SKETCH-EPITOMES : DISCRIMINATIVELY MINIMALIST REPRESENTATIONS FOR OBJECT CATEGORIES

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Abstract

Freehand line sketches are an interesting and unique form of visual representation. Typically, such sketches are studied and utilized as an end product of the sketching process. However, we have found it instructive to study the sketches as sequentially accumulated composition of drawing strokes added over time. Studying sketches in this manner has enabled us to create novel sparse yet discriminative sketch-based representations for object categories which we term category-epitomes. Our procedure for obtaining these epitomes concurrently provides a natural measure for quantifying the sparseness underlying the original sketch, which we term epitome-score. We construct and analyze category-epitomes and epitome-scores for freehand sketches belonging to various object categories. Our analysis provides a novel viewpoint for studying the semantic nature of object categories.

Index Terms— sketch, object category recognition, sketch sequence analysis, pattern recognition, epitome, sparse, minimalist

1. INTRODUCTION

Sketches, as a form of visual representation, exhibit a great variety from realistic portraits to sparsely drawn, stylistic ones. In particular, consider freehand (i.e. hand-drawn) sketches of objects. An instance of such a sketch can be seen in Figure 1. Though containing minimal detail, the object category to which it belongs is easily determined. This suggests an inherent sparseness in the human neuro-visual representation of the object. Therefore, studying such sparse sketches can aid our understanding of the cognitive processes involved and spur the design of efficient visual classifiers.

Freehand line sketches are typically formed as a composition of primitive hand-drawn curves (called strokes) added sequentially over time. A significant body of work has examined such sketches in the context of classification and content-based retrieval problems [1][2][3][4]. In these problems, the end product of the sketching process, i.e. the full sketch, is typically considered in toto. However, we believe it can be quite instructive to study the temporal process of sketch formation itself, starting with the first hand-drawn stroke until the last stroke which finalizes the sketch. Our belief originates in a surprising discovery we have made: For a given sketch, there exists a minimal discriminative subset of all its strokes which contribute to the sketch’s identity (category) being recognized consistently and correctly. We term the sketch composed using this minimal stroke subset as a category-epitome. Figure 2 shows examples of freehand line sketches and their corresponding sparse category-epitomes.

In this paper, we describe how these sparse category-epitomes are obtained. The category-epitome has a unique feature which sets it apart from other methods of sparse sketch generation: The process of epitome construction guarantees that the most fundamental strokes which enable category recognition (discrimination) are retained. To quantify the sparseness of an epitome, we provide a natural measure termed epitome-score. We analyze the epitomes and corresponding epitome-scores for freehand sketches across various object categories. Our analysis provides a novel viewpoint for studying the semantic nature of object categories.

Fig. 1: In spite of minimal detail, we can recognize the line sketch easily and correctly as belonging to the category cup.

2. RELATED WORK

In his seminal work [5], Marr suggested an abstract representation called the primal sketch – a sparse, sketch-like representation of generic images in terms of image primitives. Inspired by his theories, methods for formalizing the notion of primal sketch have been proposed [6] and primal sketch representations have been used as features for object detection [3], texture characterization [7] and for super-resolution [8]. Yet another line of research aims to generate sketches from one or more source images [9] without explicit recourse to the idea of primal sketch. A common feature in all these works is the utilization of photographic images as the starting point. In contrast, our starting point is the sketch stroke data created by human beings. This provides a glimmer of hope that the sparse neurovisual representation of the object being sketched is transferred to the sketch in the process of drawing, at least in part.

In addition to the artificial (i.e. not generated by human hand) nature of sketch generation, the works mentioned above do not attempt to quantify the sparseness of the resulting sketch. They also do not examine the temporal nature of sketch composition.
fore, these sketches have been obtained by crowdsourcing across the general population. As such, they are a good starting point for analyzing the underpinnings of the sketching process by humans. A contrast, recent work by Berger et. al.\[10\] analyzes the temporal aspect of sketching in the context of mimicking artist style. However, their emphasis is on synthesizing abstract facial sketches rather than recognition. Moreover, their sketches are produced by professional artists. In contrast, our sketches have been generated by crowdsourcing from the general public. The idea of identifying and utilizing a discriminative subset of strokes was employed by Karteek et al.\[11\] for classifying online handwritten data. Another work close in spirit to ours is the unpublished, but publicly available manuscript of Jiang et al.\[12\] which examines the temporal evolution of sketches from a visualization perspective. Finally, the work of Eitz et al.\[13\] examines how humans tend to draw objects by analyzing a large number of sketches spread across commonly encountered object categories. We employ their database of sketches in this paper.

3. BUILDING THE SKETCH CLASSIFIER

3.1. The sketch database

The sketches used in our study have been taken from the publicly available freehand line sketch database of Eitz et al.\[13\]. This database contains a curated set of 20,000 hand-drawn sketches evenly distributed across 250 object categories. As mentioned before, these sketches have been obtained by crowdsourcing across the general population. As such, they are a good starting point for analyzing the underpinnings of the sketching process by humans. A few examples from the database can be seen in the top row of Figure 2. The dominant appeal of this database is that the temporal stroke information (the sequential order in which the strokes were drawn) for a sketch has been provided. As we will see in Section 3.3 it is precisely the temporal stroke information that forms the basis for obtaining the category-epitome and the corresponding epitome-score for sketches.

3.2. Sketch data augmentation

The database of Eitz et. al. contains 80 sketches per category. To increase the number of sketches per category available for training the classifier (Section 3.4), we perform data augmentation by applying geometric and morphological transformations to each sketch. Specifically, each sketch is initially subjected to image dilation using a 5 × 5 square structuring element. A number of transforms are applied to this thickened sketch – mirroring (across vertical axis), rotation (±5, ±15 degrees), combinations of horizontal and vertical shifts (±5, ±15 pixels), central zoom (±3%, ±7% of image height). As a result, 30 new sketches are generated per original sketch. The data augmentation procedure results in 2400 sketches per category, for a total of 600,000 sketches across 250 categories.

3.3. Sketch feature extraction

As the top row of Figure 2 demonstrates, the spatial density of sketch strokes can be quite small. Moreover, extracting typical image features (e.g. based on texture) is ruled out and edge information is quite sparse. Nevertheless, a number of alternatives have been proposed as sketch features. For a survey of these methods in the context of sketch-based image retrieval, refer to\[1\]. We extract Histogram of Oriented Gradients (HOG\[14\])-like sketch descriptors using the pipeline described by Eitz et. al.\[13\]. The collection of descriptors so obtained are then combined using Fisher image representation approach\[15\] to obtain a feature vector for each sketch.

3.4. Sketch Classification

As an initial exploration and for ease of analysis, we consider only the first 50 alphabetically sorted sketch categories. We build a sketch classifier by utilizing 80% of the augmented sketches (Section 3.2) from each category for training and the rest for testing. Doing so provides 2400 × 0.8 × 50 = 96,000 sketches for training and 80 × 0.2 × 50 = 800 sketches for testing\[4\].

From each test sketch, its Fisher feature vector (Section 3.3) is obtained. A multi-class Support Vector Machine (SVM) classifier employing a Radial Basis Function (RBF) kernel was trained on the Fisher feature vectors by employing 5-fold cross validation and grid-based parameter search. The accuracy of the resulting classifier was 60.25%. For context, the accuracy (for the same split ratio of training and test sketches) obtained by Eitz et. al.\[13\] is 54% with the caveat that the number of categories are larger than ours – 250.

In the overall scheme of things, the sketch classifier is only useful to the extent that it lets us determine the category-epitomes. Seen in this light, the accuracy of the classifier assumes secondary importance. However, a classifier with good performance is still desirable as it ensures a larger coverage of the test set. In addition, such a classifier could potentially help obtain sparser category-epitomes compared to a counterpart whose performance is relatively poor. Nevertheless, to progress towards our goal of determining category-epitomes, we settle for the existing performance of the sketch classifier. In the next section, we shall see how the sketch classifier is actually utilized in constructing the category-epitome.

\[1\]Testing is done only on the original sketch subjected to dilation and not on its subsequently transformed variants generated for data augmentation. Hence the factor of 80 for each test category instead of the full 2400 as in training.
Fig. 3: Constructing the category-epitome for an airplane sketch: The sketch has 9 strokes. $S_1 - S_9$ are the cumulative stroke sequence canvases. A red cross mark indicates a misclassification(0) while a green tick mark indicates correct classification(1). Canvas $S_4$ outlined by a cyan rectangle is the category-epitome. Note that even though canvas $S_3$ is classified correctly, we consider category-epitome as canvas $S_4$, the temporally earliest, correctly classified canvas whose successors are classified correctly as well.

4. OBTAINING THE CATEGORY-EPITOME

4.1. Constructing Cumulative Stroke Sequences

As the first step in determining the category-epitome, we construct sequences of cumulative strokes derived from correctly classified test sketches. Suppose the sequence of strokes in the temporal order they were drawn in a test sketch is given by $S = \{s_1, s_2, \ldots, s_N\}$ where $N$ is the total number of strokes in the sketch. To construct the corresponding cumulative stroke sequence, we begin with a blank canvas. Strokes from the given sketch are successively added to the blank canvas in the temporal order. As each stroke is added, intermediate canvases $S_1, S_2, \ldots, S_N$ are created. Specifically, the intermediate canvases are given by $S_1 = \{s_1\}$, $S_2 = \{s_1, s_2\}$, $\ldots$, $S_N = \{s_1, s_2, \ldots, s_N\}$. At the end of this process, we obtain the cumulative stroke sequence $CSS = \{S_1, S_2, \ldots, S_N\}$. Figure 3 illustrates the creation of cumulative stroke sequence for a sketch from airplane category.

4.2. Constructing the category-epitome

Having generated the cumulative stroke sequence for a sketch as described above, the category-epitome can be constructed. Using the classifier from Section 3, each intermediate canvas of the cumulative stroke sequence is classified to obtain a binary labeling – the label classifier from Section 3, each intermediate canvas of the cumulative sequence is given by $	ext{l}_i$. As each stroke is added, intermediate canvases are classified correctly as well. Figure 2 shows sketches from various categories and their corresponding category-epitomes.

4.3. Epitome-score : Quantifying the category-epitome

Our procedure for obtaining the category-epitome, described above, also provides a natural method for quantifying the “epitome”-ness of the original, full sketch. Using $e$ obtained from Equation (2), we define the epitome-score $E$ of a sketch as:

$$E = \begin{cases} \frac{e}{N}, e \neq 1 \\ 0, \quad e = 1 \end{cases}$$

(3)

where $N$ is the total number of strokes in the sketch. $e = 1$ corresponds to the situation where merely drawing the first stroke conveys the epitome-ness of the sketch. Therefore, we have defined the corresponding epitome-score $E$ to be 0 for consistency across sketches. Our definition of epitome-score $E$ essentially conveys the sparseness underlying the sketch – the smaller its value, the more sparse the sketch is likely to be. Epitome-scores very close to 1, on the other hand, indicate that very few strokes in the original sketch are redundant. Fortunately, very high epitome-scores are not the norm, as we will see – sparsity is pervasive across categories. Referring once again to Figure 3, the epitome-score for the airplane sketch is computed as $E = \frac{4}{9} = 0.44$.

5. ANALYSIS

5.1. Epitome-scores across categories

We begin our analysis by computing the median of epitome-scores for sketches on a category-by-category basis. Figure 4 displays the median epitome-scores (shown as filled circles in the figure) for test sketches across 50 object categories. It is heartening to observe that 42% (21/50) of the categories have median epitome-scores below 0.5 and 80% (40/50) of the categories have scores below 0.75. These trends suggest an inherent sparseness for visual representation of object categories because the smaller the epitome-score, the sparser the category-epitome sketch. If we examine the scores closely, the epitome-scores for some of the categories (apple and boomerang) are 0. For these categories, the sketches (see Figure
The varying lengths of error bars in Figure 4 indicates that some object categories may have multiple representative category-epitomes rather than a single, unique representative. For example, the sketches of the category (human) arm are likely drawn with a fairly consistent appearance by humans. This consistency influences the sketch classifier and can cause it to produce category-epitomes which exhibit a minor amount of variations, thus resulting in a compact distribution of epitome-scores (shorter error bars). In contrast, the variety in sketches of a category such as carrot is reflected in the corresponding category-epitomes and by extension, in the longer error bars of its epitome-scores.

5.2. Epitome-score as a proxy for semantic level of detail

A different perspective can be gained by examining categories for a given value of epitome-score. For each category, we count the number of test sketches whose epitome-score exceeds a threshold and normalize by the number of test sketches in the category. To facilitate analysis and avoid visual clutter, we select 4 prototypical categories whose plot contours occupy the extremities (towards top-left corner and bottom-right corner) of the original plot. In addition, we select 6 other prototypical categories whose plot contours lie between the extremity plots previously mentioned. The resulting plot can be viewed in Figure 5.

Epitome-score can be considered as a proxy for semantic level-of-detail. Viewed in this light, the plot from Figure 5 suggests the varying epitome-score budgets across categories – some categories require a considerable level of detail before their epitomals avatars are revealed (e.g. categories with plots towards the lower right such as bridge and bicycle). On the other hand, categories with plots towards the upper left corner (apple, boomerang) have relatively less stringent demands on level of detail.

To view a larger set of category-epitomes, t-SNE[16] visualizations of epitomes for select categories and additional results which support the analysis presented in this section, visit http://val.serc.iisc.ernet.in/sketchepitome/se.html.

6. FUTURE WORK

A number of directions exist for future work. One obvious direction would be to improve the performance of existing sketch classifier in terms of number of categories as well as accuracy. A well-performing classifier which utilizes fewer training samples translates to a potentially larger set of test category-epitomes for analysis. We also intend to compare our current distribution of category-epitomes/epitome-scores and related analysis with that obtained when human subjects are asked to identify the cumulative stroke sequences. For this comparison, we plan to use the benchmark sketch database created by Rosália et al. who employ a human-evaluation based technique to identify a subset of 160 non-ambiguous object categories from the 250 originally provided by Eitz et al. However, as the number of categories increases, visualizing trends (Figures 4-5) becomes a challenge. Therefore, novel visualization methods need to be explored or alternately, the number of categories needs to be curated in a meaningful manner for representative sketch analysis.

Rosália et al. define a non-ambiguous sketch as one whose identity is agreed upon by at least 2 people among the subjects surveyed.
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