Toward Adaptive Guidance: Modeling the Variety of User Behaviors in Continuous-Skill-Improving Experiences of Machine Operation Tasks

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Abstract. An adaptive guidance system that supports equipment operators requires a comprehensive model of task and user behavior that considers different skill and knowledge levels as well as diverse situations. In this study, we investigated the relationships between user behaviors and skill levels under operational conditions. We captured sixty samples of two sewing tasks performed by five operators using a head-mounted RGB-d camera and a static gaze tracker. We examined the operators’ gaze and head movements, and hand interactions to essential regions (hotspots on machine surface) to determine behavioral differences among continuous skill improving experiences. We modeled the variety of user behaviors to an extensive task model with a two-step automatic approach, baseline model selection and experience integration. The experimental results indicate that some features, such as task execution time and user head movements, are good indexes for skill level and provide valuable information that can be applied to obtain an effective task model. Operators with varying knowledge and operating habits demonstrate different operational features, which can contribute to the design of user-specific guidance.

Keywords: Human behavior analysis · Skill improving · Adaptive guidance · Egocentric vision · RGB-d · Machine operation · Gaze · Hotspots.

1 Introduction

In the domain of assembling or operational applications, smart assistant systems have been well adopted and evaluated [1–8]. Implementing such systems can optimize task processes, improve outcomes, save physical energy, reduce mental workload, and provide economic benefits [9,10].

One of the most important points of such an assistant system for meeting the demands of different users in rapidly changing task situations is the breadth of the guidance content and the adaptability of the provision of instructions. As addressed in [1]:

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“the ability to flexibly aid users’ needs to be emphasized to broaden the applicability of wearable computers. All the pilots using the wearable computer wanted to be able to customize the procedure to their own way. The system should not limit the methods of completing a task to one.”

and in [10]:

“the trade-off between the positive and negative aspects of overlaid AR content is likely related to the experience-level of the individuals. Future AR applications should tailor AR content to address the needs of each individual.”

Therefore, an effective guidance system should (i) provide a variety of guidance content that is compatible with a sufficient variety of possible users and (ii) support what is needed with situational awareness and behavior understanding for each user during the task execution process. For instance, during an operational task, professionals may want to customize the guidance in their own ways with instructions on only few key steps; while novices may require step-by-step instructions or detailed explanations. Thus, we expect that the guidance includes an extensive task model consisting of task procedures that can track the workflow and guide users at each step; meanwhile, it covers variety of patterns of operation methods, as well as details and explanations which could satisfy the needs of diverse users. We also expect a timely context-aware ability, the instructing method should be associated with user operational behaviors and experience levels [12], e.g., when they fell difficult, unfamiliar, hesitate, or unconfident, etc. Depending on the situation of the user, the guidance system can provide instructions before or during the current operation step, or simply ignore the current step to display the next step.

To achieve the above goals, the user’s experience level is considered as a key component [10][13]. Experiences from multiple users with different skills could be good resources for guidance content creation and user behavior analysis. For instance, manuals or expert’s experiences are usually employed to generate guidance in previous studies, however it usually offers few standard solutions; while amateur’s operation experiences can enrich the guidance content, that is, various methods, easy-to-understand details and even common mistakes, which help to obtain better models for guiding low-skilled users. Furthermore, skill levels also affect detailed operational behavior. For example, low-skilled users may spend extra time searching for items and reviewing results, while high-skilled users can perform tasks efficiently with minimal effort [27]. Analyzing and modeling various user behaviors can provide useful information about how a guidance system can help users with various skill levels and the difficulty of each operational step in a particular task.

This paper provides a new solution for smart guidance systems related to machine operation tasks. Concerning the multiformity of the task model, previous studies [14][15] that created the structure of a task model using hand-machine interaction regions and integrates expert and beginners’ operational behaviors to acquire an extensive task model. The method provided a solution for dealing
with behavior diversity. However, the integration method requires prior knowledge of user skill levels, i.e., several experts’ experiences were manually selected as a baseline for the task modeling. In this paper, we proposed an automatic experience selection method to build the baseline for the task model. Concerning user behavior analysis and situational awareness, previous studies [16, 27] have shown complicated temporal and spatial patterns and large variations in typical operational tasks and the intricacy of the user demands. In this paper, we systematically gathered the behaviors of five participants who gradually learned operational tasks, and analyzed various features changing by user’s skill levels and operation procedure difficulties. The machine operation environment is illustrated in Fig. 1.

2 Related Work

Skill learning Skill learning is more than simply following the rules to accomplish the task. A traditional Japanese expression describes the 3-step learning process as “Shu-Ha-Ri” [17], which can be translated as “obey, break, and create.” Obeying the rules and facts is suitable for early stages of learning. A similar theory has been presented in the literature [18]. In that study, skills acquisition is defined in five stages: novice, advanced beginner, competence, proficiency, and expertise. The novice learning process has been described as ”being contingent on concept formation and the impact of fear, mistakes, and the need
for validation” [19]. These additional aspects of the novice learning process, unlike professionals’ delicate behaviors, provide important clues for analyzing user behavior and skills.

**Skill comparison studies** Concerning skill levels and learning states, several studies have investigated the relationship between user behaviors and skill levels in a variety of applications. In surgery and sports, the quality of actions, such as accurate pose and economy and fluidity of body movement, can indicate high skill levels. Al-Naser et al. [20] quantified the quality of daily human actions by capturing body poses using wearable IMUs, and gauged the performance of any participant using expert action data. Uemura et al. [21] noticed a significant difference in the hand motion between expert and novice surgeons, i.e., expert surgeon hand motions are more stable. Zhang et al. utilized motion features to develop video-based skill evaluation for surgical training [22]. These studies have shown behavior differences between expert and novice surgeons in some feature domains, such as performance time, speed of using instruments, number of errors or procedure repetitions during an operation, and eye-hand coordination [21]. Khan et al. [23] reported significant gaze pattern differences between novices and experts when watching videos of surgeries. Experts tend to focus more on the target. Novice surgeons also focus on the target; however, they also tend to track the instruments. Some studies have adopted deep features to assess human skills in videos. Doughty et al. [24] proposed a supervised deep ranking model to determine skills in a pairwise manner for non-specific task using CNNs. They found that skills levels are not necessarily uniform throughout a task, i.e., skills levels could differ between steps in a given task. Parmar and Morris [25] learned spatio-temporal representations of motion and appearance with 3D CNNs to assess action quality in multiple diving tasks. Li et al. [26] adopted a RNN-based spatial attention model to assess hand manipulation skills. Rather than assesses skills, our goal is to clearly analyze the continuous-skill-learning process and investigate detailed behavioral differences among users.

**Behavior analysis methods** For machine operation experiences, reliable and automatic measurements based on multiple features are required to investigate the intricate temporal and spatial patterns, as well as large variations in each operational procedure and the difficulty of individual procedures. Previous studies have investigated the relationship between gaze, head, body, and operational characteristics. Land and Hayhoe [27] tracked eye movements in tea-and sandwich-making tasks. Pelz et al. [28] monitored eye, hand, and head coordination in a block-copying task. The actions reveal a temporary synergistic linkage of eye, head, and then hand movements. One noteworthy observation is that, in a task that involves sequential movements, the gaze often shifts to the next object in the sequence prior to completion of the current activity. A previous study [29] constructed a graphical model for egocentric gaze prediction that considered the strong coordination eye, head, and hand movements in object manipulation tasks. The gaze prediction results indicated that egocentric gaze often aligns with the head orientation.
Here, we aim to automatically detect user behaviors in machine operation tasks. A sewing task is a quick operational process that does not involve significant wait time between operations. We use a combination of features to describe user behaviors in prior to and during operation. For a more comprehensive understanding of behavior differences, we systematically gathered and analyzed user behavior records of a continuous learning process of operators who were initially novices. Through this analysis, we aimed to delineate features to characterize skill levels and investigate differences between users, which we refer to as inter-person variability. We also expect to provide reliable semantic explanations of features that are closely related to skill levels and describe how such features relate to the actual guiding process.

3 Key Idea

Our goal is to develop a comprehensive machine operation model that can be used to guide various users with different skill levels and different operating habits.

We selected a sewing machine as a good representative of machines commonly used in daily life. The sewing machine is placed on a table. The operators are seated in front of the table. All required materials are within reach. Interactions with the sewing machine include various actions in a variety of patterns, such as push, slide, rotate, seize, and cut. Such actions are not easy for first-time users. Thus, such users require guidance or usage learning. The operational behaviors of the sewing machine include gaze, head motions, and hand motions associated with physical contact (Touches) with the machine. To capture the operational behaviors of users during a task, we use a head-mounted RGB-d camera to take advantage of egocentric vision (first-person vision). A fixed gaze tracker is set at the machine surface to capture operator gaze points. Features, such as head and hand motions, and hand–machine interactions, are extracted from the data captured by the RGB-d camera and the gaze tracker.

We focus on modeling changes of behavior of novice users in contentious-skill-improving experiences and inter-person variability by systematically analyzing data obtained from machine operation experiments. Novices’ behaviors can provide worthy understanding about the manner in which they perceive the operational environment and formulate knowledge to deal with difficult operation situations. In addition to the above analysis of multiple users, we asked users to rate the difficulty of each operation in each experience, and investigated how the subjective perception of the difficulty of the task procedures vary among users and how such perceptions change through learning.

We are interested in identifying indications of skills improvement. We also expect that features that are primarily correlated to skill levels and operational difficulties will be delineated as the amount of data captured is sufficient to reveal inter- and intra-person differences. Other than deep neural network based methods, we suggested the extracted behavioral features can enhance the interpretability and online learning ability for guidance systems.
4 Operational Behavior Detection

We recruited five participants and recorded six operational trials for each of two sewing tasks for each participant, i.e., a total of 60 trials. Note that none of the participants had experience using a sewing machine before recording. Task 1 was “sew a specific symbol” and task 2 was “cut the thread and restore the machine to initial state.” Each participant alternately performed two tasks, Task 1 and then Task 2, and repeated six times. Each participant wore a head-mounted RGB-d camera (Intel RealSense D415 [31], 30 fps), and egocentric vision from the camera was recorded. A commercial gaze tracker (Tobii Eye Tracker 4C [32], 90 Hz) was installed on the base of the machine (Fig. 1), continuously captures the user’s gaze during the task process. From the egocentric vision and gaze tracking data, we extract basic features in both pre- and in-operation periods, such as hand motions, and higher order features, such as the relationship between basic features.

4.1 Visual Features

A 2D global map of the sewing machine surface is prepared beforehand. Every egocentric view is aligned on the global map and global locations of detected visual features are obtained.

Gaze User’s gaze is captured as 2D locations on the gaze tracker’s view field. We need to register the view field of the gaze tracker to the machine surface. To do that, we first calibrated the gaze tracker for each operator using calibration points on a computer screen. Then, we applied the region of the screen to the machine surface. Examples of gaze distributions around hotspots on the global map are shown in Fig. 9.

Hand and hotspots To detect a hand, we first segment the foreground from RGB-d images by considering the common operation distance. Then, a skin-color model is constructed for each user at the initial period of operation. Hand locations are detected in every frame by filtering with this skin-color model and depth. As crucial interaction areas on the machine surface, hotspots are detected automatically by clustering the touches in spatio-temporal locations between the hand and machine. After hotspots have been extracted, we mapped them to the global map using SIFT features and homography transformation. Detailed descriptions of the above processes can be found in the literature [30].

4.2 Behavioral Features

In object-related actions, eyes are often involved in identifying objects for future use and planning operations to be performed on such objects [27]. Based on this observation, we define a basic operational unit (OU) as the sequential of "pure-gazing (saccade/fixation)”, “hand-approaching”, and “operating”.

The pure-gazing period is the period between the end of the previous physical hand–machine contact and the moment the hand is within sight range. The hand-approaching period is the period between the end of a pure-gazing period and
the time at which the hand operation begins. The operating period is the period in which physical touches occur.

An operation unit covers the pre-operation and in-operation periods of an operation step in the task. Each record of an operational experience can be divided into a sequence of such OUs. We obtain the following behavioral features using the above visual sensing and the above definition of basic units.

![Fig. 2: The operational units corresponds to the operation steps.](image)

**Temporal duration** For each OU, the absolute duration of each period is measured as a behavioral feature.

**Distance, velocity, frequency, and variance** We consider the distances among the hand, gaze target, and the hotspot are also essential features to characterize behaviors. In the global 2D map, distances are calculated during each OU. In addition, we use distance changing speed, its variance, and the frequency of distance change speed. They are defined as:

\[
V = \Delta(d),
\]
\[
\delta^2 = E[(d - \bar{d})^2]
\]
\[
f = C(d)/T.
\]

Here, \(d\) is the distance between two regions, \(\Delta\) is its difference, and \(\bar{d}\) is its mean. \(C\) is the number of sign changes of the distance in a period. The frequency is derived by dividing sign change number by the period duration.

**Head movement** Head motion is represented in angular velocity, which is estimated using the global motion vector of the egocentric RGB-d camera as follows:

\[
V_h = \arctan(V_c/s_i \ast s_s/f),
\]

where \(V_h\) is the head motion and \(V_c\) is the camera global motion; \(s_i\) and \(s_s\) are the size of image in pixels and the size of the camera CMOS sensor in millimeters, respectively; \(f\) is the focal length in millimeters.

We also calculate the correlation between gaze and head motion to investigate their synergy.
4.3 Correlation to Skill Level and Difficulty

The correlation between each of the above features and user skill level, and the correlation between each feature and the difficulty of an operation step are important clues for modeling a task and user behaviors.

However, estimating the skill level of a user at a certain trial in an experiment is difficult. For this purpose, we assume that the skill level of each operator improves monotonically through the experience accumulating process. Thus, we rank the skill level as ordinal data aligned by task trial, e.g., the skill of a user in trial 1 is considerably no better than the skill in trial 3.

Operational difficulty is obtained by subjective rating of task procedures using a six-point scale. Each participant was asked to rate the difficulty of each operational steps from 0 to 5 (easiest to most difficult) after each trial. To filter out noise caused by detection errors, we ignored touches to hotspots for less than the threshold duration (<0.3s). The difficulty score may change in different trials. For example, in trial 1, a user could find rotating a dial very difficult; however, the same procedure may feel easier in subsequent trials. The change in perceived difficulty may be related to skill level improvement.

Thus, the correlation between feature values and skill levels is considered for each trial whereas the correlation to difficulty is considered for each step of the operation. The correlation coefficient of features to the ordinal scale of skill level was calculated using Spearman’s rank correlation [33], and the correlation coefficient of features to operational difficulty scores was derived using the Pearson correlation [34].

5 User Behavior Analysis Result

For each operation step, we first detected the operating period based on touches to a hotspot. Then, we detected the pre-operating periods using gaze and hand clues as mentioned above in Section 4. To simplify the notation in the following sections, the pure-gazing, hand-approaching, and operating periods in the OU are denoted G, A, and O, respectively.

We extracted the aforementioned features from all trial records. Then, we compared the difference between them in the continuous skill improving experience records. Correlations among behavioral features, skill improvements, and subjective difficulty provide useful information for task modeling and guidance design, i.e., features with strong correlation can be good indexes for user skill levels and operational difficulty.

5.1 Behavior Changes through Skill Improvements

- Overall feature

Fig. 3 (a) shows the overall trends of features by accumulating differences among trials. The sum of differences among trials of a feature for a participant
Fig. 3: (a) Overall trends of features (sum of differences) among trials and (b) inter- and intra-person standard deviations of features.

is calculated as follows:

\[ D_u = \frac{1}{T} \sum_{t=2}^{T} (f_u^t - f_u^{t-1})/\frac{1}{T} \sum_{t=1}^{T} f_u^t. \]  

(3)

Here, \( f \) is the feature value, \( u \) is the index of a participant and \( t \) is the index of trial. Then, the differences are averaged for all participants in two tasks.

The inter- and intra-person standard deviation of different features are shown in Fig. 3 (b).

\[ \delta^2_{\text{intra}} = \frac{1}{T} \sum_{t=1}^{T} (f_u^t - \bar{f}_u)^2 \quad \text{and} \quad \delta^2_{\text{inter}} = \frac{1}{U} \sum_{u=1}^{U} (\bar{f}_u - \bar{f})^2 \]  

(4)

Here, \( \bar{f}_u \) is the mean feature value of all trials from a participant and \( \bar{f} \) is the mean of \( \bar{f}_u \) from all participants.

Most of the features show the same trend in both tasks (Fig. 3 (a)), which indicates the change of operational behaviors is task-independent in our experiment. Three groups of features show an obvious downtrend as experience increases (e.g., task duration, gaze variance, and head movement); whereas two features show an uptrend (i.e., hand speed in the A period and gaze frequency in the G period). From an overall trend point of view, after skills are improved, users can complete tasks faster on average, and gaze and head movements are more stable; moreover, hands approach the target faster. The gaze frequency in the pure-gazing period increased slightly, which was mainly affected by the significant reduction in the period duration. Besides, others do not show a clear trend with user skill improvement.

From Fig. 3 (b), the standard deviation of individual features ranges from 6.8% to 70% for inter-person variations and from 14% to 114% for intra-person variations, respectively. Note that duration and gaze variance show large variability within a participant, which is similar to their trend. Gaze variance also shows largest inter-person variation, which indicates a big difference in user gaze habit.

- **Trends with skill improvement (intra-person)**
Fig. 4: Detailed trends of features in trials (1–6) of different periods in OUs (averaged over five participants) of two tasks

Fig. 4 shows the detailed changes in multiple features from early to late trials (1–6) of the two tasks. Our main focus is on features where all participants show a significant trend as their skills improve, that are, duration, gaze, and head movement.

1) Duration

The overall execution time almost decreased monotonically for the two tasks (Fig. 4(a)). For task 1, overall execution time of all participants decreased from an average of approximately 120s to 50s, and for task 2 overall execution time decreased from approximately 50s to 30s. The biggest reduction is pure-gazing time; then the hand-approaching time. The operating time is also reduced, but not as fierce as other periods.

The results show that for initial experiences, low-skilled users required more time to complete the task. The process involves a significant amount of pure-gazing (search or hover) and longer hand-approaching times prior to each operation step. After participants became familiar with the tasks, they reduced their gaze behavior and speed up decision-making before starting the operation.

Note that the duration of O period demonstrates a slight upward trend in some of the later trials. Presumably, this is caused by the participants’ intention to further improve of their performance. For example, one participant stated that he tried to stitch the symbol better by adjusting the cloth more carefully than in previous trials.
(2) Gaze movement

The average distance of gaze–hotspot is shown in Fig. 4 (b), and the overall gaze variance is shown in Fig. 4 (c). They overall decreased as user experience increased, especially the gaze variance decreased dramatically in all periods. However, the gaze frequency (e) and velocity (f) did not shown an obvious trend.

At the initial trials, gaze had both large distance and variance in all periods. This was probably because novices may require more check-around to retain relevant information prior to the operation and more result confirmation during the operation. As skill improved, users located their gaze averagely closer to the interacting area, and the gaze movement range is much narrower in small variance.

We note that gaze–hotspot distance demonstrates a bowl shape for both tasks in the G period. At the early trials, users did a lot of pre-operation search (large distance with large variance); in the middle trials, users tend to shift their gaze directly to the future operation region (small distance with small variance); when they became familiar with the process in later trails, they did not need to concentrate on the specific spot to locate hotspots and direct their hands. This indicates the user’s memory formulation for future operation positions, and then the user relies on the memory to guide the operation.

![Fig. 4](image)

Fig. 5: (a) Correlation between gaze and head. Movement is shown in horizontal and vertical directions respectively. (b) Change of correlation scores between gaze and head with skill improvement (averaged for all participants).

(3) Head movement

The average head velocity and variance are both decreased monotonically from early to later trials for all users, as shown in Fig. 4 (f). This shows that the stability, i.e., less motion, of the user’s head could indicate a high skill level.

Fig. 5 (a) shows the overall correlation of gaze and head movements on 12 trial for both tasks. Note that gaze and head movements are almost uncorrelated in the vertical direction, and are weakly correlated in the horizontal direction compared to the kitchen operation scenes in a previous study [29].
We then confirmed head–gaze movement correlation trends during skill improvement, as shown in Fig. 5 (b). From the average score on the horizontal axis, the correlation between gaze-head movement decreases as the skill level increases. This is presumably because a skilled user well knows the location of a target and tends to use eye movement. The mental and physical cost of eye movement is much less than moving the head; thus, we tend not to move the head unless it is essential.

- **Inter-person differences**

We then looked at detailed behavior differences among participants. As the greatest inter-person variability, Table 1 shows the detailed feature values of each user for *head movement*, *duration*, and *gaze movement*.

We noticed that Participant 1 had the longest operation time in G (the gaze movement was also large), A and O, and the head movement was very slow. This indicates that the participant tend to search more or hesitate before taking action, while performing slowly during task execution. In providing guidance to such users, explicit instructions may be required.

Participant 2 had the shortest G period, while gaze and head were very stable at all periods. For such users with very little search behavior, they may not need any guidance before the operation.

Participant 3 performed a lot of search in the pre-operation periods (the longest G, large gaze variance in G and A); however, he/she was concentrated on performing specific operations (gaze variance and velocity in O are small). In contrast, participant 5 made decisions quickly prior to beginning the operation (small gaze variance in G and A), and often checked the progress or outcomes during the operation (gaze variance and velocity in O are large). When providing guidance for these different types of users, timing is important, that is, guidance should be provided at the appropriate time in the process (for example, before beginning or during operation).

| V_{head} | δ_{head} | t | δ_{gaze} | V_{gaze} |
|----------|----------|---|----------|----------|
|          |          |   |          |          |
| G        | A        | O | G        | A        | O        |
| U1       | – –      | ++ | +++      | ++       | +        |
| U2       | – –      | –  | – –      | – –      | – –      |
| U3       | +        | ++ | –        | ++ –     | + –      |
| U4       | ++       | –  | – –      | – – –    | – – –    |
| U5       | +        | –  | – –      | – – –    | ++ + +   |

“++” and “– –” are ≥ 30% difference and “+” or “–” are ≥ 10% difference from the average feature value of 5 participants.
Participant 4 had the fastest head movement, the shortest operation time, and small gaze movement, which may indicate that the user is relatively skilled and may not require much guidance during the operation.

In conclusion, differences in inter-personal behavior could contribute to the design of adaptive guidance.

- **Reliable clues to skill levels**

![Graph showing detailed trend of top skill-correlated features from each user.]

Fig. 6: The detailed trend of top skill-correlated features from each user.

The correlation coefficients of all features to the subjective skill levels are shown in Fig. 6 (a). The top three groups of features with strong correlation to skills are (i) duration, (ii) head variance and velocity, and (iii) gaze-hotspot distance and variance.

Considering feature reliability to determine the skills of experiences from multiple users, interpersonal differences should be considered. See from Fig. 3 (b), the inter-personal variation in head movement is minimal, followed by period duration. Compared with the above two features, the correlation between gaze movement and skills is smaller, and its inter-personal variation is relatively larger. Thus we can conclude that, in our experimental environment, head movement and duration are more reliable indicators of user skill levels than gaze movement. We can consider the design of user skill assessment approaches based on these features.

Fig. 6 shows the detailed feature values changes for each participant. The duration commonly dropped within the first two trials, particularly in the G period. Once the user got familiar with the task after a few trials, the time reduction was small and smooth, reaching a minimum at the fifth trial. Head variance shows a similar trend, with all users drastically reducing their head movements to very low levels after the second trial. The reduction in subsequent
trials is not as smooth as the duration. This indicates that participants have learned most of the operations in the first two experiments. Furthermore, the gaze variance in O period shows an oscillation in the middle trials. This shows that during the learning process, the users’ gaze first learned to concentrate on the hotspots (trail 2), then began to check other places (trail 3). Overall, participants showed similar learning rates during the task, so we can use the above features to evaluate their skills.

Fig. 7: (a) Correlation of features to skills. (b) Correlation of features to operation difficulties

5.2 Operational Difficulty

After identifying reliable clues for skill levels, we examined differences among operation steps and their operational difficulties. The difficulties of task steps could be a subsidiary hint for guidance offerings.

Fig. 8 (a) shows the average of user-rated difficulties of six hotspots on 12 trial for both tasks. The difficulties of some steps (e.g., steps 4 and 6) decreased sharply as the learning progressed. For these kind of operations, once a user knew how to perform them (e.g., push a button), they were no longer considered difficult. We call refer to this type kind of difficulty as “know-how difficulty.” In contrast, some other operations are consistently rated difficult (e.g., step 3, stitch the cloth). We refer to this as “skill-required difficulty.” These types of operations may require more comprehensive user guidance, such as showing the details of a method or an alternative easier way.

Fig. 8 (b) shows the distribution of feature values over all participants (depicted in terms of the variance of feature values). The operations with averagely high difficulty scores (steps 3 and 6) demonstrate large variance among features, especially for the duration and gaze variance. This illustrates a bigger behavioral differences when performing more difficult procedures.

Fig. 7 (b) depicts the correlation coefficients of the features and the user-rated difficulty scores over all the operation steps of both tasks. The result show
that (i) the gaze variance and velocity of the G period, and (ii) the gaze velocity and frequency in the O period are strongly correlated to operational difficulty. This implies that the more difficult an operation step is, the more frequently the operator will search other regions prior to initiating operation. In addition, faster gaze movement during the operation will occur, which is probably due to result checking.

The above analysis provides clues for designing a metric to indicate operational difficulties for user guidance. Although, not all users require assistance with the difficult steps, providing support for most users on those difficult steps may enhance the overall efficiency of the task execution.

- **Supply: Gaze target differences**

  The users’ gaze location was distributed differently when operating a same hotspot during skill improvement, as shown in Fig. 9. The hotspot locations are shown in cyan and the gaze locations are shown in red to yellow with accumulated heat. We compared the accumulated gaze location in earlier trials (1–4) between that in later trials (9–12).

  For overall gaze distribution, the user’s gaze was directed to a location where operational outcomes (effects) are occurring. For example, when rotating the hotspot 2 (sewing pattern), the gaze was directed to the pattern display panel above the dial. When operating on hotspots 3, 5, and 6 (cloth, needle position, and start\stop), the gaze was primarily directed toward the moving needle. However, if there is no operational outcome region, the gaze was primarily located on the on-going interacting region (hotspots 1 and 4). This result supported the top-down control property of the gaze 27, and this gazing behavior of skilled users can be a good clue for identifying skill level.

  Then, we found that the user’s gaze located differently for different trials, which showed a good clue to indicate user skill levels. From hotspot 1 (speed),
we can see that, initially, the users’ gaze focused on an interacting region (trials 1–4), and after skills improved (trials 9–12), the gaze shifted to the next operation region before the current operation was complete. We consider that this occurs because the interaction itself is quite simple without any operational outcome region. Once users have mastered this step, they can plan for future steps and do not need to persistently concentrate on the current step. For hotspot 6 (start\stop), when the users’ skills were low (trials 1–4), they need to check both the button been interacting with and the operational outcome region; however, in later experiences (trials 9–12), there was no need to concentrate on the button. From hotspot 4 (thread setting), in later trials, users do not perform this operation because they have learned that it is an unnecessary procedure.

From the observations, we can conclude that low-skilled users’ gaze tends to locate more on the current interacting regions because they are not familiar with the current operational step. However, the operational outcome region always attracts considerable attention during the operation regardless of the user’s skill level. In future work, quantifying the user gaze target to reveal their skills and then offering suitable guidance content based on the gaze clue could be an interesting topic.

![Fig. 9: Gaze distribution difference (heat) around hotspots (cyan) in early and late trials for six different hotspots on the global map (accumulated with all participants)](image)

6 Baseline Selection for Task modeling

6.1 Baseline

We aim at the creation of user guidance content, e.g., to generate an extensive task model from a variety of user records. Because it is difficult to directly integrate experience with a great deal of diversity into a single model, we can think of an online task modeling process that involves the following. First, construct a baseline model from several selected operation records, which are correct and common task execution methods. Then, gradually integrate more records with larger variations or more operational methods to the baseline model.
A baseline is essential for task modeling because it provides a template for coordinating other experiences. By providing routines that cover key methods of tasks, a rich diversity of experiences can be accurately and successfully aligned and integrated into the baseline. Therefore, it is important to develop an automated approach that selects multiple experiences from dozens or hundreds of different experiences.

In our previous study [15], a few expert experiences were manually selected as the baseline. In this section, to enable automatic mw processes, we describe two baseline selection methods.

6.2 Challenges

Directly ranking the most skilled experience among all records is difficult, due to a lack of efficient features or criteria for evaluating skills:

1. Behavioral features extracted above are greatly affected by inter-person variation and inter-hotspot variation, i.e., the operational habits of different people vary significantly, and individual user behavior varies greatly between different operational patterns.

2. Features are too local. The top skill-correlated features could be efficient indexes to select high-skilled records as the baseline; however, they do not represent the global optimal (the most-skilled experiences) among all operation experiences.

3. Relative ranking methods may cause multiple ranking loops and could be invalid with large numbers of experiences [24].

As a solution, we aim to find a group of most-skilled experiences among all experiences rather than assessing the skill level of each experience.

6.3 Global Feature (top-down) Approach

Two properties are expected as baseline experiences to ensure successful alignment and integration of other experiences:

- Property 1: Correct.
  Baseline should contain little noise or unnecessary operations. Failures will occur if the baseline lacks critical operating steps and contains massive errors and unnecessary operations. If the baseline is too verbose or incomplete, particularly for alternative operating methods with forward/backward jump transitions, the alignment algorithm [15] will have difficulty finding suitable states for these operational observations in the HMM.

- Property 2: Common.
  Baseline should be representative methods. If the baseline is too unique operation ways, most of the experiences with common operation manner are hard to be aligned.

Based on the required properties of the baseline, we use the statistics of the operation sequences from all experiences as global features to find the group of high-skilled experiences.
Assumption 1: A high-skilled experience contains few unessential interactions. This is related to Property 1. Generally, an experience performed by a high-skilled operator rarely employs unessential interactions because the operator tends to complete the task economically (e.g., with minimal operation steps) and efficiently (e.g., quick operation on each step).

![Fig. 10: Frequency of operation patterns (hotspots) from all experiences of two tasks.](image)

Essential interactions are indispensable to task goals. Almost every operator must perform these interactions to proceed toward task completion.

Unessential interactions are dispensable or harmful operations, such as unnecessary interactions, repetitions, or mistakes.

The histograms of hotspot occurrences from all experiences for the two tasks are shown in Fig. 10. Note that the occurrence of hotspots is apparent in two categories: the majority ($\geq 50\%$ experiences) and the minority ($<50\%$ experiences). As shown in the figure, the occurrence rate of hotspots 1, 2, 3, 5, 6, and 7 is much higher than half the total number of experiences whereas the occurrence of hotspots 4, 10, 11, 12, 13, and 14 is much lower than the total number of experiences. The two categories have clear boundaries and can be used as cues to distinguish essential and unessential interactions. We can assert that the essential interactions are in the majority category. Since almost every operator needs to perform the essential interaction, it should appear in most experiences. The minority category, on the other hand, contains most of the unessential interactions; however, no essential interactions are included. Based on this observation, we can consider the following strategies to exclude as many low-skilled experiences as possible:

**Step A1**, distinguish the major and minor interactions by their occurrence in all experiences.

**Step A2**, filter out those sequences with relatively higher portion of minority interactions.

After Steps A1 and A2, the remaining experiences which include almost all of the essential interactions that are considered baseline candidates.
Assumption 2: Typical high-skilled experiences have common patterns of interactions although the order of interaction may differ.

This is related to Property 2. Typically, a task requires a specific combination of operating patterns and specific operating frequencies of those patterns. Most successful cases should be similar to efficient operating practices in these respects; however, low-skilled experiences contain a variety of mistakes and repetitions. For example, most high-skilled users completed the task by operating hotspot A three times, hotspot B once, and hotspot C twice. We consider $(3, 1, 2)$ are the common operation properties of these patterns. Experiencing patterns and frequencies that are too far from common properties, such as $(1, 4, 0)$, may be considered low skills or unique methods. Therefore, among the remaining experiences after Step A2, we can find representative ones by featuring experiences with bag of hotspots and clustering them.

Step B, cluster the remaining experiences, find the center and remove outliers, and repeat the procedure several times.

After the step A1, A2 and B, several experiences closest to the final center are used to build the baseline. Colloquial pseudocode for the top-down algorithm is given in Alg. 1.

**Algorithm 1** Top-down baseline chosen method

**Require:**
1. The bag of all hotspots $H = \{h_1, h_2, \ldots, h_K\}$, $K$ is the number of all interaction patterns appeared in task;
2. The set of $N$ experiences $E$, each experience $e_i \in E$ is a sequences of operations $e_i = (o_1, o_2, \ldots, o_m)$, where $i \in 1 \ldots N$ and $m \in \mathbb{Z}^+$, and any operation $o_j \in H$.

**Ensure:**
A set of selected high-skilled experiences $E_{\text{optimal}}$.

1. Calculate the occurrence frequency of each $h_k$ in an experience $e_i$ as the bag of feature of this experience, $f_i = \{f_{i1}, f_{i2}, \ldots, f_{ik}\}$, where $f_{ik} \in \mathbb{Z}_0^+$ and $i \in 1 \ldots N$; the set of $f_i$ from all experiences is represented as $F$.
2. Calculate the occurrence frequency of each $h_k$ from all experiences as $f_{hk}$.
3. **Step A1** distinguish major and minor interactions.
   - If $f_{hk} \geq \Delta_a$, $f_{hk} \in H_+$ (major set), else $f_{hk} \in H_-$ (minor set), where $\Delta_a$ is the frequency threshold.
4. **Step A2** filter out experience with higher minor interactions.
   - If the number of elements in $\{e_i \cap H_+\} \geq \Delta_b$, remove $f_i$ from $F$, where $\Delta_b$ is the threshold of minor element number. After check all experiences, $F \rightarrow F_+$, the number of elements in $F_+$ is present as $N$.
5. **Step B** cluster the remaining experiences to find the representative optimal.
6. **while** $N \geq \Delta_a$ **do**
   7. Calculate the center of $F_+$ by its average, as $f_{e+}$.
   8. For each $f_{i+} \in F_+$, the distance to the center $D_i = ||f_{i+} - f_{e+}||$.
   9. **if** $D_i \geq \overline{D}$ **then** remove $f_{i+}$ from $F_+$; where $\overline{D} = \sum_{i=1}^{N} (D_i)/N$.
10. **end while**
11. The set of correspond experiences to the final $F_+$ is returned as $E_{\text{optimal}}$. 
Algorithm 2 Bottom-up baseline chosen method

**Require:**
1. The bag of all hotspots $H = \{h_1, h_2, \ldots, h_K\}$, $K$ is the number of all interaction patterns appeared in task.
2. The set of $N$ experiences $E$, each experience $e_i \in E$ is a sequences of operations $e_i = (o_1, o_2, \ldots, o_m)$, where $i \in 1 \ldots N$ and $m \in \mathbb{Z}^+$, and any operation $o_j \in H$.
3. The set of $N$ selected features $S = \{s_1, s_2, \ldots, s_N\}$ ranked at top correlation scores to the difficulty.

**Ensure:**
A set of selected high-skilled experiences $E_{\text{optimal}}$.

1: Extract all the instances of a hotspot $h_j$ from all the experiences as $h_j = \{h_1^j, h_2^j, \ldots, h_M^j\}$;
2: Use one feature $s_n \in S$ to find top $k_1$ high-skilled (or easy) instances of hotspot $j$ in $h_j$ as $h_j^{s_n}$;
3: Derive the union set of $h_j$ indicated by each of the selected features, as $h_j^S = h_j^1 \cup h_j^2 \cdots \cup h_j^N$;
4: Majority vote hotspot instances that have top $k_2$ highest occurrence frequencies in $h_j^S$ as $h_j^{\triangle}$, the corresponding experiences with $h_j^{\triangle}$ is represent as $E_j^{\triangle}$;
5: Get the union set of experiences with high skills in several chosen hotspots $\{h_{j1}, h_{j2}, \ldots, h_{jk}\}$, as $E_{\text{optimal}} = E_j^{\triangle1} \cup E_j^{\triangle2} \cdots \cup E_j^{\triangle k}$.
6: Majority vote experiences that have top $k_3$ highest occurrence frequencies in $E_{\text{optimal}}$ as $E_{\text{optimal}}$.

**6.4 Local Feature (bottom-up) Approach**

In this subsection, we provide an alternative solution for selecting high-skilled experiences using the low-level behavioral features.

As mentioned previously in Section 6.2, the features extracted above can explain the skill improving process of each operator effectively; however, inter-person differences and inter-hotspot differences have a significant effect on these features. For example, for inter-person differences, some operators cannot demonstrate comparable higher skills because other operators have naturally steadier head (or gaze) movements, or who are always likely to perform the operation actions faster. In addition, for inter-hotspot differences some operational procedures inherently require more monitors or result check, while others require little attention. These factors make direct comparison of experiences between different operators difficult.

To deal with this problem, we considering a three-level bottom-up solution. The basis of the method is as follows:

**a.** If multiple features constantly manifest good performance in an operation instance, this operation is considered high-skilled.

**b.** If multiple operations are simultaneously manifest high-skilled in an experience (especially difficult operations), this experience is considered high-skilled.

Using the following two-step bootstrap aggregating [35] approach, we can find a group of high-skilled experiences without ranking all experiences.
Step i. Features to operation instance.
Select several top-correlated features to find instances which are considered as high-skilled (or easy) for each hotspot.

Step ii. Operations to experience.
An experience with many operations detected as high-skilled (or easy), particularly for those difficult procedures, is considered as a high-skilled experience and a candidate for the baseline.

The bottom-up algorithm is described in Alg. 2.

6.5 Baseline Detection Result
In the top-down method, for Step A1, consider the recall rate of interactions in hotspots detection, we relax the occurrence threshold (from 50% to 25% of total experience) to distinguish between majority and minority interactions. For Step A2, we eliminate experiences with one or more minority interactions. For Step B, we remove 50% of the remaining experiences in each loop until there are no more than five experiences. In the bottom-up method, for the instance selection parameters $k_1$, $k_2$, and $k_3$, we empirically selected 10, 8 and 5, respectively.

Table 2 shows the baseline detection results of the above algorithms. Each method shows the top three candidate sequences of the baseline experiences. Senescences of task steps are represented by hotspots indexes. "[*]" is the repetition of detected sequences. "()" contains order-changeable steps.

| Task 1 steps | Task 2 steps | R | P | F |
|--------------|--------------|---|---|---|
| Ground Truth (from manual) | (1 2) 6 3 8 7 3 7 6 3 6 | 1 | 1 | 1 |
| Top-down | 1 2 5 6 3 6 7 6 3 6 [*3] | 5 7 12 1 2 [*2] | 2 1 5 7 12 [*4] | 0.955 | 0.955 | 0.955 |
| Bottom-up (all hotspots) | 1 2 5 6 3 6 7 6 3 6 [*3] | 2 1 5 7 3 12 | 5 7 3 12 1 2 | 1 2 10 13 13 14 5 10 | 0.888 | 0.788 | 0.835 |
| Bottom-up (difficult hotspots) | 1 2 5 6 3 6 7 7 6 3 6 | 2 1 7 12 12 | 5 7 3 12 1 2 | 5 7 3 1 2 | 0.858 | 0.775 | 0.814 |

From the standard operation procedure of the tasks (ground truth), task 1 has a Dof of 2 with two order-changeable procedures, and task 2 involves two methods where each method has two order-changeable procedures. Task 2 has a Dof of 4.

All the methods recalled half of the task Dof, i.e., detected one method for task 1 and two methods for task 2.

The top-down method achieves the best performance in both recall and precision, the detected baseline candidates are closest to the ground truth. Due to its global optimal property, the results include no unnecessary procedures; however for task 1 the results include an extra procedure and a missing procedure.
The bottom-up method, which detects with the combination of all hotspots, achieved same result for task 1. However, for task 2, it detected many unessential procures in the 3rd baseline candidates. This is likely because this experience shows good performance on most of its operations; however, the method cannot differentiate among good, useless, or harmful operations. Similar phenomena appeared in the detection result for task 1 with bottom-up methods with only difficult hotspots, as well as it miss-recalled some essential operations for task 2. The results of the bottom-up method shows the local features and operations can indicate high-skilled experience to a certain degree, but not always the global optimal.

6.6 Task Modeling Result with Different Baselines

Fig. [11] below illustrates the task models built with different baselines for the two tasks. We compared the task models built with ground truth baseline, the automatic detected baseline by top-down method, and the baseline with a random chosen experience.

The task models for the baseline developed using the top-down method is very similar to the ground truth for both states and transitions. While the models from random-chosen baseline lacked some states, the operation procedures in the model are not complete and some alignments are not successful, particularly for the jumping transitions in the model. For example, when an essential operation is missing at the alignment forward routine, the current pattern may jump backward to find a state with the same observation in the HMM or may fail to find the any states thereby creating an extra state.

We can conclude that the top-down baseline selection method that considered the properties of the operations, i.e., essential and unessential, and the combination of patterns and frequencies, can automatically find good baseline experiences for task modeling.

7 Conclusion

In this paper, we proposed approach to model the multiformity of the task and analyze the behavior of users with variety of experience levels, by considering the properties of user-machine interactions, and the physiology of user perception. We detected the characteristics of skill and behaviors in machine operation tasks, and use user behaviors to select baseline experiences for task modeling. The experimental result shows some features are good indexes of operator skill levels and operational difficulties, particularly for task duration, head movement, and gaze properties. We also demonstrated that a totally unsupervised baseline selection approach can be adopted to derive an extensive task model for guidance. In future, we need to design metrics based on user skill levels, operational difficulties, and inter-person differences for designing adaptive user instructions.
Fig. 11: The models for integrating expert and beginner experiences for two sewing tasks with different baselines. From top to bottom are manually selected groundtruth baseline, automatically detected baseline with top-down method, and the random baseline by randomly choose an experience as the baseline. The saturation of the nodes indicate the sum of In-Out transition probabilities of the nodes.
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