Image Retrieval Based on Wavelet Transform and Neural Network Classification

Recuperación de Imágenes sobre la Base de la Transformada Ondeleta y su Clasificación Mediante Redes Neuronales

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Abstract

The problem of retrieving images from a database is considered. In particular, we retrieve images belonging to one of the following six categories: 1) commercial planes in land, 2) commercial planes in air, 3) war planes in land, 4) war planes in air, 5) small aircraft in land, and 6) small aircraft in the air. During training, a wavelet-based description of each image is first calculated using Daubechies 4-wavelet transformation. The resulting coefficients are used to train a neural network (NN). During classification, test images are treated by the already trained NN. Three different ways to obtain the coefficients of the Daubechies transform were proposed and tested: from the entire image color channels, from the histogram of the biggest circular window inside the image color channels, and from the histograms of the square sub-images in the image color channels of the original image. 120 images were used for training and 240 for testing. The best efficiency of 88% was obtained with the third method.
Key Words: Image Retrieval, Wavelet Transform, Neural Classification.

Resumen.

Se considera el problema de la recuperación de imágenes desde una base de datos de imágenes. En particular, se recuperan las imágenes que pertenecen a una de las siguientes seis categorías: 1) aviones comerciales en la tierra, 2) aviones comerciales en el aire, 3) aviones de guerra en la tierra, 4) aviones de guerra en el aire, 5) avionetas en la tierra, y 6) avionetas en el aire. Primeramente se calcula una descripción con base en la transformada ondeleta de cada imagen mediante la ondeleta Daubechies-4. Los coeficientes resultantes se usan para entrenar una red neuronal. Durante la clasificación, se prueba el sistema con imágenes ya tratadas por la ya entrenada red neuronal. Se propusieron y probaron tres métodos diferentes para obtener los coeficientes de la ondeleta Daubechies-4: desde los canales de color RGB de la imagen completa, desde el histograma de la mayor ventana circular inscrita en los canales de color RGB de la imagen, y desde los histogramas de sub-imágenes cuadradas insertadas en los canales de color RGB de la imagen. Se usaron 120 imágenes para el entrenamiento de la red neuronal y 240 para probar el sistema. La mejor eficiencia de 88% se obtuvo con el tercer método.
Palabras Clave: Recuperación de Imágenes, Transformada Ondeleta, Clasificación Neuronal.

1 Introduction

Information processing often involves the recognition, storage and visual information retrieval. It is conceived that an image contains visual information and that what is important within such information retrieval process is to return the original image or a group of images with similar information [1]. Image retrieval refers to seek and recover visual information in form of images, within a collection of databases of images, being one of their investigation areas the organization and retrieval based on the content, in color terms.

Most of the information in the cyberspace is images, approximately 73% [2]. This information, in general, is not well organized. In the cyberspace we can have images of all kinds: photos of people, flowers, animals, landscapes, and objects in general. They can be organized and recovered using image color contents. The implementation of a system able to differentiate among 10,000 classes of objects is still an open research subject. Most of the existing

systems work efficiently with hundreds of objects. When this number grows up to thousands, such systems became to be more complex and their performance decreases quickly [2]. As a first step in this direction, we present in this paper a simple but effective methodology to learn and classify objects with similar characteristics. Intuitively, such a problem would to be much more difficult to solve than the problem of complete classification of objects with different characteristics [3]. Thus, we are interested in the decision: if a photo of a given airplane belongs to one of six categories shown in Figure 1.

Here, we present a short state of the art about researches most related to the subject of this paper, and emphasize the main differences and advantages of our work with those reported in the literature.

In [11], Park et al. used Haar wavelets and a bank of perceptrons to retrieve images from a database of 600 images (300 for training and 300 for testing). They report an 81.7% of correct recall for the training set, and 76.7% for the testing set.

In [14], Zhang et al. describe how by combining again wavelets and neural networks, images can be efficiently retrieved from a database in terms of the image contents. They report performance near to 80%. To reduce the noise, images were filtered by passing them four times by the wavelet decomposition/synthesis process.

In [15], Manish et al. also used wavelets to retrieve images distorted with additive noise. They report that while the added noise is under 20%, any image from the database is correctly retrieved. From 20%, the performance of the proposal decreases drastically. In [16], Puzicha et al. report an efficiency of 93.38% using histograms and non-supervised classification techniques. Next, in [17], Mandal et al. report an efficiency of 87% combining wavelets and histograms. Finally, in [18], Liapsis et al. present a system with efficiency near 93% when textural features are combined with color features, and 52% when only textural information is taken into account, and 83% when only color information is used as the describing feature on a database composed of 210 images of the Corel Photo Gallery.

From this small analysis, one can see that various theoretical and practical approaches combine visual features (color, shape and texture), wavelets and neural networks to retrieve images from a database. Our proposal also uses wavelets and neural networks to retrieve an image from a database. It mainly differs in how the describing features are obtained. In our case, we get the image features by three different ways: 1) from the three color layers of the image, 2) from the histogram of the biggest circular window in each color layer, and 3) from the histograms of series of small square windows inside each color layer of the image. We use a circular window, because one knows that the histogram computed from a circular window is invariant to image rotations [16], which is not true for the case of square windows.

Fig. 1. Kinds of objects to differentiate. (a) Commercial plane in land, (b) commercial plane in air,
(c) war plane in land, (d) war plane in air, (e) small aircraft in land, and
(f) small aircraft in the air. Images were taken from http://www.aircraft-images.co.uk

The rest of the paper is organized as follows. In section 2 we talk a little bit about the tool (the Wavelet Transform) used to obtain the image features and to describe the objects we wish to classify. In section 3, we present the different steps composing our proposal. In section 4 we present some experimental results that demonstrate the efficiency of the proposal. Finally, in section 5 the conclusions and future research directions are given.

2 Wavelet Transforms

One can find in textbooks a number of classification techniques based on spectral data representation. These methods provide appropriate results but require a lot of computation. On the other hand, wavelet transform is a well-known tool for signal/image analysis. It provides a time–frequency representation of the data as well [21]. In this paper, we propose to solve the feature extraction problem by the use of the discrete wavelet transform (DWT) expecting to obtain good image retrieval results at a low computational cost.

Basically, WT represents a signal f by its linear approximation $\hat{f}$ onto a fixed subspace of dimension N in the orthogonal basis $\{\varphi_n\}$ (more generally, in biorthogonal basis or in frames) [4]:

$$\hat{f}_n = \sum_{n=0}^{N-1} \langle \varphi_n, f \rangle \varphi_n \tag{1}$$

Such a representation, for continuous signals with discontinuities, produces better approximations than a Fourier series. For discrete-time signals, this property permits to represent well signals described by piecewise polynomials [4]. One knows that images belong to the class of signals described by piecewise polynomials. A class of Daubechies wavelets forms an orthonormal basis and, for our opinion, can be useful to perform the analysis of images to the end of their classification.

2.1 Daubechies 4 Wavelet

Daubechies wavelets are widely used in signal processing. For an integer r, Daubechies wavelet can be defined as [5], [6]:

$$\Phi_{r,j,k}(x) = 2^{j/2} \Phi_r(2^j x - k), j, k, \in Z \tag{2}$$

Function Φ_r has the property that $\Phi_r(x-k) | k \in Z$ is a sequential orthonormal base in $L^2(R)$, where j is a scale, k is a translation, and r is a filter. Daubechies wavelets are compactly supported and have the highest number of vanishing moments for a given support width [6].

The Daubechies WT with $r > 2$ (in our case, we worked with $r = 4$) presents an energy concentration that preserves the trend of the information when it is considered only as a low pass filter. Besides, the wavelet filters for sub-band decomposition derived from Daubechies wavelets are of non-linear phase. For this reason they are rarely used in image processing applications, such as denoising and compression. However, Daubechies wavelets can be successfully used for DWT image analysis applying the derived from the mother wavelet high pass and low-pass filters in the dyadic sub-band image decomposition.

2.2 Multi-resolution and Sub-band Decomposition

Due to the normalization of the functional space in the design of the base wavelet, the coefficients in the frequency bands tend to be more dominant and of greater magnitude than the coefficients of the highest frequency bands. In the contrary, the coefficients of the lowest frequency band are grouped in the upper left corner, mean while the coefficients of the higher frequency bands are in the other three image corners [7].

In order to obtain the information contained in the images, one needs to perform sub-level signal decompositions to separate the signal characteristics and to analyze them independently. From this idea so called multilevel filtering approach emerges. By iterating this filtering process until a desired precision level, one gets the well-known multi-level decomposition scheme also known as decomposition tree or wavelet decomposition, depicted in Figure 2. By decomposing the image into frequency sub-bands, one obtains detailed information about it. This methodology is known in the literature as multi-resolution analysis.

Figure 2 shows the bank of filters in octaves with J stages. The upper part is the analysis stage, where H is the low pass filter and G the high pass filter. The filtered signals next are sub-sampled by 2. The lower part corresponds to the process of synthesis, where $\overline{G}$ and $\overline{H}$ are the reconstruction filters followed by up- sampling of 2.
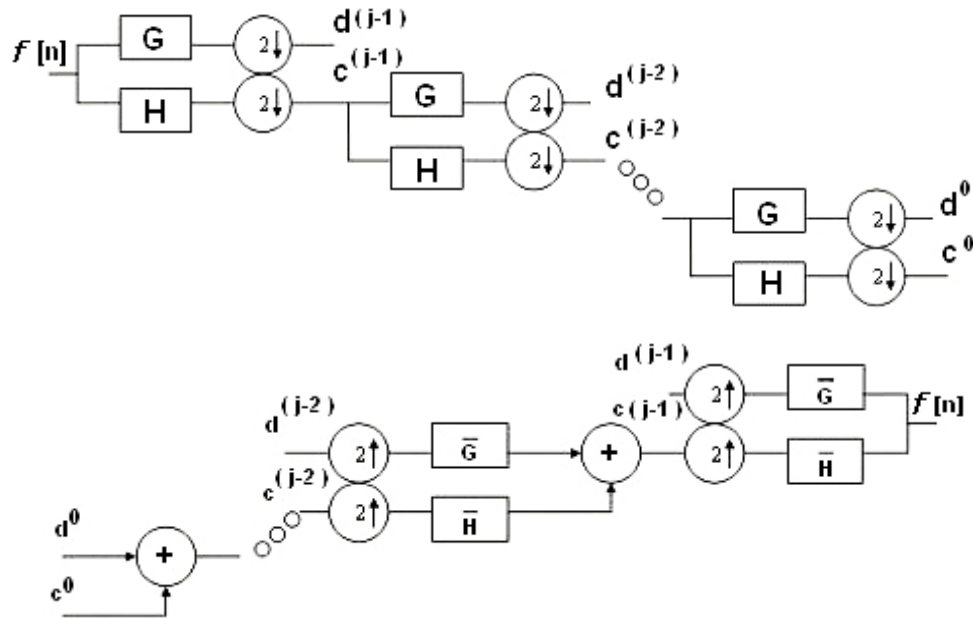
Fig. 2. Pyramidal algorithm or sub-band coding

The coefficients of the orthonormal decomposition/reconstruction filter pairs in the case of Daubechies 4 wavelet function can be expressed as follows:

$$G(n) = \left[\frac{1-\sqrt{3}}{4\sqrt{2}}, -\frac{3-\sqrt{3}}{4\sqrt{2}}, \frac{3+\sqrt{3}}{4\sqrt{2}}, -\frac{1+\sqrt{3}}{4\sqrt{2}} \right] \quad H(n) = \left[\frac{1+\sqrt{3}}{4\sqrt{2}}, \frac{3+\sqrt{3}}{4\sqrt{2}}, \frac{3-\sqrt{3}}{4\sqrt{2}}, \frac{1-\sqrt{3}}{4\sqrt{2}} \right] \tag{3}$$

$$\overline{G}(n) = \left[-\frac{1+\sqrt{3}}{4\sqrt{2}}, \frac{3+\sqrt{3}}{4\sqrt{2}}, -\frac{3-\sqrt{3}}{4\sqrt{2}}, \frac{1-\sqrt{3}}{4\sqrt{2}} \right] \quad \overline{H}(n) = \left[\frac{1-\sqrt{3}}{4\sqrt{2}}, \frac{3-\sqrt{3}}{4\sqrt{2}}, \frac{3+\sqrt{3}}{4\sqrt{2}}, \frac{1+\sqrt{3}}{4\sqrt{2}} \right] \tag{4}$$

Figure 3 shows the magnitude of the frequency response of the Daubechies 4 analysis filters given by the equations (3). It is interesting to note that the magnitudes of the frequency responses of the synthesis filters given by equations (4) are the same as those of the analysis filters (equations (3)). This is due to the orthonormality of the Daubechies 4 wavelet and its associated scale function.
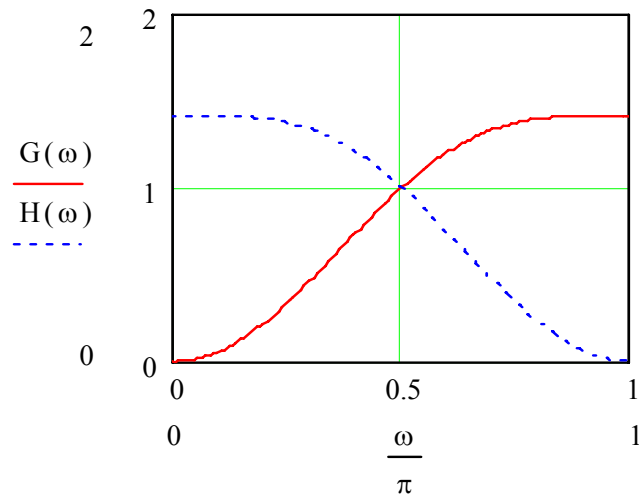
$$G(\omega)$$

$$H(\omega)$$

Fig. 3. Frequency response magnitudes of Daubechies 4 wavelet filters

3 Methodology

We pretend to retrieve images from a database taking into account their content, and this in terms of object's shape and image's color distribution. To retrieve an image efficiently, we propose to combine the multi-resolution method, the wavelet transforms (both described in section 2) and a neural network.

In a first step, our indexing procedure applies a Daubechies 4 wavelet transform to get the desired describing features. These features are represented by the wavelet coefficients. These coefficients tend to represent the semantics of the image, that is, the distribution and size of the forms in the image plus the local variation of the color of the objects and background.

L*a*b* is a perceptually uniform color space and HSV is approximately a perceptually uniform space for representing color. Performance of these color spaces is superior to that of the commonly used RGB color space, which is not perceptually uniform [19] [22].

In this work we use three bands of a color image in RGB model, because it is the color space more commonly used, to extract the describing features, without any preprocessing of the image. From each image is calculated the following:
1. The wavelets coefficients of the color channels of the entire image,
2. The wavelets coefficients of the histogram of the biggest circular window inside each color image channel, and
3. The wavelets coefficients of the histograms of the square sub-images dividing each color channel of the original image.
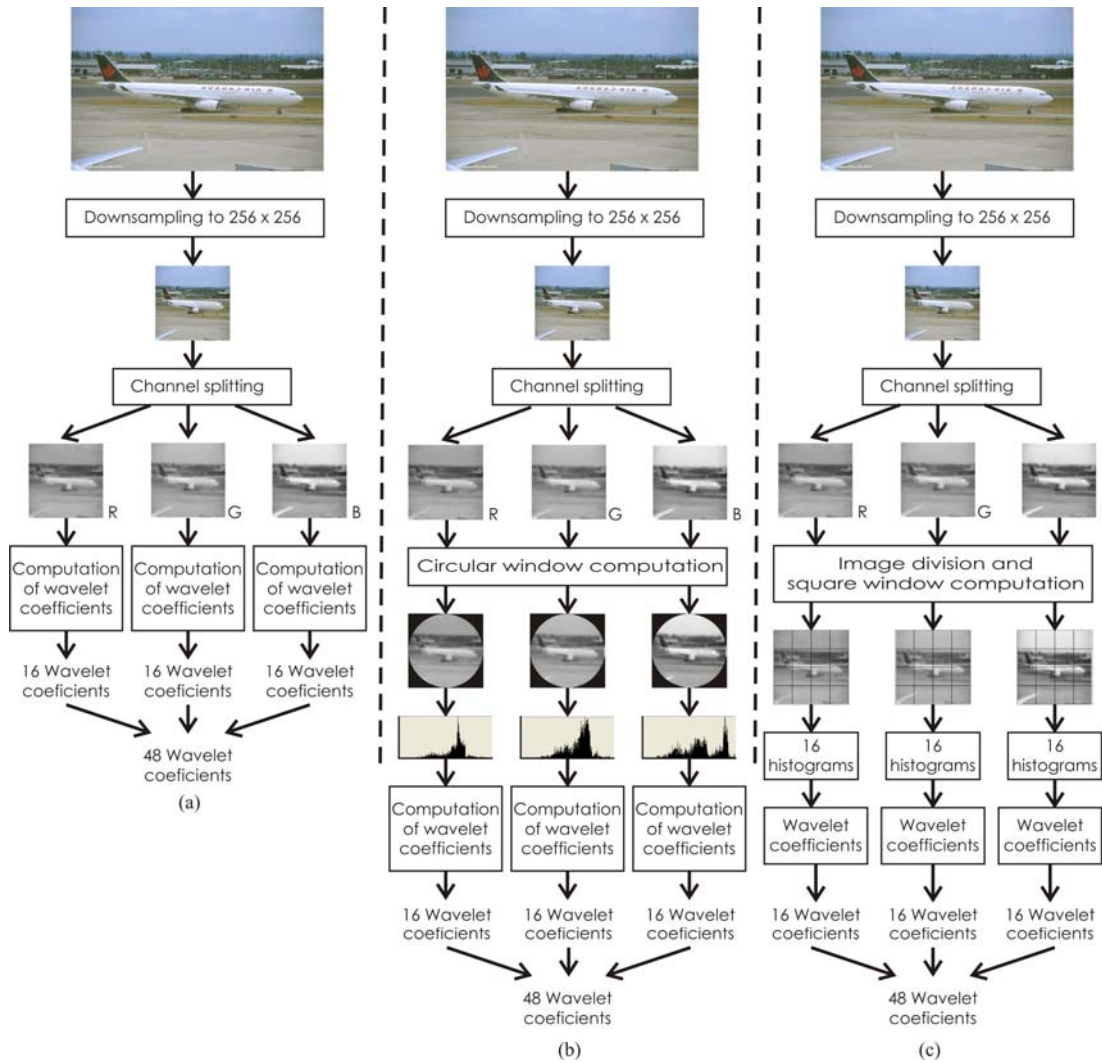
Fig. 4. Mechanism used to get the wavelet coefficients for training. (a) From the three RGB channels of the entire image.
(b) From the histogram of a biggest circular window for each RGB channel, and
(c) From the histograms of the 16 square sub-images dividing each image RGB channel of the original color image

We use the histograms of each image color plane because it is well known that a histogram is well known that it is invariant to translations and rotations of the image. Due to an histogram does not provide any information about the position of pixels, we decided to combine each of the three above mentioned procedures with the multi-resolution approach described in section 2 to take into account this feature. Additionally, from this point the size of all images to be processed is supposed to be normalized to 256×256 pixels.

3.1 Wavelets Coefficients from Each Channel of the Entire Color Image

Figure 4 (a) shows how the wavelets coefficients are obtained from the entire image. From the original image of 800 x 224 pixels we first get an image of 256×256 pixels by down sampling it. Then, we split the resulting down sampled image into its three R, G and B channels. Next, for each image channel we apply the multi-resolution procedure described in Section 2 to compute the desired wavelet coefficients, 16 in total. To this end, at the first

resolution level we applied the procedure described in section 2 in the horizontal direction, getting thus an image of 128×256 pixels. Applying next the same procedure for the columns, we get an image of 128×128 pixels. This procedure continue level by level to get images of sizes 64×64, 32×32, 16×16, 8×8 and 4×4 pixels. Because we apply this procedure to three channels, we obtain 48 describing wavelet coefficients to be used for training. It is worth to mention that this idea was already used in [8] with very good results.

3.2 Wavelets Coefficients from the Histogram of a Circular Window Fitting into Each Image Channel of the Entire Color Image

The histograms of each channel of an image provide information about the color distribution in the image but it ignores the spatial information about the positions of the pixels in the image [9]. The image histogram was used in [10] for image indexing. In our work, we propose, as an alternative, to obtain the describing features from the histogram of each RGB channel of the image applying the multi-resolution procedure described in section 2.

Figure 4 (b) shows how the wavelets coefficients are obtained now from the histogram of each color channel of the image. As in the first case, from the reduced image of 256×256 pixels we split the images in three channels R, G and B. For each of these images we obtain the biggest circular window that fit in the image. Then, from this circular image window we compute the normalized histogram that has the important well-known property to be invariant to rotations. From this 256-bin histogram, we next apply the multi-resolution procedure described in Section 2 until getting a 16-bin version of it to get finally 16 wavelet coefficients. Because we do this for three-color channels, we get again 48 describing wavelet coefficients to be used for training.

3.3 Wavelets Coefficients from the Histograms of Square Sub-images Dividing Each Image Channel of the Original Color Image

Figure 4 (c) shows how the wavelets coefficients are obtained now from a set of sub-images dividing the image of each channel. As in the first case, from the reduced image of 256×256 pixels we split the images in the corresponding three channels R, G and B. Then, each 256×256 pixels image is divided into 16 squared sub-images of 64×64 pixels each. Next, for each squared sub-image we compute the histogram and apply the multi-resolution procedure described in section 2 to get 16 coefficients per image, one vector from each sub-image. Because we do this for the three-color channels, we get again 48 describing wavelet coefficients to be used for training [20].

3.4 Neural Network Architecture

Figure 5 shows the neural arrangement of the chosen neural network model. It is a network of perceptrons composed of three layers:

1. The input layer with 48 nodes, corresponding to the 48 elements of the describing wavelet vector $[x_1 \quad x_2 \quad \cdots \quad x_{48}]^T$ obtained as explained in sections 3.1 to 3.3.
2. A hidden layer with 49 nodes. We tested with different numbers of nodes for this layer and selected that with the best classification results.
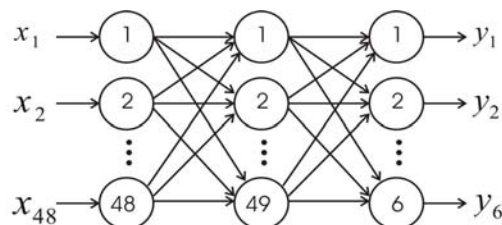3. The output layer with 6 nodes, one for each airplane class.

Fig. 5. Architecture of the neural network model selected for airplane classification

3.5 Neural Network Training

Several procedures to train a neural network have been proposed in the literature. Among them, the crossed validation has shown to be one of the best suited for this purpose [12]. It is based on the composition of at least two data sets to evaluate the efficiency of the net. Several variants of this method are known. One of them is the π-method [13], [14]. It distributes the patterns in a random manner with no replacements in a training sample.

For training, we took 120 images of airplanes from the 1068 available at: http://www.aircraft-images.co.uk. We distributed these 120 images over 5 sets $C_1, \ldots, C_5$. Each set of 24 images contains four images of each of six airplane classes shown in Figure 1. We perform NN training as follows:

1. We took sets C_2, C_3, C_4, C_5 and with them trained the NN. 1000 epochs where performed. We test the NN with sample C_1 and get the first set of weights for the NN.
2. Now, we take sets C_1, C_3, C_4, C_5 and with them train the NN. Again 1000 epochs where done. We test the NN with sample C_2 and we get the second set of weights for the NN.
3. We repeat this process for training sets: C_1, C_2, C_4, C_5, C_1, C_2, C_3, C_5 and C_1, C_2, C_3, C_4, to get third, fourth and fifth weighting sets for the NN.

As a final step, we took other 120, 240, 480 images and so on up to the complete set of 1068 images, and the performance of the NN was the same that in case when cross validation was used. Thus, the set of the obtained weights constitutes the weights of the neural network to be used.

4 Experimental Results

In this section, we test the efficiency of the methodology described in section 3. For this purpose, we used 120 images (20 images of each of 6 classes) for training the neural network and added to them another 120 images from the 1068 of the database, in total 240 testing images. We took each time one of 240 images and input it to the system. At each time, the classification efficiency using the previously trained neural network in its three modes was tested. Table 1 shows the obtained classification results.

**Table 1.** Percentage of classification

Training coefficients for the neural network obtained from:	% of classification
Each color channel of the entire image	73.0
Histogram of the biggest circular window fitting into each color channel of the entire image	83.0
Histograms of each of 16 square sub-images dividing each color channel of the original color image	**88.0**
Human system (more than three hours)	100.0

As it can be appreciated from this table the best performance (of 88%) was achieved for the neural network trained with the wavelet coefficients calculated from the histograms of the 16 square sub-images of each color channel of the original image. The worst performance (of 73%) was obtained when the neural network was trained with the 48-wavelet coefficients from each channel of the entire image. From these experiments, we can also see that the local training, at least for the used image set, provides better classification results than the global training.
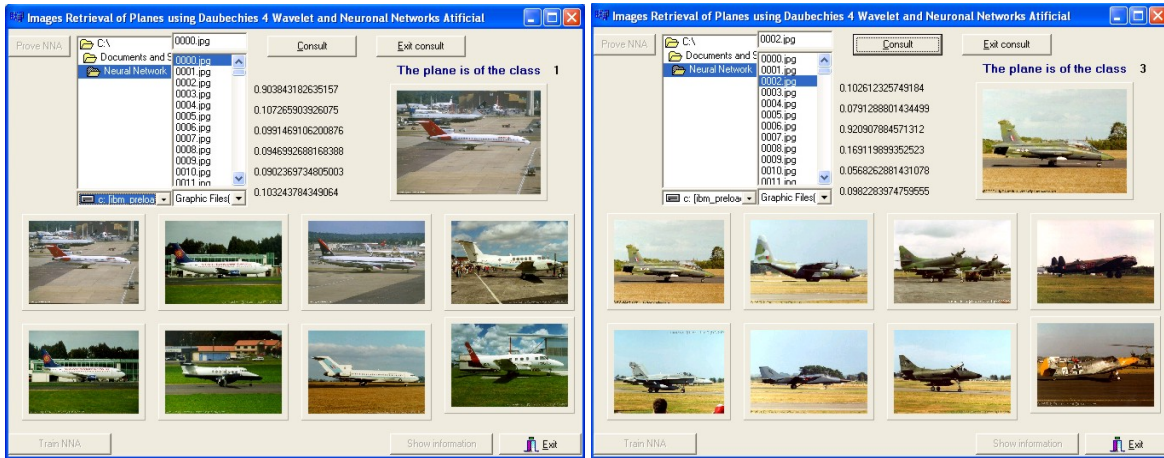
(a)   (b)
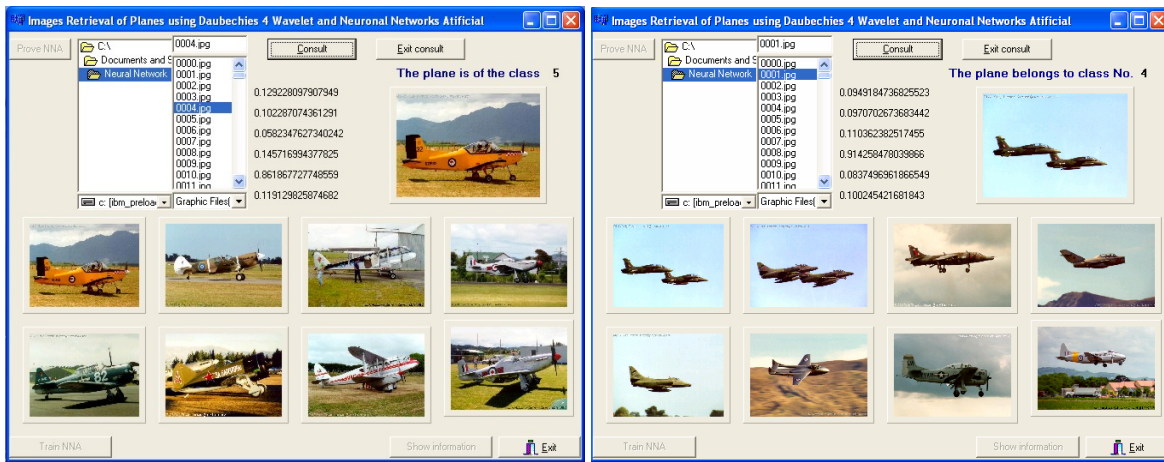
(c)   (d)

Fig. 6. Four outputs of the system, when at the input is presented an image of: (a) commercial airplane in land,
(b) a war airplane in land, (c) a small aircraft in land, and (d) a war airplane on air

Figures 6 (a) to 6 (d) show graphically four of the classification results. The system is configured to show always the best ranked most similar 8 images with respect to the input. In addition, as the reader can appreciate, the system always responds first with the input image, because this is obviously the best classified image.
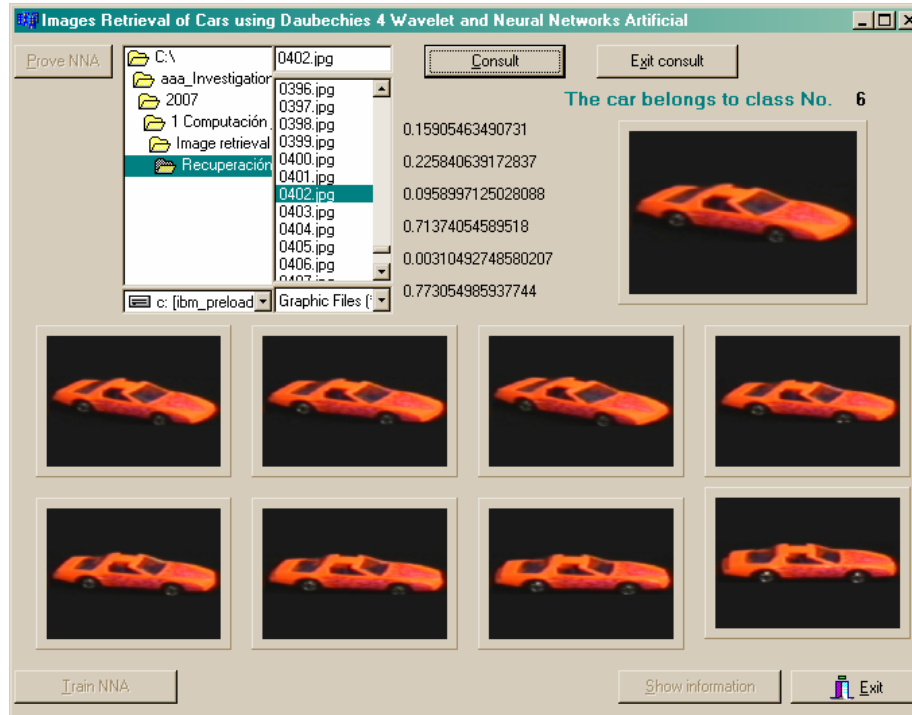
Fig. 7. System output when car image is inputted. Images were taken from
http://www.cs.columbia.edu/CAVE/research/softlib/coil-100.html

It is worth to note that when images of some complexity are used, it is not possible to observe some order of similarity. Figure 7, obtained from a simple image of an isolated object located in a contrasting uniform background, shows clearly the order of similarity, that is, the second image is more similar to the original than the third image, and that to the fourth image, and so on.

5 Conclusions and Ongoing Research

In this paper, we have described a simple but effective methodology to retrieve color images of airplanes. The system was trained to detect an image in the presence of one of six different classes of airplanes as shown in Figure 1. R, G and B plains of the color image were employed for indexing. We test the performance of the neural network of perceptrons trained with three different wavelet-based describing features: two global and one local. From the experiments, we have shown that the local proposal describing features from the 16 square sub-images in the image channels of the original image was better with the efficiency of 88%.

One of the main features of our approach is that no previous segmentation of the object class is needed. During training, we presented to the system an object whose class was known beforehand.

Actually, we test the performance of our proposed system with other databases, of the same kind of objects and combined. At the end of the future research, we hope that the system shows photos of flowers if a photo of a flower is presented to the systems, in spite of the database could contain not only images of flowers but also of people, airplanes, and so on.

We are also trying to combine some interesting visual operators to detect distinctive parts of the objects, invariant descriptors for images transformations such as affinities and several kinds of classifiers to find which combination can provide the best results.

Acknowledgements

References

1. **A. Del Bimbo (1999).** Visual Information Retrieval, Morgan Kaufmann Publishers.
2. **S. M. Lew (2000).** Next-Generation Web Searches for Visual Content, Computer, Information Retrieval, Volume 33, Number 11, Computer Society IEEE. Pp. 46-53.
3. **C. Leung (1997).** Visual Information Systems, Springer.
4. **M. Vetterli (2000).** Wavelets, Approximation, and Compression, IEEE Signal Processing Magazine. 1:59-73.
5. **I. Daubechies (1988).** Orthonormal bases of compactly supported wavelets, Comm. Pure and Applied Mathematics. 4: 909-996.
6. **I. Daubechies (1992).** Ten Lectures on Wavelets, CBMS-NSF Lecture Notes 61, SIAM.
7. **Z. Xiong, K. Ramchandran** and **M. T. Orchard (1997).** Space-Frequency Quantization for Wavelet Image Coding, IEEE Transactions on Image Processing, 6(5):
8. **N. Papamarcos, A. E. Atsalakis,** and **Ch. P. Strouthopoulos (2002).** Adaptive Color Reduction, IEEE Transactions on Systems, Man and Cybernetics – Part B: Cybernetics, 32(1):
9. **R. C. González, R. E. Woods** and **S. L. Eddins (2004).** Digital Image Processing Using Matlab, Pearson Prentice Hall.
10. **F. D. Jou, K. Ch. Fan** and **Y. L. Chang (2004).** Efficient matching of large-size histograms, Pattern Recognition Letters, 25:277-286.
11. **S. B. Park, J. W. Lee** and **S. K. Kim (2004).** Content-based image classification using a neural network, Pattern Recognition Letters, 25:287-300.
12. **P. McGuire** and **G. M. T. D`Eleuterio (2001).** Eigenpaxels and a Neural-Network Approach to Image Classification, IEEE Transactions on Neural Networks, 12(3).
13. **A. E. Gasca** and **A. R. Barandela (1999).** Algoritmos de aprendizaje y técnicas estadísticas para el entrenamiento del Perceptrón Multicapa, IV Simposio Iberoamericano de Reconocimiento de Patrones, Cuba. Pp. 456-464.
14. **S. Zhang** and **E. Salari (2005).** Image denoising using a neural network based on non-linear filter in wavelet domain, Acoustics, Speech, and Signal Processing, Proceedings IEEE International Conference ICASSP '05, 18-23 March. 2:989-992.
15. **N. S. Manish, M. Bodruzzaman** and **M. J. Malkani (1998).** Feature Extraction using Wavelet Transform for Neural Network based Image Classification, IEEE Proceedings of the Thirtieth Southeastern Symposium on System Theory, 1:412-416. 1998.
16. **J. Puzicha, Th. Hofmann** and **J. M. Buhmann (1999).** Histogram Clustering for Unsupervised Segmentation and Image Retrieval, Pattern Recognition Letters, 20: 899-909.
17. **M. K. Mandal** and **T. Aboulnasr (1999).** Fast Wavelets Histogram Techniques for Image Indexing, Computer Vision and Understanding, 75(1-2):99-110.
18. **S. Liapis** and **G. Tziritas (2004).** Color and texture image retrieval using chromaticity histograms and wavelet frames, Multimedia, IEEE Transactions on Multimedia (5):676 – 686.
19. **Everest Mathias** and **Aura Conci (1998).** Comparing the Influence of Color Spaces and Metrics in Content-Based Image Retrieval, Anais do X SIBGRAPI (10):1-8.
20. **Zhiyong Zeng** and **Lihua Zhou (2006).** A Novel Image Retrieval Algorithm Using Wavelet Packet Histogram Techniques, Systems and Control in Aerospace and Astronautics, 1st International Symposium: 1194-1197.
21. **De Bianchi, M.F., Guido, R.C., Nogueira, A.L.** and **Padovan, P. (2006).** A Wavelet-PCA Approach for Content-Based Image Retrieval, System Theory, Proceeding of the Thrity-Eighth Southeastern Symposium (38):425-428.

22. **Utenpattanant, A.; Chitsobhuk, O.** and **Khawne, A. (2006).** Color Descriptor for Image Retrieval in Wavelet Domain, Advanced Communication Technology, The 8th International Conference (1):818-821.

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