

# Texture Features Based Bag of Visual Words for a Spine MRI Images

<sup>1</sup>Khawla H. Ali, <sup>2</sup>Entesar B. Talal, <sup>3</sup>Nadra J. Alsaad

**Abstract**—This paper explores texture features based image descriptors that makes use of the spatial gray level of bag of visual words model to discriminately improve classification performance for spine MRI images. At first, construct feature vector by using Tamura texture features of six properties of features like: coarseness, contrast, directionality, line-likeness, regularity and roughness for spine MRI images. The second step is to generate a bag of visual word (BoW) to encode feature vector into visual words. Features of these types are used to classify seven categories of different types of spine MRI image such as: spinal cord, disc highlight ,spinal canal size, spinal alignment, in vertebral disc, nerves and abnormalities, to classify them and help the diagnose what cause the back-pain. Experiment results on spine MRI shows significant improvement of classification.

**Keywords:** Tamura texture features, visual words, K-means, classification .

## I. Introduction

In recent years, there are developments in digital images especially in medical images in various modes, such as X-rays, magnetic resonance imaging (MRI), computer tomography (CT), ultrasonography (US), etc.

Medical image classification is an important issue for physicians in diagnoses for Clinical and medical researches. However, traditional methods of medical image classifications based on global features include color features, texture features and shapes features have many inaccurate classifications.

Medical image classification has been grow and active research in biomedicine field. In this paper we deal with MRI scan of spinal structures to help the diagnose what cause back-pain.

In recent years, with the massive development of local descriptors in computer vision and pattern recognition, the bag of visual words extracting from local features like key points or image patches has introduced as activated search for image classification and image retrieval [1, 2, 12 and 13].

Image classifications have been significantly active topic research with hundreds of publications in the past years. Texture features are often used to analyze images especially for medical images. In this paper, at first, texture features are extracted by using Tamura features then create bag of visual words, usually K-means are used to cluster centers of features which are extracted from all training images, then these cluster centers are used to generate visual word vocabulary for all images to get word vector representations.

In [1] introduced an X-ray image categorization and retrieval method based on batches of visual words. In [2] improve SIFT features for medical images, while in [3] evaluate different representations of histopathology by using SIFT and bag of visual words. All the above methods construct the histogram for image representation by assigning the descriptors of local features to a single visual word has nearest in the vocabulary, which is called nearest neighbor (NN) assignment. The medical applications in [4, 5 and 6] do not investigate of newest development of BoW like sparse coding or development of histogram of visual words in their applications. In this paper, we try to develop classification of medical images by combine Tamura texture features with bag of visual words as shown in Fig.1.

---

<sup>1</sup>Khawlah@uobasrah.edu.iq  
Computer Dept., College of Education, Univ.of Basrah  
Iraq  
[khawlahusseini@yahoo.com](mailto:khawlahusseini@yahoo.com)

<sup>2</sup>Entesar@uobasrah.edu.iq  
Computer Dept., College of Education, Univ.of Basrah  
Iraq  
[entesar.barges@gmail.com](mailto:entesar.barges@gmail.com)

<sup>3</sup>Nadra @ uobasrah.edu.iq  
Computer Dept., College of Education, Univ.of Basrah  
Iraq  
[nadrajo@yahoo.com](mailto:nadrajo@yahoo.com)

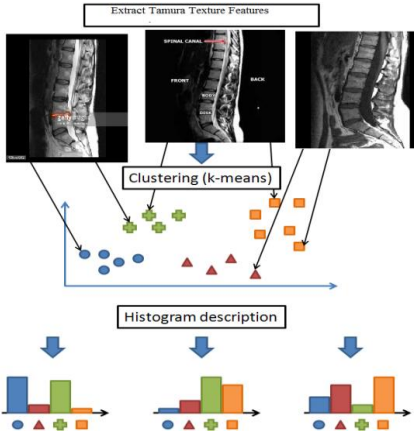


Figure 1. Creation of vocabulary visual words

## II. Texture features for medical images

Texture is described as normal property in all most surfaces. The complex nature of texture features has derived a large number of representations. In the perceptual type of texture features consist of features that are corresponding to visual human interpretation. In this paper, we use Tamura texture features. Their importance due to their properties with the human perception. The set of perceptual texture feature that Tamura et al. (1978) presented were: coarseness, contrast, directionality, line-likeness, regularity and roughness. We used these feature for MRI spine images as show in table I. A common problem for the spine surgeons is that the mixed messages. A loss of water content in a disc makes it look darker than others, this can be normal activity [9].

With large numbers of texture features, it is natural to combine each feature value to one feature vector for best representation,  $\theta$ , as shown below :

$$\theta = (\chi_1, \chi_2, \dots, \chi_n) \quad (1)$$

Where  $\chi_i$  represents each texture feature value. We used only three features due to the most important properties for human perception. In next section we used bag of visual words for these texture features.

TABLE I

TAMURA FEATURES OF SPINE MRI IMAGES

Feature	Image 1	Value 1	Image 2	Value 2
Coarseness		0.769		0.169
Contrast		0.994		0.068
Directionality		0.754		0.342
Line-likeness		0.886		0.986
Regularity		0.546		0.874
roughness		0.453		0.523

## III. Bag of visual features based texture features for medical images

The basic steps of the bag of visual words based classification on texture features are illustrated in Fig.1, where each component represents an operation of the images. To extract local features, we represent an input image as a collection of local features.

The first step is detected local features. Let  $X$  be a bag of features of an image, and  $\{x_i\}$ ,  $L=1, \dots, L$  is a collection of local features extracted from  $X$ . practically, local features  $x_i$  are detected texture features with Tamura descriptors. the second

step is constructing visual vocabulary words by using K-means clustering, that cluster the center of features which are extracted from all images. The last step is assigning the descriptors to visual words, the image X is coded by the local feature  $\{(x_l, \alpha_l)\}$ ,  $L=1, \dots, L$ , with each  $\alpha_k$  identified with the integers  $k=1, \dots, K$ , [7].

$$\alpha_l = \arg \min_k (D(v_k, \chi_l)) \quad (2)$$

Where  $\chi_l$  is an image region L, and  $D(v_k, \chi_l)$  is the distance between a code word  $v_k$  and region  $\chi_l$  [7]. The histogram of visual words is normalized with  $L_1$  norm, generating a frequency vector  $H^X = [h_1^x \ h_2^x \ \dots \ h_k^x]$ .

#### IV. Classification

We use SVM with kernels as learning algorithm for the classifier. The kernels implicitly map the input space to a higher dimensional space [8]. We used exponential kernel  $X^2$  for features, because it has been powerful discriminative tool for classification.

$$k(x, y) = \exp\left(-y \sum_{i=1}^N \frac{(X_i - y_i)^2}{(X_i + y_i)}\right) \quad (3)$$

With our features, the classification accuracy was high; especially they can model the classes.

#### V. Experiments

We test the proposed method on spine MRI images, a set of different collection types of spine MRI images. This collection contains more than 1000 spine MRI images, provided by the web site of spine health [9] and classified in seven categories (disc highlight and hydration, in vertebral disc which explains how the disk appears, spinal-canal size, nerves, abnormalities, spinal cord and spinal alignment). Experiments demonstrate our method's accuracy of classification and flexibility for a large scale spine MRI images. The initial step of our method is to extract the local features using the method we have proposed that combines between Tamura texture features with

bag of visual words to improve classification accuracy.

In fact, to reveal the contribution of our model using classification of spine MRI images, we introduce table II, which outline acquired values for each MAP testing [10, 11]. We note that our method significantly different of spine MRI images of the in vertebral disc compared to other types of spine images. These inspections are committed by the curves of precision\ recall shown in Fig 2.

TABLE II  
AVERAGE ACCURACY OF DIFFERENT TYPES OF SPINE MRI IMAGES

Type of spine MRI image	MAP
Spinal alignment	0.2826
Disc highlight	0.2655
In vertebral	0.9455
Spinal cord	0.7544
Spinal canal	0.8755
Abnormalities	0.8321
Nerves	0.7446

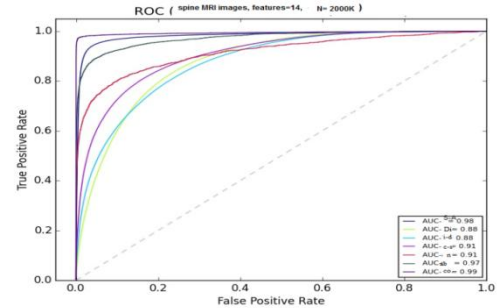


Figure 2: Performance measure for different types of spine MRI images

#### VI. Conclusion

This paper has addressed the problem of classification of spine MRI images based bag of visual words, which are extracting Tamura texture features as words to develop discriminating power of bag of features based medical image classification. We have introduced a method to encode texture local features to visual words of bag of features. Experiments demonstrate our method's accuracy of classification and flexibility for a large scale spine

MRI images. In future work, we investigate of efficient algorithm to detect local features of various large scales of medical images. In future work, we investigate of efficient algorithm to detect local features of various large scales of medical images.

## References

- [1] Avni, U; Greenspan, H; Sharon, M, et al. X-Ray image categorization and retrieval using patch-based visualwords representation. 2009 IEEE International symposium on biomedical imaging: from Nano to macro, vols. 1 and 2 pages: 350-353 Published: 2009.
- [2] Zhi, Li-Jia ; Zhang, Shao-Min; Zhao, Da-Zhe; Zhao, Hong; Lin, Shu-Kuan. Medical image retrieval using SIFT feature. Proceedings of the 2009 2nd International Congress on Image and Signal Processing, CISP'09, 2009.
- [3] Caicedo, J.C.; Cruz, A.; Gonzalez, F.A. Histopathology image classification using bag of features and kernel functions. Artificial Intelligence in Medicine. Proceedings 12th Conference on Artificial Intelligence in Medicine, AIME 2009 Pages: 126-35—xix+439 Published: 2009.
- [4] M.J. Gangeh, L. S\_ensen, S.B. Shaker, M.S. Kamel, M. de Bruine, M. Loog. "A Texton-Based Approach for the Classification of Lung Parenchyma in CT Images". Medical Image Computing and Computer-Assisted Intervention - MICCAI 2010, vol. 6363, p. 595-602, 2010.
- [5] S.H. Raza, R.M. Parry, R.A. Mo, A.N. Young, M.D. Wang. "An Analysis of Scale and Rotation Invariance in the Bag-of-Features Method for Histopathological Image Classification". Medical Image Computing and Computer-Assisted Intervention - MICCAI 2011, vol. 6893, p. 66-74, 2011.
- [6] T. Tamaki, J. Yoshimuta, M. Kawakami, B. Raytchev, K. Kaneda, S. Yoshida, Y. Takemura, K. Onji, R. Miyaki, S. Tanaka, "Computer-aided colorectal tumor classification in NBI endoscopy using local features, Medical Image analysis, vol. 17(1), p. 78-100, 2013.
- [7] Jingyan Wang, Yongping Li, et al. "Bag-of-Features Based Medical Image Retrieval via Multiple Assignment and Visual Words Weighting", IEEE Transaction on Medical Imaging, vol. 6, no. 1, 2007.
- [8] T. Tommasi, F. Orabona, B. Caputo, "Discriminative cue integration for medical image annotation", ELSEVIER, Pattern Recognition Letters 29 (2008).
- [9] MRI scan of spine, spine health, <http://www.spine-health.com>
- [10] Riadh B., Abir M. and Jalel A. , "Using a Bag of Words for Automatic Medical Image Annotation With a Latent Semantic", International Journal of Artificial Intelligence & Applications (IJAA), Vol 4, No.3, May 2013

- [11] Ahmed M., Abdullah A., Bassem Z., M. Awedh , " medical image classification using multivocabulary", Asian journal of applied research , 8(1), 2015.
- [12] Asavari G. J., A. S. Deshpande, "Review of Face Recognition Techniques", International Journal of Advanced Research in Computer Science and Software Engineering, Volume 5, Issue 1, January 2015
- [13] Khawlah Hussein A. I, T. Wang, "On the Development Robust and Fast Algorithm of Action and Identity Recognition", American Journal of Networks and Communications; 4(5), 2015.

### About Authors



**Khawlah H. Ali** received M.Sc. degree from the University of Basrah in 2001 and the Ph.D degree from the Huazhong University of Science and Technology (HUST), Wuhan, China in 2015. She is author of many published papers in different fields and her current interests include computer vision and pattern recognition , image processing, machine learning and security applications in computer fields.



**Entesar Barges Talal** finished the BSc. in the University of Basrah, college of education, Dept. of computer science at 2006. The M.Sc. has been finished in the University of Basrah, college of science, Dept. of computer science at 2015 with specialization biometric and pattern recognition. interest with many fields like machine learning, computer vision, Artificial intelligent, web design and semantic web. The languages programs that she support Pascal, C++, prolog, visual basic, php, HTML, java script, Matlab.



**Nadra Jamil Ali Alsaad** finished the BSc. in the University of Basrah, college of education, Dept. of physics at 1977. received Diploma ( Micro computer & Micro processor Applications degree from the University of Essex in 1981, UK. The M.Sc. has been finished in the University of Sussex, UK. Lecturer in Basrah university Education college, Computer Dept. / Iraq. During this period she taught different subjects, published few books in Arabic and local paper