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Master's Thesis

Time Transient Interests' Model
A Model Indicating Person's Individual Interest Real Time within the City

Chihiro Sato

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Graduate School of Media Design
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Time Transient Interests' Model
A Model Indicating Person's Individual Interest Real Time within the City*

Chihiro Sato

Abstract

In the recent years, countless numbers of services use sensors in mobile phones for recognizing current activities and location of where-you-are at the moment. There also have been sensors installed in urban environments to gather and make the people's sensed data collaborative. However, most of these do not attract people living in a daily routine. They cannot understand what exactly the people expect or need in real life.

This paper introduces TTI Model, a model that can understand people's individual real time interest and what is going on right now in the city. It aims to encourage people living in daily routines to explore the city by providing customized information using unintentional activities. This model considers everyday-activity in the city such as wandering around, shopping, or taking a walk, by inputting users' data using sensors. TTI Model, based on Bayesian Networks, uses inputs connected with the real world and calculates the real time interest probability of a person.

Keywords:

modeling, Bayesian Networks, city, sensor, interest

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1. Introduction

1.1. Introduction

This paper introduces Time Transient Interests' (TTI) Model, a model that can understand people's individual real time interest and what is going on right now in the city. TTI considers people living in the urban area's everyday-activity in the city such as wandering around, shopping, or taking a walk; targeting locations mostly within the *Yamanote*-line, in Tokyo, Japan. This happens by inputting users' real time 3D accelerometer and GPS sensor data to the TTI Model based on Bayesian Networks that works on *Netica* using java. This research aims to encourage people living in the urban area to explore the town by providing customized information using the everyday-activities.

In the recent years, the internet has supported many services such as internet shopping, search engines, and navigation systems to customize for each and every person. Amazon.com's website consists of recommends on items that “other people like you have taken a look or bought”, as well as Google's search engine is customized for each and every user.[1, 2] These services are being used by not only on desktop computers but on mobile phones as well. This can happen because people-centric sensing has become very mobile. Sensors in recent mobile phones can be used for recognizing current activities and location of where-you-are at the moment, and can be used for the countless amounts of new sensor based applications.

At the same time, there have been sensors installed in urban environments, to gather and make the people's sensed data collaborative.[3] Traditionally, finding out what is going on in cities have been supported by city guide magazines or television programs, but these are being displaced due to the internet. Recently, there have been many location-based services that allows user to search for any restaurants or stores by entering a set of queries.[4]

However in the real world, people in Tokyo are living in a daily routine. People such as businessmen or students are living their everyday lives repeatedly and do not have enough time or energy to do nothing so special. They ride commuting trains to go to work or school early in the morning, execute whatever tasks they have, and ride the crowded train to go home whenever they finish. This is basically repeated from Monday to Friday. People spend quite a long time in commuting trains every day, but most of the people have never gone off the line.

This research aims to encourage people living in daily routines to ride off trains and explore the town by providing customized information using unintentional activities. In order for this to happen, there is a need to analyze people's lives through ethnographic research, and understand what the people really have interest in.

TTI Model, based on the Bayesian Networks, understands the transition of people's interests as a probability and give a guide of the city to "places you may like" by defining and giving relationships to the interests that people have. It helps to give people the new understanding of the city when just walking around and keeping track of your real time data. This experience can happen by collecting people's real time data using 3D accelerometer and GPS sensors, sending information through internet to the server that has this Bayesian Networks model inside and giving the guide. TTI is an model that enables life of people in the city happier, exciting, and makes people want to explore and consider more when going out to the city.

TTI is a java based model that generates personal predicative preferences calculating the probability of time transient interests. This is based on a Bayesian Networks mathematical model suggested by Pearl in the late 1980s. Probabilistic graphical model generates Bayesian Networks that possesses an ability to describe dynamics and uncertainty, and also to connect and calculate incompatible types of variables together as one model.[5] Bayesian Networks working within TTI aggregates people's change of interest according to time and provides a meaningful guideline for the people in the city.

This paper validates TTI model, working within Sentio service produced by the *Ekirei* project, by a prototype produced to define the Interest of people in the city and put the real time data.

1.2. Sentio

Sentio is a project that aims people to have new urban experience, obtaining "serendipity" within everyday life. It targets people living in the urban area and not tourists, especially university students within age 20 and 30 that live around Tokyo area, for they are interested in all sorts of leisure activities. Sentio supports people's daily lives by understanding what the person likes and connecting with others that have the same types of favorites. It consists of an application, a corsage-like device, a watch-like device, and an engine that connects all.

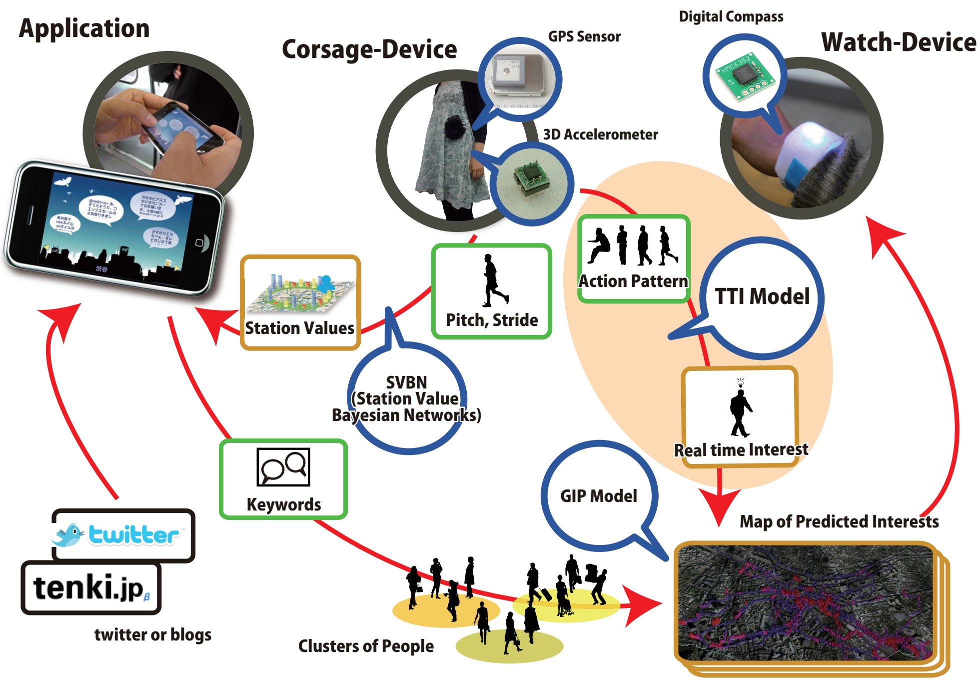

Figure 1.1. Sentio Service System

The Sentio application shows what is going on at all 29 Yamanote stations. When riding the Yamanote line and taking a look outside the window, a person can also take a look at the application that shows comments taken from the internet such as blogs or twitter, and capture the station's image of the town while riding the train. It also shows what station is most likely for you to get off and have a quest. This application aims people have itchy feet and get outside to walk around and explore the city the person normally passes by.

Figure 1.2. Sentio Application Viewer

A corsage-like device to be worn on the user's waist on a person's waist collects the person's unintentional data by a 3D accelerometer and GPS sensors included inside.

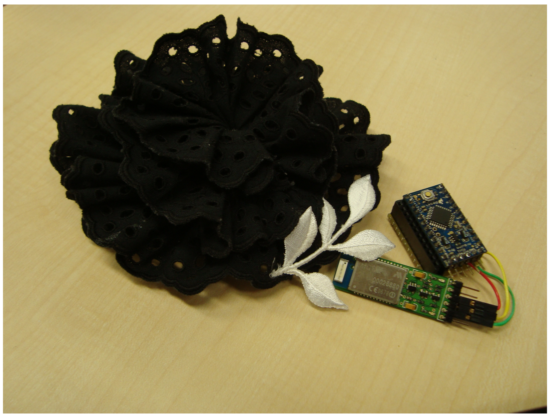

Figure 1.3. Corsage-Device

These sensors understand whether the user is walking fast or slow or standing still. By inputting these data into an model that can calculate the person's curiosity level at the moment, this device tags the value of the interest probability with the data of the GPS sensor, and forms an “Interest Map” of each and every user. This map is used to cluster users like with each other, and forms an interest prediction model of the people who have some interests in common within a server.

The corsage-like device also collects the pitch and stride of a person that is used to calculate which of the 29 Yamanote-line stations best suits you. This is used to recommend the suitable station the user shall get off and take a walk and explore, to be displayed in the application.

The GPS data of a high interest probability predicted from the prediction model will be sent to a watch-like device the user wears. This device consists of 9 full colored LEDs, placed as if a compass, and a digital compass inside. The device recommends by pointing which way may suit the user, and lead the user to the place.

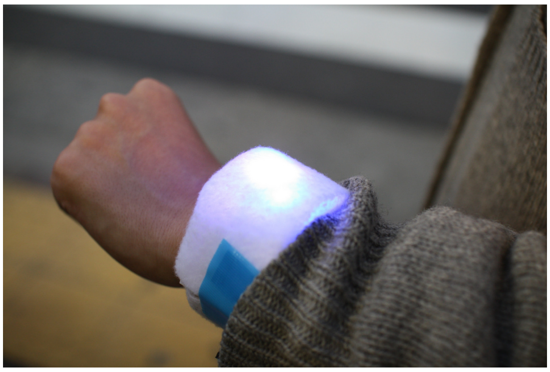

Figure 1.4. Sentio Watch Device

This project is based on the essence found from a fieldwork; featuring on a person's movements to find out a person's interest within the city. A person gradually loses speed when walking and finding something that interests him/her. Walking slowly at a constant speed is also an aspect when interested in something. When actually stopping after a gradual decrease of speed, a person is very curious at the time. It should be able to abstract a person's real time interest within the city by collecting person's unintentional movements when wandering around.

This paper will describe the model which calculates the person's real time interest level, the TTI model, working within the device and the engine. TTI model will be validated by a prototype produced to define the *Interest* of people in the city by inputting real time data.

1.3. Structure of this paper

This paper is structured as follows. Section 2 reviews how the "City" has been analyzed historically, the limitations and advantages found in other service applications of expanding city experience, and also found in other modeling tools. Section 3 introduces the background of the TTI model, along with a brief explanation of Bayesian Networks in use for events under uncertainty, and presents the TTI model mathematically in detail. Section 4 presents the results of the model in data in several field tests. Section 5 provides conclusions and directions for future works.

2. Related Works

2.1. City Theory

K. Lynch has done a set of studies in the cities of the United States, Los Angeles, Boston, and Jersey City, to define what makes what the city's form actually means to the people who live there by describing mental maps obtained from residents in cities.[6] These mental maps form the image of the city. He has shown potential value as a guide for the building and rebuilding of cities, and that the urban setting is composed of 5 elements; nodes, landmarks, paths, edges and districts.

M. McCullough offers an account of the intersections of architecture and interaction design, arguing that the ubiquitous technology does not obviate the human need for place.[7] As digital technology is becoming invisibly embedded in everyday things, everyday activities become mediated and networks extend rather than replace architecture. He expresses an alternative to anytime-anyplace sameness in computing, and shows that context not only shapes usability but ideally becomes the subject matter of interaction design.

The world has become flat, as T. Friedman says, by the globalization and network evolution. Where ever a person lives, it does not matter for a global commission.[8] On the other hand, R. Florida mentions the influences of a person's choice of living for there are many different types of cities.[9] There are cities that attract only certain types of people, such as artists, economists, or superstars. Every city has their own personalities, attracting many different types of people.

There somehow should be a way of connecting the globalization due to the network evolution and the personality of such places. In order for this to happen, there is a need to understand the personalities of places, and also connect with the people that actually live and breathe in the place.

2.2. City Applications

2.2.1 CitySense

There is a service that uses Bayesian Networks as a system model called CitySense, provided by Sense Networks, Inc.[10] It is a service that analyzes and sorts user's real time data using GPS sensors within a portable phone. It can understand user's activity patterns and tell users where the other people who act similar to you that exists at the moment. The CitySense system uses Minimum Volume Embedding Algorithm which is "a state-of-the-art method for summarizing large, high-dimensional data compactly" that basically has five main steps.[11, 12] It calculates the raw similarity between the pair of objects, finds the most important pairs of objects that show an unusual high level of similarity and connect each other. It recovers a low-dimensional version of the original objects remaining the relationships that were deemed important; the low-dimensional representation of the data is recovered by a single value. Their clustering system is based on the formula below.

$$LR(S) = \frac{Pr[Data|H_a(S)]}{Pr[Data|H_0]}$$

Compared to this, TTI model can deal the data without combining the variables all together. Dealing the variables by dynamic Bayesian networks can calculate the leave the raw data. Not only GPS information can carry out people's real time activities, for us can obtain data from 3D accelerometer and other variables as well.

2.2.2 Magitti

Magitti is an activity-centered mobile leisure-time guide that aims to pursue urban activities by giving recommendations about nearby venues timely and personally relevant, executed by Bellotti in Palo Alto Research Center. [13] It targets young urbanites, especially 19-25 year olds who go out and are interested in all kinds of activities, in Japanese cities. It automatically generates recommendations for the user's content matching without having to issue and query infers user activity from context and patterns of user behavior, by predicting the user's ongoing and future activities and uses models of the user's preferences.

Magitti predicts ongoing and future activity and what information will be most useful within the predicted activity based on user preferences, by using machine learning techniques to make a chain of predictions. It uses context filtering to narrow down the overloading offerings to dense urban areas, without the user having to explicitly define their profile or preferences. The system infers interests and activities from models that are learned over time implicitly, based on individual and aggregate user behavior.

The modeling is only based on time and location, for their aim is to enable mobile context and activity inference with no special infrastructure or hardware. The research Liao et al. [14] has done uses Relational Markov Networks and other techniques for location-based sensing. It infers certain activities such as "Shopping", "DiningOut", "Visiting", "AtHome", "AtWork".

2.2.3 CenceMe

CenceMe is an iphone application that shares inference of the presence of individual information sensed from the mobile phones through social networking applications such as Facebook or Myspace. [15, 16] It is a personal sensing system that enables members of social networks to share their presence with their buddies in social networking applications in a secure manner. The presence of the user's is captured as a status in terms of the activity, disposition, habits, and surroundings. It is an application that combines the inference of the presence of individuals using off-the-shelf, sensor-enabled mobile phones.

This works on a system called AnonySense. [17, 18]. AnonySense is architecture for applications based on collaborative, opportunistic sensing with privacy by using personal mobile devices. AnonySense allows applications to submit sensing tasks that will be distributed across anonymous participating mobile devices. This receives the verified sensor data reported back from the field, and provides the first secure implementation of an participatory sensing model. There is an underlying threat model and trust model of AnonySense, and the location-blurring feature provides statistical k-anonymity.

2.3. Modeling

2.3.1 Context Awareness Modeling

Context Awareness, the ability of capturing and processing contexts, has developed generalized concepts for approaching the development of context aware systems. For this to happen, it needs context modeling, the process of abstracting and representing contextual information for further processing. Context is a set of the associated actions and any situation to characterize situation of a place, person, or object. [19]

Many researches are executed of context-awareness [20, 21, 22], and there are many techniques to model the context. Mark-up scheme models, which consist of hierarchical data structures based on markup tags such as attributes and comments. Graphical models, a quite intuitive approach to model context, are to represent contextual entities and their relationships graphically. Object-oriented models consist of encapsulating contextual information into objects, which emphasizes re-usability and controlled access to contextual information. Logic-based models are based on logic, which define conditions on which concluding expressions or facts may be derived from sets of other expressions or facts. [23]

There is a context aware system that employs a context model, which represent sets of actions by means of generalization and specialization.[24] To enrich the context with the probability of those action to be taken, the activities in the hierarchy are represented by Bayesian Networks.[25]

2.3.2 Bayesian Networks as a Modeling tool

Bayesian Networks has been presented by Pearl in 1988,[5] and has been used to model events under uncertainty. Many researches has undergone about Bayesian networks, such as Russell and Jensen, which consists of a graphical structure and a probabilistic description of the relationships among the variables in a system. [25, 26] It has become a popular artificial intelligence representation for reasoning under uncertainty for its effectiveness in describing dynamics, and has been used for object-oriented way of modeling as well. [27]

Bayesian Network approach is used to conduct decision analysis of nutrient abatement measures in Morsa catchment, Norway. [28] It uses Bayesian Networks as a meta-modeling tool in integrated river basin management. It combines information available only probabilistically in existing cost-effectiveness studies, the eutrophication models, non-market valuation studies, and expert opinions.

Bayesian networks are used to integrate a combination of process-based models and expert opinions to predict probability distributions. [29] It describes relationships as one-way causal structure influences at a particular time or fixed eventual state conditions. It is also used for watershed management decisions by a model to phosphorus management in a small catchment in Utah [30]. The Bayesian Networks integrated variables with decision making cost. It mentions the need to validate completed Bayesian Networks using independent information, but it is quite difficult when the probability distributions of the networks come from sources other than data observed or when there is no data. The cases point out that there is a limitation of the causal structure within Bayesian networks and the sensitivity problem of a discrete probability distribution.

Modeling by using a belief network engineering process based on the spiral system lifecycle model has been researched. [31]

2.4. Positioning of this Research

This paper will evaluate Time Transient Interests'(TTI) Model, an Bayesian Networks based model that calculate people's individual real time interest by inputting personal activities based on context-aware modeling. The most important characteristic of the model is the fact that the input of the model is connected with the real world.

3. Concept Support

3.1. Fieldwork of a person's walk (Kagurazaka)

We had a female university student take a random walk on July 9th, 2009 in Kagurazaka, a town in Shinjuku that consists of many aspects of the past. Kagurazaka consists of many narrow roads that can easily lead to places that cannot be seen from the main broad road. It was this student's first time coming to Kagurazaka, so she had hardly any information about the town, though she has always had some interest. This student seldom takes a walk around without any certain plans, and wanders within cities she is not so familiar with. We thought she was a good model of walking due to having walking as one of her hobbies. She also likes to take a look at things from the past and likes cities such as Kyoto, a well known Japanese ancient capital. She knew that Kagurazaka has aspects of the past by obtaining information from the TV or the internet.

Figure 3.1. Kagurazaka, a town consisting aspects of the past

We had her walk around the town with a 3D accelerometer and a GPS sensor taped on her arm, and kept track of the whole walk by taking pictures and recording with a video camera. The sensors were used to understand what kind of movements she takes when walking around the town, and tag the movements with a GPS value to keep track of where she walked. The sensors were connected to a laptop, which another person held and walked around together with.

Figure 3.2. Student with the sensor walking around Kagurazaka

She walked around the town for about an hour. She found many things that interested her for example, a temple, an old general store, a bookstore, a small park, and a store that sells a snack “Peko-chan dumpling”. She especially was curious at stairs at the end of a narrow road. This road suited her image of Kagurazaka, a nostalgic town.

By mapping the GPS data she walked on a map we found out that the GPS data was dense at places where she was curious. This means she literally spent time at places that captured her heart. By analyzing the video recording her activities within the walk, we found out she gradually lost speed when coming across an old general store and a bookstore, which she actually was curious about. When walking the narrow road that captured her heart the most, her walking speed was very slow. She seemed to repeat the action of stopping her feet for a second but start walking again very slowly.

On the other hand, after an hour of random walk, she received a telephone call from one of her friends. She realized that she had been walking for over an hour already and felt that it was time for her to go back to the station. She turned around and started

Figure 3.3. Places she felt interest in

Figure 3.4. Places she felt interest in

Figure 3.5. Places she felt interest in

Figure 3.6. Places she felt interest in

heading toward the station, where she started her walk, and walked the broad street that she has already walked earlier. The speed of walking was faster compared to the previous time she was looking around and seemed to be curious. She seldom stopped suddenly at a red light, but after the signal changed green, her tempo of walking was constantly fast. Below is a map analyzed by mapping the track of the person's walk, brighter dots representing faster walk and darker dots representing slower walk.

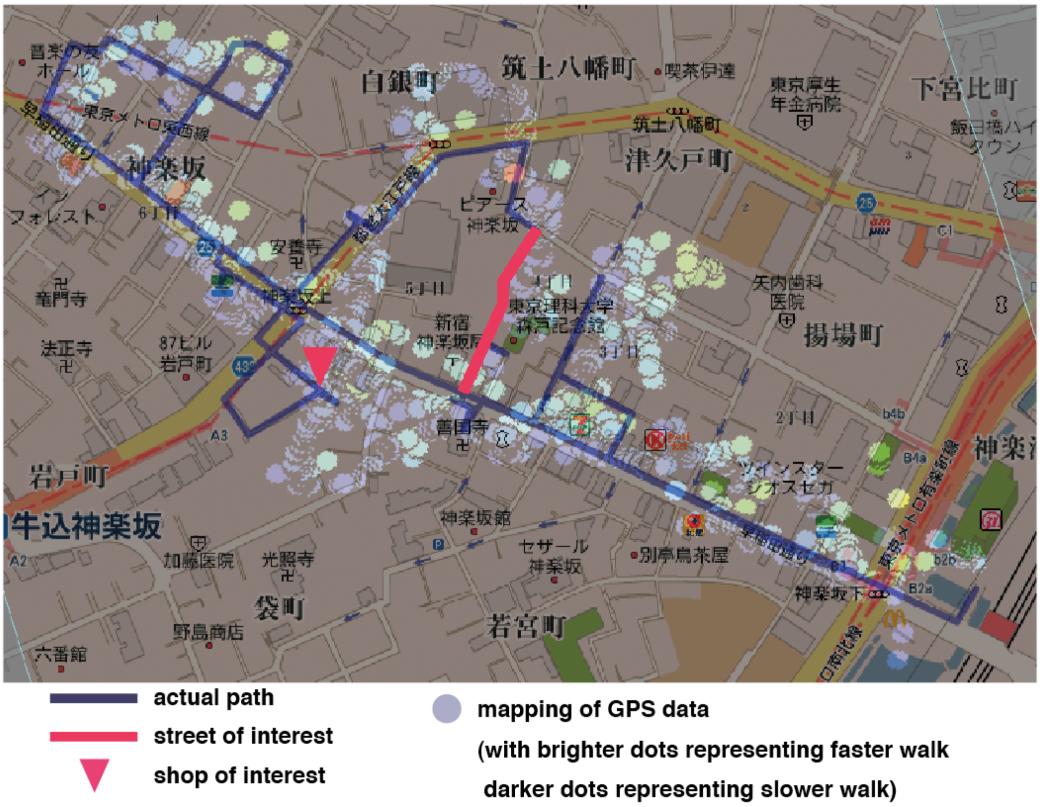

Figure 3.7. Kagurazaka analyzed map

From her movements, we found out that a person gradually loses speed when walking and finding something that interests him/her. Walking slowly at a constant speed is also an aspect when interested in something. When actually stopping after a gradual decrease of speed, a person is very curious at the time.

However, when walking at a rather fast tempo constantly, a person does not have such interest at the moment. Such fast speed of a person means persuading the goal, such as “going back to the station” at the moment. Her overall curiosity level is quite low when walking at a constant fast speed. Also, a sudden stop without any gradual decrease would also mean less curiosity level. Stopping at lights does not mean high curiosity.

From this fieldwork, we figured it may be possible to extract a person’s real time interest by considering the speed of a person walking and the speed change. We figured it would be possible if using sensors to capture the actions of the person. Below is a formula of capturing the interest of a person at a certain time t.

$$Interest_t = S_t(Sensor, Action)$$

[Formula: Interest Meta-Model]

By inputting the action captured from the sensor to a model S at a certain time t, the interest of the certain time t can be calculated. The model S will be the TTI model, to be expressed later on in the paper. It considers the speed of a person walking and especially focuses in on the speed change. It transfers these data in to the current curiosity level of the person’s walk, real time, and calculates the real time curiosity level by using the person’s movements at the moment, the walking speed.

3.2. Capturing a person’s walking (Device)

3.2.1 Sensing data

We decided to use a corsage-like device consisting 3D accelerometer and GPS sensors to capture the speed change of a person. This device prototype is to be attached to the waist of a person as if it were a corsage, acquiring the x, y, z axis data. It is connected with a laptop computer by USB, to collect raw data from sensors inside. The 3D accelerometer obtains data of the x, y, z axis with java synthesized Arduino nano at a sampling rate of 50Hz. The synthesized data will be converted by FFT at a speed of 64 set of data per second to derive the power spectrum of accelerometer like other researches execute.[32, 33]

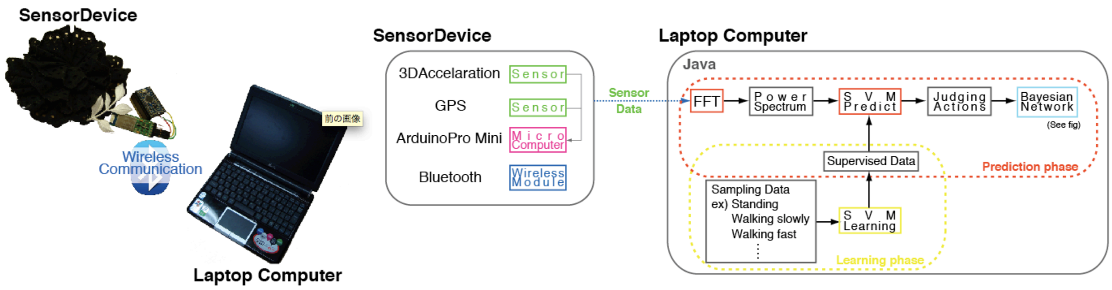

Figure 3.8. Corsage Device and laptop

The derived value of power spectrum will be categorized every second by SVM algorithm into four groups; stand still, walking slowly, normal speed, and walking fast. The output of the SVM is values 1.0, 2.0, 3.0, and 4.0, each corresponding with the four states mentioned above. This will be used at the input of the TTI model.

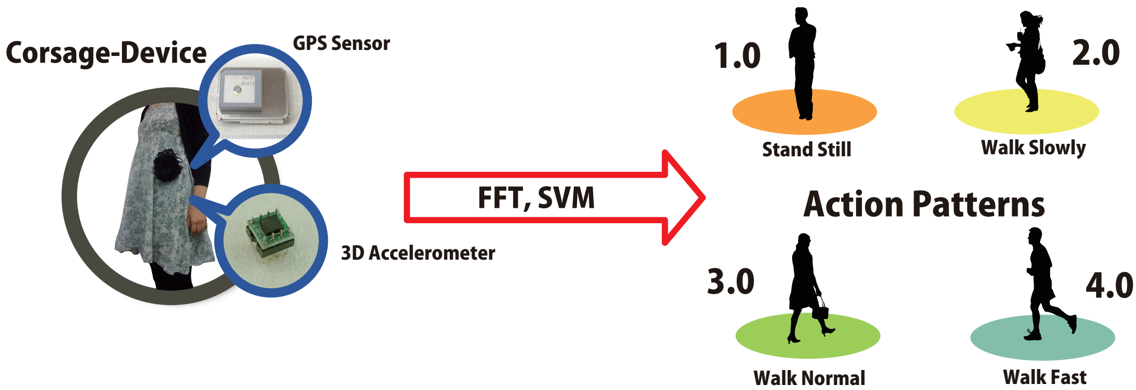

Figure 3.9. How the Action Patterns are divided

By using this device including sensors, it would be possible to calculate the person's real time interest probability at a certain time t. Considering all the sensor data from the past collected from the device, the probability of the person's interest at the time right now will be able to be calculated. This could be written as $Interest_t$, which comes from the Interest Meta-Model written as a probability, written below. The probability of interest at the moment comes from all the collected sensor data.

$$P(Interest_t|Sensor_{1:t})$$

[Formula: Probability of $Interest$]

3.2.2 Supervised Learning

Since every person's average walking speed differs, there is a need to collect data for supervised learning. We have done a test to record the walking speed of 10 university students, asking to put a 3D accelerometer by their waist. This test was executed to collect the 4 states of walking as mentioned above; standing still, walking slowly, normal speed, and walking fast. We asked the students to have 3 sets of walks of the school hallway for 10 meters, asking them to assume "the walk when finding something that interest you", "the normal walk of when not thinking about anything in particular", "the fast walk when trying to cross the yellow light". We considered these 3 types of walks as "walking slowly", "normal speed", and "walking fast".

We have used the sensor module "KXM52-1050" as our 3D accelerometer attached to Arduino Pro mini, which is connected to a laptop via USB. The data collected 64 times per second is recorded, and to be learned as the supervisor of the SVM.

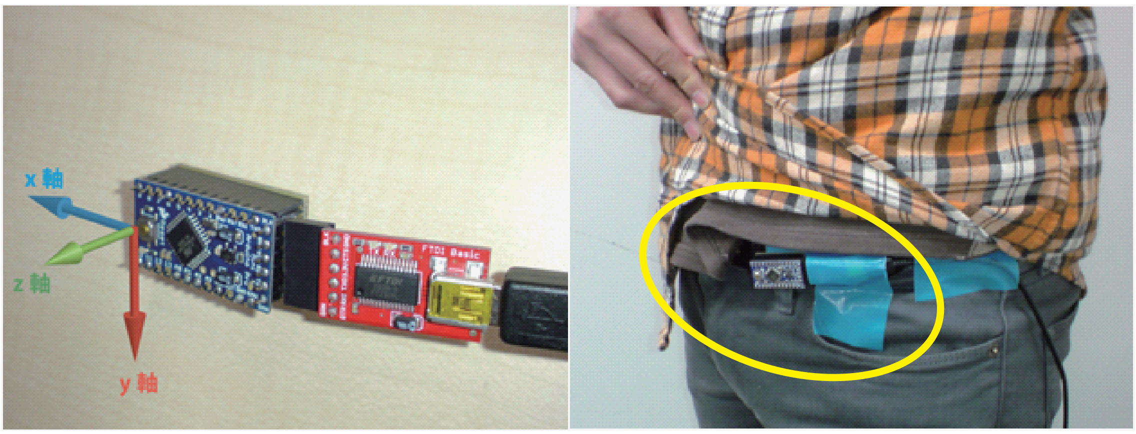

Figure 3.10. How to collect the person's walks

3.3. Bayesian Networks

3.3.1 Events under Uncertainty

There are many events in real life that are uncertain. Rational decisions of what to carry out depends on the possibility of many goals to be fulfilled and the relative importance of the goals.[26] The decision making for any diagnosis in any domains are under uncertainty, unless the diagnosis itself is *always* true or false. Unfortunately, most of the events happening in real life do not happen *always*. There can hardly be a hypothesis that is 100% sure when actually living in the real world. It is hard to determine these events with just 0 or 1, which most of the people do unfortunately in the real world, just the fact of whether the event occurs or not.

Referring to Russell's *Artificial Intelligence: A Modern Approach*, diagnosis such as "All patients that have toothache have a cavity" can be hardly inducted. Perhaps the cause of the toothache is from a gum disease or an abscess or whatever disease there can be that cause toothache. This diagnosis cannot be expressed as a propositional logical formula, for it is uncertain.

Countermeasures for this uncertainty problem are to have many preferences within the outcomes. Probability theory can be used to by understanding the degree of belief within the diagnosis. Utility theory is known for deducting and expressing preferences. Decision theory is known for combining the two theories together, as the maximum expected utility of all possible diagnosis are obtained.

TTI uses the decision theory to identify the uncertain aspect of "a person's real time interest", especially using the probability values that range from 0 to 1, called Bayesian Networks.

3.3.2 Bayesian Networks

We figured Bayesian Networks will be suitable for calculating the real time curiosity. Bayesian Network consists of a graphical structure and a probabilistic description of the relationships among the variables in a system. The probabilistic network are graphical models of causal interactions among a set of variables, which are represented as nodes of the graph, the interactions and relationship represented as directed links between the nodes, probability tables, and a class of graphs known as directed acyclic graphs also known as DAGs. The variables are represented as nodes in Bayesian Networks, and the links of the network represent the properties of conditional on the configuration of its conditioning parent variables.[34] The conditional probabilities are used to precisely model the relationship of the variables. The nodes and links of a Bayesian Networks form a directed acyclic graph, which property is required to carry out the probability calculus.

The basic Bayes' rule formula calculates probability under a certain conditions. It has become a popular artificial intelligence representation for reasoning under uncertainty for its effectiveness in describing dynamics.[27] This is the foundation of all the probability theories the Artificial intelligence systems currently use. This also can be expressed as a cause and effect of any event.

$$P(a|b) = \frac{P(a \wedge b)}{P(b)} = \frac{P(b|a)P(a)}{P(b)}$$

[Formula: Bayes' Rule]

Expressing the above formula as a graphical model, it can be seen as the below. The probability $P(a|b)$ is the posterior probability of the probability $P(a)$, the prior probability, when an event b occurs under a certain probability, also written as $P(b)$.

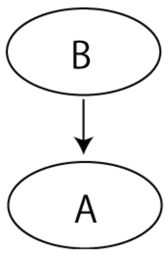

Figure 3.11. Graphical Model of Simple Bayesian Networks

The Bayes' rule is of advantage in question-answering that use evidence that only come out under certain conditions. This can be infrequently applicable as $P(effect|cause)$for describing. When more than one effect of a cause is to be expressed, it can be calculated

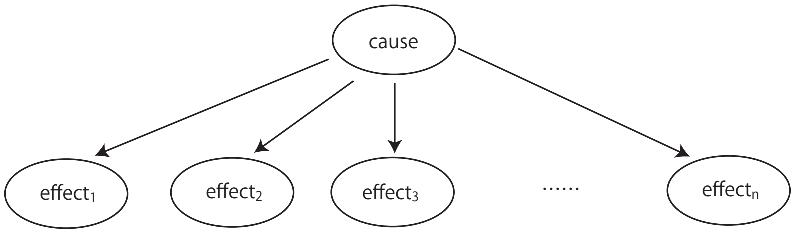

Figure 3.12. Graphical Model of Naïve Bayes

for a conditional independence to occur. This is known as naïve Bayes, or Bayesian classifier. Figure 3.12 is the graphical model of naïve Bayes.

The below formula is expressing the above graphical model as a mathematical model.

$$P(Cause, Effect_1, Effect_2, ..., Effect_n) = P(Cause) \prod_i P(Effect_i|Cause)$$

[Formula: Naïve Bayes]

Bayesian networks represent factorizations of probability distributions over limited sets of discrete random variables. For any graphical model, the below formula can be used to calculate the probability on the configuration of its conditioning parent variables.

$$P(x_1, ..., x_n) = \prod_{i=1}^{n} P(x_i|parents(X_i))$$

[Formula: Bayesian Networks]

3.3.3 Dynamic Bayesian Networks

To describe the time transition of anything, dynamic Bayesian Networks is adequate. Dynamic Bayesian Networks is constructed of a sensor model, transition model, and a prior probability. [26] Sensor model expresses the probability of a certain time slice and the cause probability when an effect occurs, shown as $P(E_t|X_t)$. Transition model expresses the change of the cause probability due to the time as it changes from time

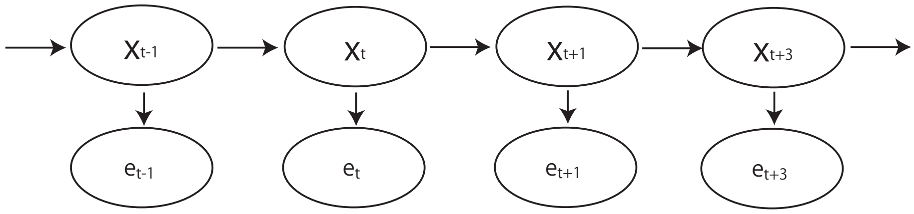

Figure 3.13. Dynamic Bayesian Networks

t to time t+1. The prior probability of the cause itself is needed for probability of the event itself to not carryout to zero.

This is basically a stack up of simple Bayesian graphs, which probability table does not change for its repetition. It can be described as the formula below.

$$P(x_0, x_1, ..., x_t, e_0, e_1, ..., e_t) = P(x_0)\prod_{i=1}^{t} P(x_i|x_{i-1})P(e_i|x_i)$$

[Formula: Dynamic Bayesian Networks]

Russell suggests filtering, based on sensor model and transition model, and also Markov process. [35]

$$P(X_{t+1}|e_{1:t+1}) = \alpha P(e_{t+1}|X_{t+1})\sum_{X_t} P(X_{t+1}|X_t)P(x_t|e_{1:t})$$

[Formula: Filtering Model]

TTI model is based on filtering; evidence of the model is set to the values the SVM algorithm divides; variables range from 1.0 to 4.0. The cause of this model, connected together by the sensor model and transition model, are “the state of movement”; variables are set to “stand still”, “walk slow”, “walk normal” and “walk fast”. Considering the fact that all sensors include noise, the values and the movement states are connected by normal distribution. The movement states excluding the prior probability are connected with the *Interest* nodes, as a naïve Bayes. Every second the sensor outputs the value undergone through the SVM, the *Interest* node is updated.

3.4. Concept (TTI Model)

Using the Bayesian networks listed above, I suggest the TTI Model to calculate the interest probability of a person using the collected real time data to put into the Interest meta-model.

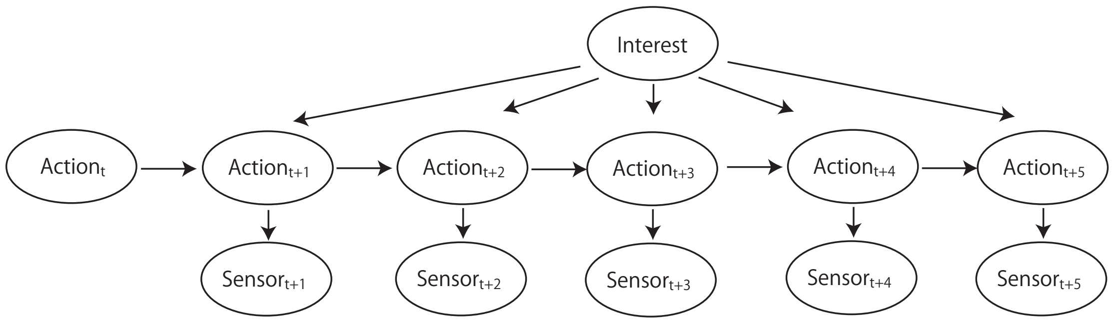

Figure 3.14. Graphical Model of TTI Model

By using the essence abstracted from the fieldwork, data collected from the sensor device, and Bayesian Networks, the present interest level can be calculated by the formula below.

$$P(Interest_t|Sensor) = \alpha P(Interest)P(Sensor_t|Action_t)\sum_{action_t} P(Action_t|action_{t-1})P(action_{t-1}|Sensor_{1:t-1})$$

[Formula: TTI Mathematical Model]

This can be put into the S model of the formula of the Interest meta-model expressed before, also written below.

$$Interest_t = S_t(Sensor, Action)$$

[Formula: Interest Meta-Model]

which means the *Interest* at time t can be described as this mathematical model.

$$Interest_t = P(Interest_t|Sensor) =$$
$$\alpha P(Interest)P(Sensor_t|Action_t)\sum_{action_t} P(Action_t|action_{t-1})P(action_{t-1}|Sensor_{1:t-1})$$

[Formula: TTI Meta-Model]

To calculate the real time interest, just obtain the probability of the *Interest* node. The inputs of the model will come from the output of the sensor device, values of which undergone the SVM algorithm. These inputs will come into the *Sensor* nodes, every second the value comes out, which are 1.0, 2.0, 3.0, and 4.0.

Each *Sensor* node corresponds with the action node as a parent node. The *Action* node consists of four states as mentioned before, "stand still", "walk slow", "walk normal", and "walk fast". The values and the movement states are connected by normal distribution, considering the fact that all sensors include noise.

The most important characteristic of the model is the fact that the input of the model is connected with the real world.

3.5. TTI Mathematical Model

To implement out the TTI Model, I have used *Netica*, a commercially available java based modeling software, using diagrams to evaluate the expected value of functions. In this software, the nodes are shown as rectangles, each of the names on the top of the square. The states are shown below the name, having the unconditional probability distributions besides them, as well as variables described by joint probability distributions conditional on the states of one or more parent nodes. The links are shown as arrows, drawn from the parent to the child.

This is the graphical model of TTI.

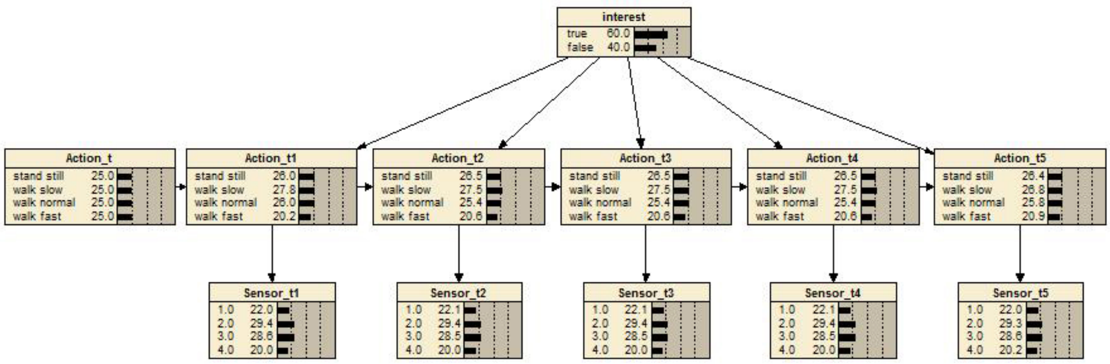

Figure 3.15. Graphical model of TTI Model

Based on the graphical model, obtain the *Interest* node every time a new value is inputted. For every time t, the probability of *Interest* node is updated. To obtain the present *Interest* at time t, consider the *Interest* before the time, specifically, from time 1 to t-1.

Below will be the mathematical model of the TTI model.

$$P(Interest_t|Sensor) =$$
$$\alpha P(Interest)P(Sensor_t|Action_t)\sum_{action_t} P(Action_t|action_{t-1})P(action_{t-1}|Sensor_{1:t-1})$$

[Formula: TTI Mathematical Model]

3.6. Description of TTI

3.6.1 Dynamic Bayesian Networks Model

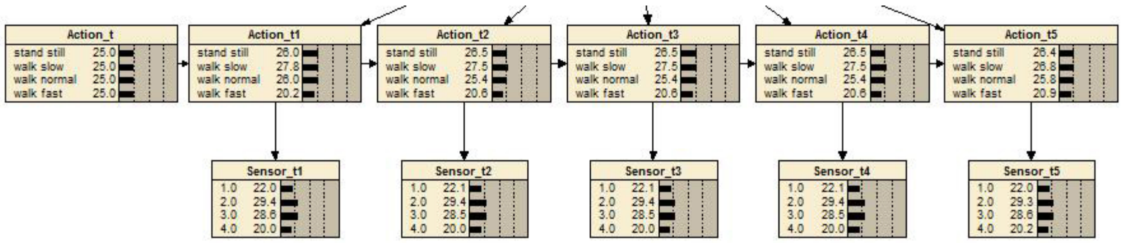

Figure 3.16. Graphical Model of Dynamic Bayesian Networks

3.6.2 Prior Probability

The prior probability of the state of movement, also known as the state of movement at time 1, is set to a binominal distribution, for all probabilities are to be equally probable. This means all four states; "stand still", "walk slow", "walk normal", and "walk fast" are set to a probability of 0.25.

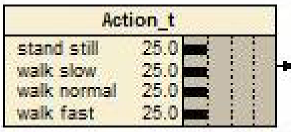

Figure 3.17. Graphical Model of Action Node Prior Probability

This prior probability is very important for the dynamic Bayesian Networks. Due to this prior probability, the probability of anything does not go down to 0 percent. If a probability is 0 percent, there is no chance of revival.

3.6.3 Sensor Model

Sensor Model is a model which each *Sensor* node corresponds with the action node as a parent node. The *Action* node consists of four states as mentioned before, "stand still", "walk slow", "walk normal", and "walk fast". The values and the movement states are connected by normal distribution, considering the fact that all sensors include noise.

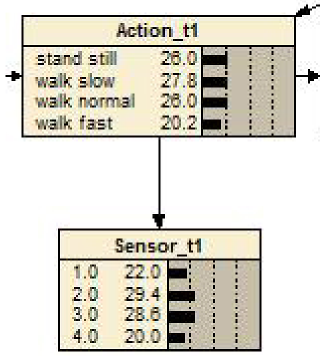

Figure 3.18. Graphical Model of Sensor Model

This is the probability table to disclude the sensor's noise.

Action_t1	1.0	2.0	3.0	4.0
stand still	40	30	20	10
walk slow	25	40	25	10
walk normal	10	25	40	25
walk fast	10	20	30	40

Figure 3.19. Probability Table of Sensor Model

3.6.4 Transition Model

This is the graphical model of the transition model of people's actions.

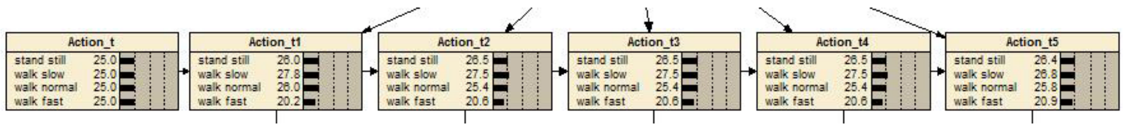

Figure 3.20. Graphical Model of Transition Model

The probability table comes from the fieldwork essence. Little change of this value causes quite a different probability.

Action_t	interest	stand still	walk slow	walk normal	walk fast
stand still	true	35	25	20	20
stand still	false	30	25	25	20
walk slow	true	35	25	25	15
walk slow	false	15	25	30	30
walk normal	true	30	35	20	15
walk normal	false	10	30	30	30
walk fast	true	20	30	35	15
walk fast	false	25	25	25	25

Figure 3.21. Probability Table of Transition Model

3.6.5 Naïve Bayes Model

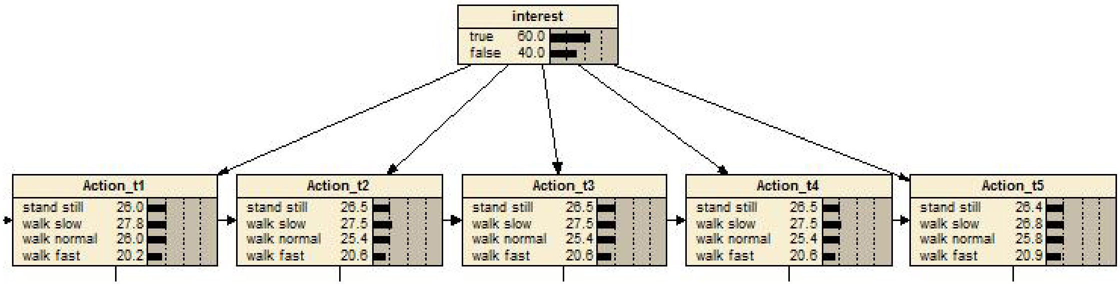

Figure 3.22. Graphical Model of Naïve Bayes structure of *Interest* Node

Action_t	interest	stand still	walk slow	walk normal	walk fast
stand still	true	35	25	20	20
stand still	false	30	25	25	20
walk slow	true	35	25	25	15
walk slow	false	15	25	30	30
walk normal	true	30	35	20	15
walk normal	false	10	30	30	30
walk fast	true	20	30	35	15
walk fast	false	25	25	25	25

Figure 3.23. Probability Table of the Naïve Bayes Model

4. Proof of Concept

4.1. Field test of a person's walk (Jiyugaoka)

4.1.1 Observation

We executed a field test of this model in Jiyugaoka, on October 1st, 2009. We had a female university student walk without and constraints for an hour in Jiyugaoka. It was her first visit in Jiyugaoka, for anything that caught her sight impressed her. Jiyugaoka is a town in Tokyo which many people feel has a Parisian essence. There are many vintage shops and general stores which many girls feel attracted to, and have many open cafes and restaurants.

Figure 4.1. Jiyugaoka, a town with a Parisian essence

The female wore the corsage-like device on her waist, and was attached to a laptop computer via USB while the test was executed. In order to process the data in real time, we had a person with laptop in hand following the subject. After the experiment, we showed the subject the whole video during the walking and asked her to evaluate the places which she actually felt interested with value between 0 and 1. In this way, we confirmed the places of interest to the subject. This female is a foreign student, and has only lived in Japan for just over a year. She has always wanted to go out and find out how amazing Tokyo is, but she has never had the chance. She was just the right person to have as our first prototype user.

First she decided to go to Marie Claire Avenue, a shopping avenue just near the station of Jiyugaoka. This avenue has many cafes and general stores, and a row of benches in the middle of the road. There were many mothers with their babies hanging around and having lunch with their lunch-boxes. It was her first time seeing any promenade that have a row of benches in the middle of the road. She seemed to smile when taking a look at the families that were having a break by the benches, and even sat down at a bench to take a look at the children. She took a look at the open cafes that have a terrace seat, show cases of stores, and a narrow array that seemed to go somewhere else besides Marie Claire Avenue.

Figure 4.2. Field test at Jiyugaoka

After spending 10 minutes at Marie Claire Avenue, she stepped into a narrow array that leads to the shopping street in front of the Jiyugaoka station. She was walking faster than the time she was at Marie Claire Avenue, but took a brief look at a old book store. She walked quite fast when passing by the station, towards a railway crossing to go to the other side of the station. She once crossed the railway, but came back immediately. She seemed to be taking a look at what was there on the the other side of the station, but perhaps did not interest her so much. When passing by under the railway crossing, she met a dog with the same clothes as the master. She stopped her feet to take a look at the dog closely.

Figure 4.3. Field test at Jiyugaoka

After 20 minutes have passed from the beginning of the test, she decided to go to a small shopping mall. There was a interior shop, which she actually took some items to her hands, but did not buy. She stopped by a couple of other shops, but did not buy anything. Her walking speed was constantly slow and stopped every once in a while. She also paid attention to a store that had a big angel in front, which was a fortune telling store.

Figure 4.4. Field test at Jiyugaoka

After about 30 minutes have passed, she stepped inside the camera store to take a look at the photos and camera inside which she spent about 5 minutes browsing. She also went took a brief look at a general store.

Figure 4.5. Field test at Jiyugaoka

From observation of her movements during the field test, I assumed that she felt interest in the following aspects. Marie Claire Avenue, families and children, railroad crossing, shopping mall, dog that she met under the railway crossing, a fortune telling shop with an angel in front of the store, camera shop, a general store, and the Jiyugaoka department store.

She especially was curious in the Marie Claire Avenue and the camera shop, for she spent quite a long time checking them out neatly. She also had fun just walking in Jiyugaoka, just looking around the area and nothing so much in particular. Objects that interest her at Marie Claire Avenue were not shops, what caught her eye the most were the mom-and-child taking a walk and resting at benches. She had fun taking a look at the people in Jiyugaoka, observing what kind of families or friends or couples come for what kind of reason. Whenever anything caught her eye, she followed the object with her eye, and also decreasing the speed she walks. After slowing down a little, she did not actually stop, but took a brief look around the area. She had a walk around a couple of times at a street which she was curious in, for example, Marie Claire Avenue, under the railway, and the crossover of the railway.

4.1.2 Prediction of TTI

The following is the interest probability of the field test predicted from the model, having the x axis as 1/64 second and the y axis as the probability ranging from 0 to 1.

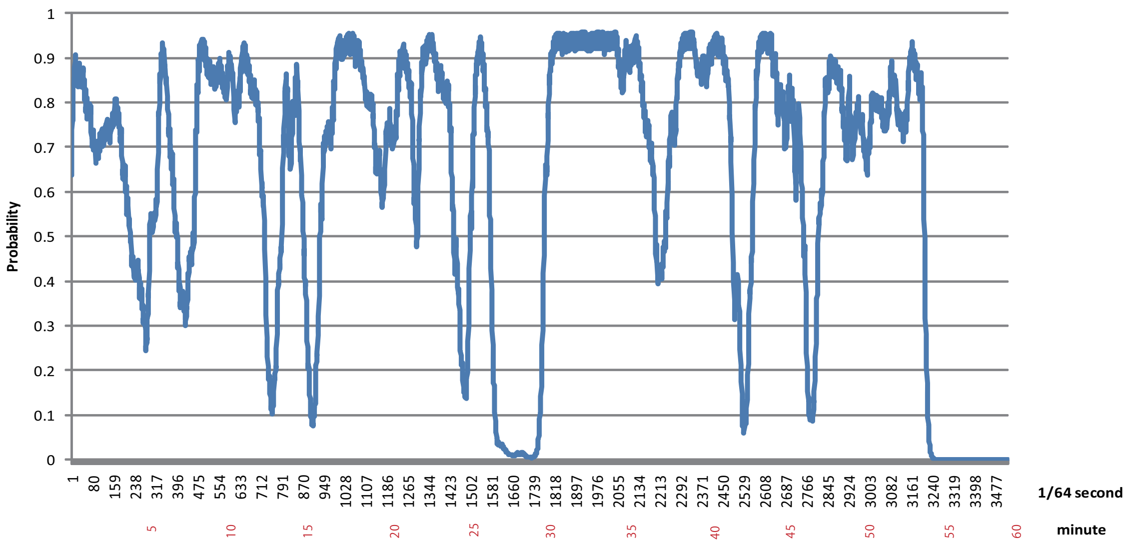

Figure 4.6. Graph predicted by TTI model of the field test

According to the time, the probability of interest changes rapidly. The probability ranges from almost nearly 0 percent to nearly 99 percent. It captures the real time interest in a small range of time. The following is the map with the interest probability mapped.

Figure 4.7. Map of Jiyugaoka

4.1.3 Verifying TTI

Below is the analysis of the model's prediction. We corresponded with the movie time range with the places she went to.

From this, it is quite easy to find out that the places she felt interest from the observation are shown as high probabilities of interest.

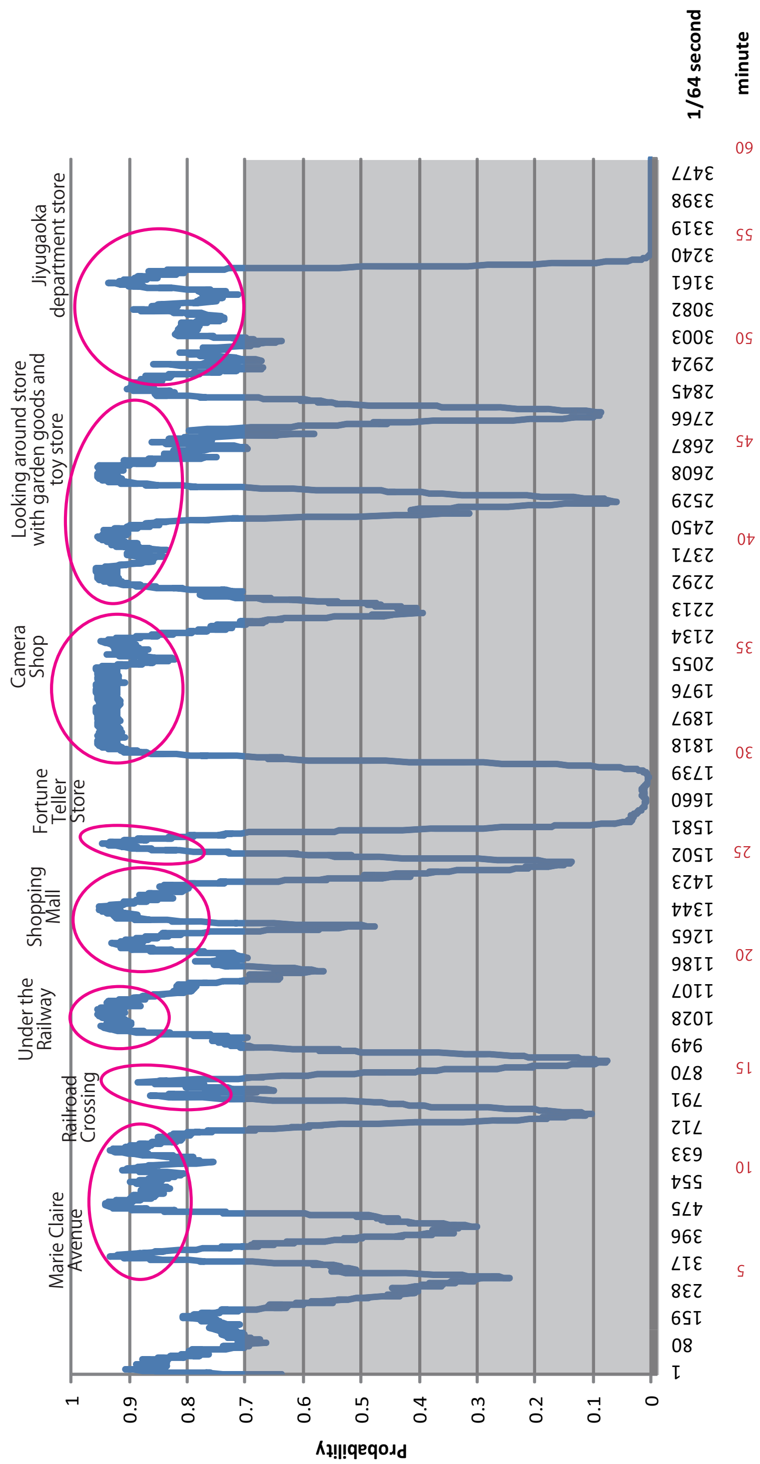

Figure 4.8. Analysis of the Prediction of TTI model

4.1.4 Comparing TTI with the interest

According to a survey attached at the appendix of this paper, the following is what she had interest in.

Marie Claire Avenue, bench, family, child, handmade lunchbox of young women, railroad crossing, shopping mall, dog that she met under the railway crossing, a fortune telling shop with an angel in front of the store, camera shop, store selling garden goods, toy store, vending machine selling garbage bags, Jiyugaoka department store.

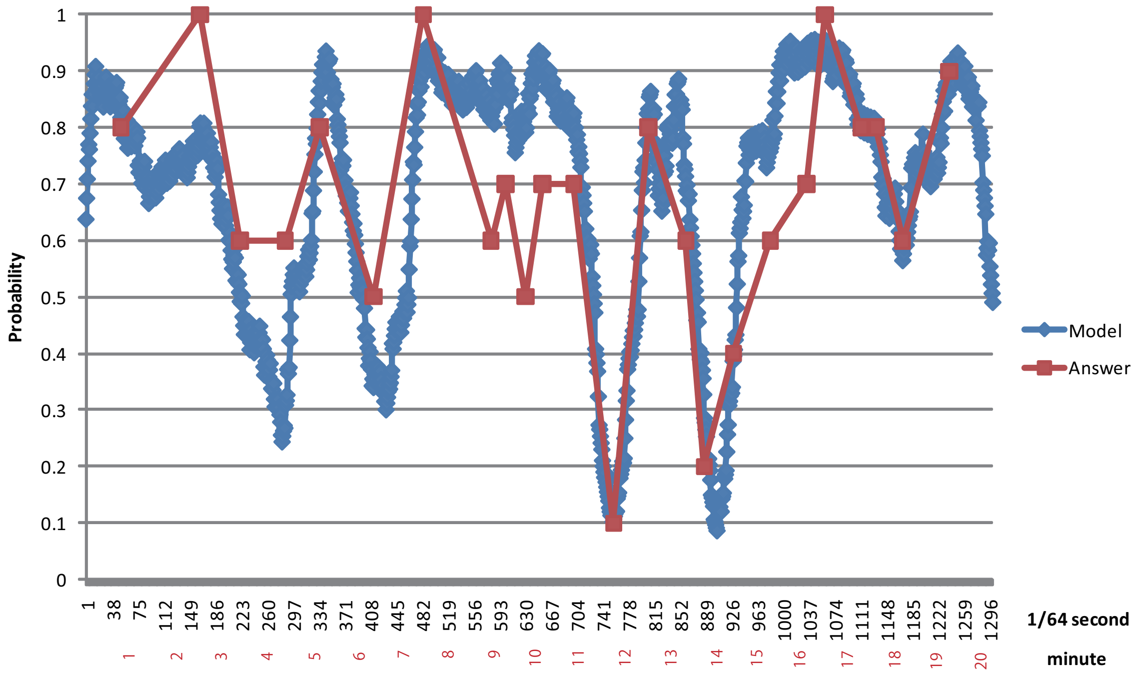

Figure 4.9. Answer and Model

From the graph, the transition of probability of interest calculated from the model and the actual interest is almost equally likely. The values the model calculated out is relatively high, because this was the first time for the subject to visit Jiyugaoka. The subject was thoroughly interested in the city of Jiyugaoka as a whole. The subject gradually slowed down when coming across something that interests her, such as a fortune-telling store, or cute children walking around. The probability of interest the model calculated is quite high because of this.

4.2. Field test of a person's walk (Hiyoshi)

We executed another field test of this model in Hiyoshi, on October 9th, 2009. We had the same female university student walk for 20 minutes in Hiyoshi.

To prove the difference between first-visit-site like Jiyugaoka and daily area, we also implemented a field test in area which the subject has familiarity, Hiyoshi in Yokohama of Kanagawa Prefecture, where the subject's university is located. We had her equipped with the device when going out of school for lunch. The test lasted for about 20 minutes, including the time for round trip between school and the restaurant.

We started the field test from our school, where she met her friend and had a short conversation. There is a signal in front of the school, which she was caught and stopped for about a minute. Then she started walking straight towards the restaurant that she wanted to go to, which took a couple of minutes. She looked around the restaurant, but decided to go by. When going past the restaurant, she stopped by a florist shop, which she had never found before, but somehow came upon her eyes. She stopped inside and looked at the flowers carefully, and finally decided to buy a bunch of flowers.

Figure 4.10is the graph predicted by the TTI model.

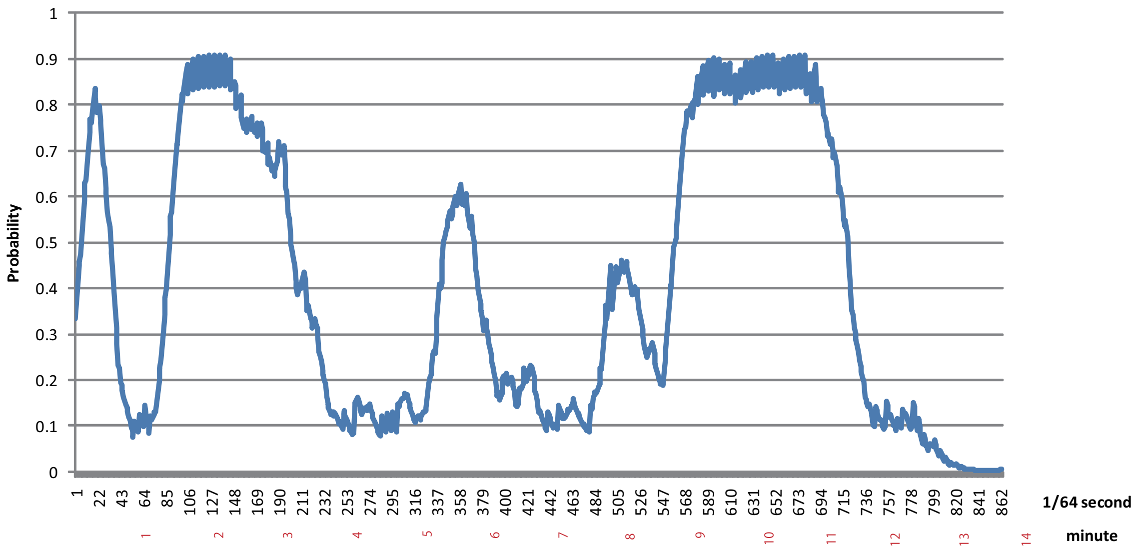

Figure 4.10. Graph predicted by TTI model of the field test

The model predicts relatively low probabilities of the Hiyoshi's interest, as is a city of her daily use, but still shows some places with relatively high probabilities. She did have some interest although considering the fact that Hiyoshi is her daily use, such as the florist shop and when she met up with her friend.

Figure 4.11 is the map of Hiyoshi expressing the actual path of her walk and the model's interest prediction mapped.

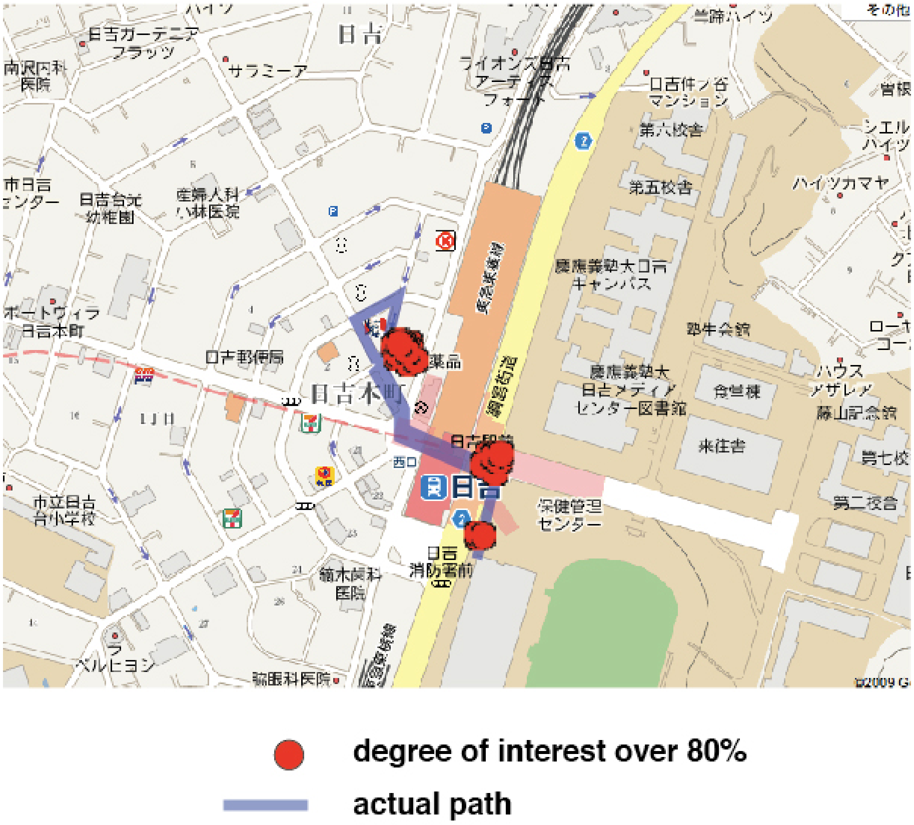

Figure 4.11. Map of Hiyoshi

In this field test, the values of the interest probability are thoroughly low due to the fact that the subject frequently has lunch at Hiyoshi and understands the area quite well, not so many new things interest her. Although this experiment was conducted within the subject's daily life, she serendipitously came across a florist shop, which she decided to drop in. This is expressed as the last mount in the graph. The second mount unfortunately is when the subject stopped at the traffic light.

The subject gradually lost speed when taking a look at the red light ahead, which made the model calculate the probability must be quite high. The probability of interest in a city which a person uses on a daily basis is thoroughly low, although some spots show comparatively high probabilities. Figure 4.12 is the analysis of the prediction of TTI model of this test.

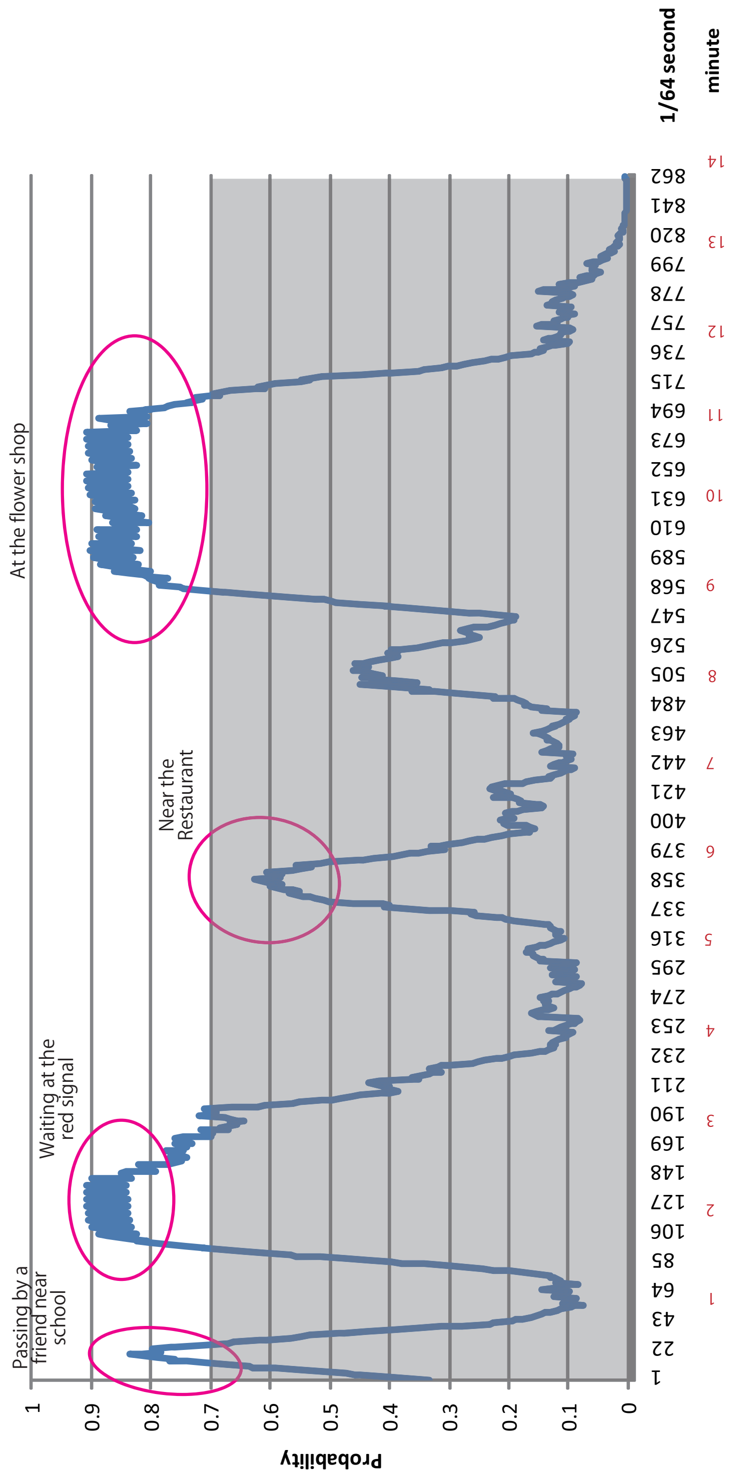

Figure 4.12. Analysis of Prediction of TTI Model

4.3. Summary of the Field tests

From the two field tests, it can be seen that it is possible to understand the person's real time interests within the city by just using the data collected from the sensor focusing on the speed of the walk. This can be said whether the person has never visited the place or the person goes to the place due to a daily use.

Of course there can be many improvements such as the fact that this model considers unfortunate stops too much so the probability at red lights are relatively too high. This could be fixed according to the fact that changing the links of the nodes of the model, or changing the inputs of the model itself. But the main aspect of this model will not change, which is the characteristic of the model's input is connected to the real world, no matter using what kind of sensors.

5. Future Works

5.1. Conclusion

In this paper, I have described Time Transient Interests' Model, a model understanding people's individual real time interest and what is going on right now in the city. Its aim is to encourage people living in daily routines to explore the city by providing customized information using everyday-activities in the city. TTI Model, based on Bayesian Networks, uses inputs connected with the real world and calculates the real time interest probability of a person.

Unfortunately, the model cannot eliminate the person's stop at red signals, or other unfortunate stops within the city. For the model's refinement, I would like to eliminate aspects of the stop of lights. I would also like to add aspects of the experience of a person towards to city as well by using decision networks and Bayesian networks for the next step.

5.2. Field test of many people's walk (Ebisu)

We have executed a test of the Sentio service with 20 university students in Ebisu, Tokyo. The following is the result of the interest probability tagged to the map of Ebisu, the Interest Predicted Map of Ebisu. The places that have a high tower is an area that people felt interest in, according to the TTI Model.

In the Sentio service, this data can be used to give to the GIP Model, a model predicting a person's place of interest by attaining daily activities within the city. GIP Model develops an interest map by using the probability calculated from TTI, and also clusters by using keywords of interest. It is possible to predict a place suited for the

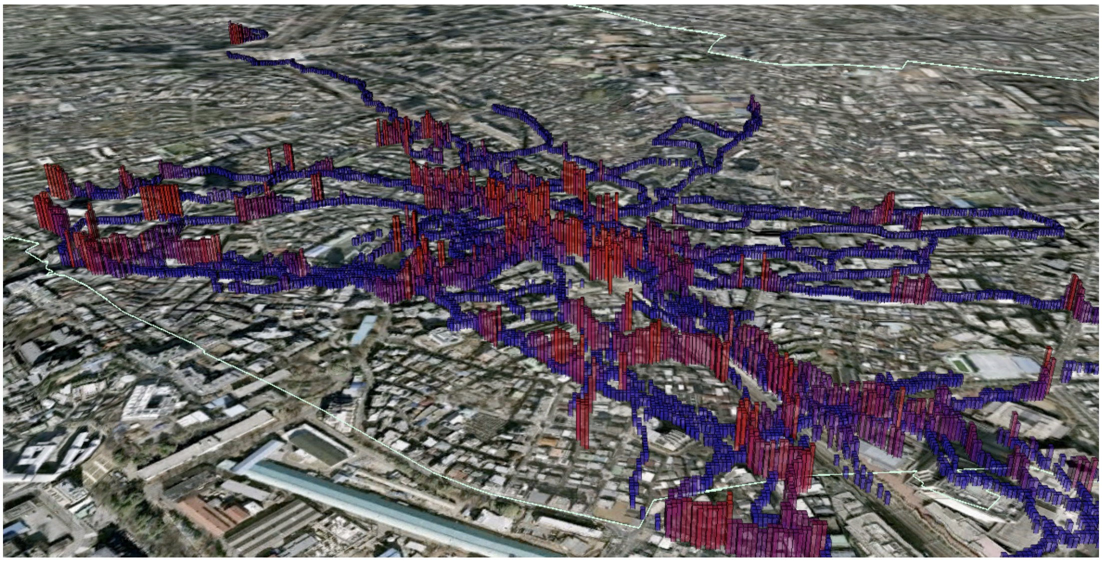

Figure 5.1. Ebisu Interest Map

user in the city. This can be used for understanding what place in the city people feel interested in, and to suggest what place the user should go to.

5.3. Future Works to model *City*

This model can be used for understanding what place in the city people feel interested in. If understanding what people's real interest, people can receive feedbacks about what they really like and want. People are moving individually within the city having their own feelings, interests, and purposes but current marketing theory only divides people into groups such as male/female or the age, which cannot afford people what they really want. People want something else besides marketing. When understanding a person, it would be possible to offer something more than regular marketing to understand a person to understand the city.

We plan to use this personal model to create a more public model which would enable the users of the time to categorize by not the static marketing data, but by using the real live data based on the real time activity. If the mathematical model of a crowd of any category can be made, we will be able to find out a trend or a style of the time very easily. The probability of place can be understood from TTI model gives you a new understanding of the city when just spending your daily life and keeping track of your real time data.

By modeling the relationship of people's interests and defining the factors, we can handle the time transition of people's interest. Eventually, I aim to model the feelings, lifestyle, personality, and what categories the user has interest in to model the city. This *Interest* node is updated as time goes by, when the Interest node reaches a certain point, the possibility of the place will be recommended to the user. The user can have a new point of view of the city by going to the place where this model recommends, for which this recommendation is based on the evidence of the user's daily activity. The experience of finding out your new favorite place which you would have never gone to without this can happen by collecting people's real time data of their interest using this model.

I believe the personal model and the city models can be used in the future for matching the right music to the right place, which I personally feel there is a need to change for the fact that the world now does not let that happen. As a pianist, I feel this model would be able to change the world of music in the recent years.

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番号	場所	時間 (video)	興味 (0ー1)	実験体として当時感じたこと	その後、分析として思ったこと
1	出発	0:08	0.8	ベンチが道の両側ではなく、真中にあるような散歩道を見るのは初めてだね。マリクレア通りって、雑誌と同じような名前を付けるのは何だろう	道の形、名前、なんでも初めてなので、興味がわいた
2	Marie Claire Avenue	1:55	1	ベンチに座っている親子はみんな幸せそうだね、天気もいいし。このようなところにいれば、お店がどんなものを売っているかはどうでもいい	かわいい子供とおしゃれな親子は結構興味のキーワードになりうる。けれど、照れくさくて、特に止まって見たりはしなかった
3	ナチュラル系のカレー屋	3:30	0.6	晴れた日に室外でカレーを食べるのは気持ちいいかな	町にオープンしている(室外の席があるか、窓ガラスから中が見えるか)食べ物屋は大体無意識に見ちゃう
4	マリクレア通りの端	6:38	0.6	特に入りたい店がないけど、もう一回このマリクレア通りの雰囲気を味わいたいなあ	ここでは理想な家族のシナリオが見えるような気がする
5	ベンチに座った	9:38	1	一人のかわいい子供がいる。親がそばにいないらしい。しばらく見てみたい	子供好き
6	跡付け	10:20	0.6	前見たおしゃれな子連れと再びあったので、しばらくつけてみたい	おしゃれな子連れ
7	小道に入ろう	10:34	0.7	ちょっと違う雰囲気の小道を見て、入ってみよう	
8	小道で歩く	10:34～	0.5	微妙な感じ	
9	駅前商店街の変なソロンの前	12:20	0.7	あやしそうなサロンみたいなお店、何なんだろう	
10	駅前商店街の古本屋	12:50	0.6	何となく古本屋に興味がある。外に出した本はほとんど料理関係。	
11	鉄道の下のトンネル	12:58～	0.1	暗くて、ただ早く抜けたい	
12	踏切りの前	15:06	0.8	踏切りをクロスすることは何となく楽しい	踏切り好き
13	踏切りの後	16:10	0.6	ビルの上でお茶を飲んでいるような二人の彫刻がのっている。ちょっと近づいて見たい	唐突なもの
14	ビルの下	16:30	0.2	車と人が混んでいて、先見えない気がして、戻ろうかな	混雑を避けたい
15	戻りの道	17:30	0.4	あるビルの上で天使のような彫刻をちらっと見た、特に何も思わなかった	唐突なもの
16	戻りの道	17:40	0.7	犬がベービーカーに乗っているのを見て、おもしろい	
17	壁にある絵	18:30	0.6	どっかの雑誌で見たことある気がするなあ、自由が丘ぽい絵だね	
18	自由が丘の歴史の写真	18:40	0.7	歴史に興味があるけど、近づいてみることができなくて、ちょっとがっかり	歴史的なもの
19	犬と同じ格好をしている飼い主	19:06	1	写真を撮ればいいのになあ。わざと「カッコいい」と声を出して言ったけど、相手は反応してくれなかった	ペットとカッコイイ飼い主 歴史の写真を見えなくてがっかりした途端、これを見て、Serendipityだと思う
20	Marie Claire Avenue	21:18	0.8	靴を脱いで、ベンチで囲まって座って、ハンドメードの弁当を食べている若い女性たち。くつろいでいる昼はいいな	ハンドメード弁当 くつろいでいる昼
21	トレインチの直前	22:01	0.8	曲がろうと思いきや、スズキがのっているあれを見て(町田と藤沢だけにあると思ってきた)、通すことにした	動物の形をした何か
22	トレインチ	22:30	0.6	ちょっとしたしゃれうつのところに見える。ちょっと見ても悪くない	
23	ベンチの下にいる犬	22:45	0.9	触りたいなあ。けれど飼い主がそばにいるので、何もない風をした	犬
24	インテリアお店の外	24:50:00	0.7	店に入る気が特にしないけど、ちょうどテーブルクロスを買いたいから、外にあるやつらをちょっと触って見た	ちょうど自分が買いたいことがある 家庭用品
25	線路の沿いで戻る	26:04:00	0.8	線路の沿いが何となく楽しいなあ	初めてな場所だし、地図を持っていないし、線路の沿いで歩くと、安全感がある。そして、何となくドラマチック的な感じもある
26	マリクレア通り				
27	先の天使があるビル	27:30:00	0.8	よく見たら、天使の間で「太極」があるなんて、何なんだろうと思って、実は占いだと発見。西洋と中国、キリストと仏、よくごまかしているね	
28	占い	27:45:00	0.9	せっかくだから、階段から覗きたくなる	
29	ポパイカメラ	31:54～	0.9	店の外の看板を見て、「子供カメラマン」展示も店内でやっているって、見たい	こども 写真 ちょうど自分も写真フレームを買いたい
30	店に入ったら	32:20:00	1	子供たちが撮った写真の中、ごみ箱の写真に「ロボット」の名前を付けた作品もあった。私と同じことを思ったね。	
31	どこかの裏路地	53:00:00	0.6	おしゃれそうな洋服屋	洋服
32	洋服屋の向こう	53:05:00		この竹、本物なの？都市ではちょっと珍しいかな？	都市である田舎ぽいものに意外と興味がある
33	ガーデングッズが多い店が集中している	*ここからは後半のビデオ* 6:25	0.8	時間があれば、ガーデンニングをやりたいなあ	日本的な理想のシナリオ
34	ベンチ	7:05	0.7	ちょっと座って休憩を取って、くつろいだ。壁でかわいい絵があるし、いいなあ	
35	ガーデングッズの店	8:50	0.7	ガーデンニングをやりたいなあ	日本的な理想のシナリオ
36	ハートの形をした葉っぱ	9:14	0.9	恋人などと一緒に発見したら、いいなあ、今は別にだけど	
37	テーブルクロス	9:30	0.6	かわいやつが見つかったら、買いたい。だけどなかったなあ	買いたいもの 家庭用品
38	すし屋の前	11:50	0.7	木製の道具を見て、好奇心がちょっと湧いた	見たことないもの
39	玩具屋	12:04	0.9	自分の子供をできたら。。。	おもちゃ好き、特に布製・糸製のやつ、次は木製
40	ゴミ袋を売る販売機	13:50	0.9	ゴミ袋も販売機で売るの？何で？	見たことないもの
41	「　　」がある「状元楼」	14:20	1	「　　」を打ちたい。打っちゃった。音が意外と大きかった。めっちゃ楽しかった！	中国ぽいもの
42	自由が丘デパート	12:54～	0.9	先のしゃれうつと比べて、ここは意外と古くて渋い感じがする。けれど、かなり面白いと思った。洋服屋の隣が魚やなんて	おしゃれなところにある意外と渋いもの
43	ひかり街	18:33～	0.7	自由が丘デパートを抜けて、また気が済まない、ひかり街もささっと通しちゃおう	
44	二階に上ったばかり	25:40:00	0.7	犬たちが道で混んでいる	
45	自由が丘デパート二階にある窓ロ	26:50:00	1	ここからものすごく近いとかろで電車が走っているなんて、なんかすごい！	雑誌で見たから、本物を見たい