

# A Deep Textual Searching for Visual Semantics of Personal Photo Collection with Hybrid Similarity Measure\*

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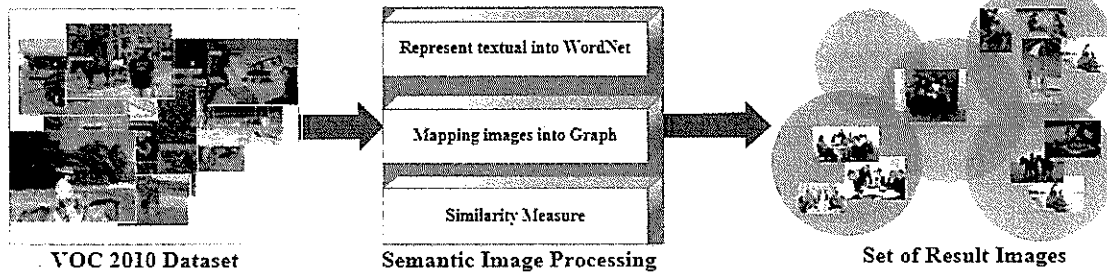
*Abstract*—In recent years, photos on the Internet or personal computers are the important contents for human's life. There are many automatic algorithms to retrieval effectively those photos but it still suffers from semantics accuracy. Researches have been studied to satisfy user demands for the semantic model semantics using set of features or keyword annotation technique which were textual contents but still challenging. Keyword in photos give the best evidence to identify what photos are. However, it does not always relate to the meaning of photos. For this reason, we propose a textual description with hierarchical concept and comparison of the feature set with hybrid similarity measure. The experimental results indicate that our proposed approach offers significant performance improvements in the interpretation of semantic meaning with the maximum of 80.4%

## I. INTRODUCTION

Personal photos are the most popular contents on media communication channels. According to taking photos quickly and easily, so the number of photos has increased rapidly. When people need to find a desired photo, they often search in photo collections, that is related to an event (a social event, or a personal event). The traditional methods to retrieve image data is the text matching between given a query-by-example paradigm. This method cannot present the semantic meaning of the images. Therefore, researcher has attempted to find the various methods to organize them closer to the user in mind. However, it is still challenging to extract real textual relationship from photo collections. Semantics of photos interpretation is not capable without some mechanism for understanding contents that are not directly visible.

Researchers had begun to combine textual descriptions and visual features into images. Dominant objects were manually annotated with the most relevant textual descriptions. Annotated textual descriptions (i.e, a keyword, or a simple sentence) in the database was compared against those descriptions to detect the specific keywords of the image. All kinds of objects are provided into semantic relations between queries and annotated images with human. Fan et al. [1] have proposed a semantic-sensitive framework for image content representation by using salient objects. The salient objects are defined as the connected image regions that are visually significant and maintain the dominant visual properties for the corresponding object classes. Some researchers have constructed more meaningful concept clusters of co-occurring keywords technique. For example, a user needs to find an image "a man resting on the beach". The irrelevant images that are labelled with a set of beach keywords are also returned. Jun Yang [2] has developed a prototype system iFind for image retrieval, which implemented a semi-automatic image annotation strategy. A set of keywords on the image is related to the semantic contents. A weight is assigned to each link to show the descriptive power of the corresponding keyword. Although, this research improved the accuracy, it still has a limitation that this method cannot consider words that have more than two kinds of sense (i.e, stone, rock, leopard, jaguar, and so on). iFind lacks to find the similarity between different words that is another problem posed by the richness of natural language, such as synonyms, polysemy and other complex word relevancy. In order to overcome this limitation, WordNet

Figure 1. Overview Visual Semantics of Personal Photo Collection



[3] has been applied to improve keyword sense for finding similarity between words. Hwang [4] has been studied to extract semantic similarities from titles of Wikipedia Documents and context information in abstract of documents. His researches show that WordNet has great potential to be a fundamental data for the semantic document retrieval system. Moreover, Cho [5] conducted different similarity measurement using annotated keywords based on WordNet networks for enhancing the accuracy of semantic image retrieval system. All these works have shown that considering controlled vocabularies, such as Ontologies, WordNet, for image annotation can open up new research directions to deal with these problems. The Model can be used to model the relations between terms and can provide a solution to deal with our issue. Therefore, we have proposed a novel framework to annotate the personal images using terms belonging to the hierarchical concept from WordNet. Graph theory is used to represent the visual image contents. The rest of paper is structured as follows. Section 2 describes the concept WordNet and describe theory for graph representation. Section 3, we present various semantic similarity measure depend on WordNet framework and hierarchical graph structure. The experimental results are described in Section 4. We conclude this paper in Section 5.

## II. PROPOSED VISUAL SEMANTIC PERSONAL SYSTEM

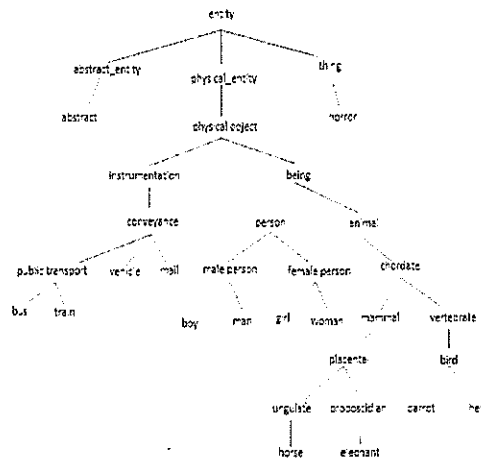
We first describe in our proposed system in four main steps: (1) representation the textual descriptions into electronic thesaurus WordNet. We select a set of personal photos from PASCAL VOC dataset [6] (2) create a feature and transform content into a graph structure, (3) comparison of the feature set with semantic similarity measure, and last step gives an

evaluation of the described semantic similarity measures as shown in Fig. 1.

### A. Mapping Contents into WordNet

The first thing to consider within the proposed approach of recognition is what information to use in an image content. Based on our observation, a semantic image is emerging from major contents and the association between object and environment. Each content has different types however some types possibly have similar semantics. For example, “parrot”, “hen” and “duck” are semantically analogous because they are also the same meaning of “bird animal”. This textual relation might be proven useful in the part of semantically related contents. Therefore, we have proposed a novel framework by using WordNet [3] concept that is related to PASCAL VOC dataset [6]. WordNet is an electronic thesaurus that contains over 80,000 noun synonym sets called synsets. A synset is a set of words from English language that is organized the concept of synset as a class of closely related synonyms representing the same word sense. There are various types of

Figure 1. Textual synsets with WordNet framework



semantic links among synsets, which constitute a highly interconnected network of synsets. Each words in WordNet has hierarchical relations. Following the idea of WordNet, we use a hierarchical network as the representation of the concept, shown in Fig. 2.

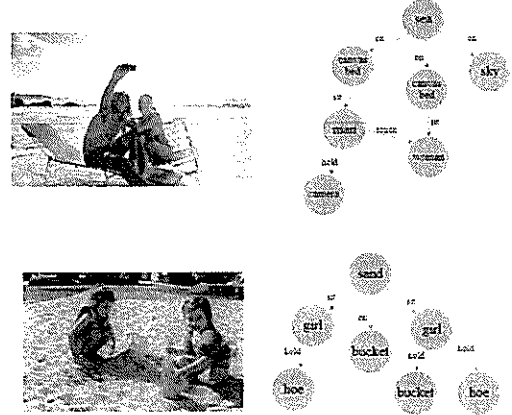
### B. Semantics Photo Representation into Graph Structure

In a photo collection, we define the representation of data collection with image ( $I$ ),  $I(x_1, \dots, x_i)$  where  $i$  is number of tuples in images. Each personal image is including many objects such as man, car, sky etc. We represent the images as an directed graph  $G(V, E)$  where  $V$  denotes the set of objects and  $E$  denotes the set of all relationships between any two objects in the graph. In order to define the novel graph classes and develop a graph similarity approach, we need some graph theoretical preliminaries. Let  $V \neq \emptyset$  be a set of vertices.  $G = (V, E), |V| < \infty$  is a finite directed graph where  $E \subseteq \binom{V}{2}$ .  $V$  is called the vertex and  $E$  is called the edge set. Let  $V \neq \emptyset$  be the set of vertices. We call  $G = (V, E), E \subseteq \binom{V}{2}, |V| < \infty$  a finite directed graph. Let  $G = (V, E)$ , be a finite directed graph and  $S = (\hat{V}, \hat{E})$ , be a subgraph of  $G$  that is  $\hat{V} \subseteq V, \hat{V} = \{v_1, \dots, v_n\}$  and  $\hat{E} \subseteq E, \hat{E} = \{e_1, \dots, e_m\}$ . Therefore, the graph is a collection of subgraphs for ease in browsing and retrieval. We denote the subgraph  $S$  of  $G$  with  $S \subseteq G$ . The  $S$  is induces subgraph of  $G$ . After that we show an example of how graph would be constructed for an image in Fig.3. Image is represented with 6 objects that is including man, woman, canvas bed, sea, and sky. The edges contain a set of relationships among objects such as hold, on, touch. We also formulate a semantic similarity measure to finding of actual images in next section.

### III. SEMANTIC SIMILARITY MEASURE CATEGORIES

Several techniques of determining the classification of similarity measures have been proposed in the literature [6]. Therefore, we are classified similarity measure into three main methods including (1) edge counting, (2) information content and (3) hybrid method.

Figure 3. Example of graph representation with textual contents.



#### A. Edge counting method

Shortest path [7] is simple and powerful measure in edge counting method that is measure the similarity between two terms as a function of the length of the path linking the terms and on the position of the hierarchical terms in the taxonomy. Let be  $c_1$  and  $c_2$  two concepts for which, the similarity measure in hierarchical structure can be formulated as follows:  $Sim(c_1, c_2) = 2 * Max(c_1, c_2) - \rho$ , where  $Max$  is the maximum path length between  $c_1$  and  $c_2$  in the taxonomy and  $\rho$  is the shortest path relating concepts  $c_1$  to concept  $c_2$ .

#### B. Information content method

Information content (IC) method [7] is another measure that use the information content of concepts to measure the semantic similarity between two terms. Information content is computed according to RIK and JNC measure.

- Resnik Measure (RIK) is IC concept that uses information content to get the probabilities of each concept and computed how many times the concept appears in the Corpus. Let  $freq(c)$  defines  $\sum_{c_i \in R} count(c_i)$ , where  $\in$  stand for subsuming relationship, to get the frequency of word  $c$ , it summations all the count of each word  $c_i$ , which is subsumed by word  $c$ . Next, the probabilities of each concept are calculated by the following relative frequency. The formula is  $Prob(c) = freq(c)/N$ . So, the IC of concept  $c$  can be computed by taking negative logarithm of relative probability. Second, RIK calculates IC of a concept by taking the negative

TABLE I. COMPARING EXPERIMENTAL RESULTS OF RECALL (%) WITH SHORTEST PATH, RIK, JNC, AND KNAPPE MEASURES.

Categories	Performance (%)											
	Shortest path			RIK			JNC			Knappe		
	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall	F1
leisure	69.9	65.0	67.4	73.5	75.0	74.3	70.5	74.0	72.2	83.0	78.0	80.4
office	70.9	73.0	71.9	78.8	78.0	78.4	76.0	73.0	74.5	78.4	76.0	77.2
ceremony	67.0	67.0	67.0	70.5	67.3	68.8	81.8	72.0	76.6	79.8	82.2	81.0
sport game	67.3	68.0	67.7	78.2	79.0	78.6	72.6	77.0	74.8	81.6	84.0	82.8
family time	67.0	69.0	68.0	67.0	69.0	68.0	71.4	75.0	73.2	79.6	82.0	80.8
<b>Accuracy</b>	<b>68.4</b>			<b>73.5</b>			<b>74.2</b>			<b>80.4</b>		

logarithm of probability. Finally, semantic similarity between two concepts will be calculated as follows:  
 $IC(\text{concept } c) = -\log(\text{Prob}(c))$ .

- Jiang and Conrath Measure (JNC): JNC measure's performance is the best among other similar measures. JNC calculated from the same notion of the  $IC$  and takes into account the distance between selected concepts as follows:  $Sim(c_i, c_j) = 1/[IC(c_1) + IC(c_2) - 2 * IC(lcs(c_1, c_2))]$ , where  $lcs(c_1, c_2)$  is the IC value of lowest common subsumer between two concepts  $lcs(c_1, c_2)$ . RIK measure only consider the information content of subsuming word. JNC combines node-based and edge-base approach therefore similarity between  $c_1$  and  $c_2$  is difference.

#### IV. HYBRID METHOD

Knappe R. [8] defines a good similarity measure. This technique combines the above ideas that using the information of generalization and specification of two compared concepts. The measure expression is formulated as follows:  
 $Sim(c_i, c_j) = p * |\varphi(c_1) \cap \varphi(c_2)| / |\varphi(c_1)| + (1 - p) * |\varphi(c_1) \cap \varphi(c_2)| / |\varphi(c_2)|$ , where  $p$  is value in  $[0,1]$  which determines the degree of influence of generalization. The  $\varphi(c_1)$  and  $\varphi(c_2)$  correspond to description sets of  $c_1$  and  $c_2$ .

#### V. EXPERIMENTAL RESULTS

In our experiments, the dataset used in this paper is downloaded from PASCAL VOC dataset [6]. We manually selected 950 personal images for training and 1,200 validation images which used for testing. Each image contains dominant

objects and each object is annotated as belonging to one of the WordNet defined classes. Sample images are shown in Fig.1(c). In this works, we focus on images of 5 categories: outdoor leisure, office working, ceremony, sport game and family time. The evaluation of the accuracy of similarity measure described above. We occupy shortest path, RIK, JNC, and Knappe as the measurement tool. To evaluate the method, precision, recall, f-measure and accuracy [9] are applied.

For our tests, we consider the method with four measures show the experimental results in Table 1. The average accuracy of Shortest path provides only 68.4% because this measure is designed to compute with only the concept of hierarchical structure. RIK and JNC measure are extension of Shortest path with set of information contents. The results of ceremony category in RIK can achieve the better precision of 70.5% when the ceremony category in JNC gains up to 81.8%. JNC is similar manner as RIK but JNC measure is insight to the shortest path length between  $c_1$  and  $c_2$  and the density of concepts along this same path. Knappe seems the suitable measure since it can produce the highest average accuracy of 80.4%, compared to 68.4%, 73.5%, and 74.2% for Shortest path, RIK, JNC. We are concluded that, the accuracy of Knappe measure is suitable for searching in hierarchical structure in the semantics of personal photo collections. In the future, we would like to find relationship parameter in similarity measure algorithm.

#### V. CONCLUSION

In this paper, we have presents a novel technique for deep searching in the semantic personal images. The major information contents are using relationship of textual synsets

from electronic thesaurus WordNet. Then, the personal images are comparing the performance with hybrid similarity measure. The results indicated that proposed method offers a good interpretation to the semantic personal images. This represent technique is an important method for apply to the photo searching system and other electronic digital library systems. Fig.4 shows a representative set of semantic personal image

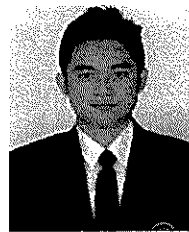
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Figure 4. The example of personal photos in each category. (a) leisure; (b) office; (c) ceremony; (d) sport ge; and (e) family time.



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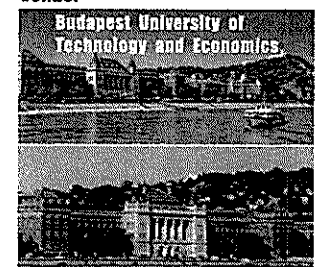
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