

**AUTOMATIC PHOTO TO IDEOPHONE MANGA MATCHING**

Technical Report

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June 12, 2020

**ABSTRACT**

Photo applications offer tools for annotation via text and stickers. Ideophones, mimetic and onomatopoeic words, which are common in graphic novels, have yet to be explored for photo annotation use. We present a method for automatic ideophone recommendation and positioning of the text on photos. These annotations are accomplished by obtaining a list of ideophones with English definitions and applying a suite of visual object detectors to the image. Next, a semantic embedding maps the visual objects to the possible relevant ideophones. Our system stands in contrast to traditional computer vision-based annotation systems, which stop at recommending object and scene-level annotation, by providing annotations that are communicative, fun, and engaging. We test these annotations in Japanese and find they carry a strong preference and increase enjoyment and sharing likelihood when compared to unannotated and object-based annotated photos.

**Keywords** ideophone, mimetic, onomatopoeic, manga, comic, photo, GloVe, annotation

1 Introduction

Photo annotations in camera and messaging applications are on the rise. This includes a wide variety from geo-based recommendations (like the game score for a photo taken in a sports arena) to rich augmented reality on faces in the picture. Beyond this, annotations have little relation to the current photo’s visual content. Currently, some systems can recommend an annotation as the object name or matching sticker of that exact object for manual placement on the photo, this still does not capture the expression and visual nature of ideophones and onomatopoeia that is seen in graphic novels, manga, and comic strips.

In this work, we present a system for automatically predicting and placing onomatopoeic annotations on photos based on the content of the photos themselves. This is accomplished by applying a suite of visual object detectors to the photo and then mapping to a dictionary of onomatopoeic terms through an intermediate semantic embedding, wherein the onomatopoeic terms (in Japanese) are represented by their explanations (in English) and compared against the object recognition vocabulary (also in English).

We compare this system against a baseline of simply suggesting annotations that are directly drawn from object and scene classification engines. While these baseline annotations are very much aligned with the semantic content of the images, we find that users overwhelmingly prefer mimetic and onomatopoeic annotations for the purposes of sharing photos for communicative purposes. This suggests that the task of annotating photos with semantic tags is not aligned with many users’ practice of using photos for communication purposes.

2 Related Work

For decades, a large amount of computer vision research has focused on identifying objects [10, 6] (such as cars, bikes, and people) and other contextual factors [21, 19] (like grass, sky, and pavement) within images. Recent advances in deep learning [9] and increases in the availability of training data [16] have made these applications ultimately very
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feasible, to the extent that they are readily available in many commercial applications (such as Google Photos or Flickr). Simultaneously, users have gained access to increasingly powerful smartphones, with the capability of capturing and immediately sharing high quality photographs. While these smartphone applications enable the overlay of any arbitrary label, users rarely want to just state the semantic content of the image (for example: “train”) and much prefer to use the communicative or evocative meaning (“chug, chug, chug”).

This assumption is informed by user-centered work [2] about the behavior of users tagging their own photos and using those tags for communication purposes. Largely, photographs contain semantic content, but the purpose of tagging is often for communicating contextual factors, such as location, time, and experiences. This, again, suggests that while semantic image tagging might be important for retrieval applications, it might not be appropriate for sharing and communication.

There has been some work on Manga-style generation such as using the device accelerometer or other methods to detect movement or silence and render the mimetic term [17, 12] or to stylize (comic-ize) the image [5] without the term. There’s a host of work around Computational Manga and Anime [18] which also deals with style and composition but not ideophones or mimetic text. Perhaps the most related work are the sticker recommendations from the SnapChat application. These are geographic and time based recommendations for stickers which are to be manually placed on the photo, resized, and saved. The geo-lookup finds the temperature outside and the movement speed of the camera in addition to several events like a holiday or a local sports score.

3 Photo to Ideophone Matching

For the photo to ideophone matching, we propose a fully automated approach where a user takes a photograph with a camera or app (or selects a photo from a collection) and the annotation is recommended and automatically composited and rendered on the photo or print. This requires three steps: an initialization, a matching, then an execution. This process can be optimized to live embedded on a device but could be cloud-connected as well.

3.1 Initialization

A dictionary of ideophones is needed. We selected the JADED network’s open-source community driven dictionary with a large Japanese ideophone to English definition repository with 1,329 contextual manga related terms [15]. A typical example would be: 格ー: *the sound of a mechanical clock’s internal mechanism*. In effect, any language, or icon even, for the term can be used, however the definition needs to be in English. Here, the English term would be tic-toc. The dictionary from the JADED network provides Japanese as a matching pair of Hirigana and Katakana, romanji, several English equivalents, and an explanation (the definition). For example: ジー, ジー; ji-; (1) *whine* (2) *stare*; (1) Like when microphone is too close to the speakers, see also *Ui-n*; (2) As in staring at someone, or looking at something for an extended period of time. Comes from the “ji-” in “jiro jiro miru” (じろじろ見る).

Next for each definition, we construct a score based on a term vector created using a GloVe [13].

$$\frac{\sum_{i=1}^{n} \text{GloVe}(t_i)}{n}$$

(1)

Where GloVe(t) is the GloVe score for the given term t. We selected the pretrained Wikipedia 2014 + Gigaword 5 vector (6B tokens, 400K vocab, uncased, 50d) as the model to use. For every term in our dictionary, this becomes 1,329 50 dimension score vectors.
3.2 Matching

With the dictionary model complete, we need to construct a similar photo vector. Given any photo, we run a set of visual classifiers. We use SqueezeNet as the object classifier as well as a food classifier with 2000 dishes based on MobileNet, as well as, a face and smile detector. [8, 7, 1] Each classifier returns a set of objects $o$ and confidence scores for those objects $c_o$. The smile classifier returns a floating-point score from $0.0 \ldots 1.0$ where 0.0 is a frown and 1.0 is a smile. For the sake of consistency, we report this as a smile for anything $\geq 0.5$ normalized from $0.0 \ldots 1.0$. Similarly, a frown is scored the same way for scores $< 0.5$ normalized inversely (so a smile score of 0.1 would map to a frown at 0.9). For each classifier, we compute a GloVe vector similar to Eq (1) however, we weight each object by its detection confidence as:

$$\sum_{j=1}^{n} c_{o_j} \text{GloVe}(o_j)$$

This results in three 50 dimensional vectors. For each classifier vector, we find the top 5 minimal Cosine distance between itself and the ideophone dictionary GloVe vectors from §3.1. Now, the closest vector can be picked and the term can be recommended. We returned the top 5 in the previous step to allow for some jitter to prevent a single term from being printed repeatably.

3.3 Compositing

Photo and term in hand, compositing the mimetic term is the next step. This requires knowing where to place it so not to disturb the image or occlude the subject. There are several methods to find salient (and inversely non-salient) regions in an image particularly from the multimedia literature [11, 20, 14]. For this system, we opted to implement a simplified method for non-salient region detection. First, using OpenCV’s findContours function, we find largest contour in the image. We then split the image a quadrant plane at the midpoint. Then, we find the quadrant with the smallest intersection to the largest contour. With a target quadrant, the term is composited and rendered in the photo’s corner at a random size and angle, both at an empirically threshold to be mostly level and not too large, onto the photo. The final output is produced (see Figure 1b for an example).

3.4 Fabrication

The initial camera system was put into a custom fabricated camera for field testing. A Raspberry Pi Zero with a camera was used with the Google AIY [1] accelerator kit (for running computer vision models). The Ideophone GloVe vectors were sparse compressed using python3 and the vector matching is computed on the CPU. The term matching takes 30 seconds on average while the computer vision modules take about 90 seconds (as each model has to be loaded and unloaded as the device carries limited memory). Finally, the photo is printed via WiFi to an Instax SP2 mobile photo printer. The whole system is self contained and needs no network uplink or interface aside from the camera shutter actuator.

4 Evaluation

We begin with a preliminary evaluation of the ideophone matching method. A larger experiment would be needed to test people on their own photos with either our fabricated camera (see Figure 2) or a camera app on a mobile phone to measure how people feel about mimetic annotations on their personal photos and photo messages. For the preliminary evaluation, we needed to collect photos. Here we used top terms from the YFCC100M dataset [16] to select a sample of
photos across a variety of topics and quality levels. Photos were chosen from the dataset or from the personal collection of the authors that matched the search for common terms like cat, smile, lightning. Several photos were selected from the YFCC100M dataset to ensure aesthetic coverage. For example, a scan of some money and a receipt. This was done to represent a personal camera roll as photo content types tend to vary on personal devices. [4]

Next, we designed a short survey to gauge how people felt about a set of photos, how they compared these photos to their annotated versions (object term versus mimetic term), and finally a side by side comparison of two annotated photos. The survey was written in English and Japanese; we used English for testing the survey with 5 people and ran the survey with 10 participants (60% female) in the Tokyo Metro area. Fluent and proficient Japanese language readers were recruited using a third party service and participants were paid 15 USD. The ages ranged from 28 to 50 with a median of 33. Half of the participants were Japanese and all could read hiragana, katakana, and kanji. The survey was completed in an average of 23 minutes. For photography experience, all the participants used a cameraphone with 4 of them using some other device as well (a DSLR or a point and shoot camera). All the participants took over 10 photos a week and used photos in messaging services in addition to some photo sharing websites. The participants had a diverse employment background: computer engineers, office managers, bartenders, and teachers. There was an even comic book and manga reading habit across the participants (from infrequently to frequently).

The first section of the survey gathered information on the participants. Next each participant was shown a set of random photos with a set of Likert 5-point scale questions asking if they typically take photos like this, if they find the photo aesthetically pleasing, if they find the photo interesting, if they would share a photo like this, and if they would print a photo like this (via an instant printer or photo lab). (see Figure 3) The instructions for all three photo-question parts of the survey were to imagine they took the photo themselves. Answers to “I typically take photos like this,” were normally distributed least likely to most likely (6, 9, 13, 11, 6). Aesthetic judgments were slightly different (11, 6, 10, 12, 6) and had more negatives which is likely due to selection of everyday cameraphone images for the experiment.

We also asked of the un-annotated photos from the first section how likely they were to engage with the photo via clicking like, sharing, or printing the photo. For the next section we use the same photos randomly presented with an object-based annotation and a mimetic-based annotation from our method (Figure 4). For the purpose of this exploration, we wish to see, by participant, is there an increase or decrease in favor across those three dimensions. Comparing the object-based annotations to the unannotated we see 10.5% of the questions increased in score and 12.6% decreased. The ideophone-annotations increased by 17.0% and decreased by 9.6%. This anecdotally shows an engagement increase for the ideophone annotations, but more participants, and data, would be needed for a further comparison and tests. The last comparison section asked participants to pick an object versus ideophone annotation using new, unseen photos (see Figure 5). These question and choices were also randomized. The ideophone term annotations were picked over the object terms at a ratio of 2.2 : 1.

Finally, there was a write in section asking what they liked and didn’t like about the annotations. Most participants said the annotations (object and mimetic) were accurate; P1 expressed the accuracy of the matching given this survey comes from overseas. The mimetic words were generally thought to “reinforce the ideas in the viewers that the image wants to bring across.” (P9) or, simply put, found joy in them “Thank you for making me laugh several times.” (P8) The exception of a bowl of noodles “Onomatopoeic is better than a noun, except ’noodle’ picture” (P6); here the onomatopoea was ずるずる or “slippery” in Japanese (which was in the dictionary as (1) being dragged and (2) “eating soup noisily and without care for the surroundings”). P7 stated the more aesthetic photos (in this case a shot of lightning in the night sky) should not be annotated at all as it detracts from the beauty of the image; this is congruent with past work on how people feel about filtering photos by Bakhshi et al. [3]. Both negative comments about the annotations were seen in the study questions as well. A few participants, P5, P6, and P10, thought the text should be rendered at a higher quality and composited with some transparency; this was an effect of building the system optimized for a 640×480 instant printer but did not surface during our survey testing period. One participant (P9) stated their own images would affect their answers (they were requesting if that would be possible).

5 Conclusion

Ideophones are an overlooked area of automatic photo annotation. These mimetic and onomatopoeic terms can be used to increase the engagement on photos; we have shown how a semantic embedding can map visually recognized objects to known ideophones via their definitions. We find improvements in visually compositing text is important but placement was adequate in this limited study. A photo aesthetics classifier could also be added as not to proactively modify high quality images. Our system can also be extended to matching any set if items (terms, graphics, etc.) with a matching definition. However, there exist more opportunities for improvements in the matching system. Scene graphs or automated captioning can be used to gather a better understanding of the visual content for mapping. Also, as most
Figure 3: A question from the opening of a survey: a photo of a girl sleeping and a set of Likert questions asking if a user takes a photo like that or finds it aesthetically pleasing or engaging and if they would share this photo. The questions below are on a 5-point scale: if they typically take photos like this, if they find the photo aesthetically pleasing, if they find the photo interesting, and if they find they would share a photo like this.

(a) An object based annotation.  
(b) A mimetic based annotation.

Figure 4: Following the baseline questions (see Figure 3), a subset of questions was asked about the same photos annotated by our Ideophone method and a standard object based label.

Figure 5: The comparison section of the survey asked participants to pick between an object based and an ideophone based recommendation; these were presented randomly. Left: コシラ (Godzilla), Right: かおー (Roar)
cellphone cameras can capture video and stills simultaneously, detecting which object is in motion from the video [17] could further improve matching terms to salient objects.

6 Acknowledgements

Thanks to Takahiro Nori for translating the survey and to Nami Tokunaga and Xiaojing Zhang for the early testing. Figure 4’s cat photo μδισαγματε on Flickr; all other images are author owned.

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