Automatic Generation of Suitable DWT Sub-band
An Application to Brain MRI Classification

Mohamed Mokhtar Bendib[1], Hayet Farida Merouani[1] and Fatma Diaba[2]
[1]*LRI Laboratory, Badji-Mokhtar University, Annaba, Algeria*
[2]*LMA Laboratory, Badji-Mokhtar University, Annaba, Algeria*

Keywords: Magnetic Resonance Imaging, Brain MRI Classification, Discrete Wavelet Transform, Undecimated Wavelet Transform, Genetic Programming.

Abstract: This paper addresses the Brain MRI (Magnetic Resonance Imaging) classification problem from a new point of view. Indeed, most of the works reported in the literature follow the subsequent methodology: 1) Discrete Wavelet Transform (DWT) application, 2) sub-band selection, 3) feature extraction, and 4) learning. Consequently, those methods are limited by the information contained on the selected DWT outputs (sub-bands). This paper addresses the possibility of creating new suitable DWT sub-bands (by combining the classical DWT sub-bands) using Genetic Programming (GP) and a Random Forest (RF) classifier. These could be employed to efficiently address different classification scenarios (normal versus pathological, one versus all, and even multiclassification) as well as other automatic tasks.

1 INTRODUCTION

The MRI is a powerful acquisition technology that allows to efficiently explore the human brain through different views (Axial, Coronal, and Sagittal) and modalities (T1, T2, Flair). Many important clinical tasks are highly dependent on the MRI: brain pathologies detection, treatment validation, surgical planning, etc.

Up to now, brain MRI analysis is mostly performed in a supervised way. Nevertheless, the human expertise is tiring, subjective, and greatly impacted by the immediate environment. For all these reasons, it is necessary to conceive automated and reliable tools for diagnostic support.

Recognizing abnormal brains and identifying the pathology type, are two central tasks assured by the physicians. Thus, several works have tried to automatically address them (Chaplot et al., 2006) (El-Dahshan et al., 2010) (Zhang et al., 2011) (Lahmiri and Boukadoum, 2011) (Saritha et al., 2013) (Kalbkhani et al., 2013). All these methods repeats the same reasoning: 1) DWT application, 2) empirical selection of sub-bands, 3) feature extraction, 4) learning and testing. By doing so, the final performances are inevitably limited by the information contained on the selected DWT outputs.

The present work proposes a method to automatically search for (discover) new appropriate sub-bands, in order to efficiently address different classification tasks. It applies UWT (a special variant of the DWT), combines the resulting sub-bands through GP, and evaluates the pertinence of the resulting representations by means of a RF classifier.

The rest of the paper is organized as follows: Section 2 presents the employed methodology. Section 3 explains the validation phase. Section 4 concludes the paper by evoking some future directions.

2 METHODOLOGY

The flowchart of the proposed method is illustrated in Figure 1. Note that this scheme can address different classification scenarios:

- -Normal versus pathological.
- -Each pathology against the rest (one versus all).
- -Multiclassification.

In what follows, each step of system is explained in more details.

Bendib M., Merouani H. and Diaba F..
Automatic Generation of Suitable DWT Sub-band - An Application to Brain MRI Classification.
DOI: 10.5220/0005333001660170
In *Proceedings of the 10th International Conference on Computer Vision Theory and Applications* (VISAPP-2015), pages 166-170
ISBN: 978-989-758-091-8

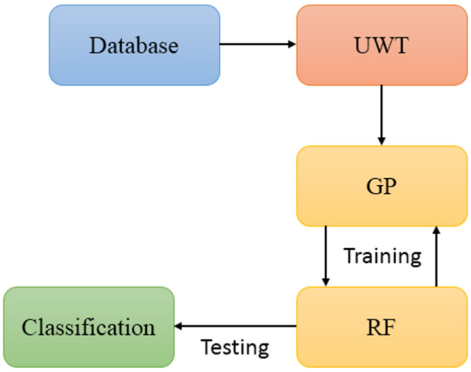


Figure 1: Overview of the proposed system for creating new appropriate sub-bands.

2.1 DWT

The DWT (Mallat, 1989) of a signal $x(n)$ can be written as:

$$cA_{j,k}(n) = \left[\sum_n x(n) l_j^*(n - 2^j k)\right] \qquad (1)$$

$$cD_{j,k}(n) = \left[\sum_n x(n) h_j^*(n - 2^j k)\right] \qquad (2)$$

$cA_{j,k}$ and $cD_{j,k}$ are the approximation (low frequency content) and detail (high frequency content) coefficients of the signal $x(n)$, respectively. l is the low pass filter whereas h is the high pass filter. j and k designate the wavelet scale and translation factor, respectively.

When applied to a two-dimensional signal, the DWT produces four sub-bands **LL** (approximate coefficients), **LH** (Horizontal Details), **HL** (Vertical Details), and **HH** (Diagonal Details) at each scale. The DWT employs a subsampling process that reduces the size of the data (by half) at every scale. That means that the resulting sub-bands have different sizes and cannot be intuitively combined. Therefore, to address this problem, we make use of a special variant of the DWT, which is the Undecimated Wavelet Transform (UWT) (Nason and Silverman, 1995). Whatever the scale, this signal analysis technique produces sub-bands that have exactly the same size as the original signal.

2.2 Random Forests (RF)

RF (Breiman, 2001) is an ensemble-learning paradigm that grows and combines multiple decision trees in order to make prediction (classification or regression). When compared to other learning methods, RF has a fewer input parameters and runs quickly on vast databases. It can handle a huge amount of variables (without any normalization) as well as incomplete data. Moreover, cross-validation is not necessary because RF generates an unbiased estimation of the generalization error during the training phase (out-of-bag classification error). The RF learning process is an iterative scheme that includes for every tree to:

-Select a subset from the training set by picking n times with replacement.
-Grow the tree on the selected subset.
-At each node of the tree, randomly choose m variables and compute the best split based only on those ones.

Note that after the training phase, it is not necessary to prune the resulting trees. Furthermore, the response of the model to a new data instance is often taken as the mode of the responses returned by all the units.

2.3 Genetic Programming (GP)

GP (Koza, 1992) is an evolutionary computation technique, which can be considered as a systematic and domain independent method, for getting computers to automatically resolve problems, without the need of clearly telling them how to do (Langdon et al, 2008). It consists of applying the Darwinian evolution theory (Darwin, 1864) on a population of programs (which are generally tree shaped) through several iterations, by applying different operators. The GP formalism used in the present work is described below:

2.3.1 Terminals and Nonterminals

The terminals used in the proposed method consist of the sub-bands that are produced by the UWT; these are matrices of 256*256 size. Nonterminals are taken from usual mathematical functions; +, -, *, /, ABS, SQRT, LOG, POW2, POW3, SIN, COS, MIN, MAX. These are applied at the matrix level (so as to avoid undefined outputs). Besides these functions, some other operations that are specifically related to the matrix formalism could also be employed (inverse, transpose, etc.).

2.3.2 Individuals

Each individual is composed of a single tree; a combination of several sub-bands.

2.3.3 Initialisation

Initializing an individual implies initializing its tree. This task is tackled by the Ramped half-and-half method (Koza, 1992), which produces trees of different sizes and shapes.

2.3.4 Selection

This operation allows to select the individuals that will contribute to form the next generation. It consists of performing a stochastic binary tournament.

2.3.5 Crossover

This operator permits to combine the genetic material. It consists of randomly picking two positions on two individuals and aggregating two parts of them in order to form a new individual.

2.3.6 Mutation

This operation enables to prevent early convergence. It includes randomly selecting a sub-tree and replacing it by another randomly generated tree.

2.3.7 Fitness

In the proposed method, computing the fitness of a given individual involves the execution of its corresponding tree, the use of the resulting values to train and test a RF classifier (employing two distinct datasets), the computation of the number of correct classifications in the testing set, and the deduction of the accuracy. To avoid a rapid growth of the individuals, the accuracy is combined with the individual size (number of nodes in the tree), which results in:

$$Fitness = \frac{Accuracy}{\alpha * Size} \tag{3}$$

α serves to control the influence of the size on the fitness.

The evaluation of the fitness function may involve a relatively high complexity. However, we think that using an appropriate programming language (e.g. C++) and a multithreaded implementation would greatly ease that issue.

3 VALIDATION

The data used in this study consists of T2 weighed 256 × 256 axial brain images, which were collected from the Whole Brain Atlas database (http://www.med.harvard.edu/aanlib/home.html). Six categories are considered: Alzheimer, Chronic Subdural Hematoma, Fatal Stroke, Glioma, Hypertensive Encephalopathy, and Normal. Figure 2 gives an overview of each category.

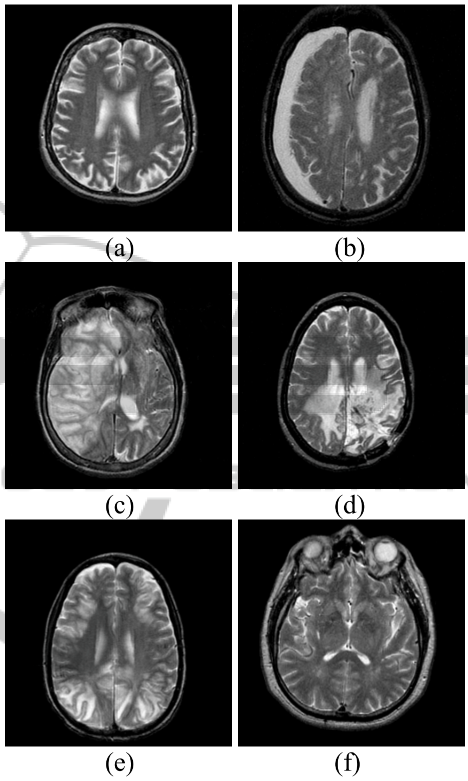


Figure 2: Instances from the different categories that are considered in the proposed Method: Alzheimer (a), Chronic Subdural Hematoma (b), Fatal Stroke (c), Glioma (d), Hypertensive Encephalopathy (e), Normal (f).

Twelve samples are randomly selected from each category and three subsets P1, P2, and P3 are created by randomly dividing each category. P1 and P2 are used to train and tune the system whereas P3 is employed to evaluate the performance.

Figure 3 gives an overview of the UWT outputs (each sub-band repents a specific view of the original signal). Figure 4 depicts what is expected from the proposed system (highlighting a given aspect of the image).

4 CONCLUSIONS

In this paper, the brain MRI classification problem was tackled by a new strategy. This latter can address different classification scenarios by creating

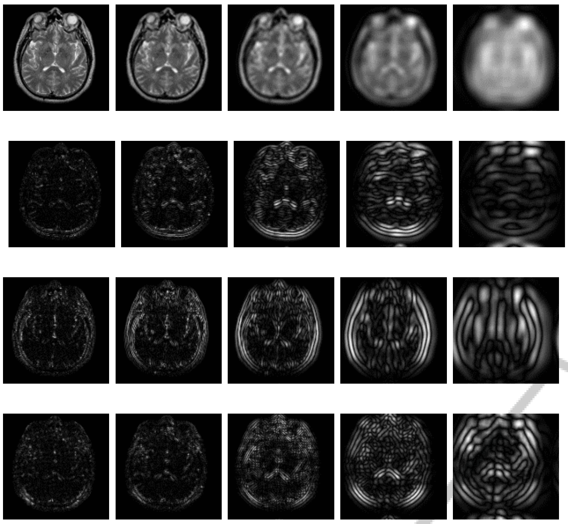
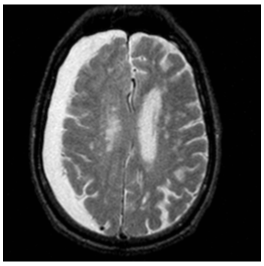
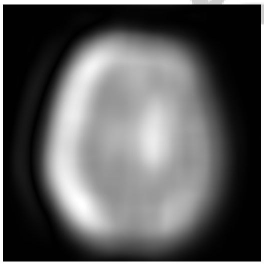


Figure 3: UWT outputs (5 levels using the Daubechies 2 (db2) wavelet): application to Figure 2(f). From left to right, the five levels (1→5). From top to down, the LL, LH, HL, and HH components, respectively. This work assumes that it is possible to discover more pertinent sub-bands (to address different classification scenarios) by combining the base UWT sub-bands.



(a)



(b)

(c)

Figure 4: an example of a pertinent handcrafted combination using the db2 wavelet: (a) the approximation coefficients of the first UWT decomposition level of Figure 2(b), (b) the approximation coefficients of the fifth UWT decomposition level of Figure 2(b), and (c) result of (a) minus (b). From (c), one can note that a large part of the hematoma is highlighted (next to some other small non-pertinent regions).

new useful sub-bands (from the base UWT sub-bands) using GP. The newly created representations can be used as they are, or they can serve as a base for an efficient feature extraction or reduction phase. We are currently testing the proposed method according to the different scenarios defined earlier. Note that the fallout out of the proposed scheme goes far beyond the problem treated in this paper, since it could allow the creation of sub-bands that can efficiently highlight a given structure (thalamus, caudate nucleus, etc.) or a given cerebral matter (White Matter, Gray Matter, or Cerebrospinal Fluid). Thereby, some important tasks like segmentation or quantification could be greatly enhanced.

The current state the of the system enables to exploit the sub-bands that are produced by only one wavelet at a time. However, one can envisage to use the outputs of different wavelets simultaneously.

REFERENCES

Breiman, L., 2001. Random forests, Machine Learning. 45(1), 5-32.

Chaplot, S., Patnaik, L. M., Jagannathan, N. R., 2006. Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network. Biomedical Signal Processing and Control 1(1), 86-92 (2006).

Darwin, C., 1864. *On the origin of species by means of natural selection or the preservation of favoured races in the struggle for life*. Cambridge University Press. Cambridge, UK.

El-Dahshan, E. S. A., Hosny. T., Salem, A. B. M., 2010. Hybrid intelligent techniques for MRI brain images classification. Digital Signal Processing 20(2), 433-441.

Kalbkhani, H., Shayesteh, M. G., Zali-Vargahan, B., 2013. Robust algorithm for brain magnetic resonance image (MRI) classification based on GARCH variances series. Biomedical Signal Processing and Control 8(6), 909-919.

Koza, J., 1992. *Genetic programming: On the programming of computers by means of natural selection*. MIT Press. Cambridge, MA, USA.

Lahmiri, S., Boukadoum, M., 2011. Classification of brain MRI using the LH and HL wavelet transform sub-bands. In *IEEE International Symposium on Circuits and Systems* 1025-1028 (Rio de Janeiro).

Langdon, W. B., Poli, R., MacPhee, N. F., Koza, J. R., 2008. Genetic Programming: An Introduction and Tutorial, with a Survey of Techniques and Applications, in *Computational Intelligence: A Compendium, Studies in Computational Intelligence* 115, 927-1028, Springer Heidelberg. Berlin, Deutschland.

Mallat, S. G., 1989. A theory for multiresolution signal decomposition: the wavelet representation. In *IEEE Transactions on Pattern Analysis and Machine Intelligence* 11(7), 674-693.

Nason, G. P., Silverman, B. W., 1995. The stationary wavelet transform and some statistical applications. *Wavelets and Statistics, Lecture Notes in Statistics* 103, 281-299.

Saritha, M., Joseph, K. P., Mathew, A. T., 2013 Classification of MRI brain images using combined wavelet entropy based spider web plots and probabilistic neural network. Pattern Recognition Letters 34(16), 2151-2156.

Zhang, Y., Dong, Z., Wu, L., Wang, S., 2011. A hybrid method for MRI brain image classification. Expert Systems with Applications 38(8), 10049-10053.