Pointedness of an Image: Measuring How Pointy an Image is Perceived

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Abstract. For computers to understand human perception, metrics that can capture human perception well are important. However, there are few metrics that characterize the visual perception of humans towards images. Therefore, in this paper, we propose a novel concept and a metric of *pointedness* of an image, which describes how pointy an image is perceived. The algorithm is inspired by the Features from Accelerated Segment Test (FAST) algorithm for corner detection which looks on the number of continuous neighboring darker pixels surrounding each pixel. We assume that this number would be proportional to the perceived *pointedness* in the region around the pixel. We evaluated our method towards how well it could capture the human perception of images. To compare the method with similar metrics that describe shapes, we prepared silhouette images of both artificial shapes and natural objects. The results showed that the proposed method gave nearly equivalent perceptual performance to other metrics and also worked in a larger variety of images.

Keywords: Human perception · Pointedness · Measurement.

1 Introduction

Understanding human perception by computers requires appropriate metrics that can capture human perception well. Despite this fact, there are few metrics that characterize the visual perception of images.

A psychological study [12] has suggested that our vision system uses shape information as one of the basic visual features. In this context, in this paper, we introduce a novel concept and a metric of *pointedness* of an image, which we define as "How pointy an image is perceived by humans." For example, a photo of a pineapple would be intuitively perceived more pointy than that of an orange because we think of a pineapple as a more pointy, or thorny object than an orange. Thus, the *pointedness* of the former image should be higher than the latter.

There are several studies that have proposed metrics to measure the concepts of *circularity* [1, 4], *roundness* [6], or *compactness* [2]. Since they are designed to describe shapes for use in applications like 3D editing, they do not necessarily match human perception well. Thus, we aim to solve this limitation and propose a metric designed to describe human perception foremost. Besides, these metrics measure those concepts only from binary images that basically contain one or several shapes.

In our proposed method to measure *pointedness*, we take advantage of a classical method of Features from the Accelerated Segment Test (FAST) corner detection algorithm [9], which first calculates a simple intensity comparison for each pixel in an image. While a single corner in an image may be perceived pointy, the algorithm does not calculate a *pointedness* score. Therefore, we extend the intensity comparison part of the FAST algorithm to calculate a feature map, and process it further to obtain a *pointedness* score for an image.

Our main contributions are:

- Introducing the concept of *pointedness* of an image which describes how pointy the image is perceived by humans.
- Developing a method to calculate the *pointedness* of an arbitrary gray-scale image.
- Performing a subjective analysis of visual perception of depicted shapes with regard to the *pointedness*.

2 Related Work

2.1 Human Perception Towards Shapes

Psychological studies delve into how the human visual system perceives the world around us. Prominently, Gestalt psychology [7] started research on shapes and visual perception. Following, a study by Treisman et al. [12] proposed a theory of visual attention suggesting that our vision focuses on several specific features including information of colors, orientations, and shapes at the preattentive stage of the recognition of an object. Furthermore, a recent study by Huang et al. [5] also proved that preattentive shape features can be explained by three basic dimensions of segmentability, compactness, and spikiness.

These studies suggest that how pointy or round a shape is plays an important role in our visual perception.

2.2 Metrics Describing Shapes

There are metrics related to our study, such as *circularity* [1, 4], *roundness* [6], or *compactness* [2]. Strictly speaking, these three terms are defined as different

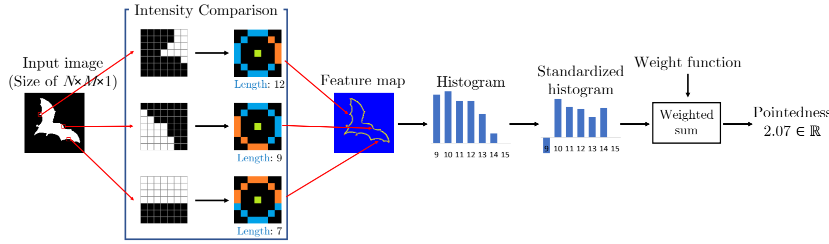


Fig. 1: Process flow of the proposed method. From an input image, we first calculate a feature map, where each pixel represents the number of continuous surrounding darker pixels. Next, we determine a histogram for the high intensity values. After standardizing the resulting histogram, we obtain the *pointedness* of an input image by calculating the weighted sum of the histogram.

concepts. However, they are often considered to represent the same concept in a 2D Euclidean space: "How close the shape is to a circle" [10]. Although those definitions are not unique and vary from paper to paper [10], the most common definition is

$$\text{Circularity} = \frac{4\pi\text{Area}}{\text{Perimeter}^2}, \tag{1}$$

where Area is the area and Perimeter is the perimeter of a target shape. This measurement ranges from 0 to 1, and equals 1 if and only if the shape is a circle.

Because of this definition, *circularity* is mostly designed to work on contours or silhouettes. Our proposed metric of *pointedness*, in contrast, is designed to work on gray-scale images in order to tackle this limitation.

2.3 FAST Algorithm

Features from Accelerated Segment Test (FAST) [9] is an algorithm used for corner detection. The core idea is a circle-wise intensity comparison. First, intensities of 16 circle-wise pixels around a target pixel p are compared with an intensity of p, and then each of the surrounding 16 pixels are classified by a threshold into three categories: darker, brighter, and similar. Next, the numbers of continuous darker/brighter pixels are counted respectively and the decision whether p is a corner or not is made according to those numbers.

3 Pointedness Calculation

In this paper, we propose a novel method that measures the introduced concept of *pointedness* from an input gray-scale image. We expect that foreground objects have high intensity and the background has low intensity. The process flow of the method is illustrated in Fig. 1.

First, we obtain a feature map from an input image, which describes the degree of *pointedness* for each pixel in an image. Here, we utilize the idea of

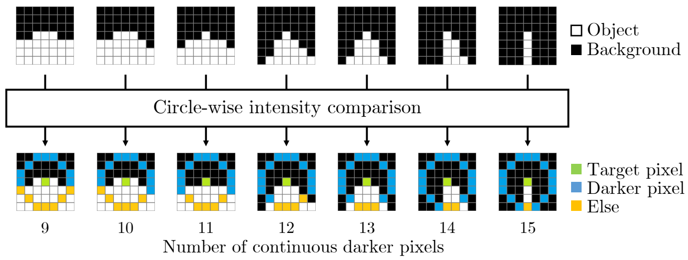


Fig. 2: Examples of regions with a large number of continuous darker pixels. This approximates the *pointedness* at the pixel.

a circle-wise intensity comparison in the FAST algorithm. In detail, for each neighboring pixel p_s surrounding a target pixel p, if the intensity of p_s is less than the intensity of p minus a threshold t, p_s is classified as a darker pixel. Then, we assume that the number of continuous darker pixels surrounding each pixel can be used for the calculation of a *pointedness* score for the region. For example, if the number of darker pixels is high, the shape around the point would be perceived pointy, while if it is low, it would be perceived less pointy. Examples of this idea are shown in Fig. 2. We obtain a feature map of which each pixel denotes the number of surrounding darker pixels at the point. A region around the pixel where the number of darker pixels is eight, has a flat contour, while one where the number of darker pixels is less than eight, has a dented contour. According to findings in psychological research [5], something is perceived pointy by humans if we expect a potential danger of grasping it. Therefore, in this study, we do not treat a dented contour as pointy, and we assume that only a value between nine and fifteen has influence on the *pointedness* of an image.

Next, by counting the values between nine and fifteen in the feature map, we obtain a histogram with 7 bins. If x_n is defined as the occurrence of pixels with a value of n, the value of the n-th bin, y_n, is described as

$$y_n = \frac{x_n}{\sum_{n \in \{9,\ldots,15\}} x_n}. \tag{2}$$

Let Y_n be a random variable that represents the probability of y_n. We here assume Y_n to have a normal distribution denoted as $Y_n \sim \mathcal{N}(\mu_n, \sigma_n^2)$.

Then, in order to obtain a standardized normal distribution, we standardize Y_n for every n, obtaining a standardized histogram. Each bin of the histogram is described as a variable $\frac{Y_n - \hat{\mu}_n}{\hat{\sigma}_n}$, where $\hat{\mu}_n$ and $\hat{\sigma}_n$ are estimated values of μ_n and σ_n calculated as,

$$\hat{\mu}_n = \frac{1}{n}\sum_{i=1}^{m} y_{ni}, \quad \hat{\sigma}_n = \frac{\Gamma(\frac{n-1}{2})}{\Gamma(\frac{n}{2})}\sqrt{\frac{1}{2}\sum_{i=1}^{m}(y_{ni} - \hat{\mu}_n)^2}, \tag{3}$$

where y_{ni} is an observed value taken from Y_n of the i-th image and $\Gamma(x)$ is the gamma function.

(a) Experiment 1: Artificial shapes (b) Experiment 2: Natural shapes

Fig. 3: Datasets used in each of the experiments.

Lastly, because the relationship between the number of darker pixels and the *pointedness* is not necessarily linear, we calculate a weighted sum to obtain the *pointedness* score P for an image, formulated as

$$P = \sum_{n \in \{9,\ldots,15\}} \mathrm{hist}(n) w(n) = \sum_{n \in \{9,\ldots,15\}} \left(\frac{y_n - \hat{\mu}_n}{\hat{\sigma}_n} \right) w(n), \tag{4}$$

where $\mathrm{hist}(n)$ represents the frequency of the n-th bin of the standardized histogram, and w represents a manually designed weight function for each bin. The weight function should be a monotonically increasing function that maps an interval of $[9, 15]$ to $[0, 1]$. In this way, it can give a corresponding weight for each number of darker pixels.

The obtained score P is in the range of $(-\infty, +\infty)$, and this value is expected to be proportional to human perception towards *pointedness*. For the case where P should be finite, we can obtain the score in the range of $(0, 1)$ by applying a sigmoid function to P obtained by Eq. 4 that is defined as

$$\mathrm{sigmoid}(x) = \frac{1}{1 + e^{-x}}. \tag{5}$$

4 Evaluations on Binary Images of Shapes

We conducted two subjective experiments to evaluate how well the proposed method can capture the human perception towards the proposed concept of *pointedness*. Although our method can be applied to arbitrary gray-scale images, we chose binary images in these experiments for the comparison with the related metric of *circularity* [10]. Each experiment used 12 images of 128×128 pixels which are shown in Fig. 3. In the first experiment, we prepared binary images each of which contains an artificial shape. These shapes were created by distorting radial frequency patterns [13], which are defined by deformations of circles through sinusoidal modulation of the radius in polar coordinates. In the second experiment, we selected silhouette images of more natural objects from the MPEG-7 Core Experiment CE Shape 1 Dataset [8]. We separated the experiments in this way because we assumed that the human responses to those images might differ depending on whether the images were familiar or unfamiliar to them.

Table 1: Subjective evaluation of two experiments. Each entry shows the Pearson's correlation between the scores determined by the metric and the scale obtained in a user study.

Type	Method	Weighting	Experiment 1 (full dataset)	Experiment 2 (full dataset)	Experiment 2 (w/o Lizard)
Comparative	−Circularity	—	0.859	0.632	0.514
	Circularity^{-1}	—	**0.919**	**0.772**	0.494
Proposed	Pointedness w/o Sigmoid	$a = 0.5$	0.844	0.627	0.611
		$a = 1.0$	0.830	0.651	0.586
		$a = 2.0$	0.782	0.683	0.542
	Pointedness w/ Sigmoid	$a = 0.5$	**0.919**	0.673	**0.639**
		$a = 1.0$	0.904	0.664	0.596
		$a = 2.0$	0.853	0.664	0.541

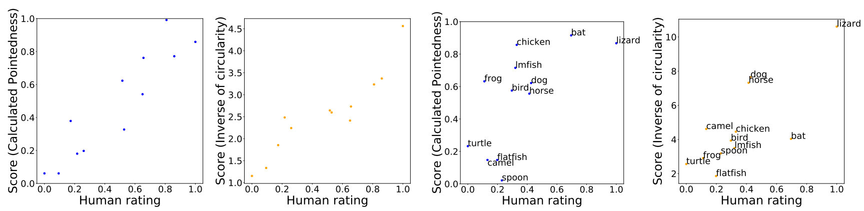
In both experiments, the same eight Japanese participants in their 20s conducted the survey. We showed the participants a randomly selected pair of images. Then, we asked them to choose intuitively which image looked more pointy. No more instructions were given in the process. After the participants answered for all the ${}_{12}\mathrm{C}_2 = 66$ pairs of images, we obtained the ground-truth scales in the range of [0,1] by applying Thurstone's paired comparison method [11] to the ${}_{12}\mathrm{C}_2 \times 8 = 528$ answers.

The results of the two experiments are shown in Table 1. As a metric, we measured Pearson's correlation between the ground truth scale and the calculated *pointedness*. As a weight function for the calculation of *pointedness*, we prepared a simple function with a hyper-parameter a, which is defined as

$$w_a(n) = \left(\frac{n-8}{7}\right)^a \quad (9 \leq n \leq 15). \tag{6}$$

As comparative methods, we used a *circularity* measurement defined by Eq. 1. Since this measurement is thought to measure the opposite concept of our *pointedness*, we calculated −Circularity and Circularity^{-1} instead.

We can observe that the proposed method gives nearly equivalent correlations to *circularity* in both of the experiments. However, the correlation 0.772 given by the inverse of *circularity* in the second experiment appears surprisingly large. To analyze this, we plotted the calculated *pointednesses* and the inverse of *circularity* values in Fig. 4. Here, we used the sigmoid function and the weight function with $a = 0.5$ for the calculation of *pointedness*. From this, we found that the image of "lizard" had a strong impact on the calculation of the correlation in the second experiment because its ground-truth was much higher than the others. Therefore, we performed the second experiment without using the "lizard" image, where the results were closer to the expected correlations. From these, we recognized one limitation of our method that the calculated *pointedness* mainly focuses on some specific pointy points in an image, not the whole shape as we humans do, resulting in few differences among relatively pointy images (e.g. "chicken", "bat", and "lizard").



(a) Experiment 1: Artificial shapes (b) Experiment 2: Natural shapes

Fig. 4: Scatterplot of the calculated *pointednesses* (left) and inverse of *circularity* values (right) for images used in each of the experiments.

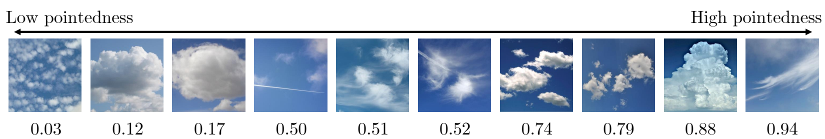


Fig. 5: Example of cloud images and their *pointednesses* calculated by our method.

5 Application to More General Images

Pointedness can be measured from arbitrary gray-scale images with our method. Therefore, we applied our method to several images of clouds since those images seemed to suit our method well. We selected 10 images from Flickr[6], which captured one or more clouds clearly in the center of the images. Then, we sorted those images according to our *pointedness* metric.

The result is shown in Fig. 5. Here, we set the threshold $t = 10$, a relatively low value, so that our method can consider the texture patterns of the surface of the clouds for the *pointedness* calculation. We then calculated gray-scale images and resized them to 512×512 pixels. Here, we chose a weight function with $a = 0.5$.

From Fig. 5, we confirmed that the broad tendency of the calculated *pointednesses* matches our perception, although the order and the rating might vary from person to person.

The application to arbitrary images is a very difficult task. We recognize that our current method mainly focuses on contours of shapes in an image and thus in the next step, we need to consider pointy features of objects which do not appear as contour information. However, the subjective evaluation conducted in Sect. 4 showed that our proposed method could capture *pointedness* reasonably well. Furthermore, our method could also measure *pointedness* of a sub-region of an image by applying a mask to a feature map.

[6] https://www.flickr.com/

Our method is designed to capture human perception. Thus, the main application of our method is to investigate and analyze psychological phenomena around human vision such as sound symbolism [7] and synesthesia [3] based on data-mining approaches. Quantifying those phenomena would give meaningful insights for computers to understand human perception in vision-processing related tasks.

6 Conclusion

In this paper, we introduced the concept of *pointedness*, which describes how pointy an image is perceived by humans. Moreover, we proposed a method to measure the *pointedness* from an arbitrary gray-scale image. We conducted two experiments to investigate how well our method can capture human perception towards binary images, and confirmed that our method gives a high correlation, indicating that it has a correlation with human perception towards *pointedness*.

Future work includes the application of the proposed method to attention maps generated by deep learning models in order to further analyze the relationship between computer vision and human perception.

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