Maximizing Users Comfort Levels through User Preference Estimation in Public Smartspaces

Abstract—**In recent years, the ubiquitous computing system attracts people's attention as the system to provide useful services (e.g., automatic temperature control) without explicit operations by users. There are many existing methods for controlling appliances according to the user's preference by describing each user's preference and rules. However, these methods cannot be applied to public spaces where many general users with different preferences exist. In this paper, we propose an architecture and a method for controlling devices that affect the users comfort level (e.g., air conditioner) in public smartspaces. Our goal is to maximize the comfort level of users with various preferences by appropriately controlling devices. Furthermore, to efficiently collect user preferences for the large context domain, we propose a method for estimating user's comfort level for an unknown context from the already known user's comfort level for some contexts and the distance to those contexts. To evaluate the proposed estimation method, we conducted the questionnaire to measure the user's comfort levels for various contexts, and evaluated the accuracy of the proposed estimation method by comparing the measured sample with the estimated one. As a result, our method estimated user's comfort level in error within 1 among 4 comfort levels.**

Index Terms—**user preference estimation, context-aware device control, information appliances, smartspace**

I. INTRODUCTION

Recently, design and development of ubiquitous computing systems is getting easier thanks to remarkable progress of sensor networking technology and device technology[1][2].

In the ubiquitous system, many embedded devices with sensors and actuators are deployed in various spaces such as home, office, railway station, and so on. These devices identify *context* comprising user location, user preference, temperature, light intensity, and so on, in cooperation with each other and allows the ubiquitous system to work according to these context values. Therefore, a space embedding the ubiquitous system called *smartspace* can provide useful services without explicit operation of users. The main objective of smartspace is automated device control in consideration of contexts, called *context-aware control*. For context-aware control, not only providing service for convenience in our daily-life environment but also saving energy consumption in device control such as search and shutdown of disused devices is expected.

There are some studies on context-aware device control that adapt to dynamic context change [3][4][5]. In [4], Iwamoto, et al. proposed a framework for taking snapshots of application (service) state. This framework allows a user to continue to use the same service in another space. In [5], Nishigaki, et al. proposed a rule-based framework for context-aware device control, called CADEL. CADEL can detect conflict between rules, automatically. Therefore, users can easily describe a consistent device control scenario.

These existing frameworks and systems allow users to easily control devices in a context-aware manner under specific environments with specific users. However, they, in advance, need device control rules and priority among rules depending on user preferences. However, for context-aware device control in a public space where general users with unknown preference come and go, it is difficult to describe rules and priority among them. Therefore, we need a new context-aware device control method for arbitrary environment and general users in order to diffuse ubiquitous computing systems.

In this paper, we suppose spaces for context-aware device control with general users, called *target spaces*. In addition, we assume that users have various preferences on temperature, humidity, sound volume, light intensity, favorite TV genre, and so on. Under these assumptions, our goal is to maximize the comfort level of all users in each target space. To achieve this goal, we propose a context-aware device control method and user preference estimation method.

In the proposed device control method, we assume that there is a server for controlling devices (e.g., air conditioner, lamp, etc) in each target space. This server has information of the target space such as installed devices, context of the space obtained from embedded sensors, and so on. In addition, we assume that each user is equipped with a mobile device which can send the user preference information to the server when the user enters the space. We assume that user's context consists of user's activity status (e.g., busyness, mental state, etc) and physical quantities values (e.g., temperature, humidity, light intensity, etc) on the present location. In addition, each user has a comfort level for each physical quantity value or a device's state like TV's showing channel of a context. We call the pair of a context and the comfort levels for the context, *user preference information*. Users move over multiple different spaces. We assume that users have different preference depending on the place and the situation. For example, the user's preference is different between an office and a home.

In order to allow a server to control devices based on the preference information of all users, the users' mobile terminals have to transmit the preference information for all possible contexts. However, the context domain is very large, and it is very difficult to collect comfort levels for each user and for all the contexts. Therefore, we propose a user preference estimation method that complements the comfort level for an unknown context from the known pairs of comfort levels and

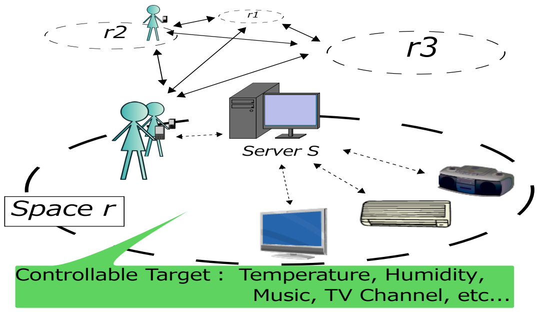

Fig. 1. Proposed Method Model

contexts and distances between the unknown context and the known ones. Therefore, the user's mobile terminal can get a user preference information for arbitrary context when there is preference information for a sufficient number of contexts.

To evaluate the proposed estimation method, we conducted questionnaires to measure the user comfort level for various contexts, and evaluated the accuracy of the method by comparing the measured sample with the estimated one. As a result, our method estimated the user comfort level in error within 1 among 4 comfort levels.

The remainder of this paper is structured as follows. Sect. II defines the target environments. We present the context-aware device control method in Sect. III. We describe the method of measurement and estimation of the user preference information in Sect. IV. We provide the architecture to realize the proposed methods and experimental validation in Sect. V and Sect. VI, respectively. Finally, we conclude the paper in Sect. VII.

II. Assumptions

Let R denote the set of target spaces. For each space $r \in R$, there is a server sv_r. In each target space $r \in R$, there is the set of *controllable targets* comprising temperature, humidity, TV channels, and so on, which we denote by T_r. Let U denote the set of users with mobile terminals capable of wireless communication. Each user u can go in and out freely each space r. Each user u has the preference information denoted by $u.pref$. We describe details about the user preference information in Sect. IV.

Each user u in a target space r sends preference information $u.pref$ to server sv_r when entering r. Let D_r denote the set of controllable devices in r. Let d_{t_r} denote the device of D_r that can control an item t_r of controllable targets T_r[1]. Each device d_{t_r} has the set of *target values* for t_r, denoted by $V_{d_{t_r}} = \{value_1, value_2, \ldots, value_n\}$. $V_{d_{t_r}}$ is given in advance.

A. Definition of context

The context includes various factors, such as surrounding conditions (e.g., temperature, humidity, location, event, etc), user's activity, and so on. We assume that these factors are independent, and define the context as the set of factors, as follows.

$$c = (e_1, e_2, \cdots, e_m)$$

Here, note that e_i is the value of i-th factor, such as temperature. The context c includes factors of all controllable targets T_r.

We show below an example of user's context c and controllable targets T_r in space r.

$$c = (\textit{temperature}, \textit{humidity}, \textit{location}, \textit{mental state}, \textit{activity})$$

$$T_r = (\textit{temperature}, \textit{humidity})$$

We assume that each factor of context c has a value of the finite set of discrete values[2].

B. User preference information

We define that the user preference information $u.pref$ of user u is the set of the comfort level for each controllable target of T_r in each possible context c. Therefore, user preference for context c, denoted by $u.SA(c)$ is represented by a tuple $(sa_1, sa_2, \ldots, sa_{|T_l|})$ where sa_i is the comfort level for the value of i-th controllable target in c. In addition, we represent comfort level sa_i of the controllable target t_r in lv levels (for example, when $lv = 4$, sa_i is fine, good, fair, or poor). The user preference information $u.pref$ of user u for the set of all possible contexts denoted by C is defined as follows.

$$u.pref \stackrel{def}{=} \bigcup_{c \in C} u.SA(c)$$

In addition, we define the overall comfort level $u.sa(c)$ for context c of user u as the average comfort levels of $|T_r|$ controllable targets as follows.

$$u.sa(c) = \sum_{i=1}^{|T_r|} \frac{sa_i(c)}{|T_r|}$$

III. Context-Aware Device control method

In this section, we propose a context-aware device control method that maximizes comfort levels of all users in target space r. First, we formulate our target problem, as follows.

A. Problem definition

Let U_r and $SA(U_r)$ denote the set of users in the target space r and the sum of all users' comfort levels in U_r (called the *space comfort level*), respectively. In addition, Let $u.c$ denote u's context. Then, r's space comfort level is represented as follows.

$$SA(U_r) = \sum_{u \in U_r} u.sa(u.c)$$

Our target problem is to decide the values of controllable targets of $u.c$ for each user that maximizes the space comfort level. Thus, the objective function is defined as follows.

[1]If a device has functions that can control multiple items of controllable targets T_r such as temperature and humidity, we represent the device by multiple logical devices that control those controllable targets, respectively.

[2]We assume that the value domain of the controllable target which has continuous values such as temperature is discretized beforehand.

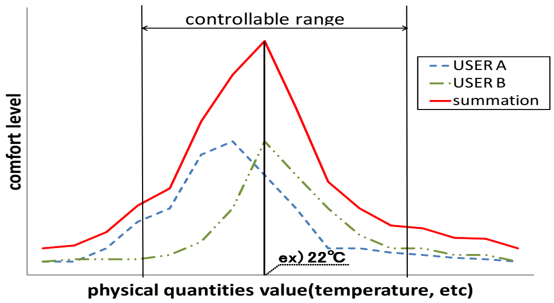

Fig. 2. Comfort Level Functions of Users

$$\text{maximize } SA(U_r)$$

We can modify the above objective function to that maximizing the minimum value of users' comfort levels (e.g., maximize $(Min_{u \in U_r} u.sa(c))$).

We denote controllable targets of context $u.c$ by $u.c_1, u.c_2, ..., u.c_{|T_r|}$. The following equation must be satisfied since the value of each controllable target should be the same among all users of U_r.

$$\forall u_1, u_2 \in U_r (u_1 \neq u_2) \forall i (1 \leq i \leq |T_r|),$$
$$u_1.c_i = u_2.c_i = d_i.value$$

Here, d_i is a device that can control the i-th controllable target.

B. Proposed method

We propose a context-aware device control method to solve the problem defined in the previous section. In our method, a user u transmits u's preference information $u.pref$ to server sv_r when entering space r. sv_r decides a value for each controllable target so as to maximize the comfort levels of all users and sets the decided values to the devices. Let d_{t_r} denote the decided value for a controllable target $t_r \in T_r$.

The following procedure is applied for each control target t_r of T_r. First, server sv_r generates a utility function as shown in Fig. 2 from each user's preference information. If sv_r does not know the comfort level for some values of a controllable target, it estimates the comfort levels for those values based on the method proposed in Sect. IV-B. Second, sv_r sums up comfort level functions of all users ("summation" in Fig. 2). Finally, it selects a value that maximizes comfort levels of all users and sets the value to a device.

IV. Measurement and Estimation of the User Preference

Our proposed method in Sect. III needs each user's preference information that includes comfort levels for all possible contexts. However, it is difficult to obtain the information since the context domain is very large. We can imagine that the marginal number of questions that the user can answer at a time is for 10 to 100 contexts. In addition, it is difficult to answer the expected comfort level for the context different from the current one, resulting in inaccurate preference information. Hence, we need to devise a method to obtain accurate information on user's comfort levels for all possible contexts through a reasonable number of questions.

A. User preference measurement

We propose a method that asks a user the context level of the current context c when the comfort level is not set for any context within distance len_{min} from c. In this method, each user needs to input the comfort level only when the current context significantly changes from the already appeared contexts. Therefore, the number of the user's inputting the comfort levels is suppressed. We estimate the comfort level for an unknown context u from the comfort levels for the known contexts near u. By setting an appropriate length to len_{min}, we believe that good estimation can be obtained.

B. Comfort level estimation

Let $level(v_{e1}, v_{e2})$ denote the function representing the difference degree between two values of a context factor. For example, this function has four level values (4: different, 3: somewhat different, 2: somewhat similar, 1: similar).

In the case of location, if the user's preference in "a seminar room" is completely different from "home" and "the seminar room" is similar to "a meeting room", we can define the level function for the user's location as follows.

$$level(\textit{home}, \textit{seminar room}) = 4$$
$$level(\textit{meeting room}, \textit{seminar room}) = 1$$

In the case of temperature, 1 degree Celsius difference does not affect the comfort level so much, but 10 degrees Celsius difference will cause the big difference in the comfort level. Thus, we can define the level function for the temperature as follows.

$$\begin{aligned} & \vdots \\ level(1°C, 2°C) &= 1 \\ level(2°C, 3°C) &= 1 \\ & \vdots \\ level(1°C, 11°C) = 4 & \\ & \vdots \end{aligned}$$

We suppose that the level function for each context factor can be generated by questionnaires and is given beforehand.

We define the distance between two contexts $c_1 = (e_{11}, e_{12}, ..., e_{1m})$ and $c_2 = (e_{21}, e_{22}, ..., e_{2m})$ as follows.

$$len(c_1, c_2) =$$
$$\sqrt{\frac{w_1 level(e_{11}, e_{21})^2 + \ldots + w_m level(e_{1m}, e_{2m})^2}{w_1 + w_2 + \ldots + w_m}}$$

Here, $w_1, ..., w_m$ are weights of context factors, respectively. We think that weights of context factors are different among users.

1) Estimation error: We use *estimation error* as the index for evaluating the accuracy of estimation or optimize weight. We discuss the weight optimization method in Sect. IV-B3.

Suppose that a user has the preference information for n contexts $c_1, ..., c_n$. For user preference $u.pref = \{SA(c_1, ..., SA(c_n)\}$, we calculate the estimation error Δ as follows.

(i) For each context c_i $(1 \leq i \leq n)$, estimate the comfort level for c with the preference information $u.pref - \{SA(c_i)\}$. We denote the estimated comfort levels for c_i by $SA_g(c_i)$.

(ii) Calculate $\Delta(c_i)$, that is the difference between $SA(c_i)$ and $SA_g(c_i)$.

(iii) Calculate the average difference Δ for $\Delta(c_1), ..., \Delta(c_n)$ and regard Δ as the estimation error.

2) Estimation of user preference: We propose the estimation method of the user preference for the unknown context c with existing preference information.

We estimate the comfort level $sa_{c,t}$ for controllable target t of context c from the existing preference information, as follows.

$$sa_{c,t} = \frac{1}{\sum_{i=1}^{n} \frac{1}{len(c,c_i)^2}} \sum_{i=1}^{n} \frac{sa_{c_i,t}}{len(c,c_i)^2} \tag{1}$$

Here, we estimate the comfort level of a new context c by mixing those of the known contexts while making the comfort level of the nearer existing context more influential.

3) Weight optimization: When we use the uniform weights for context factors, the contribution degree of each context factor will be also uniform. However, the comfort level of each context factor significantly changes depending on users and other context factors. Therefore, for accurate estimation of the comfort level, we optimize the weights for context factors by dynamically changing them. We optimize weights $w_1, ..., w_m$ as follows.

(i) Choose i-th weight w_i at random, and change the value of w_i

(ii) Calculate the estimation error Δ

(iii) Compare the new estimation error Δ with the old one Δ_{old}. If Δ is smaller than Δ_{old}, accept a value of w_i. Otherwise accept a value of w_i at probability p calculated by Formula (2).

(iv) Repeat (i)– (iii) the specified times.

$$p = \exp(-\alpha \frac{\Delta - \Delta_{old}}{\Delta_{old}}) \tag{2}$$

Here, we assume α to be a pre-specified constant. When α is big, estimation error Δ converges early because acceptance rate p becomes low. However, it increases the chance of reaching a local optimum. In our experiment, we use $\alpha = 1000$.

V. System Architecture

We propose a system architecture for realizing our proposed method, as shown Fig.3.

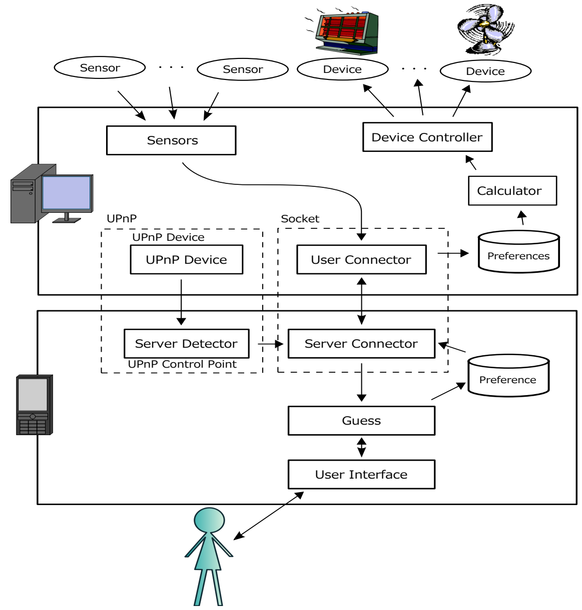

Fig. 3. architecture

A. Server-side Architecture

In order to allow a user's mobile terminal to know the existence of a server sv_r, sv_r generates "UPnP Device". sv_r advertises its hostname and port number to users' mobile terminals via UPnP. The server sv_r recognizes join/leave of a user u when connection established/disconnected with u's mobile terminal. sv_r receives the preference information from users' mobile terminals and stores the information on its repository. When sv_r receives the preference information of all users on its responsible space r, it calculates the target values for devices that maximize the users' overall comfort levels.

B. User-side Architecture

Each user's mobile terminal makes a connection with the server sv_r when finding "UPnP Device" of sv_r. The user terminal sends sv_r the preference information after establishing a connection. In addition, the user terminal asks the user for a comfort level about the current condition at adequate time and stores the answer in the preference information.

C. Implementation of transmission function

In our method, users' mobile terminals must communicate with the servers of various target spaces. The mobile terminals must know the information on the servers of target spaces by broadcast or some kind of methods. The server can communicate with mobile terminals using broadcast such as UPnP. However, to hide the user preference information from other users with encrypted communication, our architecture utilizes the connection oriented communication (TCP socket communication).

question	answer
temperature	fine, good, fair, poor (if you select fair or poor) hot, cold
humidity	fine, good, fair, poor (if you select fair or poor) dry, wet
mental state	calm down, normal, feel heat
busyness	busy, normal, free
location	seminar room, work room, home, ...
hygro-thermograph	current temperature/humidity

TABLE I
QUESTIONNAIRE FOR PREFERENCE INFORMATION

user A	11
user B	10
user C	7
user D	10
user E	17

TABLE II
THE NUMBER OF ANSWERS

temperature	$\pm$ 2 $°C$
humidity	$\pm$ 5 %

TABLE III
ACCURACY OF THERMOMETER AND HYGROMETER

VI. EXPERIMENTS

In order to evaluate the proposed method, we measured the estimation error and compared with other conventional methods. We also measured the transition of the estimation error by increasing the number of contexts for which the preference information is known.

A. Experimental Settings

We generated the user preference information from answers of questionnaires to users as shown in Table I before experiments. Here, questionnaires were designed to conform to the context definition in Sect. II. Questionnaires were collected for about 2 months from December 2009 to January 2010 and the number of examinees was five. We show the number of answers of each user in Table II. We show the accuracy of thermometer/hygrometer used for questionnaires in Table III.

B. Evaluation Method

To evaluate the accuracy of the proposed preference estimation method, we compared our method with the following four methods with respect to the estimation error.

(1) No context method: determining the comfort level of an unknown context to be the comfort level of the most similar known context without considering context factors other than the target controllable target t_r.
(2) k minimum distance method: estimating the comfort level of an unknown context by simply averaging the comfort levels of the known contexts with k minimum distances from the unknown context
(3) Proposed method (all contexts): estimating the comfort level of a context by applying Formula (1) to all known contexts.
(4) Proposed method (k contexts): estimating the comfort level of a context by applying Formula (1) to k nearest known contexts.

Furthermore, we compared the methods (2)– (4) for both cases of uniform weights and optimized weights. In this experiment, we define the comfort level in for levels: 4-fine, 3-good, 1-fair, or 0-poor. Moreover, we did not allow users to choose 2-normal, to avoid ambiguous answers. We regard that estimation may fail when $\Delta > 1$, since the comfort level estimated as “1-fair” can be actually “3-good”. Thus, we need estimation accuracy such that $\Delta < 1$.

We also measured the variation of the estimation error Δ by incrementally adding comfort levels for new contexts, as follows.

(i) Initialize the set of preference samples by three randomly selected questionnaires data.
(ii) Add one questionnaire data to the set of samples.
(iii) Estimate the comfort level for added sample from the remaining samples, and apply the weight optimization procedure in Sect. IV-B3 1000 times.
(iv) Repeat from step (ii) until all questionnaires are added to the set of samples.

We measured the estimation accuracy with the questionnaires for user C.

C. Results

1) Estimation accuracy: We show the average estimation error in Figs. 4 to 7.

a) Effect of weight optimization: The estimation error was improved by about 10% compared to “no context” method when using weight optimization as shown in Fig. 4 and Fig. 5 for temperature or in Fig. 6 and Fig. 7 for humidity.

On the other hand, without weight optimization, the estimation error of our proposed methods and k minimum distance methods increased and the accuracy compared to no context method was reduced. This is because the proposed methods consider the influence of the context difference to the comfort level (e.g., a user in different activity status feels different comfort levels for the same value of the temperature, humidity, and so on). On the other hand, the proposed methods with uniform weights increased the estimation error because of the contribution of context factors that actually do not affect the comfort level very much.

b) Difference in controllable targets: In Fig. 4 and Fig. 6, we see that the estimation error of temperature is bigger than that of humidity. This result suggests that the comfort level of humidity does not so much depend on the situation, although a different result may be obtained in the rainy season.

In the case of temperature (Fig. 4), the estimation error of no context method is 1.280 that is the biggest of all methods. On the other hand, our proposed methods (all contexts and k contexts) achieved estimation error between 0.948 and 0.966. In the case of humidity (Fig. 6), even no context method achieved estimation error of 0.607. This result suggests that the comfort levels of humidity are not influenced by other context factors so much. Nevertheless, our proposed methods achieved estimation error between 0.410 and 0.432, that is more accurate than no context method.

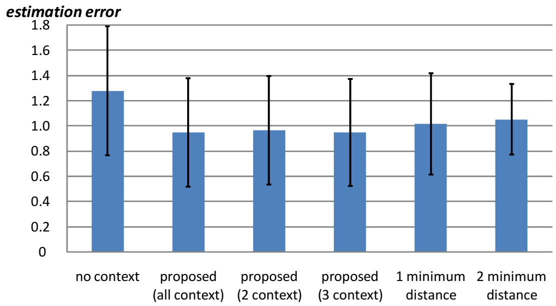

Fig. 4. Average estimation error (temperature, optimized weights)

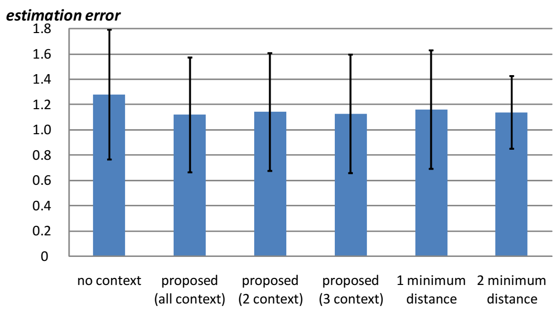

Fig. 5. Average estimation error (temperature, uniform weights)

2) Weight optimization: We show the transition of the estimation error by applying weight optimization steps in Fig. 8, where one step corresponds to one iteration of steps (i)–(iv) in Sect. VI-B.

In Fig. 8, the estimation error of our method using three contexts stabilized earlier than that of the 3 minimum distance method. This is because the proposed method estimate the comfort level considering weights of context factors, while the 3 minimum distance method just averages the comfort levels for three contexts.

This result shows that our proposed method can adaptively adjust the weights of context factors even when the user preference information dynamically changes, especially in the phase that the comfort levels are not yet measured for sufficiently many contexts.

VII. Conclusion

In this paper, we proposed a context-aware device control method for general users with different preferences on controllable targets (temperature, TV channel, etc) in their staying space. We also proposed a method for efficiently collecting and accurately estimating users' preference information since it is difficult to control devices in a context-aware manner in public spaces where general users go in and out.

We evaluated the proposed user preference estimation method using the questionnaires data collected from 5 users over 2 months and confirmed that our method can estimate the user comfort level in error within 1 among 4 comfort levels. We believe that our method has sufficient accuracy to be used for context-aware device control in public smartspaces.

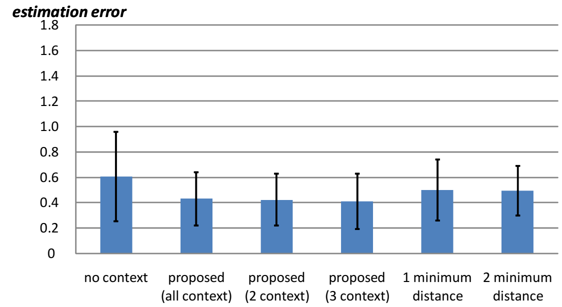

Fig. 6. Average estimation error (humidity, optimized weights)

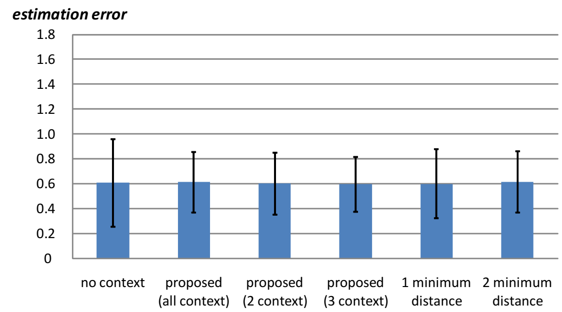

Fig. 7. Average estimation error (humidity, uniform weights)

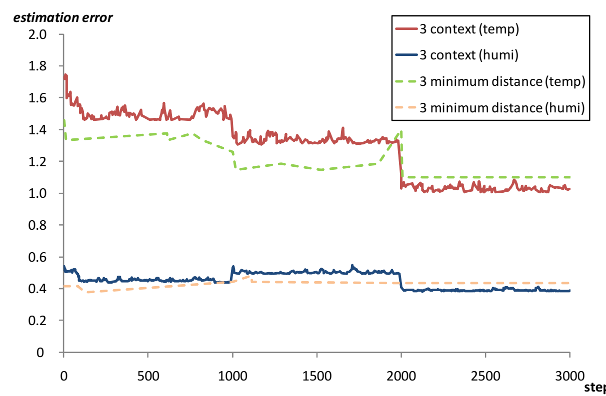

Fig. 8. Transition of estimation error

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