# Information Retrieval by Image Recognition Using Ontology Mapping with Neural Networks

Sooksawaddee Nattawuttisit and Sasiporn Usanavasin

***Abstract*—** To expand ontology meanings, an effective ontology mapping approach is needed to map related or similar knowledge from heterogeneous sources together. Especially, the mapping approach also can be applied to support image recognition in order to enhance its retrieval information. In this paper, we propose the ontology mapping with back propagation method to learn image objects, and link to their personal information to increase the completeness of user inquiry. In our approach, we adopt the multilayer feed-forward neural network couple with back propagation algorithm to learn the image patterns, store their similarity values, check and map with target images, and link to their target information from knowledge domains at the final process. Our experiments clearly present the accuracy of overall testing which can reach to 81.3%.

***Keywords*—** Ontology Mapping, Image Recognition, Neural Networks, OMNN-IMAGE.

## I. Introduction

THE Semantic Web and search engines nowadays have become widely used in several domains to support intelligent systems. One of the advantages in ontology mapping implementation is to interpret formal images, understand the meanings or meaningless of those images, and link their concepts to retrieve complete information from vast heterogeneous sources quickly.

By using neural network technique in our mapping approach, it can automatically compute and recognize the similarity of images, and classify them from similar meanings of ontology sources together. Therefore, it gains improving the accuracy of mapping results [1], [2]. In this paper, we also use the back propagation algorithm [3], [4], [5], [6] to train weights so it can recognize the image mapping between ontologies.

In this paper, we therefore propose an enhanced ontology mapping approach which we integrate on the top of neural networks to retrieve mapping images information efficiently. The main contribution of our approach is to link mapping query images to their target information from ontology sources (knowledge domains) to fulfill the completeness of users' retrieval information on the basis of a mapped concept meaning.

Section 2 discusses literature reviews of related works. Section 3 discusses about the problem overview. Our OMNN-IMAGE approach and the experimental results are provided in Section 4 and 5 respectively. Finally, a conclusion is given in section 6 with future works for next generations.

Sooksawaddee. Nattawuttisit is with the Information Science Institution, Sripatum University, Bangkhen, Bangkok, 10540, Thailand, phone: (+66) 863878908; fax: (+66) 26417448; email: joe_telemagic@yahoo.com

Sasiporn. Usanavasin is with Thammasat University, Sirindhorn International Institute of Technology, School of Information, Computer, and Communication Technology (ICT), Bangkadi, Muang Pathum Thani, 12000, Thailand, email: sasiporn.us@siit.tu.ac.th

## II. Related works

M. Mao, Y. Peng, and M. Spring [7] propose a neural network based constraint technique to improve the accuracy results as well as the performance of Ontology Mapping. However, it has some limitation on complex constraints, and needs weight optimization to improve its efficiency.

G. Forestier, et al. [8] propose the building steps of a knowledge-base of urban objects allowing to perform the interpretation of HSR images in order to help urban planners to automatically map the territory. The knowledge-base is used to assign segmented regions into semantic objects. A matching process between the regions and the concepts of the knowledge-base is proposed, allowing to bridge the semantic gap between the images content and the interpretation. The results highlight the capacity of the method to automatically identify urban objects using the domain knowledge.

V. Stefanos, et al. [9] propose a framework that encompasses advanced image analysis and indexing techniques to address the need for content-based patent image search and retrieval. The proposed framework involves the application of document image pre-processing, image feature and textual metadata extraction in order to support effectively content-based image retrieval in the patent domain.

V. Nebot, Victoria, and R. Berlanga [10] present mining association rules from semantic instance data repositories expressed in RDF/(S) and OWL to derive appropriate transactions which will later feed traditional association rules algorithms. This process is guided by the analyst requirements, expressed in the form of indexing patterns. They experimentally performed on semantic data of a biomedical application show the usefulness and efficiency of semantic indexing approach.

## III. Problem overview

From literature review, many researchers have introduced several mapping approaches based content matching [11],

[12], [13]. However, this mapping methodology still has limitations to identify image objects or related image information with annotation keywords [14]. Nowadays, the increasing availability of multimedia based on image resolution is an opportunity to characterize and identify knowledge objects. Thus, the augmentation of the precision led to a need of image mapping using image-based approaches [15]. In this paper, an important challenge is the use of domain knowledge for image identification, and the accuracy and performance of mapping results from the machine learning techniques [16] greatly classify a quality of defined a major formalization and exploitation from the domain knowledge. [17], [18].

## IV. OUR APPROACH

Based on the problems overview, we propose our new approach called OMNN-IMAGE system. It uses a multilayer feed-forward neural network with back propagation method to recognize images, and use ontology mapping to relate their related information. Our main concept is for object categorization to classify source images represent the same ontology concepts by degree of similarity values, and associate them with related information in corpus library at the final process. In this section, it consists of four sub-section which describe 1) Learning Patterns; 2) The samples of ontology concepts; 3) The structure of multilayer feed-forward neural network; 4) OMNN-IMAGE process

1) *OMNN-IMAGE model* – The OMNN-IMAGE system design is for our ontology mapping based pattern recognition process. The model is enhanced from Ontology Based Object Categorization system (OBOC) [19] to enable the use of ontologies for object categorization for autonomous system.

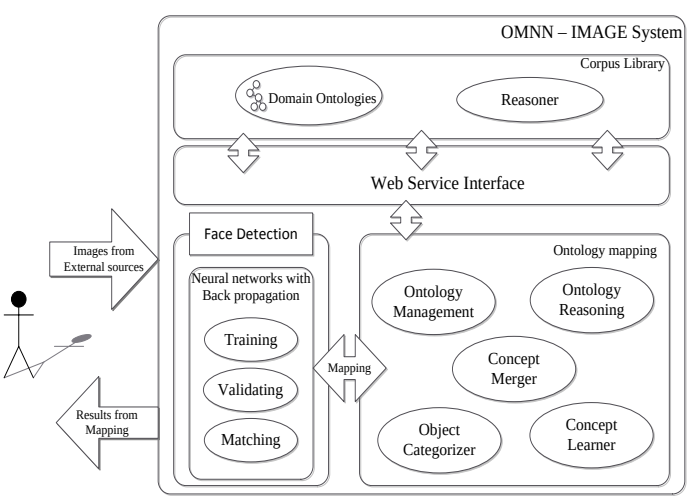


Fig. 1 The Model of OMNN-IMAGE System

2) From OMNN-IMAGE model, There are five modules as shown in Fig. 1. Each module has its own process which is described in sub-section A - E respectively.

*A. Object Categorizer*

The object categorizer is an internal part of OMNN-IMAGE perception system and it is responsible for categorizing objects based on concept names, object properties, and instance values.

*B. Ontology Management*

Manage and communicate ontology aspects (names, properties, relations, and instances) between source and target ontologies as well as relate mapping images which come from detection module to domain ontologies for additional information.

*C. Ontology Reasoning*

Performs queries on the ontology using reasoning services of a third party component racers, located on a server. The queries performed will determine whether a recognized image objects or a set of categorized concepts can be categorized as a defined concepts in the ontology.

*D. Concept Learner*

Queries the ontology for categorized concepts to infer identifiable properties and features of the object that it represents. For example, if the concept learner is provided with the concept name "Presonal_name" then it will access the ontology management entity to query about the properties of that specific concept.

*E. Concept Merger*

It is responsible for identifying semantic relationships between concepts. Given multiple ontologies and concept names it determines which concepts refer to the same object based on common properties and restrictions. This can allow heterogeneous systems to communicate about the same objects.

3) *Image recognition with Back propagation* – We construct Two-layer neural network structure which consists of an input layer *i* with 3 neurons, one hidden layer *j* with 3 neurons, and output layer *k* with 3 neurons, and use back propagation method for pattern learning. The structure is as shown in Fig. 2.

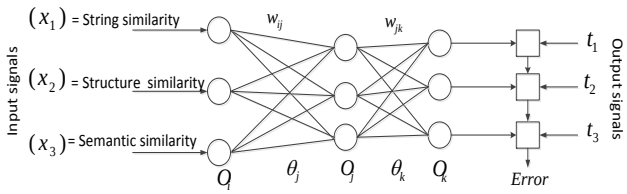


Fig. 2 Two-layer Feed-Forward Neural Network Structure

TABLE I
THE TERMINOLOGY OF TWO-LAYER NEURAL NETWORK

| | |
|---|---|
| $x_i$ | Neuron units at input layer *i* (consists of $x_1$ = String similarity, $x_2$= Structure similarity , and $x_3$= Semantic similarity) |
| $w_{ij}$ | The weights between input layer *i* and hidden layer *j* |
| $w_{jk}$ | The weights between hidden layer *j* and output layer k |
| $o_i$ | The output value from neuron at input layer *i*. |
| $o_j$ | The output value from neuron at hidden layer *j*. |
| $o_k$ | The output value from neuron at output layer *k*. |
| $t_1 - t_3$ | The target values. |
| $\Theta_j$, $\Theta_k$ | The biases for all network neurons at hidden layer j and output layer *k* respectively. |

There are five processes of image pattern recognition in OMNN-IMAGE system which classify the matched image, and send to ontology management module to retrieve the related information. These patterns are used to supervise the network to recognize the images as shown in Fig 3.

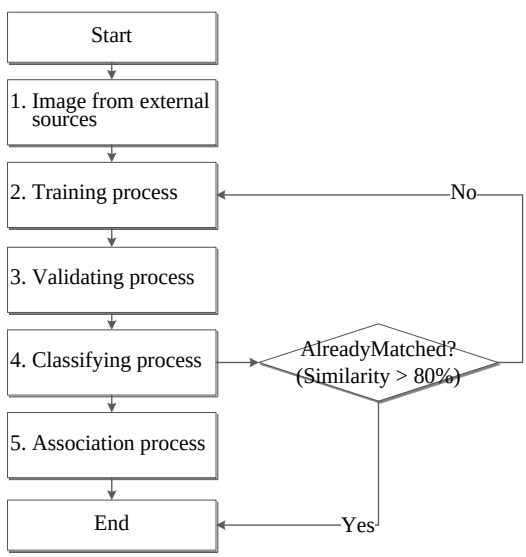


Fig. 3 The Process Flow of OMNN-INDEXING

*3.1 Loading process* – This process is for loading image from external source into the system.

*3.2 Training process* - The training process uses the backpropagation method for supervising the neural network to learn our patterns with training data sets. During the process, the weights will be adjusted and updated so as to minimize the errors between targets and the actual outputs by comparing the value of mean square error (MSE). The modifications are processed in the backward direction. It iteratively runs until the errors are minimized, and met with our "Stop" condition (as we set the value of MSE $\leq$ 0.001). Then, it will stop, and continue to the validating process (fine-tune purpose). The algorithm below is shown for the training process.

**Algorithm: Back propagation**
**Setup Two-Layer Feed Forward Neural Network**

- Set No. of Input Neurons =3 ($i$ = 3);
- Set No. of Hidden Neurons= 3 ($j$ = 3);
- Set No. of Hidden Layer = 1;
- Set No. of Output Neurons= 3 ($k$ = 3);
- *D*, a data set of training inputs
- Set initial learning rate $\eta$ = 0.2;
- Set initial momentum rate $\alpha$ = 0.1;
- Set MSE $\leq$ 0.001

**Method:**

(1) Initialize all weights and biases in network;
(2) **while** terminating condition is not satisfied {
(3) **for** each training set *D* {
(4) // Propagate the inputs forward:
(5) **for** each input layer unit *j* {
(6) $O_j = I_j$; //output of an input unit is its actual input value
(7) **for** each hidden or output layer unit j {
(8) $I_j = \sum_i w_{ij} O_i + \theta_j$; //compute the net input of unit *j* with respect to the previous layer, *i*
(9) $O_j = \frac{1}{1+e^{-I_j}}$;} //compute the output of each unit *j*
(10) //Backpropagate the errors:
(11) **for** each unit *j* in the output layer
(12) $ERR_j = O_j(1-O_j)(T_j - O_j)$; //compute the error
(13) **for** each unit *j* in the hidden layers, from the last to the first hidden layer.
(14) $ERR_j = O_j(1-O_j)\sum_k ERR_k w_{jk}$ ; //compute the error with respect to the next higher layer, *k*
(15) **for** each weight $w_{ij}$ in network {
(16) $\Delta w_{ij} = (l) ERR_j O_i$ ; // weight increment
(17) $w_{ij} = w_{ij} + \Delta w_{ij}$ ; } // weight update
(18) **for** each bias $\theta_j$ in network {
(19) $\Delta\theta_j = (l) ERR_j$ ; //bias increment
(20) $\theta_j = \theta_j + \Delta\theta_j$ }; //bias update
(21) }}

*3.3 Validating process* - This validating process is the same as training process, but we use validation samples. During this process, the network will be fine-tuned by learning some noisy patterns from the validation samples. The purpose is to prevent the performance dropping from overtraining in training process. When the output error is met on terminating condition, this process will stop and continue to matching process.

*3.4 Classification process* - This matching process is similar to training process. However, we use actual testing data sets for matching. This process uses feed-forward part, and learned weights (without back propagate error steps) by repeating the steps from 4 – 9. The outputs from this matching process will be matched with the given

patterns. As a result, we will get four groups of similarities which are categorized by similarity degree for high, medium, low, and dissimilarity (not including the error ones which patterns the system cannot recognize).

*3.5 Association process* – This process use ontology reasoner to logically infer and determine the semantic relationship between two matching concepts and related their information from domain ontologies in corpus library. This is a final process which system can retrieve related information from two concepts actually represent the same objects with high capabilities. For example, we can model T-Box in this following statement.

**T-Box in statement**

Mr_A_Face = ∃ hasColor.(White) ⊓ hasComponent. (ShortHair ⊓ OvalFace)

**Element: Face**

Color1: White ≥ 0.98

Component1: ShortHair ≥ 0.80

Component2: OvalFace ≥ 0.89

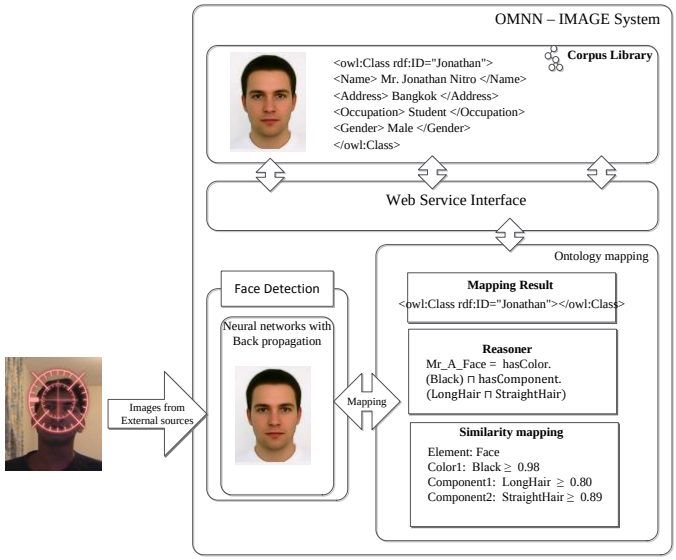


Fig. 4 The Data flow of OMNN-IMAGE system

## V. THE EXPERIMENTAL RESULTS AND EVALUATION

In the MATLAB environment, we configure two layers of feed forward neural network with backpropagation method. The initial weights are in the range from -1.0 to 1.0, and set the parameters for the learning rate (η) to 0.2, the momentum rate (α) = 0.1, the mean square error (MSE) = 0.001. We use training samples totaling 1,000 ontology concepts, and divided them into 70% for training, 10% for validating, and 20% for testing.

From the analysis, we get the results from the MATLAB output files which show the accuracy of overall testing can reach to 81.3% as it is shown in Fig. 5.

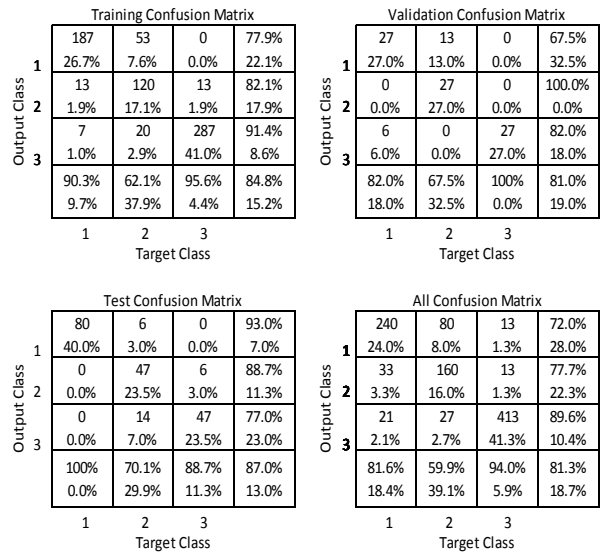


Fig. 5 The Results from MATLAB Confusion Matrix Table

The system can match most of our testing samples with the recognized patterns. There are 174 out of 200 concept pairs which output and target are matched correctly from the system. However, we checked from the MATLAB output files, we found 9 pairs are in misclassified regions. 6 of them should be in "High" degree of member groups, but they fall into "Medium" group. The others (3 pairs) should be in "Low", but it fell into "Medium" group. Hence, there are only 165 images which are correct mapping.

After mapping completion, an ontology concept which represents the right image object class will be checked with domain ontology to relate its information which is in corpus library database, and it therefore will be stored as a linkage with their Uniform Resource Identifier (URI) as a final step. The examples of information stored in database table are given in Table II.

TABLE II
THE EXAMPLES OF SIMILARITY INDEXING TABLE

| No. | Source | Target | Similarity Levels | Ontology Source URI | Ontology Target URI |
|---|---|---|---|---|---|
| 1 |  |  | High | #Antony | #Antony, Phille |
| 2 |  |  | Medium | #Bird1 | # Bird1_in_Beach1 |
| 3 |  |  | Medium | # Bird1_Dog1 | #Dog1 |
| 4 |  |  | Low | #Bird1 | #Bird1_Dog1 |
| 5 |  |  | Dissimilarity | #Bird_in_Beach1 | #Beach1 |

TABLE III
THE EXAMPLES OF SIMILARITY INDEXING TABLE

| No. | Target | Ontology Target URI | Related information from Corpus Library |
|---|---|---|---|
| 1 |  | #Antony, Phille | <owl:Class rdf:ID="Jonathan"><br><Name> Mr. Jonathan Nitro </Name><br><Address> Bangkok </Address><br><Occupation> Student </Occupation><br><Gender> Male </Gender><br></owl:Class> |
| 2 |  | #Bird1_2 | <owl:Class rdf:ID=" Bird1_in_Beach1"><br><Name> Parrot </Name><br><Location> Island </Location><br><Color1> Blue </Color1><br><Color2> Red </Color2><br></owl:Class> |
| 3 |  | #Dog1_3 | <owl:Class rdf:ID="Dog1"><br><Name> Brownie </Name><br><Location> Bangkok </Location><br><Color> Brown </Color><br><Size> Small </Size><br></owl:Class> |
| 4 |  | #Bird1_Dog1 | <owl:Class rdf:ID="Bird1_Dog1"><br><Name> Miggy </Name><br><Location> Bangkok </Location><br><Color1> Brown </Color1><br><Color2> Black </Color2><br></owl:Class> |
| 5 |  | #Beach1 | <owl:Class rdf:ID="Beach1"><br><Name> Phuket beach </Name><br><Location> Thailand </Location><br><Color1> Blue </Color1><br><Tree1> Coconut tree </Tree1><br></owl:Class> |

## VI. CONCLUSION

In this paper, we propose the idea of ontology mapping based on image contents which is particularly designed to enhance the context of information retrieval capabilities and support fast query response for future multimedia applications. From our experiment, we do prove of our concept by using the MATLAB simulation. However, it is not every image in the real world that is totally different. Some are quite similar. This leads to improper matching to the system. For future works, we will develop more logic for DL system to determine classify the ambiguous images in order to prevent the limitation above, and increase high performance of ontology based image content mapping.

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**Sooksawaddee Nattawuttisit** An 8th semester student pursuing Doctor of Philosophy in Information Technology at Information Science Institution of Sripatum University (ISIS), Bangkok, Thailand.

**Dr. Sasiporn Usanavasin** A director of Master of Science Program in Software Engineering at Thammasat University, Sirindhorn International Institute of Technology, School of Information, Computer, and Communication Technology (ICT), Bangkadi, Muang Pathum Thani, 12000, Thailand.