ACTIVITY-BASED TRAVELER AGENT BEHAVIOURAL MODEL FOR MIXED TRAFFIC FLOW

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ABSTRACT

The modeling of traveler's daily travel behaviours in mixed traffic system is a complex problem, mainly due to the complex nature of travel behaviours and the situations in mixed traffic flow. This paper explores an Activity-Based Traveler Agent behavioural Model (A-TAM) for mixed traffic flow, combining the ideas of activity-based traffic demand model, the hierarchical structure in behaviours, agent approach and subjective utility optimisation method. In the case study, A-TAM has been applied to model cyclists' behaviour at unsignalised intersections under mixed traffic flow conditions, and the validation results of the cyclists' model which proved A-TAM promising.

INTRODUCTION

Recently traffic simulation technologies, especially microscopic traffic flow simulation models, have been widely used in many areas of urban traffic management and optimization. Yet most microscopic traffic simulation models are unable to realistically represent the urban traffic system with mixed traffic flows in developing countries such China, where bicycles, cars and pedestrians conflict frequently on urban roads and at intersections, especially at unsignalised ones. Due to the complex nature of travel behaviours and the situations in mixed traffic flow, the modeling of travelers daily travel behaviours in mixed traffic systems are a complex problem. However, new progress in computer science, traffic modeling and simulation have given inspiration to this problem, which are; agent approach in simulation, activity-based traffic demand model, microscopic behavioural models of different road users (driver, cyclist, pedestrian) and related behavioural studies in psychology and social science.

As Ralf Schleiffer (2002) points out that "intelligent agents ….their simple determinism is suitable to illustrate and to describe the dynamic structure of human behaviour with reference to traffic and transportation". Agent-based simulation appears to have the potential for modeling behaviours for different road users (driver, cyclist, pedestrian) in mixed traffic flow. Each road user could be modeled as an autonomous agent with its own knowledge and goals. For example, Dia (2002) gives a microscopic agent-based simulation of driver's route choice behaviour on real-time traffic information and Ronald and Sterling (2005) provides a BDI agent simulation model for pedestrians. Researchers also study the frame and structure for agent-based microscopic traffic flow simulation models (Sun, 2002; Yu, 2006). Hoogendoorn and Bovy (2004) proposed a route-choice and activity scheduling theory and model for pedestrians using hierarchical model framework and subjective utility maximisation theory. Beuck et al.(2007) reports on their recent case study of a multi-agent traffic simulation for real-world Berlin scenario, where they suggest the differentiate between the physical layer and the mental layer of a multi-agent simulation.

The purpose of our research is to build a general traveler agent behavioural model in mixed traffic system, as a behavioural model basis for developing an urban mixed traffic flow simulation model, with large-scale and great details (e.g. describing the conflictions of bicycles and motorcars at intersections). Thus the model has to cover human daily travel behaviours of all levels, from trip planning to specific moving (e.g. turning to avoid collision). A-TAM, the theoretical model we proposed here seems to meet all these requirements.

The paper first outlines the three-level model framework by analyzing a typical traveler's daily travel behaviour, and follows the descriptions of agent structure and behavioural models on each level. A case study in Beijing is presented, and ends with a discussion and brief conclusions.

MODEL FRAMEWORK

Followed are a typical travelers daily travel behaviours:

When a traveler α plans to go out, they must have at least one ***goal***. Accordingly at least one *activity i* is to take place at D_i with enough time T^i for achieving the

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goal(s). We assume that after all the travelers final destination is home (D_H), so D_i (i=1, 2…) and D_H form a "trip chain". Traveler α chooses and orders the activities *i* according to there preferences, goals, and information on road networks and thus forms a Trip Plan Activity (TPA), which includes the planned activities to be taken (*i*), their expected locations (D_i) and expected finish time T_i ($T_i \le T^i$), the traffic mode to the activity location D_i (M_i), trip route R and departure time T_O.

Above are traveler's pre-trip behaviours (trip planning), followed are in-route behaviours, including two major types: path finding and moving.

When α is in-route at a specific transport facility Ω (a link or intersection) during the trip, we assume that the traveler would make a list of **Expected Temporal Activities** (**ETA**) according to the specific traffic situations when finding a path in Ω. The **ETA** includes the ETA *j*, temporal destination TD_j (where ETA *j* taking place) and the expected finish time T_j. As the time for path finding process is very limited (usually a few seconds), and the vagueness of the traffic condition information, we assumed that the planned path is a polygon made of a series of *key points* (i.e. TD_j) between the original (α actual location) and destination. We can speculate that α may have an idea on when they will reach the *TDs*, while the actual moving process is up to the subconscious, i.e. the traveler moves to the *TD* automatically.

When α moves along the planned path, by the energy saving principle (Kölbl and Helbing, 2003), α usually tends to move directly from current position to the temporal destination TD_i, if there are no influences. Yet, sometimes unexpected situations appear, which would affect α's moving behaviour (i.e. unexpected conflicting), in A-TAM this unexpected conflicting is regarded as a special type of activity, called ***Unexpected Activity*** (**UA**), α would take ***Reaction*** (RA) to avoid the confliction, and at the same time try to adhere to the planned path as much as possible.

From the analysis on a typical traveler α 's behaviour, we can see that daily travel behaviours are comprehensive and consist of behaviours of different complexity. Psychologists suggest a classification of stimuli into simple or standard situations and complex or new situations (Helbing, 1995). Clearly, the trip planning and path finding behaviours are behaviours in complex or new situations, and the moving (including walking, driving, riding) and reactions to unexpected conflictions are of simple or standard ones. In their pedestrian behavioural model, Hoogendoorn and Bovy (2004) distinguished pedestrian's choices at three levels. Similarly, the traveler's daily travel behaviours are divided in three levels:

1) Strategic level: including decision making/adjustment of ***Trip Planned Activity*** (***TPA***, consist of destinations, route **R**, traffic modes and departure time) pre-trip or in-route;
2) Tactical level: including decision making/adjustment of ***Expected Temporal Activities*** (ETA) and thus the path **P** at facility Ω according to the traffic situation and **TPA**.
3) Operational level: including all moving (riding/driving/walking) behaviours (speed, accelerations), along the planned path **P** and Re-Actions (**RA**) to Unexpected Activity (**UA**).

In this hierarchy structure, expected utilities at lower levels influence choices at higher levels. Choices at higher levels condition choice sets at lower levels. In this way, A-TAM model cover nearly all daily travel behaviours (see **Fig.** 1): from decision making, on trip goal and activity, traffic mode, departure time and route choice, to path finding (or path choice) at a certain facility, and the concrete moving behaviours (moving speed, acceleration, turning). The agent attribute square covers the models of three levels, showing that the agent's attributes such as gender, age, preferences for traffic mode and routes, travel patterns, home location, goals, car ownership, income, perception of network would affect behavioural models of all levels. The subjective utility optimisation theory is used to model traveler's decision making (choice) behaviour, which has been applied in some travel behaviours.

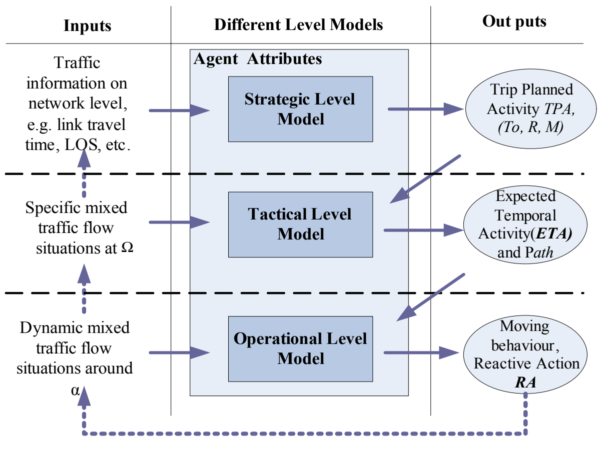

Fig. 1: Model Framework of A-TAM

By information feedback (dotted lines in **Fig**. 1), A-TAM model supports dynamic activity planning, route /path choice behaviours at strategic and tactical levels. Agent α could judge and update $ETA(t+\Delta T)$ and $Path(t+\Delta T)$ according to the changed traffic situations in Ω at an internal of ΔT. Similarly, α could judge and update there $TPA(t+\Delta T_s)$ according to the latest network traffic information, such as travel time (T_Ω) and Level-of-Service (LOS_Ω) of the facility Ω.

MODEL DESCRIPTION

Intelligent Agent Architectures

The inspiration of the agent architectures proposed in this study stems from earlier research work by Dia (2002). The agents possess a mental state which is composed of various mental elements; beliefs, capabilities, commitments, and behavioural and commitment rules and a physical state which is composed of related attributes, dynamic situation and perceptions as shown in Fig. 2.

Beliefs: Belief is a fundamental part of the agent's mental model. For the purpose of traveler behavioural models, these beliefs will include information about the travelers travel patterns, preferences for routes, perceptions of the situations on network and around other travelers travel behaviours.

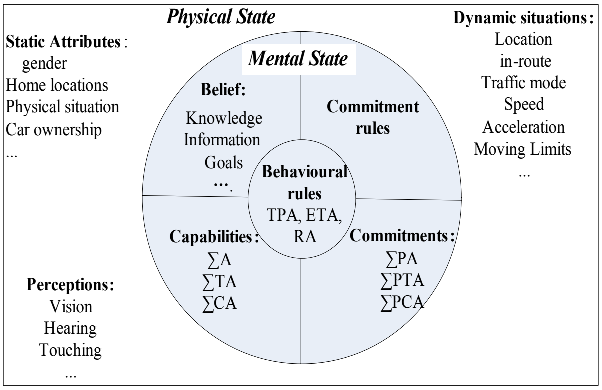

Fig.2: Intelligent Travel Agent Model

Capabilities: A capability is a construction used by the agent to associate an action with that actions necessary pre-conditions. For the purpose of traveler's behavioural models, capabilities represent the activity sets that the traveler can perform, presented as Activity set ∑A, Temporal Activity set ∑TA and Conflicting Activity set ∑PCA for each level model.

Commitments and commitment rules: A commitment is an agreement to attempt a particular activity at a particular time, if the necessary pre-conditions for that activity are satisfactory at that time. For the purpose of traveler behavioural models, commitments represent the plausible activity sets meeting certain conditions, presented as Plausible Activity set ∑PA , Plausible Temporal Activity set ∑PTA and Potential Conflicting Activity set ∑PCA.

Behavioural rules: If the behavioural rules conditions are satisfied by the environment, then the rule is applicable and the action it specifies are performed. For the purpose of traveler behavioural models, actions represent the model outputs of different levels, presented as **TPA**(t) (Trip Planned Activity), **ETA**(t) (Expected Temporal Activity) and **RA**(t) (ReAction), which are all time dependent vectors.

Static attributes: Static attributes refer to the attributes such as gender, home location D_H (also O_H), physical situation, car ownership, etc. which will be unchanged in A-TAM, and the **Dynamic attributes** refer to the changeable variables such as location, in-route state, traffic mode, moving speed, acceleration, moving limits etc. Agents attributes (static and dynamic) would influence it's travel behaviours.

Perceptions: Perception is the information obtaining and filter function module, which determines what information of the environment reaches agents beliefs.

Strategic Level Model

Fig. 3 shows the model structure on the strategic level. The inputs of model on strategic levels include environment information as network situation. The activity choice set **∑A** is not an ordered set however, some activity could be order dependent, for example, if the happening activity *i* is the pre-condition of activity *j* , when *i* didn't happen, then *j* could not happen. Thus the activities sets meeting this order dependency form plausible activity set **∑PA**. The model outputs are *ordered vector sets* Trip Planned Activity $TPA=\{(i,D_i,T_i,M_i)\}_{T_O,i\in\sum PA}$, $i=1,2\ldots k$, where *k* is the activity number of TPA, and route $R=\{\Omega_j\}$, j＝1，2…m, where *m* is the facility number in R, obviously $R=\{\Omega_j\}$ must form a continuous route on network. The agent applied subjective utility optimisation as its behavioural rules in this model.

Note that on a strategic level, position variables referred to traffic facilities, e.g. $x(T_{i-1})$ could be facility Ω_j. And the current and near future location of α and the network traffic situations would affect **TPA** simultaneously. Meaning, the chosen route **R** and TPA are co-dependent, they will determine and affect each other, so we hypothesise, α makes a combined decision on **TPA** and **R** minimising the expected disutility or cost C:

$$C\ (\{(i,D_i,T_i,M_i)\}_{T_O,i\in\sum PA},R)$$
$$=\sum_{i\in\sum PA}C_i(D_i,T_i,M_i,R,x(T_{i-1}))$$
$$\text{s.t. } \vec{x}(T_O)=O\ ,\ T_i\le T^i \qquad (1)$$

Where $\vec{x}(T_O)=O$ is the agent departure time boundary condition, and $T_i \le T^i$ is the time condition of activity i; $C_i(D_i,T_i,M_i,R,x(T_{i-1}))$ stands for the combination of travel cost from $x(T_{i-1})$ the place where the activity finished (i-1) to D_i and $\phi_i(T_i)$ the utility of activity i:

$$C_i(D_i,T_i,M_i,R,x(T_{i-1})) = \sum_{\Omega\in R_i}[T_\Omega(M_i,T_{i-1})+F_\Omega(M_i,T_{i-1})]+\phi_i(T_i) \qquad (2)$$

Where $T_\Omega(M_i,T_{i-1})$ and $F_\Omega(M_i,T_{i-1})$ are the travel time and fare at Ω of route R_i (the route from D_{i-1} to D_i) at T_{i-1} via traffic mode M_i).
Optimising subjective utility/cost function C, the model output is:

$$\{\{i\}^*,\{T_i\}_{i\in\sum PA}{}^*,\{M_i\}_{i\in\sum PA}{}^*,R^*,T_O\} = \arg\min C\ (\{(i,D_i,T_i,M_i)\}_{T_O,i\in\sum PA},R) \qquad (3)$$

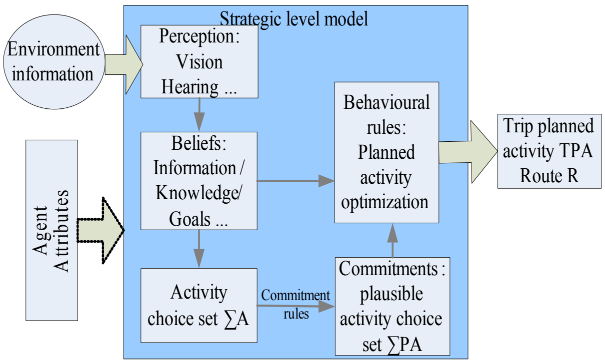

Fig. 3 Model on Strategic Level

Tactical Level Model

Fig. 4 shows the model structure on the tactical level. On this level the path finding behaviour is also activity based, except for the activity type is temporal activity, similar to the strategic level model, the temporal activity choice set is ∑TA and the plausible temporal activity choice set **∑PTA**. The model inputs are the outputs of strategic level model and the dynamic traffic situations in Ω. The model outputs include ordered vector set. Expected Temporal Activity $ETA=\{(j,TD_j,T_j)\}_{j\in\sum PTA}$, j=1,2…$n$, where n is the activity number in **ETA**, and path $P=\{(TD_j,T_j)\}$ stands for the ordered pairs of the location and time of j.

Note that possible influence factors of **ETA** include the current and near future location of α and the dynamic specific mixed traffic situations at Ω. That means, the planned path **P** and **ETA** are co-dependent, they will determine and affect each other, so we hypothesise α makes a simultaneous decision on **ETA** and **P** minimising the expected disutility or cost **C**. On this level, positioned variables are two dimensional vectors with an accuracy of about 1 meter in the special coordination of Ω.

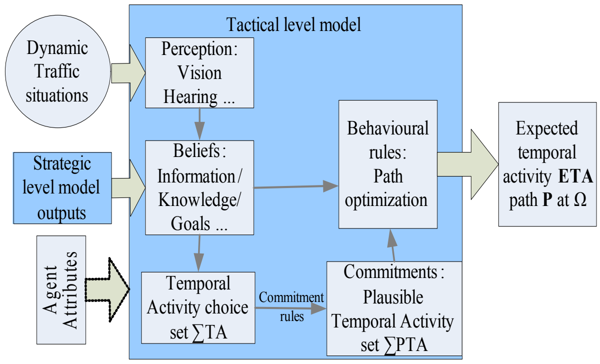

Fig. 4 Model on Tactical Level

The combined subjective disutility/cost **C** of **ETA** and path **P** is:

$$C\ (\{(j,TD_j,T_j)\}_{j\in\sum PTA},P) = \sum_{j\in\sum PTA} C_j(TD_j,T_j,\vec{x}(T_{j-1}))$$
$$\text{s.t. } \vec{x}(t_o)=\vec{x}_0,\ \vec{x}(\tau)\in\Omega\big|t_0\le\tau\le t_1 \qquad (4)$$

Where the first condition stands for the initial location of agent α; the second condition is the agents moving scope. C_j stands for the sum of travel cost moving from $\vec{x}(T_{j-1})$ to TD_j and the benefit of j.

Operational Level Model

The operational level model in A-TAM describes traveler's reaction level behaviours, such as the car following behaviour when driving a car which are usually rather automatic and taking place in a very short time (a few seconds or less). The *Social Force model* (Helbing, 1995, 1997) which stems from the famous *Social Field Theory* (Lewin, 1951) in psychology is adopted to describe the agent's operational level behaviour, moving (driving/walking/riding) alone, the planned path and conflicting avoidance behaviours. The *Social Field Theory* proposes that human behaviour is the function of both the person and the environment, expressed in symbolic terms as:

$$Behaviour=f(Person,Environments) \qquad (5)$$

This means that the individual's behaviour is related both to the individual's personal characteristics and the social situation in which the individual finds themselves in. The Social Force model (SF model) has been applied in the pedestrian dynamic behaviours and gained good results in the last decade (Helbing, 1995, 1997; Lakoba et al., 2005).

The A-TAM social force model includes three function modules (see Fig. 5): **Intended motion**; describes agent's intention of trying to get to the nearest temporal destination TD_j at T_j as planned in the tactical level model. **Effective field;** with the traffic situation nearby perceived by **Perception;** module as effective influence source (exerting tensions) and, **Balance** module; synthesising and balancing all the tensions "social force" from the TD_j and effective objects from the above two modules puts out the reaction RA.

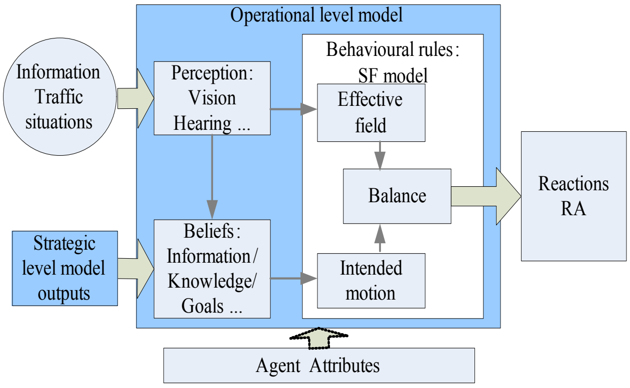

Fig. 5 Model on Operational Level

The SF model for the behaviour of individuals under the influence of a social field shows some analogies with the physical model for the behaviour of electrons in an electric field (e.g. of an atomic nucleus), and the SF model is generally formulated as:

$$\frac{d\vec{x}}{dt} \approx \vec{F}_\alpha(\vec{x},t) + \xi \qquad (6)$$

with $\vec{F}_\alpha(\vec{x},t) = -\nabla \vec{w}_\alpha(\vec{x},t)$ (7)

Where $\frac{d\vec{x}}{dt}$ denotes the change rate of individual behaviour $\vec{x}$, and the fluctuation term ξ describes individual behavioural variations, the vectorial Quantity $\vec{F}_a(\vec{x},t)$, drives the systematic change of the behaviour $\vec{x}(t)$ of individuals α. $\vec{F}_a(\vec{x},t)$ is denoted as social force acting on α. The potential $\vec{w}_\alpha(\vec{x},t)$ can be understood as *social field*, and the social force $\vec{F}_a(\vec{x},t)$ is given by its derivative (by its gradient ∇).

Clearly, the force $\vec{F}_a(\vec{x},t)$ must represent the effects of the environment on the behaviour of α. However, the social force is not exerted by the environment on the traveler's physical body. It is rather a quantity that describes the concrete *motivation* to act. In the case of the cyclist riding or drivers driving or pedestrians walking behaviour, this motivation evokes the physical production of an acceleration or deceleration force as a reaction to the perceived information that the traveler obtains about there environment.

CASE STUDY

Huang and Wu (2007) studied the cyclists microscopic travel behaviour at unsignalised intersections in mixed traffic flow in Beijing, by applying parts of the A-TAM model framework (the tactical and operational level models). In this case, the cyclists Temporal Activity **TA** is defined as "avoid conflicting objects" (motorcars, bicycles, pedestrian or obstacles). Clearly, the cyclist planned path **P** would influence the **TA**. In order to construct a reliable subjective utility function for the tactical level model, stated preference (SP) data where collected in Beijing, interviewing approximately 1000 Beijing cyclists to obtain influence factors and their preferences in path finding behaviours at unsignalised intersections. Video data was collected at two typical unsignalised intersections (cross and three leg), and an image capture software *VSpeed* (Bai, 2005) calibrated via Differential Global Position System (DGPS), data was used to capture dynamic motion data of all moving objects (motorcars, bicycles, pedestrians) at the intersections see (Fig 6).

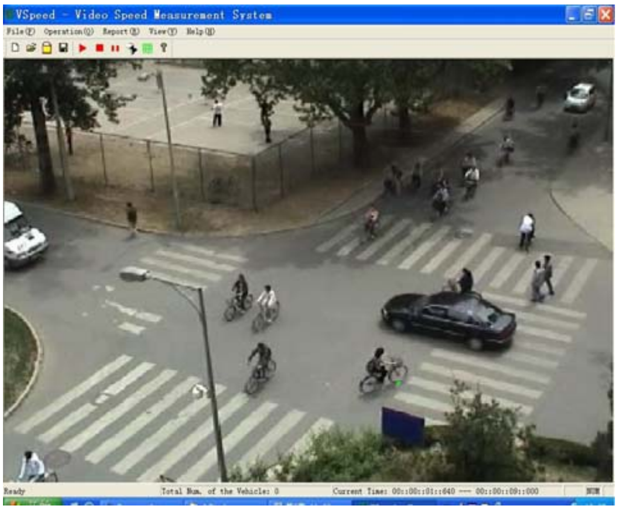

Fig. 6: Dynamic Data Capture

Data collected from over 100 conflicting cases were used in the model validation, including simple circumstances (with one conflicting motorcar/pedestrian/bicycle) and complex situations (with two or more conflicting motorcars/pedestrians/bicycles). Validated items are bicycle (agent) accelerations, speeds and positions. The general model validation results are presented in Fig. 7, proving the proposed model is promising in describing the cyclists crossing behaviour at unsignalised intersections. Further details in one of the case studies refers to the paper of L. Huang and J.Wu (2007) listed below.

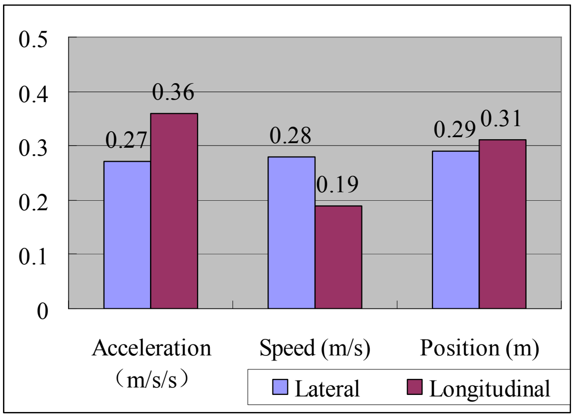

Fig. 7: Average Difference between the Model Outputs and Empirical Data

CONCLUSIONS

In this paper, we propose an Activity based Traveler Agent behaviour Model for mixed traffic flow, A-TAM. The hierarchical model framework and activity-based travel behaviour modeling ensure A-TAM could reasonably describe most daily travel behaviours, from trip planning to a specific moving behaviour. The application of agent approach and subjective utility method also enhance its modeling potential. The case study in Beijing of cyclist's behaviour simulation in mixed traffic flow at unsignalised intersections proved the A-TAM promising in describing cyclist's behaviours in mixed traffic flow.

A-TAM proposed here is an attempt on general travel behavioural model for urban mixed traffic flow simulation, yet there seems much work to do in specifying the model of all levels and the model framework itself.

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