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Similar Visual Complexity Analysis Model Based on Subjective Perception

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ABSTRACT The visual complexity analysis is a fundamental and essential attribute applied almost everywhere in visual computation. However, the existed methods mainly focus on the assessment by preference, which is identical to the statistical rating and measurement through quantization of specific metrics. Neither of them can pay attention to the flexibility of implicit logic and the influence of subjective factors in the analysis process. Therefore, the visual complexity analysis model based on individual perception is proposed, which combines objective features with subjective opinion to achieve an evaluation task that is more consistent with the visual complexity attributes of human understanding. Instead of a statistic model of rating scores, the proposed partial relation is used to represent users' subjective labels. After *tahn* function based pre-processing, the pair data can be learned by optimal algorithms for maximization of data margin and item dissimilarity distance. There are three visual features, Gist, Hog, and Color histogram, to depict the visual complexity globally and locally. Through data collection in a small database, the improved SVM strategy is used to train the model considering both two aspects of visual factors (objective and subjective factor). Then the model predicts the visual complexity in a vast database, and the results are highly consistent (more than 90%) with the manual evaluation through correlation coefficients such as Person, Kendall, and Spearman. The Chinese university logos and PubFig dataset are selected as research objects because of their natural visualization and latent symbolic semantics, and superior performance of the proposed model, as compared to the state-of-art algorithms, is demonstrated experimentally.

INDEX TERMS Visual complexity, subject perception, partial relationship, SVM, optimization.

I. INTRODUCTION

Visual complexity is an essential criterion to represent the quality and physical perception in various vision fields, such as visual retrieval, classification, transportation studies [1]–[3] and aesthetic evaluation [4]. There are three perspectives can be used to measure visual complexity, degree of describing, degree of creating and degree of the organization [5]; however, none of these is suitable for quantitative evaluation considering the human factor (subjective perception) involvement.

The operations of visual complexity ranking take two models [6]: ranking by preference and ranking by the process. The former is identical to the statistic model, which lacks the data sensitivity of human perceptual nature, and the latter compares the items subject to specific metrics which produce unchanging orders. Recent years, Dai et al. [7] proposed a regression process to learn the model of logo shape complex. They select four objective measurement indexes to evaluate shape complexities numerically, and the results match eighty percentage manual evaluation. Besides, there are several works to assess visual aesthetics by the adaptive stylization of patch [8], inferring human attention [9] and deep learning structures [10]. The difficulties of evaluating visual complexity are the human subjective perception prevails in the evaluation process, especially when the compared objects are highly similar. The fluctuation, confliction, and instability of subjective perception [11] make the computable model hard to build.

In this paper, the novel computational model to evaluate the visual complexity is proposed in terms of logo patterns which are rich in semantics and semiological meanings. It is

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hypothesized that the desired ranking trends, which are both user data sensitive and capable of discovering underlying ranking logic, will be consistent with the manual criterion of human perception with subjectivity. Instead of traditional statistic probabilities on user studies, we introduce the usage of a partial relation pair to represent the subjective user data. After *tahn* function based pre-processing, the pair data can be learned by optimal algorithms for maximization of data margin and item dissimilar distance. Based on our best knowledge, this is the first work to evaluate visual complexity through users' subjective perception, and the pioneering work to build a computational model of human perception.

The main contributions of this paper are, therefore:

(i) The partial relation is proposed to represent subjective data for the convenience of both computation and user understanding. For manual scoring data, instead of the statistic probability model, the partial relation (binary comparison) is used to combine multiple features of two items in terms of the inequality, and the subjective decision ($>$, $\sim$) is recorded as the label. In this way, the collected partial relations are capable of calculating by heuristic algorithm, and the binary comparison is explainable for users.

(ii) Propose a computational subjective model based on the human perception of collective intelligence. The objective features are widely used in the visual comparison, computer vision, and computer graphics. However, subjective evaluation is essential during decision making, which is ignored by other studies as the difficulties of capturing and modeling. In this work, it proposes the framework to evaluate visual complexity by considering human subjective perception which is challenging and beneficial for visual evaluation automation.

II. RELATED WORK

In 2017, Yu et al. [7], [12] proposed the computational model for shape complexity by regression process, which is the representative work in recent years. There are four selected features, such as shannon information entropy and weighted rotation angle entropy as a local feature, and an average difference of neighbor angle and global distance entropy as a global feature, to be shape representation proceeded in SVR model. The labels come from human users study analyzed by statistics. Comparing with the human manual score, the value of the Pearson and Kendall correlation coefficients are close to 0.8 in the test set. In this work, only simple logo shapes are compared; however, features of the human factor in the decision-making process, especially for complex visual evaluation, are not under consideration.

Instead of visual classification, the visual complexity evaluation is more like the process of making a sequential order to the potential objects, the ranking process [13]. The SVMRank model [14] is an instance of SVM for efficiently training ranking model among categories, such as shoes, natural view, and smiling faces. The attributes inside categories are represented as S set; the ones belong to different categories are

(a) logos in reference[2] (b) our logos

FIGURE 1. Logos with different similarities.

described as O set. The optimization of the loss function makes sure more significant margin outside categories and smaller margin inside categories. However, the SVMRank and its improved deep models [15] work well on the inter-class ranking, but the intra-class ranking with high similarities because of the deficiency of human factors. In high similarity cases, the subjective prevails over objective during the decision making the process.

Inspired by works mentioned above, the novel way to evaluate visual complexity considering subjective factors is proposed to simulate human decision-making as close as possible.

III. SUBJECTIVE REPRESENTATION

Visual complexity can be measured from both subjective and objective. In cases of references [4], [9], logos with apparent differences in complexity, shown in Fig.1a, makes the objective prevails over personal factors. Therefore, the SVR mechanism makes sense for building learning model. In this paper, the motivation is the computation of subjective perception in visual complexity evaluation, especially for objects with high similarities. The Chinese university logos are selected as research objects because of their natural visualization and latent symbolic semantics, shown in Fig.1b. How to evaluate the visual complexity in a group of highly similar objects is a challenging problem for current machine learning research area as the human subjective perception involved. The novel mechanism is proposed to solve this problem through the machine learning model, shown in Figure 2. A partial relationship can represent subjective user preferences. After the *tahn* function pre-processing, the selected features can be used to train the subjective model. The details will be introduced in section III and section IV, with the first step of subjective representation.

A. PARTIAL RELATION REPRESENTATION

Enjoying the great potential in AI, it is believed that the most significant gains will come from approaches to combining human and machine intelligence, in particular harnessing the intelligence of groups, the collective intelligence [16]. User studies will be one of the efficient research methodologies to collect personal information when subjective perception is required. The traditional way to represent the user's data by the statistic model of scoring includes mean, variance, standard deviation, and so on. In this way, the model is not sensitive to data for heuristic learning. As the unstable subjectivity and impossibility of complete testing of sample data, the statistic results only represent the general probability

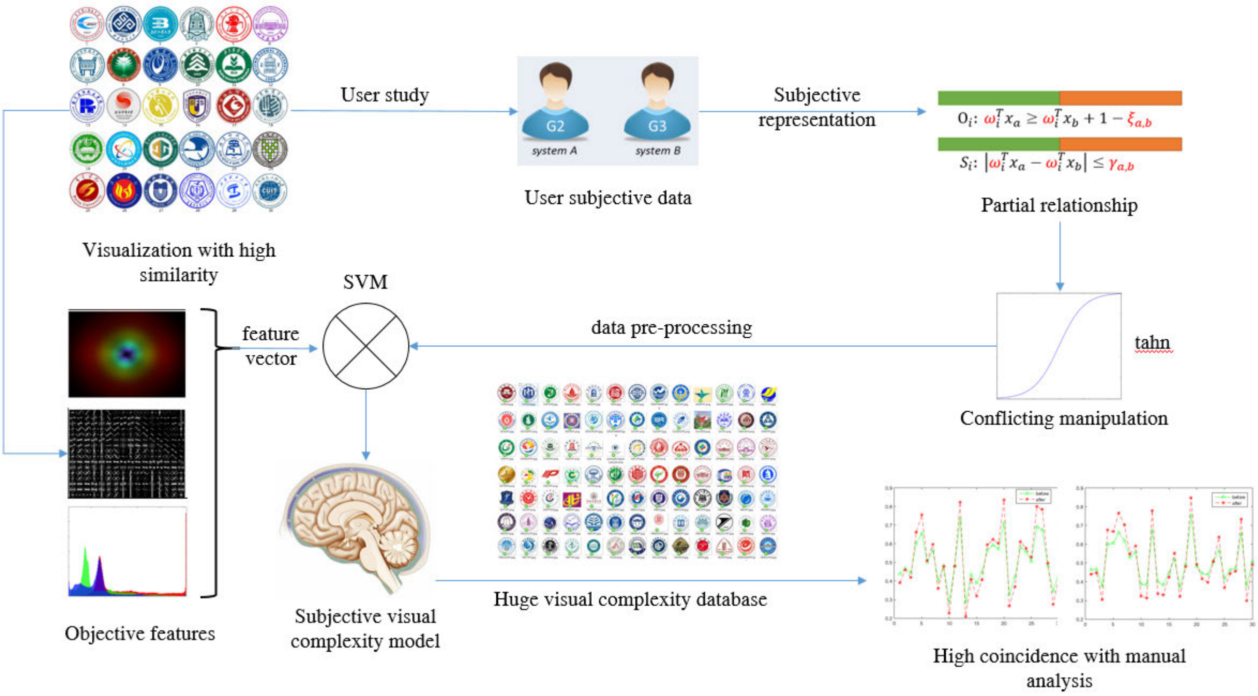


FIGURE 2. The proposed visual complexity analysis framework based on subjective perception. For the visual comparison objects (logos), the user subjective data can be represented in forms of the partial relationship (in section III). As there always many uncertainties and conflicts for subjective assessments, the conflicting manipulation by *tahn* function is necessary. Then, the objective features (Gist, Hog, and Color histogram) are used to train the subjective model by the proposed SVM algorithm (in section IV).

distribution instead of the similar distance of individual, which is vital for training model through intelligent algorithms. The Chinese university logos are selected as research objects because of their richness of semantics and visual similarities. In limited logo numbers (n = 30), it is still a problem to make a persuasive sequential list according to their subjective perception, even for human users. The binary decision is more accessible than multiple options for human candidates [17]. Therefore, candidates are required to make a decision only between two logos, and the pair comparison results will be recorded by partial orders, such as ordered pair O, 'A > B', and unordered pair U, 'A ∼ B'. The designed experiment interface is shown in Figure 3.

For the partial order A>B and A∼B, the relationships can be represented as equation 1 and equation 2.

$$f(x_i) > f(x_j) \tag{1}$$
$$f(x_i) = f(x_j) \tag{2}$$

where x_i and x_j are two logos and $f(x_i)$ and $f(x_j)$ are the objective features of x_i and x_j, respectively. The (>) and (=) are defined by users subjective perception.

In this way, there are many inequality equations received after the user study. The objective can be reformulated as learning N functions:

$$r_n(x_i) = \omega_n^T x_i \tag{3}$$

FIGURE 3. User study interface.

for n = 1, . . . , N, such that the maximum number of the constrains is satisfied:

$$\forall\,(\mathrm{i}, \mathrm{j}) \in O_n : \omega_n^T x_i > \omega_n^T x_j \tag{4}$$
$$\forall\,(\mathrm{i}, \mathrm{j}) \in U_n : \omega_n^T x_i = \omega_n^T x_j \tag{5}$$

B. SUBJECTIVE DATA PREPROCESSING

Because candidates make a decision based on their subjective perception, it is unavoidable that there are many conflicting comparison results. For example, for logo A and logo B, some believe A is more complicated than B, some believe A is less complicated than B, others treat them with equal. In statistic data analysis, the average accumulative scores represent the final logo complex degree without worrying about the conflicting issue. In the proposed partial relation way, the ratio of conflicting is comparatively high as the subjective is unstable and fluctuant [11], and every pair of the order will contribute to the final subjective model. The pre-processing by than-function is proposed to solve the conflicting problem without losing the original nature, as follows:

$$p\,(A > B) = \frac{P(A > B|x_i = A, x_j = B)}{P(x_i = A, x_j = B)} - \frac{P(B > A|x_i = A, x_j = B)}{P(x_i = A, x_j = B)} \tag{6}$$

$$conf_{ij} = \frac{e^{p(A>B)} - e^{-p(A>B)}}{e^{p(A>B)} + e^{-p(A>B)}} \tag{7}$$

As the unordered pair represents a similar degree between A and B, only the ordered pair is workable for equation 6. The constraint for ordered pair can be reformulated as

$$\forall\,(\mathrm{i, j}) \in O_n : conf_{ij}\omega_n^T x_i > conf_{ji}\omega_n^T x_j \tag{8}$$

IV. SUBJECTIVE MODEL OPTIMIZATION

There are a set of training logos I = {i} represented in $\mathbb{R}^n$ by feature-vectors x_i. According to equation 4, 5, and 8, this is still an NP-hard problem. It can be approximated the potential solution with the introduction of slack variables ζ_{ij} and γ_{ij} as reference [18], the ordered and unordered pairs can be reformulated as inequalities,

$$conf_{ij}\omega_n^T x_i - conf_{ji}\omega_n^T x_j \geq 1 - \zeta_{ij}; \quad \forall(i,j) \in O_n \tag{9}$$

$$\omega_n^T x_i - \omega_n^T x_j \leq \gamma_{ij}; \quad \forall(i,j) \in U_n \tag{10}$$

Then the optimization problem can be represented as equation 10, which can be solved by the SVM model on pairwise difference vectors.

$$\begin{aligned}
&minimize\ \frac{1}{2}(\left\|\omega_n^T\right\|_2^2 + C(\sum \zeta_{ij} + \sum \gamma_{ij}))\\
&s.t.\ \omega_n^T\left(conf_{ij}\omega_n^T x_i - conf_{ji}\omega_n^T x_j\right) = 1 - \zeta_{ij}; \ \forall(i,j) \in O_n\\
&\quad \omega_n^T\left(\omega_n^T x_i - \omega_n^T x_j\right) = \gamma_{ij}; \quad \forall(i,j) \in U_n\\
&\quad \zeta_{ij} \geq 0\\
&\quad \gamma_{ij} \geq 0
\end{aligned} \tag{11}$$

where C is the trade-off constant between two terms in which the first term is used to maximizing the margin between objects and the second term is used to satisfying the pairwise constraints.

The linear function is introduced in this paper, and the equation 11 can be easily extended to kernels. In the case of quadratic penalization of the training errors, the gradient of equation 12 is

$$\nabla = \omega + C(\sum f_\zeta\,(x_i, x_j)\zeta_{ij} + \sum f_\gamma\,(x_i, x_j)\zeta\gamma_{ij}) \tag{12}$$

and the Hessian is

$$\mathrm{H} = I_d + C(\sum x_i x_j^T \zeta + \sum x_i x_j^T \gamma) \tag{13}$$

where d is large, and the data is sparse. Instead of building Hessian explicitly, the linear system $H^{-1}\nabla$ can be solved efficiently by conjugate gradient [19].

It should be noticed that the proposed SVM model enforces the desired orders on the training items as the constraints in equation 9 and 10. At that basis, the margin representing similarities between the nearest objects will be as large as possible. In other words, the learned ω represents all the subjective information conveyed by order and un-order pairs. The proposed algorithm is shown in Algorithm 1.

Algorithm 1 Subjective Visual Complexity Evaluation

Require:
User subjective data: partial orders feature matrix: $\boldsymbol{f(x_i)}$
Ensure:
Weight vector: $\boldsymbol{\omega_{ij}}$
1: Input partial orders, O set and U set
2: calculate $\boldsymbol{conf_{ij}}$ based on equation (7)
3: $\boldsymbol{O' = conf_{ij}O}$
4: compute $\boldsymbol{\nabla}$ and **H** based on equation (12) and (13)
5: optimize equation (11) by conjugate gradient
6: output $\boldsymbol{\omega_{ij}}$

V. EXPERIMENTS AND ANALYSIS

A. EXPERIMENT SETUP

The experimental environment is Windows 10 system, 16G DDR3, GTX1070 graphic card with 8G memory, and MATLAB R2015b. Kumar and Bhavani [20] proposed to use filtering technique and combination of multiple features for human activity recognition in videos. Inspired by that, the proposed feature vector consists of global feature Gist [21], local feature Hog [22], and color feature Color-Histogram [23]. There are four groups of experiments. The first group is a visual comparison of Chinese university logos for ranking quality assessment in section 5.3. The second group is the accuracy comparison between subjective model prediction with other new algorithms in section 5.3. The third group is the consistency comparison with the manual evaluation by correlation coefficient index in section 5.4. The last group is the experiment with certainty data on PubFig [14] dataset in section 5.5

B. DATA COLLECTION AND ANALYSIS

There are 40 candidates (12 males and 28 females, from 18 to 25 years old) to evaluate randomly selected 30 logos from our logo database as train set and different 30 logos as a test set. The candidates are required to score their perception individually. It is the labor-intensive mental work, which means the number of train and test set should be limited to a small scale. During the user study, the candidate will make decisions within no less than 5 seconds for the avoidance of hasty selection. They need to select the corresponding buttons based on their opinions without influence from each other. All the data can be recorded automatically, such as the complex result, confidence degree, selection history and so on for further analysis. Considering the negative impact of longtime mental work, it should allow the candidate to test

(a) train set (b) test set

FIGURE 4. Train and test logos.

TABLE 1. User study data analysis.

Analysis	Data
total_test_pairs	6300
effective_pairs	865
conflict_pairs	812
non-conflict_pairs	53
conflict_ratio	0.9395
test_cover_ratio	0.9946

no more than 100 groups one time. The training data and test data are shown in Figure 4.

The user study is a five days process, and every candidate is required to do only one time per day. The preliminary analysis of the subjective data is shown in Table 1. The *total_test_pairs* is the total number of binary comparison, and there are 6300 pairs. The *effective_test_pairs* are pair number removing repetition ones. For the train and the test set with 30 items, there are 865 pairs (the non-repetition pair number is 30*29 = 870) are tested, the *test_cover_ratio* is 99.46%. There are 812 pairs with a conflicting score, but 53 pairs without conflicting, the*conflict_ratio* is 93.95%. The data confirm the hypothesis that the subjective perception prevails over in comparison among large similar objects, and the subjective perception is unstable and fluctuant, which leads to high *conflict_ratio*. The data analysis results prove the necessity of the subjective model.

As mentioned before, the data pre-processing will reduce the side effect of conflicting status. It re-calculates the score in a traditional way ($A > B$, $A+ = 1$, $B+ = 0$; $A = B$, $A+ = 0.5$, $B+ = 0.5$), and the figure of final score tendency is shown in Figure.5. It is demonstrated that the data after pre-processing does not break the original nature of partial orders.

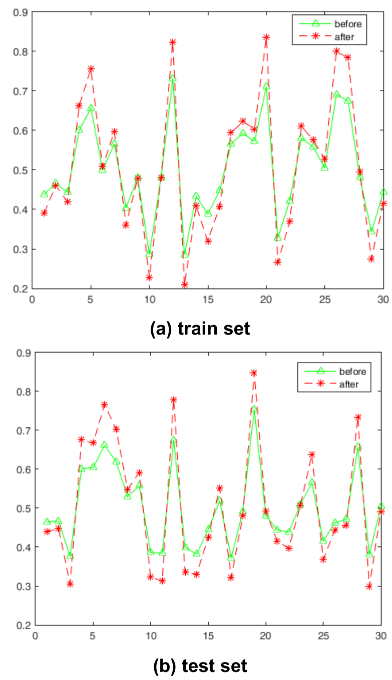


FIGURE 5. Statistic score before and after data pre-processing.

C. COMPARISON EXPERIMENTS

There are two groups of comparison, the visual comparison between subjective model and manual scoring and the quantitative experiment with the other ranking algorithms, such as logo complexity[7], [12], SVMrank[14], and Deeprank[15].

Through the user study, the manual scoring results can be used to generate visual complex ranking based on statistic approach, and the proposed subjective model also makes the

(a) train set

(b) test set

FIGURE 6. The top 5 and bottom 5 logos in train and test set. From the left to right, the degree of complexity is diminishing.

ranking. As the visual complexity is individually different, it should choose the group comparison instead of sequential comparison for impressive and stable results. In Figure 6, the visual complexity of the top and bottom five are compared between subjective model prediction and manual scoring results in the train set and test set, respectively. After the user study, the short interview proceeds with candidates about their rationale of visual complexity evaluation. They said they make decision generally based on the fineness of the pattern lines. In the train set (Figure 6(a)), the model prediction and manual scoring make the same result for the top 5, and the same selection with the different sequence for bottom 5. It is clear to find that all the top 5 logos has fined details on pattern, and the shapes of the bottom 5 logos are simple and plain. In the test set (Figure 6(b)), a similar conclusion can be generated, but two exceptions exist (with the red rectangle, No.20 and No.5 in the test set). The fourth manual scoring logo (No.20) in the top 5 test set does not appear in the subjective model prediction top 5 list. It is the ranking fifteen in subjective model prediction. The raw data source is analyzed to find that there are 15 times comparisons of No.20 (the average comparing times are 7.2) and it prevails in significant comparisons. Therefore, although the details of the No.20 is not beautiful enough, the statistic model still places it in a higher position. The same thing happens to the No.5 logo. There is one five times comparison, three of which are at a disadvantage. As a result, the statistic model set the No.5 logo at a lower position. Through the first experiment, the subjective model is more reliable and real to reflect candidates' subjective perception, without disturbing by the comparing times.

The second group of the experiment compares our results with the work reproduction of reference [7], [12] SVM-rank [14], and Deeprank [15], and proposed model without data preprocessing. The predicted accuracy is compared in the train set and the test set. The expected accuracy is the ratio of accurate partial order numbers in all partial order numbers, shown in equation 14. The accuracy comparison results are

TABLE 2. Quantitative comparison of visual complexity.

algorithm	accuracy	
	train	test
LogoComplxity	0.7264	0.6735
SVMRank	0.8029	0.7835
Deep rank	0.8521	0.8043
Ours	0.8712	0.8183
Ours+preprocessing	0.9536	0.9377

TABLE 3. Quantitative comparison of visual complexity.

Algorithm	Pearson		Kendall		Spearman	
	train	test	train	test	train	test
LogoComplexity	0.5061	0.3073	0.3980	0.2870	0.5200	0.4390
SVMRank	0.7325	0.6017	0.4527	0.4239	0.5730	0.5012
Deep rank	0.8536	0.8327	0.7210	0.6568	0.8290	0.7973
Ours	0.9121	0.8356	0.7425	0.6368	0.8839	0.8065
Ours+preprocessing	0.9551	0.9055	0.8398	0.9065	0.9419	0.8916

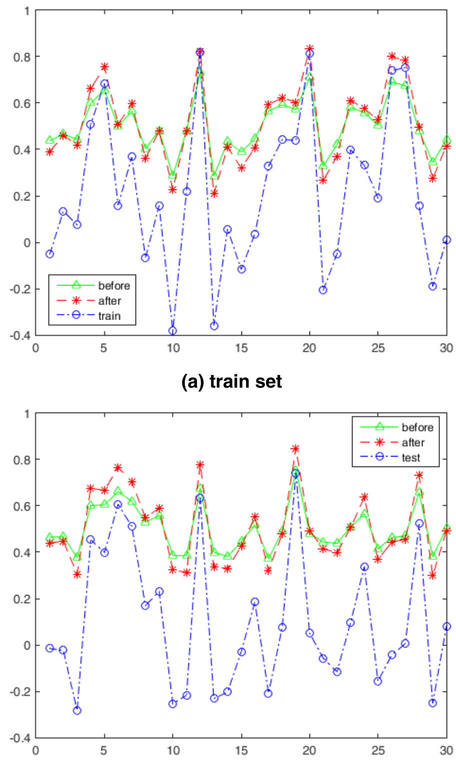
shown in Table 2.

$$accuracy = \frac{PairNo_{right}}{PairNo_{right} + PairNo_{wrong}} \tag{14}$$

In Table 2, the accuracy is around 70% for **LogoComplexity** as the logo set is high similar no matter their shape and structure. Just the objective features, such as **RankSVM** and **Deep rank**, cannot be suitable to represent the user's subjective perception accurate enough. The accuracy of **RankSVM** is around 80%, and the **Deep rank** is less than 85%. With the involvement of subjective perception, the accuracy of our work is 87% in the train set and 81% in the test set. The result is not satisfactory because there are many conflicting partial orders (the conflict_ratio is 93.95% shown in Table 1). After data preprocessing, the accuracy of our model is more than 90%, 95.36% in the train set and 93.77% in the test set. Based on the second experiment, it demonstrates that the proposed subjective model with confliction preprocessing can explain more than 90 percent of users' perceptual behavior. The statistic scoring of the proposed subjective model prediction is shown in Figure.7. In Figure.7, although the data scale between train line and the manual score is different, the entire changing tendency is still highly similar. Even for the tiny fluctuation in manual score, our model can represented them exactly.

D. HUMAN CORRELATION EXPERIMENT

The proposed model is learned from human subjective perception in terms of a partial relationship. The correlation between our model scores and human scores is a criterion to evaluate whether subjective opinion can be represented correctly. The correlation coefficient is a statistical measure of some types of correlation, including Pearson, Kendall, and Spearman. The Pearson correlation coefficient is a measure of the strength and direction of the linear relationship between two variables; the Kendall correlation coefficient is a measure of the portion of ranks that match between two data sets; and the Spearman correlation coefficient is a measure of how well the relationship between two variables can be described by a monotonic function. In this paper, the three correlation coefficients are used to measure the relationship between the proposed model and human judgment, see in Table 3.



(a) train set

(b) test set

FIGURE 7. Statistic score of proposed subjective model.

In Table 3, as the LogoComplexity only calculated the human-made features without concerning the subjective perception, the correlation coefficients are quite different from the personal score in objects with high similarities (logo). Both RankSVM and Deep rank algorithms just calculating the users' subjectivity in terms of classification information, but the similar individual distance. Their correlation coefficient is not satisfactory, as well. In our proposed model, the three correlation coefficients are more than 80% in the train set but dropped to 70% in the test set. The reason is that there are several conflicting partial orders. During the optimization process, the conflicting data will reduce the accuracy of the final prediction score. After the data preprocessing, the three correlation coefficients are close to 90%, which means there are 90 percent our proposed model can simulate human subjective judgment.

E. EXPERIMENT ON CERTAINTY DATA

The Chinese logo database belongs to the dataset with uncertainty data, i.e., the subjective user perception. To assess the proposed algorithm comprehensively, we evaluate the proposed algorithm on PubFig. [14], the popular database for ranking learning approach.

The PubFig databset contains 800 images from 8 random identities including Alex-Rodriguez (A), Clive-Owen (C), HughLaurie (H), Jared-Leto (J), Miley-Cyrus (M), Scarlett-

TABLE 4. Relative value of attributes on PubFig databse.

Classes	A	C	H	J	M	S	V	Z
Male	6	8	7	5	2	1	4	3
White	1	2	3	5	7	6	8	4
Young	5	3	2	4	8	6	1	7
Smiling	4	4	3	1	6	5	2	5
Chubby	8	4	3	1	6	7	1	5
VF	5	5	5	1	3	4	5	2
BE	6	7	5	8	1	2	4	3
NE	4	6	5	2	1	3	7	8
PN	1	2	8	3	3	4	3	7
BL	7	5	1	2	6	8	3	4
RF	6	4	1	3	8	7	2	5

TABLE 5. Quantitative comparison of the five attributes on PubFig Dataset.

	Algorithm	*SVMRank*	*RAD*	*Deeprank*	*Ours*	*Ours+Pre*
Certainty	*White*	78.16	75.33	85.12	**85.76**	/
	Chubby	76.50	79.91	86.30	**87.25**	/
	BE	80.13	80.35	**87.19**	85.36	/
	NE	80.68	80.87	**89.60**	83.25	/
	BL	79.56	82.13	**88.35**	86.60	/
Uncertainty	*White*	71.39	69.56	79.58	/	**85.20**
	Chubby	69.54	72.50	82.33	/	**84.08**
	BE	72.34	73.53	83.03	/	**84.16**
	NE	74.50	72.90	80.87	/	**82.87**
	BL	72.96	74.95	79.65	/	**83.19**
Avg		67.62	76.20	84.20	**84.77**	

Johansson (S), ViggoMortensen (V), Zac-Efron (Z). All these 8 identities are assigned with relative values of 11 attributes, such as, Male, White, Yough, Smiling, Chubby, Visible-Forehead (VF), Busky-Eyebrows (BE), Narrow-Eyes (NE), Pointy-Nose (PN), Big-Lips (BL), and Round-Face (RF). The relative strength values on eight clesses are shown in Table 4.

To evaluate the effectiveness of the proposed algorithm, we compre the following attributes (White, Chubby, BE, NE, and BL) among ranking learning approaches: SVMRank, Relative Attributes with deep features (RAD), and Deeprank [15], in which the RAD adopts the SVMRank method with deep learning features extracted form the seventh fully connected layers of the AlexNet [24] which is pre-trained on ImageNet images for the LSVRC2012 [25].

We change the relative value on PubFig into the partial relationship by changing the pair comparison inside same categories into the U set and the pair comparison in different categories into the O set according to their relative values. For fully comparison, there are two types of data are involved, the certainty data which is the partial relationship generated from the original relative value in PubFig, and the uncertain data which including extra 10% noisy data into the database to simulate the conflicting issue of human subjectivity.

On the PubFig dataset, it includes 241 training images, and can generate more than seven thousand pair comparison for every single attribute. The similar evaluate scheme mentioned in section 5.3 is adopted. The experiment results are shown in Figure 4.

Based on the results in Table 5, it is clear that the proposed algorithm outperforms the state-of-the-art methods on the PubFig dataset. The SVMRank approach is based on linear optimization model for each attribute. The average accuracy is 8.58%, 16.58%, and 17.15% below the RAD, Deeprank, and our model. The RAD is based on the deep features and obtains better performance than SVMRank, which demonstrates the effectiveness of the deep visual features. However, the RAD method still does not good enough as the applied linear function similar to SVMRank. There are two extra fully connected layers are added and trained in the Deeprank process. The performance is much improved in certainty dataset as the combination of deep visual feature and nonlinear ranking function. However, when the 10% noises added, the certainty data becomes the uncertainty one, which leads to a significant drop in accuracy (nearly 7% drop). The reason for adding noise to the dataset is the simulation of human subjective evaluation. In the human judgment, it is hard to keep all the evaluation unified. As a result, we increase some opposite effects to the partial relationship with a probability of ten percent. The accuracy of SVMRank, RAD, and Deeprank are all decline to some extent. The *tahn*-based data preprocessing is capable of avoiding the influence of uncertainty data. Therefore, the accuracy of our proposed algorithm keeps relatively stable around 0.85.

VI. CONCLUSION

In this paper, the visual complexity is represented by the subjective perception in terms of partial orders. For human user study, to reduce the influences of conflicting data, the *tahn*-based data preprocessing is proposed. Through the conjugate gradient, the linear SVM model is used to optimize partial orders for subjective visual complexity model. The promising comparison experiments with other approaches prove the feasibility of the proposed model. The three correlation coefficients represent that our model can evaluate the visual complexity as close as human judgment.

In this paper, the objective feature of logos is manual features (Gist, Hog, and Color histogram) for computational convenience. The effect of unsupervised feature extraction (deep learning) is our next work. The visual complexity is part of visual aesthetics, and the future work to build a computable model in aesthetic evaluation for visualization is necessary.

REFERENCES

[1] F. Chen, M. Song, X. Ma, and X. Zhu, "Assess the impacts of different autonomous trucks' lateral control modes on asphalt pavement performance," *Transp. Res. C, Emerg. Technol.*, vol. 103, pp. 17–29, Jun. 2019.
[2] G. Wu, F. Chen, X. Pan, M. Xu, and X. Zhu, "Using the visual intervention influence of pavement markings for rutting mitigation—Part I: Preliminary experiments and field tests," *Int. J. Pavement Eng.*, vol. 20, no. 6, pp. 734–746, 2019.
[3] X. Zhu, Z. Dai, F. Chen, X. Pan, and M. Xu, "Using the visual intervention influence of pavement marking for rutting mitigation—Part II: Visual intervention timing based on the finite element simulation," *Int. J. Pavement Eng.*, vol. 20, no. 5, pp. 573–584, 2019.
[4] D. C. Donderi, "Visual complexity: A review," *Psychol. Bull.*, vol. 132, p. 73, Jan. 2006.

[5] S. Lloyd, "Measures of complexity: A nonexhaustive list," *IEEE Control Syst.*, vol. 21, no. 4, pp. 7–8, Aug. 2001.
[6] H. Lei, J. Xia, F. Guo, Y. Zou, W. Chen, and Z. Liu, "Visual exploration of latent ranking evolutions in time series," *J. Visualizat.*, vol. 19, no. 4, pp. 783–795, Nov. 2016.
[7] L. Dai, J. Zhang, R. Peng, J. Wang, and J. Yu, "Computational measure of logo shape complexity," *J. Comput.-Aided Des. Comput. Graph.*, vol. 29, pp. 1793–1798, 2017.
[8] A. Gilbert, J. Collomosse, H. Jin, and B. Price, "Disentangling structure and aesthetics for style-aware image completion," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 1848–1856.
[9] P. Wei, Y. Liu, T. Shu, N. Zheng, and S.-C. Zhu, "Where and why are they looking? jointly inferring human attention and intentions in complex tasks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 6801–6809.
[10] S. Ma, J. Liu, and C. Wen Chen, "A-lamp: Adaptive layout-aware multi-patch deep convolutional neural network for photo aesthetic assessment," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jul. 2017, pp. 4535–4544.
[11] J. Cui and M.-X. Tang, "Integrating shape grammars into a generative system for Zhuang ethnic embroidery design exploration," *Comput.-Aided Des.*, vol. 45, pp. 591–604, Mar. 2013.
[12] J. Zhang, J. Yu, K. Zhang, X. S. Zheng, and J. Zhang, "Computational aesthetic evaluation of logos," *ACM Trans. Appl. Perception*, vol. 14, Jul. 2017, Art. no. 20.
[13] J. Gao, T. Zhang, X. Yang, and C. Xu, "Deep relative tracking," *IEEE Trans. Image Process.*, vol. 26, no. 4, pp. 1845–1858, Apr. 2017.
[14] D. Parikh and K. Grauman, "Relative attributes," in *Proc. Int. Conf. Comput. Vis. (ICCV)*, Nov. 2011, pp. 503–510.
[15] X. Yang, T. Zhang, C. Xu, S. Yan, M. S. Hossain, and A. Ghoneim, "Deep relative attributes," *IEEE Trans. Multimedia*, vol. 18, no. 9, pp. 1832–1842, Sep. 2016.
[16] G. Mulgan, "Artificial intelligence and collective intelligence: The emergence of a new field," *Ai Soc.*, vol. 33, pp. 631–632, Nov. 2018.
[17] A. Tversky and D. Kahneman, "The framing of decisions and the psychology of choice," *Science*, vol. 211, no. 4481, pp. 453–458, 1981.
[18] T. Joachims, "Optimizing search engines using clickthrough data," in *Proc. 8th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Jul. 2002, pp. 133–142.
[19] S. Keerthi and D. Decoste, "A modified finite Newton method for fast solution of large scale linear SVMs," *J. Mach. Learn. Res.*, vol. 6, pp. 341–361, Mar. 2005.
[20] K. S. Kumar and R. Bhavani, "Human activity recognition in egocentric video using HOG, GIST and color features," *Multimedia Tools Appl.*, pp. 1–17, 2018.
[21] F. M. Kheirkhah and H. Asghari, "Plant leaf classification using GIST texture features," *IET Comput. Vis.*, vol. 13, pp. 369–375, Sep. 2018.
[22] Z. Xiang, H. Tan, and W. Ye, "The excellent properties of a dense grid-based HOG feature on face recognition compared to Gabor and LBP," *IEEE Access*, vol. 6, pp. 29306–29319, 2018.
[23] H. Liu, F. Zhao, and V. Chaudhary, "Pareto-based interval type-2 fuzzy c-means with multi-scale JND color histogram for image segmentation," *Digit. Signal Process.*, vol. 76, pp. 75–83, May 2018.
[24] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst. (NIPS)*, 2012, pp. 1097–1105.
[25] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, "ImageNet large scale visual recognition challenge," *Int. J. Comput. Vis.*, vol. 115, no. 3, pp. 211–252, Dec. 2015.

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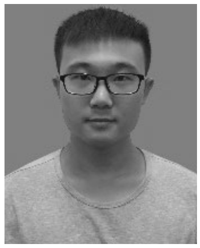

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