A novel graphical user interface for high-efficacy modeling of human perceptual similarity opinions

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ABSTRACT

We present a novel graphical user interface (GUI) that facilitates high-efficacy collection of perceptual similarity opinions of a user in an effective and intuitive manner. The GUI is based on a hybrid mechanism that combines ranking and rating. Namely, it presents a base image for rating its similarity to seven peripheral images that are simultaneously displayed in a circular layout. The user is asked to report the base image's pairwise similarity to each peripheral image on a fixed scale while preserving the relative ranking among all peripheral images. The collected data are then used to predict the user's subjective opinions regarding the perceptual similarity of images. We tested this new approach against two methods commonly used in perceptual similarity studies: (1) a ranking method that presents triplets of images for selecting the image pair with the highest internal similarity and (2) a rating method that presents pairs of images for rating their relative similarity on a fixed scale. We aimed to determine which data collection method was the most time efficient and effective for predicting a user's perceptual opinions regarding the similarity of mammographic masses. Our study was conducted with eight individuals. By using the proposed GUI, we were able to derive individual perceptual similarity profiles with a prediction accuracy ranging from 76.83% to 92.06% which was 41.4% to 46.9% more accurate than those derived with the other two data collection GUIs. The accuracy improvement was statistically significant.

Keywords: graphical user interface, high-efficacy modeling, perceptual similarity opinions, similarity of mammographic masses, individual perceptual similarity profiles

1. INTRODUCTION

The Medical Image Perception Society (MIPS) is an international society that promotes research in medical image perception. One of the goals of this society is to create tools to benefit clinical radiology by reducing observer error [1] [2]. The reduction of observer error is a critical avenue of research because at least half of diagnosis errors are perceptual [3] [4]. Since the primary element involved in cancer detection is a radiologists ability to correctly interpret and perceive the information that they receive [5], understanding and being able to model this perception is an area requiring study. This is an important area of study because current modeling techniques do not create models with results better than 50% accuracy [6]. The purpose of this study was to propose a novel way for data collection and analysis of human perceptual opinions and demonstrate its advantages compared to conventional data collection strategies commonly used in the field of radiology.

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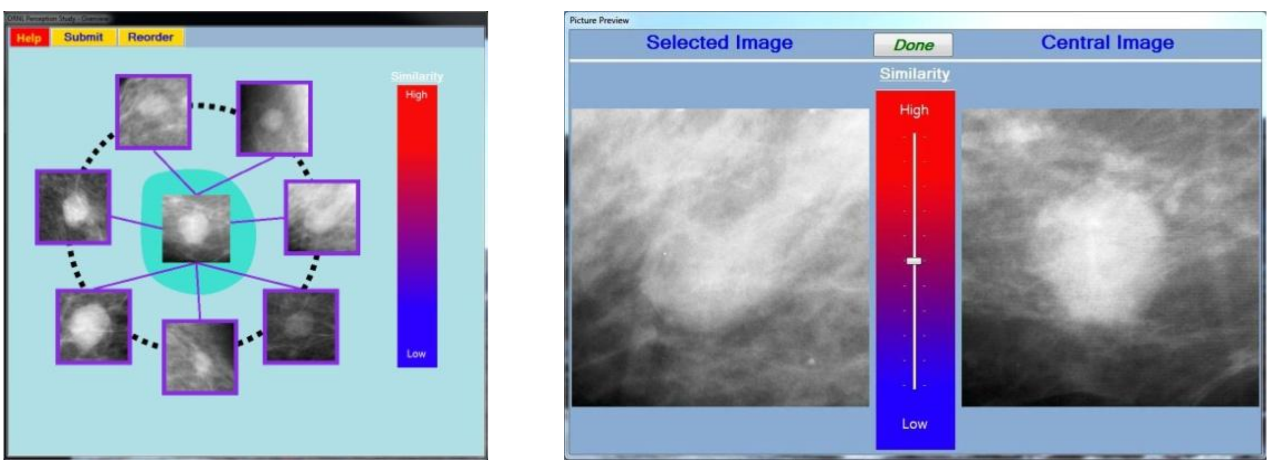
2. RELATED WORK

General perceptual subjectivity has been studied in the past. For example, Neumann and Gegenfurtner [7] studied how perceptual similarity factored into image retrieval algorithm and system design. Sanchez et al. [8] studied the modeling of subjectivity in the visual perception of orientation in image retrieval. Zhang and Zhang [9] explored the issue of subjectivity in measuring image retrieval performance. Rorissa [10] studied the relationships that exist between perceived features and similarity of images. Rorissa et al. [11] studied the relationships between feature and perceptual visual spaces.

Perceptual subjectivity specifically relating to radiologists has been investigated in the past. Kundel et al. [12] stated that holistic perception may play an important role in the development of expertise in radiographic interpretation. This gives credence to the continued study of the effects of perception on the interpretation and analysis of radiographic images. Two studies that have specifically analyzed perception in this environment are Mazurowski et al. [13] and Sahiner et al. [14]. These studies addressed the topic of observer variability in assessing the similarity of two mammographic masses. In a study done by Xu et al. [6], the idea of observer variability and assessment was taken one-step further in creating personalized predictive models for the assessment of perceptual subjectivity. However, the design, implementation, and data analysis of high-efficacy data collection strategies has not been given much attention, and in this study, we work to fill this gap.

3. METHODS AND MATERIALS

The collection of the data for the creation of the statistical models of human visual perception was done with three different GUI’s. The first GUI (GUI_1) was implemented using a novel data collection method. This method presents the user with a base or query image in the center of seven peripheral images, against which he/she is asked to report the pairwise similarity on relative high (red) to low (blue) color-coded scale (See Figure 1). The second GUI (GUI_2) implemented a ranking data collection method. The user is presented with three images, and he/she is asked to identify the pair with the highest degree of mutual perceptual similarity (See Figure 2). The third GUI (GUI_3) implemented the data collection method that is most often used in Radiology, the user is presented with two images and he/she is asked to provide a visual similarity rating using a fixed (1-10) scale (See Figure 3).



Main Program View

Picture Viewer

Figure 1: Example of GUI_1 used in the study.

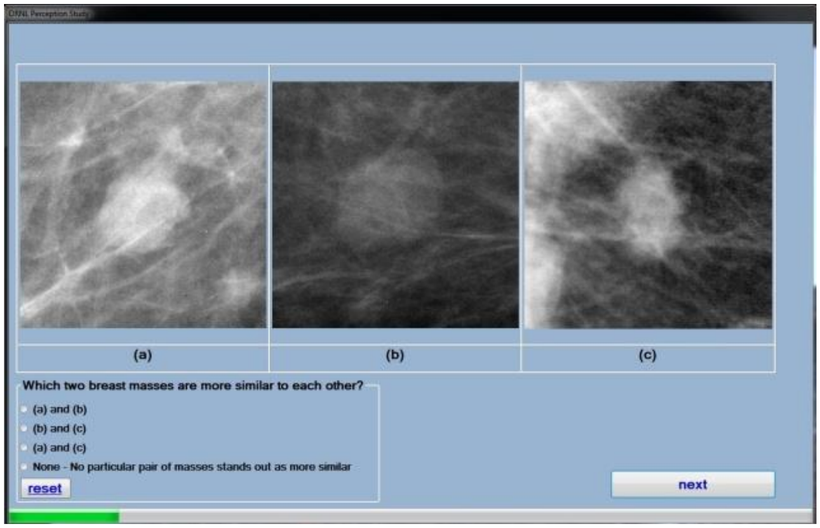


Figure 2: Example of GUI_2 used in the study.

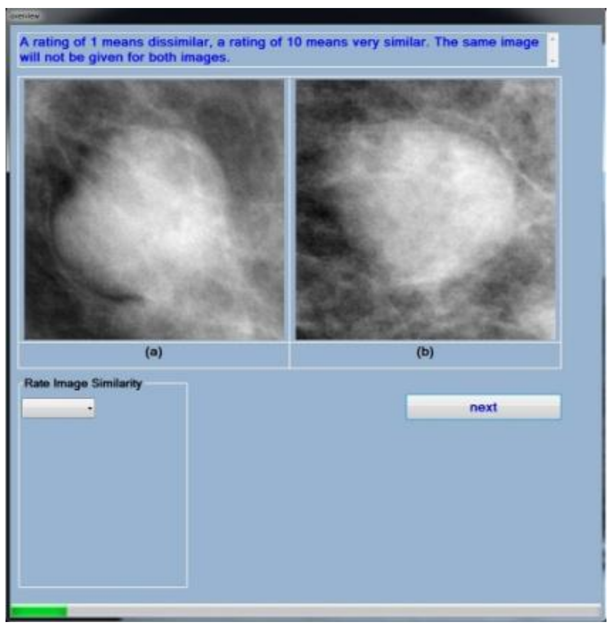


Figure 3: Example of GUI_3 used in the study.

Our proposed GUI (GUI_1) was developed with two key factors in mind in order to facilitate effective and efficient sampling of the user's perception. The first factor was ease of use. We wanted to provide an innovative GUI design that is easy for new users to pick up and use with little or no instruction. The second factor was to provide a GUI layout that would not be visually distracting to the user. The idea of reducing visual distraction lead us to work with the "Principles of Good GUI Design", as proposed by Hobart [15], in mind in order to create the most efficient and user-friendly designs. The main factor from his design principles that we focused on was providing just the right amount of detail on the top level of the program. This became an area of concern as we began to present more information to the user on the main screen of the GUI. To overcome this issue, we introduced a two-level hierarchic view structure into our interface design in order to selectively present the most relevant subset of information to the user at any given time.

The first perceptual level of GUI_1 is the main program view (See Figure 1). It shows the current set of seven images and the query image against which the ratings are based. This page was designed to provide continuity across each of the users ratings. This is accomplished through three separate mechanisms. The first mechanisms are colored borders around each of the peripheral images. These borders correspond to the current rating that that image has based on the relative high to low color coded rating scale. When the study starts, the scale is set in the middle, allowing the user to increase or decrease the similarity accordingly. The second continuity mechanism are colored radii emanating from the query to each of the peripheral images. These radii are there to reinforce the idea that the ROIs are being rated against the query image as well as pairwise with each other. This line too takes on the current rating for the specific ROI that it is connected to. The third continuity mechanism is a central manipulatable mass which expands and contracts based on the users current perceived similarity of each individual image. This continuity mechanism allows the user to get an immediate visual queue of global similarity, i.e., which images are ranked most and least similar (See Figure 4). This design makes it easy for the user to transition from one image rating to the next while keeping the current scope of the ratings in the foreground of their minds.

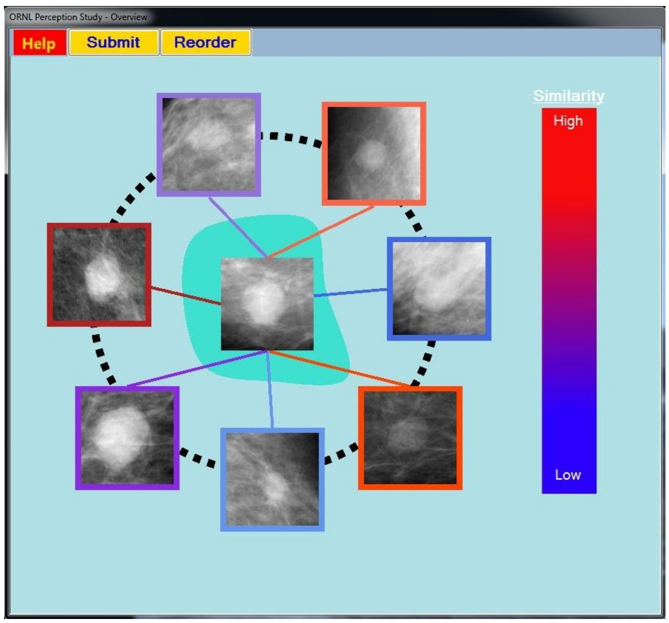


Figure 4: Main page view of GUI_1 after rating.

The second and final view of GUI_1 is the Picture Viewer (See Figure 1). To navigate to this view the user clicks on one of the seven images around the ring, and that image and the central query image are displayed in an enlarged panel. This view removes all other distraction from the rating process and allows the user to give their full attention to the images at hand. After the image is analyzed, the user can either use the mouse of the arrow keys to move a slider bar up or down, indicating that the image is either more or less similar to the query image. The decision to go with a relativistic rating scale vs. a numerical rating scale stems largely from the findings of Xu et al [16] in which they found it to be much more intuitive to users to specify relative similarities, and that by using relative similarities, users were able to give a more consistent rating over the entirety of the survey. This is in contrast to GUI_3, which implements the more often used hard numeric rating approach. After the users are done assigning a relative value, they exit this screen and continue with the remaining images. After all of the seven images are rated in relation to the central image, and pairwise against each other, the user clicks on the reorder button at the top of the screen, and a new query and set of images is displayed. This process is continued for nine rounds. In the event that the user does not want to finish all nine rounds of rating there is a submit button that will allow the user to exit the process.

Eight subjects were recruited for this study to provide their opinions using all three GUIs. The images that were used in this study were Regions of Interest (ROI) taken from publicly available full mammograms from the Digital Database for Screening Mammography (http://marathon.csee.usf.edu/Mammography/Database.html). The ROIs included masses of variable shapes and margin. The subjects were asked to assess the visual similarity of the masses. The masses were novices and they were not given any other instruction. However, to ensure that the subjects will not be simply influenced by differences in the size of the masses but they will focus on finer details of the images, they were presented with pairs of triples of masses of approximately similar size. Using GUI_1, the subjects were presented with nine query images. Therefore, the subjects had to provide 9 x 7 = 63 opinions. To maintain the workload relatively similar, using GUI_2, the subjects were presented with 72 triplets, and using GUI_3, with 72 pairs. Finally, each GUI tracked both number of user mouse clicks and time consumed to completion. These are critical metrics for comparing the efficacy and usability of each GUI design.

4. RESULTS

To ensure the comparability all three data collection methods, each had to be modeled in the same way. For this study, we used GUI_2 as the baseline for creating the statistical model. That is, each of GUI_1 and GUI_3 can be modeled in such a way as to create comparisons similar to GUI_2, in which the two most similar images out of three are selected. The images used in GUI_1 and GUI_2 were randomly selected from a pool of images in order to populate the study, while ensuring no duplicate sets of images. The images in GUI_3 were randomly selected using the following method: First, 24 sets of three images were randomly generated from the pool such that there were not duplicate images. Second, 24 single images were randomly generates such that there were no duplicates in this set, or the previous set. Third, these 24 single images become the base image of comparison in three sets of two images. That is, one set of three images, say {a, b, c}, and one of the single images, say {d} are used to create three sets of duplet images, i.e., {d, a}, {d, b}, and {d, c}. Creating comparisons in this manner created 72 duplet images for GUI_3.

Creating the statistical model for GUI_1 was accomplished by using the query image as a baseline image, and using non-repeating sets of three exterior images to create three sets of duplet image comparisons. By modeling the user ratings in this way, we are able to determine the two most similar images out of each set of three exterior images, thus creating comparisons similar to those in GUI_2. Creating image comparisons in this way for GUI_1 we were able to create seven choose three image comparisons from each round of rating. This means that a user need only perform seven pairwise ratings in order for this model to collect 35 different samples. This is in comparison to each of the other two GUI's in which seven ratings only produce seven different samples. This order or magnitude increase in collection efficiency allows our GUI to collect samples extremely efficiently.

Creating the statistical model for GUI_3 on the other hand, such that it is similar to GUI_2 can be accomplished by careful selection of the images used in the study. This is the reason that the image set creation for GUI_3 was detailed as above. By selecting images in this manner, we are able to create image comparisons that are exactly similar to those that are done in GUI_1, just in a different format. That is, a single image is used for comparison against three different images, and the two most similar images are selected. In this way, we are able to create the statistical model for GUI_3 so that it models those of GUI_2.

The process that we went though in order to create each of the statistical models as detailed above was to create a machine-learning algorithm to predict the users opinions (as collected by each GUI respectively). The idea and use of local learning was first proposed by theoretical machine learning researchers [17] [18] [19]. One study Xu and Tourassi [20] used this approach to evaluate a local learning approach for computer-assisted diagnosis of breast cancer. Following their paradigm of using local learning, the algorithms we used were created using the statistical modeling software Weka. Using this software, we were able to utilize 15 different machine-learning methods that are built-in to find the model that best predicted user's opinions. To use these methods, we used the Gray-Level Co-occurrence Matrix (GLCM) texture features [21] of each of our study images. These texture features were extracted using ImageJ, and a Texture Analyzer plugin developed by Julio Cabrera [22]. The texture features that we extracted and used were Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM), Entropy, and Energy. Using these extracted texture features and the individual results from each user for each GUI, we were able to create individual perceptual similarity profiles to predict user's choices. The best model for each study participant for each GUI is show below in Table 1 (For a breakdown of each study participants perceptual similarity profile for each of the 15 machine learning algorithms under each GUI, see Tables 3, 4, and 5 at the end of this report). The best performing algorithms predicted individuals opinions with accuracy between 34.7% and 47.2% using the data collection methods typically used in perceptual similarity studies (i.e., GUI 2 and GUI 3). Applying the same machine algorithms on data collected with the proposed GUI 1, the best models predicted individual's selections with a dramatically higher accuracy ranging between 76.2% and 92.1%. These improvements were consistent and statistically significant for all study participants.

Table 1: Accuracy of the predictive models applied to derive individual user profiles based on data collected from each of the three data collection methods.

STUDY PARTICIPANT	**% ACCURACY**		
	GUI_1	**GUI_2**	**GUI_3**
1	80.63	45.83	50.00
2	76.83	34.72	45.83
3	77.78	47.22	41.67
4	76.19	41.67	45.83
5	82.22	38.89	45.83
6	84.13	45.83	29.17
7	92.06	40.28	45.83
8	77.78	45.83	33.33

The following figure, Figure 5, compares the relative workload (in terms of time to completion for each study subject under each data collection method), and Figure 6 compares the number of clicks required under each data collection method. The average time commitment across study participants for each GUI was as follows:

GUI_1: 331.5$\pm$110.5 (sec) GUI_2: 524.5$\pm$240.0 (sec) GUI_3: 690.4$\pm$385.6 (sec)

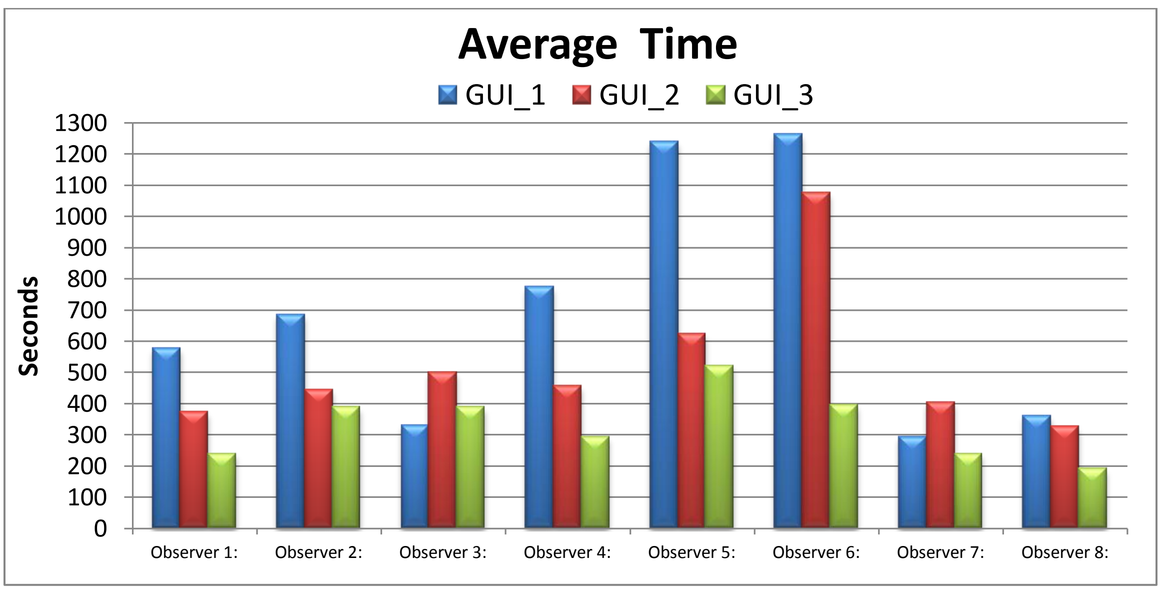


Figure 5: Average time to completion for each study subject under each data collection method.

Even though GUI 3 required significantly less time than either GUI_1 or GUI_2, there was no statistically significant difference between the time commitment required for GUI_2 and GUI_3. A similar trend was observed with respect to the number of clicks required for each study participant to complete the task using GUI_1 and GUI_2.

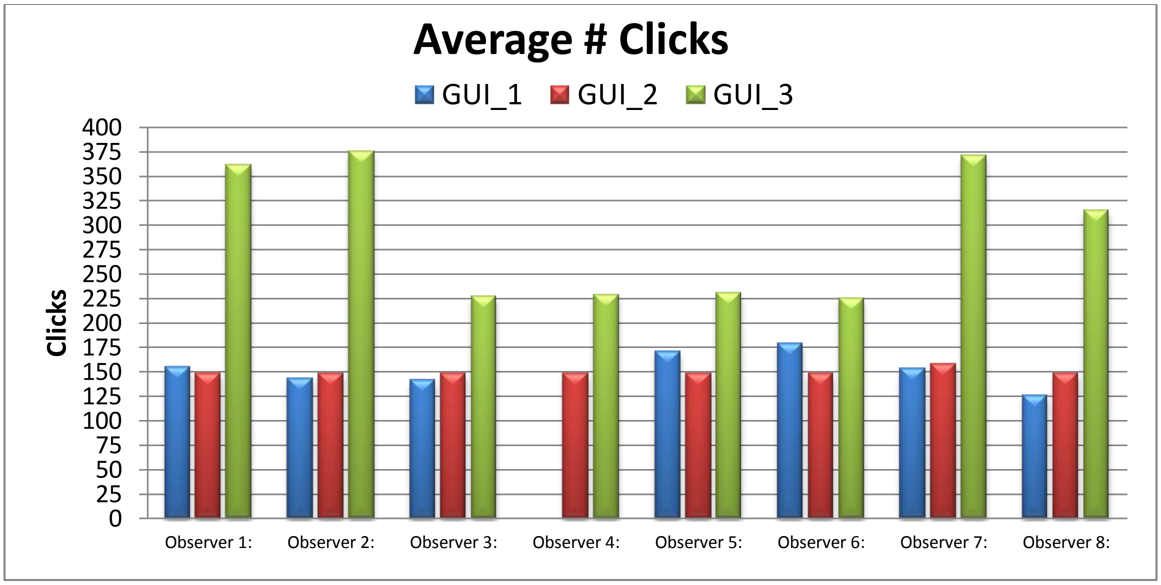


Figure 6: Average number of clicks for each study subject under each data collection method (**for Observer 4, the number of clicks was accidentally not recorded under GUI_1).

Since the time commitment for GUI_1 was noticeably higher than for the other GUIs, an issue that must be addressed is whether predictive accuracy using the peer data collection methods could be comparable if the user was allowed to invest a similar amount of time reviewing cases using GUI_2 or GUI_3. In order to facilitate an unbiased comparison between the three different GUI's where each GUI consumes an equal amount of time for every participant, we performed additional analysis by reducing the amount of data that we collected from GUI_1 when training the predictive model. That is, instead of using data from nine base cases, we performed user modeling by using data collected of every user for only four base cases. Under this scenario, the average time spent with GUI_1 was 203 seconds less (or 38.3% less time) than GUI 2, and 9.9 seconds less (or 4.02% less time) than with GUI 3 (See Figure 7). The average number of clicks

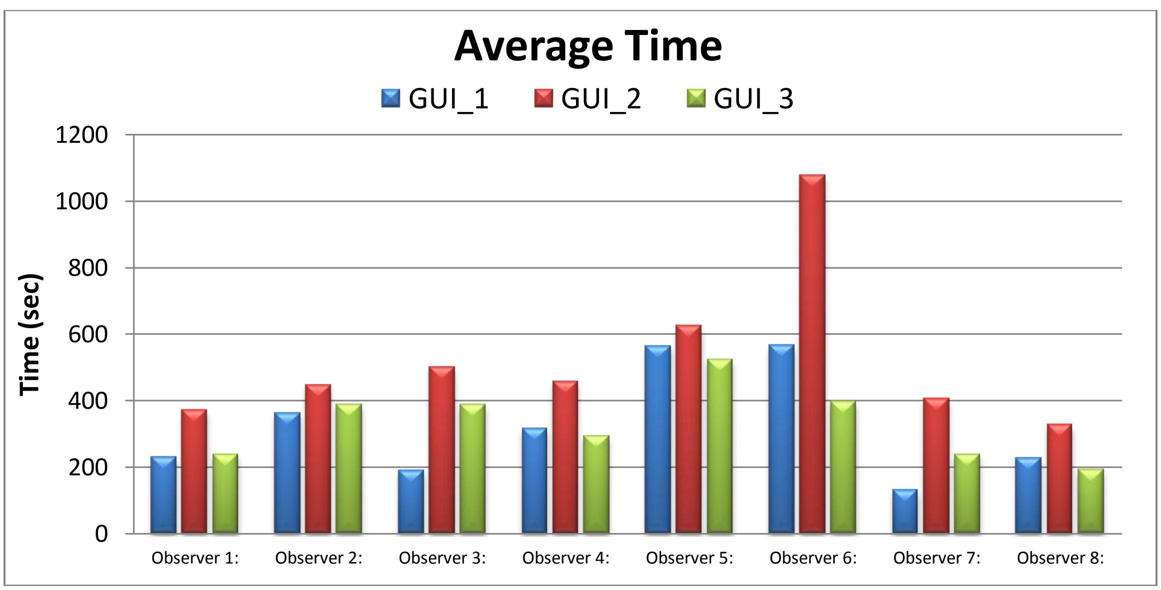


Figure 7: Average time to completion for each study subject under each data collection method using the reduced data set for GUI_1.

per user in GUI 1 was 375% less than GUI 2 and 134% less than GUI 3 (See Figure 8). Even when the average usage

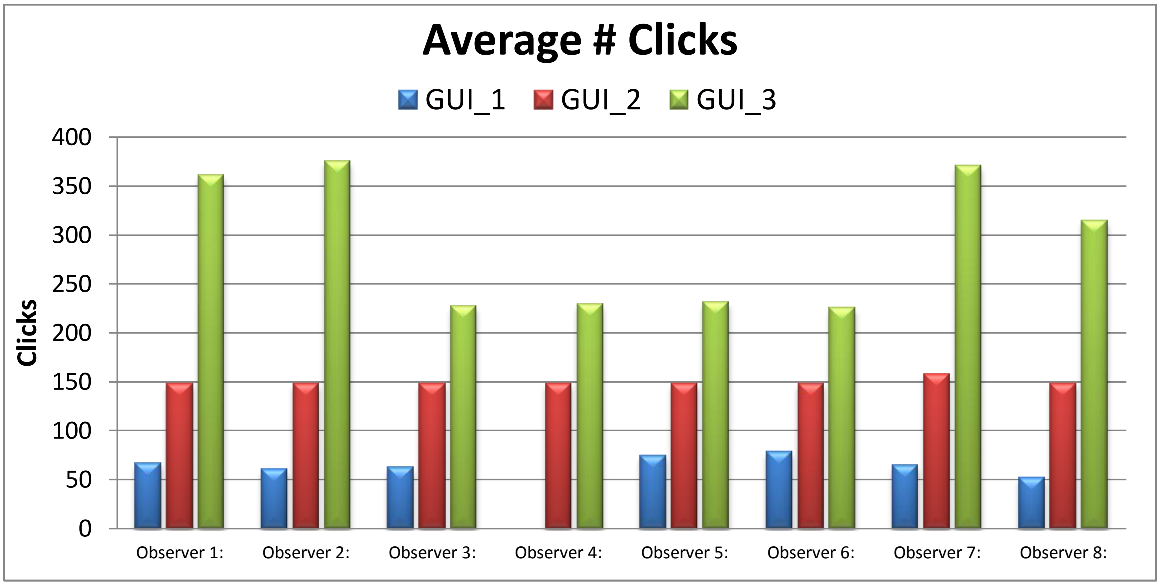


Figure 8: Average number of clicks for each study subject under each data collection method using the reduced data set for GUI_1. (**for Observer 4, the number of clicks was accidentally not recorded under GUI_1).

time and number of clicks for GUI_1 was less than both GUI_2 and GUI_3, we were able to derive user models that predicted user's opinions with comparable accuracy as before (See Table 2). We believe the reason why the new GUI enables superior predictive modeling of user perceptual similarity opinions is that individual perceptual similarity judgment collected from one common base case using GUI_1 is far more self-consistent than using the other two GUIs. Hence, even if under the equal time consumption assumption, our new GUI collects less data but of higher quality, which leads to a more reliable end predictive model than using the two peer GUIs, which leads to a more reliable end predictive model than using the two peer GUIs. In short, data quality triumphs over data quantity for our perceptual similarity modeling study.

Table 2: Study results using a reduced data set for GUI_1.

STUDY PARTICIPANT	**% ACCURACY**		
	GUI_1	**GUI_2**	**GUI_3**
1	79.29	45.83	50.00
2	75.00	34.72	45.83
3	81.57	47.22	41.67
4	78.57	41.67	45.83
5	84.29	38.89	45.83
6	94.29	45.83	29.17
7	91.43	40.28	45.83
8	79.29	45.83	33.33

5. CONCLUSION

Our results suggest that the GUI according to which perceptual similarity data is collected does have a significant impact on the reported outcomes of human perception subjectivity studies. We have proposed an intuitive and visually appealing GUI for cost-effective user opinion collection in human perception image similarity studies.

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Table 3: Performance of different machine learning methods using GUI_1 for data acquisition.

Machine Learning Method	Observer #1	Observer #2	Observer #3	Observer #4	Observer #5	Observer #6	Observer #7	Observer #8
Ada Boost	38.4127	46.3492	37.4603	40.6349	45.0794	33.3333	50.4762	37.1429
Bagging	70.1589	69.8413	63.8095	65.7413	73.6508	75.8730	83.1746	65.3968
Bayes Net	37.1429	57.1429	51.1111	56.8254	57.7778	48.2540	59.6825	51.1111
Decision Stump	38.4127	46.3492	37.4603	40.6349	45.0794	33.3333	50.4762	37.1429
DMNBtext	45.0794	46.0137	40.6349	37.7777	45.0794	43.1746	58.7302	43.4921
Logistic	52.0635	52.6984	51.4286	44.4444	57.4603	52.0635	60.6349	52.6984
Multilayer Perceptron	60.0000	59.6825	50.1587	57.1587	71.4286	68.8889	77.4603	60.6349
Naïve Bayes	41.2698	36.8254	42.8571	39.3651	37.7778	38.4127	48.5714	38.4127
PART	74.6032	73.3333	66.3492	72.3810	72.3810	76.1905	89.8413	61.5873
Random Forest	71.4286	75.2381	73.6508	70.4726	81.2698	81.2698	90.7937	74.2857
RBF Network	42.5397	46.9841	47.3016	44.1270	43.1746	49.8413	60.3175	43.1746
Rotation Forest	80.6349	76.8254	77.7778	76.1905	82.2222	84.1270	92.0635	77.7777
Simple Cart	67.9365	68.5714	72.3810	61.5873	74.6032	75.5556	84.4444	57.4603
SMO	46.0317	39.6825	48.8889	43.4921	46.9841	43.1746	61.9048	43.1746
Stacking	38.4127	38.4127	31.7460	29.2063	39.3651	38.7302	41.1746	33.0159

Table 4: Performance of different machine learning methods using GUI_2 for data acquisition.

Machine Learning Method	Observer #1	Observer #2	Observer #3	Observer #4	Observer #5	Observer #6	Observer #7	Observer #8
Ada Boost	8.3333	6.9444	47.2222	41.6667	34.7222	45.8333	37.5000	36.1111
Bagging	29.1667	25.0000	38.8889	20.8333	29.1667	30.5556	31.9444	40.2778
Bayes Net	0.0	34.7222	47.222	37.5000	38.8889	41.6667	40.2778	45.8333
Decision Stump	8.333	6.9444	47.2222	41.6667	34.7222	45.8333	37.5000	36.1111
DMNBtext	41.6667	29.1667	33.3333	27.7778	33.3333	34.7222	31.9444	36.1111
Logistic	23.6110	20.8333	27.7778	22.2222	26.3889	33.3333	22.2222	34.7220
Multilayer Perceptron	45.8330	30.5556	30.5556	18.0556	29.1667	31.9444	23.6111	31.9444
Naïve Bayes	37.5000	25.0000	22.2222	25.0000	23.6111	31.9444	18.0556	22.2222
PART	38.8889	27.7778	40.2778	23.6111	26.3889	31.9444	25.0000	31.9444
Random Forest	41.6667	23.6111	29.1667	19.4444	19.4444	31.9444	27.7780	26.3889
RBF Network	34.7222	22.2222	34.7222	27.7778	26.3889	39.1667	27.7778	29.1667
Rotation Forest	23.1111	27.7778	29.1667	26.3889	20.8333	26.3889	23.6111	34.7222
Simple Cart	36.1111	29.1667	40.2778	38.8889	38.8889	36.1111	40.2778	45.8333
SMO	33.3333	31.9444	41.6667	30.5556	37.5000	31.9444	40.2778	43.0556
Stacking	0.0	34.7222	43.0556	37.5000	38.8889	41.6667	40.2778	45.8333

Table 5: Performance of different machine learning methods using GUI_3 for data acquisition.

Machine Learning Method	Observer #1	Observer #2	Observer #3	Observer #4	Observer #5	Observer #6	Observer #7	Observer #8
Ada Boost	8.3333	33.3333	20.8333	25.0	33.3333	25.0	12.5	4.1667
Bagging	37.50	20.8333	29.1667	33.3333	41.6667	12.5	29.1667	25.0
Bayes Net	33.3333	45.8333	33.3333	41.6670	25.0	0.0	0.0	33.3333
Decision Stump	8.3333	41.6667	20.8333	25.0	33.3333	25.0	12.50	4.1667
DMNBtext	29.1667	4.1667	29.1667	12.50	45.8333	16.6667	45.8333	20.8333
Logistic	41.6667	16.6667	25.0	25.0	29.1667	25.0	16.6667	12.50
Multilayer Perceptron	41.6667	16.6667	33.3333	20.8333	25.0	20.8333	37.50	12.50
Naïve Bayes	41.6667	12.50	29.1667	25.0	37.50	20.8333	37.50	25.0
PART	20.8333	41.6667	41.6667	41.6667	23.50	29.1667	29.1667	12.50
Random Forest	41.6667	23.6111	29.1667	19.4444	19.4444	31.9444	27.7780	26.3889
RBF Network	50.0	12.50	29.1667	33.3333	33.3333	16.6667	29.1667	8.3333
Rotation Forest	29.1667	16.6667	33.3333	33.3333	33.3333	20.8333	37.50	20.8333
Simple Cart	37.50	37.50	29.1667	45.8333	33.3333	16.6667	8.3330	16.6667
SMO	50.0	12.5	29.1667	33.3333	37.50	20.8333	33.3333	16.6667
Stacking	37.50	45.8333	37.50	45.8333	37.50	0.0	0.0	33.3333

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