Inferring User Intents from Motion in Hearing Healthcare

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Abstract

Sensors in our phones and wearables, leave digital traces of our activities. With active user participation, these devices serve as personal sensing devices, giving insights to human behavior, thoughts, intents and personalities. We discuss how acoustical environment data from hearing aids, coupled with motion and location data from smartphones, may provide new insights to physical and mental health. We outline an approach to model soundscape and context data to learn preferences for personalized hearing healthcare. Using Bayesian statistical inference we investigate how physical motion and acoustical features may interact to capture behavioral patterns. Finally, we discuss how such insights may offer a foundation for designing new types of participatory healthcare solutions, as preventive measures against cognitive decline, and physical health.

Author Keywords

Hearing impairment; user behavior; health; aging; augmented audio; activity; motion; mental health

ACM Classification Keywords

H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction

In the past century humans have gone through a cultural evolution, drastically transforming dietary patterns and manual labor, leading to mostly sedentary work and spending hours in front of computer screens. The resultant lack of physical activity has contributed to a dramatic rise in lifestyle inflicted type 2 diabetes, heart disease and dementia [9]. There is an urgent need for conceptualizing new preventive approaches, where awareness of motion will be fundamental in order to deliver personalized participatory healthcare solutions [14]. To target the comorbidity of chronic diseases we need to integrate both physical, mental and social aspects of health.

Several studies have linked lack of physical activity to mental health issues, including dementia, cognitive decline [8] and depression [16]. Even small measures of physical activity has a preventive effect on mental health [4], and for some disorders are positively correlated with higher self rated quality of life [1]. Likewise, hearing loss is correlated with lack of physical activity [2, 3]. Additionally, a connection between hearing loss and cognitive decline has been established [11]. One of the major risk factors for dementia is caused by untreated hearing loss [10]. Recent research indicates that physical exercise may alleviate hearing loss in mice [5]. This may indicate a direct relation between hearing health and physical activity in humans.

The introduction of Internet connected hearing aids offers new insights into the life's of hearing aid users. Contextual features, such as motion and activity data combined with GPS location gives an objective measure of the level of physical activity. Combining this with the corresponding acoustical sound environment may potentially offer a more personalized treatment of hearing loss.

Capturing contextual user preferences

A longitudinal study, aiming to learn preferences for hearing aid settings dependent on the context, were carried out in the winter 2017-2018 at Eriksholm Research Centre, Denmark. 10 participants volunteered for the study (9 males, 1 female). The median age was *62.9 years (std. 11.5 years)*. All participants are regular smartphone users, and have used hearing aids for a year or more. All subjects used either an Android or iOS compatible phone. Data was logged for eight weeks, or more. One subject dropped out after four weeks, and was excluded.

Location data consists of clustered GPS positions, while motion activity is estimated by the smartphone accelerometer sensors. User interactions include changes between four acoustically contrasting program settings, and volume adjustments, either initiated on the hearing aid, or via the accompanying smartphone app. Soundscapes are modeled as a vector representing aspects of sound pressure level and modulation characteristics processed by the hearing aids. All data is time stamped. An example of subject 3's time line for a week is shown in Figure 1, where the top three bars show contextual sound environment, motion activity and user preferences related to selection of contrasting hearing aid programs. We then process the motion data using a Bayesian probabilistic approach. Subsequently, we combine the probabilities with additional contextual parameters including GPS location, inferred activity, time and day of week.

Modeling human behavior

We combine three modalities to model human behavior:1) Motion activity patterns captured by the smartphone, sampled as categorical events. 2) Locations derived from clustered GPS coordinates sampled as categorical events. 3)User initiated program changes combined with the corresponding soundscape context, segmented according to time, as discrete categorical events. Based on a naive Bayes prediction we investigate the influence of the aforementioned modalities. These predictions are shown in Figure 1, for subject 3 for four days. The top green bar illustrate changing sound environments, the blue bars shows motion activity, while the yellow-red bars shows, user initiated program changes in response to motion and soundscape, and three predicted scenarios based on activity and location, soundscape, and the activity, location, and soundscape combined.

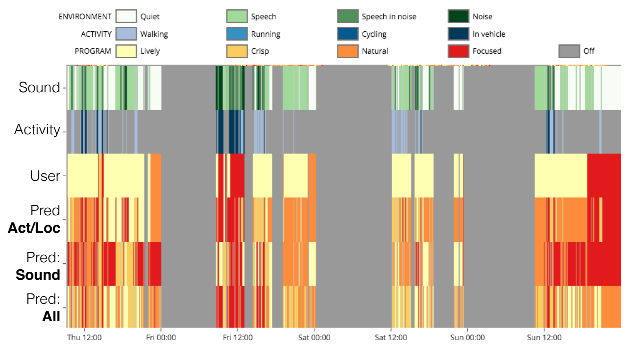

Figure 1: Naive Bayes prediction of contextual program preferences for subject 3 over four days. The upper three tracks (green, blue and yellow gradients), represent the soundscape environment, motion activity and user selected programs, respectively. The following three tracks of color bars (yellow gradients) show conditional probabilities for user preferred programs, based on a) motion activity and location alone (*Act/Loc*), b) soundscape environment alone (*Sound*), c) motion activity, location, soundscape and time combined (*All*).

Changes in motion and location generate discrete events in time series data, providing a visual segmentation of soundscape data. Motion can also be interpreted as contextual information, when location is not available. As an example, a subject walks to lunch around 12. The location is not updated, but the inferred motion, walking, indicates a change of environment. This is confirmed by the soundscape data, reflecting that the environment changes from a quiet office to a noisy canteen. Motion in our study not only defines a specific state, but may also mark the beginning or end of a segment in the acoustical soundscape. From Figure 1 we see that changes in motion may trigger user intents related to program changes, which might not seem evident when considering the acoustical soundscape alone. Thus, motion plays and integral part in predicting user intents and behavior. Additionally, the amount of motion also characterizes the overall level of activity or physical exercise reflecting the lifestyle of the user. We speculate such features related to fitness might potentially correlate with other healthcare metrics e.g. a lower resting heart rate. Further analyses of variability in motion patterns could indicate declining trends in physical activity. This could potentially be used in personalized preventive healthcare solutions, to proactively monitor the onset of diseases before symptoms are observed [14]. We enrich the data by using GPS location. Using clustering algorithms, we determine various places visited by the user. This can then be used to further segment the data, and helps predict user intents. We also categorize the places using Google places API.

Individual behavioral patterns are reflected in the coverage of data related to contextual sound environments, motion activity and user initiated interactions. While the sound data is sampled once per minute $f_{sound} = \frac{1}{minute}$, both motion activity (including location) and user interactions are discrete events $f_{motion} = [0 : n]$, and $f_{interaction} = [0 : n]$. We interpret these discrete events as conscious actions by the user, which can be used in a probabilistic model. The data is treated as time series data, segmented into hourly and daily bins, along with a bin for the full experiment.

Combining knowledge of motion, time, activity and location, with individual preferences, facilitates participatory hearing healthcare solutions. Such user preferences continuously change dependent on the contextual environment, activity, time or cognitive state of the user [6]. It is essential as Korzepa et al. [7] has argued to incorporate user intents for predictive modeling. Here, physical motion and activity is a central component. Our Naive Bayesian approach illustrates the impact when including or omitting contextual parameters related to soundscape, motion, and location, in order to predict user intents over time, see Figure 1.

We wish to further investigate how contextual data form sequential patterns. An alternative could be to interpret GPS locations as clusters forming spatial trajectories. The current position in a motion sequence would be predicted based on the preceding and subsequent locations. GPS coordinates are thus treated as a vocabulary similar to word2vec embeddings [12]. Such sequences have been shown to capture demographic patterns that may be used to classify gender, age or marital status of the users [15]. Likewise deep learning neural networks may be trained to predict patient outcomes, by combining embeddings from multiple modalities e.g. interventions, test results or prescribed medicine in electronic healthcare records, as shown by Rajkomar et al. [13].

Discussion

The prohibitive costs of healthcare will cause a shift from reactive treatment towards data driven personalized, predictive and preventive approaches. Based on our pilot study we suggest: *First*, in order to infer personalized hearing healthcare insights, complementary motion, location and soundscape environmental parameters need to be combined. *Second*, analyzing large amounts of longitudinal data gathered through internet connected devices, we may provide predictive hearing healthcare suggestions of contextual coping strategies learned from multiple users. *Third* applying a data driven approach to model user intents, patterns may be extracted as a basis for developing next generation preventive healthcare tailored to the needs of each individual. However, to provide personalized, predictive, and preventive hearing healthcare, the user needs to be an integral part of a continuous feedback loop involving context-aware devices and health care professionals.

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