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Identifying Relationship between Hearing loss Symptoms and Pure-tone Audiometry Thresholds with FP-Growth Algorithm

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ABSTARCT
Considerable numbers of studies have related audiometry hearing threshold values with various diseases and conditions that cause hearing loss. The purpose of this study was to find the relationship that exists between pure-tone audiometry threshold values and hearing loss symptoms in a medical datasets of 339 hearing loss patients using association rule mining algorithm. FP-Growth (Frequent Pattern) algorithm is employed for this purpose to generate itemsets given 0.2 (20%) as the support threshold value and 0.7 (70%) as the confidence value for association rule generation. Interesting relationships were discovered and the results were compared to earlier findings using the same method on a sample datasets of 50 hearing loss patients with 0.1 as the minimum support and 0.7 confidence thresholdsfor the association rule mining. There is similarity in the correlation that exists between symptoms and the pure-tone hearing thresholds from the initial study results and the correlation in the current study results. The experimental result with 339 patients medical datasets extends previously published findings on 50 patients' medical datasets and the sets of symptoms that appear together is consistent with current knowledge of those symptoms occurring together as evidenced clinically.

Keywords
Threshold, Pure-tone, FP-Growth, sensorineural, tinnitus, vertigo

1.INTRODUCTION
With the rate at which medical data is accumulating, mining for knowledge from the data is essential for decision-making support and prediction. Pure-tone audiometry data can be used to measure auditory threshold as a function of stimulus frequency[1]. [2]Indicates a relationship between Meniere disease and low frequency sensorineural hearing loss.[3]Indicates, a connection between high-frequency sensorineural hearing loss and noise exposure, and the association of cardiovascular risk generated by smoking and diabetes with both high and low-frequency hearing loss. Pure-tone air and bone conduction thresholds audiometry were obtained from unscreened population of older adults to observe the rate of changes over the period of 10 years. The baseline measurement predictors for that period are reported for specific age groups of both genders. The threshold changes over the said period for those at the age of 50 to 60 years old were found to be more at the higher frequencies while changes in threshold were at lower frequencies for the aged (80 years and above)[4]. Age-related changes in pure-tone audiometry were also observed in a longitudinal study on hearing thresholds of 813 adult males. The results shows steady rate of hearing loss at higher frequencies andincrease in the rate of hearing loss at lower frequencies[5]. A study on the effect of age and noise related hearing loss on high frequency thresholds was carried out on 187 industrial noise-exposed and 52 non-industrial noise-exposed subjects. The test-retest in the study shows high frequency audiometry (HFA) as a technique that is as reliable as the conventional in indicating noise-induced hearing loss and can be used more reliably to monitor hearing loss of individual cases over time period. Results from this study show both exposed and non-exposed subjects to have hearing loss at high frequencies (10-18 kHz). The effect of age seems more predominant than that of noise in the higher frequencies, this influence is not the same for the conventional frequency range (0.25-8kHz)[6]. In a similar study[7], results suggest ear with noise-induced hearing loss does not aged at the same rate with non-noise damaged ear. The study examined 15 year change in audiometric threshold of 203 men with mean age of 64 years to determine whether high frequency notches influences auditory aging. To determine if the rate of change in pure-tone hearing thresholds is differed by sex among Korean subjects, a slope of linear regression was used to measure the rate of change in pure-tone thresholds at 0.25-8kHz. Results indicates significant sex differences in pure-tone thresholds with thresholds of women lower than men at frequencies above 2kHz and hearing impairment worse in men than women at high frequencies 4-8kHz[8]. In another cross-sectional study to find differences in age-related audiometric results, a group of 473 subjects aged between 70 to 75 years were examined using pure-tone audiometry. Results indicate no significant differences in pure-tone thresholds between these age groups[9]. To study longitudinal changes in thresholds and the effects of threshold

levels on these longitudinal changes, high frequency pure-tone thresholds of 188 older adults between the ages of 60 to 81 years were analysed using the slope of linear regression to measure the rate of change in pure-tone thresholds[10]. [11]Suggests pure-tone audiometry as a reliable method to describe hearing status of a population after cross-sectional analysis of pure-tone hearing thresholds of 778 subjects of French descent aged 70 years and above. In a 5-year study, 342 diabetic veterans and 352 non-diabetic veterans who were tested on different audiometric measures, including pure-tone thresholds, results shows diabetic patients at the age of 60 years and younger have hearing loss at the high frequencies[12]. [13]Have also related age and genes to specific audiogram shapes.

2. RELATED WORKS

A number of studies have employed different machine learning and statistical methods in exploring and analysing audiometric data.[14]Have used a combination of statistical and neural techniques on audiology medical records with the aim of looking for factors influencing which patient will benefit from hearing aid. Audiogram shapes were clustered into homogeneous and heterogeneous groups using K-means clustering with the aim of helping clinicians in the diagnosis of hearing loss in the future[15]. [16]Experiment with multi-layer perceptron neural network and support vector machine in classifying ear disorders from otoneurological data. [17]Uses K-nearest neighbour and naïve Bayes classification algorithms to determine the classification accuracy of combining machine learnt knowledge with expert's knowledge. The results showed accurate classification when machine learnt knowledge is combined with the experts' knowledge.

3. METHODS

Hearing thresholds were obtained on 399 patients record across all ages (3-88 years) measured at 11 frequencies ranging from 0.125-8kHz from pure-tone audiogram collected over 10-year period from 2003 to 2012. The thresholds were the patients' first audiometry test results obtained from Hospital PakarSultanah Fatimah file archive. Other attributes in the medical record such as diagnosis and bio data (age and gender) of the patients during the first visit were also collected. This is to avoid obtaining improved result after patient undergoes treatments.

The data was collected using hand-held digital scanner which is used to scan the document and saved in portable document format (PDF) format. This is later converted into digital format. The result is free text data comprising of diagnosis, age, gender and also numeric data in the form of audiometry thresholds. This is done by manually entering of each record into a text document. The data is saved in a in a format the FP-Growth algorithm can accept.

Some of the hearing loss symptoms, age, gender of the patients and audiometry thresholds were abbreviated. For example, the symptoms of tinnitus as (TNTS), vertigo as (VTG). Others like Meniere disease, otalgia, ottorhea, giddiness, and rhinitis were not abbreviated. The gender of male and female were represented as (F) for female and (M) for male. Ages of the patients were divided into three groups and represented as (E) for early, (M) for mid and (L) for late. For example, 55 years was represented as 5M (mid 50's), late 80's like 89 years was represented as 8L. Hearing thresholds were represented with colon in between the frequencies and the sound dB. For example, 500:45R signifies threshold at frequency of 500Hz at 45dB for the right ear (R) and 8000:80L signifies high frequency of 8kHz at 80dB in the left ear (L).

Template-based approach is adopted as the approach that incorporates subjective knowledge for evaluating the quality of extracted itemsets[18]. This allows us to restrict the itemset generated by the frequent pattern growth (FP-Growth) algorithm. Hence, filtering all the itemsets and returning only those containing any of the symptoms of TNTS, VERTIGO, MENIERE, OTALGIA etc.

4. COMPARISON OF CLUSTER ANALYSIS WITH ASSOCIATION ANALYSIS

Clustering algorithm has been used in various studies to find patterns and relationships in audiometry dataset. It is a type of unsupervised learning that involves partitioning a set of objects into groups, such that the objects in the same group are similar while those in other groups are dissimilar [19]. [15] Have used K-means cluster analysis in grouping similar audiograms shapes shared by homogenous subjects and separating the ones shared by heterogeneous subjects. [20]. [21][22] Employs clustering algorithm in grouping distinctive audiometric profiles of hearing impaired children. However, association analysis with FP-Growth algorithm is more efficient in extracting related items in a dataset.

The relationship between items in a cluster is based on distance metric while that between items in the symptoms-based filtered itemsets is based on minimum support and confidence threshold. There is more of relationship between items that frequently appear together in certain percentage of the data than those grouped together based on similarity.

Generated itemsets from FP-Growth algorithm are classified into groups based on symptoms while only similar items are grouped in the same cluster using cluster analysis.

Table 1 and Figure 1 below depict the comparison between cluster analysis and association analysis in uncovering relationship in a dataset.

Table 1.Comparison of Cluster Analysis with Association Analysis

	Content	**Relationship Between Items**	**Filtering**
Association Analysis	Itemsets	Support and Conf. Threshold	Symptom-Based Itemsets
Clustering Analysis	Similar Items	Based on Distance metric	Similar Items

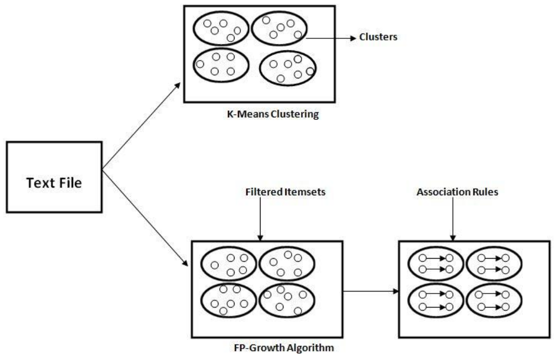

Figure 1: Comparison of Cluster Analysis with Association Analysis

5. FP-GROWTH ALGORITHM

Machine learning methods can enable the discovery of hidden patterns or rules occurring in dataset[17]. The discovery of knowledge can be determined when these patterns are new, useful and understandable[23]. Hence, knowledge discovery process transform data into knowledge[24]. The two most conventional ways of finding interesting patterns in data are association rules and frequent itemsets[25]. FP-Growth algorithm is built from Apriori algorithm[26]with different techniques of generating itemsets that commonly occur together in a dataset. FP-Growth algorithm can find frequent items more efficiently than apriori algorithm in that it scans the dataset only twice to generate itemsets. The first scan counts the frequency of all the items and removes the infrequent ones. The rule is, superset containing that item will also be infrequent and the second scan builds the FP-tree data structure which is traversed to mine frequent itemsets[26]. [27]Propose an efficient algorithm based on the FP-Growth for mining the complete set of all correlated pairs on transaction databases. FP-tree data structure has been used in combination with decision tree to generate CT scan brain images and classify the images for diagnosis[28]. FP-tree data structure is efficient and scalable for mining both long and short frequent patterns and is believed to be faster than any frequent pattern mining algorithm[29]. Storing of the datasets in the FP-tree structure results to faster execution time than many of the itemsets generation algorithm commonly used, with two orders of magnitude better in performance than algorithm like Apriori[26].

The extent of relationship between items within an itemset can be measured in terms of support and confidence. Support is the number of times a rule is applicable within a given dataset. An audiometry data ***ADj***contains itemset***S*** if ***S*** is a subset of ***AD.*** It can be represented mathematically:

$$\sigma\,(\boldsymbol{S}) = |\{\boldsymbol{ADi}|\boldsymbol{S} \subseteq \boldsymbol{ADi},\, \boldsymbol{ADi} \in \boldsymbol{D}\}| \qquad (1)$$

σ (***S***) denotes support for an itemset***S***. ***ADi***refers to individual audiometry data with ***S*** as its subset (***S***$\subseteq$***ADi***) which means every item of ***S*** is also an item in ***ADi***and ***ADi***is an element of the dataset (***D***).

Confidence measures the reliability of inference made by an association rule[18]. It suggests a strong correlation between items within an itemset in the antecedent and consequent of the rule[18]. For example, the high confidence in rule TNTS→2000:30 shows high probability for 2000:30 hearing threshold to be in individual audiometry data (***ADi***) that contains TNTS. Confidence determines the frequency of appearance of items in itemset (***S***) in data (***ADi***) that contains item (***T***). The metrics for this can be represented:

$$Support\ (\boldsymbol{S}) \ = \frac{\sigma(\boldsymbol{S})}{N(\boldsymbol{ADi})} \qquad (2)$$

$$Confidence\ (\boldsymbol{S} \rightarrow \boldsymbol{T}) = \frac{\sigma(\boldsymbol{S} \cup \boldsymbol{T})}{\sigma(\boldsymbol{S})} \qquad (3)$$

FP-Growth algorithm was used to find frequent itemsets within the patient's audiometry dataset. The minimum support threshold of 0.2 (20%) was chosen for itemset generation and 0.7 (70%) as the confidence threshold value for association rule mining. Although, it is difficult to find minimum support and confidence threshold that give satisfactory result, we chose 0.2 as the minimum support value and 0.7 as confidence value because rules are generally uninteresting if they apply to less than 10% of the dataset[30].

5.1 FP-Growth Algorithm

Input: Dataset (***D***)

Minimum Support (*minS*)

Output: Set of frequent patterns

Step 1: Constructing the FP-Tree

I) Removing items not meeting minS

For each element in header table

If element <*minS*

Delete element

If no element meet minimum support

Exit

II) Sort element by global frequency

III) Populate tree with ordered frequent itemset

IV) Build the FP-Tree

Start with null set (*Ɵ*)

Add frequent items to *Ɵ*

If path exist

*Add*itemset to existing path

Else

Create new path

V) Mining frequent items from the tree

- Extracting conditional pattern bases
- Recursively ascend the tree

If leaf node != None

Add leaf node to prefix path

- Create conditional FP-Trees

Start from the bottom of header table

Construct conditional FP-trees

Mine the conditional FP-trees

VI) *For each* Frequent Itemset (***S***)

For each item (***T***) in ***S***

If ***T*** == Symptoms

Return ***S***

6. RESULTS

The result of initial study carried out on 50 patient's medical record and pure-tone audiometry measures[32] is depicted in table 2, 3 and 4. This is compared with the result for the current study on 339 patient's audiometry data which is in table 5 and 6.

Table 2. Initially observed Tinnitus association rules from the conditional FP-tree

Min. Supp.	Assoc. Rule(Tinnitus)	Conf.
0.1	TNTS →2000:30R, F	1.000
	TNTS →500:55L, 250:60L	1.000
	1000:30R,TNTS →2000:30L	0.881
	TNTS →4000:65L,F	0.947
	500:15R → NH, TNTS	0.716
	ONOFF TNTS →2000:45L	0.788
	500:15R, 2000:10R →ONOFFTNTS	0.711
	TNTS , M →250:60L	0.902
	500:20R→TNTS, 1000:15R	0.817
	TNTS →1000:60L, M	0.891
	TNTS, M→BILATERAL, 500:20L	0.798
	TNTS →GIDDINESS, 250:35R, F	0.703
	TNTS, M →NH, 500:20L, BILATERAL	0.777
	TNTS→250:30R,F	0.883
	500:15R,→ONOFF TNTS	0.799
	2000:20R →TNTS, M	0.867

Table 3.Initially observed Vertigo association rules from the conditional FP-tree

Min. Supp.	Assoc. Rule(Vertigo)	Conf.
0.1	VTG→ 4000:65L, F	0.958
	VTG →1000:10L, BILATERAL	0.805
	VTG→1000:10L, NH	0.809
	250:35R →VRTG, F	0.772
	VTG, M →500:20R, NH, BILATERAL	0.702
	VTG→1000:10L, 500:20L	0.782
	VTG →500:15R, F	0.878
	2000:20R →VTG, M	0.791
	VTG →1000:10L, F	0.813
	VTG →2000:25, F	0.790
	500:15R →1000:10R, VTG	0.761
	2000:15R →4000:10R, VTG	0.707
	4000:10R, VTG →500:20L, NH	0.801
	4000:10R, VERTIGO → BILATERAL,NH	0.798
	2000:15R → VTG, F	0.885
	250:35R, VTG →500:25, F	0.801
	VTG, 1000:10L→1000:15R, BILATERAL	0.813
	1000:60L →2000:55L, VTG	0.859

Table 4.Initially observed Giddiness association rules from the conditional FP-tree

Min. Supp.	Assoc. Rule (Giddiness)	Conf.
0.1	GIDDINESS →250:35R, F	0.899
	500:20R → GIDDINESS	0.790
	TNTS, GIDDINESS→250:35R, F	0.840

Table 2, 3 and 4 above, shows the relationship between hearing loss symptoms, gender and audiometry thresholds from initial study on 50 hearing loss patient's dataset[32]. As previously explained TNTS represents tinnitus, VTG means vertigo, NH means normal hearing, BILATERAL means both ears, M and F represent the two genders of male and female while L and R signifies left and right. 0.1 (10%) was chosen as support value for itemsets generation and 0.7 (70%) as confidence value for association rule. Interesting relationships were discovered between pure-tone audiometry thresholds and three different symptoms of tinnitus, vertigo and giddiness.

Table 5. Currently observed Tinnitus/Vertigo association rules from the conditional FP-tree

Min. Supp.	Assoc. Rule (TNTS/VERTIGO)	Conf.
0.2	TNTS, VTG→500:20R, M	0.931
	TNTS, VTG→250:40R, 400:45R, F	0.768

Table 6.Currently observed Giddiness association rules from the conditional FP-tree

Min. Supp.	Assoc. Rule (GIDDINESS)	Conf.
0.2	GIDDINESS→1000:10L,500:20L,250:25R	0.755
	GIDDINESS,VTG→500:20R	0.890

The association rules for the current studies are shown in table 5 and 6. When comparing between the results from initially observed tinnitus association rules in table 2 with that of currently observed tinnitus and vertigo association rules in table 5, results in table 2 shows correlation between symptoms of tinnitus and normal hearing threshold at 0.5kHz (500:15R,→ONOFF TNTS) in the right ear "R". This is reflected in the current study on 339 patients where results from table 5 shows correlation between symptoms of tinnitus and vertigo and normal hearing threshold at 0.5 kHz (TNTS, VTG→500:20R, M) also in the right ear "R" in male patients. Similar relationship can be found in initially observed vertigo association rules in table 3 where a similar correlation also exist between normal hearing threshold and vertigo (VTG, M →500:20R, NH, BILATERAL), (VTG →500:15R, F).

Current study results in table 5 shows association rules (TNTS, VTG→250:40R, 400:45R, F). Similar rules can be seen in the initial studies in table 2 (TNTS→250:30R, F), (TNTS, M →250:60L) and (TNTS →GIDDINESS, 250:35R, F). This shows similarity of initial study results and that of the current study where both shows low frequency mild-moderate hearing loss in patients with condition of tinnitus. The result in table 3 also reflects this; (250:35R →VRTG, F).

The current study result in table 6 shows correlationbetween the symptoms of giddiness and somepure-tonethresholds. Thissignifiescorrelationbetweengiddiness and normal hearing at highfrequencythresholds in the left and rightear; (GIDDINESS→1000:10L, 500:20L, 250:25R). Similar resultisreflected in the initial study result in table 4; (500:20R → GIDDINESS).

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7. CONCLUSION AND FUTURE WORK

The results from previous study on 50 patient's audiometric data were analysed. Interesting relationship between pure-tone audiometry and other attributes in the medical datasets were uncovered and represented in the form of association rules extracted from frequent itemsets. These rules suggest the existence of strong connection between items within sets of itemsets. Similar results were compared with that of recent study on 339 patient's audiometric data using the same method but with increase in itemsets generation support threshold from 0.1 used in the previous study to 0.2. The two results were found to correspond. This indicates relationship between those symptoms within that range of pure-tone thresholds. However, there is the need for prior knowledge about relationships between these attributes because association analysis does not necessarily indicate causality[18]. For example[31]indicate tinnitus patients have higher thresholds in mild and higher frequencies. This corresponds with our result. More data is needed for future experiment to confirm this. In the near future we would include both air and bone conduction thresholds and use FP-Growth algorithm to trim the data down to only important information which we can use to predict hearing loss symptoms given the two thresholds of a patient.

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