A HUMAN SUPPORT SYSTEM IN A SMART HOME ENVIRONMENT

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Abstract

In this work we describe the principles of the life support system of the smart home inhabitant. The system involves monitoring the activity and classification of the activity types of inhabitants using artificial intelligence methods, controlling the duration of their actions, the response functions and the necessary social support. The system is implemented on the Google Smart Home platform.

1. INTRODUCTION

Automatic assistance for a human in everyday life and emergency situations, and social, specialized medical and other support are current topics in technical, and social research [2]. This is a part of the program for the creation of a comfortable and safe environment for humans with their pets, and, in particular, it involves the equipping a person's home with additional “smart” hardware and software tools [10].

The organization of such an environment may also include the implementation of various strategies to support the life of the inhabitant, for example, assistance in tracking the schedule of medication, strolling, exercises, etc. Such a home is often called "smart home" [11, 12].

In addition to the basic tasks solved with smart home systems that offer the optimization of household with static smart household devices, we can recognize a subclass of specific tasks for the inhabitant life support [1]. To solve such problems it is necessary to obtain accurate information about the current activity of a person.

In many cases to determining the current human activity we can use static devices, wearable devices, or a combination of them. Activity recognition systems differ by the approach that has been taken. It could be classification, recognition of predefined types of activity, or clustering, automatic recognition of activity type templates.

This paper describes the developed and implemented program system designed for monitoring and recognition (classification) activity of the inhabitants of a smart home using wearable sensors, a smartphone and a fitness tracker. Classification problems were solved by various methods of machine learning.

The obtained information is used to create a human support system that includes a subsystem for monitoring the duration of actions of inhabitants to maintain a healthy rhythm of life as a personal request or the doctor’s recommendation.

In the presented work we describe the implementation performed with the Google Smart Home management programming environment [13]. We focus on the problems of choosing appropriate classification methods and creating a classifier of the activity of smart home inhabitants. As an example, a subsystem for monitoring the duration of activity was designed and implemented.

2. DATA DESCRIPTION

In previous studies [2], we used open access human activity data [14, 15] and the information obtained from wearable devices to select appropriate classification methods and the system configuration. The analysis of these datasets showed insufficient accuracy in recognizing the type of activity for practical usage. Therefore, for this study, an experimental dataset about the activity of an inhabitant of smart home was prepared. The data over a period of three weeks using wearable sensors were collected

Considering the information of large number of sensors, the readings of which are merged to a single class can lead to decreasing of classification accuracy [3]. Therefore, a fitness tracker and a smartphone, which are currently the most common sensors, were selected. With their readings we can determine the location of a person inside the home and his condition.

With using a smartphone, information about a human's indoors location is collected. This can be done basing on the readings of the Bluetooth or Bluetooth Low Energy receiving signal strength indicators

(RSSI) with a fitness tracker or smart watch and the indicators of signal strength of the smartphone connection with a Wi-Fi router [4]. The RSSI values are in the range from -100 to 0, the closer the value is to 0, the stronger the signal. In this work we assume that there is only one Wi-Fi router in the system, that is accessible from all the locations of the smart home environment.

The fitness tracker allows us to get more detailed information about the current type of an inhabitant's activity. In applications that use the information collected by the accelerometer, it is possible to use only the readings converted to the steps number, because the accelerometer readings are not transmitted from the fitness bracelet directly to the smartphone to save energy.

To get information about the heartbeat and the number of steps, the open source Gadgetbrige application for Android devices was used. This application is designed to replace the applications of fitness tracker manufacturers, because various device vendors use their own protocols for interacting with the wristband and smartphone. The functionality that allows getting RSSI information has been added to the application.

The resulting data set contains the following data types:

- heart rate;
- number of steps;
- Bluetooth RSSI;
- Wi-Fi RSSI;
- activity time;
- type of activity.

Information of 9 types of activity was collected: work, eating, cooking, walking, video games, inactivity, sports, shower, household.

The interaction with a user on sleep monitoring and control is implemented by applications of manufacturers of fitness trackers, so this type of activity was not considered for collecting information and solving the problem of monitoring the duration of activity.

Therefore, to configure the system, we got a dataset with 26709 records, each activity type contains no more than 4800 records.

3. DATA ANALYSIS AND EXPERIMENTS DESCRIPTION

For the recognition of activity type, we used machine learning algorithms that were commonly applied to solve problems related to human activity recognition. The experiments were made with using the cross-validation method, which divides the sample into 10 folds (groups of samples of equal size). The recognition accuracy (the ratio of correctly predicted values to the total size of the test subset) and standard deviation are shown in table 1.

Table 1: Accuracy comparison

Algorithm	Accuracy	Standard deviation
Neural network	0.739	0.01
K Nearest neighbours	0.815	0.006
Random forest	0.824	0.008
Naïve Bayes classifier	0.677	0.005
AdaBoost	0.456	0.003
Support Vector Machines	0.679	0.008

From the table we can see that the classifiers with a random forest containing 100 trees [5], and K nearest neighbours with K=10 have highest classification accuracy. The recognition quality of high movement activities using the random forest classifier is significantly lower than using the K nearest neighbours method, as shown in table 2. The accuracy of activity type recognition (precision) is calculated as the ratio of correctly defined objects of a class to the sum of correctly and falsely classified values.

Table 2: Precision comparison

Activity type	K nearest neighbours	Random forest
Work	0.922	0.947
Eating	0.515	0.488
Cooking	1.000	1.000
Walking	0.692	0.768
Video games	0.724	0.788
No activity	0.846	0.877
Sports	0.579	0.304
Shower	0.823	0.872
Household	1.000	1.000

To increase the recognition accuracy and take advantages of both types of classifiers, the hierarchical classification approach was applied, which allows us to consistently specify the belonging of an object to the classes the structure of which is a tree. All activities were divided into 2 basic types: dynamic and static.

In this work various combinations of classifiers using K nearest neighbours methods and random forest as basic recognition methods were reviewed, as the training of classifiers on a subset of the original set of classes changes the quality of classification. The accuracy of recognition of activity classes from the data set obtained with hierarchical classifiers is shown in tables 3 and 4. The first classifier recognizes the basic type of activity, the second one — passive activities, and the third one — dynamic activities.

The approach that uses the K nearest neighbours algorithm to recognize dynamic activities and the random forest method at the remaining points solve the problem of low classification precision for high movement types of activity.

Table 3: The comparison of precision for hierarchical classifiers

Activity type	Random forest, K nearest neighbours, Random Forest	Random forest, Random Forest, Random Forest
Work	0.931	0.950
Eating	0.685	0.598
Cooking	1.000	1.000
Walking	0.715	0.715
Video games	0.753	0.786
No activity	0.866	0.879
Sports	0.474	0.474
Shower	0.804	0.804
Household	1.000	1.000

Table 4: The comparison of precision of hierarchical classifiers

Activity type	K nearest neighbours, Random Forest, Random Forest	Random forest, Random Forest, K nearest neighbours
Work	0.943	0.950
Eating	0.539	0.598
Cooking	1.000	0.996
Walking	0.694	0.658
Video games	0.770	0.786
No activity	0.874	0.879
Sports	0.480	0.711
Shower	0.847	0.773
Household	1.000	1.000

The selected hierarchical classification scheme is shown in Figure 1. The basic activity type is recognized by the base classifier using the random forest algorithm. Two subsequent classifiers refine obtained result. The first is recognizing static types of activities using the random forest method, and the second is recognizing dynamic activities using K nearest neighbours.

The implemented classification algorithm increases the precision of recognition "sport" activity type from 0.304 with the use of a random forest, up to 0.711.

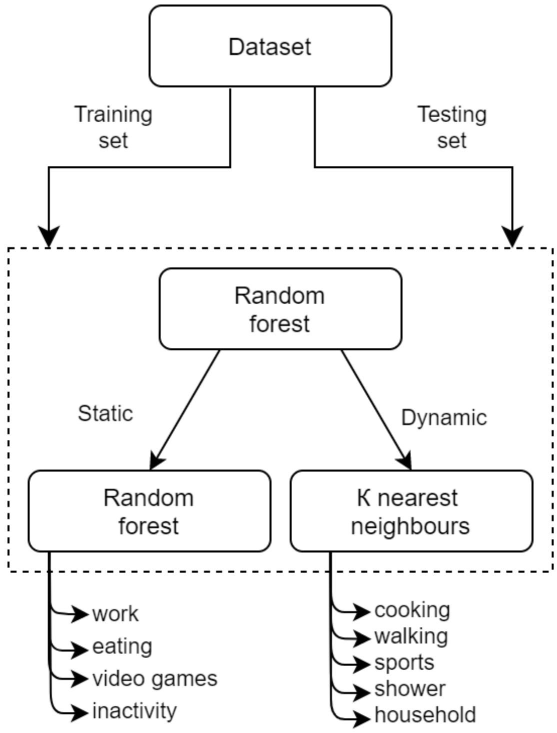

Figure 1. Hierarchical classification schema

The implemented system allows recognizing 9 types of activity with an accuracy of 0.838 using a hierarchical approach, and with data obtained from a heart rate sensor, step counter, Bluetooth and Wi-Fi RSSI.

The system can be compared with existing solutions by the set of sensors used, the classification algorithm used, the number of recognized classes, and the accuracy of classification:

- In [6], the authors used random forest algorithms and the support vector machines method to recognize 5 classes of activity (sitting, standing, doing household, working on an exercise bike with low activity, working on an exercise bike with high activity) based on the accelerometer and heartbeat data obtained from a smart watch. The classification accuracy is equal to 89.2% for the random forest algorithm and 85.6% for the support vector machines method.
- The article [7] describes a hierarchical modification of the support vector machines method for recognizing four types of activity with 99% accuracy. The method is based on data obtained from smartwatches: when a person is sitting or standing, walking or running.

- In [8], the author used 2 devices equipped with an accelerometer and a gyroscope. One of the sensors was attached to the wrist, and the second is located in the pants pocket. F-measure (the harmonic mean of precision and recall, where recall is defined as the ratio of correctly defined class objects number to the sum of correctly and falsely classified values) of the recognized types of activity was close to 1. A hierarchical classifier that divides the types of activity into the types that involve only the hands and the other types of activity was used. The algorithms of the naive Bayesian classifier and K nearest neighbours are used as the basic classification algorithms.

The implemented classifier provides the accuracy of recognizing the activity of a smart home inhabitant, which is comparable to the accuracy of recognizing human activities in the presented researches.

4. THE SYSTEM MONITORING THE ACTIVITY DURATION

The using existing hardware and software implementations of smart environment management simplifies the user interface development. This approach also allows us to store and exchange of information of several human support modules that use the same sets of information to solve several independent tasks [9].

Monitoring the duration of human activity in the Google Smart Home environment takes place using two functional features: the user changes the desired parameters of the duration of recognized actions, and receives a notification when the specified limits are exceeded.

The details of interaction of an inhabitant and the system are shown in Figure 2.

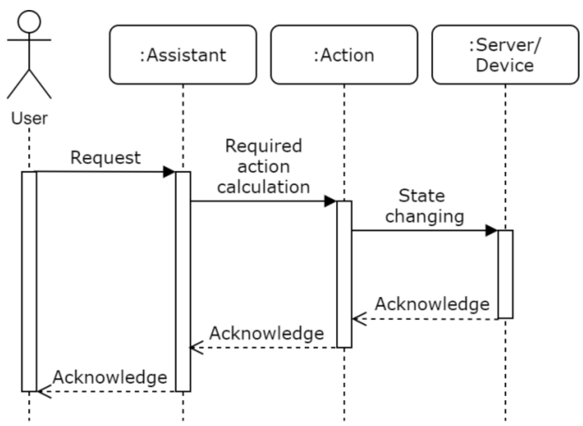

Figure 2. Interaction with Google Smart Home environment

The user sends a request to change the time of the activity duration using the voice or text interface of Google Assistant. The assistant calculates the required action for execution, where action is an implementation of a custom script for the smart environment management. The action handler sends the received parameters to the server via the REST API. The server returns a message confirming the update of the information.

Figure 3 shows a sequence diagram of the process of receiving a notification by an inhabitant about exceeding the established limits for the duration of activity. After receiving the heart rate and the count of steps from the fitness tracker, Gadget Bridge application adds the Wi-Fi and Bluetooth RSSI values and sends the information to the server where the described activity classifier is installed.

If the duration of the recognized activity type is outside of the established limits, smart home inhabitant receives a notification on the smartphone.

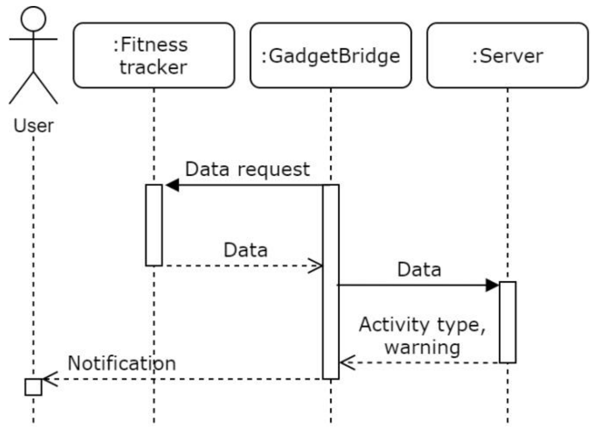

Figure 3. Notification receiving diagram

5. CONCLUSION

In this work, the problem of classification of the smart home residents activity was solved by hierarchical classification method including random forest and K nearest neighbours algorithms. The accuracy is 0.838, which is sufficient for a practical application of the classifier.

The use of the developed and implemented system for monitoring the duration of human activity in the smart home environment allows supporting the inhabitants and helps to maintain an optimal life rhythm by receiving notifications on a smartphone.

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