

Chapter 23

Estimating which Object Type a Sensor Node is Attached to in Ubiquitous Sensor Environment

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ABSTRACT

By simply attaching sensor nodes to physical objects with no information about the objects, the method proposed in this paper infers the type of the physical indoor objects and the states they are in. Assuming that an object has its own states that have transitions represented by a state transition diagram, we prepare the state transition diagrams for such indoor objects as a door, a drawer, a chair, and a locker. The method determines the presumed state transition diagram from prepared diagrams that matches sensor data collected from people's daily living for a certain period. A 2 week experiment shows that the method achieves high accuracy of inferring objects to which sensor nodes are attached. The method allows us to introduce ubiquitous sensor environments by simply attaching sensor nodes to physical objects around us.

INTRODUCTION

In ubiquitous sensor environments, we can effectively manage behaviors of applications by using information about the type of object a sensor node is attached to. In fact, many studies focus on

context-aware services that depend on the types, states, and state changes of physical objects in a home where sensor nodes are attached to the objects. An example service is one that issues a caution when a door is left open at midnight. However, when hundreds of sensor nodes are attached to objects, we cannot manually tell the nodes what types of objects they are attached to.

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The advances that have been made in wireless communication, sensing, and power-saving technologies mean it will not be long before we can employ many small and cheap sensor nodes. In anticipation of such a development, we propose a system framework named *Tag and Think* (TnT).

With this approach we can automatically infer the types of objects and the states they are in simply by attaching general-purpose sensor nodes to indoor objects about which we have no information. In TnT, after collecting sensor data from a general-purpose sensor node that has been attached to a physical object for a certain period of time, the method determines the presumed model of the object type from prepared models that matches the sensor data. Also, the method estimates the state changes that occurred in the object throughout the period. For example, if a sensor node is attached to a door, our method infers the type of object to which the node is attached and detects state changes of the door, e.g., ‘door open’ and ‘door close.’ Converting raw sensor data into human understandable symbols such as ‘door open’ is important in human-machine symbiosis. General-purpose sensor nodes equipped with such widely used sensors as accelerometers and illuminometers have an advantage over object-specific nodes in terms of deployment cost. They can reduce the time and effort spent on introducing sensor network environments because the sensor nodes are simply attached to objects. On the other hand, most object-specific sensors such as magnetic door sensors and window sensors are required to be installed in appropriate position and direction. Accelerometers and illuminometers are most common in entertainment, security, and maintenance purposes, have been growing in importance. This means we can expect both their cost and size to decrease. As ubiquitous and sensor environments become more common, object-specific nodes will be embedded in many objects during the manufacturing process. However, before the environments will become common, our framework may be useful as the first step to the ubiquitous

computing deployment. We introduce and evaluate a method designed to infer object type and state changes by using knowledge constructed based on a person’s common knowledge.

BACKGROUND AND GOAL

Obtaining states and state changes of objects is becoming possible by attaching cheap sensor nodes to indoor objects (Intille et al., 2003). This has triggered surveillance studies concerned with end-user sensor installation. The following comments on end-user installation can be found in Beckmann (2004): “the monetary and time cost of professional installation is prohibitive for non-critical applications” and “leveraging the fact that an end-user is a domain expert for his own home can lead to an application better tailored to his needs or preferences.” However, some problems have arisen as regards end-user installation. For example, Beckmann et al. (2004) revealed that some end-users could not understand the meaning of the association itself in the experiment, where a bar-code reader and bar-codes attached to sensor nodes were used to associate a sensor node and the type of object to which the node is attached. Also, it takes an average of 84 minutes for participants to deploy ten sensor nodes in an experiment (this is not only the time needed for the association). If there are dozens of nodes, manual association will become a burden for end-users. Tapia et al. (2004) also mention that installation without association would dramatically reduce the installation time when engineers install the sensors in a home.

Our goal is to infer what type of object a sensor node is attached to simply by attaching the sensor node to the object. To achieve this, we prepare models of object types that can be used in every end-user’s home throughout the world. By comparing the models with sensor data obtained from a sensor node for a certain period and by estimating a presumed model that matches the sensor data,

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