ADAPTIVE ROTE-LEARNING TUTORING ALGORITHM

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This paper presents an adaptive algorithm implementing "rote learning" teaching strategy to be used in an intelligent tutoring system for auditory-verbal education. The algorithm was developed considering the hypothesis that an adaptive way of presenting the instructional material improves the learning time. In the end the algorithm is compared to a non-adaptive version in training a virtual student represented by a feed-forward neural network. It has been discovered that the adaptive way of generating the instructional material is superior to a completely random situation.

Keywords: auditory-verbal education, adaptive algorithm, rote-learning, intelligent tutoring algorithm

1. Introduction

Auditory-verbal education is an effective method used in training children with hearing loss that have been implanted with an auditory aiding device, to discover and master this sense with the overall goal of using it in acquiring the spoken language [1], [2], [3]. In order to encourage these children to use hearing as one of the main channels of interacting with the environment, specialists recommend an intense recovery program designed to enhance the abilities of recognizing noises, sounds, preverbal sounds [4], etc. Once the child becomes familiar with its newly (re)discovered sense and its auditory experience is developed up to a reasonable level, exercises are being shifted towards a more verbal approach, the non-verbal sounds used in practice sessions being replaced with verbal sounds, vowels, simple words... all needed to develop the spoken language.

The work presented in the current paper was partly motivated by the following important aspects related to auditory-verbal therapy (education):

- specialist recommend to commence auditory verbal therapy as soon as the child is discovered to have auditory problems [5]. Of course, he should also be immediately implanted with a hearing enhancement device [6]. This is highly important when taking into consideration, for instance, that a newly identified three years old auditory deficient has the same auditory experience as a new-born.

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When the child reaches the age of four he is going to be auditory proficient just as a one year old non-hearing affected child. Also, there is an optimum biological moment in life when certain "knowledge" can be easily comprehended or mastered. Therefore, if the problems are discovered at a later moment the situation can only get worse.

- specialized cabinets where the therapy is being conducted are scarce when compared to the demand. This is even more important when analyzing the situation of our country. In Romania there are few auditory-verbal (AV) specialized center and only one in Bucharest - Grădinița nr. 65 pentru hipoacuzici [7]. All this means that therapists are insufficient and are unable to efficiently help all the children in need.

- automated e-learning type systems designed to be specifically used in the auditory-verbal therapy are to our knowledge rare and insufficiently developed so as to be used as tools that can compensate the lack of specialists. Knowing that an important aspect of AV therapy is the implication of the family and the home environment [8], such systems could proof useful furthermore as many of the implementations can feature remote access.

- some of the very first exercises the child is required to complete are those in which he is asked to listen and identify sounds that are emitted by different objects. Even if this may sound as very simple, the information learned from these can be viewed as the fundamental knowledge of the field. By comparison it is like learning the very first lexical elements of a foreign language or learning the multiplication table in elementary school. As simple as it may sound, this is the foundation stone of the interaction with the environment, and therefore it is highly important in developing the individual and ensuring his later integration in society.

Knowing all these facts, we view our work as an important step forward in enhancing the AV therapy by means of a cross-disciplinary approach where elements of information technology and artificial intelligence can be introduced in such systems that can train children with little help from the specialist. The current paper is organized in two parts: first, we will present an adaptive tutoring algorithm based on the rote-learning strategy to be used in a simple exercise where the child is required to learn the association of sounds and images (known as stimuli) representing the emitter of the sound. Then we will compare the performance of such an algorithm in training a virtual student represented by a feed-forward neural network [9], [10], [11] in memorizing the association of stimuli, to a classical training method where the stimuli are presented in a non-adapted manner. We believe that such an algorithm is an important feature that needs to be developed and included in an actual implementation of an auditory-verbal tutoring system. This way the system will be able to more closely represent the actual training a human specialist performs with the advantage that elements that influence the performance of the human, like mood, fatigue, lack of experience, etc., do not influence the automated training and therefore, all the decision made by the system are purely objective.

2. Adaptive tutoring algorithm

Knowing that the child has no previous experience in the auditory field, the very first auditory knowledge is always acquired via rote learning. Rote learning is fundamentally based on the principle of repetition. For example, a fundamental exercise a child is supposed to practice is based on the repetition of image-sound stimuli pairs, for every such presented pair the child being asked to look at the image and listen to the sound, of course, with the goal of teaching him the connection between the sound and its emitter (the object in the image). After the child lost interest or a period of time elapsed, the next stimulus is presented and so on. Interleaved with such so called *training sessions* the child has to pass different *test sessions* in which the performance of memorization is evaluated. A test session is similar in nature to the case of a "question with multiple possible answers". The child is presented with several images and only one sound is being played. Obviously the child is required to identify the emitter of the sound. Fig. 1 and Fig. 2 present an example of these two kind of sessions implemented in a simple auditory-training application developed by our team.

The role of the test session is to record the errors the child makes in identifying the stimuli presented. This way, in the real life therapeutic situation, a specialist is able to determine if the current level of performance is high enough to pass the child to the next types of exercises or to decide upon the stimuli presented in the next training session (if the current level is not sufficient). Yet, as stated before, our goal is to minimize the implication of the specialist in its decision so as to eliminate as much as possible the case in which a subjective or wrong decision over the continuation of the exercise is made. By having an objective measure of evaluating the child it is possible to integrate a decision mechanism that is itself objective in nature and not influenced by human factors as fatigue, lack of experience, etc. Therefore we believe that this is a good opportunity of integrating a simple yet smart algorithm that adapts rote learning to the current needs of the training process and decides upon the future stimulations based on objectives measures that are always, when recorded, going to give the same results.

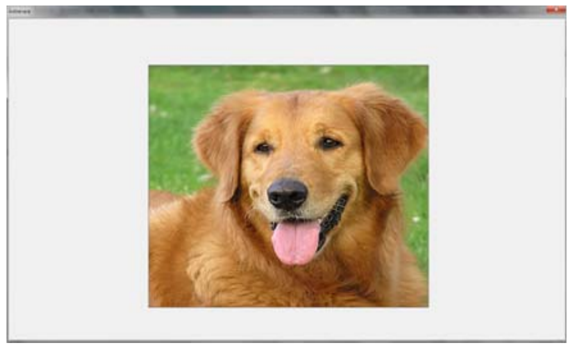

Fig. 1. Image from a training session in an auditory-verbal training application. The image is displayed while a sound emitted by the animal is being played. In this case the user is only required to listen and learn the sound-image association. Notice the simplicity of the interface as it is desired to remove any elements that my influence the focusing ability of the user (child).

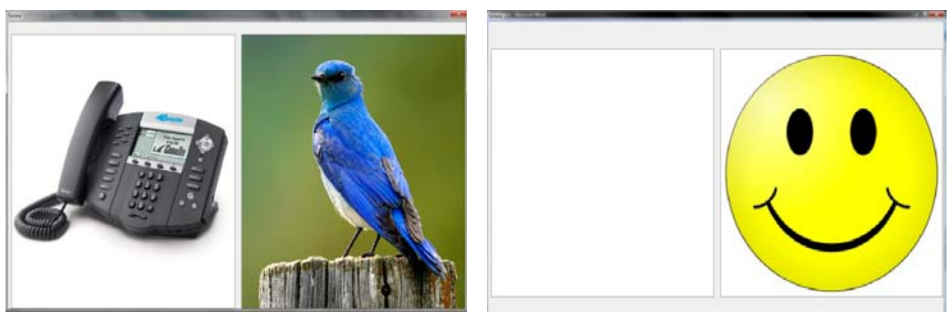

Fig. 2. Right - Image from a test session in an auditory-verbal training application. The screenshot represents two sound emitters while on the speakers only one sound is being heard. The user is required to correctly select the object or animal that generated the sound.
Left - In the case of a correct choice, the feedback is immediately generated.

In order to, integrate all described above into a fully functional algorithm the first step to be taken is to establish a method upon which stimuli are generated in the training session. Considering that in the real life situation the emission of stimuli can be characterized as stochastic and, of course, influenced by the experience of the specialist and the performance of the child, then using a random variable to describe the emission of stimuli is a natural choice as the real process of choosing the stimuli is itself stochastic. A second aspect that is important to establish at this point is to associate meaning to the outcomes of the random variable. One might say that the outcomes should represent directly an index identifying a pair image-sound yet such a situation would be associated to a (potentially) large number of components of the discrete probability density function describing the variable. This would mean that not only many of the stimuli would be missed when the emission is ran in a training sessions, but the enforcing of the stimuli, when required, could also be less significant. A second, simplifying, choice is to partition the database of stimuli into classes according to some criteria and enforce (adapt) the classes of stimuli and not the stimuli directly. This is the choice we made and all the subsequent reference to stimuli emission should be understood as the emission of an index identifying a class of pairs image-sound and not an image-sound pair itself.

A schematics of the developed algorithm is presented in Fig. 3. It should be noticed the two distinct sessions described above: the training session and the test session. The training session elapses only after all the *N* currently selected stimuli are presented. Of course, the initial distribution of emission is completely uniform, the only time when this is not the case would be if the child interrupts the practice and continues it later. This means that the initial distribution at the subsequent use of the system should be the one determined after the last test session carried out by the child at the previous use. Anyway, for an initial case when the algorithm teaches a child with no previous training, the distribution is:

$$p_X(x, t=0) = \frac{1}{K} \tag{1}$$

where K is the total number of categories, x is a given category of stimuli and t is the session counter.

Every time a training session elapses, the test session is ran with the goal of computing (evaluating) the classification errors the child makes. This is an objective measure defined by our algorithm, easily to measure and not prone to human errors. Considering that $E(x, t)$ is the number of misclassified stimuli and $T(x, t)$ is the corresponding total number of stimuli in the class x presented in the test session t, then the classification error for class x in session t is:

$$p_{err}(x,t) = \frac{E(x,t)}{T(x,t)} \tag{2}$$

After the test session, the algorithm is supposed to adapt the distribution of emission so as to enforce those categories where p_{err} is greater. We propose the following formula to be used to adapt the probabilities in the distribution:

$$p_X(x,t+1) = \frac{\delta + p_{err}(x,t)}{\sum_{j=0}^{K-1}\left[\delta + p_{err}(j,t)\right]} \tag{3}$$

The small increment δ is used to enable the adaptation even for the very unlikely case when all p_{err} are simultaneously null.

This is also a an objective aspect of our solution when compared to a human supervisor. The way in which the stimuli are going to be emitted in the future training session are always going to be dependent on a consistent measure.

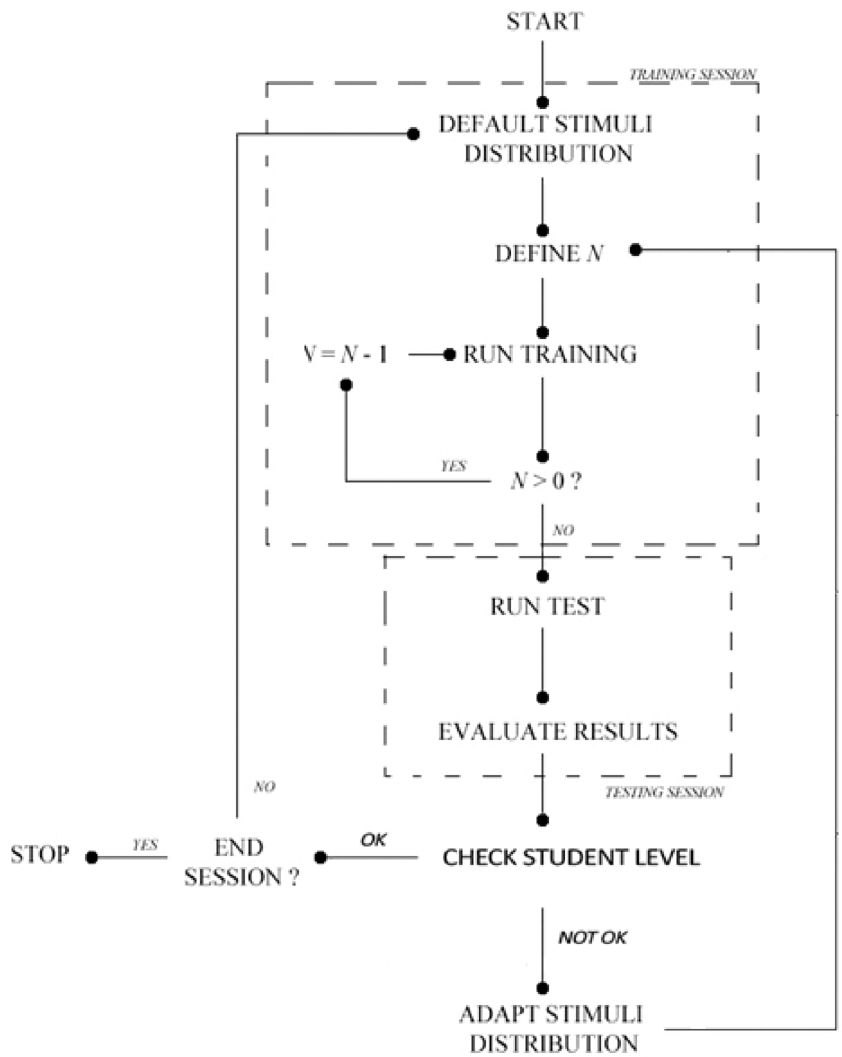

Fig. 3. Schematics of the adaptive algorithm used in a simple exercise to be used in auditory-verbal therapy.

The only downfall of the above algorithm is that in some particular situations the adaptation performed is highly uncorrelated with the previous shape of the distribution and, thus, the formula may force the unintentional omission of stimuli (those considered to be learned due to small errors). Such total lack of enforcement for some categories would mean that the child is more prone to forget them, a more elegant approach meaning that some degree of enforcement being kept for a number of sessions, even after the errors for that category, are small enough. This way the child is more likely to memorize the stimuli. The situation is similar to the stability-plasticity dilemma [12], [13] for neural networks as we will see further below.

To correct the problem presented above we propose to limit the maximum value for a given probability to a threshold value T, the excess of information being redistributed to those probabilities below T according to the relative size between them. This process can be performed in the following manner:

i) establish a threshold $T \in [0, 1)$.

ii) Compute $p_X(x, t + 1)$ according to (3) and compare the probabilities with the threshold.

iii) Divide the probabilities into two sets, M_{P1} and M_{P2} according to the relative value to T.

iv) Compute the total amount of information greater than T according to:

$$A = \sum_{i \in M_{P1}} (p(i,t) - T) \tag{4}$$

v) Set all the probabilities in M_{P1} to T.

vi) Sort elements in M_{P2} and select the smallest probability, p_{min}.

vii) Compute the set C according to:

$$C = \left\{ c \mid c = \frac{p(i,t)}{p_{min}}, p(i,t) \in M_{P_2} \right\} \tag{5}$$

viii) Compute all the P_2 incremental values that will be added to the components of M_{P2}:

- establish the condition that the sum of the incremental values should be equal to A.

$$A = \sum_{i=0}^{P_2-1} \Delta_i = \sum_{i=0}^{P_2-1} (c_i \cdot \Delta_{\min}) = \Delta_{\min} \cdot \sum_{i=0}^{P_2-1} c_i \tag{6}$$

- compute the Δ_i according to:

$$\Delta_{\min} = A \cdot \left(\sum_{i=0}^{P_2-1} c_i \right)^{-1} \tag{7}$$

$$\Delta_i = c_i \cdot \Delta_{\min} \quad \text{where} \quad i = 0 \ldots P_2 - 1 \tag{8}$$

ix) The probabilities in M_{P2} will be adjusted according to:

$$p_X(i, t+1) = p_X(i, t) + \Delta_i \,, \quad i = 0 \ldots P_2 - 1 \tag{9}$$

An example of how this process works is presented below in Fig. 4. The depicted distribution *after* the process of enforcing with (3) is described by the probabilities, [0.0784, 0.8823, 0.0392]. This is represented on the left side column. Each case on the right side column is an illustration of the distribution after the threshold limitation described above in (4) - (8). The thresholds used are 0.5, 0.6 and 0.7.

It is to be noted that the probabilities that initially had an insignificant value (1 and 3) when compared to 2, are now more strongly represented, meaning that the associated stimuli have a better chance of being emitted in the subsequent training session. At the same time the relative size between each other is maintained meaning that the exact relative adaptation as generated by (3) remains intact.

A downfall of the algorithm comes into play when taking into consideration the value for the threshold T. In some cases if T is not large enough then the redistribution process could build up probabilities that exceed T. This could be avoided if

$$p_X(\max, t) + \Delta < T \tag{10}$$

where in this case $p_X(max, t)$ is the largest component in M_{P2} and Δ is the associated change computed using (8). Unfortunately, this situation is hard to predict as the probabilities are changing after every training session. A solution would be to study the algorithm on a batch of subjects and experimentally determine a good value for T before using the algorithm in a real environment.

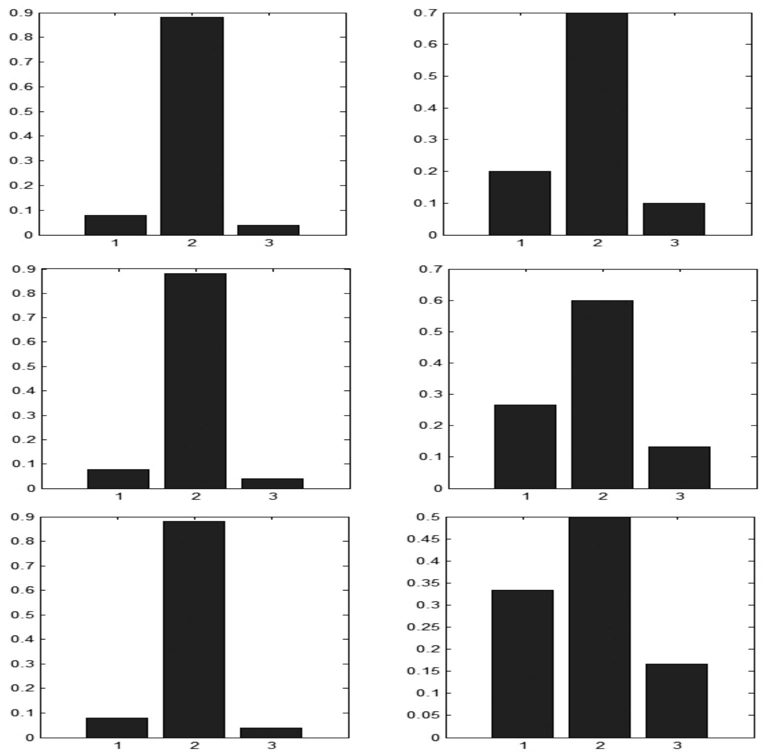

Fig. 4. Example of the limiting criteria imposed to the probability density function. The distribution to be limited (left column) is [0.0784, 0.8823, 0.0392]. On the right column three cases are presented where the limiting threshold is chosen to be 0.7 (top), 0.6 (middle) and 0.5 (bottom). Notice the relative proportions of the probabilities below threshold after the limitation.

3. Testing the tutoring algorithm in a simulated environment

At the current moment, due to the lack of access to a specialized training center, we decided to test the algorithm using a simulated environment where the student to be taught is represented by a feed-forward neural network. We decided to emulate as closely as possible the real life situation, beginning from the hypothesis that a feed-forward neural network has certain similarities to the process of memorization exposed by humans, similarities that are important for our experiment. That is, in both cases memorization is achieved through a repetitive process and, more importantly, both the network and the human being tend to remember better those patterns repeated more often than those neglected.

Further on, we impose certain restrictions to the experiment that are necessary to give significance when comparing to the real life situation: 1) the database of stimuli is represented by completely separable information in order to assure the fact that the network will eventually learn the information. Also, the database should not contain a large number of stimuli so as to resemble the real life case where the child is not required to memorize hundreds of images. 2) the stopping condition is the passing of a threshold of the error rate. 3) the training criteria for the neural network should be the *online* back-propagation method, were a subset of the available training data is presented at every epoch before adjusting the connecting weights. Unlike the 'classic' batch backpropagation [14], this is not seen as a 'true' gradient descent method [15] but it is still a popular method of training, especially when the network needs to learn in a 'live' manner (that is when the training set is not previously known). Fortunately, this method can be easily extended to integrate our tutoring algorithm presented in section 2. After every epoch, the subset of data to be presented is going to be generated using an adapted distribution, according to the recognition errors computed and the enforcing process described in the previous section. 4) test sessions need to check the current memorization level achieved by the network. For this to be recorded, a recognition criteria needs to be specified so as to count the correctly and incorrectly classified stimuli needed in (2). For every input in the test session the recognition criteria is given by the following formula:

$$err_i = \begin{cases} 1, \|t_k - o_k\| < Q \\ 0, otherwise \end{cases} \qquad (11)$$

where the norm represents a measure of distance, Q is a specified threshold, t_k is the targeted output and o_k is the output of the network. Adding up all err_i for every category of stimuli we get $E(x,t)$.

After several trial and error verifications the parameters established for the experiment were the following: 1) three layered network organized with 4, 4, 3 neurons in each layer trained on 30 two-dimensional vectors partitioned in three classes. 2) 300 epochs of training, in each one 10 random inputs being presented. 3) the stopping threshold STOP was chosen to be 0.1. 4) the process was repeated 512 times for different Q's and learning rates. 5) the limiting value for the probabilities was chosen to be 0.5.

We present below the results for the training of the network using the online non-adapted case - Table 1 - and the online adapted case using our tutoring algorithm - Table 2.

Table 1

Results of the online training method with no adaptation

Learning rate	No. of epochs before stop condition is reached
0.035	100
0.04	89
0.05	**71**
0.06	**71**
0.07	73

Table 2

Results of the online training method with adaptation

Learning rate	No. of epochs before stop condition is reached	*Q*
0.035	76	0.6
0.04	67	0.6
0.05	60	0.5
0.06	**58**	**0.7**
0.07	62	0.5

4. Conclusions

Our algorithm performs better at every choice of learning rate and significantly better when the learning rate is either very small or very large. When comparing the best results in both cases we obtained an improvement of almost 20% in the number of epochs necessary to train the network. This means that the adaptation of the emission of stimuli is an important aspect that can generate good real life results with the condition that the enforcing is performed under certain restriction. Preliminary tests, not displayed here, showed that a non-limited adaptation presents no gains compared to the classic online training due to stability problems.

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