

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/224202426>

Learning Character Design from Experts and Laymen

Conference Paper · November 2010

DOI: 10.1109/CW.2010.66 · Source: IEEE Xplore

CITATIONS

5

READS

29,725

4 authors, including:



Md Tanvirul Islam

East Delta University

23 PUBLICATIONS 29 CITATIONS

[SEE PROFILE](#)



Yong Peng Why

University of Hull

28 PUBLICATIONS 459 CITATIONS

[SEE PROFILE](#)

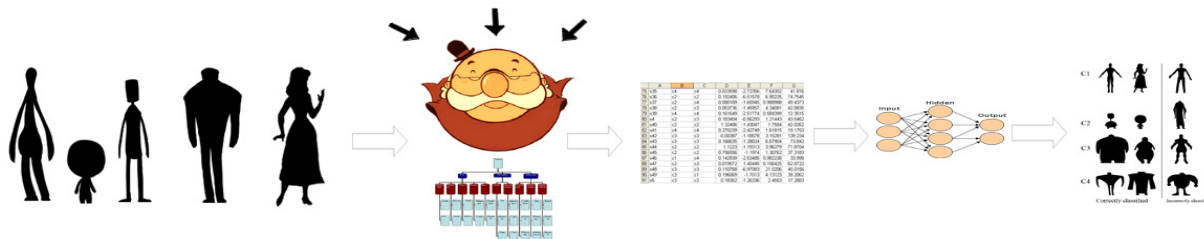
Learning Character Design from Experts and Laymen

Md. Tanvirul Islam
School of Computing,
National University of
Singapore
tanvirulbd@gmail.com

Kaiser Md. Nahiduzzaman
School of Computing,
National University of
Singapore
kaisernahid@gmail.com

Yong Peng Why
FASS (Psychology),
National University of
Singapore
psywyp@gmail.com

Golam Ashraf
School of Computing,
National University of
Singapore
gashraf@nus.edu.sg



Abstract— The use of pose and proportion to represent character traits is well established in art and psychology literature. However, there are no Golden Rules that quantify a generic design template for stylized character figure drawing. Given the wide variety of drawing styles and a large feature dimension space, it is a significant challenge to extract this information automatically from existing cartoon art. This paper outlines a game-inspired methodology for systematically collecting layman perception feedback, given a set of carefully chosen trait labels and character silhouette images. The rated labels were clustered and then mapped to the pose and proportion parameters of characters in the dataset. The trained model can be used to classify new drawings, providing valuable insight to artists who want to experiment with different poses and proportions in the draft stage. The proposed methodology was implemented as follows: 1) Over 200 full-body, front-facing character images were manually annotated to calculate pose and proportion; 2) A simplified silhouette was generated from the annotations to avoid copyright infringements and prevent users from identifying the source of our experimental figures; 3) An online casual role-playing puzzle game was developed to let players choose meaningful tags (role, physicality and personality) for characters, where tags and silhouettes received equitable exposure; 4) Analysis on the generated data was done both in stereotype label space as well as character shape space; 5) Label filtering and clustering enabled dimension reduction of the large description space, and subsequently, a select set of design features were mapped to these clusters to train a neural network classifier. The mapping between the collected perception and shape data give us quantitative and qualitative insight into character design. It opens up applications for creative reuse of (and deviation from) existing character designs.

Keywords— shape learning; shape psychology; perception games

I. INTRODUCTION

Artists typically use shape, size, pose and proportion as the first design layer to express role, physicality and personality traits of a character. The establishment of these traits in character design is one of the most important factors in the process of successful storytelling in any comic book, graphic novel, storyboard or animated feature. Recent advancement in digital multimedia technologies has encouraged user-generated content in the form of videos and images, accompanied with textual labels or descriptions. But the process of creating humanoid characters with appropriate role, physicality or personality traits still requires expert skill and labor.

Though characters are remembered mostly for their roles in the story, several layers of visual detailing are employed to bring their roles to life. Starting with basic shape and proportion, artists create layers of skin tones, hair styles, attire, accessories, key postures, gait, action energy, mannerisms and facial expressions [4,5]. Furthermore, drawing styles may vary widely across cultures, media and entertainment genres. Thus, it may take years of learning and practice for novice artists to pick up the necessary skills to create impactful characterizations for a certain target audience [18].

Every year thousands of new characters are designed worldwide for the billion dollar markets in animated features and games [33]. While computers are used mostly for shape modeling, animation and rendering, conceptual character design still relies heavily on the skills and experience of the art department. For this reason, tools that could abstract character design rules from finished art would be really useful to the expert character designer of this industry. It would also be helpful to novice users for picking up better drawing skills [18].

Artists are usually good at drafting characters, using an intuition of how lay audiences will visually perceive them. However, we find that this process could be improved significantly if there was a mechanism for audiences to tangibly feedback their perception of the character design in some manner. Unlike application software, where products undergo beta testing with select user groups, the character creation process is too expensive/secretive to allow mass user-feedback. We address this problem by building an intelligent shape→trait model, created from user perception data and existing character art. We annotate and analyze existing character art, available as images or 3D models on the Internet, as a rich source for learning rules of good character design from artists. This perception prediction model will provide a useful feedback loop to artists, right from the draft stage of the character design.

In this paper, we focus on the pose and body-part proportion layer as it plays a vital role in design and perception [4,5]. We adopted casual online games as a tool to collect motivated mass perception data, as there were significant challenges in gathering meaningful data in a large feature space through other means like interviews or surveys. Players need to select appropriate tags for displayed character silhouettes, and later match up their tags to the most appropriate silhouette, as a way to progress in the game. We explain the game design, data analysis, training and validation results in the rest of the paper.

II. RELATED WORK

Automatic extraction of information from cartoon images of humanoids poses a number of challenges like perspective distortions, obscured body parts due to posing, and exaggerated non-standard body parts (unlike real humans). We did not find any method that provides a robust solution to this ill-posed problem. Since our goal is not the automation of data collection, which by itself is a significant challenge, we designed a user-friendly system to allow manual annotation of shapes.

We first review papers on art analysis and reuse. Sykora et al [28, 29, 30] proposed example-based frameworks for reusing traditional cartoon art. Gingold et al [12] used primitive shapes for creating a 3D model by placing primitives and annotations on 2D sketches. Fiore et al [9] proposed a system where a stylised brush tool is used to freely draw extreme poses of characters. But these works did not take into consideration the abstract traits of characters in order to create new art. Our work is different from these papers as we propose mapping models between physicality and abstract character traits.

Next, we review a variety of shape representation strategies for learning and cognition of visual data. Edelmann and Intrator [7] proposed the use of semantic shape trees to represent well-structured objects like the hammer and

airplane. Their goal was to recognize object classes, starting bottom-up with low level features. A drawback of this method is that it needs explicit modelling of the object grammar. Gal et al. [10] propose 2D histogram shape signature that combines two scalar functions defined on the boundary surface, namely a local-diameter and average geodesic distance from one vertex to all other vertices. Though this approach is robust to minor topological changes due to articulation in meshes, the representation lacks intuitiveness. Hsu et al. [16] use CART data mining on body distance measurements (e.g. waist-girth, hip-girth, etc.) and body mass index to classify them into Large/Medium/Small categories for garment production.

Third, we review classification models on anthropomorphic data. In most of these models, the feature vectors used are fairly low level; e.g. Cartesian points, curves, distances and moments. PCA has been used to reduce the dimensionality of low-level point features for generating caricature drawings of human faces [13, 20]. Wang et al. [35] used rotational regression to learn deformation offsets of vertices in relation to driver skeletal joints. Meyer and Anderson [23] propose a computation cache for neighbourhoods of key points undergoing lighting or deformation calculations, again using PCA analysis on point features. Marchenko et al. [21] differ from all these approaches by combining ontological metadata (e.g. artist name, style and art period) with low-level image features (e.g. brushwork and colour temperature). Though they do not do any shape analysis, they implement a practical learning framework that improves learning results with human-understandable conceptual knowledge layers. Gutiérrez et al [22] also build ontology to facilitate digital character design, but they analyze different body parts independently. This seems to be in conflict with the Gestalt school of thought [26], which postulates that we perceive shapes in relation to one another, as well as an overall sum of parts (instead of scrutinizing details of individual parts independently). Moreover, Gutiérrez et al [22] do not have focus on perception problems.

Fourth, we review related works in art and psychology. Goldberg [14] studied the structure of phenotypic personality traits and Arvid [2] compared personality preferences in different styles of graphical interface design using survey approach. Ueda et. al [31] adopted multi-scale convex/concave structure matching approach to learn visual models from shape contours. Funge et. al [19] established a framework for cognitive modelling knowledge, reasoning and planning for digital characters. Zbigniew [37] gave a structural study into shape understanding and tried to address the visual thinking problems. Hsueh-Yi et. al [17] propose shape retrieval using some cognitive psychology-based principles. Though we find useful information related to pose and body-proportions outlined in art books [4,5,6,15] as well as shape perception literature [25, 26], we

chose to discover it through our mass-feedback guided learning framework instead.

Lastly, we review an emerging topic well known as Games With A Purpose (GWAP). GWAP systems are designed to be enjoyable, ensuring motivated data collection, thus minimizing the probability of random white noise. According to human-computer interaction researchers, it is important to introduce the elements of enjoyment and fun in user interfaces [27,36]. Games and role-playing activities are becoming popular modes of learning for children [24]. Our inspiration comes from previous works of using a game to learn character design done by Ashraf et al [3] and using data mining techniques to learn psychology traits performed by Islam et al [18]. Our modeling approach is different from these works as we do not represent shapes explicitly, relying on a few pose and proportion parameters instead.

III. DATA COLLECTION OVERVIEW

We used finished art as our source images. These images are then manually annotated to compute the pose and proportion feature vector (shown under Fig. 2). In our online game, we expose a simplified silhouette of the character and a randomized subset of role, physicality and personality stereotype labels. The silhouette simplification ensures that users do not identify the real roots of a possibly popular character (contextual familiarity). The lack of texture or accessory details further focus the perception experiment on shape and pose only. Data analysis was performed on both stereotype labels and body-vector space. The input images were taken from three types of data source: Amateur drawings, popular art (simplified), and unknown 3D art (front rendered). Collecting images from these three different sources ensured a wide variety of styles (see Fig. 1). We also picked the images carefully so that all major stereotypes of characters were included in the input image repository. In our 250+ image repository, our art team drew 56 figures, and over 200 characters were sourced from the Internet.

The input images are then manually annotated (see Figs. 2 and 3) to calculate the pose and shape proportion. Each character is annotated with the following features:

- l_h = height of head and neck
- l_u = height of upper portion of the body
- l_l = height of lower portion of the body
- b_h = breadth of abdomen
- b_s = width of shoulder
- θ_a = vertical angle of arm
- θ_l = angle between legs

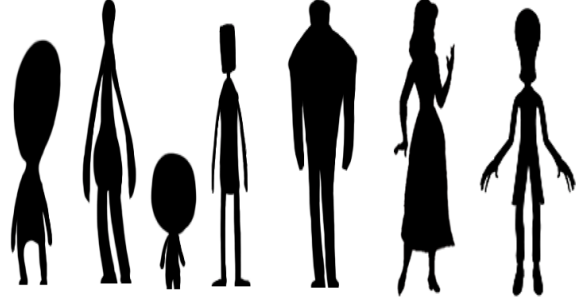


Figure 1: Simplified Character Silhouettes

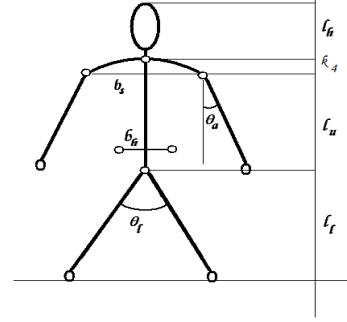


Figure 2: Pose-Proportion Feature Abstraction

We then calculate a normalized feature vector that is invariant to different character heights:

$$\begin{aligned}
 k_1 &= l_h / (l_u + l_l) \\
 k_2 &= b_s / b_h \\
 k_3 &= l_u / l_l \\
 k_4 &= \text{verticalOffset}(\text{neck}, \text{shoulder}) \\
 k_5 &= \theta_a \\
 k_6 &= \theta_l
 \end{aligned}$$

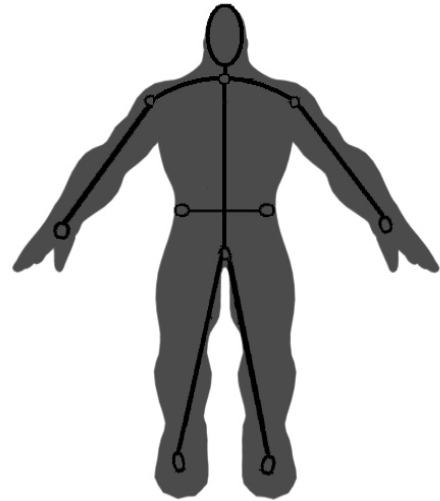


Figure 3: Silhouette annotation with connected dots

The character trait labels used in the game are listed in Fig. 4. The three top tier nodes represent broad categories, the 2nd tier nodes represent archetypes, and the leaf nodes represent stereotype labels used in game. We chose Personality archetypes from the well-known OCEAN Big Five model, a subset of Role archetypes identified by the Greek philosopher Aristotle, and a couple of orthogonal Physical archetypes devised by us. The labels from different parts of this tree are randomly exposed with uniform distribution, in order to prevent any biased results due to inequitable label sampling.

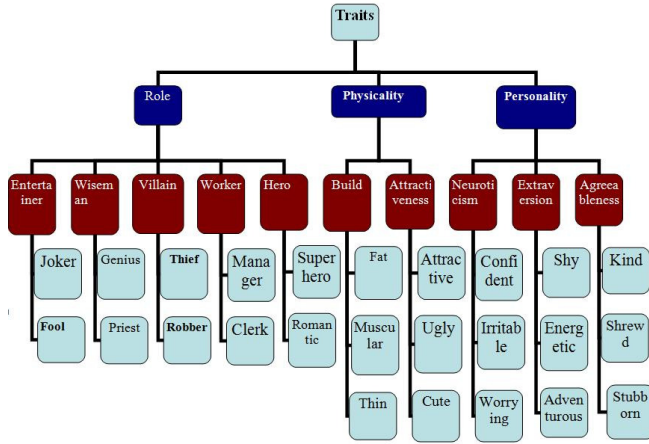


Figure 4: Character Attribute hierarchy

IV. GAME DESIGN

Our game is a casual online puzzle set in a small town, where all the people have lost their shadows. The player takes on the role of a temporary apprentice to the shadow-maker and has to help create and return the shadows to the townspeople. The player rates each silhouette (displayed in random sequence) with label(s) as shown in Fig. 6, and periodically needs to match the best available silhouette to a system-generated label(s) as shown in Fig. 7. Since perception feedback cannot be “right” or “wrong”, it poses a challenge towards making this single-player game interesting. The system-generated label is drawn from one of the user ratings in the same session, and a right/wrong answer is conclusively decided based on whether the player once again picks up the same shadow that he/she originally rated with the same label(s).

There are 7 levels in the game. The first 3 are for role, physicality and personality ratings. The next 3 levels are the combinations of physicality-role, role-personality, and personality-physicality. The last level involves simultaneous rating of role-personality-physicality. The user needs to click on the most appropriate label before a time-out. He/she

can also pass, if there are no suitable labels for a given exposure.

From our user studies, we found that the players enjoyed the game. This explains why we were able to collect meaningful data within a short period of 5 days, with about 600 levels of game play recorded over the Internet. This amounts to a total of over 5000 label ratings for the 250 images combined (approximately 20 ratings/character).



Figure 5: Labeling physicality traits in-game



Figure 6: Label matching mechanic for reinforcement

V. DATA ANALYSIS

We have two different types of data related to the character silhouette in our repository. First type is the shape-proportion data of all the images and second type is the user perceptions on those images. To mine meaningful

information from these two sets of data we need to preprocess them separately and then combine them later. Our game is designed in such a way that it collects users' perception on different characters. There are in total 25 different trait labels that a user can assign to any character shadow. These trait label hierarchy has already been explained in Fig. 4, where a subset of the leaf nodes is randomly exposed to players, for every character exposure. As different players play the game many times over the Internet, different (and possibly conflicting) labels are assigned to each character silhouette. Over time some pattern emerges in the user assigned trait labels. Our goal would be to find correlations between role, physicality and personality labels, as well as find cohesive mappings between the character feature vector and the traits.

We first describe our label filtering and clustering ideas, followed by neural network training of physical features to identified label clusters.

Various user labels an image with various traits. As we have 25 different traits labels t_i where $i=1$ to 25, for each of these labels will have different number of scores corresponding to a single image. This way, for all the images we can create a matrix $S[i,j]$ of scores where each row represents a distinct label and each column represents a unique image. Now if we define $L_s[i]$ as the sum of all the scores for trait t_i over all the images then,

$$L_s[i] = \sum_{j=1}^{250} S[i, j]$$

represents the total number of hits on a particular label over all the game sessions. Now we define M_L as,

$$M_L = \max(L_s[i]) \text{ where, } i = 1 \text{ to } 25$$

Comparing with M_L , we can detect how significant is the total hit count of any trait t_i . If it is too low then we can assume that sufficient data was not cumulated about that particular trait label t_i to allow us to draw any reliable inference. If ε is the threshold of acceptance then we consider only those traits t_i for which

$$\frac{L_s[i]}{M_L} \geq \varepsilon$$

This value of ε is derived by an iterative trial and error method. In our case it was 0.46. The specific criterion for this trial and error method is described later. After this process we get traits $t_{i1}, t_{i2}, \dots, t_{im}$ as survivors. These m labels have significant amount of hits to draw statistically significant conclusions.

After filtering the labels, we have got 13 different labels on which we have significant amount of user inputs. As there are many labels of different categories, there might be some correlation among the occurrences of these labels. For

example, a person might perceive a character with distinct physicality and pose as having some correlated role or personality. To find such correlated label groups we do unsupervised clustering over these labels. Fig. 7 illustrates the clustering idea with a graph, where the X-axis elements are the character silhouette IDs, and the Y-axis represents frequency for different label curves. In the figure, we see that the frequency distribution for the 'muscular' label has a similar shape to that of 'confident' over all 250 image samples. This reveals that whenever people perceive a character as muscular they also tend to perceive it as confident. The label 'fat' has a different distribution which means it belongs to a different class. Though this analysis can be also done with correlation tests between label pairs [3], clustering provides a more generic framework for identifying tuples of closely related labels.

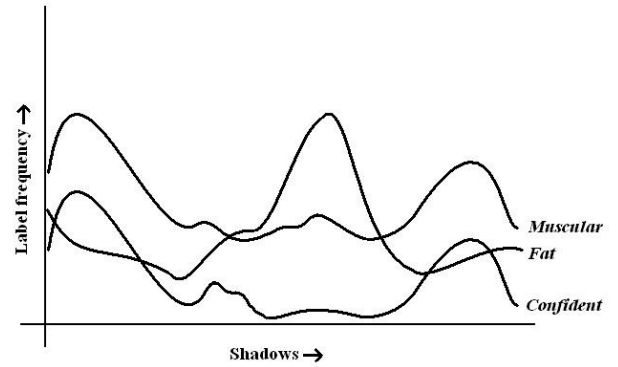


Figure 7: Label Clustering

We performed unsupervised clustering using Expectation Minimization technique provided by the WEKA toolkit [38]. Minimum Standard Deviation was set to 1.0E-6. We got four clusters of labels namely,

- cluster1(C1)---> Attractive, Kind, Manager
- cluster2(C2)---> Ugly, Cute, Shy, Fool, Clerk, Thin
- cluster3(C3)---> Fat
- cluster4(C4)---> Muscular, Confident, Superhero

For convenience, afterwards we will describe cluster 1 by C1, cluster2 by C2 and similarly C3 and C4. Here we observe that, C4 has an intuitive meaning, people use to association of Muscular, Confident and Superhero traits to similar images. Fat stands alone as a distinct cluster. C1 is also understandable. Only C2 is a slightly odd association of Ugly with Cute, Shy, etc. Perhaps, it is because cute and ugly characters both share certain structural traits like small body and big head, and thus not so distinguishable when texture or accessory details are missing.

The clustering method thus allowed us to meaningfully reduce our labels space substantially, which is crucial for

any automated learning system. We perform a voting for each training image, to supplant the individual label frequency scores with a single cluster association. So, if for some image g_k we have m score for label ‘muscular’, c score for label ‘confident’ and s score for label ‘Superhero’ then the final score for C4 is $S[4] = m + c + s$. In this way, for each image g_k , we have got 4 different $S[i]$ scores, where $i = 1$ to 4. Now, in order to decide which cluster an image actually belongs, we take a weighted vote on these four cluster scores. It is calculated in the following way: If $N[i]$ is the number of member labels in a cluster, for each image we take $(S[i]/N[i])$ as the scaled cluster score. If we get the maximum value for $i = u$ then that image is assigned cluster C_u .

After this label pre-processing step for each image, we now have four distinct sets of images, one for each cluster. We will now describe the neural network classification model.

As described in section 4 we have a 6 dimensional vector $k[i]$, where, $i = 1$ to 6, as a descriptor of poses and proportions of a character. This is already a reduced form for the character silhouette that we have gathered for analysis. No further reduction of dimension is done.

As described above, we distill four sets of images, each associated to a label cluster. The pose-proportion feature vector described in Section III substitutes the character raster image. This is the input data for the machine learning phase.

We create multilayer perceptron neural network as shown in Fig. 8. It has 6 inputs (k_{1-6} pose-proportion features), 4 outputs (c_{1-4} binary label cluster assignments), and one hidden layer with 5 nodes. We tried a few different structures, and eventually settled with this one after the training error came down to an acceptable range.

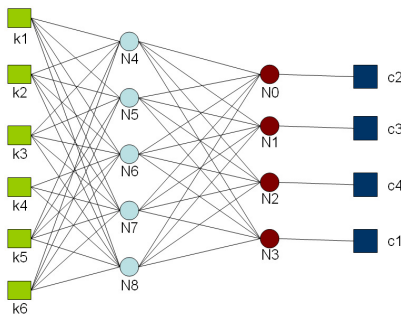


Figure 8: Neural Network Model

From the previous stages of analysis we got conclusive clustering results for 214 images. We train the Network using a percentage split of 66% for the training set (141 characters in training set, 73 used as test set). The result of the test set validation is listed in Table 1. We see that the

system correctly classifies 83.56% of the test instances, which proves it to a decent neural network model.

As shown in the Confusion Matrix in Table 3, the classifier predicts the C2 (cute/shy/fool/clerk/thin) cluster most accurately, followed by the C1, C4 and C3 clusters. A few visual samples of successful and unsuccessful classifications are shown in Fig. 9. We have provided the structure and weights of our neural network in Tables 4 and 5 for further experimentation and usage for our readers’ benefit, who may not have a large training set at their disposal.

Table1: Neural Network Training Statistics

Correctly Classified Instances	61	83.56 %
Incorrectly Classified Instances	12	16.44 %
Kappa statistic	0.775	
Mean absolute error	0.1702	
Root mean squared error	0.2733	
Relative absolute error		46.00 %
Root relative squared error		63.69 %
Total Number of Instances	73	

Table 2: Classification Accuracy

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
0.89	0.03	0.80	0.89	0.842	0.98	c1
0.95	0.04	0.90	0.95	0.923	0.95	c2
0.75	0.06	0.86	0.75	0.8	0.95	c3
0.81	0.10	0.77	0.81	0.791	0.91	c4
0.89	0.06	0.84	0.84	0.835	0.94	Avg

Table3: Confusion Matrix

C1	C2	C3	C4	Classified as
8	0	0	1	C1
0	18	0	1	C2
2	1	18	3	C3
0	1	3	17	C4

Table 4: Weight table for the Output layer

Sigmoid Node	Threshold	Node 4	Node 5	Node 6	Node 7	Node 8
Node 0	-9.20	10.04	-6.81	12.73	6.08	-5.51
Node 1	-2.62	2.68	3.11	-10.65	1.38	4.21
Node 2	2.14	-4.33	0.48	-5.93	-4.95	-8.05
Node 3	-1.25	-8.75	-6.47	-11.69	4.17	-3.36

Table 5: Weight table for the Hidden layer

Sigmoid Node	Threshold	k1	k2	k3	k4	k5	k6
Node 4	14.18	9.77	5.39	8.91	4.27	-3.95	5.57
Node 5	-1.64	3.54	9.97	1.88	-12.24	1.14	5.32
Node 6	12.14	21.90	-5.28	-3.92	14.19	2.99	-2.13
Node 7	-0.91	9.47	6.92	-1.83	6.77	4.17	-8.95
Node 8	-0.27	2.19	-8.22	3.01	-11.98	-3.90	3.16

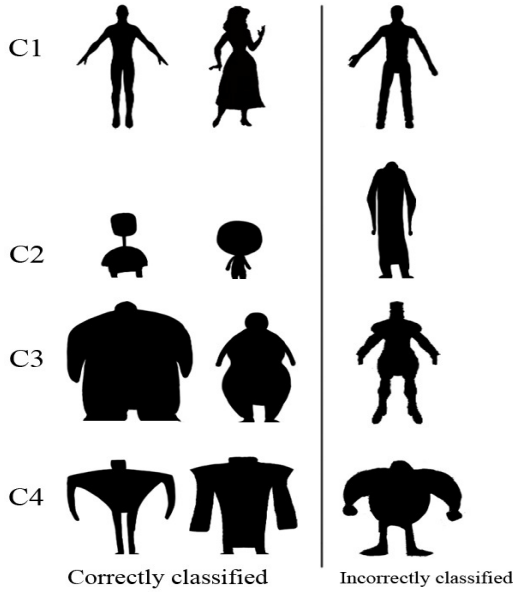


Figure 9: Select visual results of validation tests

VI. CONCLUSION

The entire premise of this paper is to discover what laymen perceive of character design, with no prior knowledge of design rules. We used annotated art from shapes generated by experts and junior artists, using a limited arbitrary set of proportion/pose features. We have implemented a character perception game as an entertaining and fun game with a purpose. This game was used to gather user data for labelling characters into label clusters. We have achieved a decent precision and recall rate for our Neural Network model of role, physicality and personality traits. We have validated our claims with 73 characters as outlined in Table 1 and Table 2. The accuracy of the test set is 83%. Ground truth was established by virtue of majority voting from a large number of user-rated labels, similar to the training set.

To the best of our knowledge, this is perhaps the first attempt to analyze full-body humanoid character designs in a hybrid proportion/pose/label feature space. This paper makes an important contribution towards putting a feedback

loop to character design, with the aid of multimedia applications and technology. We have included the trained neural network weights and structure information so that others may verify our classifier with their own data. We have tested this model on independent data sets (e.g. on small sets of doodles done by some of the authors), with prediction accuracies between 70 ~ 95%.

Our pose and proportion representation is currently quite limited to describing characters in neutral frontal pose. We hope to experiment with richer feature sets, like body part shape, color, and texture. We are also in the process of designing more games to collect different forms of perception data, with new game mechanics, such that we can generate large perception data stores from casual surfers and players. We are integrating our model into a rapid character drafting system, that will pop up friendly advice and tags as different parts of a character's body are drawn.

VII. ACKNOWLEDGEMENTS

We gratefully acknowledge the feedback from our reviewers in improving this paper. We are also thankful to the artists/programmers/designers, supervised by Jason Beene, who created the Shadow Shoppe game at the Singapore-MIT GAMBIT Game lab at Boston, 2009. This research is part of a Media Development Authority of Singapore (GAMBIT) funded project, titled *Computational Aesthetics: Shape Psychology in Character Design*, WBS: R252000357490.

VIII. REFERENCES

- [1] Angelidis, A. and Singh, K. 2006. Space deformations and their application to shape modeling. In ACM SIGGRAPH 2006 Courses, ACM Press, New York, NY, pp. 10-29.
- [2] Arvid Karsvall. 2002. Personality preferences in graphical interface design. Proceedings of the second Nordic conference on Human-computer interaction.
- [3] Ashraf G., Why Y. P., and Islam M. T. 2010. Mining human shapes perception with role playing games. In 3rd Annual International Conference on Computer Games, Multimedia and Allied Technology, Singapore, pp 58-64.
- [4] Bancroft, T., Creating Characters with Personality, ISBN: 0-8230-2349-4
- [5] Beiman, N., Prepare to Board! : Creating Story and Characters for Animated feature
- [6] Camara, Sergi, All about techniques in drawing for animation production, 1st ed.2006, Barron's Education Series, Inc.
- [7] Edelman, S. and Intrator, N. 1997. Learning as extraction of low-dimensional representations. In D. Medin, R. Goldstone, and P. Schyns, editors.
- [8] Fails, J.A. and Olsen, D.R. 2003. Interactive machine learning. In Proceedings of the Eighth International Conference on Intelligent User Interfaces (Miami, Jan. 12-15). ACM Press, New York, 39-45.

- [9] Fiore, F. D., Reeth, F. V., Patterson, J., and Willis, P. 2008. Highly stylised animation. *The Visual Computer* 24, 2, 105–123.
- [10] Gal, R., Shamir, A., and Cohen-Or, D. 2007. Pose-Oblivious Shape Signature, *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 2, pp. 261-271
- [11] Gil-Jiménez P., Lafuente-Arroyo S., Maldonado-Bascón S. and Gómez-Moreno H 2005. Shape Classification Algorithm Using Support Vector Machines for Traffic Sign Recognition, *Lecture Notes in Computer Science*, Volume 35, 12/2005.
- [12] Gingold, Y., Igarashi, T., and Zorin, D. 2009. Structured annotations for 2D-to-3D modeling. *ACM Transactions on Graphics (TOG)* 28, 5, 148.
- [13] Gooch, B., Reinhard, E., Gooch A. 2004. Human facial illustrations: Creation and psychophysical evaluation, *ACM Transactions on Graphics (TOG)*, v.23 n.1, p.27-44.
- [14] Goldberg, L. R. 1993. The structure of phenotypic personality traits. *American Psychologist*, 48, 26-34.
- [15] Hart, C., *Cartoon Cool: How to Draw New Retro-Style Characters*
- [16] Hsu C-H, and Wang M. J. 2005. Using decision tree-based data mining to establish a sizing system for the manufacture of garments, *The International Journal of Advanced Manufacturing Technology Springer London Issue Volume* 26, Numbers 5-6 / September, 2005.
- [17] Hsueh-Yi Sean Lin, Ja-Chen Lin, Hong-Yuan, Mark Liao. 2005. 3-D Shape Retrieval Using Cognitive Psychology-based Principles. In *Proc. Seventh IEEE International Symposium on Multimedia (ISM)*.
- [18] Islam, M. T., Nahiduzzaman K. M., Why Y. P., and Ashraf G. 2010. Learning from humanoid cartoon designs. In *10th Industrial Conference on Data Mining ICDM*.
- [19] John Funge, Xiaoyuan Tu, Demetri Terzopoulos. 1999. Cognitive Modeling: Knowledge, Reasoning and Planning for Intelligent Characters. In *Proc. ACM SIGGRAPH*
- [20] Liu, J., Chen, Y., Gao, W. 2006. Mapping Learning in Eigenspace for Harmonious Caricature Generation, *Proceedings of the 14th annual ACM international conference on Multimedia*.
- [21] Marchenko, Y., Chua, T. S., Jain, R. 2007. Ontology-Based Annotation of Paintings Using Transductive Inference Framework. *MMM* (1): 13-23.
- [22] Gutiérrez M. A, et. al. 2007. An ontology of virtual humans: Incorporating semantics into human shapes. *Journal of Visual Computing*.
- [23] Meyer, M. and Anderson, J. 2007. Key Point Subspace Acceleration and soft caching. *ACM Trans. Graph.* vol: 26, issue 3, article 74.
- [24] Malone, T.M. 1980. What makes things fun to learn? Heuristics for designing instructional computer games. In *Proceedings of the Third ACM SIGSMALL Symposium and the First SIGPC Symposium on Small Systems (Palo Alto, CA, Sept.18–19)*. ACM Press, New York, 162–169.
- [25] Olya Veselova and Randall Davis. 2004. Perceptually Based Learning of Shape Descriptions. In *Proceedings of the Nineteenth National Conference on Artificial Intelligence (AAAI)*, pp.482-487.
- [26] Pizlo Z. 2008. 3D Shape: Its Unique Place in Visual Perception, MIT Press, Cambridge MA, ISBN: 978 0262162517.
- [27] Shneiderman, B. 2004. Designing for fun: How can we design user interfaces to be more fun? *Interactions* 11, 5 (Sept.–Oct. 2004), 48–50.
- [28] Šykora, D., Buriánek, J., and Zárara, J. 2005. Sketching cartoons by example. In *Proceedings of Eurographics Workshop on Sketch-Based Interfaces and Modeling*, 27–34.
- [29] Šykora, D., Dingliana, J., and Collins, S. 2009. As rigid-as-possible image registration for hand-drawn cartoon animations. In *Proceedings of International Symposium on Nonphotorealistic Animation and Rendering*, 25–33.
- [30] Šykora, D., Sedláček, D., Jinchao, S., Dingliana, J., and Collins, S. 2010. Adding depth to cartoons using sparse depth (in)equalities. *Computer Graphics Forum* 29, 2.
- [31] Ueda N., Suzuki S. 1993. Learning Visual Models from Shape Contours Using Multiscale Convex/Concave Structure Matching, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 4, pp. 337-352.
- [32] Vapnik, V. N. 1999. *The Nature of Statistical Learning Theory (Information Science and Statistics)*. Springer.
- [33] Vogel H. L., *Entertainment Industry Economics: A Guide for Financial Analysis*, 7th Edition, Cambridge University Press.
- [34] Von Ahn, L., Laura Dabbish. 2008. Designing games with a purpose, *Communications of the ACM*, v.51 n.8, August.
- [35] Wang R. Y., Pulli K., Popović J. 2007. Real-time enveloping with rotational regression, *ACM Transactions on Graphics (TOG)*, v.26 n.3.
- [36] Webster, J. 1988. Making computer tasks at work more playful: Implications for systems analysts and designers. In *Proceedings of the SIGCPR Conference on Management of Information Systems Personnel (College Park, MD, Apr. 7–8)*. ACM Press, New York, 78–87.
- [37] Zbigniew Les, Magdalena Les. 2008. *Shape Understanding System: The First Steps toward the Visual Thinking Machines*. Springer.
- [38] Garner, S. R. 1995. WEKA: The Waikato Environment for Knowledge Analysis. In *Proc. of the New Zealand Computer Science Research Students Conference*.