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A hybrid image retrieval system for microscopy images

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Scientific literature provides the authoritative data source for most scientific fields. Numerous microscopy images rich in information, in particular, are contained within scientific publications. The retrieval of these imaging data currently requires a keyword search and labor-intensive human reading of individual articles. An efficient image retrieval tool would be significantly beneficial for researchers.

Information retrieval [5] engines have been widely used for searching scientific articles with one or a few keywords. However, such tools are not accurate and efficient for image retrieval because images in scientific literature are not always well labeled by textual description. To this end, we propose a hybrid image retrieval tool to retrieve images from scientific literature. In the proposed system, we take advantage of recent progress in content-based image retrieval approaches [4, 8, 9, 10], which directly measure the similarity between images by encoding images into fix-length feature vectors. Specifically, the proposed image retrieval system uses both the content of images and textual information (extracted from the image or given from the user) for image retrieval. First, keywords provided by the user are fed into the Image Acquisition Module, which selects relevant articles from different journals and extracts candidate images to build the database. Then both the query and all the images in the collected database are fed into the Image Analysis Module, which encodes the content of images into feature vector and extracts important textual information from the images. Finally, we compute the distance between the query image and the images in the database with both visual information and texture information and retrieve the most similar ones.

More details about the proposed image retrieval system are shown in Fig. 1. With the keyword provided by the user (e.g. “nano”), we apply the EXSCLAIM! [1, 2] Pipeline to search relevant scientific articles from journals (e.g. Nature, ACS family) and extract microscopy images (e.g. ~64k) as candidate images to build the database. Then we build the image analysis module with an off-the-shelf feature extractor [3, 4] and a scale bar detector [6, 7]. The feature extractor encodes the content of the image into a 2048-d feature vector and the scale bar detector detects the scale bar information from each image. As shown in Fig. 2, we first sort the candidates with the visual distance (e.g. cosine distance between feature vectors) between images and then use the scale bar information to re-rank the candidates.

As future work, caption information will be included in the hybrid image retrieval system, since authors tend to include essential description in the caption. For materials imaging data, retrieving images with only the content of the image is not sufficient to give confident results. Different materials may look visually similar in a certain scale. In this paper, we use scale bar information to eliminate the candidates that are measured in a different scale, but it could fail in case when scale bar information is not available in the image. Thus, incorporating the information from the captions could provide extra information to improve the performance of the image retrieval system.

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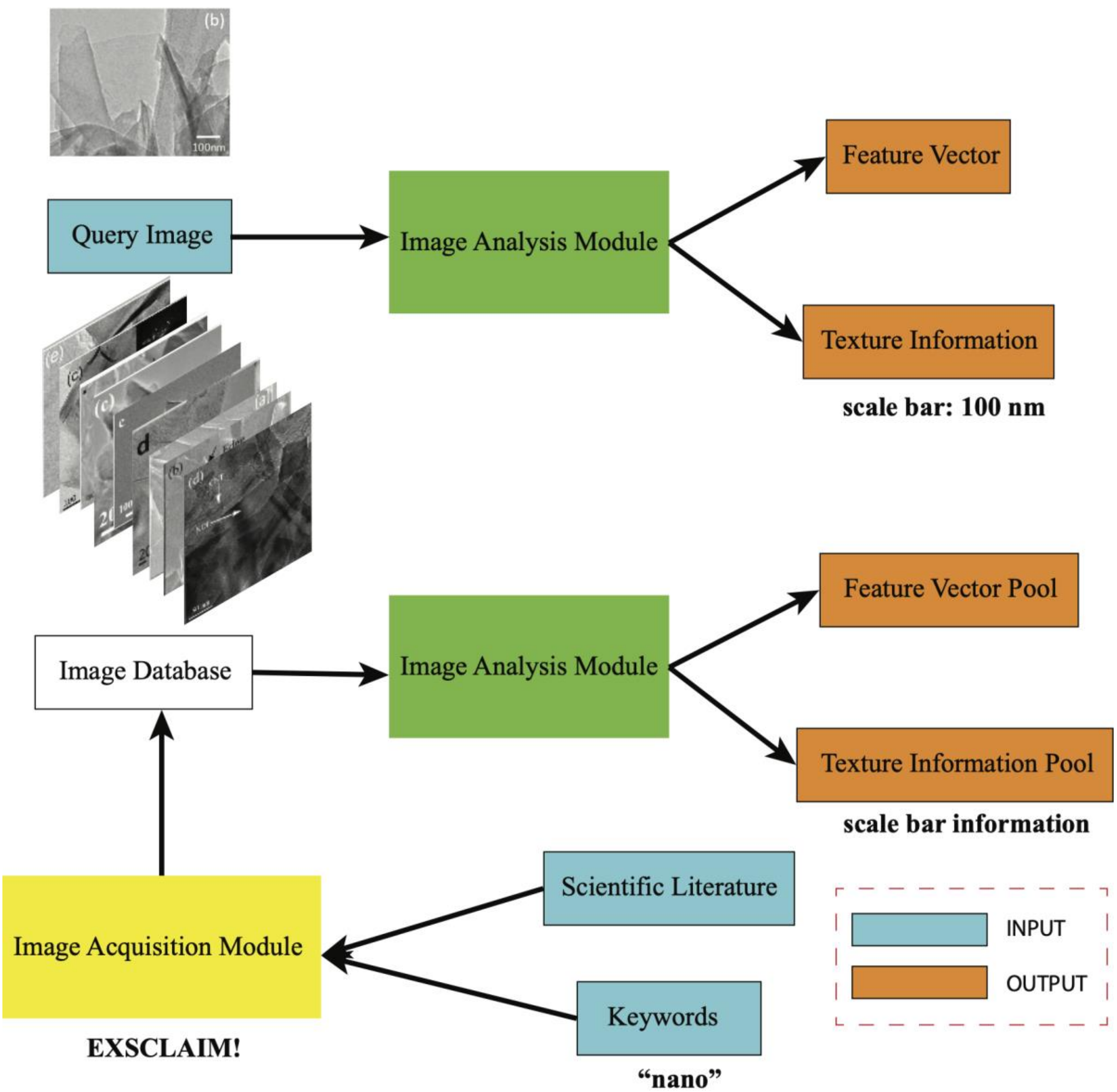

Figure 1. The pipeline of the proposed image retrieval system.

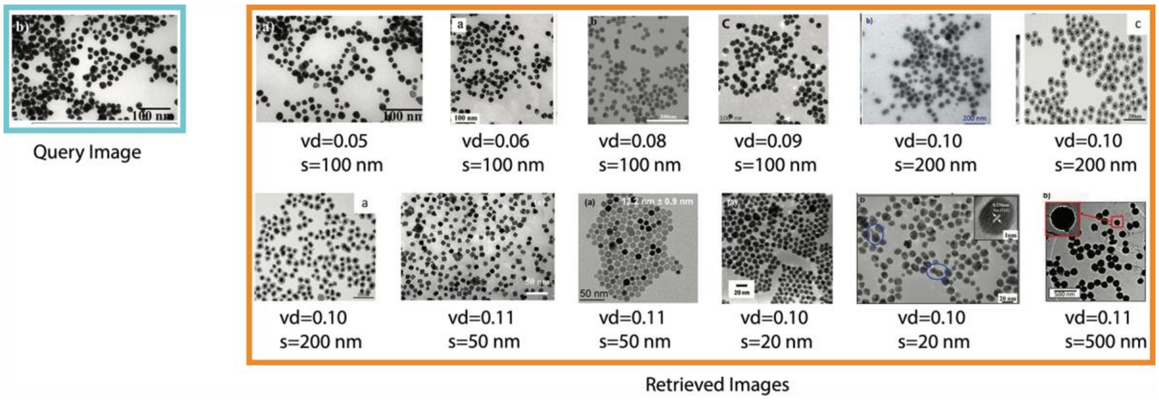

Figure 2. An example of the image retrieval system. "vd" and "s" denotes the visual distance and scale bar label, respectively.

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