From Music to Emotions and Tinnitus Treatment, Initial Study

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Abstract. The extended tinnitus database consisting of 758 patients with information repeated from the original database of 555 patients, along with the addition of visits and a new questionnaire, the Tinnitus Function Index and Emotion Indexing Questionnaire, is used to mine for knowledge. New patients in the extended database represent those patients that have completed the Tinnitus Function Index questionnaire (TFI) [10]. The patient visits are separated and used for mining and action rule discovery based on all features and treatment success indicators including several new features tied to emotions (based on a mapping from TFI to Emotion Indexing Questionnaire (EIQ) [14]; EIQ questionnaire is used by our team to build personalized classifiers for automatic indexing of music by emotions). We propose a link between TFI and EIQ leading to a creation of new features in the extended tinnitus database. Then, we extract knowledge from this new database in the form of association action rules to assist with understanding and validation of diagnosis and treatment outcomes.

1 Introduction and Domain Knowledge

Tinnitus, sometimes called "ringing in the ears" affects a significant portion of the population [1]. Some estimates show the portion of the population in the United States affected by tinnitus to be 40 million, with approximately 10 million of these considering their problem significant. Many definitions exist for tinnitus. One definition of tinnitus relevant to this research is ". . . the perception of sound that results exclusively from activity within the nervous system without any corresponding mechanical, vibratory activity within the cochlea, and not related to external stimulation of any kind". Hyperacusis or decreased sound tolerance frequently accompanies tinnitus and can include symptoms of misophonia (strong dislike of sound) or phonophobia (fear of sound). Physiological causes of tinnitus can be difficult or impossible to determine, and treatment approaches vary. It should be mentioned here that we are not dealing with damaged hearing which clearly can not be treated by music.

Tinnitus Retraining Therapy (TRT), developed by Jastreboff [6, 7], is one treatment model with a high rate of success and is based on a neurophysical approach to treatment. TRT "cures" tinnitus by building on its association with many centers throughout the nervous system including the limbic and autonomic systems. The limbic nervous system (emotions) controls fear, thirst, hunger, joy and happiness. It is connected with all sensory systems. The autonomic nervous system controls such functions as breathing, heart rate and hormones. When the limbic system becomes involved with tinnitus, symptoms may worsen and affect the autonomic nervous system. TRT combines counseling and sound habituation to successfully treat a majority of patients.

Conceptually, habituation refers to a decreased response to the tinnitus stimulus due to exposure to a different stimulus. Degree of habituation determines treatment success, yet greater understanding of why this success occurs and validation of the TRT technique will be useful. The treatment requires a preliminary medical examination, completion of an Initial Interview Questionnaire for patient categorization, audiological testing, a visit questionnaire referred to as a Tinnitus Handicap Inventory (THI), tracking of medical instruments, and a follow-up questionnaire. The interview collects data on many aspects of the patient's tinnitus, sound tolerance, and hearing loss. The interview also helps determine the relative contribution of hyperacusis and misophonia. A set of questions relate to activities prevented or affected (concentration, sleep, work, etc.) for tinnitus and sound tolerance, levels of severity, annoyance, effect on life, and many others. All responses are included in the database. As a part of audiological testing, left and right ear pitch, loudness discomfort levels, and suppressibility is determined. Based on all gathered information a patient category is assigned. A patient's overall symptom degree is evaluated based on the summation of each individual symptom level, where a higher value means a worse situation. The category is included in the database, along with a feature that lists problems in order of severity (Ex. TH is Tinnitus first, then Hyperacusis).

Patient Categories

- Category 0: *Low Impact on Life, Tinnitus Present*
- Category 1: *High Impact on Life, Tinnitus Present*
- Category 2: *High Impact on Life, Subjective Hearing Loss Present*
- Category 3: *High Impact on Life, Tinnitus not Relevant, Subjective Hearing Loss not Relevant, Hyperacusis Present*
- Category 4: *High Impact on Life, Tinnitus not Relevant, Hyperacusis Present, Prolonged Sound-Induced Exacerbation Present*

The TRT emphasis is on working on the principle of differences of the stimuli from the background based on the fact that the perceived strength of a signal has no direct association with the physical strength of a stimulus, using a functional dependence of habituation effectiveness model. Therefore, once a partial reversal of hyperacusis is achieved, the sound level can be increased rapidly to address tinnitus directly.

As we already mentioned, TRT requires completion of an Initial Interview Questionnaire for patient categorization, audiological testing, and completion of a visit questionnaire referred to as a Tinnitus Handicap Inventory. The Tinnitus Functional Inventory (TFI) is a new visit questionnaire also required by TRT. Its questions (new features) are tied to emotions. In this paper, we define a mapping between TFI features and the set of features used in Thayer′s Arousal-valence emotion plane and the mood model for music annotation as described by Grekow and Ras [3]. This way, features related to emotions are used to build emotion-type bridge between tinnitus and music.

Our previous research on tinnitus recommender system was based on knowledge extracted from a dataset without TFI so we did not use emotions as features and the same no reference to music was made [18, 23, 24].

From the extended tinnitus database (it includes TFI), provided by Jastreboff, we extracted action rules showing that larger positive improvement in emotions yields larger improvement in tinnitus symptoms. The concept of action rule was introduced by Ras and Wieczorkowska [14] and investigated by others [2, 5, 12, 13, 16, 20, 22]. We use Action4ft-Miner Module from Lisp-Miner Project [11, 17] to discover action rules.

All of us agree that music invokes emotions in most of us. The general finding of the literature is that the experience of negative emotional states leads people to sharply decrease their exposure to complex, novel and loud music, and simple music at a soft listening level actively soothes negative emotions.

There is a lot of research done in the area of automatic indexing of music by emotions [8, 9, 15, 21, 19]. In [13] we introduced the Score Classification Database (SCD) which describes associations between different scales, regions, genres, and jumps. This database was used to automatically index a piece of music by emotions. Also, we have shown how to use action rules extracted from SCD to change the emotions invoked by a piece of music by minimally changing its score. By a score, we mean a written form of a musical composition. In [3], we built hierarchical classifiers for automatic indexing of music by emotions.

Following the approach proposed in [13], we can use action rules to change score of a music piece and the same we can control emotions it invokes. We believe that by applying this strategy to tinnitus patients, we can develop a very successful emotion-based treatment and hopefully control it in real time.

2 Action Rules

An action rule is a rule extracted from a decision system that describes a possible transition of objects from one state to another with respect to distinguished attribute called a decision attribute [14]. It is assumed that attributes used to describe objects in a decision system are partitioned into stable and flexible attributes. Values of flexible attributes can be changed. This change can be influenced and controlled by users. Action rules mining initially was based on comparing profiles of two groups of targeted objects - desirable and undesirable. The concept of an action rule was introduced by Ras and Wieczorkowska and defined as a term $\omega \wedge (\alpha \rightarrow \beta) \Rightarrow (\phi \rightarrow \psi)$, where ω is a conjunction of fixed condition features shared by both groups, $[\alpha \rightarrow \beta]$ represents proposed changes in values of flexible features, and $[\phi \rightarrow \psi]$ is a desired effect of the action. Symbol $\wedge$ is interpreted as logical "and".

When applied to medical data, action rules show great promise; a doctor can examine the effect of treatment choices on a patient's improved state as measured by an indicator that indicates treatment success, such as the Total Score on the Tinnitus Handicap Inventory [24, 23]. For example, action rule discovery can be used to suggest a change on a flexible attribute like emotional score in order to see the changes in treatment success as measured by positive change in total score for tinnitus patients in the Tinnitus Handicap Inventory.

3 LISp-Miner for Action Rule Discovery

Ac4ft-Miner procedure is a part of the robust LISp-Miner system developed by Jan Rauch and his colleagues (http://lispminer.vse.cz). LISp-Miner includes an advanced system of software modules that have been developed to implement classification and action rule discovery algorithms on data sets. The 4ft-Miner procedure is used in this research to discover new action rules in the tinnitus data sets covering only new patients (those completing the Tinnitus Functional Index). It has three basic theoretical resources: the GUHA method, association rules and the action rules.

The GUHA method is a method of exploratory analysis with a purpose of providing all interesting facts derived from the analyzed data. Association rules are the rules which express associations or correlation relationships among data items. Action rules express which action should be performed to improve the defined state. Ac4ft-Miner can be thus described as follows: "Ac4ft-Miner finds rules that express which actions should be performed to improve the defined state. It achieves it by examining the dependencies among the data given as an input". Ac4ft-Miner system mines for G-action rules. G-action rules are generalizations of action rules [14]. They may have stable and flexible attributes on antecedent and succedent part of the rule [17]. The input to Ac4ft-Miner is a data matrix and a definition of the set of relevant G-action rules from which true rules are selected [16]. LISp-Miner allows some reduction of the patterns of interest but this requires specific knowledge of the ontology that the dataset satisfies. Attribute values in a rule can be restricted by adding left and right cuts, effectively reducing the values of interest for specific variables. Additionally, variables can be defined as stable and flexible with respect to the decision variable of interest. The desired change in attributes on the left hand side of rule and right hand side of rule can also be defined by using variables "state before" and "state after".

Association rules are mined with the form $\phi \approx \psi$ with ϕ and ψ representing Boolean attributes antecedent and succedent respectively. The association rule represented by $\phi \approx \psi$ means that the antecedent and succedent are associated in a way represented by $\approx$ which is called the "4ft-quantifier". This is represented by a quadruple data matrix shown in Table 1:

M	ψ	$\neg\psi$
ϕ	a	b
$\neg\phi$	c	d

Table 1. Data Matrix

The a-priori algorithm for association rules discovery is not employed in our research, and the procedure we use follows a complex bit-string method; an explanation of it is provided by Rauch, Simunek, and Nekvapil [11, 16]. Let us assume that $Dom(A) = \{a_1, a_2, a_3, .., a_k\}$, where $Dom(A)$ is a domain of the attribute A. For any $i \in \{1, 2, ..., k\}$, the expression $A(a_i)$ denotes Boolean attribute that is true if the value of attribute A is a_i. Assume now that $A_0 \subset Dom(A)$. Similarly, $A(A_0)$ denotes Boolean attribute that is true if there is $a \in A_0$ such that the value of attribute A is a. This way, we can mine for association rules of the form $[A(\_) \wedge B(\_)] \approx C(\_)$ where $(\_)$ is not a single value but a subset of the set of all values of the corresponding attribute. In particular, we can mine for rules of the form $[A(\_) \wedge B(\_)] \rightarrow C(\_)$. The expression $A(\_)$ denotes the Boolean attribute that is true for a particular row of data matrix if the value of A in this row belongs to $(\_)$, and the same is true for $B(\_)$ and $C(\_)$. This approach makes it easy to mine for conditional association rules that are mentioned in [16].

4 Experiments and Results

The tool used in this study is $Ac4FtMiner$ for association action rule discovery with connection to Microsoft Access. This study utilized the Emotion Indexing Questionnaire (see [14]) which consists of two parts. In its first part, users are asked to answer a number of questions including their musical preferences (what formal musical training they have, what kind of music they listen to when they are happy, sad, angry, calm), and a group of questions asking about their current mood (emotions listed in Table 2). In its second part, users are asked to annotate a number of music pieces by emotions listed in Thayer$'$s arousal-valence emotion plane [3]. The second part of the questionnaire is used to build classifiers for automatic indexing of music by emotions. Each emotion in the first part of the questionnaire (Table 2) is represented by a rating scale of 0 to 4 with 0 meaning emotion was absent and 4 meaning emotion was extreme, as measured over the previous one week period including the day the questionnaire was completed.

$Tense$	$Grouchy$
$Angry$	$Energetic$
$Worn-out$	$Unworthy$
$Lively$	$Uneasy$
$Confused$	$Fatigued$
$Shaky$	$Annoyed$
Sad	$Discouraged$
$Active$	$Muddled$
$Exhausted$	$Efficient$

Table 2. List of emotions used in EIQ

Table 3 shows the mapping between the terms (emotions) used in the Tinnitus Functional Index (TFI) and emotions listed in Table 2 (the first part of the Emotion Indexing Questionnaire (EIQ)). The terms used in TFI (first column in Table 3) were normalized to be between 0 to 4 as the TFI questions use rating scale of 0 to 10 with 0 as absent and 10 as the worst case. Questions one and four on the TFI are rated as percentages and hence they were normalized to fit the range 0 to 4. Next, in the extended tinnitus database, we replaced the terms used in TFI by emotions used in EIQ. Pearson correlation coefficient was calculated between these terms using the function $corrcoef(X)$ provided in $Matlab$. Emotions like Tensed and Angry are perfectly correlated with Pearson correlation coefficient equal 1.

Then $Ac4FtMiner$ action rule discovery software was applied to the new extended tinnitus database to analyze if changes in emotional scores positively affect the total score from Tinnitus Handicap Inventory. The total score is a sum of emotional score, functional score and catastrophe score in THI [7].

Before the rules are established, we need to analyze the data further. Every patient can be characterized by more than one emotional state. If two attributes (emotions) are strongly correlated, then we must be able to characterize the patient using only one of them. Weaker the correlation between the attributes on the antecedent part of the rule, stronger is the need to use both of them in characterizing the patient.

Assume that two patients in the extended Tinnitus database are represented by vectors $\alpha_1 = [a_1, b_1, ...]$ and $\alpha_2 = [a_2, b_2, ...]$, where $a_1, a_2 \in Dom(a)$, $b_1, b_2 \in Dom(b)$. Distance $\rho(\alpha_1, \alpha_2)$ with respect to attributes a, b is calculated by the following formula:

$$([dist(a_1, a_2)+dist(b_1, b_2)]/2+Q(a(a_1, a_2), b(b_1, b_2))*[dist(a_1, a_2)+dist(b_1, b_2)]/2$$

TFI	EIQ
$In\_control$	$Active$
$Annoyed$	$Annoyed$
$Cope$	$Efficient$
$Ignored$	$Unworthy$
$Concentrated$	$Efficient$
$Think\_clearly$	$Efficient$
$Focused\_attention$	$Efficient$
$Fall/stay\_asleep$	$Fatigued$
As_much_sleep	$Fatigued, Exhausted, Worn-out$
$Sleeping\_deeply$	$Exhausted$
$Social\_activities$	$Energetic$
$Enjoyment\_of\_life$	$Lively$
$Work\_on\_other\_tasks$	$Efficient$
$Anxious, worried$	$Uneasy$
$Bothered, upset$	$Tensed, Angry$

Table 3. Mapping between TFI and EIQ

where $Q(a(a_1, a_2), b(b_1, b_2))$ is computed from the Pearson correlation coefficient $P(a, b)$ with respect to all tuples having minimum one of the properties b_1, b_2, a_1, a_2. The definition is given by:

- $Q(a(a_1, a_2), b(b_1, b_2)) = [-P(a(a_1, a_2), b(b_1, b_2)) + 1]/2.$

The value of Q is always in the range [0,1] and it is equal to 0 when attributes are perfectly correlated. To calculate the distance $\rho(\alpha_1, \alpha_2)$ with respect to more than two attributes, we can use reducts in rough sets theory for that purpose [4].

Having defined the distance between tuples in the extended tinnitus database, we are ready to search for action rules showing the expected changes in the total score triggered by changes in patient's emotions. Such rules have been discovered by $Ac4FtMiner$ and they are listed below:

Rule 1: Attributes in the antecedent part of the rule are "Active", "Fatigued", "Worn-out". Attribute in the succedent part of the rule is "Total Score" from THI. Quantifiers defined as after and before state frequency must be greater than or equal to 4.00. The correlation index for active and worn-out is 0.3714, for active and fatigued is 0.4038 and for Worn-out and fatigued is 0.9366.

Action rule generated is as follows:

$[Active(< 3; 4)) \rightarrow Active(< 2; 3))] \wedge [Fatigued(< 2; 3)) \rightarrow Fatigued(< 0; 1))] \wedge [Worn - out(< 2; 3)) \rightarrow Worn - out(< 0; 1))] \Rightarrow [ScT(< 18; 36 >) \rightarrow ScT(< 0; 16 >)]$

The rule above states that if the emotional state of the patient shows improvement (lower the score, better it is), the total score of the patient also improves. Also, our research shows that the doctor can use a music recommender system to identify the right piece of music to be played in order to improve patient's emotional state and the same treat Tinnitus. The confidence of the rule is 0.36. For the antecedent part of the rule, distance between the attributes based on Pearson correlation coefficient is 5.9821. Worn-out and fatigued are highly correlated and patient can be represented by just one of the emotions. The total score changes show that severity of tinnitus changes from mild to slight.

Rule 2: Attributes in the antecedent part of the rule are "Active", "Annoyed", "Worn-out". Attribute in the succedent part of the rule is "Total Score" from THI. Quantifiers defined as after and before state frequency must be greater than or equal to 4.00. The correlation index for Active and Worn-out is 0.3714, for Active and Annoyed is 0.6610 and for Worn-out and Annoyed is 0.4094.

Action rule generated is as follows:

$[Active(< 4; 5 >) \rightarrow Active(< 2; 3))] \wedge [Annoyed(< 4; 5 >) \rightarrow Annoyed(< 2; 3 >)] \wedge [Worn - out(< 4; 5 >) \rightarrow Worn - out(< 0; 1))] \Rightarrow [ScT(< 58; 76 >) \rightarrow ScT(< 0; 16 >)]$

This rule also states that improvements in emotional state of the patient affect the total score in a positive way. Effect on life by tinnitus is greatly improved. Confidence of the rule is 0.45. For the left hand side of rule, distance between the attributes based on Pearson correlation coefficient is 19.94. The total score changes show that severity of tinnitus changes from severe to mild.

Rule 3: Attributes in the antecedent part of the rule are "Discouraged", "Energetic", "Lively". Attribute in the succedent part of the rule is "Total Score" from THI. The correlation index for Discouraged and Energetic is 0.6984, for Energetic and Lively is 0.8035 and for Discouraged and Lively is 0.8088.

Action rule generated is as follows:

$[Discouraged(< 4; 5 >) \rightarrow Discouraged(< 0; 1))] \wedge [Energetic(< 4; 5 >) \rightarrow Energetic(< 0; 1))] \wedge [Lively(< 4; 5 >) \rightarrow Lively(< 0; 1))] \Rightarrow [ScT(< 72; 108 >) \rightarrow ScT(< 0; 16 >)]$

This rule also states that improvements in emotional state of the patient affect the total score in a positive way. Effect on life by tinnitus is greatly improved. Confidence of the rule is 0.714. For the left hand side of rule, distance between the attributes based on Pearson correlation coefficient is 8.86. The total score changes show that severity of tinnitus changes from catastrophic to mild.

These three rules show correlations between the improvement in the emotional state of a patient and improvement in tinnitus treatment. From the extended tinnitus database, we also extracted action rules (not listed in the current paper) showing that larger improvement in patient's emotions yields larger improvement in the total score. Clearly, music invokes emotions in most of us. The same, music may be used as a tool to treat tinnitus patients. By identifying a music piece that can invoke possibly highest positive emotions listed in EIQ for a given patient, we should guarantee a nice speed up of his/her successful tinnitus treatment. Clearly, emotions invoked by music are very personalized. This is why we need to build personalized recommender systems for tinnitus treatment based on personalized systems for automatic indexing of music by emotions.

5 Conclusions and Acknowledgements

TRT is a complex treatment process, which generates a lot of data over time: some attributes have relatively stable values while others may be subject to change as the doctors are tuning the treatment parameters while symptoms of patients are altering. Understanding the relationships between and patterns among treatment factors helps to optimize the treatment process. Interesting action rules about the relationship among new emotional features and total score of the patient were revealed which show that improvement in emotional state brought by music brings significant changes in the total score from THI recorded over the course of the treatment. The database needs to be further extended to include stable attributes like characteristics pertaining to patients to investigate further the relationship between tinnitus treatment and patient emotional state. This will help to develop more specific rules and allow doctors to prescribe more personal treatment using music. The emotional indexing questionnaire can be used to better understand the emotional state of the patients.

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