International Journal of Applied Engineering Research ISSN 0973-4562 Volume 14, Number 6 (2019) pp. 1259-1264

Novel Image Label Indexing Approach to Explore Efficient Medical Image Retrieval

[1]Shaik. Jakeer Hussain, [2] Dr. R. Kiran Kumar

[1] Research Scholar, Department of Computer Science, Krishna University, Machilipatnam, A.P., India.
[2] Assistant Professor, Department of Computer Science, Krishna University, Machilipatnam, A.P., India.

Abstract

Medical imaging is a aggressive concept of different medical concepts i.e cancer and other related diseases, present days, different types of medical images are captured and stored in digital format in medical research centers. Facing this type of large volume of image data with different types of image modalities, it is very important to implement efficient content based image retrieval (CBIR) for medical research centers. Image label indexing is another implemented procedure for medical image retrieval. Conventionally different types of CBIR approaches are proposed to provide unsatisfied medical image retrieval results. So that in this paper, we propose a Novel Unsupervised Label Indexing (NULI) approach to retrieve labels of images using machine learning terminology. We define machine learning as matrix convex optimization with cluster based matrix representation which can be used to improve the efficiency in image retrieval system. We define an empirical study on different types of medical image data sets, in that our proposed approach gives better results using search based image annotation (SBIA) schema. Our experimental results gives boosting performance significantly compare with existing approaches.

Keywords: Image retrieval, search based image annotation, label indexing, machine learning, label refinement and convex optimization.

I. INTRODUCTION

The issue of finding comparative medical pictures in a large volume of image data store in light of substance is called Content Based Image Retrieval (CBIR) [1]. The conventional Text Based Image Retrieval (TBIR) approach has numerous pragmatic impediments [2] like the medical pictures in the accumulation being clarified physically, which turns out to be more troublesome as the extent of the medical picture gathering increments. Another essential confinement is the insufficiency in speaking to the medical picture content. CBIR approaches are proposed to defeat the impediments of content based medical picture recovery. As an ever increasing number of doctor's facilities buy medical picture archiving and communication systems (PACS), the therapeutic symbolism worldwide is progressively gained, exchanged and put away carefully [3]. The expanding reliance on present day therapeutic symptomatic procedures like radiology, histopathology and modernized tomography has prompted a blast in the quantity of restorative medical pictures put away in doctor's facilities. Advanced medical picture recovery system is vital in the rising field of restorative medical picture databases for clinical basic leadership process. It can recover medical pictures of comparative nature (like same methodology and sickness) and attributes. The medical pictures of different modalities are turning into an essential wellspring of anatomical and utilitarian data for the analysis of ailments, medicinal research and instruction [4]. In a hybrid CBIR framework in therapeutic space, unobtrusive contrasts between medical pictures can't be viewed as unessential. Subsequently, a Content Based Medical Image Retrieval (CBMIR) framework having a sort of in variance (as for any change) is of esteem [5, 6]. The real constraints related with existing restorative CBIR are (1) as a rule, doctors need to peruse through a substantial number of medical pictures for distinguishing comparable medical pictures, which takes parcel of time. (2) Most of the current apparatuses for looking restorative medical pictures utilize content based recovery procedures. The content based medical picture recovery experiences a few impediments [7], for example, the requirement for manual explanation. Therefore, the current therapeutic medical picture hunt and recovery methods are not exceptionally proficient as far as time and precision. Another critical issue in therapeutic CBIR is to discover medical pictures with comparable anatomical areas and infections. For instance, in the instance of mind tumor medical pictures, the tumor can be at any of the diverse stages and a medical picture of the tumor in a state could be in any introduction [6, 2]. Along these lines, there is a requirement for invariant restorative medical picture recovery procedure to discover medical pictures of a comparable (same stage) tumor.

Several types of approaches relate to machine leaning approaches were introduced to provide efficient image retrieval from medical image sources. Image annotation is a beneficial concept for real time applications, for example different medical research detection of approximate matched images relevant to input query image. Image annotation is a better concept to retrieve approximate image related to input query image. Traditional image annotation approaches were introduced but they are supervised machine learning approaches and time consuming to collect different types of label images from large image data sets.

Lately, some growing research has tried to explore an appealing search-based annotation design for facial medical picture annotation by exploration the World Extensive Web (WWW), where a large number of weakly marked facial images are easily available. Instead of coaching explicit classification designs by the standard model-based image annotation methods, the search-based image annotation (SBIA) design is designed to deal with the computerized face annotation process by taking advantage of content-based medical picture retrieval (CBIR) techniques. The main objective of SBIA approach is to arrange correct names labels to input medical image. In particular, given a novel medical image for annotation, we first recover a narrow your search of top K most identical medical medical pictures from a weakly marked medical image data source, and then annotate the medical medical picture by performing voting on appearance associated with the top K similar medical medical pictures. To access these features in image retrieval from different medical image sources, in this paper, we propose a Novel Unsupervised Label Indexing (NULI) approach to retrieve labels of images using machine learning terminology. We define machine learning as matrix convex optimization with cluster based matrix representation which can be used to improve the efficiency in image retrieval system. Our experimental results give better boost performance with comparison to conventional approaches in real time medical image retrieval applications.

II. REVIEW OF RELATED WORK

Chu et al. [6] portrayed a learning based medical picture recovery of figured tomography (CT) and attractive reverberation imaging (MRI) medical pictures. In this approach, the cerebrum sores were consequently fragmented and spoken to through an information based semantic model. Cai et al. [7] proposed a CBIR framework for useful powerful positron emission tomography (PET) medical pictures of the human cerebrum, where bunches of tissue time movement from the fleeting space were utilized in the calculation of comparability measure for recovery. In [8], the depictions of the locales of intrigue were physically performed on the key casing from the pile of high goals CT medical pictures. These were utilized as highlights to speak to the whole medical picture. In the Bag-Of-Words (BOW) [5] system, the medical picture patches were tested thickly or inadequately by "intrigue focuses" locators and were portrayed by neighborhood fix descriptors like SIFT. These descriptors were utilized to order liver sores in CT medical pictures. In [6], a surface based examination of lung CT medical pictures was proposed through Riesz wavelets. This strategy utilized SVM to take in the separate significance of multi scale segments. Guimond et al. [9] presented client chose volume of intrigue (VOI) for the recovery of obsessive cerebrum MRI medical pictures. In [2], gather meager portrayal with word reference learning for medicinal medical picture denoising and combination was utilized. Wavelet streamlining systems for content based medical picture recovery in medicinal database were portrayed in Quellec et al. [2]. Straight separate investigation (LDA) based determination and highlight extraction calculation for arrangement and division of one dimensional radar signs and two-dimensional surface and archive medical pictures utilizing wavelet parcel was proposed by Etemand and Chellappa [3]. As of late, comparative calculations for concurrent scanty flag portrayal and segregation were proposed [24– 29]. In [10], Chen et al. proposed in-plane turn and scale invariant grouping utilizing word references. This approach gives Radon-based pivot and scale invariant grouping as connected to content construct medical picture recovery with respect to Smithsonian disengaged leaf, Kimia shape and Brodatz surface datasets. Fei et al. [3] depicted a CT medical picture denoising in light of meager portrayal utilizing worldwide lexicon. This approach enhanced low dosage CT mid-region medical picture quality through a word reference learning based denoising strategy and quickened the preparation time in the meantime. Distinctive classes of medical pictures (created by various offices, for example, dermatology and pathology) were managed diversely for applications, for example, CBIR. A brilliant survey of the cutting edge of CBMIR and future headings was exhibited in [2]. A few multi-goals examination systems by means of wavelet, ridgelet, and curvelet-based surface descriptors were examined for CBMIR [3]. The calculation proposed in that distinguished different tissues in view of the discriminative surface highlights with the guide of choice tree grouping. This technique excessively fused some preparation information for understanding its destinations. The main idea behind to find annotated with indexed medical pictures that are similar to an evaluated medical picture and then use the conditions allocated by the annotations of the similar medical pictures to annotate the evaluated medical picture. Wei Li et al. [13] recommended a Maximum Information gain Model-based approach to automatic medical picture annotation. In training phase, a basic noticeable terminology, composed of blob-tokens to describe medical picture content, is created at first; then the basic relationship is generated between the blob-tokens and keywords by a Maximum Entropy Design created with the training set of noticeable medical pictures. At the stage of annotation, for an unlabeled medical picture, the most likely associated keywords and phrases are predicted based on the blob-token set generated of the given medical picture. Munirathnam et al. [14] suggested some techniques to use a framework of annotated conditions, created from published text ontology, for bringing improvements in computerized medical picture annotation and retrieval. In particular, the dwelling is used to implement efficient annotation for unlabeled images by including medical pictures as a framework for the recommended or requested category strategy for automatic image annotation.

III. SEARCH BASED IMAGE ANNOTATION (SBIA)

The SBIA strategy as appeared in figure 1 has the accompanying design of stream of usage comment with various arrangement progressively applications with highlights extractions:

In medical picture ordering SBIA have following execution steps:

1. Image data accumulation
2. Image discovery with class marks
3. High dimensional medical picture visual highlights extraction
4. Machine with learning methodology for marked

information

5. Retrieval of comparative medical picture
6. Image explanation by gathered comparative medical pictures in light of characterized marks.

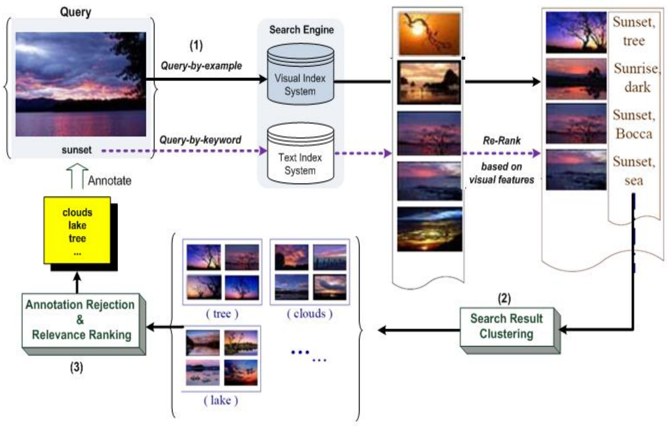

Figure 1. SBIA scalable image search with different image results

The initial four stages play out the pre-medical picture explanation errand for various medical pictures, while the last 2 stages play out the post and in medical picture activities. As appeared in figure 3, the initial step does information accumulation from various medical picture sources with reference to gather diverse people names list with explained medical pictures. For this, one needs to seek distinctive web medical pictures and investigate medical pictures identified with various names as marks in medical picture information. In the second step, we process medical pictures for investigating medical picture related data, which comprises of medical picture arrangement and location, medical picture include extraction and medical picture highlight introduction. In the third step, we extricate file highlights of medical pictures by applying some medical picture ordering system like utilizing region delicate hashing (LSH), an extremely famous ordering way to deal with characterize medical picture highlights. Other than the ordering approach, another key approach is to utilize an unsupervised characterization technique to broaden nature of the feebly marked medical pictures. All the above methods performed amid and before comment assignment in medical picture recovery depend on question preparing medical picture seek. Particularly medical picture comment for getting to medical picture highlights; we initially started comparable medical picture recovery procedure to seek the greater part of the best medical picture results.

IV. UNSUPERVISED LABEL IMAGE INDEXING

In this section, discuss about general design and execution process for novel computational approach i.e NULI in the following sequence: information about initial factors for function removal, conversation about problem development in medical picture annotation, criteria execution to catalog medical picture annotations, approximation collection process on function removal to determine medical picture recovery.

We define $X \in \mathbb{R}^{m\times d}$ as the extracted image features, in which m is the number of images and feature dimensions. $\Omega = \{m_1, m_2, ..., m_n\}$ refers to the names of person for image annotation, where m is the names of the persons. $Y \in [1,0]^{m\times n}$ refers to the labeled matrix to define weak label information with ith row and Y_i represents sequential order of the image $Y \in [1,0]^{m\times n}$. In NULI system, Y is the disturbance which is imperfect just regarding each poor brand pictures Yi,j for ith picture with different marked titles, where as mj appears for connection between picture and name, known or unidentified for different picture resources that gather information with a individual query image.

a. The main representation of our NLIR approach is defined s a labeled matrix ($F^* \in \mathbb{R}^{m\times n}$) that occurs with first image label, matrix Y. Here, it is pertinent to define content with labeled matrix Y with data examples X themselves. To implement this image annotation problem, we propose and develop convex optimization classification based on label key smoothness. This smoothness function addresses the optimization problem to minimize the loss function as defined below:

$$E_s(F,W) = \frac{1}{2}\sum_{i,j=1}^{n} W_{ij} \| F_{i*} - F_{j*} \|_F^2 = tr(F^T LF)$$

Where $\|.\|_F$ fabulous norm, W is weight matrix with convex constructed n images to optimize the above loss function. Then, regulation matrix is reflected as follows:

$$F^* = \arg\min_{F\geq 0} E_s(F,W) + \alpha.E_p(F,Y)$$

Where α is the regulation matrix parameter then, non-zero elements regulation based on feature dimensions is as follows:

$$E_p(F,Y) = \| (F-Y)oS \|_F^2$$

Here, S is the sigma matrix to define regularization parameters with the following functions with different formations allowed for soft regularization formulation, which includes convex sparsity constraints as shown in the following formulation:

$$F^* = \arg\min_{F\geq 0} E_s(F,W) + \alpha E_p(F,Y)$$
$$s.t. \| F_{i*} \|_1 \leq \in, i = 1,2,......n$$

Where $\alpha > 0$ and $\in > 1$. The matrix formation in real time image retrieval "convex-constraint formulation" or "CCF" in short. We apply convex optimization techniques to formulate convex grouping operations. Next, we define matrix convex optimization clustering approach to solve optimization tasks with feasible operation.

Input: $Q \in \mathbb{R}^{(m.n)\times(m.n)}, c \in \mathbb{R}^{m.n}, t \in \mathbb{R}$

Output: X*

Begin

$\alpha_0 = 1; k = 1; z^{(0)} = x^{(0)} = x^{(-1)} = 0;$

$repeat$

$CaseSRF: Achieve = x^{(k)} with, above, equations;$

$CaseCCF: Achieve = x^{(k)} with, above, equations;$

$$\alpha_k = \frac{1 + \sqrt{4\alpha_{k-1}^2 + 1}}{2}$$

$$z^{(k)} = x^{(k)} + \frac{\alpha_{k-1} - 1}{\alpha_k}(x^{(k)} - x^{(k-1)});$$

$k = k + 1;$

$Convergence;$

The marketing alternatives criteria procedure is shown Algorithm 1 with more suitable conditions. Here, provide an efficient label development for image data results for accomplishing possible functions immediately business presentation, especially for possible methods to marketing of different brands in matrix formation. To define NULI implementation, it is essential apply effective label representation for different images with preferable conditions on automatic image annotation with preferable acceleration in optimization problem evaluation.

V. PERFORMANCE RESULTS

Data sets: We draw out different individuals information's with their titles having some reputation and list them in real-time atmosphere, for example, we determine web URL as (http://www.imdb.com.). Consequently, we gather titles with billboard that is the images of the most famous individuals with time frame, beginning from very first year of beginning. Then, we publish a name as a keyword and key phrase to look for relevant images from different picture resources using google. After gathering information /information about picture from different web URLs, implement Java JDK system with Net Legumes to determine and get the top images recovered instantly. Later, this information source is known to as "Referred and Comprised Medical Image Database". We publish question as name and then get 100 different images from different web picture sources

Results: Our experimental evaluation, mainly compare with traditional approach i.e (hybrid image retrieval system) and proposed approach (NULI) in terms of accuracy in labeled medical image retrieval, precision, recall, image annotation with label performance and time efficiency. Accuracy, Precision and Recall calculation from different image sources may aggressively as follows:

$$\text{precision} = \frac{\text{No. of relevant images retreived}}{\text{Total no. of images retrivd}}$$

$$\text{recall} = \frac{\text{No. of relevant images retreived}}{\text{Total no. of relevant images in database}}$$

$$Accuracy = 2\frac{precision * recall}{precision + recall}$$

Calculate the accuracy. Image sources contain different types of images with different parameter formations & features and labels. To retrieve weakly labeled image from image sources, perform hybrid approach and NULI approaches and elaborate the results with accuracy in weak label image retrieval from different image sources. The following figure 2 shows the accuracy for both the techniques.

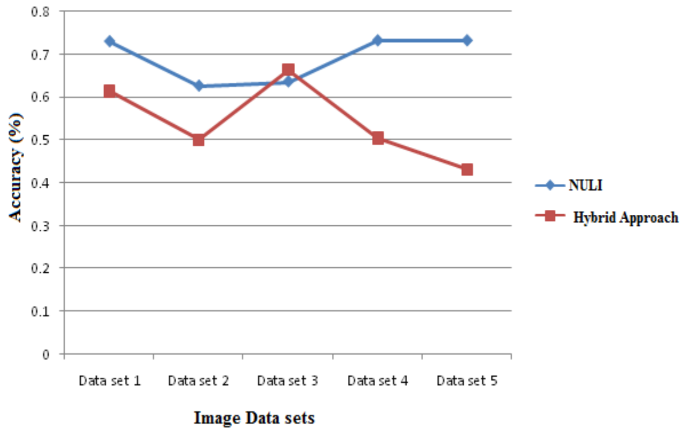

Figure 1. Accuracy of different images

In image retrieval applications, precision is the main parameter to explore the efficiency of the proposed approach with comparison of traditional techniques. Precision values of both proposed and existing approach shown in figure 3.

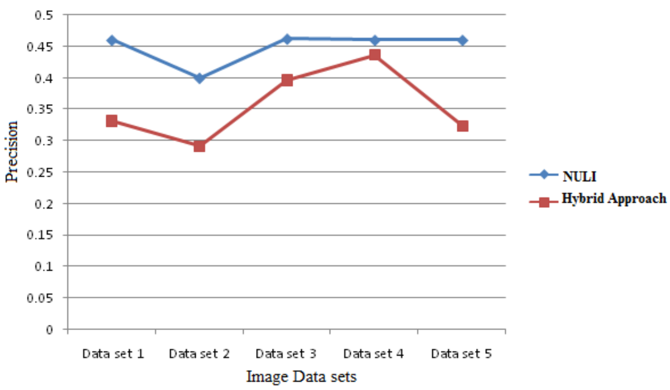

Figure 3. Precision of different image with different techniques.

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 14, Number 6 (2019) pp. 1259-1264
© Research India Publications. http://www.ripublication.com

In image retrieval applications, recall is a reference parameter to explore the efficiency of the proposed approach in terms of weak label class references.

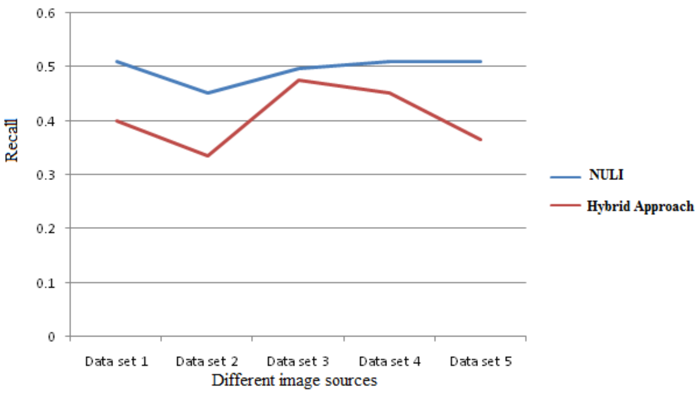

Figure 4. Recall values of different images with different data sets.

A shown in the above figures, image hybrid image retrieval gives less performance to retrieve the top-most images for automatic image annotation with their names from the image data source, where as our approach takes lesser time. This means that our approach is significantly better compared to the traditional approaches with different image features in image annotation.

VI. CONCLUSION

We present and apply a novel image indexing approach i.e. NULI strategy with convex optimization category for applying huge information pre-processing for weakly-labeled information in picture listing. We also develop approximation-based collection criteria to improve perfection and remember performance in huge web-based picture recovery tasks. Our trial outcomes show efficient picture listing with different trial studies on extensive web-based pictures. Our tests in search-based annotation generate scalability measure outcomes as compared to the current techniques in picture recovery.

REFERENCES.

[1] Dayong Wang, Steven, “Mining Weakly Labeled Web Facial Images for Search-Based Face Annotation”, IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 26, NO. 1, JANUARY 2014.

[2] Put your Paper link.

[3] T.M. Lehmann, Mark O. Guld, Deselaers Thomas, Keysers Daniel, Schubert Henning, Spitzer Klaus, Ney Hermann, B.B. Wein, Automatic categorization of medical images for content based retrieval and data mining, Comput. Med. Imaging Graph., 9 (2) (2005) 143–155.

[4] H.D. Tagare, C. Jafe, J. Duncan, Medical image databases: a content based retrieval approach, J. Am. Med. Inf. Assoc. 4 (3) (1997) 184–198.

[5] W. Yang, Z. Lu, Yu. M, M. Huang, Q. Feng, W. Chen, Content-based retrieval of focal liver lesions using Bag-of-Visual-Words representations of single- and multiphase contrast enhanced CT images, J. Digit. Imaging 25 (2011) 708–719.

[6] Depeursinge Adrien, Foncubierta Rodriguez Antonio, Van de Ville Dimitri, Muller Henning, Multiscale lung texture signature learning using the Riesz transform, Med. Image Comput. Comput.-Assist. Interv.-MICCAI (2004) 517–524.

[7] G. Csurka, S. Clinchant, G. Jacquet, Medical image modality classification and retrieval, in: Proceedings of IEEE International Conference on CBMI, 2011, pp. 193–198.

[8] M. Aharon, M. Elad, A.M. Bruckstein, The K-SVD: an algorithm for designing of overcomplete dictionaries for sparse representation, IEEE Trans. Signal Process. 54 (11) (2006) 4311–4322.

[9] Tian Tian Chang, Jun Feng, Hong Wei Liu, Horace H.S.I., Clustered microcalcification detection based on a multiple kernel support vector machine with grouped features (GF-SVM), in: Proceedings of IEEE Conference on Pattern Recognition (ICPR), 2008, pp. 1–4.

[10] Guanqun Bao, Kaveh Pahlavan, Motion estimation of the endoscopy capsule using region-based kernel SVM classifier, in: Proceedings of IEEE International Conference on Electro/Information Technology (EIT), 2013, pp. 1–5.

[11] Amjad Zaim, Taeil Yi, Rick Keck, Feature-based classification of prostate ultrasound images using multiwavelet and kernel support vector machines, in: Proceedings of IEEE International Conference on Neural Networks (IJCNN 2007), 2007, pp. 278–281.

[12] I. Ramirez, P. Sprechmann, Guillermo Spiro, Classification and clustering via dictionary learning with structured incoherence and shared features, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, June 2010.

[13] K. Kreutz-Delgado, J.F. Murray, B.D. Rao, K. Engan, T.W. Lee, T. Sejnowski, Dictionary learning algorithms for sparse representation, Neural Comput. 15 (2003) 349–396.

[14] K. Engan, S. Aase, J. Hakon-Husoy, Method of optimal directions for frame design, in: Proceedings of IEEE International Conference on Acoustics, Speech, Signal Processing, vol. 5, 1999, pp. 2443–2446.

[15] S. Mallat, Z. Zhang, Matching pursuits with time frequency dictionaries, IEEE Trans. Signal Process. 41 (12) (1993) 3397–3415.

[16] W.W. Chu, C.C. Hsu, A.F. Cardenas, R.K. Taira, Knowledge based image retrieval with spatial and

temporal constructs, IEEE Trans. Knowl. Data Eng. 10 (December (6)) (1998) 872–888.

[17] W. Cai, D. Feng, R. Fulton, Content-based retrieval of dynamic PET functional images, IEEE Trans. Inf. Technol. Biomed. 4 (June (2)) (2000) 152–158.

[18] C. Shyu, C. Brodley, A. Kak, A. Kosaka, A. Aisen, L. Broderick, ASSERT: a physician-in-loop content-based image retrieval system for HRCT image databases, Comput. Vis. Image Underst. 75 (1999) 111–132.

[19] A. Guimond, G. Subsol, Automatic MRI database exploration and applications, Int. J. Pattern Recognit. Artif. Intell. 11 (1997) 1345–1365.

[20] Yue Gao, Rongrong Ji, Wei Liu, Qionghai Dai, Gang Hua, Weakly supervised visual dictionary learning by harnessing image attributes, IEEE Trans. Image Process. 23 (12) (2014) 5400–5411.

[21] S. Li, H. Yin, L. Fang, Group sparse representation with dictionary learning for medical image denoising and fusion, IEEE Trans. Biomed. Eng. 59 (December (12)) (2012).

[22] G. Quellec, M. Lamard, G. Cazuguel, B. Cochener, C. Roux, Wavelet optimization for content-based image retrieval in medical databases, J. Med. Image Anal. 14 (2010) 227–241.

[23] K. Etemand, R. Chellapa, Separability based multiscale basis selection and feature extraction for signal and image classification, IEEE Trans. Image Process. 7 (October (10)) (1998) 1453–1465.

[24] F. Rodriguez, G. Sapiro, Sparse representation for image classification: learning discriminative and reconstructive non parametric dictionaries, Technical Report, University of Minnesota, December 2007.

[25] K. Huang, S. Aviyente, Sparse representation for signal classification, Neural Inf. Process. Syst. 19 (2007) 609–616.

[26] Q. Zhang, B. Li, Discriminative k-svd for dictionary learning in face recognition, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2010, pp. 2691–2698.