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Advances in Applied Science Research, 2017, 8(2):30-37

ISSN : 0976-8610
CODEN (USA): AASRFC

Application of Octonions in the Cough Sounds Classification

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ABSTRACT

Artificial neural networks (ANN) have become the standard for computer classification of various digital patterns. However, the training process of ANN can be time consuming and there are several problems that need to addressed, such as local minima. Octonionic neural networks represent computational models with input, output and weights expressed in the form of 8-dimensional numbers. Octonion multiplication has several special properties, including non-commutativity and non-associativity. We assume that the mentioned special properties are useful in the process of modeling the time dependency of sequence of successive parameters in a time stream with direct implementation of octonion multiplication. Based on this assumption we propose new activation functions "ReLU" and "majority base" for octonionic neurons.

Keywords: Octonions, Hypercomplex numbers, Artificial neural networks, Speech recognition, Classification algorithms

INTRODUCTION

Artificial neural networks (ANN), as computational models inspired by biological neural networks, have become a standard tool in computer science for the classification of various digital patterns. They are used primarily in applications dealing with image processing, speech recognition, time series prediction, robotics and others [1]. Traditional artificial neural networks use real numbers for input data representation. The internal parameters of ANN, so-called weights, are also represented as real numbers. Several problems can be encountered during the process of training ANN:

-The training can be slow, even on powerful hardware;

-The performance of network is improving in a slow manner;

-The ANN reaches a certain level, from which it is very hard to further improve the performance.

ANN work as universal function approximators [2]. The aim of our research is the development of a classification algorithm for objective cough sound analysis.

Objective evaluation of cough would be useful in clinical practice, clinical research and in the effective assessment of novel therapies [3]. Since the 1950s, researchers have attempted to objectively evaluate various cough patterns [4-7]. Several systems were developed with the aim of automatic cough identification and quantification thereof [8-11]. Our long-term strategy is to analyze the frequency of cough in continuous cough sound recordings from the chest surface. We used different classification methods: binary trees, ordinary artificial neural networks and recurrent neural networks. The classification algorithm achieved a sensitivity of 82% and a specificity of 96%. However, our aim is to further improve the specificity of the currently employed algorithm [12].

The process of developing the cough monitoring device consists of several steps. Data collection is the first step, followed by event detection. Since the sound recordings are relatively large files, reduction of input data and decomposition to single sounds is necessary. The elimination of relatively quiet areas in the recording is a straight forward task. However, even though the recording is targeted primarily at cough sounds, other biological or ambient sounds are also present and may cause false positive classification which in turn results in overestimation of cough sounds. It this case, even if the sensitivity is high, the overall performance of the classification algorithm is degraded.

This first stage of data reduction is not sufficient by itself and must be complemented by the computation of sound features. Mel-frequency cepstral coefficients (MFCC) are frequently employed in speech recognition algorithms, however many authors have a tendency to implement and evaluate their own parameters – including statistical parameters and time or frequency domain parameters [13,14].

The most difficult step in the process of cough sound analysis is the classification algorithm itself. The computer program/algorithm divides all sounds into 2 classes - the cough sounds and non-cough sounds, based on computed features. The internal parameters of the classification model must be determined with the help of machine learning algorithms. Since we work with large datasets, this can be a time-consuming task. This article will focus on the classification methods and associated algorithms since this is a crucial part of the cough monitor. Hence, the methods of sound recording and cough sound feature extraction are not the subject of this study.

CLASSIFICATION AND DECISION TREES

The binary tree algorithm is a relatively simple algorithm and is mainly used for classification purposes. The classification trees principally execute multiple decisions to finally determine which class, category or variable is represented by the input data. The structure of the algorithm and branching thereof is reminiscent of a tree; therefore we call them classification or binary trees. The random forest tree is a special type of classification tree algorithm which is currently most employed. Typically it consists of dozens or hundreds of trees - creating a so called forest. Decision trees are used as an alternative classification tool to ANN or Hidden Markov Models (HMM).

Larson et al. have achieved a sensitivity of 92% using the random forest algorithm in cough sound classification with a low rate of only 17 false positive cough sounds per hour. They discovered that 10 parameters were sufficient for reliable classification using their computer algorithm. The training of the classifier was set to a maximum number of trees equal to 500 [14]. In the past we also employed decision trees for cough sounds classification. The binary tree achieved an average sensitivity of 86% and a specificity of 91% in classification of voluntary coughs and non-cough sounds in healthy patients. However, the performance of the algorithm decreased in patients with respiratory diseases. The resulting sensitivity dropped to 28% only [12].

Binary trees, especially with random forest algorithms, can be trained relatively fast. But they are quite slow in the prediction or classification of data, especially if the input data is from large datasets. Increased accuracy can be achieved by increasing the number of trees; however this results in a speed decrease. Significantly faster execution times can be obtained when simulating one ANN model when compared to a massively parallel random forest tree. Although currently available multicore processors and graphics cards allow more complex computations, not all classification algorithms can be efficiently programmed for parallel processing. Sometimes it is hard and time-consuming to transform common sequential algorithms into efficient parallel forms. Random forest trees can also provide less accurate predictions if the data is beyond the range of trained parameters.

HIDDEN MARKOV MODEL

HMM is an important classifier method [13,14]. It is a statistical model and works with states and transitions between them. The transition can occur at any time in the signal and is expressed by the transition probability. Therefore, every state has its own statistics described by the probability density function (PDF). The state in HMM can be a vector of input parameters and in speech recognition these states are represented by MFCCs. We can imagine the HMM as a black box which generates a sequence of output symbols, classes or simply numbers. The observer does not see the sequence of states the model is passing through. The training of HMM is in fact based on the search of internal parameters of the model generating the desired sequence of output numbers or symbols with the highest accuracy. Currently there is no analytical solution to HMM training and as such, the Baum-Welch algorithm, based on iterative approach, is frequently used. Therefore the Markov models are denoted as hidden. They are often used in speech recognition and pattern classification. In speech recognition, HMM is connected with the statistical modeling of the sound event. HMMs can model temporal variations in signals and treat data sequences in the time stream as a random parametric process [14].

Mel-frequency cepstral coefficients (MFCC) are often used as input parameters in many computer models for speech recognition as well as cough sound classification. Matos et al. created a monitor for cough frequency – the Leicester Cough Monitor (LCM). This system is portable and uses a microphone with audio recorder. Data required for the cough sound analysis is collected in ambulatory environment. MFCCs are computed from audio recordings and are used as input data for the HMM. The computer model, however, requires individual audio calibration for every participant. Their computer classification program achieved an average true positive rate of 71%. False positive rate was 13 cough sounds per hour. After discarding low intensity cough sounds, the average true positive rate increased to 82% and the false positive rate decreased to 2.5 cough sounds per hour. This improvement in classification was achieved by employing the energy threshold method. However, almost 29% of cough sounds were eliminated for each participant. Further improvements increased the average true positive rate to 91% and decreased the false positive rate to less than 1% [9].

The HMM is often used as a standard tool in speech recognition methods. Rhee et al. created an Automated Device for Asthma Monitoring (ADAM) [15]. This system contains several tools for monitoring of asthma symptoms such as questionnaires, recording of cough sounds with smartphones and several others. The MFCCs, average loudness and other parameters are used as input vector for classification of the cough sounds, similar to approach proposed by Matos et al [8,9]. The HMM was selected as classification model (tool). This system differs from others as it allows real time evaluation directly on the smartphone. A significant drawback of this method lies in short battery life of the smartphone – typically only several hours – so frequent recharging is necessary. Despite this, Rhee et al. [15] attained a sensitivity of about 70 % and only few false positive cough sounds.

Tracey et al. states that HMMs as computer statistical models can track the time evolution of the cough sound. Since HMMs analyze the entire sound event, they consider them useful especially for the classification of isolated cough sounds. Furthermore, they suggest that a frame-by-frame analysis can be better in the classification of overlapped cough sounds and ambient sounds. They see possible improvement in the classification by replacing simple class non-cough sounds with multiple different classes [13].

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks represent a mathematical computational model inspired by biological neural networks. ANN has become a standard tool in computer science for the classification of various digital patterns. They are used primarily in applications dealing with image processing, speech recognition, time series prediction, robotics and several others [1]. Traditional artificial neural networks use real numbers for input data representation and the internal parameters of ANN, so-called weights, are also represented as real numbers. ANN is considered to be one of the most successful computer classification models. According to the authors thereof, ANN can be useful in cough sound analysis, since they have the capacity to model nonlinear relationships between input parameters [2].

Several problems may appear during the process of ANN training - the learning of ANN can be slow, even on powerful hardware or the performance of the network is improving either slowly or reached a certain final level, beyond which it is very hard to further improve the performance thereof. ANN work as universal function approximators [16]. Local minima can also be a problem during the training process. In certain cases the performance of ordinary ANN can be insufficient and as such is strongly dependent on the problem type and learning method complexity. Thus computer scientists are constantly researching new means to improve the performance of neural networks. The use of complex numbers in ANN models proved successful in many real-life applications [17,18] and complex-valued ANN became increasingly popular. The input/output data and internal network parameters are formulated (expressed) as two-dimensional numbers - this modification helped increase the functionality of neurons and also improved the performance of ANN. It is well known that classical, non-linearly separable XOR problems can only be solved with single layer, complex valued neural network instead of two layers, real valued neural network. The complex valued neuron has better plasticity and flexibility and ANN learns faster and generalizes better [17]. Single neurons are able to learn input/output mappings that are non-linearly separable in the real domain.

In our study we used ANN model for determining cough sounds from other sounds [12]. It contained 4 layers with 21, 14, 7 and 2 neurons, respectively. First 3 layers contained sigmoid activation functions and the last layer was linear. A dataset of 12 000 sounds was used in the training process with Levenberg-Marquardt optimization algorithm. We achieved a sensitivity of 82% and a specificity of 96% on the dataset of 95000 sounds. Drugman [19] developed a system for recording, analyzing and classifying cough sounds from ambient sounds. They used lapel microphones for the recording of sound events and the analysis of sound recordings included computing different spectral, statistical and user-defined features. They also used standard MFCCs; band pass filter parameters and chroma features. In the frequency domain they employed statistical parameters such as spectral spread, centroid, variation and flux. The input of their 3-layer neural network consisted of the mentioned parameters. They decided to connect adjacent time frames to classify every 150 ms of data. In the end, a sensitivity and specificity of almost 95% was attained using the mentioned classification model. Drugman has also demonstrated that increasing the number of neurons in an ANN can increase classification rates [19]. When using 64 neurons in their ANN model, they increased the sensitivity up to 94%. Swarnkar et al. [20] proposed a novel method for automatic identification of cough sounds based on the ANN architecture using non-Gaussianity score, formant frequencies, log energy for every frame, zero crossing rate, MFCCs, kurtosis and bispectrum score as features in their classification model. Each 100 ms segment of sound contained 201 mathematical features. The neural network model then classified sounds into two classes – cough sound or other sound. Their network consisted of single input layer with 201 neurons and 4 hidden layers with 50, 20, 10 and 5 neurons, respectively. They used sigmoid activation function for every layer of the network and the network was trained with the Levenberg-Marquardt algorithm. Their model achieved a sensitivity of 93.4% and a specificity of 94.5%. Their sound database for training and testing the model consisted of 3 patients [20]. Tracey et al. in their study compared several approaches for cough sounds classification. MFCCs, their first and second differences, became the input features for the mathematical models. They used 3 different classification methods: artificial neural networks, support vector machines (SVM) and sequential minimal optimization (SMO). The neural network model with multilayer perceptron (MLP) architecture achieved the best classification performance. For the training dataset, the neural network achieved a sensitivity of about 89% and a specificity of 87.5%. On the testing dataset obtained from 10 randomly selected patients they achieved a sensitivity of 81% and a false positive rate of 3.3 per hour [13].

Deep neural networks (DNN) belong to relatively new computer classification methods. These networks have outperformed many states of the art ANN in various applications. The most promising results were in image classification and speech recognition. DNN often contain more than 3 layers of neurons and the largest one can have millions of weights. The computation time naturally increases with the size of network. Over fitting, vanishing gradient problem and computation time are common issues of naively trained DNN. Randomly initialized weights are potential source of problems in the vanishing gradient issue. However Liu et al. [21] showed in their research how pretrain strategy can improve overall performance of DNN in the cough sound classification. They used deep belief network (DBN) composed with multilayer stacked Restricted Boltzmann Machines. They obtained with this method a good initialization for the network. This unsupervised step is followed by standard back propagation algorithm in order to fine-tune the weights. Their mixed classification model (HMM -DNN) outperformed original model (Gauss mixture model - HMM) by 14% in the specificity. They recommend pretrained DNN classification model for better overall performance in cough sound classification [21].

As we have mentioned, the cough sound classification works with large datasets. The sound record of only one patient can contain dozens of thousands sounds. Many authors are referring the creation of sufficiently large cough sounds datasets in clinical conditions as difficult [13,14]. In the time of massive development of information technology, it is possible to use the internet as an unlimited source of various digital files. The respiratory sounds as well as other sounds are available from several internet sources. Common video portal as YouTube can be helpful in creating datasets of cough sounds. But there are also other institutions providing cough sounds datasets to download completely free. This can be helpful, because we obtain sound files where the person, environment and recording conditions change significantly [22]. Although the clinicians can doubt the inequality of recording conditions among subjects, the internet sources of cough sounds datasets can considerably speed up the development of suitable classification algorithm. Since the variability of the cough sounds among patients and their environment's is so high, there is basic need to face this problem with the creation of as large dataset of sounds as possible.

DIFFICULTIES WITH CLASSIFICATION OF THE COUGH SOUNDS

The cough sound detection process must address several issues. The need for particularly high specificity is one of the biggest issues. Since 24 h sound recordings contain significantly more non-cough sounds (speech, noise, technical artifacts and other sounds) than cough sounds, the computer classification algorithm must have a very high specificity [14]. Even after discarding sounds with low intensity, cough sounds can occupy as little as 1-2% of the entire sound recording. If the specificity of the classification model is not sufficiently high, the number of false positives can exceed the true positives several times, which degrades the results of classification.

Another important problem that needs to be addressed is the exceptionally high variability of the cough sounds. The cough sounds vary not only among different patients but also in a single patient. The patient's cough may change its basic parameters from 1 min to another. It is therefore necessary to question whether one computer model is sufficient to correctly classify cough sounds. Larson et al. [14] think that one classification algorithm requires hundreds of models in order to achieve high specificity and overcome problems associated with variability. Another option is to personalize the classification model for individual patients [14].

FROM COMPLEX ANN TO HYPERCOMPLEX NUMBERS

The extension of the ANN models reaches beyond complex numbers. Hyper complex numbers represent a direct extension of complex numbers into higher dimensional space. There are only four algebras types where normed division is possible:

-Real numbers (1 dimension),

-Complex numbers (2 dimensions),
-Quaternions (4 dimensions),
-Octonions (8 dimensions).

Octonions represent the highest possible normed division algebra over real numbers. They are usually represented by the capital letter O. Octonions are 8 – dimensional numbers and we can treat them as octets or 8-tuples. Octonions are employed within various fields of research, such as string theory, special relativity and quantum logic, electrodynamics, digital signal processing, machine graphics and wireless data communication [23]. Octonions are referred to as the most essential mathematics for artificial intelligence research and modelling of the brain and behavior. Goertzel, an acknowledged artificial intelligence researcher, used octonions to model short term memory [24]. Piaget used octonions to model cognitive development, including schemata imbedding and the theory of relations. They are also used as mathematical tool for computer modeling of abstract structures of the states of consciousness [24]. Let's denote octonion x as:

$$x=x_0+x_1\, i+x_2\, j+x_3\, k+x_4\, E+x_5\, I+x_6\, J+x_7\, K$$

where:

i, j, k, E, I, J, K are imaginary units - bases, their square root is -1

$\{x_i\}$ i=0, 1, 2, …7 are real numbers

Addition and subtraction of octonions is performed by adding and subtracting the corresponding terms and hence their coefficients, such as vectors. Multiplication of octonions is more complicated and we must follow special rules from a multiplication table. Such rules do not exist if we are working with real numbers. If we multiply two octonions x and y, the order of multiplication of both terms is important – resulting in non-commutativity of octonion multiplication. However, the most exceptional aspect of octonion multiplication is non-associativity:

$$x\, y=-y\, x \qquad (x\, y)\, z=-x\, (y\, z)$$

There are algebras with higher dimensions, such as, e.g. sedenions (16 dimensions), but they all have zero divisors. We chose octonions as the number framework for our ANN because octonions represent the last normed division algebra. Another reason why we chose octonions is their exceptionality in non-associativity and non-commutativity of multiplication. The main advantage of using octonions in our ANN model is their unique ability to deal with a sequence of successive data or events in a time stream. Due to their non-associativity of multiplication, their use in computer models is plausible from a mathematical point. In our opinion a sequence of successive events or parameters in a time stream can be expressed and modeled with direct use of octonion multiplication. The imaginary bases of octonions (i, j, k, E, I, J, K) can also be employed in direct modeling of temporal states of neurons within a neural network to express the system dynamics. In our research, we are employing neural networks for the classification of sounds. However, if we want to express different events or patterns in the process of classification of sounds, we can use any octonionic base.

In our research, we are working with 5 h sound recordings and evaluate 32 parameters characteristic for speech detection. The mentioned parameters are obtained via analysis in the frequency domain. We also use an analytic window with a length of 1024 samples which moves through the whole sound recording with a step of 512 samples (50% overlap). The spectral characteristics are computed for each position of the moving window using the Fast Fourier Transform (FFT). The analysis of speech or general sounds deals with relatively short time steps – so called frames. We are calculating a set of 32 parameters for every single frame. The duration of simple sounds is approximately 0.4 s, thus we require 9 frames to be able to describe these sounds with our parameters. Manual evaluation of single frames (93 ms duration) is not adequate enough to properly identify sounds - we must combine values of all 32 parameters from 9 individual frames within one result. Obviously, these parameters can change over time. Therefore it is important to consider how the computer model deals with the time dependency of successive events or patterns. Recurrent neural networks model time dependency additively. The signal from the previous state of the neuron is simply added to the signal of the current state of the neuron. We reason that this approach has certain restrictions when modeling complex relations of single events or patterns occurring over time. We know that addition is commutative and thus is independent of the order of the added numbers. If we denote the output potential of a neuron in time t as Yt, the output potential of a neuron in previous time as Yt-1 and the internal state of the computer model (ANN) in time t as At, the time dependency can be modeled as:

$$Y_t=A_t+k\, Y_{t-1} \qquad \text{where k is a real number coefficient}$$

There are many scenarios, especially if we work with time series data, where additive superposition of signals from successive time steps is insufficient. This type of problem is best solved using octonions. Let's suppose a sequence of 3 consecutive events (A, B, C) recognized on the outputs of neurons of ANN and denoted as single octonionic bases i, j and E. Event A denotes the presence of silence in the recording, successive event B denotes the increase of the intensity of sound and finally the third event C denotes the detection of speech. If we use the imaginary octonionic bases i, j and E to model the time dependency of these 3 consecutive events, the direct use of octonionic multiplication enables us to express the unique dynamics of events over time.

silence >>>> increase of the intensity of the sound >>>> speech detected

$$j \times i \times E = -k \times E = -K$$

We see that the multiplication of 3 different octonionic bases results in a unique octonionic base K. However, if we reverse the order of events to (C, B, A), the final multiplication product is K instead of -K.

Speech detected >>>> increase of the intensity of sound >>>> silence

$$E \times i \times j = -I \times j = K$$

It is evident that the special properties of octonion multiplication enable better description of event or pattern dynamics over time. The events (A, B, C) are denoted as single imaginary octonionic bases only for simplification purposes. Every event or pattern on the neuron output can be expressed as a standard octonion with 7 imaginary bases. We also proposed several own activation functions for neurons.

Let's suppose that the signal in time t, travelling into the neuron, is expressed in octonionic form:

$$x_t = 0.15 + 0.7\,i + 0.9\,j - 0.4\,k + 0.1\,E + 1.3\,I - 0.25\,J + 0.3\,K$$

The activation function is then used to express the activity of the neuron. The simplest activation function is a pure linear function, sometimes denoted as purelin. This function does not change the signal. There are also several logistic or sigmoidal activation functions for complex neural networks that can be extended within the scope of octonionic neural networks [25]. We propose two special activation functions, partially inspired by deep neural network analogs - ReLu (rectified linear unit) and maxpool unit. In the following activation functions we denote the input neural signal as x_t, referred to above and the output neural signal as y_t, which is the result of signal travelling from the activation function. The "Majority base" is an activation function which preserves only the octonionic base with maximum value, while other bases are discarded - it is not necessary to consider real bases. The majority base activation function then transforms the input signal in the following manner:

$$y_t = 0.15 + 0.7\,i$$

"ReLU" is an activation function which preserves only octonionic bases with positive values and bases with negative values are discarded:

$$y_t = 0.15 + 0.7\,i + 0.9\,j + 0.1\,E + 1.3\,I + 0.3\,K$$

Octonionic neural networks are much more flexible when compared to ordinary ANN. The signal travelling into the octonionic neuron is expressed as 8 individual numbers or bases instead of a single number. Octonionic neural networks offer the possibility to create own activation functions for neurons. Let's assume that the majority octonionic base on the neuron output in time t_{-1} is K and in the next time frame t is also K. We can then define special rules for the activation of the neuron output. For example, the signal from the neuron is propagated only when the majority octonionic base does not change in two successive time frames. In another example, let's assume that the majority octonionic base of the neuron output in time t_{-1} is K and in the next time frame t changes to J. This special activation rule assumes that the signal from the neuron is propagated only when the majority octonionic base in two successive time frames was modified in a specific manner (in our case changing K to J). There are several other special rules for activation of the neural output, such as the case when the signal from the neuron will propagate only if the sign of the majority octonionic base is reversed in two successive time frames (majority base I is reversed to –I). The reversal sign was not chosen randomly but because of the order of octonion multiplication. There are many possibilities with respect to the use of the unique properties of the octonion multiplication table and the creation of special neuron activation rules. ANN can contain hundreds or even thousands of neurons. Every neuron can have its own activation function such as ReLU, majority base or ordinary linear function. In our research we prefer modular neural networks, where individual components of ANN (activation functions and weights) are found as a result of a genetic algorithm.

The input parameters and weights of octonionic neural networks are 8-dimensional numbers. The signal travelling into a neuron is therefore a set of 8 numbers working like independent entity, not vector. The simulation of octonionic neural network requires at least 120 times more basic operations of multiplication and addition against standard ANN. But this is true only in case both – the octonionic neural network and the standard ANN consist of same number of layers, neurons, weights and input parameters. The multiplication of 2 octonions requires 120 operations (64 multiplication and 56 additions). At first sight this seems to be a drawback. But computer scientists showed that neural networks working with signals in the form of hyper complex numbers generalize in many cases better and faster [17,18]. Layer of complex neurons can replace 2 layers of real neurons and octonionic neuron can replace several layers of neurons. Since the input parameters may be expressed as 8-dimensional numbers, much less octonionic neurons are needed in octonionic neural networks to cover the input dataset. The hyper complex neural networks tend to converge faster than the standard ANN. In result, the required number of octonionic neurons, network layers and training epochs is smaller and therefore the time needed for the training of octonionic neural network is comparable to standard ANN. The unique functionality of the octonionic neural networks can be tested in various computer models of real-life applications. We reason that the classification model based on octonionic neural networks can improve the overall performance and decrease the number of erroneously classified cough sounds.

CONCLUSION

The main purpose of this study was to compare frequently employed classification algorithms for cough monitoring and to analyze major issues associated with this topic. We propose the use of 8-dimensional numbers – so called octonions - to model the complex time relations of the cough sound parameters and urge on utilizing the non-associativity of octonion multiplication to model the time-dependency of data in computer models working with time series. Because the order of multiplication of individual octonions is important, the octonionic classification model can provide a general approach to dealing with time-varying data from a mathematical point of view. We also showed how to create activation functions for neurons in octonionic neural networks. These functions can improve the performance of ANN model when compared to standard activation functions.

ACKNOWLEDGEMENT

This work was supported by the project Biomedical Center Martin ITMS code: 26220220187 (co-financed from EU sources and by Center of Excellence for Research in Personalized Therapy (CEVYPET) funded by EU. This paper is supported by University Science Park of the University of Zilina (ITMS: 26220220184) supported by the Research & Development Operational Program funded by the European Regional Development Fund.

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