Extracting Service Process Models with Customers and Teams of Resources

Tuuli Klemetti, Reijo Salminen, Olli Martikainen, Riku Saikkonen, and Eljas Soisalon-Soininen

Aalto University, Finland
{tuuli.klemetti, reijo.salminen, riku.saikkonen, eljas.soisalon-soininen}@aalto.fi, olli.martikainen@pfu.fi

Abstract. This paper continues our former study on extracting service process models from location data. We extend our former work with several professional groups working in the service process. In particular, the professionals can work in teams, which have important effect in service behavior and productivity. We also include customers in the model extraction and show a practical example based on dental clinic processes. With these extensions complex service processes can be extracted and analyzed. A model for the teams is required for the optimization of team based processes. By analyzing existing and improved processes successful productivity improvements can be obtained.

Keywords: process modelling, service process, location-based, automated, teams of people

1 Introduction

The purpose of the paper was to develop automated process modeling based on wireless measurements. This approach has been used by healthcare organizations who want to improve their service processes. Business process management and further business process improvement are discussed in several studies (see e.g. [5,7]). However, most studies are artificial, and final evaluation and measurement remain unfinished. Moreover, after the estimated or recommended improvements have been implemented, the organizations have no longer been interested in evaluating whether the solutions were productive or not.

Business process improvement is an opportunity in the service sector, as the share of services is growing. For example, in Finland the share of services is nowadays over 70 percent of the gross domestic product, as noted by the World Bank. Many service improvements can be considered as cases with total factor productivity growth, which has been reported as the major source of productivity growth already by Solow in 1957 [6]. In practice, this means that new ways of working are needed.

In the current study we extend our wireless process measurement approach [8, 9] for service processes where customers are served by teams. Hence, we extract also customer movements and the behavior of the personnel working as teams. In our previous study [8, 9] we extracted the process model on one person working in the process. Now we extract the model for each customer and each person working in the process activities and then combine these models to a system model that includes different customers classes and teams. The teams are particularly important in service processes where there are multiprofessional activities. The previous paper produces separate models for individual persons in the process. These kind of models cannot be used as such for the optimization of processes with teams, since a team cannot operate if all members are not present. To make the optimization for resource allocation in teams possible we must have a combined model with teams. These models are typical in health care, where we have studied several cases in hospitals, health centers and dental clinics. Including the customers in the model gives us information about the actual load in each activity. The improvement of processes has in most cases involved new team structures. According to our experience, the organization of teams has clear effect on the process performance and productivity [1].

2 Automated Process Modelling Approach

In the previous study [8, 9] we presented our approach developed for automated process modelling. That approach can be used to extract the separate model for each person working in the process. These processes are location based, which means that each activity has its own location, for example a room.

The automated process measurement system consists of Bluetooth beacons and mobile receivers. Each location where process activities are performed is equipped with Bluetooth beacons. The Bluetooth data is collected in mobile receivers such as smartphones carried by each person (user) in study. The collected data is then used to compute activity patterns and other parameters. The presented approach has four steps:

- *Step one: planning.* First, determine targeted process activities and locations where these activities are performed. Then place Bluetooth beacons in these activity locations.
- *Step two: mobile receiver calibration.* For each process a process-specific subset of Bluetooth beacons is trained on the mobile receiver side.
- *Step three: process measurement.* Collect process data during the process execution.
- *Step four: process modelling.* Based on the information of measurement of recognized activities, model the entire process.

In the previous study the process model computed from the collected data was represented as block-structured model with boxes and arrows. Each box denotes an activity characterized with an average service time. Arrows between activities define the partial order of activities. If there are several arrows leaving a box, then each arrow is attached by the probability of transition from the current box to the box pointed by the arrow. The block-structured models are usually documented as diagrams.

In what follows we extend the wireless process measurement approach to include customers served in the activities and several people working as teams in the process. In so doing we can extract also the teams and corresponding personnel working in teams. In our empirical work it has become obvious that the allocation of personnel in teams has a major effect in the performance of the service processes. To optimize the performance of a process the necessary amounts of personnel resources needed in teams must be determined.

2.1 Input Data of the Process Modelling System

Bluetooth data is collected to analyse indoor location information, and furthermore be used to infer location-based activities. The system requires information of the activities that compose the process. We apply the definition used already in [8] :

Definition 1. *Let $a = (id, name, location, B_a \subseteq B)$ denote the basic input information of an activity: an activity identifier, a name, a location where it is performed, and a set of Bluetooth beacons that are placed to the location. Then for a service process p with n activities, $A(p) = \{a_1, \ldots, a_n\}$ denotes the set of activities in the process.*

In addition, the system also requires information of the Bluetooth devices that are involved in the process measurement. Here $B = \{b_1, \ldots, b_q\}$ is the set of Bluetooth beacons and $B(p) \subseteq B$ is the subset of beacons in the process p. Let $U = \{u_1, \ldots, u_v\}$ be the set of users carrying mobile receivers such as smartphones. The minimum information that is required to identify a Bluetooth beacon is the unique Bluetooth MAC address received. To help the positioning of users we save the received Bluetooth Radio Signal Strength Indications (RSSI) data. The details of positioning beacons in locations, the calibration of mobile receivers and measurement details are explained in the previous articles [8, 9].

In Figure 1 we present an example with three activities a_1, a_2 and a_3 in corresponding locations. In each location there are attached two Bluetooth beacons. Person u_1 is a customer who is served in activity a_1 by a service person u_3 with service time S_1. Person u_2 is a customer who is served first in activity a_2 by a service person u_4 with service time S_2, and after that in activity a_3 with service time S_3 by both persons u_3 and u_4 who work there together as a team. The customers are marked as blue and the service personnel as red, and they all carry a mobile receiver when the process is measured.

For each user $u \in U$ carrying a mobile receiver, we denote the customers served in the process $C = \{c_1, \ldots, c_r\}$ and the personnel working in the activities to provide service $W = \{w_1, \ldots, w_s\}$ so that $U = C \cup W$. It is possible that customers and personnel overlap in the process, for example this is the case when the customers do self service.

The service process p contains all possible activities. Each user u visits only in a subset $p(u) \subseteq p$, $u \in U$. The activities related to a user u are $a(u) \in A(p(u))$.

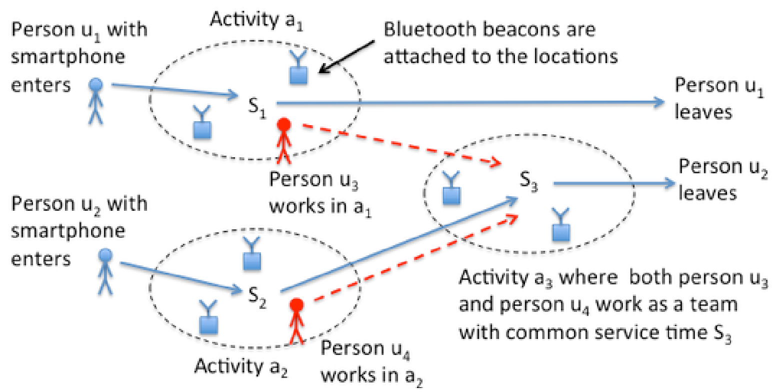

Fig. 1: An example of a modelled process

We extend now our previous single user definitions [8, 9] to the case of multiple users $u \in U$.

When the real process is executed, the measurement is done for each user and the corresponding measurement event records are collected. Measurement is done with a sampling rate f over a time period T_M, so that the timestamp of a record is $t = 0 + n \cdot f$, $n \in \mathbb{N}$. Measurement data is defined as follows.

Definition 2. *For process p, a measurement event record collected for user $u \in U$ at time point $t \in T_M$ is $e = (t, u, R(p)_t)$, where $R(p)_t$ is a set containing one RSSI value r_b for each beacon $b \in B(p)$. Here $r_b = 0$, if beacon b is not in the radio detecting range of u, otherwise r_b equals real-time RSSI value of the beacon.*

The list of activities where the user u visits is $A(p(u))[i] \subseteq A(p)$ indexed with time units $i \in I$ in the process $p(u)$, $u \in U$. It is is extracted from the measurement event records with the help of activity related beacon patterns calculated from calibration event records as explained in [8,9]. From these activities lists we also obtain for each user u the sets activity begin and end times $A_{BE}(a, u) \subseteq I^2$, which for each activity a can be used to calculate the service durations of u in a. These lists are then used in the calculation of average service times and transition probabilities for each user as follows.

For an activity $a \in A(p(u))$ the average service time is:

$$S_a(u) = 1/|A_{BE}(a, u)| \sum_{(b,e) \in A_{BE}(a,u)} (e - b) \tag{1}$$

We then compute a matrix of how many (directed) transitions occurred between the activities: $T_{i,j}(u) =$ number of transitions from activity i to activity j. From this we can calculate transition probabilities by scaling them with the total number of outgoing transitions from an activity. That is, the transition probability $P_{i,j}(u)$ from i to j is:

$$P_{i,j}(u) = T_{i,j}(u) / \sum_{k=1}^{n} T_{i,k}(u) \tag{2}$$

2.2 Process Model with Customer Classes and Personnel Teams

After process measurement we have for each user $u \in U$ the following data: The activities related to the user $A(p(u))$, the average service times $S_a(u)$ of the user in activity $a \in A(p(u))$ and the transition probabilities $P_{i,j}(u)$ from activity i to activity j. To generate the common process model for all users we need two more definitions. Let us first assume, that the users U. are divided into customers $C = \{c_1, \ldots, c_r\}$ and service personnel $W = \{w_1, \ldots, w_s\}$ so that these sets are not overlapping, $C \cap W = \emptyset$.

Definition 3. *If customers $c_1, c_2 \in C$ have same activities, $A(p(c_1)) = A(p(c_2))$, and same transition probabilities, $P_{i,j}(c_1) = P_{i,j}(c_2)$, we say that c_1 and c_2 belong to the same class k. The set of customer classes k of customers $c \in C$ is denoted by $K(C)$. We allow also customer classes with only one customer.*

The arrival intensity λ_k of customers $c \in C$ of class k can be calculated as the number of customers in k divided by the length of the measurement period T_M. Since all customers in a class k have the same transitions, we can denote their transition probabilities as $P_{i,j}(k)$.

Definition 4. *If service personnel $w_1, w_2 \in W$ have common activities, $A(p(w_1)) \cap A(p(w_2)) \neq \emptyset$, and at least in one of them, say in a_1 they have overlapping service periods, i.e. for each $(x_1, y_1) \in A_{BE}(a_1, w_1)$ there exists $(x_2, y_2) \in A_{BE}(a_1, w_2)$ so that $[x_1, y_1] \subseteq [x_2, y_2]$ or $[x_2, y_2] \subseteq [x_1, y_1]$, we say that w_1 and w_2 belong to the same team $T(a_1)$ in the activity a_1 and the team service time is $|[x_1, y_1] \cap [x_2, y_2]|$. The set of teams T of personnel W is denoted by $T(W)$. We allow also teams of personnel with only one person.*

In practice, the starting and ending times of the team service in an activity for each team member may differ, but to simplify our model here, we assume that the starting and ending times of the team service are the same for all team members. Hence, we can denote the service time of team $T \in T(P)$ in the activity $a \in A(p)$ as $S_a(T)$. Now we can define the combined model used for customers and teams.

Definition 5. *Let us consider users $u \in U$ divided in disjoint sets of customers and personnel $U = C \cup W$ so that for each $u \in U$ there is the corresponding process activities $A(p(U))$. Let us denote the customer classes as $K(C)$ and the personnel teams as $T(W)$. The combined process $P(U)$ for these users is defined to have activities $A(U) = \bigcup_{u \in U} A(p(u))$, customer classes $k \in K(C)$ and resources $T(W)$.*

According to the example in Figure 2, the process for customer u_1 is $p(u_1)$ and contains the activities a_1 and a_3, their service times and transition probabilities. The process for customer u_2 is $p(u_2)$ and has activities a_2 and a_3. In the example person u_3 works in a_1 and a_3, and person u_4 works in a_2 and a_3. Since both u_3 and u_4 work in a_3 at the same time, we consider them as a team $T(u_3, u_4)$. The combined process $P(U)$ is $p(u_1) \cup p(u_2) \cup p(u_3) \cup p(u_4)$ and it has customers u_1 and u_2 and resources u_3, u_4. The customer classes are $K(C) = \{\{u_1\}, \{u_2\}\}$ and the personnel teams $T(W) = \{\{u_3, u_4\}\}$.

In real service process cases it is not always easy to find out the real teams working in the activities. If two people are working individually in the same location, the above approach considers them as a team. Sometimes there may be two people already in the activity and a third person will arrive. To decide, is there first a team of two and then a team of three, or is the third person just late from the team of three, cannot be done by measurement only. Instead, we need to obtain more information either by interviewing the team members or by introducing some detailed information gathering features in the mobile receivers. In a long run measurement the recurring teams can be resolved, and hence more reliability in team data obtained. This needs further study. In the current paper, however, we simplify the modelling by assuming that the measured teams are those where personnel works simultaneously in activities.

Our process calculation software [1] takes as an input for a process the following data from measurement: The activities $A(U)$, the service times in activities S_a, $a \in A(U)$, the customer classes $k \in K$, the arrival intensities λ_k and the transition probabilities $P_{i,j}(k)$ of customer classes, the available resources $T(W)$ and their capabilities of working in activities. As a result the calculation gives the optimum allocation of resources in the activities and the performance of the process as a function of arrival intensities. The performance calculation and the optimization procedures for resource allocation in teams are described in [2–4]. After modelling the original process and its possible improvements, their calculation results can be compared and the most suitable improvement can be chosen.

Since we have to combine several measurement results from different mobile receivers, there must be a server in the measurement system where the results are stored. In the server the combined model is built and this obtained model is provided to the process calculation software.

2.3 Measurement System

The measurement environment consists of three main elements as described in Figure 2. The Bluetooth-beacons are sending periodically their identities, and the Smartphone application is collecting the measurement RSSI values using the Bluetooth-driver located in linux kernel. The results are sent to the Server which is located in the cloud in internet. The Android application has a login service, in which the user is asked to give userid and password, which are then compared with the available login information stored in the SQL-database located in the server. After successful login the application gives the user a new menu, in which the user can select either calibration activity or measurement activity, see Figure 3.

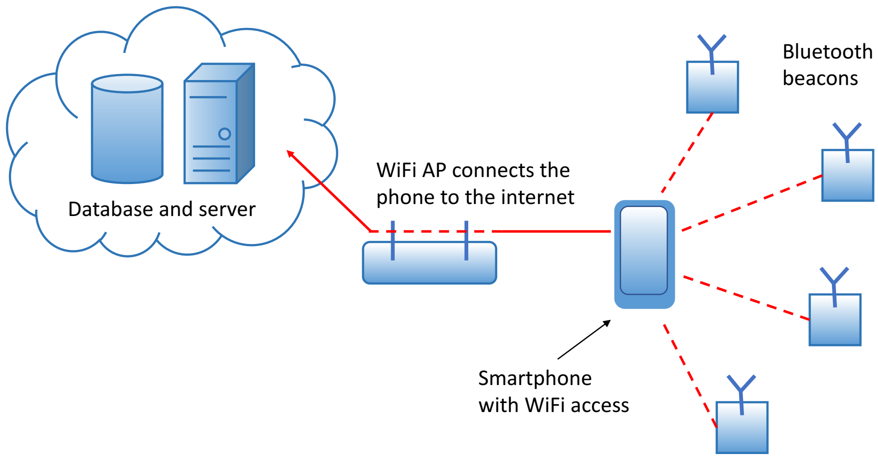

Fig. 2: The measurement environment

The Server also has stored in the SQL-database a list of accepted Bluetooth-identities, which are the unique MAC-addresses of the beacons. When the user initiates a measurement activity from the server, the user is then requested to select from a menu in which location the measurement is taking place. The locations are stored in the Server's SQL-database and do consist of a list of MAC-addresses of the beacons that are of interest in the selected measurement location. In this way only the relevant Bluetooth-beacons are measured in the location in question.

The calibration activity in the Android-application scans the Bluetooth-beacons in the proximity of the Smartphone, and stores the measurement results of the RSSI-values of the beacons over a predefined period of time, which is long enough to be able to perform the statistical procedures needed to be able to perform the needed calibration activities with the measurement results. The purpose of the calibration is to unify the measurement results, since there is remarkable differences on the individual Bluetooth-circuits and their RSSI-values due to variations on circuit and transmission characteristics. The fluctuations over time are also remarkable, and the calibration is needed to smoothen this behaviour, too.

The contents of the SQL-database are modified with database tools provided by the service provider, and also using corresponding management webpages that are located in the Server. The communication between the Smartphone and the Server is performed using WiFi-access between the Smartphone and a WiFi access point, and which is then connected to the internet using a backbone connection (wired or mobile access), and the Server has a list of php-files that

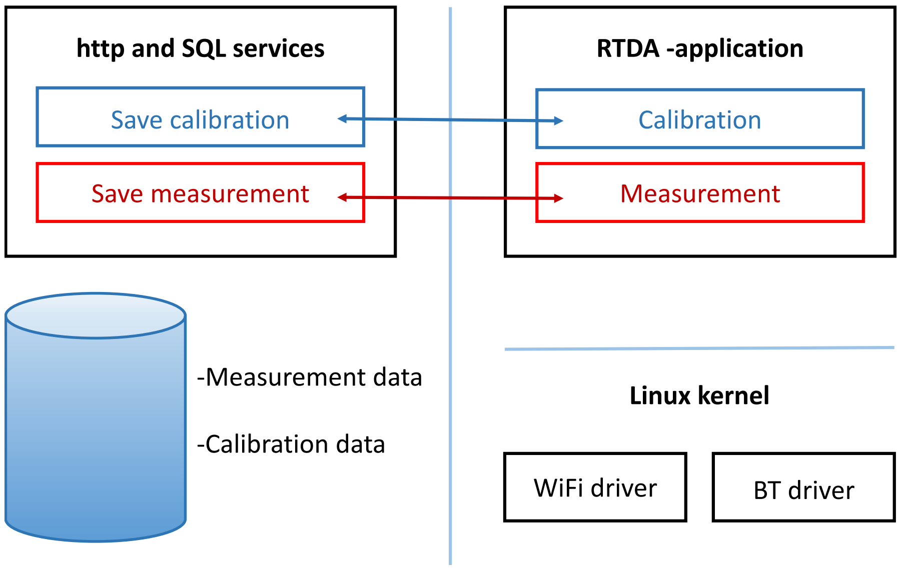

Fig. 3: The interface of the Server and the RTDA-application in smartphone

the Smartphone communicates with using http. The php-files do have the needed logic to communicate with the Smartphone and the SQL-database in the Server.

3 Laboratory Case Study

We implemented the data acquisition system for Android smartphones, and evaluated the system and the analytical approach for process model extraction in a laboratory case study. We placed 10 Bluetooth beacons in 5 locations in the computer science building in Aalto University to represent room of a dentist, three dental hygienist rooms and a waiting room for patients. The smartphones represented persons moving from a place to another and occasionally working in teams. The Bluetooth beacons used in this study were built with JY-MCU Bluetooth wireless serial port modules.

Figure 4 shows the placement of the beacons in the process measurement. Two beacons to represent one activity helps improve the process measurement results. In the case study, we script the process and operated the phones according to plan so that we could compare the results. Three smartphones represented dental hygienists, who stayed in their own rooms during the whole measurement. One phone represented a dentist that visited hygienist rooms when needed and formed a team with the hygienist. Three other phones represented patients that visited in dental care two times each during the measurement.

The measurement process gives intensities of the Bluetooth beacons as a result. The sites and routes of the smartphones can be then located based on

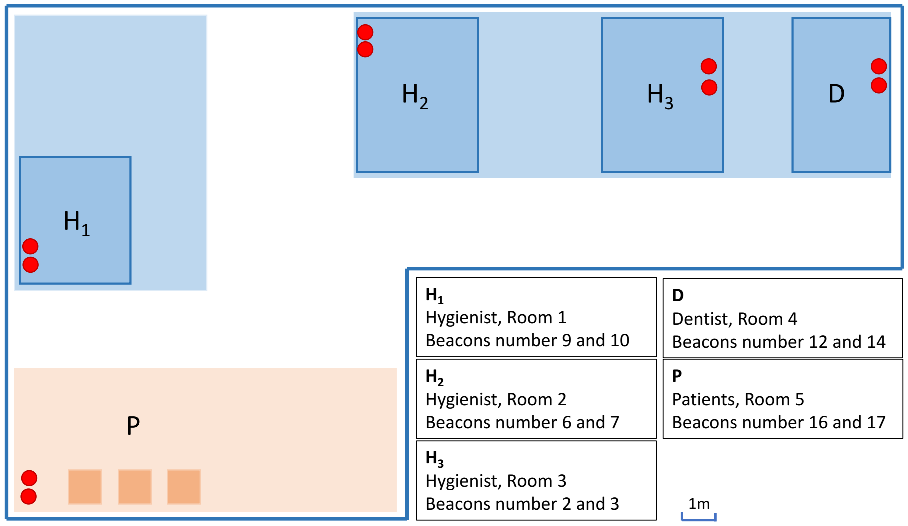

Fig. 4: Case study floor plan: beacon placement for process measurement

most intense Bluetooth signals in different moments. Table 1 shows the service times and Figure 5 presents the process model captured from the case study. By comparing with the scripted process, the result shows that the measured process model detected the correct activities. Also, the service teams were possible to identify correctly from the data.

	Personnel (W)				Patients (C)			Teams (T)		
Activity	d	h_1	h_2	h_3	p_1	p_2	p_3	(d, h_1)	(d, h_2)	(d, h_3)
H_1	6.33	81.27			20.70	36.80		6.33		
H_2	14.57		87.78			35.65	21.08		14.57	
H_3	7.28			88.17	34.88		14.18			7.28
D	17.63									

Table 1: Average service times (in minutes) of each individual or team in each activity, calculated from the data measured in the case study. The notation (d, h_1) means that d and h_1 work as a team.

Figure 6 introduce the possible paths that a patient and a doctor may pass in the process. In practise, the patient enters the waiting room and after a while is called in one of the hygienist rooms. If the hygienist considers it necessary, the dentist is called to join the hygienist to work as a team. After the dentist is no longer needed, possible paths are back to office or in another hygienist room for

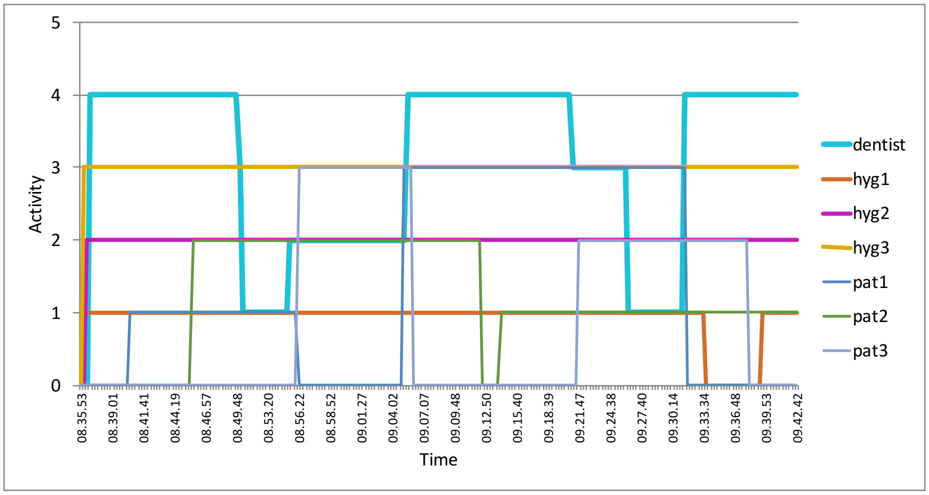

Fig. 5: Figure of the results after routes of each smartphone had been detected from the data.

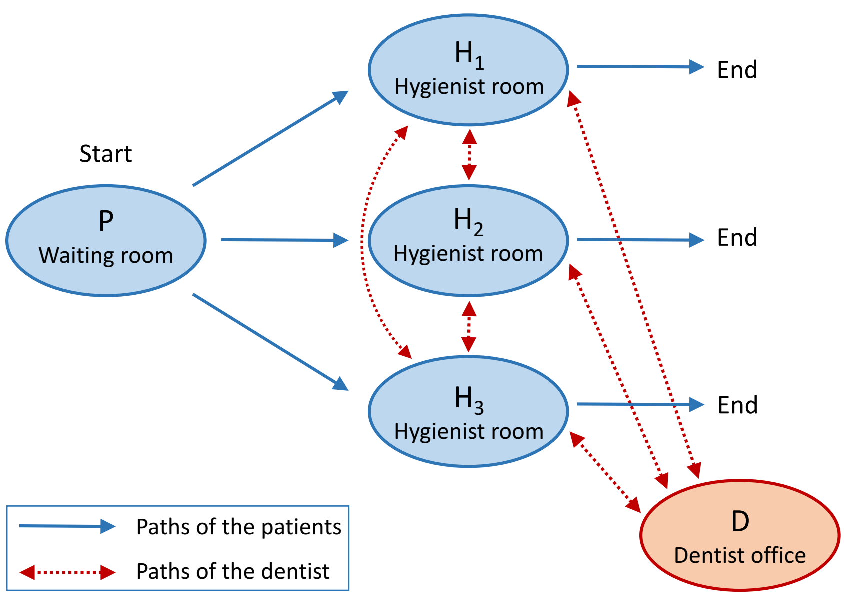

Fig. 6: The process model (activities and transitions) in the case study based on possible paths during one patient's treatment.

next patient. After the dentist leaves the activity, hygienist stays to finish the treatment followed by the patient leave the process.

Due to nature of this case study we didn't calculate transition probabilities albeit it is possible as our earlier study shows. Measurement time were reasonably short and the script was primarily made to describe the activities of the teams so the transition probabilities would not have added value to this study. Also the waiting times of the patients were irrelevant in this case because each smartphones that measured patients went thought the treatment process two times.

4 Conclusions

Process modelling is a critical factor in improving service productivity. Current process models typically consider individual personnel in isolation; however, in practice services often involve teams of employees working together. If teams are not explicitly modelled, it may be difficult to use the process model to e.g. examine the effect of a proposed change in team structure.

The current article has proposed a way to model service processes that keeps customers and personnel separate, and also models teams of personnel working together. For location-based processes (where each activity occurs in its own location) we also provided a method for automatically extracting a model from measurements. This was done by extending our previous work which generated a single-person process model based on measurements of where the person moves.

Since our interest was in location-based processes and automatic measurement, we chose to model teams as groups of personnel who have worked together in the same location (activity) for a while. The measurement data shows us who actually worked together, but an automatically generated process model obviously cannot provide more abstract constraints on teams. For example, if a service team requires any two personnel with a certain qualification to be present, all of the possible two-person combinations might not be observed during the measurement.

Other limitations of our approach relate to the automatic measurement: the inexpensive wireless positioning method from our previous work needs activity locations to be separated by a few meters and has up to 24 seconds of error in the observed service times. This is sufficient in many healthcare services, for example in our case study which simulated a dental care clinic.

The process model that our approach outputs shows the observed service times and transition probabilities associated with each activity and team or individual. One application of this modelling is to measure an existing service process before and after implementing an improvement idea, and compare the efficiency of the two produced models.

References

1. Halonen, R., Martikainen, O., Juntunen, K., Naumov, V.: Seeking efficiency and productivity in health care. In 20th Americas Conference on Information Systems. AMCIS-0251-2014.R1. (2014)
2. Naumov, V., Martikainen, O.: Method for Throughput Maximization of Multiclass Networks with Flexible Servers, ETLA Discussion Papers, The Research Institute of the Finnish Economy nro 1261 (2011)
3. Naumov, V., Martikainen, O.: Optimal Resource Allocation in Multiclass Networks,ETLA Discussion Papers, The Research Institute of the Finnish Economy nro 1262 (2011)
4. Naumov, V., Martikainen, O.: Queueing Systems with Fractional Number of Servers, ETLA Discussion Papers, The Research Institute of the Finnish Economy nro 1268 (2012)
5. Partington, A., Wynn, M., Suriadi, S., Ouyang, C., Karnon, J.: Process mining for clinical processes: a comparative analysis of four Australian hospitals. ACM Transactions on Management Information Systems (TMIS), 5(4), 19 (2015)
6. Solow, R.M.: Technical change and the aggregate production function. The review of Economics and Statistics, 312-320 (1957)
7. van der Aalst, W.M.P. (2013). Business process management: A comprehensive survey, ISRN Software Engineering, 2013, 37 pages, http://dx.doi.org/10.1155/2013/507984
8. Ye Zhang, Riku Saikkonen, Olli Martikainen and Eljas Soisalon-Soininen: Location-Based Automated Process Modelling, SIMPDA 2016 (2016)
9. Ye Zhang, Riku Saikkonen, Olli Martikainen and Eljas Soisalon-Soininen: Extracting Service Process Models from Location Data, manuscript submitted to review for postproceedings of SIMPDA 2016 (2017)