FEATURE EXTRACTION IN WIRELESS PERSONAL AND LOCAL AREA NETWORKS

RENE MAYRHOFER, HARALD RADI and ALOIS FERSCHA
Institut für Praktische Informatik, Johannes Kepler University Linz, Altenberger Str. 69, 4040 Linz, Austria
Email: {mayrhofer,radi,ferscha}@soft.uni-linz.ac.at

Context awareness is currently being investigated for applications in different application areas of mobile computing. The integration of Bluetooth and Wireless LAN technologies into a vast of mobile devices — ranging from smartphones and PDAs to portable computers – has made user context sensing based on those technologies a feasible and promising approach. In this paper, we study which of the Bluetooth and Wireless LAN technology features (like radio-signal strength, device address management, etc.) can be exploited to derive user context, and develop a procedure how low level sensor data can be brought to application level context information. We introduce a method to automatically classify heterogeneous sensor data features with supervised or un-supervised classification methods. By defining two operations, a distance metric and an adaptation operator, any feature can be used as input for the classifier and can thus contribute to context detection.

1 Introduction

Common to most of the visions for next-generation computing are the paradigms of mobile computing and context awareness;[7] additionally, they all agree that user interfaces should become less obtrusive and "smarter" with regards to adapting to the user. Our approach is to add context awareness to applications, allowing them to adapt to the situation (*context*) at hand. One of the more recent definitions of context by Dey[1] is *any information that can be used to characterize the situation of an entity, where an entity can be a person, place, or a physical or computational object*, which we adopt in this paper. The goal is to derive high level context information from low level sensor data by following a three-step approach: data acquisition, feature extraction and classification. Starting from low level sensor data based on Bluetooth and Wireless LAN (*WLAN*), appropriate features (e.g. SNR, MAC addresses in proximity, access points in range, ESSID) are extracted and classified to yield high level user context information (e.g. busy, traveling, in a meeting, in the office, at lunch, at home, telephoning, etc.).

However, these sensors do not yield single, numerical values but data with a more complex structure. Some important information that can be extracted from these sensors is categorical and non-atomic, e.g. the list of MAC addresses which are currently in communication range. Nonetheless, it could provide useful information for determining the current user context via an automatic classification of all available sensor signals. If non-atomic values should be used as input to a classification algorithm which can only work with numerical inputs, they need to be coded. The standard procedure for dealing with categorical data is to code each possible sensor value as binary input to the classification algorithm. This has been applied successfully to categorical data with a bounded set of values (e.g. department), but is problematic when the set of possible values is not known in advance or too large to be coded with binary inputs (e.g. WLAN MAC addresses would need 2^{48} input dimensions to cover all possible values). Therefore, coding categorical data as numerical inputs does not seem to be the best solution and a better method should be found.

2 Related Work

In this paper, we concentrate on feature extraction from wireless network interfaces — an overview of our research on context awareness and prediction of user context has been presented elsewhere.[5,2] Although feature extraction and classification are well-known fields of research, most publications only cover numerical, continuous features. In the field of context awareness of mobile devices, Van Laerhoven described a system with custom sensors (e.g. accelerometers, light sensors), using minimum, maximum, mean and variance as features.[4] Because the restriction to numerical features severely limits the choice of sensors, we introduce a model for utilizing heterogeneous features (e.g. list of MAC addresses and WLAN ESSID) in a common classification step. For a Kohonen SOM, a method has been described to cope with heterogeneous input values.[6] However, the general case of context detection with heterogeneous features does not seem to have been covered before and is the main focus of our work.

3 Concept

To derive knowledge about the device/user context from raw sensor data, we follow the following steps:

1. Sensor data acquisition: Sensors provide data streams (time series) of measurements. Usually some physical values like RF signals are the base for measurements, but more abstract sensors like the currently active application can also be utilized. Besides wireless network interfaces, other common sensors available on typical mobile devices include a microphone, a brightness sensor (for automatic control of display brightness) and information about being connected to the docking station. Additional sensors like GPS, GSM, compass, accelerometer, tilt, temperature or pressure sensors can easily be added by connecting them via wire or Bluetooth.

2. Feature Extraction: From raw sensor data, information can be extracted by domain-specific methods, yielding multiple condensed data values, which are called *features* F with samples $f \in F$. During feature extraction, the available data is transformed, allowing it to be interpreted better. Usually, simple statistical parameters like the mean $\bar{x}$, standard deviation σ or higher moments are used as features for time series. For wireless networks, special features like the signal strength, the current WLAN ESSID or the list of access points in range are more appropriate.

3. Classification: Several features extracted in the previous step together compose a *feature vector* $F_1 \times F_2 \times ... \times F_n$, which defines points $\langle f_1, ..., f_n \rangle \in F_1 \times F_2 \times ... \times F_n$ in the multi-dimensional *feature space*. The goal of classification is to find common patterns in the feature space, which are called *classes* or *clusters*. Because a feature vector should possibly be assigned to multiple classes with certain *degrees of membership* (the "probability" that the feature vector belongs to a class), we utilize soft classification / soft clustering approaches. These approaches can be defined as mapping a feature vector of n different features to degrees of membership $u \in [0; 1]$ for m different classes: $F_1 \times F_2 \times ... \times F_n \to [0; 1]^m$

4 Feature Extraction

This paper concentrates on the second step and its interface to the third. Based on the specific feature extractor, a feature's class is, within this paper, defined as one of the following:

- nominal (categorical, qualitative): set of values on which no order relation has been defined. A special case are binary features with $F = \{0, 1\}$.
- ordinal (rank): set of values with a defined order relation.
- numerical (quantitative): ordered set of values with defined $+$ and $\cdot$ operations (an algebraic field). We can further distinguish according to the density of values in the set between discrete ($F \subseteq \mathbb{Z}$) and continuous ($F \subseteq \mathbb{R}$) features.
- interval: intervals instead of single values, e.g. $F \subseteq \operatorname{Pot} \mathbb{R}$.

When deriving context from wireless network interface data, we can identify a number of features from different categories, which seem to be relevant for mobile devices:

- Bluetooth: list of MAC addresses in range (nominal), number of MAC addresses in range (numerical/discrete)
- WLAN: list of access point MAC addresses in range (nominal), number of access point MAC addresses in range (numerical/discrete), current ESSID (nominal), associated to access point (binary), access point MAC address associated to (nominal), signal strength (numerical/continuous), transmission rate (numerical/discrete)
- GSM: list of GSM cells in range (nominal), number of GSM cells in range (numerical/discrete), current provider (nominal), current GSM cell (nominal), signal strength (numerical/continuous)

This list is not exhaustive, but should provide a meaningful view of the wireless networks context around the mobile device.

The feature vector $\langle f_1, ..., f_n \rangle \in F_1 \times F_2 \times ... \times F_n$ formed by an arbitrary combination of these features is highly heterogeneous, making it necessary to cope with the different types and semantics of the feature space dimensions in the classification step. From our comparison of different classification methods, we concluded that only two operations are necessary on an abstract feature F (this matches the results of other research[6]). The first is a similarity measure or *distance metric*, which has to be defined on every feature, i.e. on every dimension of the feature space.

$$d : F \times F \rightarrow [0;1]$$
$$\delta = d\left(f_1, f_2\right)$$

defines the distance between two samples of the feature F, normalized to $[0;1]$; the normalization is not necessary, but eases the classification step. A general distance metric has to fulfill non-negativity, identity, commutativity (symmetry) and the triangle inequality. We would like to note that the range of values in F can change (increase) during runtime, thus the distance of two given samples can also change due to the normalization. Although this is no problem with the classification methods we are investigating, others might need modifications. Additionally, the second operator adapts/modifies a point (in one dimension) and is necessary for supervised and un-supervised learning.

$$\alpha : F \times F \times [0;1] \rightarrow F$$
$$f' = \alpha\left(f, g, a\right)$$

modifies the sample $f \in F$ towards $g \in F$ by a learning/adaptation factor $a \in [0;1]$. With these two operators, supervised and un-supervised classifiers like the Kohonen Self-Organizing Map (*SOM*) or K-Means clustering can be applied to any feature which defines them.

In the following, we will give example definitions of both operators for a selection of the features listed above.

1. signal strength: The Bluetooth, WLAN or GSM signal strength is a numerical, continuous variable; therefore, we can apply the L1 (Manhattan) metric:

   $$d\left(f_1, f_2\right) := \frac{|f_1 - f_2|}{F_{max} - F_{min}}$$

   and

   $$\alpha\left(f, g, a\right) := f + (g - f) \cdot a$$

   for samples $f_1, f_2, f, g \in F$ with maximum and minimum values F_{max} and F_{min}.

2. associated to access point: This is a binary variable with values $f \in \{0, 1\}$; the distance operator can thus be simplified to the equality relation:

   $$d\left(f_1, f_2\right) := \begin{cases} 1 \ if \ f_1 = f_2 \\ 0 \ if \ f_1 \neq f_2 \end{cases}$$

   A simple adaptation operator could be defined as

   $$\alpha\left(f, g, a\right) := \begin{cases} f \ if \ a \leq 0.5 \\ g \ if \ a > 0.5 \end{cases}$$

   which only sets it to one or the other value, depending on the current value of the adaptation factor a. A better, although more complicated variant is to implement the operator with state so that it internally sums up a and only modifies the feature value after a reaches a certain threshold.

3. number of MAC addresses in range: The number of Bluetooth peers or WLAN access points in range is a numerical, discrete variable; we define

   $$d\left(f_1, f_2\right) := \frac{|f_1 - f_2|}{F_{max}}$$

   and

   $$\alpha\left(f, g, a\right) := \begin{cases} \lceil f + (g - f) \cdot a \rceil \ if \ f \geq g \\ \lfloor f + (g - f) \cdot a \rfloor \ if \ f < g \end{cases}$$

   for a number of already detected, different MAC addresses F_{max}.

4. list of MAC addresses in range: The list of Bluetooth peers or WLAN access points in range is a nominal, non-atomic variable. Due to the non-atomicity, there are various ways for coding; but each value $f \in F$ can be seen as a set of addresses. For a list of addresses, we apply the Hamming distance (the number of different addresses)

   $$d\left(f_1, f_2\right) := |(f_1 - f_2) \cup (f_2 - f_1)|$$

   when f_1 and f_2 are sets. The adaptation operator can be arbitrarily complex; our current operator changes, according to the adaptation factor a, a randomly selected fraction of the different addresses in f and g to the addresses in g by adding and/or removing addresses in f. For performance reasons, we chose to code the list of MAC addresses as a bit vector, where already seen addresses correspond to bit positions.

5 Classification

Using these definitions, arbitrary classification methods can be used to classify feature vectors and thus derive context from wireless sensor data. Because of the resource limitations of mobile devices, it is not possible to record all sensor data; thus, batch algorithms which iterate over the whole data set at once can not be applied. On-line algorithms incorporate each input sample as soon as it arrives from the sensors and are therefore suited better. Another issue for context recognition with mobile devices is that algorithm parameters must either be constant or self-adaptive during run-time; a continuously decreasing "learning rate" as it is used in many algorithms like the SOM during its learning phase prevents an algorithm from running constantly without interruptions. For embedded systems, a distinction between learning and recognition phases does not seem to be appropriate.

Currently, we use the Growing Neural Gas[3] (*GNG*) clustering algorithm for our experiments because it offers a number of advantages over other methods, notably an unlimited number of clusters, un-supervised classification and clusters with arbitrary shapes. A short comparison of suitable clustering algorithms shows that GNG seems to be a good choice for mobile devices.[5]

All of the features listed above contribute to the classification and can therefore increase the quality of the context detection. Every feature has an unique view of the environment, yielding additional information that others can not provide. The combination of the features not only provides spatial context (in terms of qualitative localization), but also other aspects like the number of people standing nearby (if they carry Bluetooth-capable devices, which is becoming common). This can be used to determine non-spatial context, e.g. to detect a meeting situation.

6 Conclusion

We have considered to exploit Bluetooth and WLAN technologies as sensors for deriving user context. Current generations of mobile devices like smartphones or PDAs are equipped with these technologies, making them commonly available. In our approach, low level sensor data is transformed to high level context information in three steps: data acquisition, feature extraction and classification. Because some extracted features are not numerical, but categorical or even non-atomic, standard approaches to code them for the classification step do not seem appropriate. Experimental data has been collected using Bluetooth and WLAN as spatial proximity sensors over 10 days and was analyzed with K-Means and SOM classification algorithms using standard input coding. The preliminary results of our experiments suggest the use of a different input coding, e.g. the approach presented in this paper. An interface for using our feature extraction code including the different distance metric and adaptation operations in Matlab is currently being created and will allow direct, quantitative comparisons with standard algorithms. For future work, we will concentrate on the labeling of context classes by the user and on prediction of future user context, which will allow the development of proactive applications.

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