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Activity centered Design of Smart Phone User Interface: Learning App Execution Patterns with Neural Network Model

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Abstract

The user interface design of smart phone is often too simple in logic that the taxonomy of tasks frequently performed is the only basis and the UI allow the user to add their favorite Apps as they want. However, with too many Apps available for smart phone users but not many of them are used frequently, the convenience of smart phone usage can and should be developed not just by the predefined functions but to maximize its UI usefulness from user's activity analysis. In this paper, we propose an intelligent method using BAM network to minimize searching for the frequently asked Apps by recognizing and learning user's signal to execute them. This is a form of activity-centered design to maximize user's convenience in user interface of a smart phone.

Keywords: *Smart phone, Apps, User Interface, BAM network, Activity-centered Design*

1. Introduction

Activity centered design is a motto of design process that does not focus on the goals and preferences of the user but on the activity a user would perform with a given piece of technology [1]. There are too many taxonomies and tasknomies from the production designer's sense frequently titled with 'human centered design' but it may miss the irrational side of human habits. Human activity recognition task through mobile devices like smart phones using accelerometers is one of the recent trends of researches. Typically those researches interpret the problem as a supervised learning problem with sensors to classify human behaviors for monitoring general behavior [2] or a sports-specific behavior [3] or develop a gesture-based user interface [4] for maximizing user convenience. That line of researches, though, is to provide convenient functions for the smart phones production companies to allure users for sale thus pre-designed in nature and gathering practical data is an issue to solve.

In this paper, we approach this task as a personalized design issue of maximizing the convenience of smart phone on user's side especially for relatively elderly people - aka activity centered design. Since so many convenient and useful Apps are available in the mobile App market, people are used to download more than necessary number of Apps but some Apps are seldom used. However, a typical smart phone user interface displays those downloaded Apps and production-provided Apps in multiple pages so that people frequently

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wander over smart phone user interface pages or rearrange them by themselves. Although a user has multiple pages of Apps available, not many of them are frequently used thus the user interface needs to provide a function to minimize this "search for appropriate Apps from the interface" elapsed time [5]. By the standards of engineers, human behavior can be illogical and irrational. From the standpoint of people, however, their behavior is quite sensible, dictated by the activity being performed, the environment and context, and their higher-level goals [6].

Thus, we need an intelligent algorithm to associate user activity patterns with frequently used Apps by user specification. With appropriate intelligent learning algorithm, a user can execute their favorite Apps with their own learned signals regardless of number of downloaded/available Apps a user has.

In nature, this problem is appropriate for neural network applications. There are several candidate algorithms like ART2 [7] but we adopt a Bidirectional Associative Memory (BAM)[8] neural network approach to associate user activity patterns.

2. Learning Personalized Apps Execution Patterns with BAM

In general, the procedure to execute an App is as follows:

1. Click “Hold” button.
2. Push “Unlock” button as shown in Figure 1.
3. Search the target App icon through pages
4. Execute target App by touching/pressing it.

Then the activity is typically done as Figure 1.

Figure 1. Unlock and Display App Icons

Our goal is to learn the user's activity pattern to execute a specific Apps the user frequently use. The user's signal often forms a connected signs or figures. Since these signs and figures are similar, an intelligent algorithm should classify it into the right Apps the user wants to execute.

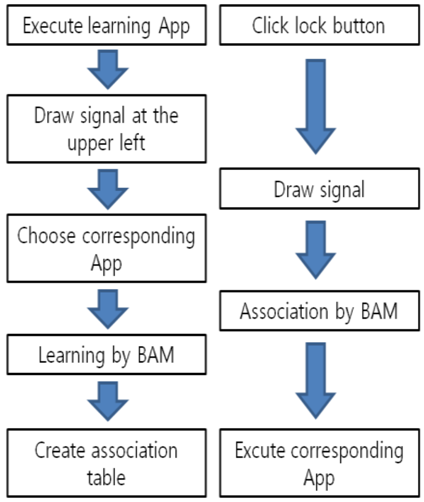

Figure 2. Overall procedures of Learning User Execution Patterns

Figure 2 summarizes the overall procedures of learning user execution patterns that this paper is aimed for. From the general user behavior enumerated from 1 to 4, step 3 is the most time-consuming one and our effort is to minimize that elapsed time if the target App is one of those frequently used Apps. There are two conditions that this learning is necessary for users.

Condition 1: Learning App should be able to obtain the “Available App Table”.

Condition 2: There is limited number of “Frequently Asked Apps” for a user.

Figure 3 demonstrates a typical user input for a "frequently-called" App on our learning App. Then the BAM learning starts. BAM is hetero-associative, recurrent network that given a pattern it can return another pattern which is potentially of a different size.

Figure 3. User Pattern Input (Red Line) for a Specific App

BAM network obtains output vector $Y(p)$ by applying the transposed weight matrix W^T to the input vector $X(p)$. Then, $Y(p)$ is again applied to the weight matrix W to produce new input vector $X(p+1)$ until there is no significant changes as shown in Figure 4.

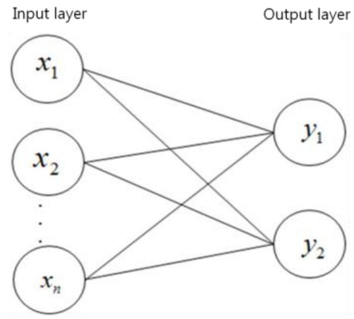

Figure 4. BAM Network Model

And the BAM learning steps in this paper are as following:

Step 1: Obtain connection strength matrix *W* for pattern pairs.
Step 2: Input patterns to *X* layer.
Step 3: Compute first output of *Y* layer Y_1 using weighted sum NET_y as follows.

$$NET_y = XW$$

$$Y_1 = \mathrm{f}(NET_y) \ = \begin{cases} 1 : \ NET_y > 0 \\ y_1 : NET_y = 0 \\ -1 : \ NET_y < 0 \end{cases}$$

Step 4: Use Y_1 as input on *Y* layer and similarly obtain first *X* layer output X_1 from *Y* layer as input using weighted sum NET_x

$$NET_x = Y_1 W^T$$

$$X = \mathrm{f}(NET_x) \ = \begin{cases} 1 : \ NET_x > 0 \\ x_1 : NET_x = 0 \\ -1 : \ NET_x < 0 \end{cases}$$

Step 5: Repeat Step 3 to Step 4 to obtain X_{i+1} and Y_{i+1} until output converges to a specific pattern (the change is less than a predefined threshold).

In this paper, this BAM algorithm is implemented by Visual Studio 2008 C# on the IBM Compatible PC with Intel™ 2 Duo 2.66GHz CPU and 2 GB RAM for the simulation experiments.

ART2 neural network learning model [7] is also considered as a learning model but it involves too many computation to obtain a stable clusters for execution signal learning. This association problem assumes that the number of frequently used Apps us not that big thus simple bidirectional association is cheap and efficient.

Figure 5. Interface for Pattern Learning

From user's side, a user simply draws a picture/signal like the right-hand side of Figure 5 and touches the corresponding App as shown on the left side. BAM learning does not limit to have one-to-one correspondence thus more than one patterns are able to associated with a target App for user's sake. Then, after learning, a user simply draw a pictured signal on the smart phone as shown in Figure 6 and the corresponding App is executed immediately.

Figure 6. App Execution Example

3. Conclusion

In this paper, we propose a method of learning specific user's behavior pattern signals to execute specific frequently-asked Apps on the smart phone. BAM network learning does the crucial job to make associations between user signals and targeted Apps. This special learning function maximizes user convenience on executing frequently asked Apps without hesitation and matches recent trend of recognizing user behavior through smart phones. This might be viewed as an activity centered user interface design and such philosophy can be extended to other applications of smart phone user interface design. A simple feasibility test is done with the original BAM [9] but, for the scalability of the research, one may use other extended forms of BAM with respect to different applications [10].

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