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Parkinson's Disease Recognition Using Artificial Immune System*

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ABSTRACT

This work deals the application of the artificial immune system to discriminate between healthy and people with Parkinson's disease (PWP). As the symptoms of Parkinson's disease (PD) occur gradually and mostly targeting the elderly people for whom physical visits to the clinic are inconvenient and costly, telemonitoring of the disease using measurements of dysphonia (vocal features) has a vital role in its early diagnosis. Taking inspiration from natural immune systems, we try to grab useful properties such as automatic recognition, memorization and adaptation. The developed algorithms have as a base the algorithm of training bio inspired CLONCLAS. The results obtained are satisfactory and show a great reliability of the approach.

Keywords*: *Parkinson's Disease, Dysphonia Measures, Speech Analysis, Immune System, Clonal Selection Algorithm

1. Introduction

Neurological disorders, including Parkinsons disease (PD), Alzheimers and epilepsy, affect profoundly the lives of patients and their families. Parkinsons disease affects over one million people in North America alone [1]. Moreover, an aging population means this number is expected to rise as studies suggest rapidly increasing prevalence rates after the age of 60 [1]. In addition to increased social isolation, the financial burden of PD is significant and is estimated to rise in the future [2]. Currently there is no cure, although medication is available offering significant alleviation of symptoms, especially at the early stages of the disease [3].

The goal of this study is to develop an application that identify persons having Parkinson's disease using bio-inspired approach: artificial immune system (AIS).

2. The Artificial Immune System

An artificial immune system (*AIS*) is a category of algorithm inspired by the principles and the operations of the natural immune system (*NIS)* of vertebrate. [4]

The artificial immune system uses three basic algorithms:

- negative selection
- clonale selection
- immune network

In this study, we apply the clonal selection algorithm.

The Natural Clonal Selection

As mentioned in (**Figure 1**), when a new antigen penetrates in the body, the immunizing answer passes by the following stages (principles of the clonal selection) [5]:

- At the beginning, the concentration of the antigen is so weak that only innate immunity is activated. As the antigen is new so, no B cell is enough specific to bind with;
- As the antigen develops, its concentration becomes enough high to activate the least specific cells B;
- Once B cells activated, they will multiply to produce a great number of clones. Each clone is a B cell identical to the cell which produces it. The number of clones is proportional to the affinity of the connection B cell-antigen;
- To increase the specificity of the antibodies and the effectiveness of the immunizing answer; the clones enter a phase of hyper changes, thus modifying the structure of their receivers (antibody). As the changes are random, the cells obtained (known as mature) can become more specific or less specific;
- When the concentration of the antigen decreases (bec-

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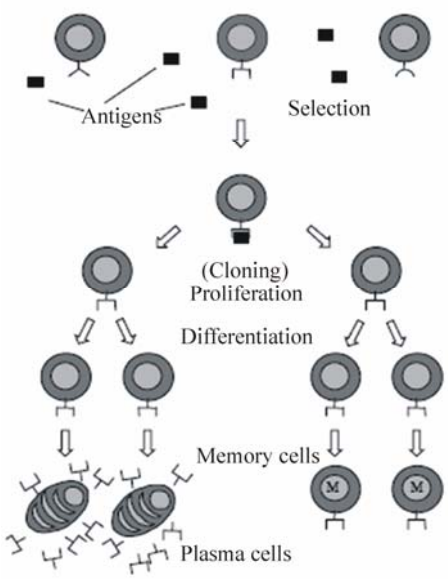

Figure 1. The clonal selection algorithm.

ause of the immunizing answer), only the most specific B cells continue to be activated, the others (the least specific) are not any more activated and end up dying. This causes to return the population of B cells increasingly specific to each generation;

- After maturation, the B cells become either of the plasma cells, or of the memory cells. The plasma cells are veritable antibody factories able to produce some in impressive quantities. The memory cells when to them, will survive a long time after the disappearance of the antigen, and can once activated to produce great quantities of antibody in very short time.

At the primary answer (a new antigen penetrates in the body), effective antibodies appear in blood after several days. But at the secondary answer (a similar antigen penetrates in the body) and thanks to the memory cells which exit from the first infection, the corresponding antibodies are produced much more quickly and in greater quantities. It is said that the system became immunized against the antigen or that it memorized it [5-7].

3. Use of Artificial Immune System

Our system of pattern recognition is based on an approach of recognition by prototypes. To be able to use the principles of the clonal selection in this system, we defined the following correspondences:

3.1. Antigen

Represent the example of training for which we want to calculate the model.

3.2. Antibody

Represent a possible solution to the current problem. If the system is confronted with the antigen *Agi*, each antibody *Abj* represents a possible model for the class *clai*.

3.3. Memory Cells

The memory cell *Abmi* represents the best model found for the class *clai*.

3.4. Affinity

An affinity represents a standard degree of similarity between two objects having the same character, in the artificial immune systems an affinity is defined between an antigen and an antibody and the value returned translates the degree of resemblance by measuring distance (Euclidean, Hamming⋯) We say that an antigen and an antibody have a high affinity only if they offer the smallest value of distance compared to the others [8].

3.5. The Cloning

The cloning is the duplication of the data in several specimens; this operation makes possible to keep information long in the workspace. A cloning is proportional to affinity because an antibody approaching more to the antigen is interesting to keep information about it which carry it for a long time and that by duplicating it in several identical specimens, and the mutation will play the role to widen the workspace [9].

3.6. The Mutation

The mutation is defined as an application from Ω to Ω, which associates to each individual X_t a new individual X_{t+1} close to X_t.

$$\text{Mutation} : \Omega \to \Omega$$
$$X^t \to X^{t+1}$$

Moreover it must allow a random research in workspace to be able to detect optima which are not visited yet [8].

The mutation varies according to the representation of the data; in this direction we find various types of mutation in the case of binary presentation or real representation.

3.7. Affinity Antigen-Antibody

Affinity between an antibody and an antigen indicates the degree of similarity between the antibody *Abj* and the antigen *Agi.*

- **Measure of Affinity**

Many measure of distance or indices of similarity exist, in our project we used two distances:

Euclidean distance:

$$d = \left[\sum \left(val_1 - val_2 \right)^2 \right]^{1/2} \quad (2)$$

Hamming distance:

$$d = \sum \left| val_1 - val_2 \right| \quad (3)$$

$$Affinity = -d \quad (4)$$

- **Number of clone Formulate**

We will calculate the number of clones in our algorithm of CLONCLAS using:

$$\text{number of clones} = \text{round}\left(B * \text{affinite}_i^2 \left| \sum_j \text{affinite}_j^2 \right. \right) \forall j \quad (5)$$

where B is the cloning parameter.

4. Clonclas Train

Our algorithm uses the principles of the artificial clonal selection to generate memory cells in the training step (**Figure 2**):

5. Methods

Parkinson's Dataset

The dataset was created at the University of Oxford, in collaboration with the National Centre for Voice and Speech, Denver, Colorado [1] and has been made available online very recently, in June 2008. [1,4].

The data explored in this paper was obtained from the Oxford Parkinson's Disease Detection Dataset, composed of a range of biomedical voice measurements from 31 male and female subjects, 23 were clinically diagnosed with PD [1]. Each subject provided an average of six phonations of the vowel /a/ (yielding 192 samples in total) [2]. The main aim of processing the data is to discriminate healthy people from those with PD, according to the "status" attribute which is set to non-PD for healthy and PD for people with Parkinson's disease, which is a two-decision classification problem [6,7].

The aim of this work is to extract clinically useful information from the sustained vowel phonations, the results of the dysphonia measures for each phonation forma feature vector which is then used as input in a regression setting.

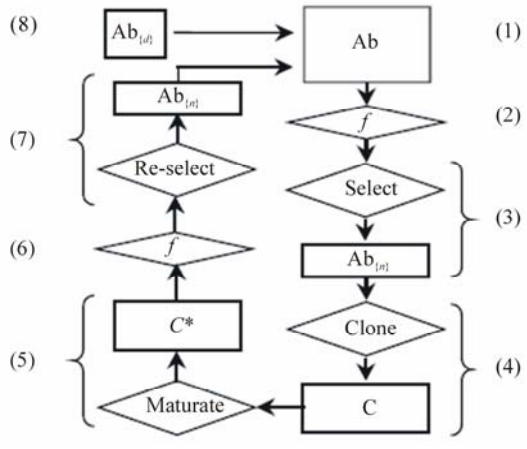

Figure 2. Clonclas train.

We applied a range of dysphonia measures which have been successfully used in similar problems aimed at separating healthy controls and PWP [1]. We used the classical dysphonia measures (**Table 1**), which include quantifying fundamental frequency perturbations (jitter), amplitude perturbations (shimmer), and signal to noise ratios (harmonics to noise ratio). We used the "MDVP" prefix to associate the measures which are equivalent to the results of the Kay Pentax Multi-Dimensional Voice Program. All measures are summarized in **Table 1**. [3]

6. Results and Discussion

At the end of the training we have a population of memory cells. This population will be used to classify the unknown forms, for that we used several algorithms of classification:

Classification by Measuring Affinity

For the first strategy we chose to classify the unknown forms by using a measurement of distance (Euclidean or distance of Hamming).

The principle of this classification is given as follows:

- In entry we have the memory cells obtained by the training (*Abm*) and a form to classify *F*;
- For any memory cell *Abmj* from *Abm*, to calculate affinity *Aff* between *Abmj* and *F*:
- To find the memory cell *Abmj* such as Aff_J is largest;

To assign the new form to the same class of *Abmj*. Results are in (**Table 2**).

For improving the results obtained we standardized the data by limiting them in the interval [0-1]. We will obtain (**Table 3**).

The evaluation of any system of recognition is to determinate the rate of recognition which represents the probability with which the system can identify if a person has or not Parkinson's disease.

The vocal disturbances are caused for roughly 90% of patients suffering from the Parkinson's disease (PD). Consequently, telediagnostic of PD by using measurements of dysphonia will relieve the clinical monitoring of old people and will increase the chances of its diagnosis early.

7. Comparative Study

We have compared our results with other studies as in (**Table 4**). According to the results of these methods, we remark that the rates of recognition are better in the AIS approach.

8. Conclusions

The experiments established in our study enable us to extract several characteristics from the artificial immune systems. We could also remark that with this new me-

Table 1. Description ofvocales mesurement used.

DESRIPTION	ATTRIBUT	MIN	MAX	MOY
Averege vocal fundamental freq	MDVP: Fo(Hz)	88.33	260.11	154.23
Max vocal fundamental freq	MDVP: Fhi(Hz)	102.15	592.03	197.11
Min vocal fundamental freq frequency	MDVP: Flo(Hz)	65.48	239.17	116.33
Several measures of variation in fundamental frequency	MDVP: Jitter(%)	0.002	0.033	0.006
	MDVP: Jitter(Abs)	7E-06	26E-05	4.4E-05
	MDVP: RAP	0.001	0.021	0.003
	MDVP: PPQ	0.001	0.020	0.003
	Jitter: DDP	0.002	0.064	0.010
Several measures of variation in amplitude	MDVP: Shimmer	0.01	0.119	0.03
	MDVP: Shimmer(dB)	0.085	1.302	0.282
	Shimmer: APQ3	0.005	0.056	0.016
	Shimmer: APQ5	0.006	0.079	0.018
	MDVP: APQ	0.007	0.138	0.024
	Shimmer: DDA	0.014	0.169	0.047
Two measures of ratio of noise to tonal components in the voice	NHR	0.001	0.315	0.025
	HNR	8.441	33.047	21.886
Two nonlinear dynamical complexity measures	RPDE	0.257	0.685	0.499
	D2	1.423	3.671	2.328
Signal fractal scaling exponent	DFA	0.574	0.825	0.718
Three nonlinear measures of fundamental frequency variation	Spread1	-7.965	-2.434	-5.684
	Spread2	0.006	0.450	0.227
	PPE	0.045	0.527	0.207

Table 2. Results of clonclas algorithm.

ALGORITHME	AFFINITY	Train	Test
Clonclas	euclidean	100%	88.54%
Clonclas	hamming	100%	87.50%

Table 3. Results of clonclas algorithm after standardization.

Affinity	Train	Test	pd	npd
euclidean	100%	92.70%	94.44%	87.50%
hamming	100%	90.63%	91.67%	87.50%

Table 4. Results for differente techniques.

Techniques	Train	Test
ClonClas	100%	92.70%
Leaveoneindividual-out [4]	-	81.53%
Bootstrap resampling [1]	-	91.40%
Leaveoneindividual-out [1]	-	65.13%
PNN-IS [6]	81.73%	79.78%
PNN-MCS [6]	81.48%	80.92%
PNN-HS [6]	81.74%	81.28%

PNN: Probabilistic Neural Network; IS: Incremental Search.
MCS: Monte Carlo Search; HS: Hybrid search.

thod we will save much time in the phase of training (compared to the networks of neurons, etc.) and we notice as well as the process of training inspired of the biological phenomenon allows thanks to the phenomenon vaccination to learn and memorize only by the use of a population of train of a small size (optimization of the base of train).

The results obtained were very encouraging and opens the doors of research towards the hybridization of the immune system algorithms with other approach such as Neural Network or genetic algorithm.

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