Abstract - In a Concept-Base, concepts are assigned attributes and weightings that express their importance. Concepts and attributes are defined based solely on the relationships that can be associated with each other. Using such definitions, a CB aims at including various meanings that human beings understand automatically based on words used, not simply definitions as described in dictionaries. This paper describes a method of adding visual information called Image-Concept and Image-Attribute for Concept-Base.

Keywords: Knowledge base, Concept-Base, Degree of association, bag-of-features

1 Introduction

Humans understand the meaning of various things. For example, humans have knowledge of “Turtle” that its classification “reptilian”, the features “slowness”, and the appearance such as “Turtle has a shell”. We think various things are defined a set of features from various viewpoints. These various things defined by various features called Concept and the knowledge base that defines it is Concept-Base[1] (CB). A CB defines the meanings of various phrases called concepts that are expressed in natural language based on their relationships to other phrases called attributes. This paper describes a method of adding visual information called Image-Concept and Image-Attribute for Concept-Base.

2 Concept-Base (CB)

A CB is a knowledge base that defines words as concepts. A concept is defined in the following equation:

\[ A = \{(a_1, w_1), (a_2, w_2), \ldots, (a_i, w_i)\} \]

where \( A \) is the concept label, \( a_i \) is the attribute, and \( w_i \) is the weight of the attribute. The word used for attribute is defined as concept in CB. Table 1 shows specific examples of CB.

An attribute of a concept is called a first order attribute. In the CB, words defined by concepts also form attributes, which can then be used to derive other attributes. Attributes derived from attributes are called second order attributes of the original concept.

3 Adding image data

As shown in Table 1, concept expressed in words (Word-Concept) is already exists at CB. In this paper, Image-Attribute extracted multiple image data is added each these Word-Concept. Attributes need to be defined as concept in CB as stated in Chapter 2. So new concepts express image data are created. Figure 1 shows overview of adding image data for CB.
4 Proposed method

Proposed method create a set of Word-Concepts and multiple image data. Features of image data that create Image-Attributes extracted from these multiple image data. These features represented bag-of-features\(^2\) (BoF).

Features of image data are extracted from each image data, so multiple features needs to be integrated to make Image-Attribute for each Word-Concepts. Integrated features called Integration-BoF is created by averaging or taking median of each VW. Created Integration-BoF is added each Word-Concepts as Image-Attributes.

4.1 Extract features from Image data

Caltec-256\(^3\) offer multiple classified images, so sets of Word-Concepts defided in CB and multiple image data are created from there. Finally, 117 Word-Concepts like Figure 2 are chosen.

- Baseball-bat, Baseball-glove, Bat, Bear, …
- Harmonica, Harp, Hawksbill, Hibiscus, …
- Waterfall, Watermelon, Windmill, …

Figure 2: Specific example of chosen Word-Concepts.

Proposed method extracts features of image data and creates bag-of-features (BoF) from each image. The main idea consists of finding keypoints, visual words (VW), which are cluster centers of the affine invariant descriptors of image patches, such as SURF\(^4\). Each image has a pair of sets of visual word \( VW_i \) and weight (rate of frequency) \( w_i \) as the following equation:

\[
image_A = \{(VW_1, w_1), (VW_2, w_2), \ldots, (VW_n, w_n)\}
\]

Figure 3: Specific example of features extracting from “Hawksbill” images.

In this paper, multiple BoF are extracted from 30 images for each Word-Concepts. For example, 30 Hawksbill BoF are extracted from different images.

4.2 Create Integration-BoF

Extracted multiple BoF is a feature of each image, for example Figure 3, but Image-Attribute that defining concept’s visual information need essential features present in all images belonging to the same sets of Word-Concepts and multiple image data. So method create Integration-BoF from each BoF by averaging or taking median of each VW. Figure 4 shows example of Integration-BoF.

Figure 4: Specific example of Integration-BoF.

Table 2 shows example of VW weight created for each integration method. In the method of average, weight 0 rarely appear.

<table>
<thead>
<tr>
<th>Image Name</th>
<th>Integration method</th>
<th>VW1</th>
<th>VW2</th>
<th>VW3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hawksbill</td>
<td>Average</td>
<td>0.000197</td>
<td>0.006685</td>
<td>0.00083</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>0.0</td>
<td>0.006355</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Table 2: Specific example of VW weight.

4.3 Adding Image-Concept and Attribute

Integration-BoF is added for Word-Concept by Image-Attribute. Image-Attribute is visual words and weight is rate of frequency. Attribute is defined as concept in CB, so there is need to add VW as a concept, it is Image-Concept. Figure 5 shows method of adding Image-Concept by using Integration-BoF.
5 Degree of Association between image and concept

Relationships between image and concept can calculate using proposed CB by Degree of Association[5] (DoA).

5.1 Degree of Association (DoA)

The Degree of Association (DoA) quantifies the relationship between concepts by using attributes that characterize the chain-reaction structure of the CB. Table 4 shows specific DoA examples.

Table 4: Specific DoA example

<table>
<thead>
<tr>
<th>Concept A</th>
<th>Concept B</th>
<th>DoA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Art</td>
<td>Artwork</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>Impression</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>Routine</td>
<td>0.0015</td>
</tr>
</tbody>
</table>

In this process, the relationship between multiple concepts is expressed quantitatively. The following shows the method used to calculate the DoA between Concept A and Concept B. This is defined as $DoA(A, B)$. For concepts A and B with primary attributes $a_i$ and $b_i$, weights $u_i$ and $v_i$, and numbers of attributes $L$ and $M$, the concepts can thus be expressed as follows:

$$A = \{(a_1, u_1), (a_2, u_2), ..., (a_L, u_L)\}$$

$$B = \{(b_1, v_1), (b_2, v_2), ..., (b_M, v_M)\}$$

The degree of match (DoM) between concepts A and B $DoM(A, B)$, where the sum of the weights of the various concepts is normalized to 1, is defined as follows:

$$DoM(A, B) = \sum_{a_i=b_j} \min(u_i, v_j)$$

The DoA is found by calculating the DoM for all of the targeted primary attribute combinations, and then determining the relationships between them. Specifically, priority is given to the correspondence between matching primary attributes. For primary attributes that do not match, the correspondence is determined by maximizing the total DoM. This makes it possible to give consideration to the DoA, even for primary attributes that do not match perfectly. When the correspondences are thus determined, the $DoA(A,B)$ between concepts $A$ and $B$ is as follows:

$$DoA(A,B) = \sum_{i=1}^{L} DoM(a_i, b_{xl}) \times \frac{(u_i + v_{xl})}{2} \times \frac{\min(u_i, v_{xl})}{\max(u_i, v_{xl})}$$

In other words, the $DoA$ is proportional to the degree of identity of the corresponding primary attributes, the average of the weights of those attributes, and the weight ratios.

5.2 Object recognition using CB and DoA

As usage of Image-Concept and Image-Attribute, Object recognition was performed using DoA.

In this paper, Image-Attributes are added to 117 Word-Concepts. 10 test images not used when creating a proposed CB are prepared for each 117 Word-Concepts added Image-Attributes.

Bag-of-features (BoF) is created from each test images. Test image’s BoF has a pair of sets of VW and weight. VW is defined as concept at proposed CB, so test image’s BoF can be regarded as concept. In other words, calculating DoA can be made between Word-Concept added Image-Attributes and unknown images. Figure 6 shows Example of DoA between image and concepts.
Figure 6: Example of DoA between image and concepts.

DoA is calculated between test image and Word-Concepts, and the Word-Concept with a large DoA value is regarded as the recognition result.

5.3 Result

Evaluation is performed by changing the number of VW. Number of test images is 1170 (10 test image prepared for each 117 Word-Concepts). Word-Concepts are sorted in descending order of DoA value. Table 5 and 6 shows evaluation result of each Integration method described in chapter 4.2. The percentage of correct answer that ranked in the top is shown “1st” column. In the same way, “2nd” and “3rd” column shows percentage of correct answer that ranked in the top 2 or 3.

Table 5: Evaluation result (average integration).

<table>
<thead>
<tr>
<th>Number of VW</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>13.08%</td>
<td>17.95%</td>
<td>21.28%</td>
</tr>
<tr>
<td>200</td>
<td>13.33%</td>
<td>18.80%</td>
<td>22.99%</td>
</tr>
<tr>
<td>300</td>
<td>13.59%</td>
<td>19.57%</td>
<td>23.33%</td>
</tr>
<tr>
<td>400</td>
<td>13.68%</td>
<td>18.89%</td>
<td>24.02%</td>
</tr>
<tr>
<td>500</td>
<td>14.96%</td>
<td>20.77%</td>
<td>24.19%</td>
</tr>
</tbody>
</table>

Table 6: Evaluation result (median integration).

<table>
<thead>
<tr>
<th>Number of VW</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>13.50%</td>
<td>18.46%</td>
<td>22.39%</td>
</tr>
<tr>
<td>200</td>
<td>14.10%</td>
<td>19.83%</td>
<td>23.68%</td>
</tr>
<tr>
<td>300</td>
<td>14.27%</td>
<td>20.77%</td>
<td>24.19%</td>
</tr>
<tr>
<td>400</td>
<td>13.33%</td>
<td>19.32%</td>
<td>23.16%</td>
</tr>
<tr>
<td>500</td>
<td>14.02%</td>
<td>20.09%</td>
<td>23.42%</td>
</tr>
</tbody>
</table>

The correct answer rate reached the highest level when the number of VW was set to 500 and integrated by average.

6 Conclusion

This paper describes a method of adding visual information called Image-Concept and Image-Attribute for Concept-Base. The proposed method added new Attributes (Image-Attribute) to the original concept (Word-Concept) by extracting BoF configured by rate of VW frequency from multiple images and integrating them.

As usage of Image-Concept and Image-Attribute, Object recognition was performed using DoA. DoA is calculated between test image and Word-Concepts, and the Word-Concept with a large DoA value is regarded as the recognition result. The correct answer rate reached the highest level when the number of VW was set to 500 and integrated by average.

Number of VW is used only from 100 to 500 in this trial, but the decline percentage of correct answer has not appeared as shown in Table 5. As a future subject, experiment is performed by changing the number of VW.

Acknowledgements

This work was partially supported by JSPS KAKENHI Grant Number 16K00311.

References


