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Boosting E-learner's Motivation through Identifying his/her Emotional States

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Abstract:

The main objective of e-learning platforms is to offer a high quality instructing, training and educational services. This purpose would never be achieved without taking the students' motivation into consideration. Examining the voice, we can decide the emotional states of the learners after we apply the famous theory of psychologist SDT (Self Determination Theory). This article will investigate certain difficulties and challenges which face e-learner: the problem of leaving their courses and the student's isolation.

Utilizing Gussian blending model (GMM) so as to tackle and to solve the problems of classification, we can determine the learning abnormal status for e-learner. Our framework is going to increase the students' motivation through utilizing the notion of agent. Furthermore, it helps to assess teacher with the learning efficiency through putting attention on the learners who have the problems to accomplish the courses' objectives.This will help educatorsto contribute to the intellectual andeducational development of their learners, to prepare them to face real-lifechallengesand to advancetheir academic careers.

Keywords: Agent, Distance-learning, Emotional states, GMM, Motivation, SDT, Voice analysis.

1. INTRODUCTION

A strong growth in digital information capacity and device development has created a technological context which has drastically changed the uses of auditory information. In the Digital area of "everything is digital" which is a rich source of information, and which lend itself to an efficient exploration in digital form. The dimension in general group of data emerged quickly.

In addition, methods of analysis, recognition, indexing and searching data of audio and video have evolved. Research in the signal domain must therefore respond to these new needs, taking into account, not only, the classical notions, but also of this new scale.

2. STATEMENT OF PROBLEMS AND HYPOTHESIS

This article is going to explore certain challenges which face distance learners. These educators will understand the focal reason behind inventing of e-learning and they will know that this is not everything about technology. However, the latter is only a part of educational process, and it must be accompanied by good quality courses which, by the way, should be developed. The scientific aims of

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this article are to understanding and interpreting learners' voice in distance learning at the emotional level to solve the problems of dropping the courses through increasing motivation in training at a distance

3. AGENT, CLASSIFICATION, SDT

3.1. A multi-agents system

A multi-agents System (M.A.S.).Is an computerized system of multiple smart agents which interact in a given environment. The multi-agent systems can be used to solve challenging problems that could not be otherwise solved by an individual agent or monolithic system. Intelligence can include certain methodical, functional and procedure approaches and certain Algorithmic researches. [1]

3.2. Classification

Classification is a procedure to to classify collected data in certain classes depending on certain similar criteria it necessitates the explaining and selection of a well-described functionality of a given class. the classification refers to supervised learning too., when the models are given with known class labels. In the opposite case, unsupervised learning, the labels are not known. Each Model in the data as a whole is represented with a group of characteristics that can be defined or continued. [2]. The classification, thus, is the process of constructing models of the training as a whole. The model which is left at the end of the construction is then used to predict the class labels of test models.

3.3. The self-determination theory

There is a number of theories which help to better understand learners' motivation; nonetheless, we will select only one: the self-determination. [3].The self-determination is a well-known modern theory to the psychologists. According to this theory, the human motivation relies on three psychological needs: the need of autonomy, Competences and the necessity of a social relationship. The meeting of these three needs leads to a feeling of satisfaction and well-being to the individual [4].

There are two types of motivation.

- Intrinsic motivation is considered as the highest of the levels of self-determination. And of motivation that an individual could attain.[5]. The intrinsic motivation is generally self-applied, and originated from a direct relation between an individual and a certain situation. It is a quite important factor in the process of learning.
- Extrinsic motivation is linked to a motivated behavior by external rewards or penalties like money, glory, grades, praise or reproach.[6]. This type of motivation comes from outside of the learner and is opposed to the intrinsic motivation which is originated inside of the individual.

Moving from high levels of self-determination motivation to lower ones, we find identified, interjected and external regulation.

- **The Identified regulation**: According to Charms, R. (1968), the identified regulation is the least autonomous ;it is realized as a result to external demand or possible reward. These actions can be considered as having a causality locus externally perceived
- **Interjected regulation**: it is when the individual does an activity just to avoid the possible feelings of guilt, nervousness or to satisfy one's ego. [7].
- **External regulation**: It is when the individual is led by external elements such as material rewards or punishment

1. ACOUSTIC PARAMETERES OF DISCOURSE

Sounds of speeches can be viewed as a group of Wave forms. Different Models in these wave forms represent different sounds of speech. For instance, Vowels and consonants. Identifying the different models which we see in these wave forms. We can distinguish between vowels, consonants. Therefore, this way, we can identify what has been said. Different aspects of these wave forms. Different aspects of these wave forms can also tell us how it is said. Which produces indications to emotions, deception, to the state of the speaker in general? As well as certain speech signal which we use to identify what it has been said, what words has been said. Other signal aspect of speech to identify how someone says it. What emotion is s/he experiencing when s/he says it? Does s/he asks a question or makes a statement. This is an example of a simple periodic sine wave.

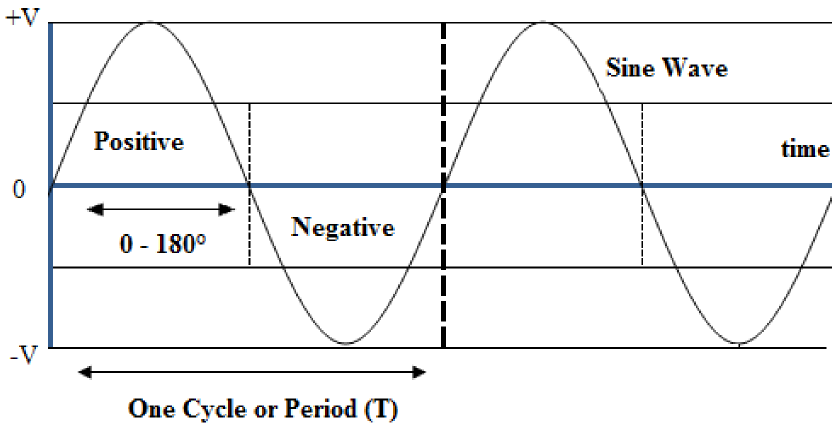

Figure 1-Simple Periodic Sine Waves.

In this study, we base ourselves on the intensity which allows offering a measurement of sonic force of the voice. And the describer of the rhythm which are in relation to the degree of motivation.

4.1. The intensity

The intensity or the energy which allows offering a measurement to the sonic force of the voice (weak or strong) the intensity in decibel dB in general especially using the Praat software [8] calculated in a part of signal with N length in the following manner:

$$I = 10\log\left(\sum_{n=1}^{N} s^2\ (n)w(n)\right) \qquad (1)$$

W is an analysis window.
In The abnormal case, the average intensity is higher with more modulation than the normal case

4.2. The rhythm descriptor

The prosody classical descriptor is a rhythm descriptor linked to the flux of elocution [9] and is descriptor by the number of vocal units through time, for instance, the number of syllables or the phoneme per minute. Nevertheless, this measurement of rhythm cannot be calculated unless we have a segmentation of speech signal in syllables or phonemes this segmentation can prove to be complex spending on the recording conditions. An alternative [10] can characterize the differences of flow in speech, a strong preposition of long trajectories, as the sign of a slow flow.

2. AUTOMATIC CLASSIFICATION OF EMOTIONS

Systems of automatic classification of emotions are based on so-called learning methods, because of their ability to learn from a sufficient amount of data the acoustic properties of each class of emotion. There are two types of classification: supervised and unsupervised. During a supervised classification each object class is provided to the apprenticeship program at the same time as the data. During an unsupervised classification, the classes are determined automatically based on the structure of the data. Automatic classification of emotions systems basically use supervised methods where considered classes are classes of emotions often determined according to the target application. There are many techniques of classification [11] in our study it will be based on the GMM.

4.3. Selection of descriptors

Standardization of descriptors: The range of values a descriptor can take varies greatly from one descriptor to another. For example, if the unvoiced window rate varies between 0 and 1, the fundamental frequency takes values of the order of several hundred.

This heterogeneity in the values can have consequences on the behavior of the descriptor space reduction and learning algorithms: descriptors with high values may have more weight than those with lower values.

Normalization techniques can thus be considered to avoid this bias. Some have also already been used successfully in emotion recognition

- The normalization technique known as min-max normalization [10].

- Sigma-mu normalization.
- Standardization by genre / speaker / phoneme [12].

Reduction of the space of representation of data: In theory, increasing the number of descriptors could improve system performance. However, in practice, the use of too many descriptors, beyond the problem of complexity generated by a dimension high space of representation of the data prior to learning steps and decision of the classification system is essential if a large number of parameter is chosen. [13].

To reduce the space of the descriptors, two options are presented:

- The projection of the space of representation of the data on a space of smaller dimension.
- The selection of the underlying set of the most discriminating descriptors (ex: selection of Fisher algorithm, genetic algorithm); This option has the advantage of directly extracting descriptors relevant to the test then the projection method step require the prior calculation of all the descriptors of the test sample.

The Fisher selection algorithm is a method whose simplicity and efficiency have been demonstrated many times [14] is derived from Fisher's discriminant analysis, which can be described in [15]. It consists of maximizing the FDR (Fisher Discriminant Ratio) ratio of the inter-class dispersion and the intra-class dispersion for each descriptor separately:

$$\mathrm{FDR}d_{\mathrm{i}} = \frac{\left(\mu_{\mathrm{i,nclasse1}} - \mu_{\mathrm{i,nclasse2}}\right)^2}{\sigma^2_{\mathrm{i,classe1}} + \sigma^2_{\mathrm{i,classe2}}} \quad (2)$$

Where $\mu_{\mathrm{i,nclasse1}}$ and $\mu_{\mathrm{i,nclasse2}}$ are the averages of the values corresponding to the descriptor di for every classes $\sigma^2_{\mathrm{i,classe1}}$ and $\sigma^2_{\mathrm{i,classe2}}$ the corresponding variances.

A selection of multi-class by Fisher algorithm with two-step decay is also possible

4.4. The Gaussian Mixing Models – GMM

GMMs are commonly/fluently used in the areas of speech recognition. For the past ten years, this model has also become the dominant approach for speaker verification systems ([16]). It has also been used successfully for the recognition of emotions. GMMs consist of modeling, For evry class $\mathrm{C_q}$ Of the data Xd in the form of a sum weighted by the coefficients $\mathrm{W_{m,q}}$ of the Gaussian probability density function.

$$\mathrm{P}\left(\frac{\mathrm{x}}{\mathrm{C_q}}\right) = \sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{w_{m,q}} \mathrm{p_{m,q}}(\mathrm{x}) \quad (3)$$

With $\sum_{\mathrm{m=1}}^{\mathrm{M}} \mathrm{w_{m,q}} = 1$ for every o classes q considered where M is a number of density components considered for the model. Each component is expressed as a function of its mean $\mu_{\mathrm{m,q}}$ and its covariance matrix

$$\mathrm{P_{m,q}} = \frac{1}{(2\pi)^{1/2}|\Sigma_{\mathrm{m,q}}|} \exp\left[-\frac{1}{2}\left(\mathrm{x} - \mu_{\mathrm{m,q}}\right)^{\mathrm{T}} (\Sigma_{\mathrm{m,q}}\ )^{-1} (\mathrm{x} - \mu_{\mathrm{m,q}})\right] \quad (4)$$

The covariance matrix used is diagonal, i.e the models are learned by considering the observations associated with each description independently.

For each class, every components of the mixture models a region different from the data space called also **cluster**. Learning consists in estimating from the observations of the same class the Gaussian parameters which make up the model of this class. For each class $\mathrm{C_q}$, the parameters to be estimated are:

- The weights $(\mathrm{w_{m,q}})_{\mathrm{m=1\ldots M}}$ associated with each of the M components of the mixture,
- The averages and covariance matrices of each components of the mixture: (E-M) [17] .

The classification can be carried out on the basis of a decision rule based on the maximum a posteriori. For each classifier, an a posteriori score (SAP) is associated corresponds to the average of the posterior log-probabilities calculated by multiplying the probabilities obtained on each analysis window. Thus the score obtained

For the classifier is:

$$\mathrm{SAP}(\mathrm{C_q}) = \frac{\sum_{\mathrm{n=1}}^{\mathrm{N}} \log \mathrm{p}(\mathrm{C_q} / \mathrm{x_n})}{\mathrm{N}} \quad (5)$$

Or x is the observation vector corresponding to the analysis window n and p the posterior probability corresponding to this window. It expresses itself according to the formula of Bayes in the following form:

$$p(C_q / x) = \frac{p(C_q)p(x/C_q)}{p(x)} \quad (6)$$

3. IMPROVING LEARNER MOTIVATION

The main objective behind our work is to establish a suitable learning environment in which the data analysis will help us understand the learners' behaviors and predict profiles that are going to fit in the improvement of motivation according to the results that we have found. Therefore, the learner will be extrinsically motivated so as to satisfy his three self-determination theory psychological needs:

- Helping learners to acquire the freedom of decision making in order to encourage their need for independence and autonomy, in the sense that they have the ability to decide and choose whatever they see is appropriate for them.
- Guiding the learners by providing them with a pedagogical support. Praising the learners when they accomplish an achievement or successfully complete a task or an activity to boost their self confidence. We can also assist the learner when he/she fails to perform well and not to make them feel unable and powerless.
- To give the learners the opportunity to share a common learning experience and give them the chance to interact with each other by utilizing competitive activities [18].

Note that the learning style that we assign to the learners during the training is proportional with their degree of motivation.

4. CONCLUSION

Our work is based on automatic learning of data. It has a plurality of classification filtering and learning algorithms that vary from each other according to their use and performance. Dynamicity of an online course can improve adapting and motivating the learner. Our approach of design and development rests on the determination of adequate learning style. We have established a rich study situation, which allowed us to exploit and collect information able to predict cognitive status of a learner and improve his motivation.

This document opens the door to future research that may adopt other systems and methods to provide more realistic outcomes such as facial expression processing. Or even detect the psychological state of an e-learner through his behavior during the course. We can also improve our system by adding more devices that will help us to orient learners in their academic careers and even in the choice of the subject of their research projects.

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