Analysis of Fine-grained Urban Temperature Collected with a Sensor Network

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***Abstract*— Temperature in a metropolitan area exhibits a complicated tendency. Rather than geographical closeness, structures of a group of buildings and streets can affect changes in temperature. To identify the tendency of fine-grained distribution of temperature, we installed a densely-distributed sensor network called UScan. In this paper we describe a system of UScan and effective placement of sensors based on our experiment in downtown Tokyo. We also propose a clustering method to analyze the correlation between the tendency of temperature and the environmental factors.**

I. Introduction

Since the vision of Smart Dust [1], [3], researchers have explored many applications for wireless sensor networks ranging from healthcare to environmental monitoring [4]. Although we cannot say that environmental monitoring is considered a killer application of wireless sensor networks, its possibility of enhancing our daily lives is still expected. Our group is interested in applying a wireless sensor network to people's urban life by providing information about climate in a geographically fine-grained way. One can find an ambient walking route and an "oasis" spot, a windy and low temperature location in hot summer. However, the distribution of temperature and the strength of wind is complicated among tall buildings in a city. To enable such applications for ambience, weather-related sensors need to be placed in a fine-grained manner. We have created a system called UScan by which temperature in fine resolution was measured in downtown Tokyo. The UScan consists of a server to collect temperature data, wireless bridges, and uParts [5], [6]. We used approximately 200 uParts and collected data during July and August 2007. This paper shows the result of our experiment using UScan and discusses the relationship between the structure of the environment and observed temperature.

The rest of the paper is organized as follows. Sections 2 and 3 describe the motivation of UScan and its system architecture, respectively. Section 4 discusses the actual placement of UScan sensors. Sections 5 and 6 show the results of experiments and the analytical methodology. Section 7 discusses the analyzed results. Finally, Section 8 describes the conclusion.

II. Motivation

There is a need for investigating real-time, real-world information in cities. CitySense [2] is a trial for acquiring such information. In contrast to CitySense, we are interested in finer granularity of sensing for providing pedestrians with accurate navigation. Density of people in streets and how direct sunlight is injected into a street can affect ambience for pedestrians. Thus we desire to expand fine-grained wireless sensor network inside a city. A similar fine-grained sensing has been done by Tokuda et al. [7], but the experiment was conducted inside only one park. The other motivation is obtaining systematic knowledge about placement of sensors. If we aim at uniformly dense deployment, the cost of deployment increases. We can omit sensor at some places if we identify similarity of sensed data beforehand. In this paper, we study a clustering technique for grouping similar sensed data.

III. System Architecture

In contrast to CitySense [2], we are interested in finer granularity of sensing for providing pedestrians with accurate navigation. UScan system architecture is shown in Fig. 1. First, uParts, sensing devices, obtain temperature values and send them to a receiver called WBridge at an interval of 30 seconds. OpenWRT is installed on the WBridge and contains two processes: Teco and Perl modules. The Teco module transfers the data to the Perl module using a UDP socket. Once the Perl module receives the data, it extracts temperature data and sends to UScan server. UScan server receives and inserts the data into UScan Database (DB). Munin Plug-in monitors the database and creates a graph. We have selected eight observation points as shown in Fig. 2. Our policy is to let each observation point characterize an environmental feature.

IV. Installation of Sensors

In urban areas such as downtown Tokyo, there are various factors to determine the environment. The existence of buildings, parks, and trees affect the flow of wind and shaded areas. In this section, we explain how we consider installation of sensors.

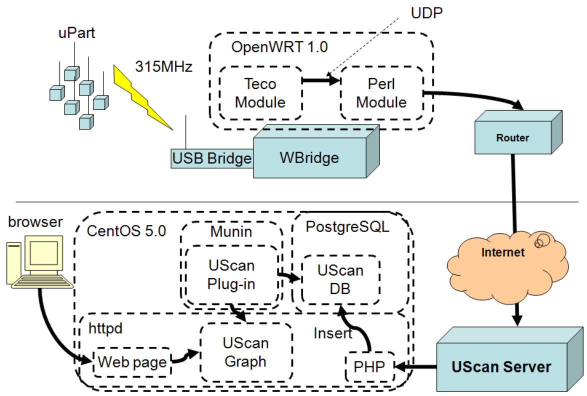

Fig. 1. System architecture of UScan experiment.

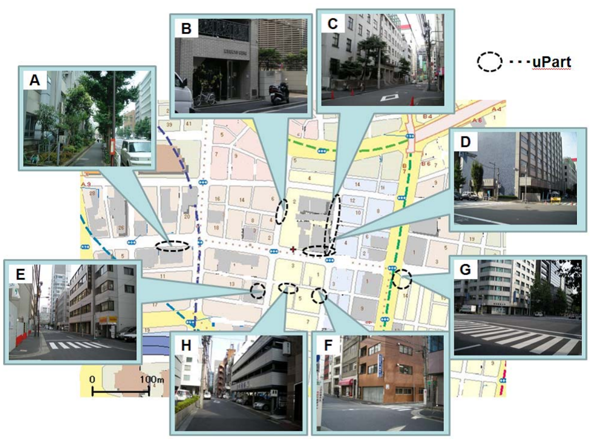

Fig. 2. Installation points of sensors.

A. Placement of Sensors

We have selected eight observation points as shown in Fig. 2. We have set the following policy: each observation point characterizes an environmental feature. For instance, both points G and A are located at a pedestrians' path of a broad street but they differ in whether shaded areas due to trees exist or not. Since tall buildings can block sunlight, direction of observation points is also an important factor for temperature. Thus, our observation points include every direction; North, East, West and South. In this way, every observation point has different environmental factors. The result of this experiment is described in Section 4.

For actual installation, we need to adjust the setting point of sensors to conduct correct measurements. Since direct sunlight affects the temperature sensor of uParts, sensors need to be placed in a shadow area all day. For example, points b and c are affected by direct sunlight as shown in Fig. 3. Hence, these points cannot be candidates for setting sensors. Point a is the most suitable place for setting sensor in Fig. 3. Similarly, point d is not appropriate for setting sensors in Fig. 4, where a sensor should be set at point f. We set 200 uParts with this policy for conducting the experiment.

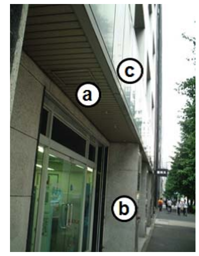

Fig. 3. Sensor installation 1.

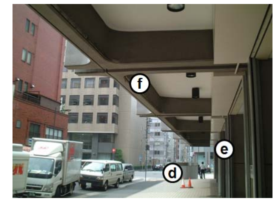

Fig. 4. Sensor installation 2.

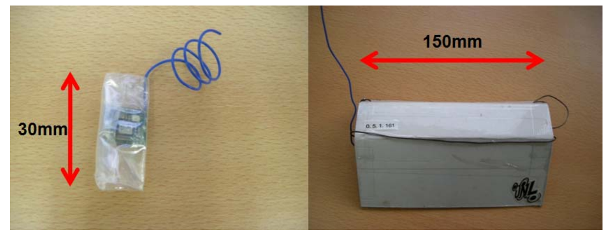

Fig. 5. uPart package.

B. Package of Sensors

To enable fine-grained urban sensing, we need to set many sensors in the observation points. However, as shown in Figs. 3 and 4, setting points of sensors are restricted. Therefore, we made two types of packages for setting sensors as shown in Fig 5. A package in the right-hand side is utilized for setting to roadside trees or rain pipes. This package focuses on shutting out direct sunlight and can also be waterproof. Temperature sensor is covered with a white roof which is made from waterproof paper. Additionally, since the sensor package is placed at a high point, to avoid falling of the sensors, the sensor package must be light. A package in the left-hand side is a simpler one. This package is utilized for setting sensors on the wall of building. To enable setting on the building wall, this package is very small and light.

V. Experimental Results

The results of experiment are shown in Fig. 6. These graphs show clear difference in temperature according to the observation points. For example, the temperature difference is as high as 9 degree Celsius at 14:00. There are also two kinds of observation points, i.e., points have peak temperature in the morning and afternoon. These observation points are in the area of 1-km radius. However, according to the Fig. 6, we can see the clear differences among graphs. This difference of temperature is caused by various environmental factors such as roadside trees, width of roads and direction. The experiments validate the importance of fine-grained sensing. In addition, There are interesting relationship between weather and temperature graphs which will be discussed later.

VI. Analysis of Fine-Grained Temperature Data

To understand fine-grained sensor data, we need an effective technique to analyze collected data. There are many analyzing techniques including classification, interpolation, and other

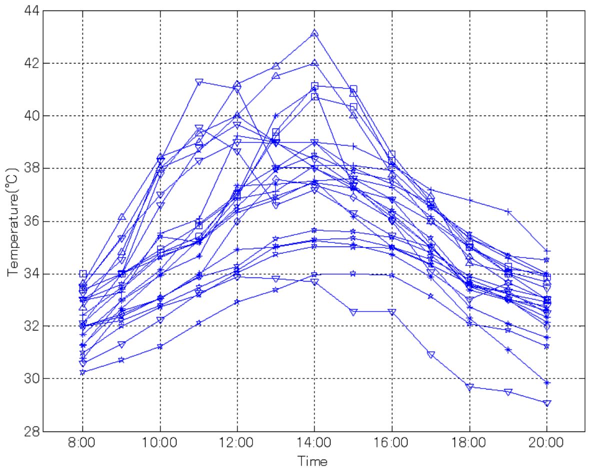

Fig. 6. Temperature changes (August 22, 2007).

mathematics-based ones. Here, we clarify the environmental factor from this experiment through clustering analysis.

A. Skewness and Kurtosis

There are a large amount of data from fine-grained urban sensor networks. It requires high processing cost to analyze detail of these data. Therefore, data analysis becomes time consuming and difficult. Clustering techniques divide data into several groups where data in the same group are similar. It helps to study large data faster and more efficient. In this paper, we calculate a skewness and a kurtosis of the time series temperature data to study characteristics of temperature. We then plot the results in a 2D-graph where clustering of temperature data is determined. The skewness and kurtosis for clustering purpose are defined as follows.

- *Definition of Skewness*
  Skewness represents the skewing rate of the temperature graph with respect to a standard time. The standard time is the middle point of time series data, i.e., the median of measured time. Skewness is defined as an average of weighted temperature. The weight (α) is decided by the number of data (n) and index (i) of time series data. In particular, the weight starts from $-\frac{n}{2}$ for the first data in time series, and increases one for each following index. The weight for the last index is explicitly $\frac{n}{2}$. The calculation of skewness is expressed in Equation 1.

$$Skewness = \frac{1}{n}\sum_{i=1}^{n} \alpha_i T_i, \tag{1}$$

  where T_i is the temperature data at time index i. According to the above equation, if a temperature graph distorts or bends to the right side, a value of skewness is positive, otherwise negative. Additionally, the more the time index is far from the standard time, the more the weight for calculation becomes high. As a result, the impact of graph distort appears apparently in the defined skewness.

- *Definition of Kurtosis*
  Kurtosis represents the variation of temperature by showing an average value of the variation. The more the variation is high, the more the value of kurtosis is high. Kurtosis is defined as shown in Equation 2.

$$Kurtosis = \frac{1}{n}\sum_{i=1}^{n-1} |T_{i+1} - T_i|. \tag{2}$$

B. Clustering Area

The skewness and kurtosis of temperature data calculated by the above equations are plotted in 2D graph where the horizontal axis represents skewness and the vertical axis represents kurtosis. Here we determine standard values of skewness and kurtosis for clustering purpose. If a temperature graph is bilaterally symmetric with respect to the standard time, the skewness is zero. Therefore the standard value of skewness is set to zero. Based on the characteristics of temperature data, the standard value of kurtosis is set to one. Clustering is done by dividing the 2D graph into four areas (clusters) based on the standard values of skewness and kurtosis.

The definitions of four clustering areas are as follows.

Area I : $Skewness > 0$ and $Kurtosis \geq 1$.

Area II : $Skewness \leq 0$ and $Kurtosis > 1$.

Area III : $Skewness < 0$ and $Kurtosis \leq 1$.

Area IV : $Skewness \geq 0$ and $Kurtosis < 1$.

We analyze temperature data by considering distribution of data in the defined clusters.

C. Clustering Map

Fig. 7 illustrates the clustering results of temperature data collected on August 22, 2007. Each symbol in the figure indicates the sensors being set at the same location with the same direction.

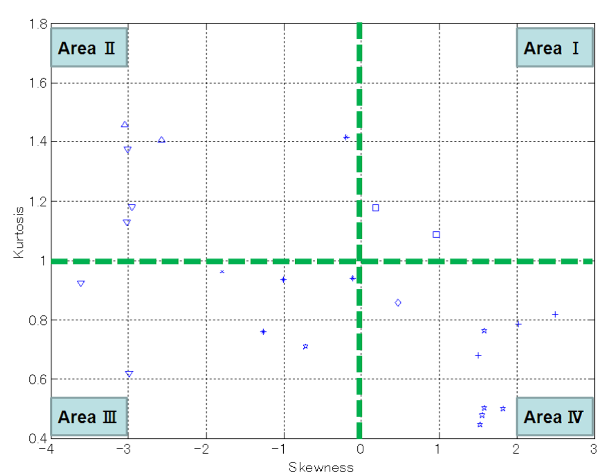

Fig. 7. Clustering map (August 22, 2007).

TABLE I

PERCENTAGES OF SUNSHINE

	21-Aug	22-Aug	23-Aug	24-Aug	25-Aug	26-Aug	27-Aug
8:00	65	100	0	5	25	50	90
10:00	75	100	10	0	85	85	80
12:00	100	100	50	25	80	75	100
14:00	100	100	40	25	100	100	20
16:00	100	80	15	50	80	90	25
18:00	40	20	0	5	10	0	20
20:00	0	0	0	0	0	0	0

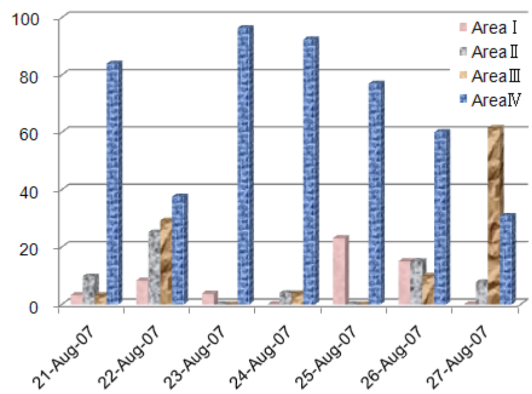

Fig. 8. Clustering results.

VII. DISCUSSION

In this section, we discuss the clustering results.

A. *Assumptions*

We perform relative data analysis by comparing with a standard date. Temperature data tends to be influenced by the weather. In additional, sunshine also influences temperature data. Therefore we decide the standard date based on the condition of sunshine. Table I shows period of sunshine in percentage every two hours. The data in the table is taken from Japan Meteorological Agency [8]. According to the table, sunshine on August 22 is the most stable (longest period) in comparison to the other days in the week (from August 12 to August 27). Thus the following discussions are compared with the standard date, August 22. Since we analyze temperature data from 8:00 to 20:00, the standard time for calculating skewness is 14:00.

B. *Comparative Study (Fig. 8).*

- 21st, 23rd, 24th, and 25th August 2008.
  The temperature graphs of these days tend to distort to the right side of the standard time in comparison with that of the 22nd because most of data are in Area IV. The right bias means the temperature after the standard time was increasing. According to the real weather information, these days had bad weather before the standard time. It is also interesting to consider the effect of sunshine period during these days. Before the standard time, there was lightning storm in the 23rd and the sky was obscure in the 21st. According to the differences of sunshine and weather, the temperature graph of the 23rd is more distorted to the right side than that of the 21st.
- 27th August 2008.
  In contrast to the above discussion, the temperature graph of the 27th distorts to the left side because most data fall in Area III. We can infer from the clustering results that the temperature was decreasing after the standard time. It is explicit from Table I that the sunshine period decreased after the standard time.
- Setting point and direction.
  There is high relationship between the pattern of temperature change and the setting point and direction of sensors. For example, according to the clustering map (Fig. 8), the triangle marks show high kurtosis because the sensors was set to face a broad street in the south direction where temperature change is known to be highly intense.

VIII. CONCLUSION

In this paper we have described our experiment of UScan. From the experiment, we can detect differences of temperature caused by various environmental factors. We have proposed a clustering method to classify temperature changes into four patterns The classification enables the cost-effective data analysis without involving high-complexity computation. Based on the clustering results, we can find similarity in the trend of temperature change in similar environment. This suggests that we can efficiently lay sensors in a few places by considering similarity. As one of our future works, we will analyze the acquired data in more detail for creating efficient fine-grained urban sensing applications.

ACKNOWLEDGMENT

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