the "non-stop scrolling" and "stop-and-go scrolling" techniques, respectively. Further details are provided in the next section.

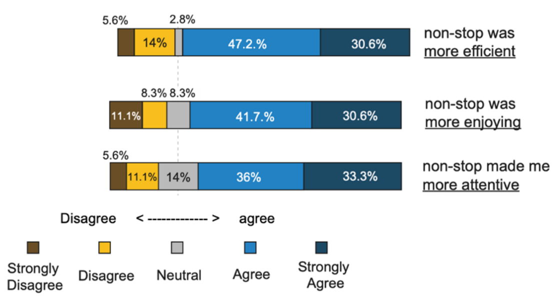

Figure 11: Questionnaire results.

7 Discussion

7.1 Speed Labeling Increases the Efficiency of Easy Image Labeling

Manual image labeling is a tedious and time-consuming process that often relies on crowd workers. There is a strong demand for more efficient methods to annotate data and expedite the annotation process. Our proposed "non-stop scrolling" labeling technique significantly increases the efficiency of an easy image-labeling task (i.e., a binary task) conducted by crowd workers without decreasing the label quality. In addition, most participants subjectively felt that the "non-stop scrolling" technique is more efficient than the "stop-and-go scrolling" technique. For example, a participant strongly agreed with it and indicated that "*It allows me to go with the flow and go smoothly to accurately label the images. I feel like I am in rhythm.*" One participant indicated, "*You can easily see the upcoming images based on their labeling speed. It encourages users to work at their own pace.*" Another participant said, "*I felt like it was easier for my brain to keep the attention and focus on the pictures as they were scrolling. Immediately once I saw how the scrolling worked, I felt like this was much better and even said that to myself.*" We believe that the reduction in task-completion time (in "human processing") brings significant benefits to manual data-annotation tasks. This is because we can reduce the cost of conducting a manual data annotation task (normally labor-intensive and costly).

7.2 Speed Labeling Increases Crowd Workers' Subjective Feelings of Enjoyment

The manual image-labeling task is a tedious process that always makes workers feel bored during the task. Enjoyable tasks are important for recruiting workers and keeping them invested and attentive. Some researchers have designed the image-labeling task as a computer game to address this issue [19]. Our results (questionnaire) showed that the proposed "non-stop scrolling" labeling technique could increase participants' subjective feeling of enjoyment during the labeling tasks. One participant indicated that "*It felt more fun if I was in a race. I wanted to keep up with the scrolling and the faster I went, the more it moved, which motivated me.*" One participant said, "*It was exciting when to process speed up when labeling quickly, yet slowed down when I needed it to.*" Another participant said, "*It is much more fun to see how fast you can get it to scroll while looking at the pictures and labeling them.*" Although most of the participants gave positive feedback to the "non-stop scrolling" technique, a few of the participants indicated they did not enjoy the "non-stop scrolling" technique during the task. For example, according to a participant "*I didn't enjoy the scrolling better; it felt like constant pressure to keep up so it was more stressful.*"

7.3 Speed Labeling Makes Crowd Workers More Attentive during a Task

Label quality (i.e., unstable and containing errors) is a critical issue in crowdsourcing tasks. One reason for this is that it is difficult to know and control the attitudes and behaviors of crowd workers during a task. Some workers may work seriously and concentrate, whereas others may not [49]. Our study shows that the "non-stop scrolling" technique made the participants think that they were more attentive during the task. One participant said, "*I felt like the scrolling/labeling speed was more in sync with myself during the task, so I felt like it was easier for my brain to be attentive to the task.*" Another participant said, "*I had to pay more attention to the continuous scrolling because what I was currently labeling wasn't always in the same location.*" Another participant said, "*It keeps me more attentive while it was scrolling continuously because it encourages me to keep labeling so I can see more and more of the upcoming images.*" However, some negative aspects were raised by the participants; for example, a participant said, "*I like the scrolling better, but it felt like constant pressure to keep up so it was more stressful." Another participant said, "I might have made mistakes because I hurried too much, but I liked it better.*"

7.4 Potential Factors Affecting Labeling Efficiency

Our formative study explored the effects of image layout (single-image, single-line, and grid) and transition methods (with and without animation) on labeling efficiency. The results showed that, in an easy image-labeling task (i.e., a task that does not require professional domain knowledge), the single-line and grid layouts are more efficient than the single-image layout. However, the labeling efficiency was comparable between the single-line and grid layouts (although the grid layout displayed more images). This is an interesting finding. However, the reason for this has not yet been investigated. In addition, the results showed that image transition with animation was comparable to that without animation (even though animation requires more time physically). This implies that users actively perform image recognition even during animation. These findings show that the image layout and transition methods are potential factors that affect labeling efficiency. We believe these two factors are important in a manual annotation task and are relevant to human information processing [43] and memory [44], which is worth further investigation in more detail.

8 Limitation and Future Work

A limitation of this study is the "non-stop scrolling" feature may cause more fatigue to workers during the labeling process, especially when a given task is too long (i.e., eyes are getting tired), and that stress may lead to mistakes. In such cases, the refresh rate or resolution may be worth further investigation. Another limitation is that users are not allowed to modify their results using the 'non-stop scrolling' feature during annotation. These aspects are left as our future work to investigate fatigue in a longer labeling task. However, we believe that it is not a serious problem in practice because tasks given to crowd workers are usually small. Crowd workers prefer to choose tasks that can be easily completed within a limited amount of time, and it is a standard practice for task orderers to split a large task into small-scale tasks.

In the future, we would like to investigate and apply the concept of "non-stop scrolling" to different labeling tasks such as audio annotation. We believe that it would be interesting if a system could provide a customized audio-scrolling speed during an annotation task. In addition, we would like to further investigate the "non-stop scrolling" feature in difficult labeling tasks. For example, a "slow" scrolling speed may force crowd workers to spend more time on a given task. This may encourage workers to think more carefully and pay more attention to a difficult labeling task (i.e., to avoid errors). In addition, we would like to investigate potential techniques that can reduce the stress felt by annotators in a "non-stop scrolling" task. For example, the system automatically slows down the speed based on the users' behavior during the task.

9 Conclusion

We conducted a formative study to explore and discuss the factors affecting the efficiency of image labeling: image layout and image transition. Based on the results, we proposed speed labeling, a "non-stop scrolling" labeling technique that can increase the labeling efficiency of easy image-labeling tasks. It adaptively changes the image-scrolling speed based on the annotators' labeling speed during the labeling process. We subsequently conducted a user study to compare the proposed "non-stop scrolling" technique to a conventional "stop-and-go scrolling" technique in an easy (binary) image-labeling task. The results showed that the proposed "non-stop scrolling" technique increased labeling efficiency by 7% (i.e., 305 more images labeled per man-hour) while maintaining high label quality. In addition, the results showed that the "non-stop scrolling" technique made the labeling process more enjoyable and made participants (crowd workers) feel that they were more attentive. Speed labeling can significantly improve human performance in an easy, simple and repetitive labeling task. This is a notable result because it is very difficult to improve human performance compared with system performance. The results show the importance and significance of human processing time in user interface design. We hope that the findings of this study will provide valuable insights for the future development of relevant tools for labor-intensive repetitive tasks.

Acknowledgments

This work was supported by JST CREST Grant Number JP-MJCR17A1, and JST, ACT-X Grant Number JP-MJAX21AG, Japan.

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