Modular Statistical Optimization and VQ Method for Image Recognition

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Abstract. In this work, a modular statistical optimization method enriched by the introduction of VQ method dedicated to obtain the effectiveness and the optimal comuting time in image recognition system is poposed. In this aim, a comparative study of two RBF and an SVM classifiers are carried out. For that, features extraction is made based on used image database. These features are gathered into blocks. The statistical validation results allow thus via the suggested optimization loop to test the precision level of each block and to stop when this precision level is optimal. In the majority of the cases, this iterative step allows the computing time reduction of the recognition system. Finally, the introduction of vector quantization method allows more global accuracy to our architecture.

1 Introduction

Image recognition is an extensively researched field that has seen many successes but still many more challenges. One such challenge concerns the great images sets management wich becomes increasingly complex and expensive in term of computing time. Also, the semantic richness of these images requires a powerful representation. These reasons make that the obtaining of the compromise between effectiveness and optimal computing time is considered as a real challenge. For this purpose, automatic image recognition in computer vision is a crucial problem, especially if one deals with heterogeneous images. Considerable efforts have been paid to this problem and rather promising results, both theoretical and experimental, have been obtained [1, 2, 3] . However, even the most efficient techniques are unable to recognize an image without errors [4]. Indeed, the similarity search between a request image and the database images require to understand, find and compare information without inevitably having directly recourse to their contents. Indeed, the image features can be seen as being structured data, which describe this information, and which can be applied to all comparison types. This quantification concept is generally interpreted as classification of features vectors extracted from treated images. We deduce two great steps, which constitute the traditional way of image recognition process, the features extraction step that allows to have an image representativeness and the features vec-

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tors classification step which allows to obtain a similarity measure between the request image and the database images. Several features extraction techniques are developed and used in images recognition systems. The extracted features vary from the low to the high level image description (color, shape, geometry, semantic knowledge... etc) [5, 6, 7]. These techniques often differ by their results quality obtained in various applications. Their generalization is thus very difficult to implement since they were initially developed for specific applications. Since one is interested in this work in the heterogeneous images recognition, the use of only one features category can carry out to erroneous results. As for the features extraction, several classification techniques are used. The majority of these methods [8, 9, 10, 11] have a weakness to manage high dimension data. That generates consequent computing times and less precise results. The classification methods based on learning concept [12, 13, 14] permit to obtain better computing times and more precise results. A specific features combination is used in [15]. This choice is justified by the fact that this combination allows to obtain the best possible images representativeness, which is robust to the geometrical variations and noises deterioration. In fact, the chosen features include low-level, wavelet transform and Trace transform features. For classification step, the radial basis functions (RBF) networks and support vector machines (SVM) were selected. This choice is justified by the faculty of these two classifiers to obtain good classes separability and by their effectiveness in term of computing time. Moreover, these techniques permit to have fluidity and processing simplicity, which make that they are appropriate to real time applications like image recognition and search field. Generally, the great challenge of any classification technique is to solve the high dimensionality problems. Indeed, the data coming from concrete training problems often appear in high or very high dimension: i.e. that a great number of variables was measured for each training example. Moreover, the we proposed an image search method based on great number features extraction. The extracted features gave good images representativeness, but the generated high dimensionality on the classification step deteriorated the global images recognition system. For this reason, a resolution of high dimensionality problem tool is essential to be able to obtain a system that ensures a compromise between precision and computing time. In this paper, we propose a novel architecture based on an optimal features use that is able to obtain an acceptable precision rate during an optimal search time. In section 2, the modular statistical optimisation is detailed. Its architecture is presented and compared to classical one. In section 3, the used vectorial quantization is exposed and discussed. The experimental results obtained with an heterogeneous image DataBase are presented and discussed in section 4. Indeed, this section presents a comparative study of obtained results with modular statistical optimisation, vector quantization, and the combination of both.

2 Modular Statistical Optimization

The idea to introduce a system optimization tool was essential when one realized during the carried out tests that the use of all extracted features could be heavy to manage. Indeed, more features vectors dimensions are significant more the classifier has difficulties for their classification. The traditional way that one followed in [15] and that one finds in many CBIR systems is a diagram which consists of the use of all extracted features in the classification step. Unfortunately, this method presents a great disadvantage, by using all features the classifier manages a great dimensions number. That involves a consequent computing time what creates a real handicap for great images databases. In fact, this problem which is the direct result of the high dimensionality problem was the subject of several works which led to cure it. In [16] the authors proposed a technique which allows when that is possible to reduce the SVM training time by using the vectorial quantization technique. The principal idea was to use the vectorial quantization to replace the training basis by a reduced one. In the same philosophy, and in order to solve this problem, the proposed architecture of figure 1 is based on a feedback loop procedure. The principal idea of this architecture is that instead of using all features in the classification step, one categorizes them on several blocks or modules and after one tries to obtain the optimal precision with the minimum of blocks.

2.1 Modular Features DataBase

The introduced modular features database in our proposed architecture (Figure 1) includes classical features (the two co-ordinates of the image segments medium, the image segments length, the segment angle compared to the horizontal axis, the gradient norm average calculated along each segment, the gray levels average of the areas on the right and on the left of the segments, areas internal contrasts on the left and on right of the segments, directed differences between the gray levels in the left and right areas of the segments, the close segments list of each segment), color histograms features, wavelet transform features (texture features and rotation invariance by wavelet transform) and finally rotation translation and scaling invariance by Trace transform. Using all these features one formed four features modules which one can describe as follows: The first module (b1) gathers the classical features, the second module (b2) gathers the color features, the third module (b3) the wavelet transform features and finally the fourth module (b4) the Trace transform features. The following table (figure 2) summarizes the obtained features blocks (B1 to B6) by combining the exposed features modules (b1 to b4). These blocks were used during the experimental tests.

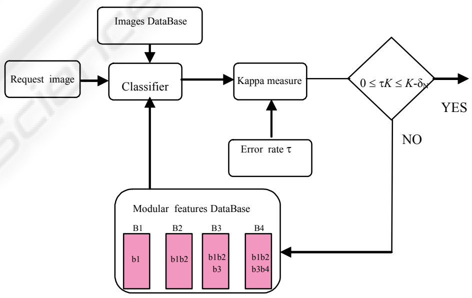


Fig. 1. Modular statistical architecture.

In figure 3, one can see a sample image with its 4 extracted features blocks.

Features Blocs	B1	B2	B3	B4	B5	B6
Concerned Modules	b1	b1b2	b3	b1b2b3	b4	b1b2b3b4

Fig. 2. Used features blocks table.

2.2 Classification

The classification block is the tool that makes it possible to obtain a similarity measure between the database images features vectors and the image request one. In our application, one used three algorithms, two for RBF and the third for SVM.

2.2.1 RBF Classifiers

Among existing neural networks, one can quote RBF classifier (radial basis function) which is one of the most used feedforward networks. That is due to the fact that it uses the local classification principle based on local kernel functions. These functions give useful answers for restricted field values, their influence field. The kernel functions concept is very significant because they solve the classes separability problem for the no linearly separable cases. Also, RBF networks can also be built extremely quickly. This last point is very important for our application, which requires a fast and simple classifier. In this work one has used two RBF algorithms. The first one is the RCE algorithm (restricted coulomb energy) introduced by Reilly, Cooper and Elbaum [17]. This algorithm is inspired by the system particles loads theory. The algorithm principle is based on the modification of the network architecture in an iterative way during the training. The intermediate neurons are added only when that is necessary. The second algorithm is the DDA algorithm (Dynamic Decay Adjustment) [18] which uses at the same time the evolutionary structure of the RCE algorithm and the management possibility of each prototype radius individually. This radius is related to its closer neighbors. Moreover, a conflict problem exists at the training phase with the RCE algorithm. This problem is solved with DDA algorithm with the use of two thresholds instead of one for the RCE algorithm.

2.2.2 SVM classifiers

The SVM algorithms were developed in the Nineties by Vapnik [14]. They were initially developed for supervised binary classification. They are particularly effective because they can solve great features numbers management problems. They ensure a single solution (not local minimum problems as for neural networks) and they provided good results on real problems. Geometrically, the SVM are the closest vectors to the optimal hyperplane that separates the two classes internal representations space. The algorithm in its initial form amounts seeking a linear decision border between two classes. But this model can be considerably enhanced while being projected in another space, which makes it possible to increase the data separability. One can then apply the same algorithm in this new space in order to obtaining a non-linear decision border in initial space. In this work, one uses LS SVM algorithm (least squares SVM)

[19]. This algorithm is based on a different optimization criterion formulation. Indeed, it based on a least square transformation which transforms the problem into a

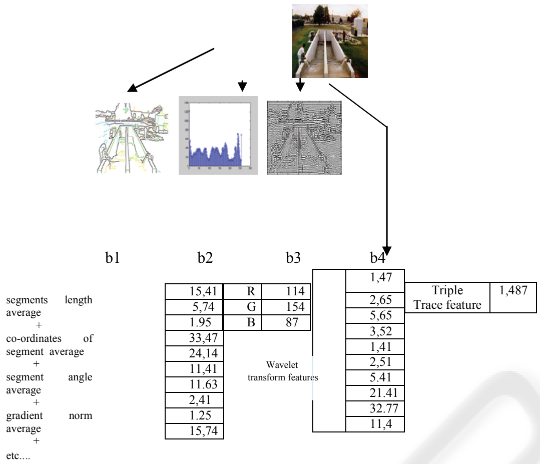


Fig. 3. Obtained features blocks for a sample image.

simple linear problem. Also, LS SVM algorithm proposes a linear resolution of the problem equations to be optimized without using the complex standard SVM quadratic programming. This choice is justified also by its implementation simplicity; its good separation effectiveness and its optimal computing time.

2.3 Statistical Optimization

Our architecture is mainly based on Kappa measure [20], which is computed from obtained confusion matrix after classification step. Indeed, this measure is the tool that allows validating obtained classification results with each introduced features block. Also, this measure determines the total agreement between classification results. Theoretically, the equation (1) makes it possible to determine Kappa value K, where P_o is the observed probability and P_e is the expected probability [20].

$$K = \frac{P_o - P_e}{1 - P_e} \tag{1}$$

In our case, this agreement depends on the found images precision rates for all request images constituting the test database. A one confusion matrix is obtained and then only one Kappa value for each introduced features block. One can thus summarize the modular statistical procedure as follows: For a given request image one introduces to classifier the first features block B1. One calculates the Kappa value of the corresponding confusion matrix. If this value is included in a given interval, one estimates that the result is good, the search for similar images is finished. But if the obtained Kappa value is not included in this interval, then the feedback loop is activated, which implies the use of another block. These steps are repeated until one obtains a Kappa value included in the considered interval. The selection criteria which one used to fix the interval thresholds is based on the following methodology: After experimental obtaining of the real precision results which based on the good found images number for each request image, one determines a P_R parameter obtained as follows: P_R = real obtained precision rate/ 100 (currently, obtaining P_R is done in experiments, but it could become automatic). This parameter is used to calculate the error rate τ = 1- P_R. It should be noted that for each features block one obtains only one error rate value. In the same way, for the same features block one obtains only one Kappa value calculated from the corresponding confusion matrix. Thus, the product (τ. Kappa) is the parameter which one introduced to create relation between the experimental obtained results and statistical estimates provided by Kappa measure. The following condition is to be satisfied to validate or not the expressed precision at the classifier output each features block: $0 \leq \tau.K \leq$ K- δ_N. Where τ is the error rate value calculated in experiments for each introduced features block. K is the calculated Kappa value from confusion matrix corresponding to each introduced features block. δ_N is a constant number equal to N.K. N is fixed according to the desired precision (generally N$\in$[0.9, 1[). Finally, it should be noted that proposed architecture could not guarantee a computing time reduction. Indeed, for disturbed images or which have a great semantic complexity, it may be that one has recourse to several iterations until coming to the use of the last block which gathers all extracted features. In this case, one will not gain in time computing but one will be certain for this case, the use of all features was a need. In other words, one not gain in time but one gain in term of data classification optimality because one does not use more data that it is necessary for classification.

3 Vector Quantization

Generally, compression by Vector Quantization (VQ) accepts an input vector *X* of *N* dimension and replaces it by a vector *y* having with more same dimension belonging to a dictionary which is a finished vectors codes set, also called classes, or barycentres since those are calculated by an iterative average of vectors *X.* The quantification step (according to a dictionary built starting from a training set) rests on the *KNN* method : a vector *X* to be classified will be affected with one of the classes under the condition which this assignment generates the smallest distortion. However, this assignment implies a binary choice, *i.e.* vector *X* must necessarily belong to the class to which the barycentre is its nearer close (according to Euclidean distance). This assignment rule can appear too idealistic whenever the distances between vector *X* and two barycentres are very close. In this case, one or the other of these barycentres could be appropriate, according to one or more criteria which can be based on some statistical properties or criteria others that the only Euclidean distance. In our work, the vector quantization will be useful to making it possible to standardize the features

distribution in the images/ features tables. The aim of this standardization is to balance the influence of each feature type. Indeed, the bias data problem could deteriorate of global system accuracy. Moreover, vector quantization is used in this paper to reduce data dimensionnality generated by the great number of used features. One can find the same philosophy is [16]. Lebrun and all were used VQ technique to reduce generated high dimensionnality by using SVM classifiers.
The principal idea is to train the SVM classifier on a representative basis of the initial Database, but with a reduced examples number. LBG algorithm [16] (used in dictionary construction step) is applied in order to reduce this examples number. The aim is to reduce the training time and to obtaind a quick rejection of the bad parameters for the model choice. The training base size increases with each iteration, until the improvement of the classification rate improvement becomes lower than a chosen threshold.

4 Experimental Results

In this section, a comparative study of three classifiers (RBF-RCE, RBF-DDA and LS-SVM) is carried out and that by using the architecture based on modular optimization which one proposed. These three classifiers were applied to the images features blocks in order to recognize images in heterogeneous images database case. For that, one used the features blocks which one mentioned previously. The objective being to reduce when that is possible the image retrieval system computing time. Also, an other comparative study is carried out between modulat stististical optimisation and vector quantization method wich is used for high dimensionality reduction in [16]. Finally, the results of the combination of both is exposed and show a small improvement of obtained accuracy. The obtained results in this section are based on the extracted features from the image database with 1000 images. A sample of those images is given in figure 4. Statistical optimization thus allows a precision comparative evaluation of each of the three used classifiers. The figure 6 graphs are an obtained error rates representation with samples of requests images test database. Those rates are given after a recall processing for each image.

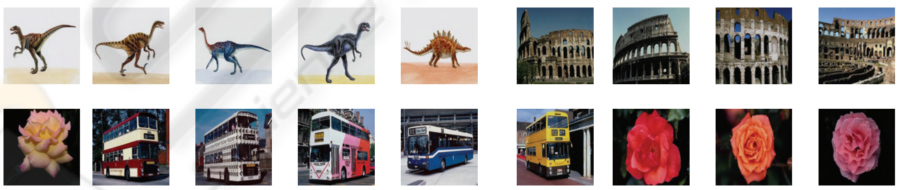
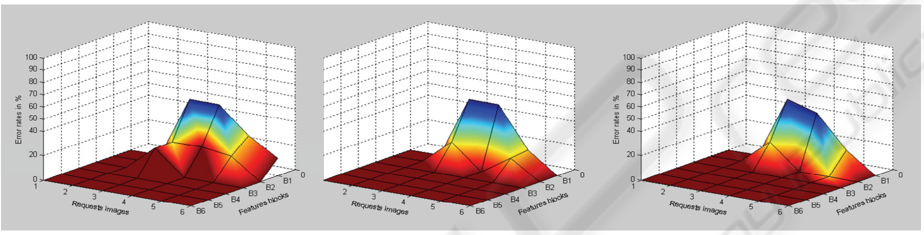


Fig. 4. Sample of used heterogeneous image database.

4.1 Comparative Study Results of the Three Used Classifiers

With the same images features, and with using our proposed architecture for each one of the three chosen classifiers (RBF RCE, RBF DDA and LS SVM classifiers), one obtained the precision results shown in figure 5. With RBF-RCE, one notices the modular architecture utility for requests images 1 and 2 since one obtains a null error rate with the use of the first block (classical features). The requests images 3, 4, 5 and 6 results show well the features modules iterative addition influence on the progressive improvement of the corresponding error rates. It is also noticed that for all used requests images one arrived at an optimal result without using all features modules (figure 5). With RBF-DDA, one notices the same phenomenon with an obtained result improvement. Indeed, it is noticed that one arrived more quickly at an optimal result for requests images 3, 4 and 6 (figure 5). With LS-SVM, one obtains the best results among the three algorithms. Indeed one notice on figure 5 that there was more speed to obtain a null error rates in the request image 5 case. Then, one deduces that modular optimization made it possible to obtain an optimal result with the three used classifiers without using inevitably all extracted features. However, one notices a greater convergence to optimal result using SVM classifier. This superiority is explained by the SVM superiority to manage features vectors great dimensions.



(A) **(B)** **(C)**

Fig. 5. Obtained error rates for each classifier. (A): Obtained error rates for RBFRCE classifier, (B): Obtained error rates for RBFDDA classifier**,** (C): Obtained error rates for LS SVM classifier.

4.2 Comparative Study Results Between our Method and Vector Quantization Method

In order to evaluate the effectiveness of our proposed method, an experimental comparison is carried out between the obtained results with modular statistical optimisation and those obtained with a very used method in the dimensionality reduction applications: the vector quantization method (VQ). To this end, we used the VQ algorithm in order to reduce dimensions of our features vectors. That is done in an iterative way, according to figure 6. This table presents the columns number of the dictionary obtained at each VQ iteration. The dictionary construction depends on the initial features number in the features basis (32 in this study).

VQ iterations	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Columns number	2	4	8	16	32

Fig. 6. Dictionary columns number for each iteration.

In figure 5 (c) and figure 7, one notices lower error rates with the first VQ iteration in comparison with those obtained with our approach.
That is explained by our random choice of initial features blocks in our approach. In VQ method, initial data choice is more optimal because it is based on specific processing. As an example, for the request image 3, one obtained an error rate of 50%

using the first features with modular statistical optimization, while with the first iteration of the VQ one obtained an error rate of 20%. However, one notices a faster convergence in the case of the use of modular statistical optimization after the first choice of the features block. Indeed, for the request image 3, one obtained the same error rate (20%) for second iteration QV and for the second choice of features block within the modular statistical optimization. Then, the vector quantization is more precise in the first iterations than modular statistical optimization since it is based on a method of successive divisions which gives convergence towards the optimal result in the first iteration. On the other hand, modular statistical optimization converges more quickly after the first chosen block. Moreover, in term of time processing, one can see in figure 8 that our method is faster than classical method wich is based on use of all images features in the same time. Also, one can see that our approach is slightly faster than VQ method because our method don't require a sorting features algorithm like

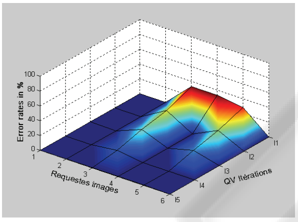


Fig. 7. Obtained error rates with vectorial quantization using LS SVM classifier.

used LGB algorithm wich is used in global VQ algorithm.

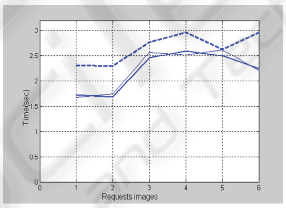


Fig. 8. Processing time diagrams: With vector quantization, (b): With modular statistical optimisation, (c): With classical approach.

However, our approach is limited because the modular statistique optimisation is applicable only if the request image is also an image of used DataBase. In other words, our approach is not yet able to reduce the processinf time of the global system with a request image wich is not present in image DataBase. Nevertheless, it is very useful in various fields such as police research files, medical imagery, satellite imagery...etc. We note that the computing time considered in figure 8 does not take into account the computing time relative to DataBase images features extration. This step is an off line operation. Finally, we specify that obtained precision rates shown in figures 5 and 7 characterize our architecture performances with a sample of 20 images among the 1000 images of global DataBase. However, other partial results approve the results presented in this paper and will be presented in a future work.

4.3 Combination Results

The principle of this combination is as follows: we keep the same modular features base of section 2.1, we apply the vector quantization method to each module which is solicited by the modular statistical optimization loop. That brings back to a new reduced confusion matrix and a new Kappa value. The modular statistical optimization procedure remains the same one and the loop will stop when the obtained error rate is minimal. The proposed architecture is thus based on two data space reduction steps. This double reduction makes it possible to present the most optimal data input to classification step. In figure 9, we can note the added value of this space data double reduction. Indeed, the precision rates are appreciably better with comparing them with figure 5 (c) and figure 7. Moreover, we need other tests to validate these first results. Finnally, we note that the final results depend mainly on the images quality beause the vector quantization method is based on the features vectors representativeness. In the contrary case, the desired complexity reduction is not guaranteed and it is extremely probable that the iterative process uses all the data relating to the features blocks without arriving at an optimal result.

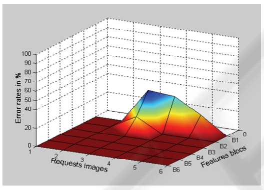


Fig. 9. Combination results with SVM classifier.

5 Conclusion

We propose in this work a statistical modular architecture dedicated to the images recognition systems. In fact, an extraction of used images database is carried out. These features are gathered into vectors, which are used as classifier inputs. A modular features database is then built by gathering the features previously extracted into blocks. Statistical optimization thus makes it possible via an iterative step to introduce these blocks one by one and to stop the process when the precision error rate reaches the desired minimum. The interest of this method is that one is not obliged to use all extracted features to obtain optimal result, which enables us to optimize in much cases the total system computing time. In the contrary case, and if one does not gain in time reduction, one gains in optimality because one is certain to have not to use more data than it is necessary to obtain the optimal result. The outcomes in comparative study based on the use of two classifiers kinds show the SVM superiority compared to RBF networks. That is explained by their great capacity to manage great information quantities and their separability fluidity. Moreover, a comparative study is carried out between our proposed approach and vector quantization method, and obtained results show the effectiveness of our method as well in the precision criterion as in the computing time one. However, our approach is not yet able to reduce the processinf time of the global system with a request image wich is not present in image DataBase. Nevertheless, it is very useful in various fields such as police research files, medical imagery, satellite imagery...etc. finally, a double dimension data reduction strategy is proposed basing on the simultaneous use of modular statistical iptimisation and vector quantization method. Preliminary results show an improvement of obtained results. Moroevere, more tests are necessary to confirm this observation. Finally, we project in the future to automate error rate obtaining thus operation that is necessary to fix the statistical optimization interval and permit to our approach to be applyed to the requests images which are not presents in initial DataBase.

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