Ontology-guided Approach to Retrieving Disease Manifestation Images for Health Image Base Construction

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***Abstract*—Building a comprehensive medical image database, in the spirit of the UMLS, can be beneficial for assisting diagnosis, patient education and self-care. However, a highly curated, comprehensive image database is difficult to collect as well as to annotate. We present an approach to combine visual object detection technologies with medical ontology to automatically mine web photos and retrieve a large number of disease manifestation images with minimal manual labeling. Comparing to a supervised approach, our ontology-guided approach reduces manual labeling effort to 1/10 on a variety of eye/ear/mouth diseases and improves the precision of retrieval by over 10% in many cases.**

I. Introduction

Medical knowledge captured in visual format is important, but much less explored than textual knowledge. Our long-term goal is to build a freely accessible, large scale and patient-oriented health image base, consisting of images of human disease manifestations, organs and drugs. Unlike existing databases, we build our image base on the backbone of the UMLS [1] and annotate images using standard medical ontologies. A challenging problem is to collect high-quality images to accurately illustrate the concepts behind tens of thousands of medical terms. Our previous work used the bootstrap method [2] to collect organ and drug images, but has limited precision on disease images. In this work, we present an ontology-guided image retrieval method to collect disease images from the web. Compared to a standard supervised method that requires labeled training data for each disease, we achieve higher precision while reduce manual effort to a minimum using pre-trained *body part detectors*.

II. Approach

First, given a disease term such as “Ascher’s Syndrome,” a raw collection of images from the web is retrieved. Next, human body part locations of the disease such as eyelid and lip, are found using the UMLS semantic network relationship of “has_finding_site.” Such body parts lead to commonly associated body parts shared across many diseases which are captured in the *body part detectors*. Then the initial collection of raw images are scanned by selected body part detectors, which are pre-trained with histograms of oriented gradient (HOG) [3] image features, to find relevant body parts at three scanning window scales. Finally, the scanning results of all detectors are combined into high level features to classify the raw image set as relevant or irrelevant. Only the relevant images are retained as illustrative of the input disease term.

Table I
Performance on Ten Eye/Ear/Mouth Disease Image Test Sets.

Disease images	Ontology-guided Method			Supervised Classification		
	P	R	F1	P	R	F1
Diseases of eye	0.791	0.716	0.742	0.762	0.777	0.768
Diseases of Ear	0.807	0.639	0.705	0.797	0.699	0.736
Diseases of mouth	0.842	0.501	0.624	0.779	0.841	0.807

Table II
Performance Comparison on Two Complex Disease Test Sets.

Disease images	Ontology-guided Method			Supervised Classification		
	P	R	F1	P	R	F1
Hand, foot and mouth disease	0.833	0.714	0.769	0.694	0.775	0.733
Ascher’s Syndrome	0.889	0.857	0.873	0.786	0.943	0.857

III. Results and Conclusion

The ontology-guided method was evaluated and compared with a standard supervised method on two kinds of test sets: 1) images of multiple diseases located on the same body part, and 2) images of diseases that locate on more than one body parts. Precision, recall and F1 measure of our method in the two tests are shown in table I and II, respectively. Table I shows that the average precisions of our image retrieval method are comparable to those of the supervised method, though our method only need one tenth of the manual labeling effort. Table II shows that for complex diseases that span multiple body parts, our method outperforms the supervised method in precision. Overall, our method achieves precisions between 70% and 90%. The resulting health image database is annotated by terms from standard medical ontologies and will enable the construction of a rich information source.

References

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