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E-learning platform based on Recommender System

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Informations	Abstract
Keywords : Recommender System Collaborative Filtering BookCrossing E-learning platform *Correspondance : gasmibtissem@gmail.com	With the considerable growth of information available on the web, users have difficulty to select the information that <i>best suits their needs</i> . In this context, recommender systems have been developed to predict users' interests and recommend product items that quite likely are interesting for them. In this paper, we propose the integration of a Book Recommender System into E-learning spaces such as Moodle.

1. Introduction

With the proliferation of the amount of information available on the web, it is difficult for user to find what he is looking for and what may be of interest to him [1]. Access to relevant information has become a real challenge.

Recommendation systems provide a solution to the problem of information overload and are able to estimate a user's interest based on some information about his neighbourhood or based on item's properties.

Several recommender systems have been proposed to filter and adapt the information for each user [2-4]. They can be *divided* into two categories: content-based approaches and collaborative filtering approaches.

In this paper, we propose the improvement of E-learning platforms, such as Moodle, by integrating a recommendation engine based on collaborative filtering algorithm. The proposed system suggests books adapted to the needs of users. We also propose the creation of a pedagogical space between administration and professors which allows the management of some pedagogical activities

The rest of this paper is organized as follows. The second section will discuss collaborative filtering methods. In the third one, we will present similarity measures used in collaborative filtering. The database used as well as the proposed system will be presented in the

fourth section. Finally, the fifth section presents our conclusion.

2. Collaborative filtering

Collaborative filtering is one of the most popular recommendation methods. It is based on the idea that people who share an interest in certain things will probably have similar interests in other things as well [5]. Thus, it recommends items to a given user that other persons who are similar in their preferences have appreciated. This method does not take into account item information; it only uses the evaluation matrix to calculate the prediction.

In order to suggest an item to a user, the collaborative filtering algorithm determines which users have similar preferences to that user on certain items. The available data is then used to calculate the prediction.

Formally, collaborative filtering is defined by a set $U = \{u_1, u_2, \dots, u_m\}$ of m users and a set $I = \{i_1, i_2, \dots, i_n\}$ of n items. Each user u_k evaluates a subset of items $I_{u_k} \subseteq I$. $R_{u,i}$ is the appreciation given by user u to item i . It can be acquired implicitly by observing the user's behaviour. In this case, any interaction of the user with the system is considered as an estimate of his interest judgment [6]. We can also obtain the evaluation explicitly by inviting users to give simple annotations based on a fixed rating scale (e.g. from $1 \equiv$ very bad to $5 \equiv$ very

good). The user evaluations are stored in a matrix called *user×item*.

Collaborative filtering techniques are grouped into two main categories: memory based algorithms and model based algorithms.

2.1. Memory based algorithms

Memory-based algorithms operate directly on the *user×item* matrix to make the recommendation. The prediction for an active user is estimated using his votes and a set of weights calculated from the judgments of users with the same preferences as him. These techniques mainly apply statistical methods, such as the k-nearest neighbors method, to identify users who are similar to the active user. They offer the advantage of being reactive by dynamically integrating new users or items. However, the complexity of processing increases with the increase of user's number and items.

Memory based approaches are based on the calculation of similarities from the *user×item* matrix. They estimate the similarities between the columns of the evaluation matrix in item-based collaborative filtering. However, in the case of user-based filtering, they calculate the similarities between the rows of the matrix.

Item-based filtering identifies items that have been measured by the same user. To suggest an item *i* to a user *u*, the ratings of user *u* on objects which are similar to item *i* are used. Each evaluation will be weighted by a degree of similarity to item *i* (equation 1).

$$P_{u,i} = \bar{R}_i + \frac{\sum_{j=1}^n (R_{u,j} - \bar{R}_j) \times corr_{i,j}}{\sum_{j=1}^n corr_{i,j}} \quad (1)$$

$P_{u,i}$ is the prediction of user *u* for item *i*.

$R_{u,j}$ is the rating of user *u* for item *j*.

$\bar{R}_i$ and $\bar{R}_j$ represent the average of the ratings for items *i* and *j*, respectively.

$corr_{i,j}$ represents the degree of similarity between item *i* and item *j*.

User-based filtering finds users who are similar. To predict an item *i* to a user *u*, the ratings from users with the same preferences as user *u* are used. Each evaluation will be weighted by a weight representing a measure of similarity to user *u* (equation 2).

$$P_{u,i} = \bar{R}_u + \frac{\sum_{k=1}^m (R_{k,i} - \bar{R}_k) \times corr_{u,k}}{\sum_{k=1}^m corr_{u,k}} \quad (2)$$

$P_{u,i}$ is the prediction of user *u* for item *i*.

$R_{k,i}$ is the evaluation of user *k* on item *i*.

$\bar{R}_u$ and $\bar{R}_k$ represent the average of user ratings *u* and *k*, respectively.

$corr_{u,k}$ represents the degree of similarity between user *u* and *k*.

2.2. Model-based algorithms

The model-based approach responds to the problem of calculations complexity of memory based approach when it faced with a large number of users and items. This method uses the matrix of user evaluations to develop a model that will be used for prediction. The model is built in the learning phase from a training corpus in order to be used online to calculate recommendations. Unfortunately, this method is not dynamic enough and its update is costly in computing time. Several techniques are used in model-based recommendation systems, such as probabilistic models, clustering methods, decision trees, neural networks, linear regression, etc. [7].

3. Similarity calculation

The calculation of similarities is a key element in the prediction process. It consists of measuring the similarity between the descriptive variables of the items or users in order to select the best neighborhood which is used to calculate predictions. Neighbourhood identification is generally based on a distance between two vectors using the most appropriate measure for the type of descriptors [8].

Several measures of statistical similarity have been exploited in recommender systems. These measures are based only on the common judgements of users. They allow building either an item×item matrix or a user×user matrix according to rows or columns. The two most commonly used measures are Cosine similarity and Pearson similarity.

3.1. Euclidean distance

The Euclidean similarity measure calculates the distance between two vectors *x* and *y* of dimension *n* according to equation 3. This measurement is very sensitive to the values of the vector descriptors [9].

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (3)$$

3.2. Cosine similarity

The Cosine similarity uses vector representation. Thus, each user (or item) is represented by a vector of votes. If the two clients (or items) are similar, their vectors are

confused; otherwise they form an angle whose cosine corresponds to the degree of similarity. The cosine of the angle formed by the two vectors i and j is calculated according to equation 4. The denominator terms are used to normalize evaluations so that users who have evaluated multiple items are not favoured [10].

$$\text{sim}(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\|_2 \times \|\vec{j}\|_2} \quad (4)$$

Cosine similarity does not take into account individual differences between users when indicating their preferences. Indeed, some users are very generous in their evaluations compared to others. This problem is corrected by taking into account the averages of each user's scores.

3.3 Pearson Correlation Coefficient

The Pearson correlation coefficient is a famous similarity measure because of its performance in calculating predictions. It is used to calculate the distances between the active user (item) and other users (items) [10]. The Pearson correlation coefficient between the two users u and v (the two items i and j) is calculated according to equation 5 (equation 6):

$$\text{sim}(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_j)^2}} \quad (5)$$

$R_{u,i}$ and $R_{v,i}$ represent the evaluation of user u and v , respectively, on item i .

$\bar{R}_u$ and $\bar{R}_v$ are the average of user's ratings u and v , respectively.

$$\text{sim}(u, v) = \frac{\sum_{i \in I} (R_{u,i} - \bar{R}_u)(R_{v,i} - \bar{R}_v)}{\sqrt{\sum_{i \in I} (R_{u,i} - \bar{R}_u)^2} \sqrt{\sum_{i \in I} (R_{v,i} - \bar{R}_v)^2}} \quad (6)$$

$R_{u,j}$ is the evaluation of user u on item j .

$\bar{R}_i$ and $\bar{R}_j$ represent the average of the ratings for items i and j , respectively.

The similarity value $\text{sim}(u, v)$ ($\text{sim}(i, j)$) is between -1 and 1. If this value is equal to -1 then the two users (items) are strongly opposed. If the value is equal to 1, the two users (items) are strongly similar. The two users (items) are independent if the value is equal to 0.

4. Description of the proposed system

4.1 Database

In order to develop this system, we used the BookCrossing dataset. This latter was collected in 2004 by Cao-Nicolas Ziegler using an online book platform. It includes 1,149,780 evaluations, between 1 and 10, made by 278,858 anonymous users on 271,379 books. This corpus also contains a short description of the books (title, year of publication, author and publisher) and some demographic information about the users (age and city) [11].

4.2 Offered Services

To improve the quality of the e-learning platform, we propose the integration of a book recommendation system as well as the management of some pedagogical activities such as automatic request generation, automatic QR code generation and notification (Fig.1).

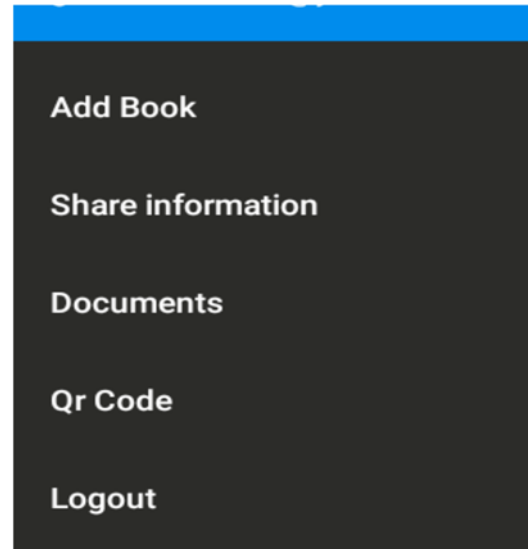


Fig. 1 : Navigation windows

Book Search Service

This service allows the research of books from BookCrossing dataset by entering keywords (Fig. 2). Once the resource has been found, the information about his title, description and publication date will be displayed. The user will have the option to view or download the resource.

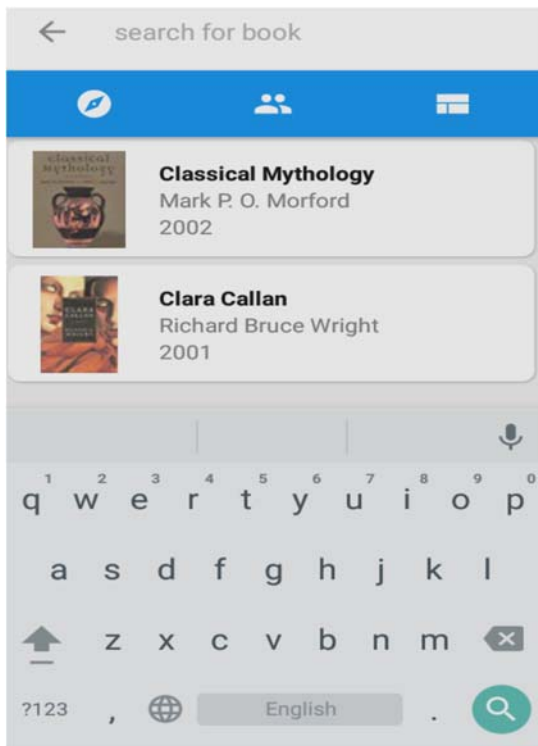


Fig. 2 :Search for work

Referral Service

The application provides to users a book recommendation service that allows them to adapt and personalize their search according to their preferences.

Book evaluation service

This service allows users to give their opinion on books by choosing ratings to be given so that the system learns user's preferences (**Fig. 3**). The score varies between 1 and 10.

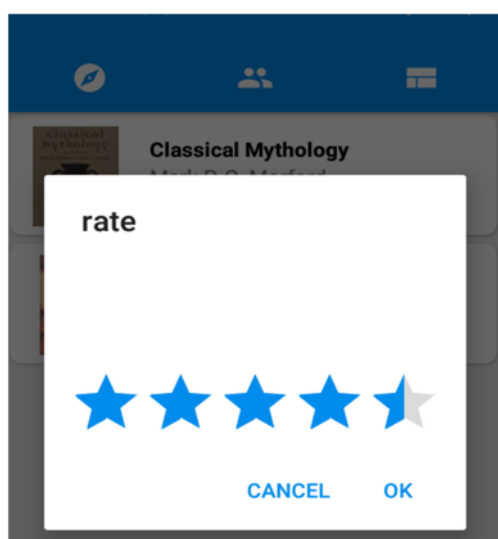


Fig. 3 :Book evaluation window

Suggested book service

This service allows users to suggest books to their colleagues by sending their description in the form of a QR code.

Information Service

This service allows user to get and share the latest news or events that are going to take place within the departments (important dates, for example.) by informing professors through notification service (**Fig. 4**).



Fig. 4 :Information sharing interface

QR code generator

This service allows the administrator of this application to generate QR code for a resource such as URL (**Fig. 5 and Fig. 6**). After creating QR code, it can be shared via the same interface.



Fig. 5 :QR code generator



Fig. 6 :Example of a QR code

Document generator

This service allows users to generate documents automatically such as work certificates of, documents concerning the Pedagogical Council (PC) or the Departmental Scientific Committee (DSC), etc. (Fig. 7).

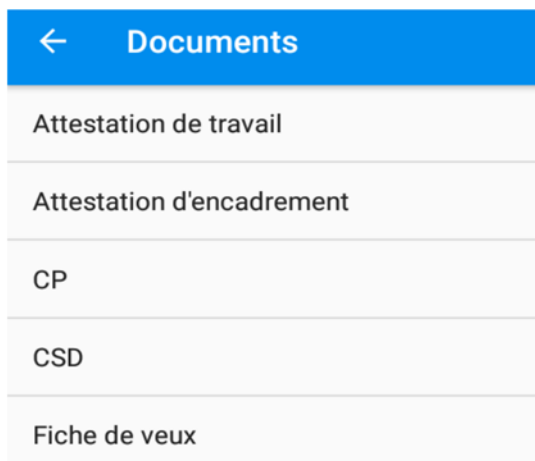


Fig. 7 :Document Generator

5. CONCLUSION

Recommender systems have become essential tools for any website that focuses on a certain type of items available in a rich catalogue. These items can be objects, cultural products (books, films, music, etc.), information items (news) or pages (hyperlinks).

The objective of these systems is to select, from their catalogue, the items that interest a particular user. They provide relevant suggestions within a large set of information.

In this paper, we have proposed the integration of book recommender system based on collaborative filtering algorithm within e-learning platforms such as Moodle. The developed system also allows the management of some pedagogical services.

References

- [1] Hussien Mohamed M., Khafagy M. H., Ibrahim M. H. (2019). Recommender Systems Challenges and Solutions Survey. International Conference on Innovative Trends in Computer Engineering (ITCE), Aswan, Egypt.
- [2] Serrano W., (2019). Intelligent Recommender System for Big Data Applications Based on the Random Neural Network. Big Data and Cognitive Computing.
- [3] Lee H., Lee J., (2018). Scalable deep learning-based recommendation systems, ICT Express.
- [4] Gasmi I., Seridi-Bouchlaghem H., Labar H., (2012). Collaborative filtering recommendation based on research habit of users. In: Proceedings of the third IEEE International Conference on Multimedia Computing and Systems, Tangier, Morocco.
- [5] Delporte J., Karatzoglou A., Matuszczyk T., Canu S., (2013). Socially Enabled Preference Learning from Implicit Feedback Data. In: Proceedings of the 13th European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, pp. 145 - 160, Springer.
- [6] Burke R., (2002). Hybrid Recommender Systems: Survey and Experiments. User modeling and user-adapted interaction, Vol. 12, N° 4, pp. 331 - 370.
- [7] Liu H., Liang Z., (2009). Implicit Rating Model in M-Commerce Recommendation System", In: Proceedings of the international conference on Computational Intelligence and Software Engineering, pp.1 - 4.
- [8] Gasmi I., Seridi-Bouchlaghem H., Labar H., Baareh A., (2015). Collaborative filtering recommendation based on dynamic changes of user interest", Intelligent Decision Technologies, vol. 9, no. 3, pp. 271-281.
- [9] Negre E., (2013). Comparison of texts : Quelques approches, Technical Reports, Université Paris-Dauphine.
- [10] Ding Y., Li X., Orlowska M. E., (2006), Recency-based collaborative filtering, In: Proceedings of the 17th Australasian Database Conference, Australian Computer Society, Vol. 49, pp. 99 - 107.
- [11] Ziegler C.N., Schmidt- Thieme L., Lausen G., (2004). Exploiting semantic product descriptions for recommender systems", In: Proceedings of the ACM SIGIR Semantic and Information Retrieval Workshop.



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Scale Invariant Features Transform for Content-Based Medical Image Retrieval Systems: an overview on recent application

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Informations	Abstract
Keywords : CBMIR SIFT SIFT for CBMIR *Correspondence : gouaidiafahima@yahoo.fr	Content based medical image retrieval systems (CBIRs) represent a special case of Content based image retrieval systems. Medical images are the information the user seeks to retrieve from the database using these systems. Content Based Medical Image Retrieval Systems (CBMIRs) are very interesting tools that help and assist doctors in diagnosis and decisions by extracting similar cases and images from medical databases. Several features have been used through the process of developing CBMIRs. Scale Invariant feature Transform (SIFT) technique has been widely used in the context of general and specialized CBIRs. We present in this paper a set of recent works that have been used the SIFT technique in a context of CBMIRs. The results from these works have illustrated the utility of this technique and the relevance of its features.

1. Introduction

The rapid development in the field of digital cameras as well as the tools for acquiring, transferring and storing images poses a major challenge for users. This challenge is the need to access and efficiently use the large amount of available images.

The development of tools allowing the optimal use of image databases and satisfactory manipulation by users is ensured through the various works in the field of image indexing and retrieval. This field constitutes one of the applications of image processing techniques and several fields of information technology.

Central to this area of research is Content Based Image Retrieval Systems (CBIRS). These systems are an effective tool for users in their research and their needs. The main focus of indexing research is on the performance of these systems, therefore the objective is to develop efficient systems to allow the effective and efficient satisfaction of the needs of different users.

The rapid escalation of medical information and quick comprehensibility to the tools for medical imaging makes it significant to store multimedia information. This advancement requires the

advancement in computer vision methods to allow the improvement of equipment that allows medical diagnosis to achieve higher accuracy. Content Based Medical Image Retrieval Systems (CBMIRs) aids doctors in making quick and accurate decisions by exploiting similar cases and images from medical databases. [1]

Several features have been used through the process of developing CBMIRs. They can be from different types including color based features, texture based features, and shape based features and local features. Among the techniques of the last type, Scale Invariant feature Transform (SIFT) technique has been widely used in the context of general and specialized CBIRs.

We focus in this paper on the presentation of an overview of the use of SIFT features in the field of CBMIRs. The overview covers the recent period that contains a set of scientific contributions that were published between 2010-2021.

2. Content based medical image retrieval systems

Content based medical image retrieval systems represent a special case of Content based image retrieval systems. Medical images are the information the user seeks to retrieve from the

database using these systems. The basic architecture of CBIRs is illustrated in figure 1. The system is generally viewed to be composed of two phases, an offline phase which concerns the database indexing and an online phase which process the query.

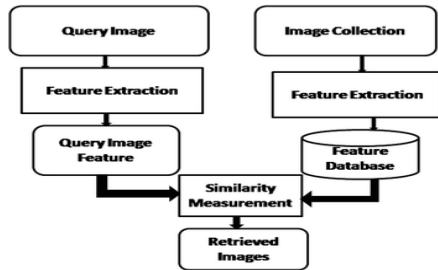


Fig. 1 : The basic architecture of CBIRs [5]

The offline phase is an indexing phase where the images found in the database are indexed using a set of characteristics generally extracted from these images. This representation of the content of the image by using the set of extracted characteristics makes it possible to reduce the dimension used during the search, the relevance of these characteristics is essential to ensure the correct representation of the content of the images in the database.

The image search phase is an online phase; the request provided by the user must be processed in order to transform it into an adequate representation similar to that of the characteristics of the images in the database.

The system performs a similarity calculation between the index of the user's query and the images indexed in the base in order to respond to the user with the list of images most similar (relevant) to his request in the base.

3. Image features

Image features are a set of numerical characteristics that are calculated from the image. The extraction of these features is a main step and part of the CBIRs systems. The image features could be calculated for the whole image or a whole part of it called a region. In this case they are called global features to differ them from local features that are generally calculated on specific local point in the image. There are three types of image global features, color based image features, texture based image features and shape based image features.

▪ Color based image features

Color is an important characteristic and widely used to characterize images in the field. The color characteristics are calculated for a chosen system,

the most used color systems are RGB (Red, Green, Blue) and HSV (Hue, Saturation, Value), more details on color systems are included in[9]. Image color can be characterized by the covariance matrix, color histogram, color moments, and color consistency vectors.

▪ Texture based image features

Texture can be defined as a visual pattern having characteristics of homogeneity which are absent in the case of single intensity. Texture is a useful characteristic for many types of images; it is widely used with medical images since many types of them are grey level images. Human perception uses texture for the recognition and interpretation of the content of images.

The texture is calculated for a set of pixels. Several techniques have been proposed for the extraction of texture characteristics, they are generally classified into two categories according to the field of extraction. These two broad categories are the spatial extraction of texture features and the spectral extraction of texture features. In the first approach, features are extracted by calculating pixel statistics in the spatial domain of the image. In the second approach, the image is transformed in the frequency space which constitutes the source of calculation of the characteristics. Among feature extraction techniques, Haralick's functions, Gabor filters and Tamura features have been widely used.

▪ Shape based image features

Shape can be seen as an important element used to identify and differentiate between different objects. Techniques for extracting shape features can be broadly classified into two categories [10]. The first category of techniques is contour based where shape features are extracted only from the contours, while the second is region based with features extraction from the entire region.

▪ Image local features

Local features and their descriptors, which are compact vector representations of a local neighborhood, are the building blocks of many computer vision algorithms. Their applications include image registration, object detection and classification, tracking, and motion estimation. Using local features enables these algorithms to better handle scale changes, rotation, and occlusion. [11]

SIFT (Salient Invariant Feature Transform) [12] and SURF (Speed Up Robuste Features)[13] are two local characteristic image extraction techniques. They have been used by many contributions in

image processing applications. SIFT calculates histograms of the gradient orientations as a feature, and SURF uses Haar wavelet approximations.

The next section will present the SIFT technique as it is the main subject of this paper. We aim to provide an overview of the use of SIFT features in the context of Content Based Medical Image Retrieval Systems (CBMIRs) and this for the period 2014-2021.

4. Scale Invariant Features Transform

Scale invariant features transform are a set of local features [14], those features are calculated at interest points in images, DoG (Difference of Gaussian) detector is used to detect such interest points and their associated regions. The DoG is scale-invariant region detector which first detects a set of interest points, then it filters this set to preserve only points that are stable under a certain amount of additive noise. First, keypoints (interest points) are identifying by scanning the image over location and scale. It detects localization and scale of keypoints as scale-space extrema of the function $D(x, y, \sigma)$, which is the difference-of-Gaussian function convolved with the input image $I(x, y)$:

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \quad (1)$$

Where k indicates a constant multiplicative factor and

$$G(x, y, \sigma_i) = \frac{1}{2\pi\sigma_i^2} e^{-(x^2+y^2)/2\sigma_i^2} \quad (2)$$

is a Gaussian kernel.

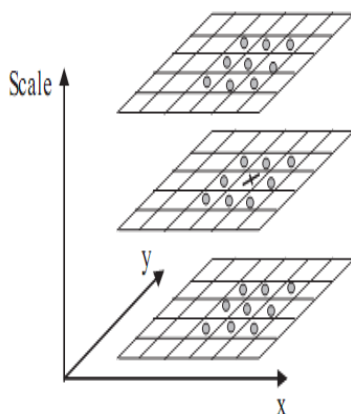


Fig.2 : Detection of extrema in scale-space by comparing a pixel(x) to its neighbors ($^{\circ}$) in the current and adjacent scales [12].

Local 3D extrema of $D(\cdot)$ are detected by comparing each pixel to its 26 neighbors, 8 neighbors in the current scale space level and 9 from both above and below space levels (see Figure 1). A point is selected

only if it is larger or smaller than any of these neighbors.

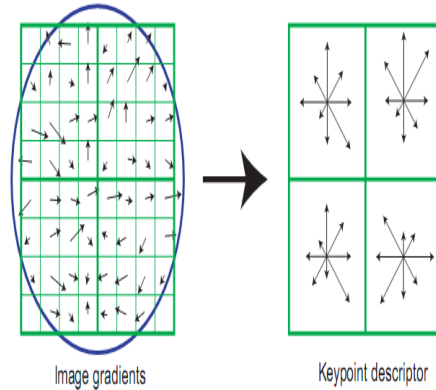


Fig.3: 2x2 descriptor array computed from an 8x8 set of samples [12].

Computation of features for keypoints detected by DoG detector is realized with the Scale Invariant Feature Transform SIFT [12]. First, an orientation, scale, and location are assigned to keypoints. The scale and location are determined by DoG detector, while one or more orientation are assigned to the keypoint based on the dominant gradient orientation of the local image patch surrounding the interest point.

An orientation histogram is used to identify dominant gradient directions by selecting peaks within. This histogram is formed from the gradients' angles of sample points within a region around the keypoint, weighted by each gradients' magnitudes.

An interest point is created with that orientation for each dominant orientation (multiple interest points might be created for the same location and scale, but with different orientations)[14].

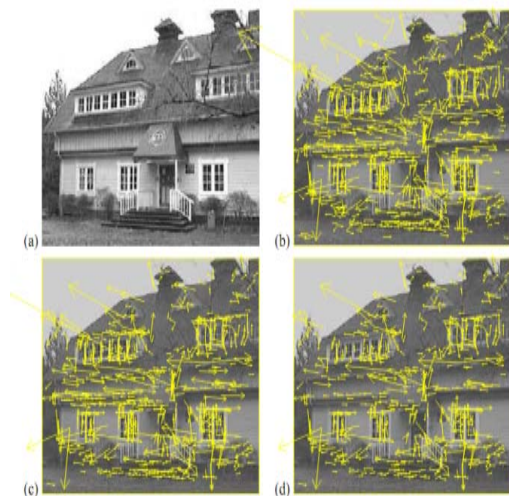


Fig.4 : Stages of keypoints selection [12].

The descriptor is formed from a vector containing the values of all the orientation histogram entries, a 4x4 array of histograms with 8 orientation bins in each is used, that means $4 \times 4 \times 8 = 128$ element feature vector for each keypoint [12]. The vector is normalized to ensure invariance to illumination conditions. SIFT features are also invariant to small geometric distortions and translations due to location quantization [14]. More details about SIFT technique are available in [14].

5. SIFT for content based medical image retrieval systems

Authors in [8] have mentioned that [2] proposed a Content-Based Image Retrieval system for Computer-aided detection (CAD) of mammographic masses. Using Scale-Invariant Feature Transform (SIFT) to build vocabulary tree. Extensive experiments are carried out on a large dataset which demonstrate the precision and scalability of the approach.

In [3] a scalable image-retrieval technique was proposed to cope intelligently with massive histopathological images for breast tissues. The article presents a supervised kernel hashing technique employing SIFT extractor technique. The classification accuracy in the presented model achieves about 88, 1%.

[4] Propose a medical images retrieval method based on a bag-of-visual-words (BoVW) with a "Pruned Dictionary" for lung nodules detection, SIFT features have been used in this work as features for the images of the ELCAP database of the lung nodules. The best overall accuracies were scored with the combinations including SIFT features

In [5] a genetic algorithm (GA) approach is presented for the selection of dimensionality reduced set of features. SIFT was one of four algorithms used in feature extraction step. This model based feature selection method is used to reduce the existing system dimensionality problem and shows that the GA driven image retrieval system selects optimal subset of feature to identify the right set of images.

Authors in [6] have proposed a retrieval system of Hepatobiliary. SIFT features have been used along with Hu-moments and GLCM. Authors illustrated that the combination of SIFT features with GLCM has achieved the best precision score in most cases.

[7] Propose a medical image retrieval system using Topic and Location Model. Scale Invariant Feature Transform (SIFT) is employed to describe the image patches represented by the keypoints. The

proposed model achieved better Mean Average Precision (86.74%), and better Precision (97.5%) compared to the recent medical image retrieval systems.

Table. 1 : results from different works.

work s	MAP (Mean Average Precision)	Precisio n (%)	Recal l (%)	Accurac y (%)	Ref .
W1	-	88.1	-	88.4	[2]
W2	-	83.0	-	88.1	[3]
W3	0.6	-	-	70	[4]
W4	0.8	80.0	30	-	[5]
W5	-	98.2	60.9	-	[6]
W6	0.86	97,5	97	-	[7]

5. Results and discussion

Works presented in this paper noted promise results for the CBMIRs, as shown in (Table 1). The scores of systems precision demonstrate utility of SIFT features extraction in CBMIRs due to its efficiency with medical images proprieties and the increasing datasets.

In W1 the precision of the proposed system changes following the change of the K (the vocabulary tree branch factor): k=1 precision=88.1%; k=5 precision=88.4%; k=20 precision=85, 4%.

SIFT features are extracted from region of interest (ROI) of mammographic, then searched in a vocabulary tree, which stores all the quantized features of previously diagnosed mammographic ROIs. Contextual information in the vocabulary tree (of depth L and branch factor k) is employed to refine the weights of tree nodes.

In W2 the precision scored 88.3%, when classification accuracy achieves about 88.1%. A kernel-based supervised hashing model is introduced to encode a high-dimensional image feature vector, extracted with SIFT method, to short binary bits using only a limited number of labeled images. Promising time and computational efficiency are noticed in this work too.

The work W3 scored 74% of accuracy, where SIFT extract features to construct the BOVW. Based on Latent Semantic Topic description a Pruned Dictionary is implemented: first, a topic-word significance value for each visual word is calculated to evaluate the connection between word and the latent topic. Then, compute an overall-word significance value to evaluate the significance of a

visual word within the entire dictionary. The words with higher values are considered meaningful with more significant discriminative power in differentiating medical images

The work W4 the MAP scored 83% and the system precision 80%, the improved SIFT was used to extract features while hybrid approach selects a reduced number of features.

The Work W5 note 98% of system precision when SIFT was combined with GLCM approach compared with another combination (SIFT + Hu-moment) wherein the precision scored 94.71%.

The work 6 has scored over 0.86 of MAP when SIFT is used to generate LDA topic model, experiments on a large dataset shows the efficiency of the system.

A remarkable improvement in the precision's scores when SIFT was combined with another methods, such in work (W5).

6. Conclusion

Content Based Medical Image Retrieval Systems (CBMIRs) are very interesting tools that help and assist doctors in diagnosis and decisions by extracting similar cases and images from medical databases.

Scale Invariant Features Transform technique (SIFT) is a powerful technique that extracts useful local features that better handle different image transformations such as scale changes, rotation, and occlusion.

We present in this paper recent works that have been used the SIFT technique in a context of CBMIRs. The results from these works have illustrated the utility of this technique and the relevance of its features.

Reference:

- [1] Palwinder K., Rajesh K.S., (2020) A Panoramic View of Content-based Medical Image Retrieval system. International Conference on Intelligent Engineering and Management (ICIEM) IEEE
- [2] Menglin J., Shaoting Z., Hongsheng L., Dimitris N.M., (2014) Computer-aided diagnosis of mammographic masses using scalable image retrieval. IEEE Transactions on Biomedical Engineering 62:783-792.
- [3] Xiaofan Z., Wei, L., Murat D., Sunil B., Shaoting Z., (2015) Towards, Large-Scale Histopathological Image Analysis: Hashing-Based Image Retrieval, IEEE Transactions on Medical Imaging 62: 496-506.
- [4] Fan Z., Yang S., , Weidong C., Alexander G.H., Sidong L., Sonia P., Ron K., Michael J.F., David D.F., Mei C., (2016) Dictionary pruning with visual word significance for medical image retrieval. Elsevier B.V. 177:75-88.
- [5] Nagarajan G., Minu R.I., Muthukumar B., Vedanarayanan V., Sundarsinghe S.D., (2016) Hybrid Genetic Algorithm for Medical Image Feature Extraction and selection. Elsevier B.V. 85: 455 - 462.
- [6] Manoj K. , Kh. M.S., (2018) Content Based Medical Image Retrieval System (CBMIRS) to Diagnose Hepatobiliary Images. Springer pp. 663-676.
- [7] Shamna P., Govindan V.K., Abdul Nazeer K.A., (2019) Content based medical image retrieval using topic and location model. Journal of Biomedical Informatics, Elsevier 91.
- [8] Manganleima M., Thounaojamrupachandra S.,(2020) CONTENT BASED MEDICAL IMAGE RETRIEVAL (CBMIR): A SURVEY OF REGION OF INTEREST (ROI) AND PERCEPTUAL HASH VALUES. Journal of Critical Reviews 7: 712-721.
- [9] Datta R., Joshi D., Li J., Wang J.Z., (2008) Image retrieval: Ideas, influences, and trends of the new age. ACM Computer Surveys, 40 :1-60.
- [10] D. Zhang, G. Lu, (2004) Review of shape representation and description techniques. Pattern Recognition 37: 1-19.
- [11] The MathWorks, Inc. 1994-2021, united state,< <https://www.mathworks.com>>
- [12] Lowe, D. G. (2004) Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision 60: 91-110.
- [13] Bay H., Tuytelaars T., Gool L.V., (2008) SURF: Speeded Up Robust Features. Computer Vision and Image Understanding 110:346-359.
- [14] E. Horster,(2009) Topic Models for Image Retrieval on Large-Scale Databases, University of Augsburg.