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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.

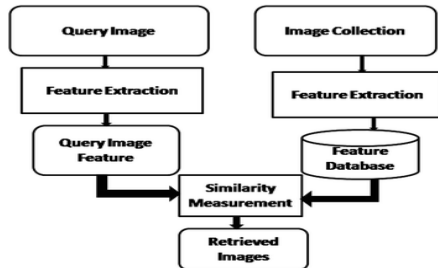


Fig. 1 : The basic architecture of CBIRs [5]

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.

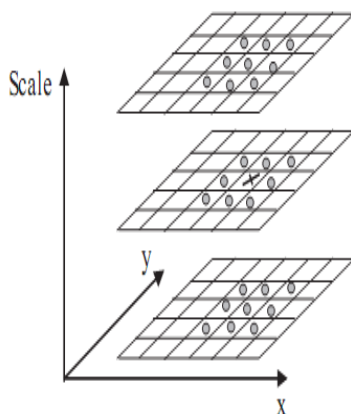


Fig.2 : Detection of extrema in scale-space by comparing a pixel(x) to its neighbors ($^{\circ}$) in the current and adjacent scales [12].

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.

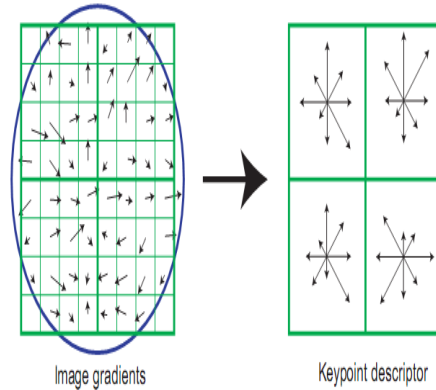


Fig.3: 2x2 descriptor array computed from an 8x8 set of samples [12].

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].

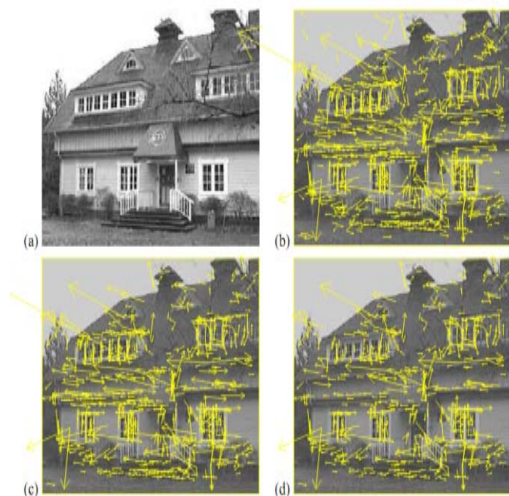


Fig.4 : Stages of keypoints selection [12].

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 built 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 present 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.



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The tools of Artificial Intelligence applied to monitoring

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Informations	Abstract
Mots clés : Monitoring Detection Diagnostic Artificial Intelligence (AI) *Correspondence : mehar.zohra@univ-oran2.dz	The purpose of this work is the presentation of the different tools of Artificial Intelligence for monitoring. These methods are divided into three major families: behavioral models, pattern recognition methods and explanatory models. Monitoring can be defined in several ways; this monitoring is composed essentially of two phases: flaw detection and fault diagnosis. The diagnosis is divided into two functions: location and identification of causes.

1. Introduction

The problems of great importance in industrial monitoring are constituted by the possibility of detecting false alarms and eventually predict failure.

The field monitoring needs mainly artificial intelligence either to exploit a know-how or to bring distributed intelligence to the lowest operational levels.

The methods by symbolic tools rely heavily on Artificial Intelligence (AI) techniques, familiar or at least shareable by the operator. Indeed, the use of Artificial Intelligence overcomes the complexity of the systems to be monitored. Moreover, in general, Artificial Intelligence due to these characteristics is relatively well suited to monitoring problems. Indeed, AI can be characterized by the ability to treat [1]:

- A large amount of information,
- non-homogeneous data, (numerical / Symbolic),
- dependent data context,
- incomplete data.

Overall, these methods will be grouped under the expression: « Symbolic modeling methods ». They are characterized by keywords that better reflect their objectives and their respective characteristics. A distinction is therefore made between symbolic models,

recognition methods, methods based on behavioral models and methods based on explanatory models, see [1].

2. Defining monitoring

Monitoring is a passive device and / or dynamic, informational, which analyzes the state of the system and provides indicators. Monitoring particular is to detect and classify failures by observing the evolution of the system, then diagnose by locating faulty elements and identifying the root causes, see [3] and [4,5].

2.1. Detection

To detect system failures, you must to be able to classify observable situations as being normal or abnormal, [5].

2.2. Diagnostic

The diagnostic system [6] suggests to the operator the possible causes of this problem, as well as fuzzy interpretations of these causes. The objective of the diagnostic system is to search for the causes and locate the organs that led to a particular observation. This function is broken down into two elementary functions: localization and identification. The localization makes it possible to determine the faulty functional subset, while identification involves

determining the causes that led to an abnormal situation. These causes may be internal (faulty subassemblies that are part of the equipment), or external to the equipment. See [7,8].

Monitoring has two main functions: fault detection and fault diagnosis, figure (Fig. 1).

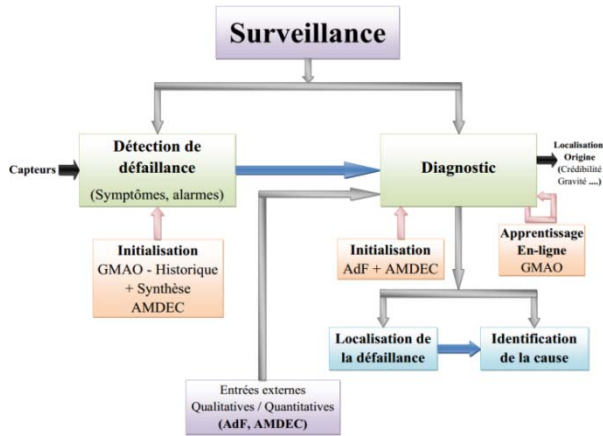


Fig.1 : The components of monitoring.

3. Purpose and objective monitoring

Monitoring is responsible for collecting permanently all signals, through indicators, from the production system, and monitors in real time the evolution of the controlled system. It thus includes all the tools to monitor the evolution of the system behavior in relation to normal operation, and to detect any anomaly or failure. In this last case, a diagnosis is established in order to locate the subsystem responsible for the malfunction and to identify the cause of the failure. This makes it possible to specify the maintenance operations to be carried out in order to restore the production system to working order. See [2].

4. Industrial Monitoring: Methods and Models

The methods of monitoring are generally divided into two groups: monitoring methods with model and without model. See [3,10] and [11] [12,13].

The figure (Fig. 2) illustrates the methods most used in industrial monitoring.

4.1 Monitoring methods with models

These are the methods most used by industrialists today; they are based on the existence of a formal equipment model and generally use automatic techniques. Are likely to diagnostic methods by functional and material modeling: The principle of these methods

consists in establishing a priori and as completely as possible, the links between the initial causes of the failures and their measurable effects.

The most commonly encountered methods are Failure Modes, Effects and Criticality Analysis (FMECA) and Fault Trees (FT). These methods are used mainly for diagnosis, see [3]. And physical modeling surveillance methods: Surveillance methods with physical model have the principle of comparing the measurements made on the system to the information provided by the Frank model [14,12]. Any deviation is then synonymous with a failure. The tools of decision theory are then used to determine if this difference is due to normal hazards, such as measurement noise or if it reflects a system failure. Methods with physical model are the methods most familiar to automation engineers. In general, these methods can be separated into two techniques: physical and analytical redundancy techniques, and parametric estimation techniques, [3].

4.2 Monitoring methods without models

There are many industrial applications whose model is difficult, or even impossible to obtain due to increased complexity or numerous stakeholder reconfigurations during the production process. For this type of industrial applications, only operational monitoring methods are those without model, they are distinguished on monitoring using signal processing statistical tools: Statistical tools fault detection are to assume that the signals provided by the sensors have certain statistical properties. A few tests are then carried out which make it possible to check whether these properties are present in a sample of the measured signals. A wide variety of tests is applicable on a sample of measurements. Among the most important, we mention: threshold-crossing test, average test and test of variance, found in [3,12] and [15]. And monitoring using Artificial Intelligence (AI) techniques, according to the bibliography studied, different categorizations monitoring methods by IA are given in general; Artificial Intelligence (AI) and use symbolic knowledge, familiar or at least shareable by the operator [16], artificial intelligence due to these characteristics are relatively well suited to monitoring problems. From our point of view, we propose a classification of these methods according to 3 types, [3]:

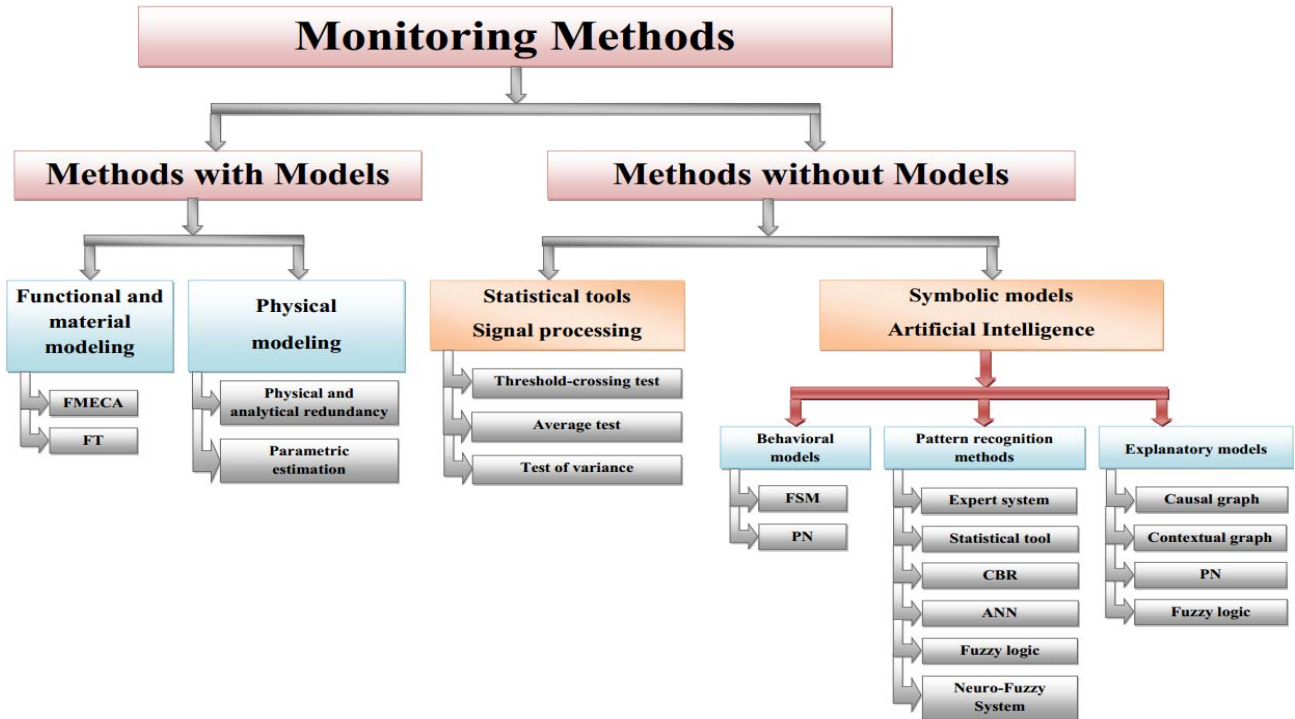


Fig. 2 : Classification of monitoring methods.

- a) **Method of modeling behavioral:** These methods are characterized in particular by the possibility of simulating the behavior of the system, from a modeling of its behavior. Most often these are models "of proper functioning" which, unlike digital models, are not based on the physical system but on a consideration in terms of mode of operation. These methods include tools such as Petri nets (PN) and the finite-state machine (FSM). In these methods, the associated keywords are: modeling / simulation, [3].
- b) **Method of pattern recognition:** These methods comprise the associative models and method of pattern recognition in the sense that they are characterized by the terms learning and recognition which apply to both pattern recognition and rule-based systems such as expert systems [3]. These techniques are more elaborate compared to simple statistical tests and are able to detect and diagnose failures [8]. These methods include: expert systems, statistical tools, case-based reasoning (CBR), Artificial Neural Network (ANN), Fuzzy logic, Neuro-Fuzzy systems, [3]. In these methods, the key words that best characterize these approaches are: learning / recognition [3].
- c) **Method of modeling explanatory:** These methods introduced by [16] are mainly

based on the representation of relationships between the different states failures and their effects (possibly observable). They are therefore based on a deep analysis of the system, so as to have sufficient knowledge in the expression of these relationships of cause and effect. The models thus obtained allow for a certain adductive approach which consists in going back to the causes of breakdowns from observations corresponding to the symptoms. Several tools of Artificial Intelligence allow such a formalization of the knowledge available on a system. These include causal graph, contextual graph, we also find approaches based on fuzzy logic or Petri nets. In these methods, the associated keyword is: causal analysis, [3].

5. Conclusion

In this work, a bibliographic review for industrial monitoring was presented. We addressed the most commonly used techniques in this field. The use of techniques and models is difficult, expensive and offering less and less satisfaction with more and more complex systems. The use of techniques without models is more suited to this problem and, more particularly the techniques related to Artificial Intelligence. Finally, we proposed a classification of these techniques into three classes.

Référence :

- [1] Palluat, N. (2006) Méthodologie de surveillance dynamique à l'aide des réseaux neuro-flous temporels, Thèse de Doctorat, Université de Franche-Comté, France.
- [2] Abbou, R. (2003) Contribution à la mise en œuvre d'une maintenance centralisée : Conception et Optimisation d'un Atelier de Maintenance, Thèse doctorat, Université de Joseph Fourier - Grenoble I, Français.
- [3] Mahdaoui, R. Contribution à la surveillance dynamique des systèmes de production évolutifs par les systèmes Neuro- Flous Temporels, Thèse doctorat, Université de Batna 2, Département de Génie Industriel, Algérie.
- [4] MAHDAOUI, R., MOUSS, H., CHOUHAL, O., KADRI, O., and HOUASSI, H. (2009) La Surveillance Industriel Dynamique par les Systèmes Neuro-Flous Temporels : Application à un système de Production, SETIT 2009, 5th International Conference: Sciences of Electronic, Technologies of Information and Telecommunications, Tunisia.
- [5] Lefebvre, D. (2000) Contribution à la modélisation des systèmes dynamiques à événements discrets pour la commande et la surveillance, Habilitation à Diriger des Recherches. Université de Franche-Comté/ IUT Belfort.
- [6] Dubuisson, B. (2001) Diagnostic, intelligence artificielle et reconnaissance des formes, Traité IC2, série productique. Lavoisier.
- [7] MEHAR, Z., Nouredine, R., Nouredine, F. (2017) Les outils de l'Intelligence Artificielle appliqués à la surveillance, 2ème Journée de la Maison du Doctorant de l'Université d'Oran 2 (MDO2), Oran, Algérie.
- [8] Racocceanu, D. (2006) Contribution à la Surveillance des Systèmes de Production en utilisant l'Intelligence Artificielle, Thèse doctorat, Université de Franche-Comté, France.
- [9] Palluat, N., Racocceanu, D., Zerhouni, N. (2004) Diagnosis aid system using a neuro-fuzzy approach. Advances in Maintenance and Modeling, Simulation and Intelligent Monitoring of Degradation.
- [10] Dash, S., Venkat, V. (2000) Challenges in the industrial applications of fault diagnostic systems, Dans: Process Systems Engineering (PSE 2000), Vol. 24 de Computers and Chemical Engineering. pp. 785-791.
- [11] Monnin, M. (2004) Surveillance et aide au diagnostic en utilisant des techniques de l'intelligence artificielle. Utilisation des réseaux de Petri flous, Mémoire de D.E.A. Université de Franche-Comté.
- [12] Zemouri, R. (2003) Contribution à la surveillance des systèmes de production à l'aide des réseaux de neurones dynamiques : Application à l'e-maintenance, Thèse de Doctorat. Université de Franche-Comté.
- [13] El Méliani, J., Lotfi, N., Hassani M. (2009) Monitoring and assistance diagnosis of a centrifuge pump by using the fuzzy Petri nets, DOI: 10.1109/ICCIE.2009.5223756.
- [14] Frank, P.M. (1990) Fault Diagnosis in Dynamic Systems Using Analytical and Knowledge Based Redundancy. A survey and New Results, Automatica, Vol. 26, pp. 459-474.
- [15] Basseville, M. (1988) Detecting changes in signals and systems - a survey. Automatica.
- [16] Basseville, M., Cordier, M.O. (1996) Surveillance et diagnostic de systèmes dynamiques : approches complémentaires du traitement de signal et de l'intelligence artificielle," Technical Report 2861. INRIA. Rennes, France.