Modeling Physiological Conditions for Proactive Tourist Recommendations

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ABSTRACT

Mobile proactive tourist recommender systems can support tourists by recommending the best choice depending on different contexts related to themselves and the environment. In this paper, we propose to utilize wearable sensors to gather health information about a tourist and use them for recommending activities. We discuss a range of wearable devices, sensors to infer physiological conditions of the users, and exemplify the feasibility using a popular self-quantification mobile app. Our main contribution is a data model to derive relations between the parameters measured by the wearable sensors, such as heart rate, body temperature, blood pressure, and use them to infer the physiological condition of a user. This model can then be used to derive classes of tourist activities that determine which items should be recommended.

CCS CONCEPTS

• **Human-centered computing** → **User models**; *Mobile devices*; • **Information systems** → *Recommender systems*; • **Hardware** → *Sensor applications and deployments*.

KEYWORDS

wearable devices; user modeling; proactive recommender systems; context modeling; machine learning

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1 INTRODUCTION

Suggesting points of interest or activities to tourists within a city is a popular and challenging recommender systems research problem. To provide interesting recommendation at the right time, context-awareness is very advantageous. Currently, mobile phones are commonly used for eliciting its user's context. However, in some situations tourists might be uncomfortable pulling out their smart phones due to the fear of them being stolen, or for other social reasons. This gives rise to wearable devices, such as smart watches for context modeling. Wallace and Press [13] showed new perspectives of looking at wearable objects by involving computer technologies into them. However, wearable devices of the last ten years such as the Fitbit Zip[1], Apple Watch[2], Google Glass[3], and the Microsoft HoloLens[4] had mixed success on the market and the smart phone is still the most prevalent mobile device.

As a tourist, it is useful to get personalized recommendations about where to visit, what to do next throughout a trip, given that the recommender has sufficient system information about the context of the tourist. Unlike classical recommender systems, mobile recommendations can also be proactive, meaning that the recommendations are pushed to the user without explicit request. This introduces the additional challenge to determine the appropriate timing of the recommendations. Wearable sensor devices help to gather various data about and around the wearer. This data can be used to acquire contextual information, and with further processing, the proper conditions can be derived to recommend tourist activities to the wearer. Our approach was, thus, guided by the following research questions:

RQ1: How can different physiological conditions be inferred using wearable sensors?

RQ2: How can these conditions be used to derive preferences for activities?

In the following section, we survey related work on tourist recommender systems based on context awareness, wearable devices, and sensor data processing. We present our data model in Section 3, which shows how to select tourist activities based on data from typical sensors found in wearable devices. Finally, we draw our conclusions and present future work in Section 4.

2 FOUNDATIONS

We argue that to improve mobile, context-aware, and proactive recommender systems, sensors in wearable devices can be useful by inferring the physiological conditions of a user.

2.1 Context-Aware Recommender Systems

It is generally believed that with the availability of contextual information of a person, such as her surroundings, location and time, the accuracy of the recommendations increases. Ashley-Dejo et al. [2] propose a context-aware proactive recommender system for tourists and find that the traditional multi-criteria collaborative filtering approach without context information had the least performance,

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[1] https://fitbit.com/au/Zip [2] https://apple.com/lae/watch/
[3] https://www.google.com/glass/ [4] https://microsoft.com/en-IE/hololens

Figure 1: Apple Health Mobile Application

while the recommendations with right context information performed the best. Meehan et al. [8] highlight the importance of considering more contextual information other than location, i.e., weather, time, sentiment, and user preferences. In our proposed model, we showcase the possibility of using physiological conditions for proactively recommending personalized tourist activities.

2.2 Wearable Devices & Data Ecosystems

Wearable devices can support humans in dealing with the overload of information in communication and computation in appropriate contexts [4]. They are also useful for measuring various physiological parameters, which can further be processed to benefit the healthcare domain. Smart textiles that stay in close contact with the skin, are used to noninvasively gather health information [5] and physical monitoring [7]. Tussyadiah [12] identified personal motivations to use wearable devices for tourism. Despite their potential, wearables have not yet become that predominant in the tourism sector. Atembe [3] compiled the limited use of wearable devices in tourism by presenting some use cases and providing the usage of wearable devices there. We work towards the usage of wearable devices in the tourism domain by showing a way to derive contextual information by using the data collected by wearable sensors and then utilizing the context to proactively recommend relevant activities during a trip suitable to her physiological conditions.

The basic assumption is that sensors in wearable devices are capable of measuring different health parameters, such as the heart rate or blood pressure, and report this to a centralized application. Through constant monitoring, the sensor data can be used to determine physiological conditions.In a second step, a recommender system can utilize these conditions as context factors to make recommendations. The feasibility of our approach is, thus, dependent on the availability of accurate sensor data. Fortunately, there are data ecosystems in place, such as Apple Health[5]. Using it on the phone, users can organize their health data. Figure 1, shows an aggregation of the activities recorded by the iPhone, and all heart-related data that can be tracked. It can be seen as a manifestation of the *'Quantified Self'* movement, where the users continuously record their body data to analyze them with the motif of self improvement [11]. The data is collected via wearables, entered manually, or by granting access to third-party applications on the iPhone. This constitutes a data ecosystem, which can be used to develop applications leveraging this data given the user consents.

2.3 Inferring Physiological Conditions

Health parameters collected by the wrist-wearable devices have already been used to deduce relevant physiological conditions from them [7]. Alfeo et al. [1] collected information about heart rate and arm motion using wearable devices to assess per-night sleep quality of the wearer. Zhang et al. [14] used wrist-worn wearable sensors to detect gestures and showed a correlation between the feeding gesture counts and caloric intake more of which lead to overeating. A wrist-worn sensing system was developed by Sugimoto et al. [10] for calculating energy expenditure, by estimating oxygen uptake from correlation between heart rate and oxygen uptake. Defining some thresholds using expert knowledge, we can find out if a person is active, relaxed or tired. Depending on the literature, we chose six conditions that can be detected using wearable sensor data and are also relevant for travelers – **active** [7, 10], **relaxed** [7, 10], **tired** [1, 7, 10], **drunk** [9], **hungry** [10, 14], **stressed** [6, 7]

3 DERIVING ACTIVITIES FROM PHYSIOLOGICAL CONDITIONS

The physiological condition of a tourist influences the suitability of the recommended activities. In this research, we use a subset of Foursquare's venue categories[6], as tourist activities for our data model. They cover most touristic activities and provide a direct mapping to concrete items, which is useful for the final recommendation step. The five categories are (1) Outdoors & Recreation, (2) Arts & Entertainment, (3) Food, (4) Residence, and (5) Nightlife. Which activity should be suggested to the tourist depends on her current contextual and physiological conditions. For example:

- If the tourist is very active, she can be suggested to do sports or adventurous outdoor activities like horse-riding.
- If a traveler has not slept for a long time or is stressed, recommending a relaxing activity might be fitting.
- Finally, if someone has not taken a break for a long time, we would recommend to refresh herself with food or drinks.

The above examples describe our assumptions of how tourists to behave in general under their particular physiological conditions. In reality, they might not follow that and act more peculiarly. Therefore, a context-aware recommender system needs to learn weights between physiological conditions derived from wearable sensors and respective activities. For this, machine learning shall be employed to observe the behavior of the tourists given their physiological conditions. The upper part of Figure 2, depicts selected positive and negative influences from physiological conditions to tourist activities. For picture clarity, we only show some of the arrows here, for those behaviors we expect to exist in general – green and orange arrows imply positive or negative correlations, having higher or lower weight values, respectively. It will take some time to train the model with sufficient data, however, we think the cold start problem can be partly mitigated using expert knowledge at the beginning, before the weights converge with more observations.

[5] https://apple.com/lae/ios/health/

[6] https://developer.foursquare.com/docs/resources/categories

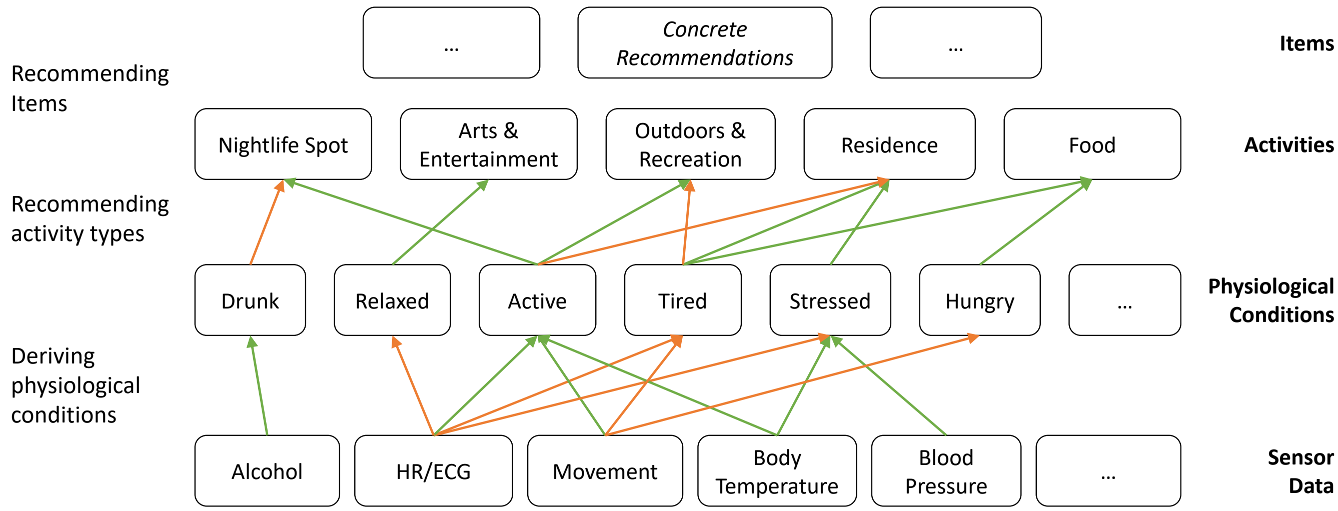

Figure 2: Model of Deriving Physiological Conditions from Sensors and Recommending Tourist Activities

The associations between the sensor values and the physiological conditions in the lower part of Figure 2 can be derived as discussed in Section 2.3. Then, we can form a 1X6 physiological condition vector, *PC* (see Equation 1), that denotes the current status of a tourist's physiological conditions, each column having a value, $c_a, c_r, c_t, c_d, c_h, c_s$ for each of the six physiological conditions: active, relaxed, tired, drunk, hungry and stressed.

$$\text{PC} = \begin{pmatrix} c_a, & c_r, & c_t, & c_d, & c_h, & c_s \end{pmatrix} \tag{1}$$

Next, we use the previously learned associative weights of our activity variables, *or* (outdoors & recreation), *ae* (arts & entertainment), fd (food), rs (residence), and nl (nightlife) to compute the fitting activity. This is done by forming a $6X5$ weight matrix, W, as shown in Equation 2. Each column holds the values yielded from the machine learning for each activity, under each of the physiological condition in each row. For example, $w_{(or/a)}$ denotes the weight value of opting for activities from the group 'outdoor and recreation' having an 'active' physiological condition.

$$\text{W} = \begin{pmatrix} w_{(or|a)} & w_{(ae|a)} & w_{(fd|a)} & w_{(rs|a)} & w_{(nl|a)} \\ w_{(or|r)} & w_{(ae|r)} & w_{(fd|r)} & w_{(rs|r)} & w_{(n|r)} \\ w_{(or|t)} & w_{(ae|t)} & w_{(fd|t)} & w_{(rs|t)} & w_{(nl|t)} \\ w_{(or|d)} & w_{(ae|d)} & w_{(fd|d)} & w_{(rs|d)} & w_{(nl|d)} \\ w_{(or|h)} & w_{(ae|h)} & w_{(fd|h)} & w_{(rs|h)} & w_{(nl|h)} \\ w_{(or|s)} & w_{(ae|s)} & w_{(fd|s)} & w_{(rs|s)} & w_{(n|s)} \end{pmatrix} \tag{2}$$

$PC.W$ results in the $1X5$ Activity Recommendation Index (ARI) vector as shown in Equation 3.

$$\text{ARI} = \text{PC} \ . \ \text{W} = \begin{pmatrix} a_{or}, & a_{ae}, & a_{fd}, & a_{rs}, & a_{nl} \end{pmatrix} \tag{3}$$

The system will recommend a concrete item from the the category with the highest ARI value based on the user preferences.

4 CONCLUSIONS AND FUTURE WORK

This paper proposes how to use wearable devices for deriving the physiological context of a tourist and by this to improve proactive activity recommendations during a trip. The wearable sensors monitor various physiological parameters, and by further processing this data, it is possible to derive the physiological context of a traveler such as being hungry or stressed. The main contribution is a model to facilitate the already available data from health-related application such as Apple Health to recommend tourist activities.

In future, we plan to implement the model in a mobile tourist recommender system. In a first offline evaluation, we would use cross-validation to determine the accuracy of the activity prediction. The challenge is to convince users to make their health-related data available for the recommender for potentially more fitting recommendations. Since data ecosystems like Apple Health make it easy to share it, we are optimistic that this is possible in general.

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