ImageCube: An Image Browser Featuring a Multi-Dimensional Data Visualization

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Abstract: Image browsing techniques become increasingly important for overview and retrieval of particular images in large-scale collections. At the same time, there are various sets of images which are associated with multi-dimensional or multivariate datasets. We believe that image browsing for such datasets should be inspired from multi-dimensional data visualization techniques. This paper presents ImageCube, a scatterplot-like browser for image collections associated with multi-dimensional datasets. ImageCube locates a set of images into a display space assigning a pair of dimensions to X- and Y-axes. It suggests preferable pairs of dimensions by applying Kendall's rank correlation and Entropy on the display space, so that users can easily obtain interesting visualization results. This paper presents a case scenario that a user finds a preferable car from an image collection by using ImageCube.

1 Introduction

With the rapid development of the imaging technologies over recent years, advanced visualization techniques for thousands of pictures are making big progress. At the same time, now we can obtain various sets of images which are associated with multi-dimensional or multivariate datasets via Internet. For example, we can obtain the images of recipes which have a variety of nutritional value, or those of cars which have a variety of performance values, and even those of medical which have a variety of diagnosis value, based on our specific requests. We believe that image browsing techniques featuring multidimensional data visualization techniques are useful to explore such kinds of image datasets. This paper assumes the following two purposes for the image browsing featuring multidimensional datasets:

Purpose 1: Overview the whole datasets, and observe the relationships between the appearance of images and numeric distributions of the multidimensional datasets. Mainly for domain specialists and analysts.

Purpose 2: Search for interested or preferred images by narrowing the numeric ranges of multi-dimensional datasets while observing the appearance of images. Mainly for end users.

It is interesting to explore and analyze such features and structures of multidimensional values assigned to images while browsing the images themselves. Scatterplots is one of the most popular and widely-used visual representations for multidimensional data due to its simplicity, and visual clarity. This paper proposes "ImageCube", an image browser featuring a scatterplot-based visualization technique. ImageCube displays a set of images into a two-dimensional space interactively selecting two dimensions of the datasets. Our implementation of ImageCube assists the dimension selection operations by suggesting interesting pairs of dimensions based on their correlations and entropies. ImageCube is helpful for users to obtain qualitative visualization results to explore and analyze features and structures of multidimensional values assigned to images.

2 Related Work

2.1 Image Browser

Image browsing is an active research topic for overview and retrieval of image collections, and therefore many image browsers have been presented.

Many of image browsers for structured sets of images suppose that images forms trees or graphs. PhotoMesa [Bederson 2001] is one of the most famous image browsers for structured sets of images. It divides a window space by nested set of rectangles to represent the hierarchy of images, and then packs them in each of the rectangular subspaces. On the other hand, many of other image browsers for unstructured sets of images scatter the images onto 2D/3D spaces like scatterplots. Several techniques applies dimension reduction techniques such as MDS (Multi Dimensional Scaling) or PCA (Principal Component Analysis) to locate the images [Yang 2006] so that similarly looking images are placed closer on the display spaces. Against our target of this research is visualization of image collections with their associated numeric values, the above mentioned techniques do not represent such numeric values.

Other techniques on image browsing arrange images along with the predefined order of images such as the order of timestamps. Huynh et al. [Huynh 2005] presented a browser which divides display spaces into rectangular subregions and arranges along the timeline. Brivio et al. [Brivio 2012] presented a technique which divides display spaces into Voronoi diagrams and arranges along with the predefined order of the images. Several others directly assigns two or three values associated to the images to the axes of 2D/3D spaces [Horibe 2009]. MIAOW [Gomi 2010] is a hybrid technique that forms hierarchy while it assigns three values to axes of a 3D space. It divides the images according to latitudes, longitudes, and times which the images are taken, while assigns the three values to axes of a 3D space. These techniques just assigns fixed numeric values such as latitude, longitude, and time to the axes of 2D/3D spaces. In our survey, ImageCube is the first and more generalized image browser for the representation of general numeric values associated to the images.

2.2 Multi-Dimensional Data Visualization

There have been various multi-dimensional data visualization techniques, including Parallel Coordinate Plots [Inselberg 1991], VisDB [Keim 1994], and Worlds within Worlds [Feiner 1990]. Some other techniques apply heatmaps or glyphs to represent multi-dimensional value. Meanwhile, Scatterplots is one of the most popular techniques to visualize multi-dimensional data. Many scatterplots implementations directly assigns two or three of the dimensions to axes of the visualization spaces, while others apply dimension reduction techniques. Scatterplot matrix is often used for overview of scatterplots selecting arbitrary pairs of dimensions; however, it requires very large display spaces if number of dimensions is large. If users do not want to use such large display spaces for scatterplots, they may need to interactively switch the pairs of dimensions to understand correlations between the dimensions. Rolling the Dices [Elmqvist 2008] is one of the novel techniques to assist the interactive selection of dimensions for scatterplots.

Dimension analysis is helpful to obtain fruitful knowledge from multi-dimensional data visualizations. Sips et al. [Sips 2009] presented a view selection technique of multi-dimensional data visualization by applying the dimension analysis. Nagasaki et al. [Nagasaki 2008] presented a correlation-based dimension selection technique for scatterplots-based visualization of credit card fraud data. This strategy is also useful to reorder the dimensions and improve the readability of Parallel Coordinates and scatter plots matrices [Peng 2004].

ImageCube features a rotation user interface similar to Rolling the Dices, and a dimension analysis with user interface widgets. In our survey, ImageCube is the first image browser which features such technical components.

3 Browsing Image Collections with Multi-Dimensional Values

This section presents our image browser "ImageCube". Specified arbitrary two dimensions, ImageCube calculates positions of images in a display space by assigning the two dimensions to axes of the display space. It then groups the images based on their positions, and selects a representative image for each group. ImageCube initially displays the representative images, and provides a user interface to click the images so that other images in the group of the clicked images are displayed in another window space. Dimension selection may be a problem for usability. ImageCube supports a function to recommend interesting pairs of dimensions.

3.1 Definition of Input Images

We suppose an image set $I = \{i_1, i_2, ..., i_n\}$ as input information, where i_i is the i-th image, and n is the number of images. We also suppose that an image $i_i = \{v_{i1}, v_{i2}, ..., v_{im}\, n_i, u_i\}$, where v_{ij} is the j-th value of the i-th image, m is the number of dimensions, a_i is the name of the i_i, and u_i is the URL or path of the i_i. Our implementation consumes input data files which describe the above values, and then automatically generates and displays the selection menu from the input information, which are used to select arbitrary two dimensions as X- and Y-axes. Also, it calculates c_{ij}, the coordinate value of the j-th dimension of the i-th image, used as positions of images.

3.2 Multidimensional Visualization

ImageCube represents two dimensions in a single visualization as many scatterplots techniques do. When a user specifies the p-th dimension as the X-axis, and the q-th dimension as the Y-axis, ImageCube places the i-th image at (c_{ip}, c_{iq}).

ImageCube supports a smooth dimension selection, by rotating the display space, like Rolling the Dice [Elmqvist 2008] supports. Suppose that the p-th dimension is assigned to the X-axis, and the q-th dimension to the Y-axis. When a user specifies the r-th dimension as the X-axis, ImageCube temporarily assigns the r-th dimension to the Z-axis, and therefore ImageCube places the i-th image at (c_{ip}, c_{iq}, c_{ir}). ImageCube then rotates the display space along the Y-axis, so that the XZ-plane gets the XY-plane, and the XY-plane gets the XZ-plane. Figure 1(Left) shows a capture of the rotation process.

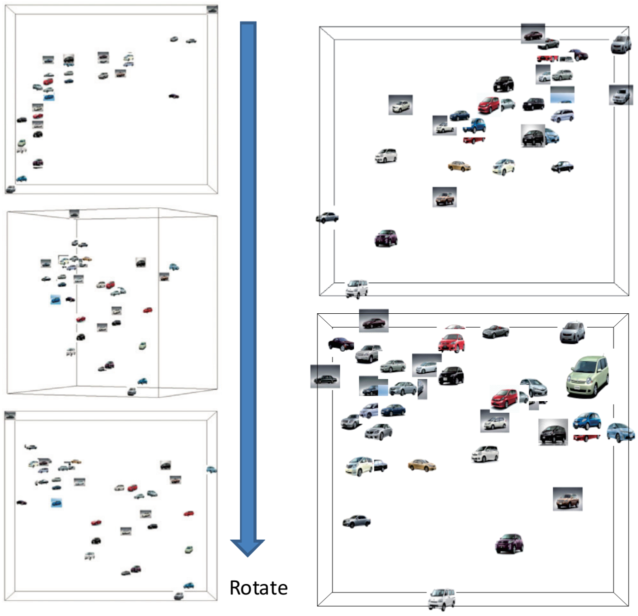

Figure 1: (Left) Image redeployment by rotation function of XY- and XZ-planes. (Upper-right) A visualization result with a high-correlation pair of dimensions. (Lower-right) A visualization result with a high-entropy pair of dimensions.

3.3 Recommendation of Dimension Pairs

ImageCube automatically generates the selection menu featuring buttons of dimensions for X- and Y-axes. Here, a major challenge is how to easily get fruitful visualization results from multidimensional datasets. ImageCube provides a mechanism to recommend interesting pairs of dimensions so that users can easily select them. Current our implementation shows the recommended pairs by coloring corresponding dimensions on the selection menu. To achieve the mechanism, we need to analyze the numerical features between arbitrary two dimensions. At present our implementation calculates the following two kinds of numerical features, Kendall's rank correlation and Entropy, between arbitrary pairs of dimensions to obtain interesting visualization results.

Kendall's rank correlation:

Correlation analysis is useful for multidimensional datasets visualization techniques, as discussed in Section 2.2. We apply Kendall rank correlation for the correlation analysis. The Kendall rank denotes the similarity of the orderings of the datasets ranked by each of the quantities.

To calculate the correlation between the p-th and the q-th dimensions, we firstly make pairs of images and extract the values of the two dimensions, (v_{ip}, v_{jp}) and (v_{iq}, v_{jq}). We then count P, the number of pairs which satisfies both $v_{ip} < v_{jp}$ and $v_{iq} < v_{jq}$, or both $v_{ip} > v_{jp}$ and $v_{iq} > v_{jq}$.

Here, Kendall's rank colletation τ is calculated as:

$$\tau = \frac{4P}{n(n-1)} - 1 \quad (1)$$

where n is the number of images.

ImageCube calculates the Kendall rank correlation for every possible pair of dimensions, and suggests the highly correlated pairs. See Figure 1(Upper-right).

Entropy:

ImageCube measures the distribution and randomness of the visualization results by applying Entropy. ImageCube internally divides the display space into N_s rectangular subspaces, and count the number of images p_i in the i-th subspace. ImageCube calculates the sum of Entropy E_{sum} in the subspaces as follows:

$$E_{sum} = \sum^{N_s}\left(\frac{p_i}{N_s}\log\frac{p_i}{N_s}\right) \quad (2)$$

ImageCube calculates the Entropy for every possible pair of dimensions, and suggests the pairs which bring high randomness. See Figure 1(Lower-right).

3.4 Overlap Reduction

The simple image location strategy described in Section 3.2 easily causes overlap of images on the display space, while displaying large-scale image collections. To improve the understanding and usability, ImageCube reduces the number of displaying images by generating groups of images based on their positions, and selects a representative image for each group. Our current implementation just selects the image which is the closest to a center of the group as the representative image of the group. It initially displays only the representative images, and other images in the group of a representative images will be displayed in another space, when a user clicks one of the representative images.

3.5 User Interface

Figure 2 shows our implementation of user interfaces of ImageCube. ImageCube is implemented in a single window, featuring a drawing area in the left side, and three tabs in the right side.

Initial setting tab: The right side of the window shown in Figure 2(Left) embeds the initial setting tab, which features GUI widgets for the initial configurations. Roles of the GUI widgets include data file selection, viewing operations, image size adjustment, and threshold adjustment for clustering.

Dimension selection tab: Figure 2(Center) shows the dimension selection tab, which features buttons for selection of dimensions to be assigned to X- and Y-axes of the drawing area. The tab also features a GUI for narrowing the numeric ranges of the dimensions.

Image selection tab: Figure 2(Right) shows the image selection tab, which displays the images belonging to the cluster of the double-clicked image shown in the drawing area. The images shown in this tab are associated with check widgets, where the checked images are displayed with independently colored borders in the drawing area. This function helps users to trace the interested images while viewing or dimension selection operations.

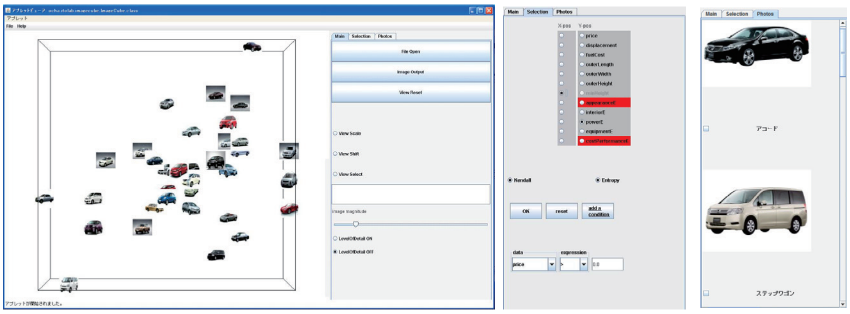

Figure 2: User interface of ImageCube. (Left) Drawing area in the left side, and three tabs in the right side. This figure shows the initial setting tab. (Center) The dimension selection tab. (Right) The image selection tab,

4 Example

We implemented ImageCube on Java 1.6.0 and JOGL 2.0, and tested on Lenovo ThinkPad T510 (CPU 2.4GB, RAM 2GB) with Windows XP SP3.

This section shows results of ImageCube applying 100 images collected from Japanese automobile catalog Web site [1] . We parsed HTML files introducing particular cars, to extract specifications and evaluations of the cars, and download their images. Consequently we obtained a 12 dimensional dataset including the following specification and evaluation values: 1) price, 2) displacement of the engine, 3) fuel cost, 4) outer length, 5) outer width, 6) outer height, 7) height of floor, 8) user evaluation of appearance, 9) user evaluation of interior design, 10) user evaluation of engine power, 11) user evaluation of equipments, and 12) user evaluation of cost performance.

This section introduces a case scenario with the image collection of cars. First of all, we were interested in correlations between prices and other variables. We checked correlation and Entropy between them, and found that displacement and fuel costs had relatively high correlations with the price. Figure 3(1) shows an example that price is assigned to the X-axis, and displacement is assigned to the Y-axis. The example denotes that they are nearly proportional; luxury sedans are relatively expensive, and station wagons are relatively low cost in this collection. Figure 3(2) shows an example that price is assigned to the X-axis, and fuel cost is assigned to the Y-axis. Equipment evaluation also had high correlations with the price, but the distribution of the images was not linear. Figure 3(3) shows an example that price is assigned to the X-axis, and equipment evaluation is assigned to the Y-axis. It denotes that equipment evaluation increases proportional to the price of low-price cars, but it becomes flat if the price is higher. On the other hand, it was our surprise that appearance evaluation was not correlated to the price. Figure 3(4) shows an example that price is assigned to the X-axis, and appearance evaluation is assigned to the Y-axis, where it seems that expensive cars do not always obtain higher evaluations of appearance.

Be derived from the above surprising result, we were interested in what impact to the evaluation of appearance. Figure 3(5)(6) show examples that outer length or outer width is assigned to the X-axis, and appearance evaluation is assigned to the Y-axis. They denote that outer length or outer width is not well correlated with the evaluation of appearance. Actually, these pairs of dimensions

[1] http://autos.yahoo.co.jp/

had relatively higher Entropies. On the other hand, Figure 3(7) shows an example that height of floor is assigned to the X-axis, and appearance evaluation is assigned to the Y-axis. The result briefly denotes that appearance evaluations are better if floors are lower, which looks a common trend both for wagons and sedans. Actually, correlation of height of floor to appearance evaluation was higher than others.

Finally, we checked what impacts to the evaluation of cost performance, and found that appearance evaluation was one of them. Figure 3(8) shows an example that appearance evaluation is assigned to the X-axis, and cost performance evaluation is assigned to the Y-axis. This high correlation denotes that appearance is very important for the user evaluation of cost performance. Again, it looks a common trend both for wagons and sedans.

This example demonstrates that we can discuss the trend of multi-dimensional values associated to the collections of images while looking at the images themselves. Actually, we could discuss what impacts to the evaluation of appearance and cost performance of cars, while looking at various values as well as designs of cars. This analysis can be applied to various fields dealing with images; for example, collections of medical images associated with medical checkup values, and collections of facial and cosmetic images associated with evaluations of subjects.

5 User experience

We conducted a user experience with 15 university student subjects, using the car catalog dataset introduced in the previous section. This experience is designed assuming [Purpose 2] discussed in Section 1.

5.1 Required time and satisfaction

We prepared the following two version of implementation for the comparison of usability.
Implementation 1: Featuring all the functions described in this paper.
Implementation 2: Missing ImageCube-specific functions. In detail, this version misses the following functions: dimension recommendation described in Section 3.3, representative image display in the drawing area described in Section 3.4, and border display described in Section 3.5.

We did not compare ImageCube with existing image browsers, because most of them do not deal with general multidimensional values associated to the input images, and therefore it is difficult to fairly compare. Instead, we conducted the experience using the above two implementations, because it can demonstrate how the features of ImageCube presented in Section 3 effectively assist the image browsing and retrieval processes.

We also prepared the following two datasets.
Dataset A: 100 images of cars manufactured by the same company, introduced in Section 4.
Dataset B: 28 images of cars manufactured by another company.

We explained the meaning of 12 dimensions introduced in the car catalog to the subjects, and asked them to answer the requirements for their wanted cars. We then divided the subjects into [Group A] and [Group B], and asked to play with the two version of ImageCube to find their wanted cars, in the following order.
[Group A] (8 subjects):
Experience A-1: Visualize the dataset A by the implementation 1.
Experience A-2: Visualize the dataset A by the implementation 2.

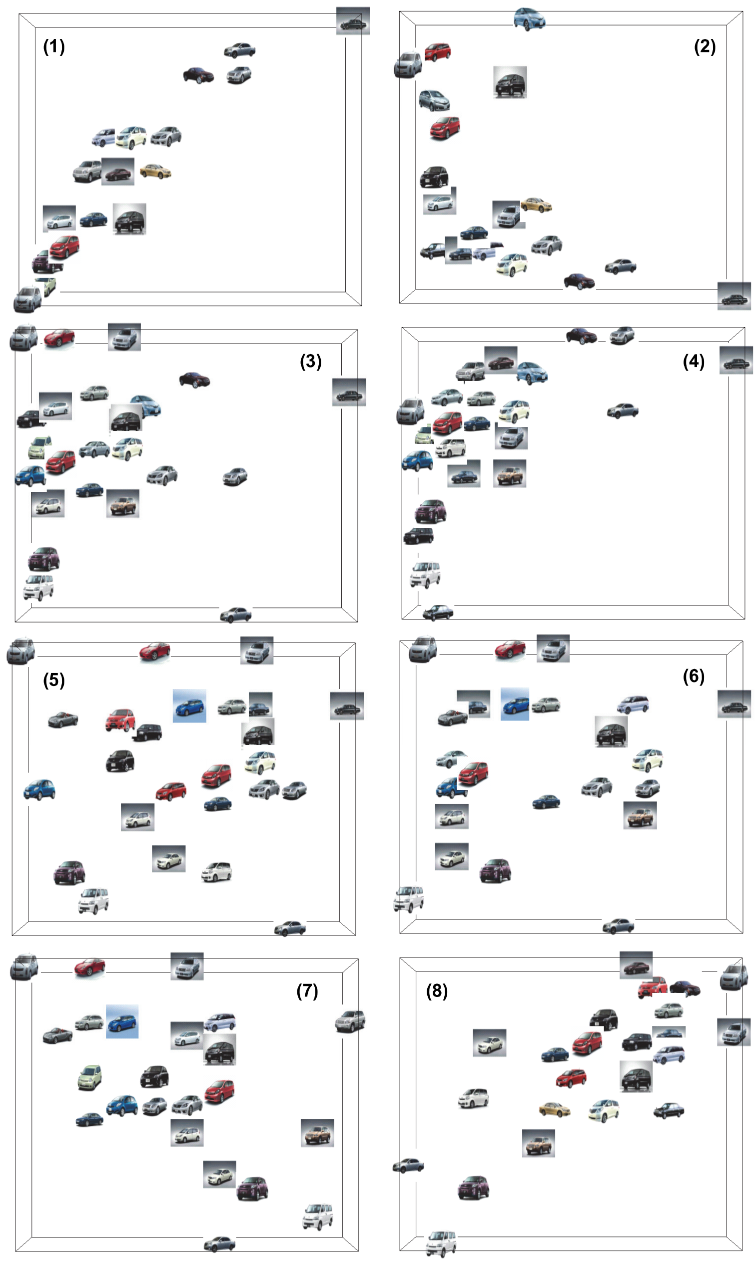

Figure 3: Examples with an image collection of cars. (1) Price for X-axis, and displacement for Y-axis. (2) Price for X-axis, and fuel cost for Y-axis. (3) Price for X-axis, and equipment for Y-axis. (4) Price for X-axis, and appearance evaluation for Y-axis. (5) Outer length for X-axis, and appearance evaluation for Y-axis. (6) Outer width for X-axis, and appearance evaluation for Y-axis. (7) Height of floor for X-axis, and appearance evaluation for Y-axis. (8) Appearance evaluation for X-axis, and cost performance evaluation for Y-axis.

Experience A-3: Visualize the dataset B by the implementation 2.
Experience A-4: Visualize the dataset B by the implementation 1.
[Group A] (7 subjects):
Experience B-1: Visualize the dataset B by the implementation 1.
Experience B-2: Visualize the dataset B by the implementation 2.
Experience B-3: Visualize the dataset A by the implementation 2.
Experience B-4: Visualize the dataset A by the implementation 1.

We measured the time required to select the favorite cars, as shown in Table 1. Also, we asked the subjects to answer which car is more preferable, if the selected cars are different between using the two implementation.

Table 1: Average time required for subjects to select the favorite car. (second)

Experience A-1 275	Experience A-2 218	Experience A-3 227	Experience A-4 332
Experience B-1 303	Experience B-2 203	Experience B-3 320	Experience B-4 190

This measurement result denotes that the implementation 2 which has less functionality requires less time except the experiences B-3 and B-4. However, the Implementation 2 was problematic as the following feedback from the subjects:
"I did not understand which dimensions bring fruitful visualization results without using the dimension recommendation function. Therefore I played with ImageCube with randomly selected dimensions."
"I cannot trace the favorite cars without using the border coloring. Finally I lost it, and compounded to select a car which was easily accessible."

These comments suggest the reason why subjects spent less time with Implementation 2. They gave up to find satisfactory cars while using the Implementation 2 in a shorter time, and compounded to select a car which was easily accessible. Actually, all of the subjects answered they could more satisfactory cars while using the Implementation 1. Table 2 shows numbers of subjects selected the same or different cars while using the Implementation 1 and 2. This result denotes approximately half of the subjects selected the different cars while using the two implementations, and consequently commented the unsatisfactory to the result brought by Implementation 2.

Table 2: Numbers of subjects selected the same or different cars while using the Implementation 1 and 2.

	same	different
Experiment A-1,2	4	4
Experiment A-3,4	5	3
Experiment B-1,2	3	4
Experiment B-3,4	2	5

The above results and comments suggest that functions featured by ImageCube bring the discovery of more satisfactory images. On the other hand, we also found that usage of such functions required relatively more time. We would like to improve the user interfaces so that users spend less operation and time as a future work.

Next, we analyzed the requirements of subjects, and found that 12 subjects mentioned three to seven numeric conditions and preferences of appearances, such as "low price, good fuel performance, good evaluation of power and equipments, and preferable design". And actually, we observed that most of the subjects selected their favorite cars by understanding numeric distributions of many dimensions while observing the shapes and colors of cars taken in the images. This result suggests that subjects played with ImageCube aligning our design policy.

By the way, we expected to apply the overlap reduction, introduced in Section 3.4, while subjects were playing with Dataset 1. However, it was not necessary for most of the subjects. We would like to test with larger datasets to test the effectiveness of the overlap reduction as a future work.

5.2 Discussion

Next, we asked subject to freely comment regarding the following three questions.
Question 1: How image browsing can be improved by using ImageCube?
Question 2: What kinds of datasets are effectively visualized by ImageCube?
Question 3: What kinds of additional functions are desirable on ImageCube?

Following are the typical comments for Question 1.

"It is easy to understand the numeric distribution during looking over the image collections."

"Performance specifications are usually described as numeric values on car catalogs, but it is not necessary to read the numeric values of all the cars. I prefer to briefly look over the numeric distribution on ImageCube, and then quickly compare the appearance of the cars which are adjacent in the multidimensional space."

"Dimension recommendation is useful to aggressively select two dimensions and compare the performance and evaluation among my favorite cars."

"It is intuitive to firstly look at the images, and then check the numeric values of the favorite cars."

"It is easy to trace the favorite cars by assigning particular colors of borders."

"It is useful to apply the overlap reduction first, and then observe the interested cluster of cars which have similar numeric values."

These comments suggest that all of functions featured by ImageCube were preferable for the subjects.

Following are the typical comments for Question 2. Several subjects mentioned that industrial items such as cameras, personal computers, mobile phones are good to be visualized by ImageCube, because their specifications contain many numeric values. Some of other subjects mentioned alcoholic drinks, cosmetics, and furniture, because they were interested in customer evaluations of these items. In addition, we got many suggestions including sightseeing places, hair catalog, and restaurants. These feedback suggests that the subjects felt ImageCube is a robustly applicable image browser.

The next section discusses the answers of Question 3.

6 Conclusion

This paper presented an image browser "ImageCube" designed for the browsing of image collections associated with multidimensional datasets. ImageCube assigns two of the multidimensional values to X- and Y- axes of the display space, and places the set of images like a scatterplots. It also features various functions, including interaction of dimensional rotation, recommendation of dimension pairs applying correlation and entropy, and overlap reduction by just displaying representatives of the image groups. This paper introduced a case study applying a car catalog dataset published on the Web, and many knowledge found by the interactive selection of dimensions while using ImageCube.

This paper also introduced a user experience using two implementations of ImageCube, where one of them was full featured and another was less featured. Some o f subjects gave up to find satisfactory images while using the less featured implementation in the experience, while they found more satisfactory images while using the full featured implementation. This result denotes that the features of ImageCube are useful for the navigation to discover satisfactory images.

The following are our potential future issues.

1) We would like to apply ImageCube to various datasets, such as medical images associated to health-related multidimensional values, cosmetics images associated to subjective evaluations, and recipe images associated to nutrition values, in addition to the discussion regarding Question 2 in the previous section.

2) We would like to develop additional functions which subjects suggested as answers for Question 3. Examples of their desired functions are as follows: switch to ordinary scatterplots without displaying images, (non-numeric) metadata assignment to the images, click operation for selection of non-display images, and drug operation for numeric range selection.

3) We would like to additionally support dimension-reduction-based scatterplot for the image placement.

4) After the above development, we would like to test the scalability with the datasets which contain more dimensions and more images, as discussed in the last paragraph of Section 5.1. Also, we would like to have usability evaluations by more user experiences.

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