Context-guided Universal Hybrid Decision Tree for Activity Classification

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Abstract— **Obtaining accurate measurements of human activities is important for a broad set of health applications. We propose a context-based hybrid decision tree classifier with a real-time portable solution for reliably classifying daily life activities and for providing instant feedback. At first, to determine user contexts, we utilize sensors typically found on smart phones or tablets to collect environment data. Then, we select different types of hybrid decision tree classifiers based on detected human context. The tree classifier can flexibly implement different decision rules at its internal nodes, and can be adapted from a population-based model when supplemented by training data for individuals. In addition, with the introduction of portable devices, the users can receive instant feedback of their current mobility status.**

Keywords—wireless health, activity classification, real time classification, context guided, decision tree

I. Introduction

Activity monitoring provides critical benefits for important concerns such as health and wellness promotion, disease treatment and disease condition detection. Through the automatic feedback of activity status to both individuals and health care providers, the quality of health can be improved while reducing the costs. Due to the rapid advance in microelectronics, MEMS inertial sensors, low power processors, and low cost monitoring systems, human activity classification is now possible. The ubiquity of mobile devices also provides a platform for the wireless healthcare community to integrate monitoring and in-field guidance for both advancing and evaluating treatment outcomes. Increased research effort has been devoted to the development of systems that monitor human activities with feasible cost, classify activities with good accuracy, and then analyze these activities with respect to different rules [1,2].

Some systems [3,4] based on naïve Bayes classifiers can provide accuracy up to 90% for classifying a small number of daily activities. However, the use of a single-stage classifier is problematic from many aspects including exploding training data requirements as the number of classes grows. Other approaches [5-7] utilized decision tree classifiers that can better handle complex decision regions by partitioning them into smaller sets with low dimensional hypothesis spaces at each stage, providing advantages such as reduced training set size, robustness to outliers in training data, extensibility of target classes, and invariance under monotone transformations.

However, decision tree methodologies can suffer from mismatches between assumed and actual distributions for different sets of classes, resulting in poor accuracy, if only a single classifier type at each node is applied. Another issue arises in clinical trials when generalizing the model to a large population. In practice, one can acquire extensive ground truth only for a small set of subjects due to high logistical costs; for the rest, at best only short training is feasible. However, if the tree can be personalized then we can get far better results. One solution is to construct a decision tree structure that fits the population, and then tune only the decision thresholds using short training sequences for individuals. This was attempted in [1], but with inadequate accuracy.

The above methods also face challenges as we scale to large and diverse user communities. The rapidly expanding activity set increases model complexity, which causes degraded classifier performance. In addition, the diverse user community has varied requirements. Thus we need a system that is personalized and provides targeted monitoring of activities under different conditions. The energy efficiency of energy-constrained monitoring sensors should be taken into consideration as well. These objectives require the capability of detecting the location and environmental context [8,9]. Context information has the potential to directly enhance activity classification accuracy and speed through reduction in search space, and reduce energy demand through context-aware optimization of sensor sampling and operation schedules.

There have been attempts to introduce context awareness into activity classification to facilitate personalization and adaptation [8,10-14]. These systems achieved limited success due to the ambiguity in the definition of context, and the lack of a system architecture that enables the adaptation of signal processing and sensor fusion algorithms specific to the task of personalized activity monitoring.

To address the abovementioned deficiencies, we propose: 1) A universal hybrid decision tree classifier to reduce training efforts; 2) A novel architecture that provides context guided personalized activity. Herein, context is separated from physical activities in order to produce a first level hierarchy, and further achieves personalized activity classification. In addition, our work presents four major contributions: 1) A tree classifier with flexibility of decision rules, adaptation to a population-based model and reduction of training cost; 2) Accurate detection of context with sensor fusion; 3) The integration of context to improve classification accuracy and energy usage; and 4) The ability to target specific physical activities of interest for a given context.

II. System Overview And Architecture

Illustrated in Fig. 1, the system consists of three parts: sensor modules, an Android device, and a backend server for offline training. Multiple sensor modules, each containing three sensors (gyro, accelerometer and magnetometer), are attached to the body. Each sensor module communicates wirelessly (dashed lines) with an Android device via Bluetooth.

The sensor modules sample data at a predefined rate, aggregate data from each sensor, and then transmit to the Android device. In the training phase, after the user employs the GUI to configure and turn on the sensors, the sensors generate and transmit data to the Android device. Meanwhile, context sensors on the Android device collect environment data such as Wi-Fi fingerprint, audio and time of day. The Android device stores these data locally. The system then prompts the user to provide ground truth labeling for each activity section and current context. When the collection of training data is done, both the sensor data and annotation files are stored in the Android device.

These training data are then used to perform offline model training via the backend server, which consists of two toolboxes. WHISFT is a suite of accurate classification methods for activities classification that has undergone extensive testing in diverse situations and clinical settings [15]. It provides an end-to-end solution for inertial sensor data processing from raw data to decision tree construction, model training and performance evaluation. The toolbox is capable of performing multimodal hierarchical classification based on a set of classifiers such as Naive Bayes and Support Vector Machine [16]. The context toolbox is another tool we developed that is able to process context data and build context classification models. We used these two toolboxes to construct and train our classification model based on our proposed algorithm. The models are then transferred to the Android platform for real-time classification.

In the real-time testing phase, the Android App not only stores sensor data locally but also caches data in a queue structure. It also loads the trained model into its classifier.

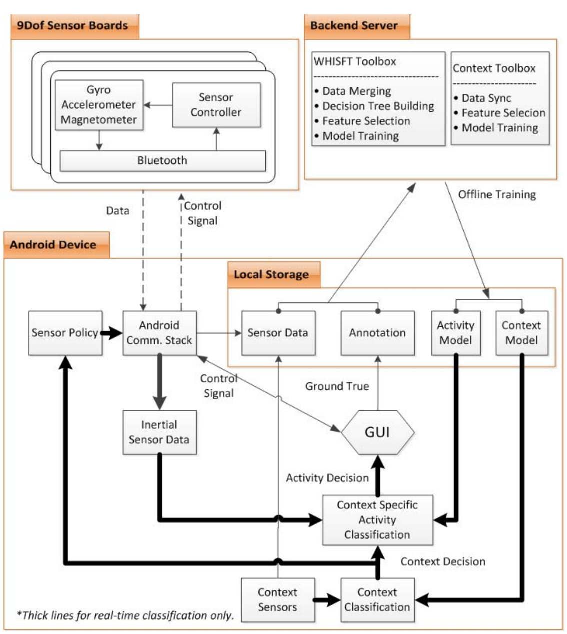

Fig. 1. System architecture

A queue structure is designed to implement a moving window for real-time data processing, where new data is pushed onto the queue, and old data is popped out. The data from the moving window is then fed into the classifier to make a classification decision. The context decision is first determined and then fed into the context specific activity classification block. Based on the context information, a specific activity model is selected to perform activity classification on the inertial data. The classification results are finally made, and then fed back to the user via the GUI.

III. Methodology

A. Universal Hybrid Decision Tree

In this section, we present a universal hybrid decision tree classifier. This type of classifier fuses various kinds of single-stage classifiers in its nodes, and can also adapt to new incoming data with minimal training. The following shows how we achieve this.

First, a tree classifier T with l internal nodes can be thought of as a classifier consisting of l single-stage classifiers, where each single-stage classifier has its own subset of classes, features and the decision rules for the node. Therefore we can write T as a combined set,

$$T = \left\{ C(t), F(t), D(t) \right\} \quad t = 1, \cdots, l \tag{1}$$

where C is the subset of classes of node t, consisting groups of classes associating with that node; F is the feature set used for node t; and D is the decision rule of that node. In this paper, the naïve Bayes classifier and the support vector machine (SVM) were used as possible types of decision rules of internal nodes. Compared to other tree classifiers where only a single type of decision rule is used [17,18], this hybrid approach takes advantage of more appropriate statistical modeling of different activity classes and therefore achieves higher classification accuracy.

Using this hybrid tree, we then find a classifier with a single structure that can classify multiple subjects' data. The reason behind this universal classifier is that we want to have a model that with minimal additional training can be personalized to subjects. Therefore when we generalize this model the amount of training effort, such as data collection and labeling, can be greatly reduced. We do this by maintaining the structure, features used and decision rules associated with the hybrid tree classifier, and only change the decision thresholds corresponding to different subjects. Thus using only a small amount of additional training we can personalize the classifier to each subject. This procedure can be stated as follows:

Begin

1. Given we have M subjects with training data named $TD_i, i = 1, \cdots, M$, and we manually form N hybrid decision tree where is tree T_i with l nodes can be written as

$$T_i = \left\{ C(t), F(t), D(t) \right\}$$
$$i = 1, \cdots, N \quad t = 1, \cdots, l$$

with $l(i)$ internal nodes. The class subset $C(t)$ is determined for every internal node. Let $TD_{j,t}$ be part of the training data TD_j whose classes that are involved in node t of the tree. $P_{e|j,t}\left(F(t),D(t)TD_{j,t}\right)$ is the probability of error of node t when applying feature set $F(t)$ and decision rule $D(t)$ on training data $TD_{i,t}$.

2. Randomly pick a tree T with l internal nodes
3. **For** $t=1$ to l
   Find the optimal set $\left(F^*(t),D^*(t)\right)$ that minimizes the weighted probability of error

$$\left(F^*(t),D^*(t)\right)=\arg\min_{(F(t),D(t))}\sum_{j=1}^{M}w_j\cdot P_{e|j,t}\left(F(t),D(t),TD_{j,t}\right)$$

   where w_j is the weighting function for the subject j, indicating the weighting of that type of people to the general public
4. **If** $\sum_{j=1}^{M}w_j\cdot P_{e|j,t}\left(F^*(t),D^*(t),TD_{j,t}\right)>th_{err}$
   Terminate the for loop, go to step 1 and try the next tree T, where th_{err} is the predefined error threshold
   End if

End for

5. Output the tree classifier

$$T^*=\left\{C(t),F^*(t),D^*(t)\right\}\quad t=1,\cdots,l \tag{2}$$

This algorithm takes the differences among people into account while maintaining a satisfactory error rate.

B. Context Detection

In pervasive computing, the definition of context by Dey [9] has been widely referenced. It is a very broad definition that contains every characteristics of a given situation, in terms of both the environment and the user. While useful for many applications, it is not suitable for leveraging context in monitoring physical activities, since in many cases a context contains physical activities that are underlying in the definition. Some alternative definitions offer different selection of divisions such as external and internal contexts [19,20] to narrow the extent, but still contain a mix of physical activities with the external environment.

In this study, we address a context as: “a subset of all attributes that characterizes an environment or situation, external to the user”. This definition clearly distinguishes between the user’s physical activities and external environmental attributes. With this refined definition, the attributes associated with a context or with a physical activity can be easily distinguished. For example, a "cafeteria" environment is a context, and its characteristics may involve certain sound profiles and a set of possible locations. In contrast, "eating in a cafeteria" is not a context, since it contains the user's physical activity of "eating". Thus, we can use context as a first level hierarchy to determine a set of activities of interest based on the user’s current situation before carrying out activity classification [21].

Since our definition of context can describe many situations, it allows users to define their own interested context set, identify the required characteristics to distinguish contexts and select necessary sensors based on their objectives. Thus, this generalization requires the system to take account diverse types of data sources such as GPS coordinates, Wi-Fi fingerprint, background audio noise, and illumination level.

To provide a reliable context decision, multiple classifiers should be employed based on the nature of various data sources and trained separately. After training, the individual classifiers are tested and assigned with voting weights (α) proportional to the perceived accuracies. When an unknown class is encountered, a decision committee (Fig. 2) performs sensor fusion as a linear combination of the individual classifiers. The context with the highest vote is chosen. The committee approach also enables adaption to individuals with varying habits. For example, a subject with a regular daily schedule might exhibit higher correlation in time of day relating to context. Thus, we would increase the weight of the classifier based on time-of-day during training, compared to a subject that is less habitual. We choose three classifiers to form our context detection committee for most of the experiment: k-nearest neighbors (kNN) with time-of-day as a feature; kNN with wireless MAC address and signal strength as features; and AdaBoost with audio peak frequency, peak energy, average power and total energy as features.

C. Integration of contexts into activity classification

After inferring context from the committee, this information can be used to enhance activity classification. We introduce the concept of context driven activity classification. Fig. 3 shows a high-level data flow diagram. The inertial data and context data go through a signal-processing pipeline where a context is first determined. From the context we can extract an activity model from a scenario. The activity model combined with the inertial data gives us an activity classification result.

Based on this framework, there is no single list of comprehensive activities that needs to be built into a monolithic classifier, compared with conventional activity classification. Alternatively, only a small set of activities would be chosen in a specific context, and this set can then be extended or reduced according to our objectives.

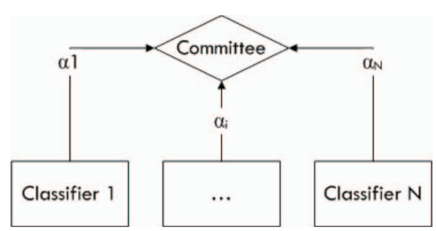

Fig. 2. Classifier committee

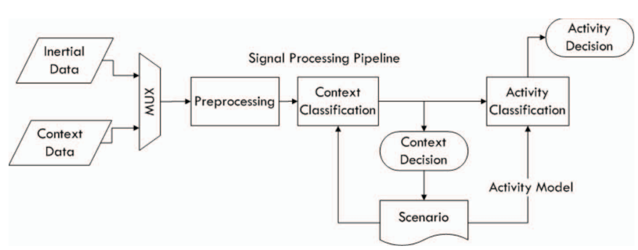

Fig. 3. High-level decision flow

This approach brings a number of advantages. First, by pre-selecting the activities of interest (or likely activities), the model complexity of the subsequent activity classification stage can be reduced. This increases the accuracy, improves classification throughput and enables sensor operating time and data sample/transmission optimization. An example of the context specific activity model we generated for the "Cafeteria" context is shown in Fig. 4. The activities are on leaf nodes, laid out in a hierarchy. At each branch either a Naïve Bayes or SVM classifier makes the branching decision using features in the model.

In addition, this approach also allows an activity set within a context to be customized to fit a specific situation. To further illustrate this concept, Table 1 lists a few possible activity models under different contexts in a clinical application. For example, in the context of patient room, physicians may wish to monitor a patient's mobility status to assess the risk of bedsores and other problems. Another example is the rehabilitation context, where physicians may wish to monitor the patient's performance in exercises and to ensure recommended daily activities are performed as instructed.

TABLE 1. EXAMPLE SCENARIOS

Context	Activity Model	Purposes
Patient room	• Sitting • Standing • Lying down	Monitor how long a patient has stayed immobile, assess the risk of bed sores and other problems
Rehabilitation	• Aerobic exercise • Walking Slow • Walking fast • Fall	Monitor patient's performance in exercises
Hall way	• Standing • Walking fast • Walking slow • Fall	Monitor a patient's general physical condition, and detect falls

TABLE 2. SCENARIOS

	Home	Lab	Cafeteria	Outdoors	Class	Bus	Gym	Library
Walking Around	X	X	X		X			X
Walking Normal				X			X	
Walking Upstairs				X				
Walking Downstairs				X				
Sitting Straight	X	X	X	X	X	X		X
Sitting Slouch	X							
Standing			X	X		X		X
Writing		X			X			X
Typing		X						
Eating	X		X					
Sleeping	X							
Running				X			X	
Cycling							X	

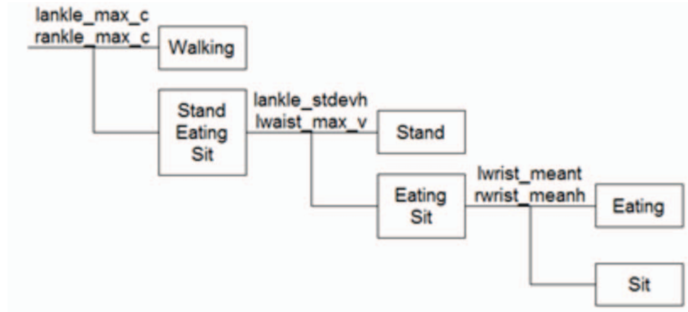

Fig. 4. Context guided model for Cafeteria

IV. SYSTEM EVALUATION

A. Data Acquisition

In this study, we used SparkFun 9DoF IMU sensors and a Nexus 7 tablet to collect 14 datasets, where each set of data contains 13 activities in 8 different contexts[1]. The procedure of data acquisition is as follows: 14 subjects each attached four 9DoF sensors on right wrist, knee, ankle and mid waist. An assistant carried a Nexus 7 tablet running the Android client to record sensor data and label the ground truth. Each subject spent 30 minutes in each context, and performed every predefined activity under that context for at least 5 minutes. The data were then separated into training (30%) and testing (70%) sets and 10-fold cross-validation was performed to obtain the classification results. Table 2 summarizes the collected activities corresponding to different contexts. In the table, the activity "Walking Around" refers to non-sustained walking segments that are typical of walking in confined spaces, while "Walking Normal" refers to sustained long distance walks typical of open space.

B. Result

1) Context Classification accuracy

The accuracies of correctly classified instances of individual classifiers in the committee and the overall accuracies are shown in Table 3. We noticed that AdaBoost using sound features yield high accuracies for most of the contexts. However, sound features are sensitive to environment variation. There were some cases where misclassification occurred due to vehicles driving nearby or long periods of silence. Time kNN depends heavily on the varied nature of when subjects visit these contexts. Hence, it is also not sufficiently accurate in cases of some spontaneous visit of contexts. Wireless kNN provides good accuracy for indoor contexts due to stable wireless environment. However insufficient accuracies occurred in some cases such as bus and outdoors. In the bus context, the classifier suffers from unstable wireless signal or unseen wireless access points due to the route of the bus. For the outdoor context case, the system tended to detect access points that belong to nearby indoor locations. We observed this issue when walking near a building caused the context to be classified as another context inside the building.

1 Data collected according to a UCLA IRB approved protocol.

TABLE 3. CONTEXT CLASSIFIER ACCURACIES (PERCENTAGES)

	AdaBoost	Time kNN	Wireless kNN	Committee
Home	100	91	100	100
Lab	78	68	98	95
Cafeteria	100	0	80	100
Outdoors	81	57	56	72
Class	81	43	95	91
Bus	100	23	30	95
Gym	64	9	93	84
Library	59	0	100	94

This experimental evaluation reveals the pros and cons of each individual classifier. However, by applying a committee approach that assigned appropriate combination of each classifier, the system is able to achieve high accuracy for all contexts.

2) *Activity Classification accuracy*

In this section, we first evaluated the classification accuracy of the universal hybrid decision tree classifier, and than verify the enhancement in classification accuracy of the context-guided approach. For the universal hybrid decision tree, we first manually determined the tree structure, and then used 30% of the data from all subjects as training data to select features and classifier types that yield the highest accuracies. After a universal tree is generated, we used the training data of each subject to determine decision thresholds for internal nodes of the tree. The thresholds for each subject have to be determined individually since properties of each set of data are different from other sets. For the case of context-guided classification, we first performed context classification and follow up by activity classification.

Table 4 summarizes classification accuracy in each context. The results indicate that without context information, our proposed tree provides good accuracy in most of the activities, except some activities involved with upper body movement. However, it can be seen that with the integration of context information, there is an overall enhancement in classification accuracy due to the reduction of search space and the size of each classifier. In addition, for those activities involving upper body movement such as typing, writing and eating, a large improvement is observed.

TABLE 5. SENSOR REQUIREMENTS

	Home	Lab	Cafeteria	Outdoors	Class	Bus	Gym	Library
Right Knee	X			X			X	
Right Ankle		X	X	X	X		X	X
Waist	X		X	X		X		X
Wrist	X	X	X	X	X			X

3) *Potential for Energy Saving*

The context driven approach allows us to adjust sensor policy dynamically according to detected context, and thus brings the potential to improve energy efficiency and operation lifetime. Based on scenarios tested in Table 2, we formed a sensor requirement profile (Table 5), in which blank cells indicate sensors that can be safety turned off without affecting the accuracy of a given context. We evaluated the improvement of system operation time by adopting sensor activation schedules based on contexts. A subject's typical daily schedule on workday and weekend is shown in Fig. 5 and 6, with the x-axis starting at 8am. Fig. 7 shows the comparison of total operation time of context driven sensor activation and continuous sensor activation, which indicates the potential benefits of context driven sensor energy management. This benefit would be more obvious in the situation where many sensors are deployed but only some small subset is required in each context.

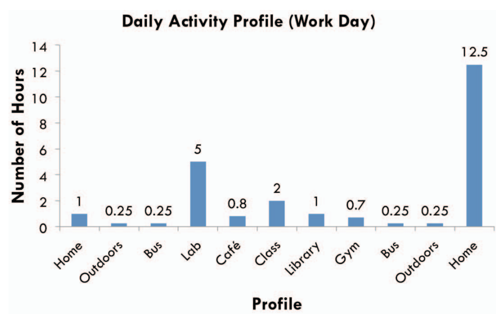

Fig. 5. User profiles (Residential)

TABLE 4. ACTIVITY CLASSIFICATION ACCURACIES

Context	Proposed Tree	Proposed Tree with Context	Improve
Home			
Sleeping	64.47	97.29	32.82
Slouching	83.18	97.83	14.65
Eating	91.03	94.24	3.21
Walking Around	92.24	100	7.76
Sitting	83.15	91.42	8.27
Lab			
Sitting	75.29	84.59	9.3
Walking Around	93.82	99.81	5.99
Typing	19.05	92.62	73.57
Writing	32.89	70.74	37.85
Cafeteria			
Standing	98.81	100	1.19
Walking Around	92.19	98.22	6.03
Sitting	72.89	93.27	20.38
Eating	86.75	94.73	7.98
Class			
Walking Around	98.01	100	1.99
Writing	33.22	92.77	59.55
Sitting	97.53	97.53	0

Context	Proposed Tree	Proposed Tree with Context	Improve
Outdoors			
Walking Normal	91.17	93.13	1.96
Running	83.26	100	16.74
Upstairs	82.48	96.84	14.36
Downstairs	61.09	74.62	13.53
Standing	100	100	0
Sitting	77.23	98.15	20.92
Gym			
Cycling	90.7	98.43	7.73
Running	100	100	0
Walking Normal	100	100	0
Sitting	81.39	93.68	12.29
Library			
Sitting	81.71	98.47	16.76
Walking Around	93.28	96.14	2.86
Standing	100	100	0
Writing	42.79	75.52	32.73
Bus			
Sitting	50.36	95.27	44.91
Standing	78.44	96.57	18.13

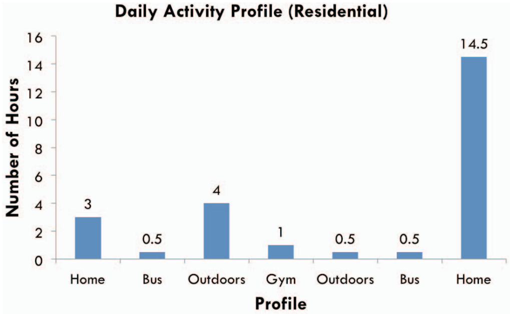

Fig. 6. User profiles (Residential)

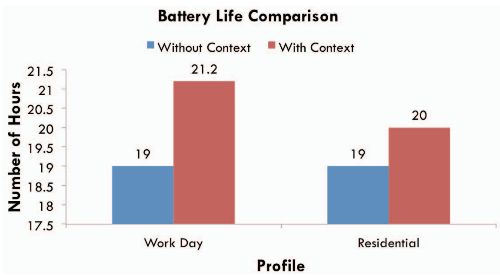

Fig. 7. Battery life comparison

V. CONCLUSION

In this study, we demonstrated the advantages of integrating the context and universal hybrid tree classifier for activity classification. The proposed universal hybrid tree structure provides flexibility at the expense of the use of intuition or domain knowledge in its construction. The effort is rewarded in relative ease of tuning it to new individuals with modest additional training. For scaling to a large population, this could lead to a drastic reduction in effort. In addition, the new context driven approach not only brings improvement in classification accuracy, but also provides the capability of controlling the activation and selection of sensors for energy saving. A number of future research directions are being pursued. Since our context driven approach depends heavily on the quality of context decision, it is of interest how to achieve precise context classification information without needing extensive training.

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