Enhancing Wearable Systems by Introducing Context-Awareness and FCA

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Abstract. Data collected from wearable devices form basis for assessment, analysis, and predictions. It is used in various fields of study such as health and education to improve status, define goals, and measure progress. Currently, there is no formal model used to define relationships among goals in a particular wearable system. Therefore, this paper proposes a novel approach based on context information and Formal Concept Analysis theory for modeling an entire problem domain using lattice theory. The resulted model shows the conceptual structure, different layers of abstractions, and hierarchical relations between wearable devices, collected data, defined goals, and predicted results. The structure is prerequisite for any further analysis.

Keywords: Context · Wearable system · Model · Formal Concept Analysis FCA · Lattice tree

1 Introduction

Wearable devices comprise built-in sensors to gather data about human's body. They can track different health metrics such as burned calories, sleeping habits and activities pattern during the day [3]. Moreover, some wearable devices can be used as health cards for their users, where users can define other inputs such as blood sugar, blood pressure and oxygen saturation [4].

Users of healthcare wearable devices aim to achieve healthy goals. The way of reaching these healthy goals can be different based on the healthy goal to be reached, the user data sensed by the wearable device, and the proper technique to reach the goal.

Wearable device continuously collect huge amount of information to track health metrics. This information is collected to update the users of their progress on reaching their set goals. However, this huge amount of contextual information is not used more than to update the users of their status. The current architecture of wearable devices does not allow this data to be analyzed. The collected data about the user is only used to track their progress on a set goal. Furthermore, there is no model that can make full use of the history of the collected data, or allow for further data analysis.

Due to the absence of a model to manage and analyze this amount of data many problems appear. People are slowly losing interest in wearable devices.

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“Consumers indicated less interest in buying smart watches (35 %), smart (sensor-equipped) clothing (20 %), smart glasses (19 %) or people tracking devices (13 %)” [5]. The main reason mentioned is that users do not feel involved. “Dean Hovey, CEO of Digifit, an online ecosystem for health trackers, said the challenge is understanding each user and hooking the people who could benefit most”. There is a need for a formal model that can hook the different information together and pave the road for further analysis to solve the mentioned consumers’ problems. That is, the current wearable applications[1] collect data to monitor information about different goals such as sleeping quality and burned calories. However, why does the device collect information about these goals? Does one goal affect another one? The answers for these questions help users to be more engaged and more motivated to accomplish their goals. The definition for relationships among two or more goals must be based on logical trustable theory. Hence, the use of a formal model to define the relationships among goals of a particular system is essential.

In this paper, we provide a new architecture for wearable devices. In this architecture, we consider the context and context history of the user. Moreover, we propose a formal model based on Formal Concept Analysis (FCA) theory that can define the data and its interrelationship. Our proposed solution allow for this huge amount of information to be analyzed. Our contributions in this work are listed hereunder:

1. Propose a data model for wearable systems.
2. Use Formal Context Analysis Theory to define a formal relationship among data components of wearable system.

2 Data of Wearable Systems

Users of wearable devices aim to achieve health goals by working on one or set of health metrics. We will refer to health goals as goals and health metrics as attributes.

In wearable systems, data is collected by different methodologies. Based on this, data is classified into three different data types explained as follows:

a. Sensed Data: user data gathered by sensors of wearable systems such as heart rate.
b. Entered Data: data entered manually by user such as height.
c. Generated Data: data that is automatically calculated using sensed or entered data such as age from date of birth.

The above mentioned data types are structured in the following manner Fig. 1:

1. **Attribute:** A health metric that is sensed by the wearable device or entered by the user. This metric affect one or more goals.
2. **Goal:** A high level definition of the health goal that the user aims to achieve.
3. **Technique:** A node that includes one or set of attributes. Every technique can influence one or more goals. A list of these goals is also included in the techinique.

[1] GymGoal2, Jawbone UP, Google Fit, 7 Minute Workout, MyFitnessPal, Amwell, MyNetDiary, Diet Assistant, Endomondo, Fitness Body, Fitoracy, Fooducate, JEFIT workout, Instant Heart Rate, Run Keeper, Ideal Weight, Daily Burn, Charge HR, Nike + Running, Weight Watcher Mobile.

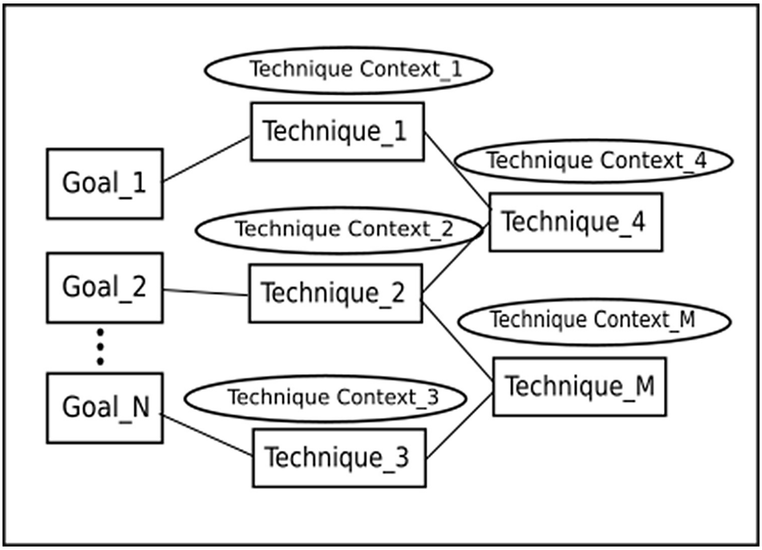

Fig. 1. Data model of wearable system

The distribution of these techniques and their relationships are based on the FCA analysis that is discussed in Sect. 3.

4. **Context:** Context is set of attributes and their values Fig. 2. This notion of context is formally defined by WAN [7]. In this paper, we propose two types of contexts;

Attributes	Values
Attribute 1	Value 1
Attribute 2	Value 2
Attribute N	Value N

Fig. 2. Context component structure

a. **User Context:** The user context defined by a set of attributes that are relevant to the user and their values.
b. **Technique Context:** The technique context includes the values of the attributes defined in the technique. The technique context and the user context have some attributes in common. The difference in the values of these attributes let users know how far they are from achieving their goals.

Whenever the data is collected, the user context is constructed by mapping each attribute of user context to its mutual attribute of the collected data Fig. 3.

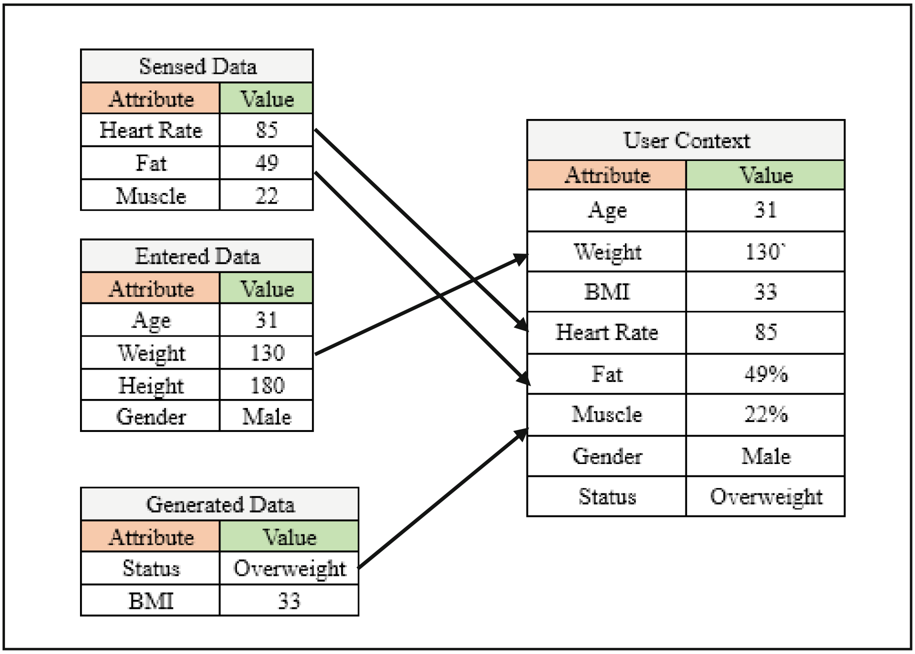

Fig. 3. Constructing user context from collected data

By now, we have introduced the data components that we will use in our work. Given these different categories of data and the huge amount of contextual information gathered by wearable device, we need a formal model that defines the relationship among different data components. This will allow the users to be aware of goals that are enhanced or affected by attributes they are working on. For example, if a user is using a wearable system to lose weight, he will work on every part that helps them to achieve their goal. However, many users do not know that decreasing weight of body is related to sleeping habits [8], which is a different health goal. Current solutions do not capture this information. However, the formal model provided in this paper, allows the user to be aware that sleeping habits will be enhanced too. Considering formalism in modeling data of wearable systems is a building block for further analysis.

The following sections, we will introduce the FCA theory and then our solution will be explained.

3 Formal Concept Analysis (FCA)

Formal Concept Analysis (FCA) *"is a method mainly used for the analysis of data, i.e. for deriving implicit relationships between objects described through a set of attributes on the one hand and these attributes on the other. The data are structured into units which are formal abstractions of concepts of human thought, allowing meaningful comprehensible interpretation (Ganter & Wille, 1999)"* [1].

Thus, as FCA supports the abstract concept by providing the intentional description or data it produces, it might be used as a clustering method. In addition, FCA provides a definition for the concept of context*[2]:

Definition 1 (Formal Context): A triple (G, M, I) is a formal context if G and M are sets and $I \subseteq G \times M$ is a binary relation between G and M. G elements are objects, and M elements are attributes and I is the incidence of the context.

For $A \subseteq G$, $A' := \{m \in M \mid \forall g \in A: (g,m) \in I\}$
For $B \subseteq M$: $B' := \{g \in G \mid \forall m \in B: (g,m) \in I\}$
A' is the set that includes all attributes common to objects of A
B' is the set that includes all objects that have all attributes in B [1]

Definition 2 (Formal Concept): "A pair (A, B) is a formal concept of (G, M, I) if and only if $A \subseteq G$; $B \subseteq M$, $A' = B$ and $A = B'$. That is, (A,B) is a formal concept if the set of all attributes shared by the objects of A is identical with B and on the other hand A is also the set of all objects that have all attributes in B. A is then called the extent and B the intent of the formal concept (A, B). The formal concepts of a given context are naturally ordered by the subconcept-superconcept relation as defined by:

$(A1, B1) \leq (A2, B2) \Leftrightarrow A1 \subseteq A2$ ($\Leftrightarrow B2 \subseteq B1$)" [1, 2]
Extent and Intent Formula
Concepts Extent = Ext (X, Y, I) = $\{A \in 2x \mid (A, B) \in B\ (X, Y, I)$ for some $B\}$
Concepts Intent = Int (X, Y, I) = $\{B \in 2y \mid (A, B) \in B\ (X, Y, I)$ for some $A\}$ [6]

Definition 3 (Lattice Tree): Concept lattice is a classification system, which is an output of formal concept analysis. Generally, a concept lattice might not need to be a tree as it is possible to include overlapping clusters. On the other hand, tree-like structures are appealing and many methods of classification produce this tree as an output [6].

4 Modeling Based on FCA Theory – Lattice Tree

Based on the FCA, we want to define the relation among specific goals and their defined attributes. Therefore, we used Lattice Miner software to create a table that defines four health goals and mapped to all or a subset of five defined attributes Fig. 4.

[2] The underlined context is an FCA terminology and it is different from the one stated in the rest of the paper.

Before we explain the model, we need to map the FCA terminologies to our data components Table 1:

Table 1. Mapping FCA to wearable system model

FCA terminology	Data component
Object	Goal
Attribute	Attribute
Tree Node	Technique

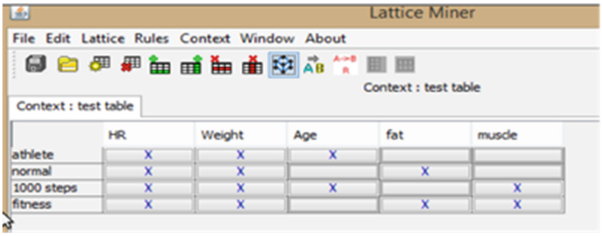

Fig. 4. Table include object and attributes sets

Then, the lattice tree is generated from the defined table Fig. 5.

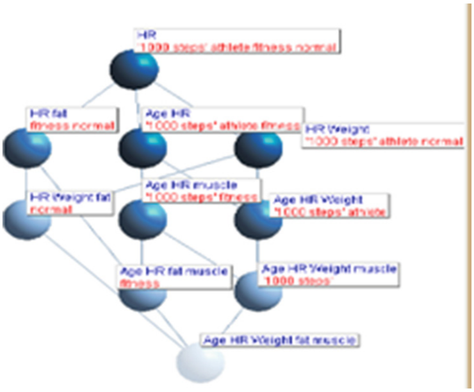

Fig. 5. Generated Lattice Tree from created table.

In the lattice tree Fig. 5, the techniques are ordered sub-concept- super-concept top to bottom techniques. Every technique includes attributes and goals influenced by these attributes. That is, the least upper bound (join) has the fewest number of attributes and is a subset of the three techniques in the second layer. If we take any possible path of a goal starting from the join down to the greatest lower bound (meet). We find the following remarks:

- The number of attributes increases as we go down the lattice tree, which is resulting from the natural relationship between the layers such that the attributes in the upper layer is a subset of the attributes set in the lower layer.
- The number of goals decreases as we travel down the lattice tree. This means that the lower we go, the more focused we are on a specific goal.
- Reaching the lowest level means reaching the ultimate improvement for a specific goal.
- The higher the technique on the lattice tree, the more goals are influenced.

5 Overall Observation

Using this model Fig. 1 in practical case will solve some existing problems such as lack of user engagement and the poor utilization of wearable systems data.

When data of user is gathered, he will be able to pick up one of the health goals provided by the wearable device. Once he starts working on a particular goal, he will be aware of influences he is making on other goals. With the help of our model, he will also be able to know information such as the techniques that affect the maximum number of goals and the ultimate level he can reach for a certain goal. More importantly, with the comparison between technique context and user context, user can know how far he is from reaching a specific technique.

The details the model provides make the user more engaged and motivated to keep working to reach their health goals. Moreover, the work done on data categorization and inclusion of context information made a better use of the gathered data.

6 Conclusion

Context-awareness and formal modeling should be introduced to wearable devices to take them to the next level. We have introduced the concept of user context and technique context for wearable system. Also, we have introduced a new classification for data of the wearable system. Afterward, we use a formal approach, i.e. lattice tree to provide a formal model goals and techniques defining relationships among them. This formal concept allows the user to be informed of goal influenced in each technique he/she passes through. The novelty of our approach is focused on the formal modeling of the whole domain problem. Thus, in this work we provided the first building block to a smarter, formal, and practical wearable systems.

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